Dynamic Anchorage Planning

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by

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degree of Master of Science

in

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İSTANBUL ŞEHİR UNIVERSITY

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science in Industrial and Systems Engineering.

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“ Equipped with his five senses, man explores the universe around him and calls the adventure Science. ”

Edwin Powell Hubble

Dynamic Anchorage Planning

Bahman MADADI

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. In this study, we present a simulation-based dynamic multi-objective anchorage planning strategy where we incorporate a time dimension by simultaneous modeling vessel arrival and departures. We consider utilization, safety, and fuel consumption performance metrics in a normalized weighted sum scheme as the objective function. 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) method for identifying the linear combination of the planning metrics that optimizes the desired linear combination of the performance metrics. We present computational experiments on a major Istanbul Straight anchorage as well as synthetic anchorages. Our results indicate that our methodology significantly outperforms current state-of-the-art anchorage planning algorithms in the literature.

Keywords: Simulation, stochastic optimization, multi-objective optimization, anchorage planning

Dinamik Ankraj Planlaması

Bahman MADADI

Öz

Deniz ticaretindeki küreselleşme ve sonrasındaki artış, dünyadaki ankraj alanlarının etkin bir şekilde planlanması ve yönetimini gerekli(zorunlu) hale getirmiştir. Bu alanlar ticari gemilere geçit ya da liman için bekleme, yakıt hizmetleri ya da kötü hava koşulları gibi çeşitli nedenlerle geçici konaklama alanı olarak hizmet vermektedir. Bu çalışmada biz, gemilerin geliş gidişlerinin eş zamanlı modellemesi ile bir zaman boyutu içeren simülasyon-tabanlı dinamik çok amaçlı ankraj alanı planlama stratejisi sunuyoruz. Faydalanma oranı, güvenlik ve yakıt tüketim performans metriklerinin normalize ağğırlıklı toplamlarını amaç fonksiyonu olarak değerlendiriyoruz. Gelen gemi için gerçek zamanlı olarak ölçülerek oluşturulan planlama ölçümlerin herhangi bir kombinasyonun durağan durumda ölçülen amaç fonksiyonu üzerindeki etkisini ölçmek için Monte Carlo Simülasyonlarını kullandık. Performans ölçümlerinin istenen doğrusal kombinasyonun optimizasyonu olan, planlanan ölçümlerin doğrusal kombinasyonunu tanımlamak için Eşzamanlı Pertürbasyon Stokastik Yaklaşımı (EPSY) metoduna başvurduk. çalışmamızda, Ä°stanbul Boğaz Ankrajı yanısıra yapay ankraj üzerinde hesaba dayalı deneyler sunuyoruz. Sonuçlarımız, metodolojimizin literatürdeki mevcut en gelişmiş ankraj planlaması algoritmalarından önemli ölçüde daha iyi olduğunu göstermektedir.

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Finally, I would like to thank my sister for all her support throughout my life, specially, during my studies.

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Abbreviations

RAIL	**R**ealized **A**rrival **I**ntersection **L**ength
PDIL	**P**rojected **D**eparture **I**ntersection **L**ength
NDE	**N**ormalized **D**istance to **E**ntry
DRAIL	**D**ynamic **R**ealized **A**rrival **I**ntersection **L**ength
DPDIL	**D**ynamic **P**rojected **D**eparture **I**ntersection **L**ength
DNDE	**D**ynamic **N**ormalized **D**istance to **E**ntry
DFS	**D**ynamic **F**used **S**afety

Symbols

Symbol	Name	Unit
m_1	Realized Arrival Intersection Length	-
m_2	Projected Departure Intersection Length	-
m_3	Normalized Distance to Entry	-
m_4	Dynamic Realized Arrival Intersection Length	-
m_5	Dynamic Projected Departure Intersection Length	-
m_6	Dynamic Normalized Distance to Entry	-
m_7	Dynamic Fused Safety	-
U	Dynamic Area Utilization	%
D	Average Distance Traveled	meter
S	Safety	meter
S^a	Arrival Intersection Length	meter
S^d	Departure Intersection Length	meter
$a()$	Anchor Circle Area	meter squared
a^t	Anchorage Area	meter squared
d	Duration	day
d^t	Total Duration (Simulation Time)	day
d^e	Distance to Entry	meter
n^a	Number of Arrivals	-
n^d	Number of Departures	-

Chapter 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, growing 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 in land. One of the efficient measures in dealing with maritime traffic is facilitating anchorage areas, which tremendously contribute to alleviating traffic congestion just as parking lots do for land. Furthermore, anchorages provide essential services to vessels such as serving as a shelter from extreme weather conditions, loading/unloading of cargo and, land services like fueling, legal issues, and repair [1]. 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 of and planning for different anchorage areas may call for different considerations, it is appropriate to examine closely a real case in order to gain some insight into the issues that we may encounter while dealing with anchorages. One of the busiest and most congested restricted 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 plays a critical role in the overall performance and safety of international maritime traffic in the Strait.

An essential part of anchorage planning is determining the optimal berth location of vessels inside the anchorage area. 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, safety, as a vital issue in maritime traffic, has not received proper attention in the literature. Specially, packing ships as dense as possible for the purpose of maximizing utilization can potentially increase the risk of accidents. Thus, safety and utilization must be considered simultaneously when determining the optimal arrangement of vessels inside anchorages. Moreover, minimizing the distance traveled and hence the fuel costs should be incorporated into the anchorage planning problem, which has the additional benefit of reducing the vessels' detrimental environmental impacts.

Previous research on anchorage planning has traditionally approached the problem as a static disk packing problem without accounting for the time dimension, which is not very realistic. The problem of anchorage planning is clearly a dynamic one as vessels arrive and depart around the clock inside an anchorage. In reality, the starting point is not an empty anchorage area and the problem is not solved when the anchorage area becomes full, which is the case in static planning strategies. In comparison, our approach takes into account both vessel arrivals and departures in real time and our simulation does not end even if the anchorage reaches its full capacity.

