

**DEVELOPING A DECISION-MAKING FRAMEWORK FOR OPTIMAL MARINE OIL  
SPILL WASTE MANAGEMENT AND TREATMENT**

by

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## **Abstract**

This research explores estimating off-shore oily waste, considering waste-waste compatibility due to the heterogeneous nature of oily waste. Firstly, hyperparameters for Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Improved Random Forest (IRF) models are optimized to develop a comprehensive oily waste estimation model incorporating liquid, solid, and total waste types. The results show that IRF is the most accurate model, with the lowest error indices and a higher correlation coefficient compared to ANN and SVR. This study then takes a step further to propose a waste allocation framework, which is tested using information on the Bella Bella oil spill incident in British Columbia. Incorporating treatment and receiving facilities' details, such as their location and capacity, the framework distinguishes all possible waste pathways for handling the waste from source to landfill. Genetic Algorithm (GA) is introduced to optimize waste transfer processes and successfully minimize transportation costs. The results show that the model can find the most optimized path to reduce transportation costs. The model's high customization, adaptability, and capacity to consider multiple nodes make it suitable for complex waste transfer networks, demonstrating its practicality in emergency situations. Efficiently allocating resources and ensuring cost-effective waste transportation while considering facility capacities and waste compatibility, the study holds practical implications for waste management practitioners, environmental authorities, and response teams.

# TABLE OF CONTENTS

<b>Abstract.....</b>	<b>iii</b>
<b>TABLE OF CONTENTS .....</b>	<b>ii</b>
<b>LIST OF TABLES .....</b>	<b>ivv</b>
<b>LIST OF FIGURES .....</b>	<b>v</b>
<b>GLOSSARY.....</b>	<b>vi</b>
<b>ACKNOWLEDGEMENT.....</b>	<b>vii</b>
<b>CHAPTER 1 INTRODUCTION .....</b>	<b>1</b>
<b>1.1 What Is a Marine Oil Spill? .....</b>	<b>1</b>
<b>1.2 Major Oil Spill Incidents.....</b>	<b>3</b>
<b>1.3 Oil Spill Effects on Different Sectors .....</b>	<b>5</b>
<b>1.3.1 Aquatic Habitat and Ecology .....</b>	<b>5</b>
<b>1.3.2 Wildlife.....</b>	<b>5</b>
<b>1.3.3 Economy.....</b>	<b>6</b>
<b>1.3.4 First Nations and Local Communities.....</b>	<b>6</b>
<b>1.3.5 Tourism .....</b>	<b>7</b>
<b>1.3.6 Human Health .....</b>	<b>7</b>
<b>1.4 What Affects Oil Spill?.....</b>	<b>8</b>
<b>1.5 Oil Spill Clean-up Strategy .....</b>	<b>9</b>
<b>1.5.1 Off-shore Clean-up Techniques .....</b>	<b>9</b>
<b>1.5.2 On-shore Clean-up Techniques .....</b>	<b>11</b>
<b>1.6 Review of Canadian Petroleum Industry and Oil Shipping Activities .....</b>	<b>12</b>
<b>1.6.1 Canadian Marine Oil Response System and Practices .....</b>	<b>12</b>
<b>1.6.2 Legislative and Regulatory Structure .....</b>	<b>13</b>
<b>1.6.3 National Oil Spill Preparedness and Response Regime.....</b>	<b>14</b>
<b>1.7 Objectives and Significance of this Study .....</b>	<b>14</b>
<b>1.8 Organization of The Thesis .....</b>	<b>15</b>
<b>CHAPTER 2 LITERATURE REVIEW .....</b>	<b>16</b>
<b>2.1 Oil Spill Waste Management and Modeling.....</b>	<b>16</b>
<b>2.2 Research Gaps in Oily Waste Estimation and Waste Management.....</b>	<b>19</b>
<b>CHAPTER 3 METHODOLOGY .....</b>	<b>21</b>
<b>3.1 Data Collection and Assumption .....</b>	<b>21</b>
<b>3.2 Artificial Intelligence (AI)-based Model Development .....</b>	<b>23</b>
<b>3.2.1 Artificial Neural Network (ANN) .....</b>	<b>23</b>
<b>3.2.2 Support Vector Regression (SVR).....</b>	<b>24</b>
<b>3.2.3 Improved Random Forest (IRF).....</b>	<b>25</b>

<b>3.3 Waste Estimation Model .....</b>	<b>26</b>
<b>3.3.1 Model Evaluation .....</b>	<b>29</b>
<b>3.4 Waste Management/Transfer Framework.....</b>	<b>30</b>
<b>3.4.1 Problem Description .....</b>	<b>30</b>
<b>3.4.2 Mathematical Modeling.....</b>	<b>32</b>
<b>3.4.3 Objective Function and Constraints.....</b>	<b>35</b>
<b>Appendix A.....</b>	<b>38</b>
<b>CHAPTER 4 RESULTS and DISCUSSION .....</b>	<b>43</b>
<b>4.1 Hyperparameter Optimization .....</b>	<b>43</b>
<b>4.2 Waste Estimation Model .....</b>	<b>45</b>
<b>4.3 Waste Allocation Framework .....</b>	<b>46</b>
<b>CHAPTER 5 CONCLUSION AND RECOMMENDATIONS.....</b>	<b>54</b>
<b>5.1 Conclusion .....</b>	<b>54</b>
<b>5.2 Recommendations .....</b>	<b>57</b>
<b>REFERENCES.....</b>	<b>59</b>

## LIST OF TABLES

<b>Table 1.1</b>	Twenty-two major oil spill incidents the world has seen.....	13
<b>Table 3.1</b>	AI-based model’s hyperparameters, their description and search space used in the Bayesian optimization .....	37
<b>Table 3.2</b>	Notations used in the designed waste management framework.....	41
<b>Table 3.3</b>	Description of the decision variable used in the designed waste management framework.....	43
<b>Table 4.1</b>	Optimized hyperparameters of ANN waste estimation model .....	52
<b>Table 4.2</b>	Optimized hyperparameters of SVR waste estimation model .....	53
<b>Table 4.3</b>	Optimized hyperparameters of RF waste estimation model.....	54
<b>Table 4.4</b>	Evaluation of the AI-based waste estimation models.....	55
<b>Table 4.5</b>	Name and location of currently operating facilities in British Columbia.....	56
<b>Table 4.6</b>	The Detailed information on oily waste handling facilities in British Columbia.....	58
<b>Table 4.7</b>	The identified path from source to the landfill with volume based on the Bella Bella oil spill incident in British Columbia.....	61