An appropriate approach to model 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, in this study, we transform the hitherto static problem of anchorage planning into a dynamic one by incorporating the time dimension along with a comprehensive steady-state analysis. In particular, we conduct a steady-state analysis to define the optimal warm-up period and the optimal 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 consistent with empirical data. For an incoming vessel, it is assumed that its anchorage duration is known at the time of the arrival for planning purposes. On the other hand, we assume exact arrival times of subsequent incoming vessels are not known, which is generally the case in practice.

In this study, we consider a multi-objective optimization strategy with three objectives: maximizing utilization and safety, and minimizing fuel costs. In order to measure these three objectives, we introduce four performance metrics that are measured over a particular period of time, once the Monte Carlo simulation reaches steady-state. These performance metrics are (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 fuel costs, 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 normalized weighted sum scheme. 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. The static planning metrics we consider are distance traveled, realized AIL, and projected DIL. The dynamic planning metrics are defined as the static metrics multiplied by the anchorage duration. For corner point evaluation, we assume a linear combination of both the static and dynamic planning metrics.

It is critical to note performance metrics are measured in steady-state for the entire anchorage whereas the planning metrics are measured in real-time for each candidate corner point for each incoming vessel. Thus, we need a methodology to determine the optimal coefficient of each planning metric (for picking the best corner point for an incoming vessel) that optimizes the objective function, i.e., weighted sum of the performance metrics. On the other hand, the impact of a planning metric on the objective function is not explicitly known. In addition, the objectives of utilization, safety, and fuel consumption 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 a fuel consumption 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 for optimization of a desired weighted sum of the performance metrics 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 particular, SPSA does not require detailed modeling information between the objective function and the variables to be optimized, and it formally accounts for the noise in function measurements. It should be noted that incorporation of a time dimension, and utilization of an appropriate stochastic optimization method for identification of the most appropriate berth location are the first of their kind in the anchorage planning literature, which we believe to be major contributions to this field.

Subsequent sections of this article are as follows: Section 2 presents a detailed description of the anchorage planning problem and its development from the general disk packing problem. Section 3 introduces the performance metrics designated to measure the achievement of the optimization objectives. 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 the computational results and comparisons against the current state-of-the-art approaches in the literature on the Ahırkapı anchorage as well as synthetic anchorages. Section 8 presents a summary and our concluding remarks.

Chapter 2

Problem Description and Literature Review

Anchorages operate year around with vessels arriving and departing around the clock. From a modeling stand point, they are spaces in the sea next to the shore with the shape of Multilateral. 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 to the minimum level in order to reduce the risk of accidents.

Despite the fact that a vessel anchors in 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 2.1. Excluding extreme environmental conditions resulting in anchor displacement, the vessel will stay inside the corresponding safety zone which is the above-mentioned circle throughout its stay.

The size of the safe anchor circle depends on the length of the vessel and its anchor chain as well as the depth of the sea in a particular location. Danton [2] defines the optimal anchor chain length as $25\sqrt{D}$, where D is the sea depth and L is the vessel length. With respect to Pythagorean theorem, the anchor circle radius is given as:

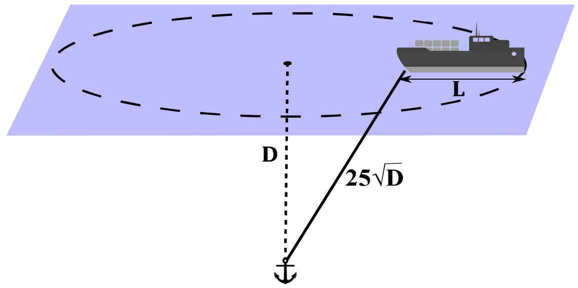


FIGURE 2.1: Illustration of anchor circle associated with an anchored vessel.

$$r = L + \sqrt{(25\sqrt{D})^2 - D^2}. \tag{2.1}$$

To avoid possible collisions between vessels, overlap between their safe zones which are their anchor circles, must be averted. Accordingly, the problem of disk-packing for disks with identical radii can be considered as the corresponding mathematical problem to the problem of capacity planning for anchorage areas. A recognized problem relevant to filling a quadrilateral area with equiradial disks is the NP-Hard circular open dimension problem (CODP) [3]. Huang et al. [4] attempted to evaluate anchorage capacity which they defined as the ratio of area occupied by vessels when the anchorage area reaches its full capacity multiplied by the duration for which the anchorage area is full to the total area. Utilizing Monte Carlo simulations, the authors benchmarked the performance of their suggested algorithms against common algorithms in the literature and demonstrated outstanding performance. Huang et al. [5] make use of MHDF and WALLPACK-MHDF algorithms which were proposed by [4] in a sea-born traffic simulation study.

Oz et al. [1] proposed a multi-objective optimization method accounting for safety and utilization using a simulation tool and achieved significant improvement in safety while maintaining the same utilization level as competing methods. Although they recognized vessels take a path to reach their berth locations and measured the risk involved in undertaking this path on arrivals and departures, they did not consider any temporal aspects of the problem. Moreover, in this particular study, the simulations start with an empty anchorage and terminate as soon as the anchorage reaches its full capacity with no ships departing the anchorage during the simulation.

It appears there are currently no studies in the literature treating the anchorage planning problem as a dynamic one with a time dimension and attempting to conduct a steady-state analysis. Furthermore, the fact that maximizing utilization is not the sole objective in anchorage planning is only recognized in Oz et al. [1] where the authors incorporated safety but it certainly calls for more contemplation and further development. Specifically, considering the notions of utilization and safety are contradictory in nature, maximizing utilization requires arranging vessels adjacent to each other and/or anchorage area boundaries as compact as possible whereas maximizing safety dictates arrangements with minimal overlap. In addition, incorporating distance considerations further complicates the problem by adding new constraints and places it far away from the traditional disk-packing problem.