## LIST OF FIGURES

<b>Figure 1.1</b>	Comparison between the number of tanker spills and growth in crude oil and other tanker trade between 1970 and 2020 (Adapted from ITOPF (2021))....	11
<b>Figure 1.2</b>	Number of medium and large tanker spills from 1970 to 2021 (Adapted from ITOPF (2021)).....	12
<b>Figure 1.3</b>	Canadian Coast Guard Regional boundaries (Adapted from Government of Canada (2022)).....	22
<b>Figure 3.1</b>	Parameters affecting the volume of generated off-shore oily waste .....	31
<b>Figure 3.2</b>	Schematic structure of the ANN model.....	33
<b>Figure 3.3</b>	A Random Forest schematic view.....	34
<b>Figure 3.4</b>	Schematic view of possible transportation paths between each two nodes in the framework.....	42
<b>Figure 4.1</b>	Results of Bayesian optimization for AI-based optimization models: a) ANN, b) SVR, and c) RF .....	53
<b>Figure 4.2</b>	The location of waste handling facilities in British Columbia.....	56
<b>Figure 4.3</b>	The common practice of oily waste management in British Columbia.....	57
<b>Figure 4.4</b>	Genetic Algorithm minimization cost graph.....	61

## GLOSSARY

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### Abbreviations

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AI	Artificial Intelligence
ANN	Artificial Neural Network
CC	Correlation Coefficient
CCG	Canadian Coast Guard
DFO	Fisheries and Oceans Canada
EPA	Environmental Protection Agency
IMO	International Maritime Organization
IRF	Improved Random Forest
ITOPF	International Tanker Owners Pollution Federation Limited
MPRI	Multi-Partner Oil Spill Research Initiative
NOAA	National Oceanic and Atmospheric Administration
NSERC	Natural Sciences and Engineering Research Council of Canada
NP-hard	Non-deterministic Polynomial-time hard
PPE	Personal Protective Equipment
RMSE	Root Mean Square Error
RMAE	Relative Mean Absolute Error
SRM	Structural Risk Minimization
SVR	Support Vector Regression
WCMRC	Western Canada Marine Response Corporation

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To all who find themselves navigating their storms, may my thesis stand as a humble symbol of hope and an invitation to persist and dare to dream, even when the odds are saying otherwise.

Thank you to each and everyone of you for being a part of this journey.

Mahboobeh



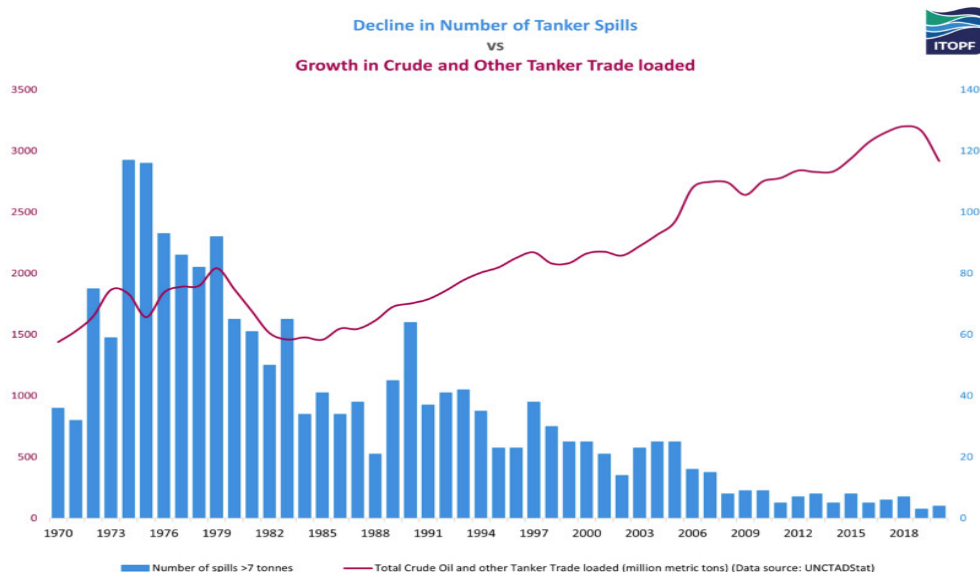
# CHAPTER 1 INTRODUCTION

## 1.1 What Is a Marine Oil Spill?

Over the past two decades, there have been ongoing debates surrounding the transition to more sustainable energy sources. Despite this, many industries continue to rely on fossil fuels. The rapid growth of industrialization and economic expansion has led to a rise in the transportation of fossil fuels, consequently increasing the risk of oil spill incidents. A marine oil spill incident occurs when petroleum hydrocarbons are accidentally released at sea due to human error or equipment failures (Li et al. (2014); Beyer et al. (2016)). Tankers, off-shore platforms, drilling rigs, and subsea piping lines are identified as the primary sources of such spill incidents (Li et al. (2014)).

The International Tanker Owners Pollution Federation Limited (ITOPF) is a London-based organization that compiles statistics on global oil demand and incidents of oil and chemical spills. They also provide technical support services for oil spill response plans. This information is made available to tanker owners, their insurers responsible for covering oil pollution incidents, and international organizations like the International Maritime Organization (IMO), as adapted from ITOPF (2021). In essence, ITOPF's core services encompass spill response, analysis of claims and damages, training, contingency planning, and advisory and informational support.

Figure 1.1 depicts a long-term analysis of global trends in oil demand versus tanker spill incidents. As shown, despite an increase in tanker movements from 1970 to 2020, the number of oil spill incidents has consistently decreased over these years. This positive trend is attributed to advancements in the shipping industry, coupled with stricter regulations and a sustained commitment to enhancing maritime safety and environmental protection through investment and exploration of innovative solutions.

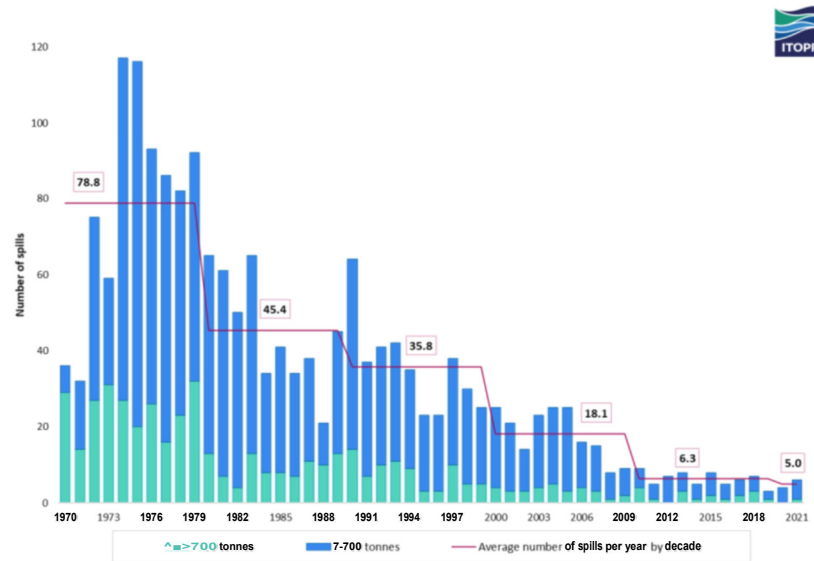


**Figure 1.1** Comparison between the number of tanker spills and growth in crude oil and other tanker trade between 1970 and 2020 (Adapted from ITOPF (2021)).

Investigating the causes of oil spill incidents offers valuable insights for managerial tasks and risk analysis. An analysis conducted by ITOPF spans tanker spill incidents from around 1970 to 2021. Spills exceeding 700 tonnes, those ranging from 7 to 700 tonnes, and those below 7 tonnes are categorized as large, medium, and minor, respectively. Figure 1.2 illustrates the trend and volume of spill incidents in the medium and large categories during this period.

As shown, the total volume of oil released due to tanker spill incidents in 2021 is approximately 10,000 tonnes, with the majority classified as medium spill incidents. While annual fluctuations are present, the overall trend shows a decline in the number of oil spill incidents. This reduction is attributed to positive shifts within the shipping industry, reinforced regulations, and governmental support for research initiatives.

The following sections will provide more details regarding marine oil spill incidents, causes, environmental impacts and related regulations.



**Figure 1.2** Number of medium and large tanker spills from 1970 to 2021 (Adapted from ITOPF (2021)).

## 1.2 Major Oil Spill Incidents

Even though the number of oil spill incidents has decreased significantly, primarily due to stringent regulations, it's essential to recognize that a single oil spill incident can still lead to catastrophic events. A summary of the twenty most significant oil spill incidents worldwide is presented in the following table. This table includes renowned incidents such as Exxon Valdez and Prestige, although they are listed further down the rank column in Table 1.1. The subsequent section will provide detailed information about the consequences of oil spill incidents.

**Table 1.1** Twenty-two major oil spill incidents the world has seen.

Rank	Ship name	Year	Location	Spill size (tonne)
1	Atlantic Empress	1979	Off Tobago, west India	287,000
2	ABT Summer	1991	700 nautical miles off Angola	260,000
3	Castillo de Bellver	1983	Off Saldanha Bay, South Africa	252,000
4	Amoco Cadiz	1978	Off Brittany, France	223,000
5	Haven	1991	Genoa, Italy	144,000
6	Odyssey	1988	700 nautical miles off Nova Scotia, Canada	132,000
7	Torrey Canyon	1967	Scilly Isles, UK	119,000
8	Sea Star	1972	Gulf of Oman	115,000
9	Sanchi	2018	Off Shanghai, China	113,000
10	Irenes Serenade	1980	Navarino Bay, Greece	100,000
11	Urquiola	1976	La Coruna, Spain	100,000
12	Hawaiian Patriot	1979	300 nautical miles off Honolulu	95,000
13	Independenta	1979	Bosphorus, Turkey	94,000
14	Jakob Maersk	1975	Oporto, Portugal	88,000
15	Breear	1993	Shetland Islands, UK	85,000
16	Aegean Sea	1992	La Coruna, Spain	74,000
17	Sea Empress	1996	Milfor Haven, UK	72,000
18	Khark 5	1989	120 nautical miles off the Atlantic coast of Morocco	70,000
19	Nova	1985	Off Khark Islan, Gulf of Iran	70,000
20	Katina P	1992	Off Maputo, Mozambique	67,000
21	Prestige	2002	Off Galicia, Spain	63,000
22	Exxon Valdez	1989	Prince William Sound, Alaska, USA	37,000

## **1.3 Oil Spill Effects on Different Sectors**

### **1.3.1 Aquatic Habitat and Ecology**

Aquatic habitats are the first areas heavily impacted by oil spill incidents. The marine environment is a complex system of plants, animals, and their surroundings. When the environment is harmed, it often affects species in the food chain, leading to further consequences for other species (IMO (2001)).

In open water, fish and whales can swim away from an oil spill by going deeper or in different directions. However, animals like turtles, seals, and dolphins, which usually live near the shore, are at a higher risk. They are affected by oil on beaches or by eating prey in oil. In shallow water, oil can also harm plants like seagrasses, kelp, and coral reefs, which many species rely on for food, homes, and breeding spots (IMO (2001)).

Oil spill incidents can also happen in swamps and marshes, where there's less water movement, making the situation worse than in flowing water. Lakes and ponds are also at risk because more types of animals can be exposed to oil. This is especially true for migrating birds, as they can spread the contamination over a larger area. While rivers are usually less affected than lakes, if a river is a drinking water source, it directly threatens human health. This concerns many communities, including indigenous communities, that rely on water bodies for their needs.

### **1.3.2 Wildlife**

The species most impacted by oil spill incidents are birds, mammals, and plants inhabiting marine environments and adjacent shorelines. These organisms face various

threats, including direct physical contact with oil, toxic contamination, depletion of food sources or habitats, and reproductive challenges (IMO (2001)).

Different species exhibit varying degrees of tolerance to oil ingestion. For instance, oil spill incidents and their vapours can be fatal to seabirds. Despite their potential resilience, once exposed to oil, these birds can accumulate it within their bodies, leading to infiltration of their nervous system, liver, and lungs. Consequently, oil enters the food chain, posing a risk of contamination to predators.

### **1.3.3 Economy**

Marine-based industries, including port operations, fisheries, tourism, and aquaculture enterprises, often experience significant adverse effects from oil spill incidents. These impacts manifest through direct losses of products due to mortality or habitat destruction, as well as restricted access resulting from harvesting bans and area closures. Furthermore, economic losses stem from decreased market demand, driven by concerns over the safety of products tainted by oil contamination (Li et al. (2014); Beyer et al. (2016)). These losses reverberate throughout the fisheries supply chain, affecting docks, processors, and supply businesses (Beyer et al. (2016)).

### **1.3.4 First Nations and Local Communities**

First Nations represent a particularly vulnerable segment of society, highly susceptible to oil spill incidents' consequences. These communities often rely on fisheries and land resources from water bodies, making them particularly vulnerable to the impacts of oil contamination in terms of polluted soils from oil pipelines and tainted seafood (Li et al. (2014)).

In addition to First Nations, other indigenous communities and rural locals with strong ties to the natural environment for subsistence and cultural practices are also affected by oil spill incidents. While compensatory frameworks exist for these communities, delays in compensation disbursement may adversely affect trust in governmental authorities, potentially leading to significant social unrest and societal disruption.

### **1.3.5 Tourism**

Tourism stands out as a particularly vulnerable sector in crises and disasters. This vulnerability arises from its interrelations with other industries, such as transportation and accommodation, hotels, airlines, and car rentals. Additionally, tourism is heavily influenced by external factors such as political stability, currency exchange rates, and weather conditions (Beyer et al. (2016)).