In this study, we attempt to tackle the anchorage planning problem with all the aforementioned considerations. Our optimization method is compared with algorithms introduced by Oz et al. [1] and Huang et al. [4] which we consider to be state-of-the-art to the day. It should be noted that while our approach is more suitable for daily anchorage planning tasks, we believe both Oz et al. [1] and Huang et al. [4] 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.

Chapter 3

Performance Metrics

In this section, we present the performance metrics intended to measure the objectives of safety, distance traveled (in lieu of fuel costs), and utilization. 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 safety. Performance metrics and related parameters are listed in Table 3.1.

TABLE 3.1: Performance metrics and related parameters

Performance Metric	Unit	Notation
Dynamic Area Utilization	%	U
Average Distance Traveled	meter	D
Safety	meter	S
AIL	meter	S^a
DIL	meter	S^d
Anchor Circle for Vessel i	-	c_i
Anchor Circle Area	meter squared	$a()$
Anchorage Area	meter squared	a^t
Duration	day	d
Total Duration (Simulation Time)	day	d^t
Distance to Entry	meter	d^e
Number of Arrivals	#	n^a
Number of Departures	#	n^d

3.1 Dynamic Area Utilization

The *dynamic area utilization* metric attempts to provide an estimate of area under the curve for the total space occupied by all vessels throughout the simulation.

We define the dynamic anchorage area utilization U as the ratio of summation of anchorage circle areas, each one weighted by its anchor duration, to the total anchorage area weighted by the total simulation time as:

$$U = \frac{\sum_{i=1}^{N} a(c_i) \times d_i}{a^t \times d^t} \tag{3.1}$$

where N denotes the total number of arrivals in the simulation, $a(c_i)$ is the area of the i-th anchor circle (associated with the i-th vessel), d_i is the anchor duration of the i-th vessel and, a^t and d^t denote the anchorage area and total simulation time respectively.

3.2 Average Distance to Entry

The *average distance to entry* metric attempts to measure the distance vessels travel inside the anchorage while arriving to and departing from their berth locations. 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 3.1. Since vessels are required to choose a direct path inside the anchorage upon arrival and departure, two times distance to entry will yield the distance traveled for each ship. Subsequently, *average distance traveled* is the total distance traveled by all vessels divided by the number of ships. Distance to entry is denoted by d^e and average distance traveled is denoted by D.

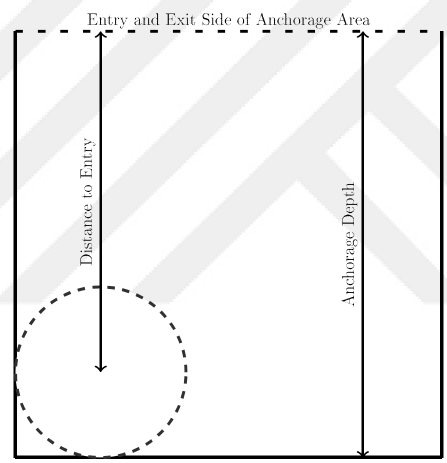


FIGURE 3.1: Distance to entry for a berth location

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 S_i^a, is defined as the summation of distances it travels inside other vessels' anchor circles until it arrives at its berth location. Average anchor AIL, denoted by $\overline{S^a}$, is defined as the sum of arrival intersection lengths for all vessels divided by the total number of vessels in the simulation, i.e.,

$$\overline{S^a} = \sum_{i=1}^{N} S_i^a / n^a. \tag{3.2}$$

Although vessels can, in fact, navigate through other vessels' anchor circle, there is a certain level of risk associated with this passage, specially since the exact location of vessels inside the anchor circle is uncertain, even under normal environmental conditions and the danger they incur is likely to be greater with longer intersections. After all, most accidents occur when ships get too close to each other. Oz et al. [1] put forth a safety metric pertaining to the number of intersecting vessels on arrival path. While crossing the least number of vessels' safety zone may seem a valid concern, we argue the distance traveled inside other safety zones is a more plausible criterion. In Figure 3.2 five different arrival paths are indicated with doted 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.

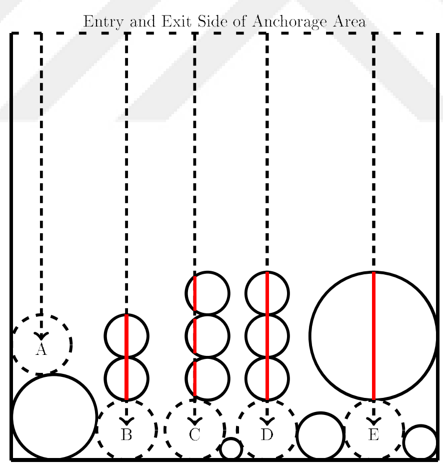


Figure 3.2: Different anchor paths with different arrival intersection values

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)* 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 S^d and n^d denote DIL and number of departures respectively:

$$\overline{S^d} = \sum_{i=1}^{N} S_i^d / n^d. \tag{3.3}$$

3.5 The Multi-Objective Model

With respect to the performance metrics described above, the objective function is defined as

$$L := W_S \times S + W_U \times U + W_D \times (1 - D). \tag{3.4}$$

In this equation, $S := (\overline{S^a} + \overline{S^d})/2$ and D is normalized by dividing by twice the anchorage depth which is the maximum possible distance traveled by any vessel. Here, W_S, W_U and W_D are weights for each one of the safety, distance, and utilization objectives respectively with $W_S + W_U + W_D = 1$ and $0 \leq W_S, W_U, W_D \leq 1$. It is assumed these weights are specified as seen appropriate by the anchorage planners per their priorities with respect to each objective. These three weights shall be denoted by the vector $\boldsymbol{W} := (W_S, W_U, W_D)$. We note all three objectives are normalized to assume values between zero and one and, since we are minimizing S and D, the term $1 - U$ is used to define a minimization problem.