Oil spill incidents near shorelines and areas populated by humans pose aesthetic concerns, necessitating safety measures due to toxic volatile vapours. Cleaning such spills is more costly and may extend over longer periods, resulting in significant losses and market decline for businesses and properties situated near beaches and waterfronts, such as restaurants, hotels, and recreational facilities. Over time, tourism in the affected area may experience crises or collapse, as these events divert tourist traffic to alternative destinations.

### **1.3.6 Human Health**

Human beings can be impacted by an oil spill incident in three significant ways, including disruption of ecological processes, resulting in direct harm. This includes ingesting seafood contaminated with oil toxins, which can lead to various health issues. For instance, consuming seafood bio-accumulated with oil toxins or breathing in oil vapours can cause

direct harm. Economic stressors affect individuals working in fields such as fishers and the tourism industry. According to Aguilera et al. (2010) and Major and Wang (2012), inhalation of vapours or consuming contaminated seafood can lead to harmful health effects ranging from dizziness and nausea to certain types of cancers and issues with the central nervous system. Although the long-term effects of hydrocarbon toxicity on humans are less studied, they have been associated with severe DNA degradation, cancers, congenital disabilities, reproductive defects, irreversible neurological and endocrine damage, and impaired cellular immunity (Binet et al. (2003); Aguilera et al. (2010)).

#### **1.4 What Affects Oil Spill?**

Once an oil slick forms on the water's surface following an oil spill incident, it undergoes various weathering processes, including photolysis, evaporation, dilution, formation of oil-water emulsions, and biodegradation (Dave and Ghaly (2011)). Specifically, the formation of oil-water emulsion leads to significant changes in water interfacial tension, density, and viscosity. Selecting the most effective method for spill clean-up largely depends on the characteristics of the oil and environmental factors. Therefore, understanding factors such as the quantity and type of spill, weather and ocean conditions, age of the spilled oil, and ocean behaviour is crucial.

The most common marine oil spills include bunker crude oil, refined petroleum products and by-products, and waste oils (Dave and Ghaly (2011)).



## 1.5 Oil Spill Clean-up Strategy

When the oil spills on top of the water's surface, it will slowly drift toward the shore due to tidal activities. Spill clean-up operations must be employed to prevent a catastrophic situation after an incident. Over the last 50 years, oil spill clean-up technologies have developed extensively. The clean-up processes at the spill location (at sea) and the shore are called off-shore and shoreline clean-ups, respectively.

### 1.5.1 Off-shore Clean-up Techniques

Off-shore response techniques are divided into mechanical/physical, chemical, biological and in-situ burning. (Dave and Ghaly (2011)).

**a) Physical techniques** primarily involve spatially controlling the oil slick using physical barriers, thereby keeping the oil's physical and chemical characteristics unchanged. Commonly used physical barriers globally include booms, skimmers, and adsorbent materials (Fingas (2016)).

Booms are floating barriers designed to restrict the movement of oil, ultimately facilitating higher oil recovery through skimmers or other response methods. They come in three main types: fence booms, curtain booms, and fire-resistant booms. Fire-resistant booms are typically employed in conjunction with in-situ burning. Fence and curtain booms serve a similar function, with approximately 60% submerged underwater and only 40% floating on the surface. Booms are typically around 15 meters long and can be interconnected as needed. While fence booms are lightweight, easy to handle, and reliable in calm waters, their stability in rough conditions with high waves and strong winds is limited.

Skimmers represent the second physical response technique commonly used alongside booms to enhance oil recovery efficiency. Depending on the skimmer type, they exhibit high stability in rough ocean conditions and can recover up to 90% of the oil. However, they are less effective when dealing with oil mixed with dispersants. Regardless of their type, all skimmers are made of oleophilic materials, which attract oil slicks that adhere to the surface. This oil can then be scraped or squeezed from the surface and collected in a small storage tank.

Utilizing adsorbent materials offers another physical approach to handling oil spill incidents without altering the oil's characteristics. Hydrophobic sorbents are employed for clean-up after skimming as a final step in response operations to capture any remaining oil on the water.

**b) Chemical methods** complement physical techniques to expedite clean-up, particularly in spill locations near shorelines or sensitive marine environments. Dispersants and solidifiers are commonly employed chemicals in oil spill clean-up, altering the characteristics of the oil. Dispersants typically consist of surfactants, which break down the oil slick into smaller droplets, facilitating faster biodegradation as they are dispersed into the deep-water column. On the other hand, solidifiers transform the oil phase from liquid to a rubber-like substance, enabling more accessible collection on the water's surface. In rough seas, solidifiers can effectively utilize wave energy to enhance dissolution in the water, resulting in a higher rate of solidification (Dave and Ghaly (2011)).

**c) In-situ burning** represents a straightforward and rapid clean-up method. However, its usage is limited due to concerns over human health and environmental impacts associated with burning by-products, including residues and the emission of thick plumes of black smoke. This method is particularly effective in snowy

conditions, such as clean-ups after pipeline leaks or when oil spills occur on top of ice. One crucial requirement is that the oil slick be sufficiently thick to sustain burning and prevent it from cooling.

**d) Biodegradation** serves as the final option for marine oil spill clean-up. While environmentally friendly and safe, its application is restricted by the slow degradation process, leading to prolonged exposure and less suitable for environments with low microbial activity.

### **1.5.2 On-shore Clean-up Techniques**

On-shore oil spill clean-ups are more straightforward than off-shore and do not require special equipment. The clean-up process can be summarized into three stages based on (ITOPF (2021)) as follows:

- A) Stage 1- Emergency phase: This phase revolves around a collection of floating oil near the shoreline and transfer to temporary storage, usually on the shore.
- B) Stage 2 – project phase: Stage 2 is a complementary phase to Stage 1, often combined. This phase involves collecting oily contaminated materials left on the shoreline. In smaller projects, any remaining oil might be left to degrade naturally.
- C) Stage 3- Polishing phase: this stage includes the final clean-ups and removal of oil stains if required.

Removing bulked oil and treating oil-contaminated beach materials (Stages 1 and 2) typically involves using skimmers to collect the oil, which is then transferred using vacuum trucks to subsequent handling facilities. The oil removal process can be done using

mechanical equipment or manual methods. Pressure washing is commonly employed to ensure thorough cleaning for hard-to-access areas along the shore.

## **1.6 Review of Canadian Petroleum Industry and Oil Shipping Activities**

Canada is among the world's top oil producers, with approximately 98% of its oil exported to the United States (Mohammadiun et al. (2021)). Alberta has the largest oil sand reserves and crude oil production, followed by Saskatchewan, which produces approximately 487,000 daily barrels. Canada relies on reliable transportation methods such as railways, pipelines, trucks, and oil tankers to transport the produced oil to its destinations, including the US and other parts of the world. The selection of transportation methods depends mainly on factors such as volume and destination.