Chapter 4

Berth Location Optimization

There are three steps involved in choosing an appropriate berth location for an incoming vessel in anchorage planning in general: identifying candidate berth locations, evaluating these candidates, and finding the best berth location. In what follows, we explain these steps in detail and discuss the planning metrics used in the berth location optimization process, which is illustrated in Figure 4.1.

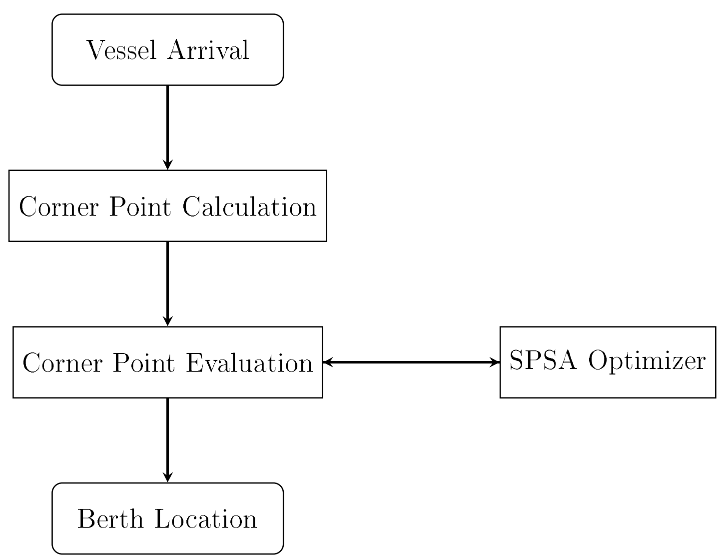


FIGURE 4.1: The berth location optimization process

4.1 Corner Point Calculation

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, a corner point CP_i for anchor circle i is specified as the point where the circle is tangent to at least two items among the anchorage boundaries and currently existing anchor circles assuming its center is at CP_i Huang et al. [6]. Corner points are classified into three types according to the items they are tangent to. *Side-and-Side (SS)* corner points are the center of the circles whose sides contact two sides of the anchorage area. *Side-and-Circle (SC)* corner points are the center of the circles contacting (but not overlapping) an existing anchor circle and a side of the anchorage area. The third is *Circle-and-Circle (CC)* corner points, which are the centers of the circles contacting two anchor circles (without overlapping). These three types are depicted in Figure 4.2. 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.

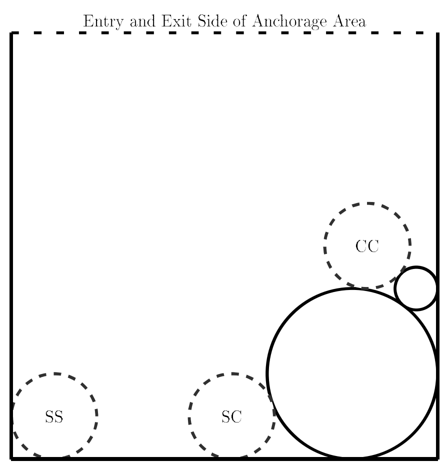


FIGURE 4.2: Three types of corner points in an anchorage

4.2 Corner Point Evaluation

Previous work on anchorage planning typically define 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. [4] suggests *hole degree*, denoted by H, as the criterion for determining the optimum berth location (illustrated in Figure 4.3). For an anchor circle i, H_i is defined as:

$$H_i = 1 - \frac{d_{min}}{r_i} \tag{4.1}$$

where r_i is the radius of CP_i and d_{min} is the minimum distance from CP_i to the closest item excluding the two contacting items. The Maximum Hole-Degree (MHDF) Algorithm of Huang et al. [4] 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. [1] uses maximum *normalized distance to entry (NDE)* in order to choose the optimal berth location. Normalization of this distance to entry happens via dividing it by the anchorage depth (as shown in Figure 3.1). 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. [4] is to pack circles as densely as possible whereas the key idea in Oz et al. [1] is to pack circles as further away from the entrance as possible. Oz et al. [1] argues while both algorithms achieve similar utilization levels, the latter results in safer anchorage planning.

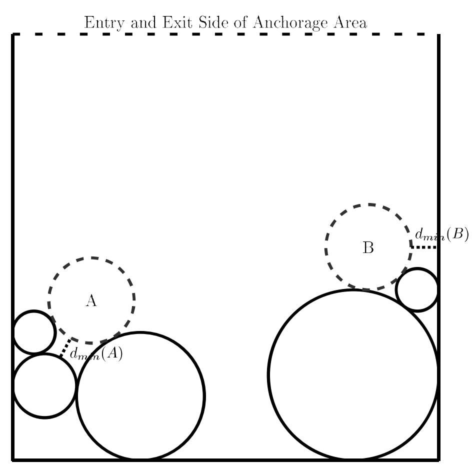


FIGURE 4.3: Illustration of two different cases for minimum hole degree

As we attempt to optimize the objectives of utilization, safety, and distance, we define a total of seven planning metrics in order to evaluate a given corner point. Three of these metrics are static and the remaining ones are time-sensitive, all of which are intended to adequately address each objective. The interactions between these 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 scoring the candidate corner points and selecting the optimal berth location. Therefore, in order to score corner points, we work with a linear function of the planning metrics that also includes certain interaction terms. In order to find the best coefficient for each term in this linear function for a given set of performance metric weights, namely, W_S, W_D, and W_U respectively for safety, distance, and utilization, we use the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm. Details of SPSA is discussed in the next section.

4.3 Planning Metrics

This section presents the planning metrics for evaluation of corner points. These metrics are computed in real time for each candidate corner point when a new vessel arrives at the anchorage. The corner point with the highest score with respective to the coefficients obtained by SPSA is declared to the berth location for this incoming vessel.

4.3.1 Realized AIL (RAIL)

Evidently, the metric we present as AIL in Section 3 can perform the task of an effective planning metric as well. Since our measure for safety 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 that arrival to overall safety. The mere difference is that in planning we calculate the AIL score for each individual candidate anchor while the average AIL used in performance measuring is the total AIL for all vessels arrived divided by the number of arrivals.