Regarding marine oil shipping, around 87% of Canadian oil is transported through the Atlantic coast, the Great Lakes, the Gulf of St. Lawrence and St. Lawrence Seaway, and associated ports. In comparison, the remaining 13% is shipped through Pacific coastal ports. Seven major ports accommodate significant oil tanker traffic, including the Port of Vancouver, Port of Montreal, Port de Quebec, Newfoundland Off-shore, Port of Saint John, Port of Hawkesbury, and Nova Scotia.

Given Canada's strategic geographical location, multiple international transit routes, and the continuous growth of industrial activities, there has been an increase in oil tanker transit along the Canadian coastline, consequently heightening the risk of oil spill incidents.

### **1.6.1 Canadian Marine Oil Response System and Practices**

The Canadian Coast Guard (CCG) operates as a strategic agency under Fisheries and Oceans Canada (DFO) and is entrusted with the task of providing timely and effective

responses to incidents involving ship-source or unknown-source pollutants in Canadian waters (Government of Canada (2022)). To facilitate efficient program delivery, Canada has been divided into three regions known as the Western, Atlantic, Central, and Arctic Coast Guards. These regional divisions were established in October 2012 to ensure swift administration of response efforts. Figure 1.3 illustrates the boundaries of the Canadian Coast Guard regions as determined in October 2012.



**Figure 1.3** Canadian Coast Guard Regional boundaries (Adapted from Government of Canada (2022))

## 1.6.2 Legislative and Regulatory Structure

Under federal legislation and various international agreements, the federal government is responsible for cleaning up any pollutants spilled in Canadian waters.

### **1.6.3 National Oil Spill Preparedness and Response Regime**

Since 1995, Transport Canada has taken the lead of federal regulatory agencies responsible for the regime based on the partnership between industry and government. This regime provides guidelines and regulatory structures for preparedness and response to marine oil spill incidents. In this regime, potential polluters pay for readiness. The three pillars of oil spill clean-up are Prevention, Preparedness and Response.

### **1.7 Objectives and Significance of this Study**

Understanding the quantity of generated oily waste is essential for proactive preparedness for oil spill response, enabling the determination of necessary resources such as materials and labour required for urgent response. This helps decision-makers allocate resources effectively to address oil spills promptly, as the longer the response is delayed, the further the oil spreads across the water body. This spread necessitates increased use of resources such as products and labour, significantly increasing the volume of oily waste generated. Therefore, prompt action is vital to minimize waste accumulation and effectively address the environmental impact of oil spill incidents.

Therefore, the objectives of this study are twofold: a) to develop an AI-based model to effectively and accurately estimate the volume of generated oily waste, and b) to develop a waste management framework for handling the generated waste based on factors such as waste type and the availability of treatment and receiving facilities, as well as landfills, to minimize the cost of waste handling.

## **1.8 Organization of The Thesis**

The thesis structure is as follows: Chapter 2 consists of a comprehensive literature review. The methods, materials, results, and discussion were described in Chapters 3 and 4. Chapter 5 explains the conclusion of the entire study and the recommendations for future studies.

## **CHAPTER 2      LITERATURE REVIEW**

### **2.1 Oil Spill Waste Management and Modeling**

In recent years, the focus on adequate pre-planning, risk assessment, and advancements in response techniques within the realm of oil spill management has intensified. This heightened attention stems from recognizing oil spills' profound environmental and economic consequences.

Researchers such as Marta-Almeida et al. (2013) and Azevedo et al. (2014) have made vital contributions to this field, whose models have emerged as valuable tools for addressing these challenges. The models proposed by Marta-Almeida et al. (2013) and Azevedo et al. (2014) have benefitted various stages of oil spill management. Specifically, these models have played instrumental roles in pre-planning activities, facilitating more informed decision-making processes. Additionally, they have proven invaluable in conducting comprehensive risk assessments, enabling stakeholders to anticipate and mitigate potential environmental and socioeconomic impacts (Bejarano and Mearns (2015)). Moreover, these models have contributed significantly to advancing response techniques during oil spill incidents. By providing insights into the behaviour and trajectory of spilled oil, as well as the effectiveness of different response strategies, they have empowered responders to devise more effective and efficient cleanup operations (Lehr et al. (2000); Ghanbari et al. (2021)).

Previous studies have underscored these contributions (Peterson et al. (2003); Dave and Ghaly (2011); Barron (2012)), which have highlighted the critical role of modelling approaches in enhancing preparedness and response capabilities. Through their empirical analyses and case studies, these researchers have demonstrated the tangible benefits of integrating modelling frameworks into existing oil spill management protocols (IMO (2001)).



Managing oily waste represents a crucial aspect of pre-planning and response strategies in oil spill waste management. Oily waste necessitates specialized handling and disposal procedures due to its hazardous nature and potential environmental impact. Despite the considerable attention given to oily waste management, a significant gap exists concerning estimating oily waste volumes generated during spill incidents.

While preliminary guidelines for oily waste management and factors influencing waste generation rates have been documented since the early 2000s (IMO (2001); IPIECA and IOGP (2014)), more emphasis should be placed on the accurate estimation of oily waste volumes. Metcalf (2014) attempted to address this deficiency by developing a general waste management plan to investigate the impact of cleanup strategies on waste generation. However, further advancements were reported as necessary to improve the accuracy and reliability of oily waste estimation methodologies (Beegle-Krause (2005); Bergstra (2012)).

Recent studies have turned to innovative approaches, such as self-learning or semi-supervised learning techniques, to bridge this gap and enhance the model's accuracy. These methodologies leverage labelled and unlabeled data to improve model performance (Tkalic (2006)) iteratively. Combining information from unlabeled data with labelled data expands the labelled training dataset over successive iterations until the entire dataset is labelled. Such techniques are the foundation for machine learning algorithms, including Random Forest (RF).

The applicability of self-learning approaches has been demonstrated across various scientific disciplines, including GIS and remote sensing (Fatehi and Asadi (2017); Zhao et al. (2017); Lottes and Stachniss (2017)); medical diagnostics (Kourou et al. (2015)), and groundwater investigation (Sameen et al. (2019)). These studies have highlighted the

potential of self-learning methods, particularly in data-scarce environments, as they require fewer labelled training data than traditional supervised learning models.

Another aspect of marine oil spill response waste management involves efficiently handling the waste. Oily waste is categorized as hazardous waste, characterized by toxicity, corrosiveness, ignitability, and chemical reactivity, primarily stemming from industrial and manufacturing processes. In many countries, the manufacturing industry contributes over 75% of hazardous waste, emphasizing the criticality of its management due to environmental and human health risks. Efficiently managing hazardous waste involves collecting, transporting, treating, recycling, and disposing of it safely and cost-effectively (Xu et al. (2014); Ghanbari et al. (2021)).