4.3.2 Projected DIL (PDIL)

Analogous to $RAIL$ for arrivals, a DIL value can be linked to each departure, and given these values for all vessels, the contribution of each vessel to safety could be easily calculated. Notice that when a vessel arrives, we are aware of departure times for that vessel and other anchored vessels, but we do not know future arrivals that may occur during the newly arrived vessel's dwell time. However, since DIL is measured upon departure and since we do not know the arrangement of the anchorage at the time of departure, it is not possible to compute the exact value of DIL at the time of the arrival. Nevertheless, we can achieve a plausible estimate for DIL simply by ignoring the new arrivals until the vessel's departure and just consider the departures of currently anchored vessels during the vessel's stay at the anchorage, which we call *projected DIL (PDIL)*. Clearly, PDIL is an underestimation of the true DIL value, yet a necessary and effective one.

4.3.3 Nearest 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* to 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 evaluation of candidate corner points.

4.3.4 Dynamic NDE (DNDE)

The next four metrics include a time dimension. The notion is inspired by the simple fact that if a vessel is going to stay for long, it seems appropriate to send it to a deep corner of the anchorage area to keep the opening and middle space clear for passage. On the other hand, if the vessel is going to leave soon, there is no reason for crossing the anchorage area twice on arrival and departure in order to anchor deep, thereby increasing *total traveled distance* and the risk of accidents. Multiplying *NDE* by the dwell time culminates in a metric we call *Dynamic NDE (DNDE)*, which comes to be of great help in increasing safety while maintaining a reasonable trade-off with distance.

4.3.5 Dynamic RAIL, Dynamic PDIL and Dynamic Fused Safety

Following the same idea, we multiply RAIL, PDIL and RAIL times PDIL by the dwell time to obtain three new metrics, respectively called: *Dynamic RAIL (DRAIL)*, *Dynamic PDIL (DPDIL)* and *Dynamic Fused Safety (DFS)*. It is intuitive when the anchorage area is idle, indicating small values for RAIL and PDIL, the dwell time is less relevant. But, for a busy anchorage with higher values for RAIL and PDIL, the dwell time becomes a pressing matter. This impact is recognized by multiplying the dwell time by RAIL, PDIL and *Fused Safety*, which is RAIL times PDIL. In short, when our safety metrics have greater values, dwell time will be weighted by greater numbers leading to greater values for dynamic safety 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:

$$m_4 = m_1 \times d \tag{4.2}$$

$$m_5 = m_2 \times d \tag{4.3}$$

$$m_6 = m_3 \times d \tag{4.4}$$

$$m_7 = m_1 \times m_2 \times d \tag{4.5}$$

where d is the anchor duration and m_1,m_2,...,m_7 respectively stand for RAIL, PDIL, NDE, DRAIL, DPDIL, DNDE, and DFS planning metrics, which are summarized in Table 4.1. For standardization purposes, the static metrics were normalized by the anchorage depth and the dynamic metrics were normalized by the anchorage depth times total simulation time.

Table 4.1: Planning metrics used in evaluating candidate corner points for an incoming vessel

Planning Metric	Abbreviation	Notation
Realized Arrival Intersection Length	RAIL	m_1
Projected Departure Intersection Length	PDIL	m_2
Normalized Distance to Entry	NDE	m_3
Dynamic Realized Arrival Intersection Length	DRAIL	m_4
Dynamic Projected Departure Intersection Length	DPDIL	m_5
Dynamic Normalized Distance to Entry	DNDE	m_6
Dynamic Fused Safety	DFS	m_7

Thus, a particular anchorage planning problem instance consists of the following components:

- Topology and depth of the anchorage.

- Performance metrics weight vector $\boldsymbol{W} = (W_S, W_U, W_D)$ 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 solution to a problem instance is then the optimal planning metrics coefficient vector that minimizes the multi-objective function L.

Chapter 5

The SPSA Algorithm

In our anchorage planning model, the variables to be optimized via SPSA are the coefficients of the seven planning metrics introduced earlier, which we denote by w_i for $1, \ldots, 7$. Thus the goal becomes finding the vector $\boldsymbol{w}^* = (w_1^*, \ldots, w_7^*)$ such that:

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w} \in \mathbb{R}^7} L(\boldsymbol{w}|\boldsymbol{W}) = \{\boldsymbol{w}^* \in \mathbb{R}^7 : L(\boldsymbol{w}^*) \leq L(\boldsymbol{w}) \quad \forall \boldsymbol{w} \in \mathbb{R}^7\}, \tag{5.1}$$

that is, $\boldsymbol{w}^*$ minimizes the objective function L (for a given $\boldsymbol{W}$) whose relation to $\boldsymbol{w}$ can be measured via simulations. Once $\boldsymbol{w}^*$ is found, candidate corner points are computed for each incoming vessel and each corner point is evaluated based on the formula:

$$s := \sum_{p=1}^{7} w_p^* \times m_p \tag{5.2}$$

and the corner point with the lowest s score is declared to be the vessel's berth location. We note that we do not impose any sign restrictions on the components of the $\boldsymbol{w}$ vector. Thus, contribution of some planning metrics to the score s could be positive whereas those of some other metrics could as well be negative.

Observe that for a given coefficient vector $\boldsymbol{w}$, the function $L(\boldsymbol{w})$ is a random variable with an unknown explicit form that can only be observed at the end of a noisy Monte Carlo simulation subject to a certain margin of error. The inputs to a Monte Carlo simulation are as follows:

- Topology and depth of the anchorage.
- Planning metrics coefficient vector $\boldsymbol{w} = (w_1, \ldots, w_7)$.
- Performance metrics weight vector $\boldsymbol{W} = (W_S, W_U, W_D)$.
- The probability distributions for vessel inter-arrival times, dwell times, and vessel lengths.

The outputs of one simulation run are the safety, distance, and utilization performance metric values measured over a certain amount of time once the run reaches steady-state. In our simulations, we use probability distributions that are consistent with empirical data obtained from the Ahırkapı anchorage.

In order to find a local minimum of a real-valued deterministic function $L : \mathbb{R}^p \to \mathbb{R}$, a wide-spread 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 actual 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 merely realizations of the loss function and 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 the noise and they do not require explicit information regarding the loss function nor its derivatives.

Kiefer-Wolfowitz finite-difference stochastic approximation (FDSA) is a powerful but computationally expensive algorithm for gradient-free stochastic optimization [7]. The number of loss function examinations in each iteration in FDSA is $2p$ (where p is the number of input variables to be optimized), making it computationally infeasible when p is large. Introduced by Spall [8], SPSA makes a significant improvement to FDSA by providing the same level of accuracy with only two measurements to construct one gradient approximation, resulting in a $p-$fold decrease in execution time.

Let $L(\boldsymbol{w}) : \mathbb{R}^p \to \mathbb{R}$ denote the loss function to be optimized where an explicit functional form for L is not available, yet one can make noisy measurements $y(\boldsymbol{w}) := L(\boldsymbol{w}) + \epsilon(\boldsymbol{w})$

where ϵ denotes noise. The gradient of L is defined as:

$$g(\boldsymbol{w}) := \frac{\partial L}{\partial \boldsymbol{w}}. \tag{5.3}$$

Similar to traditional gradient descent based algorithms, SPSA starts with an initial estimate $\hat{\boldsymbol{w}}_0$ and iterates with respect to the recursion below in order to find a locally minimum vector $\boldsymbol{w}^*$:

$$\hat{\boldsymbol{w}}_{k+1} := \hat{\boldsymbol{w}}_k - a_k \hat{g}_k(\hat{\boldsymbol{w}}_k). \tag{5.4}$$

In the equation above, a_k is an iteration gain sequence and $\hat{g}_k(\hat{w}_k)$ stands for the approximate gradient at $\hat{\boldsymbol{w}}_k$. Since it is assumed that L is not known explicitly, the gradient $g(\boldsymbol{w})$ is not readily available and thus it needs to be approximated. The perturbation amount δ is taken as $c_k\Delta_k$ where c_k is a gradient gain sequence and Δ_k is the $p-$dimensional simultaneous perturbation vector. SPSA imposes certain regularity conditions on Δ_k [8]. In particular, each component of Δ_k needs to be generated independently from a symmetric zero mean probability distribution with a finite inverse, such as the symmetric Bernoulli distribution (e.g., $+1$ or -1 with 0.5 probability). Simultaneous perturbations around the current iterate $\hat{w}_k$ are defined as:

$$\hat{\boldsymbol{w}}_k^{\pm} := \hat{\boldsymbol{w}}_k \pm c_k \Delta_k. \tag{5.5}$$

Once $y(\hat{\boldsymbol{w}}_k^+)$ and $y(\hat{\boldsymbol{w}}_k^-)$ are computed, the estimate of gradient $\hat{g}_k$ is calculated as:

$$\hat{g}_k(\hat{\boldsymbol{w}}_k) := \frac{y(\hat{\boldsymbol{w}}_k^+) - y(\hat{\boldsymbol{w}}_k^-)}{2c_k} \begin{bmatrix} \Delta_{k1}^{-1} \\ \Delta_{k2}^{-1} \\ \vdots \\ \Delta_{kp}^{-1} \end{bmatrix}. \tag{5.6}$$

SPSA requires three loss function measurements in each iteration: $y(\hat{\boldsymbol{w}}_k^+)$, $y(\hat{\boldsymbol{w}}_k^-)$, and $y(\hat{\boldsymbol{w}}_{k+1})$. The first two measurements are needed to approximate the gradient and the third one is required for measuring the performance of the subsequent iterate, i.e., $\hat{\boldsymbol{w}}_{k+1}$ [9].

The iteration gain sequence is specified as $a_k := a/(A+k)^\alpha$ where A is the stability constant and the gradient gain sequence is taken as $c_k := c/k^\gamma$. In SPSA, a, c, A, α, γ are pre-defined parameters whose proper fine-tuning is critical for superior algorithm performance. Under some mild conditions, SPSA has been shown to converge to a locally optimal solution almost surely [8]. A common stopping rule for SPSA is reaching a pre-defined number for iterations due to the fact that automatic stopping criteria does not exist for such stochastic approximation algorithms, specially when there is no specific expectation for the value of optimal solution.

Even though SPSA has been widely used in a variety of stochastic optimization problems, few studies exist on its parameter calibration. Spall [10] provides certain guidelines for identifying suitable values for the algorithm parameters. In particular, the asymptotically optimal values of α and γ 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 Δ_k is independent ± 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 the SPSA parameter fine-tuning process is provided in Section 7.

Chapter 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. [1] whose logical flow is shown in Figure 6.1 and main components are described below.

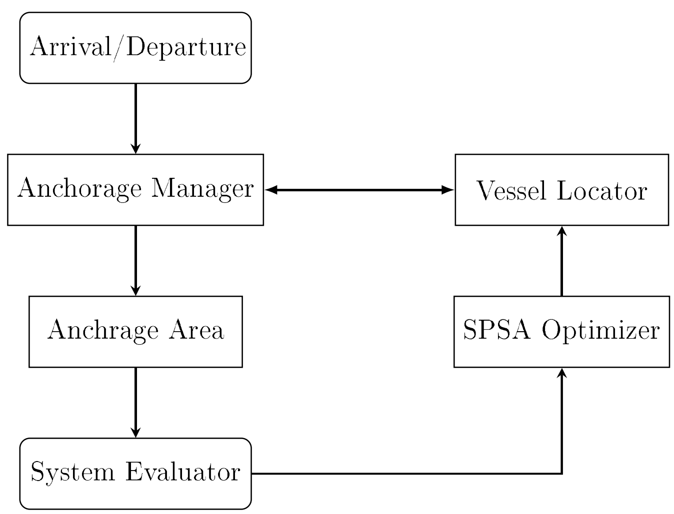


Figure 6.1: Flowchart of the anchorage simulation system

6.1 Anchorage Area

Following common practice, the anchorage area is modeled as a two-dimensional polygonal region containing anchor circles with various radii representing vessels. It is assumed (1) the anchorage has uniform depth and (2) vessel entry and exits occur through the entry side of the anchorage with the vessels following a straight path to their berth locations (per regulations). On the other hand, the uniform depth assumption is not always realistic [11], yet integration of non-uniform depth information into a multi-objective setting requires non-trivial changes and it is left for future research.