The integration of location and vehicle routing decisions in hazardous waste transportation and disposal was explored in the early 1980s. Various models have emerged to optimize objectives like travel time, transportation, and disposal risk.

Alumur and Kara (2007) addressed optimizing hazardous waste management systems with treatment and disposal facilities, introducing realistic constraints on the properties of waste types. Alumur and Kara (2007) incorporated waste-technology compatibility constraints, while Peterson et al. (2003) considered waste-waste compatibility and disposal centers, considering government regulations and air pollution standards as constraints. Few studies have directly addressed the vehicle routing problem, while Peterson et al. (2003) tackled waste management with multiple incompatible waste types. Integrating inventory control into location and routing decisions has yet to be explored.

Addressing uncertainty is crucial, as it affects planning decisions. Zhao et al. (2017) explored waste generation amount uncertainties and transportation costs. Metaheuristic

approaches like Genetic Algorithms (GA) have gained traction due to the Non-deterministic Polynomial-time (NP)-hard nature of location-routing problems.

Despite advancements, several gaps still need to be addressed. Simultaneous optimization of location, routing, and inventory plans under uncertain conditions, multi-period planning, and application of multi-objective solution approaches for medium to large-scale stochastic problems warrant further exploration. This comprehensive literature review outlines these aspects, providing a foundation for marine oily waste management framework research.

## **2.2 Research Gaps in Oily Waste Estimation and Waste Management**

Understanding the magnitude of oily waste production during oil spill incidents is crucial for proactive response planning, facilitating the allocating necessary resources such as materials and labour required for prompt intervention. Rapid response is imperative to mitigate oil spread across water bodies, minimizing resource consumption and waste generation. Therefore, timely action is crucial to reduce waste accumulation and effectively mitigate the environmental repercussions of oil spill incidents.

Hence, this study aims to achieve two primary objectives: firstly, to develop an AI-based model for the estimation of oily waste volume, and secondly, to formulate a comprehensive waste management framework considering factors such as waste type and the availability of treatment and disposal facilities with the ultimate goal of optimizing and/or minimizing waste management costs.

Based on the existing literature, this research introduces a novel, Improved Random Forest (IRF) model for marine oily waste estimation. By linking self-learning methodologies with the Random Forest algorithm, IRF aims to enhance predictive accuracy regarding oily

waste generation in marine contexts. To ensure the efficacy of the IRF model, this study employs Bayesian optimization for fine-tuning hyperparameters and conducts thorough performance evaluations through cross-validation. Furthermore, two conventional machine learning algorithms, namely Artificial Neural Network (ANN) and Support Vector Regression (SVR), are examined for comparative analysis to discern the optimal method for marine oily waste estimation.

Moreover, a comprehensive framework for managing oily waste has been developed to streamline the allocation of various waste volumes to suitable facilities, considering their capacities and geographical locations to minimize transportation costs. This model provides responders with a structured pathway for transferring waste volumes from generation points to treatment facilities, receiving stations, and ultimately landfills, considering compatibility between different types of waste and the capacities of the respective facilities. This model provides responders with optimized routes for waste transfer, ensuring efficient management even during facility disruptions or the availability of additional facilities.

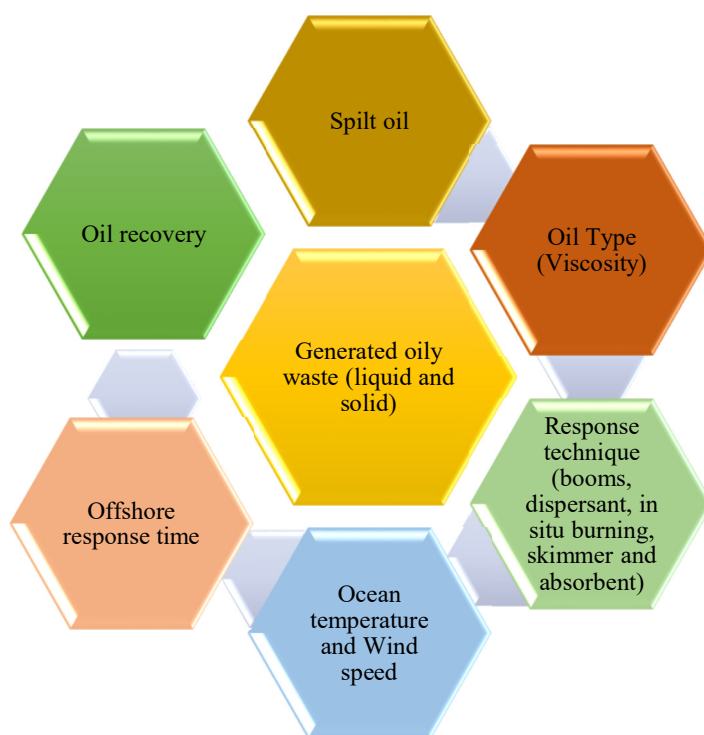
## **CHAPTER 3      METHODOLOGY**

This research aims to conduct comparative assessments of various well-known AI-based models, namely Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Improved Random Forest (IRF), for estimating off-shore oily waste following oil spill clean-ups. ANN is often considered a primary choice among researchers due to its versatility and success in addressing many problems. Meanwhile, SVR has gained increased attention in recent years for its effectiveness in handling estimation problems comprehensively. The following paragraphs will provide data collection and background information on the abovementioned models. This section will then continue explaining how to develop and evaluate estimation models.

### **3.1 Data Collection and Assumption**

Understanding the factors influencing the volume and composition of waste generated during oil spill incidents is crucial for estimating waste. However, accessing information about oil spill incidents presents significant challenges due to limited valid sources. This study compiles a comprehensive database detailing the physical and chemical characteristics of previous oil spill incidents globally to address this issue. Extensive efforts were made to gather information through literature searches, surveys, and consultations with relevant agencies such as the Western Canada Marine Response Corporation (WCMRC), DFO, and BC Ministry of Environment and Climate Change Strategy as provided in Appendix A. This database considers various aspects of oil spill incidents, including quantity of spilled oil, location, oil type, viscosity, ocean conditions, wind speed, water temperature, response techniques, duration of off-shore response operations, and volume of recovered oil

and waste (Figure 3.1). These factors significantly influence response strategies, personal protective equipment requirements (PPE), and the volume of generated waste.



**Figure 3.1** Parameters affecting the volume of generated off-shore oily waste

In cases where climatic data, such as ocean temperature, were unavailable in oil spill response reports, assumptions were made based on past 20-year average water temperatures for the incident location reported on different websites such as National Oceanic and Atmospheric Administration (NOAA), US Environmental Protection Agency (EPA), and ITOPF. Sixty oil spill incidents were ultimately selected as input data for the research model. The selection criteria prioritized oil spill incidents with 90% of the required information available.

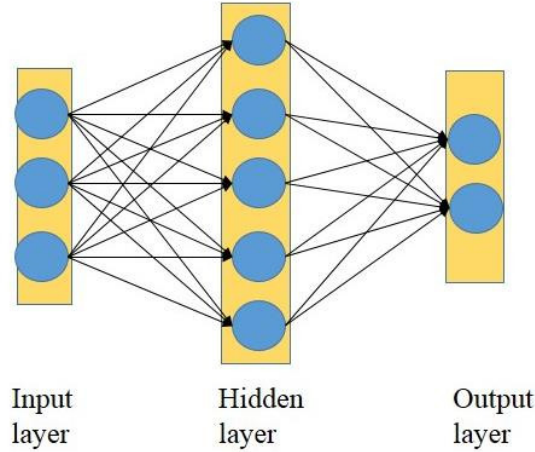
While AI-based models typically benefit from larger datasets, the decision to use 60 oil spill incidents for testing purposes was deemed sufficient. This approach helps prevent

model overgeneralization and ensures efficient pattern recognition by excluding erroneous or irrelevant data. Notably, the model's adaptability allows for optimization based on new and existing data, promising more accurate waste volume estimations as additional information becomes available.

## **3.2 Artificial Intelligence (AI)-based Model Development**

### **3.2.1 Artificial Neural Network (ANN)**

Artificial neural networks are complex mathematical systems that mimic the human brain's neural system. In brief, ANNs comprise three different layers: input, output, and hidden. Each layer consists of neurons or nodes as processing elements of the network. Neurons on the input layer will distribute the input information to the neurons of the next layer, hidden layer(s), where the information will be processed and then transferred to the output layer, where the results are produced (Zhang and Friedrich (2003)). Figure 3.2 shows a schematic structure of a simple ANN model. In training such a network, weighted connections among layers only occur in a forward direction from the input to the output layers. These interconnections are then adjusted by distributing errors through the layers to produce the most accurate outputs, which is called backpropagation. Hidden layers are advantageous over traditional logistic regression analysis techniques by modelling the interactions and relations among all the input parameters. An essential consideration in designing ANNs is choosing the number of neurons at each layer and the number of hidden layers, commonly known as hyperparameters (Zhang and Friedrich (2003); Wang et al. (2009)). This study has applied a new approach to tuning these parameters, which will be discussed in section 3.2.



**Figure 3.2** Schematic structure of the ANN model

### 3.2.2 Support Vector Regression (SVR)

Another studied model is SVR, initially designed for classification problems (Sain and Vapnik (1996)), but with the introduction of a new parameter, Vapnik's  $\epsilon$  intensive loss function, its application has been extended to solve non-linear regression estimation (Smola and Schölkopf (2004)), and time series forecasting as well (Thissen et al. (2003); Lin et al. (2006)). SVR implements Structural Risk Minimization (SRM) rather than empirical risk minimization implemented by most traditional ANNs, which ultimately results in providing an answer that is always unique and globally optimal (Lin et al. (2006)).

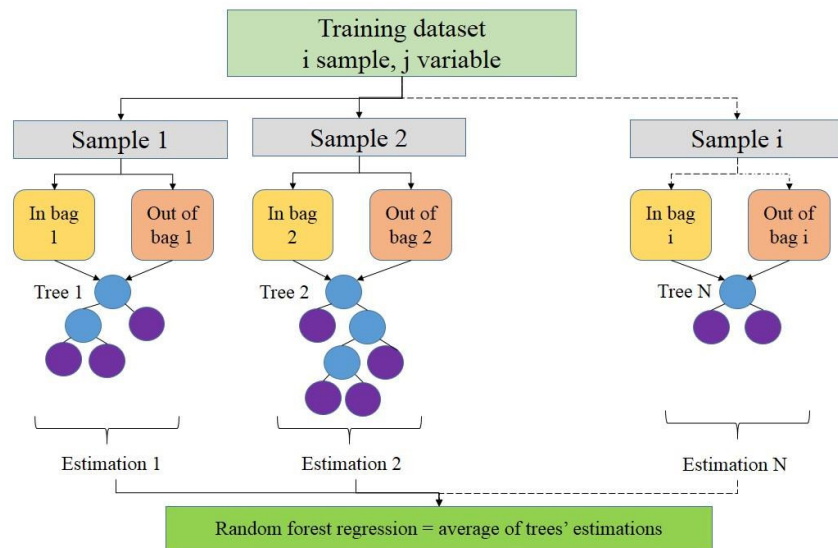
Similar to ANN, SVR uses an implicit feature space mapping from the dimension of the data to a possibly infinite feature space, which provides a non-linear representation of the modelled data, performed through a kernel function (Smola and Schölkopf (2004); Sadri et al. (2012); Goyal et al. (2014)). Defining kernel function and its parameters is not straightforward in the SVR network, as some settings might be prone to over-fitting or under-fitting. Therefore, different kernel functions should be tested to choose the one associated



with the lowest error in the validation stage. This study uses a Bayesian optimization model to determine the most competent kernel function.

### 3.2.3 Improved Random Forest (IRF)

RF, the third studied model in this work, is a classification-based regression model introduced by Breiman (2001). It is a supervised learning algorithm that uses an ensemble learning method for regression. RF operates by creating and combining many decision trees (Figure 3.3). Decision trees handle high dimensional data well, overlook irrelevant descriptors, control multiple mechanisms of action, and are amenable to model interpretation ( Svetnik et al. (2003)).



**Figure 3.3** A Random Forest schematic view

The steps of training the RF regression model can be summarized in the following steps:

1. About two-thirds of the data will be randomly selected as a training dataset called a bootstrapped dataset.
2. The remaining one-third will fall into an out-of-bag dataset, which will be used to measure the error.
3. The model's outcome is the average result of all the trees (Cutler et al. (2007)).

### **3.3 Waste Estimation Model**

As mentioned, artificial intelligence and machine learning techniques can significantly expedite decision-making processes by analyzing subtle data patterns from previous oil spill incidents. No single machine learning algorithm consistently outperforms others, as their effectiveness depends on the nature of the problem and data formats. Hence, this thesis compares ANN, SVR, and RF for off-shore oily waste estimation. Generally, developing estimation models involves establishing a formula between input and output parameters that accurately represents the problem's nature and can be extended to estimate new variables within the input parameter range the model is trained with.

The effectiveness of AI-based models hinges on the proper combination of hyperparameters, which control the model's overall performance. Typically, hyperparameters are selected through trial and error, a time-consuming process with loose guidelines on their numerical range. Moreover, hyperparameters interact with each other, complicating the optimization process. To address this challenge, robust optimization methods are employed to find the optimal configuration of each AI-based model. Traditionally, grid and random search

methods have been used for this purpose. Grid search optimizes all possible model configurations, while random search involves iterative runs of evaluating models with randomly selected hyperparameters. However, these methods overlook historical information from previous evaluations.