6.2 Vessel Arrival/ Departure Generator

The *Vessel Arrival/ Departure Generator* component is in charge of generating vessel arrivals with an associated arrival time, 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 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 are computed by the *SPSA Optimizer* component.

6.4 SPSA Optimizer

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

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

Chapter 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 7.1 shows Ahırkapı and the synthetic anchorage topology used in simulations.

- 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 safety, utilization, and distance. The weight vectors we consider are (1,0,0), (0,0,1), (5,0,1), (1,0,1), and (1,0,5).

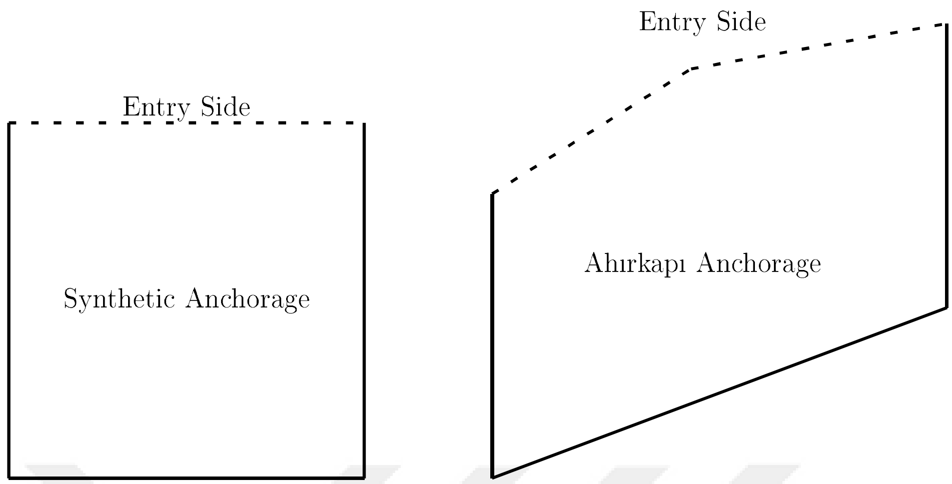


FIGURE 7.1: Anchorage topologies used in the computational experiments

Our Monte Carlo simulations require probability distributions for sampling vessel inter-arrival time, dwell time, and vessel length quantities. In this work, we make use of Ahırkapı Anchorage historical data information for the year of 2015 and we determine the best fitting (i.e., the most likely) probability distribution for each one of the three quantities, which are then used for sampling in the simulations. The probability distributions acquired from the empirical 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 (meters): Beta($\alpha = 2.4$, $\beta = 2.4$).

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: $k = 0.5$.

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.

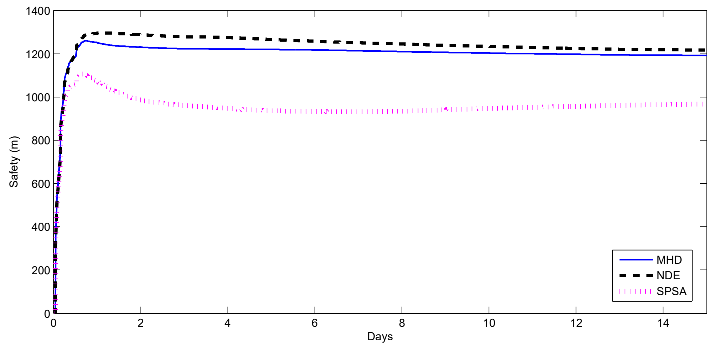
7.1 Steady State Analysis

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.

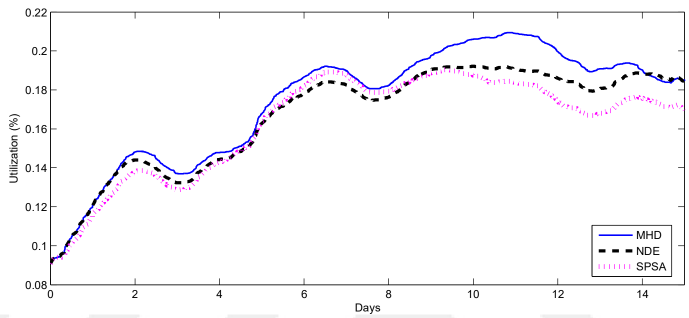
Figure 7.2 shows the trend of our performance metrics throughout the first fifteen days of simulation for all the competing algorithms for the Ahırkapı Anchorage starting with an empty anchorage. This figure, as well as similar analyses we conducted with various simulation settings suggested there is 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

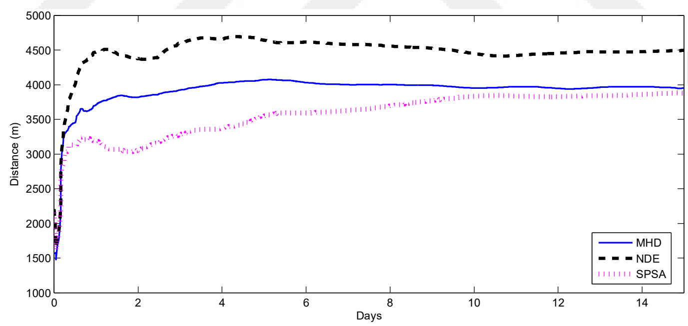
As mentioned earlier, careful fine-tuning of SPSA parameter values is of utmost importance for convergence of the algorithm to a good solution. In our implementation, we used the symmetric Bernoulli distribution with a probability of 0.5 for each ± 1 outcome for the perturbation vector Δ_k, which is a theoretically valid, simple, and very commonly used distribution in the SPSA literature. Regarding α and γ, we used the theoretically



(a) Safety



(b) Utilization



(c) Distance

Figure 7.2: Performance metrics over time for the Ahırkapı Anchorage during fifteen days of simulation time.

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 used the values of 0.17, 0.019 and 0, respectively.

The number of SPSA iterations was taken as 500, which we observed to be sufficient for convergence in general. In each iteration, for a particular planning metrics coefficient vector $\boldsymbol{w}$, the loss function measurement was taken as the average of 10 independent Monte Carlo simulations. Averaging of simulation runs is a common way of reducing the effect of noise in SPSA implementations, see, e.g., [9].

Consider, for instance, the case when $W_S = 0$, $W_U = 0$ and $W_D = 1$; Figure 7.3 shows the normalized values of objective function for this performance metrics weight vector over 500 iterations for Ahırkapı Anchorage where the measurement for each iteration is the average of 10 simulations. The coefficient vector with the lowest objective function value over the entire range of SPSA iterations is declared to be the optimal coefficient vector $\boldsymbol{w}^*$.

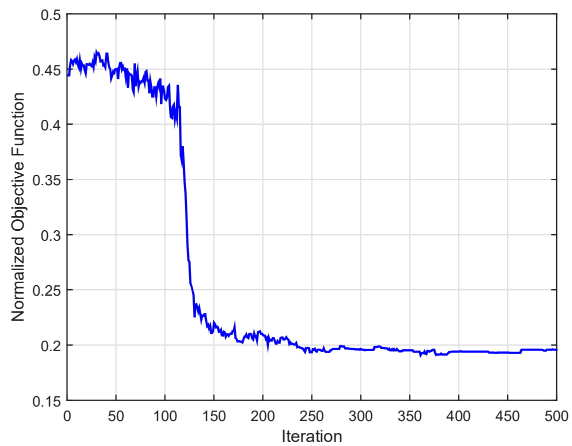


FIGURE 7.3: Normalized objective function value vs. iteration count for SPSA for the Ahırkapı Anchorage.

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 (CNR) to reduce variance.

Competing algorithms are the Nearest Distance to Entry (NDE) method of Oz et al. [1] and the Maximum Hole Degree (MHD) method of Huang et al. [4], 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_S, 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 7.1, 7.2, 7.3, and 7.4 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 (scaled between ±1) for the Ahırkapı Anchorage are shown in Table 7.5 to illustrate how these coefficients relate to each other for one particular anchorage setting.

Table 7.1: 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	**Safety (m)**	**Utilization (%)**	**Distance (m)**
MHD	480.4±13.5	0.19±0.0079	4031.6±57.5
NDE	389.3±8.7	0.19±0.0079	4289.8±19.9
RANDOM	488.0±8.9	0.19±0.0079	4046.2±26.1
SPSA: $W_S/W_U/W_D$			
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 7.2: Comparison of algorithms for synthetic average anchorage

Algorithm	**Safety (m)**	**Utilization (%)**	**Distance (m)**
MHD	685.6±23.6	0.19±0.083	4801.8±213.5
NDE	612.1±15.2	0.19±0.083	5948.1±36.0
RANDOM	958.4±13.9	0.19±0.083	4546.3±42.1
SPSA: $W_S/W_U/W_D$			
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 7.3: Comparison of algorithms for the synthetic busy anchorage

Algorithm	**Safety (m)**	**Utilization (%)**	**Distance (m)**
MHD	1190.2±15.0	0.48±0.0147	4093.4±28.7
NDE	1200.1±15.6	0.47±0.0147	4505.9±32.9
RANDOM	1231.2±15.0	0.48±0.0157	4134.8±25.3
SPSA: $W_S/W_U/W_D$			
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 7.4: Comparison of algorithms for idle synthetic anchorage

Algorithm	**Safety (m)**	**Utilization (%)**	**Distance (m)**
MHD	385.6±23.1	0.03±0.0029	6391.3±68.3
NDE	252.1±9.2	0.03±0.0029	6881.4±19.6
RANDOM	884.8±18.9	0.03±0.0029	5092.5±38.5
SPSA: $W_S/W_U/W_D$			
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 7.5: Optimal planning metric coefficients for the Ahırkapı Anchorage

$\boldsymbol{W}$				$\boldsymbol{w}^*$			
$W_S/W_U/W_D$	w_1^*	w_2^*	w_3^*	w_4^*	w_5^*	w_6^*	w_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

It is evident from the comparison tables when the priority is safety or distance, SPSA outperforms all the other algorithms. Even when $W_S = W_D = 1$, SPSA outperforms all competing algorithms in both safety 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 CNR 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 it is indicated in Table 7.3, 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 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. The differences in safety 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 safety 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. Likewise, regarding the distance metric, SPSA results in an average of 2199 meters while the closest MHD method yields an average of 4031 meters. 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.

Chapter 8

Summary and Conclusions

As maritime transportation gains momentum, anchorage planning, and related problems demand closer attention and dealing with them calls for 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 area.

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 safety, utilization, and average distance traveled (in lieu of fuel consumption & environmental impacts).

Our results indicate our SPSA-based methodology predominantly outperforms competing algorithms in safety and distance. As far as utilization is concerned, we argue the concept of corner point placement is 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 slight 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.

As for the future research, incorporating environmental conditions such as waves, wind and sea currents into the problem and developing the algorithm to account for these forces along with non-uniform depths is on the agenda. Moreover, considering more realistic arrival and departure paths instead of straight lines can potentially have a major contribution in bringing the anchorage planning problem one step closer to reality and increasing the accuracy and effectiveness of its modeling. 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 safety, utilization, and distance objectives. Future research might investigate these relationships in detail for a pareto-optimal approach to this multi-objective optimization problem.

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