This study uses Bayesian optimization to find the best combination of hyperparameters by minimizing an error index (objective function) within predefined search ranges (constraints). Unlike trial-and-error approaches, Bayesian optimization leverages past evaluations to create a probabilistic model mapping hyperparameters. The Bayesian optimization procedure involves several steps, including model initialization, acquisition function optimization, model updating, and hyperparameter selection. For detailed information on Bayesian optimization, readers are referred to Snoek et al. (2012).

1. Build a surrogate probability model of the objective function;
2. Find the hyperparameters that perform best on the surrogate;
3. Apply these hyperparameters to the actual objective function;
4. Update the surrogate model incorporating the new results; and
5. Repeat steps 2–4 until max iterations or time is reached.

Table 3.1 presents the name of hyperparameters along with their search range for optimization purposes for ANN, SVR and RF. To accurately compare the models, the objective function is set to minimize the Root Mean Square Error (RMSE) for all models (see Eq. (3.1)). Mean Square Error (MSE) and RMSE are widely used error indices for evaluating model performance. RMSE is chosen over MSE mainly because RMSE gives higher weight and punishes significant errors.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (O_i - S_i)^2}{n}} \quad \text{Eq. (3.1)}$$

Where O and S denote the observed and estimated values, respectively, to achieve a more reliable estimation of oily waste, a 5-fold cross-validation method is employed alongside Bayesian optimization to tune hyperparameters finely. This process involves randomly dividing the data in the training subset into five equal-sized parts. One part is reserved for validating the model, while the remaining four are used for training. The cross-validation process is repeated five times for each run of Bayesian optimization. The estimated hyperparameters and their accuracy are then derived by averaging the results across all runs (Diamantidis et al. (2000)).

**Table 3.1** AI-based models' hyperparameters, their description and search space used in the Bayesian optimization process

Model	Hyperparameter	Search space
ANN	Hidden Layer size	(1, 20)
	Learning rate	( $10^{-3}$ , 1)
SVR	Kernel Function	(Gaussian, RBF, Polynomial)
	Kernel scale	( $10^{-3}$ , $10^3$ )
RF	Number of estimators (trees)	(100, 5000)
	Max_features	(1, 7)
	Max_depth (The maximum number of splits a tree should make before it makes a prediction)	(1, 20)

### 3.3.1 Model Evaluation

In this study, the three most common statistical error indices, including RMSE, Relative Mean Absolute Error (RMAE), and Spearman correlation coefficient, are considered to compare the performance of waste estimation models at the test stage as follow:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (O_i - S_i)^2}{n}} \quad \text{Eq. (3.2)}$$

$$\text{RMAE} = \frac{\sum_{i=1}^n |O_i - S_i|}{\sum_{i=1}^n O_i} \times 100 \quad \text{Eq. (3.3)}$$

$$\text{Correlation coefficient} = 1 - \frac{6 \sum_{i=1}^n d_i^2}{n(n^2 - 1)} \quad \text{Eq. (3.4)}$$

Where  $n$  is the sample size,  $O$  and  $S$  denote the estimated waste from the AI-based model and the actual generated waste, respectively. This study uses Spearman correlation, a non-parametric correlation factor, to measure the association between the estimated waste from the AI-based model and the actual generated waste. Unlike other correlation measures, Spearman correlation does not assume a normal distribution of the variables. Instead, it evaluates based on the difference in their statistical ranks (as elaborated in Snoek et al. (2012)).

### **3.4 Waste Management/Transfer Framework**

Off-shore oily waste management faces more constraints related to cost and resources compared to response plans, emphasizing the importance of careful pre-planning to maximize resource efficiency. This planning can be divided into two main components: waste estimation and designing an efficient waste management framework. This section will evaluate the most effective framework for waste transfer, considering factors such as route number and cost. Accurate waste estimation is crucial for responders to arrange temporary storage and allocate resources effectively before an incident occurs. Given its significant cost implications, waste management plays a pivotal role in contingency planning for oil spill response. Efficient and optimized allocation of generated waste relies on several critical factors, including the location of the oil spill incident and available facilities, the compatibility of waste types with treatment facilities, the capacities of these facilities, the treatment rate of treatment facilities, and the number of generated points (oil spill incidents).

#### **3.4.1 Problem Description**

Industrial hazardous waste management involves handling waste at its source, transporting it to treatment or receiving facilities, and ultimately disposing of it in landfills if necessary. Through consultations with hazardous waste management contractors in British Columbia (BC), such as Terrapure, it has been recognized that waste transportation constitutes the most costly and time-consuming aspect of waste management. This challenge is exacerbated when dealing with multiple types of waste, as considerations must be made for compatibility with facilities and transport vehicles, with some waste types posing risks of dangerous reactions if co-transported. Hence, understanding the available waste treatment network is crucial for optimizing waste transportation efficiency. The key focus of this

optimization lies in determining the most effective routing system to minimize transportation costs.

BC has been selected as a case study for this study due to its relevance to the research funded by DFO for waste management purposes on the West Coast. On a typical day without spill incidents, approximately three to four trucks transport around 60 tonnes of waste to landfills in BC and Alberta. Consequently, proactive planning is essential to transport waste to each facility based on its current waste load and capacity to prevent congestion and additional storage costs. The efficient utilization of temporary storage or receiving facilities' capacity constitutes the second component of this study. Each facility is designed to accommodate a finite amount of waste.

Lastly, the third component involves selecting the optimal facility based on its capacity and location among other potential facilities. Therefore, a network incorporating all these components can aid decision-makers in promptly managing generated waste, mainly since prolonged collection and transportation times result in increased contamination and storage costs. The formulation of this model aims to optimize transportation routes to waste-compatible facilities using waste-compatible vehicles to minimize total costs. Several assumptions are considered in designing the model, including the impact of uncollected waste at generation nodes and unprocessed waste at treatment facilities leading to additional storage costs, the determination of the number of vehicles at each generation node, and ensuring that the amount of waste transferred by cars does not exceed their capacity.

### 3.4.2 Mathematical Modeling

With the assumptions outlined, a non-linear model is developed to identify the optimal waste management strategy from the generation node to the final destination (landfill), considering facility capacities and waste types to minimize transportation costs. Before delving into the model's design, defining the terms and notations utilized for the modelling process is essential, as detailed in Table 3.2.

Based on the assumption above, a non-linear model is programmed to find the optimum way of handling waste from the generation node to the ultimate destination (landfill), considering the capacity of facilities and waste type to minimize the transportation cost. Before designing the model, the terms and notations used for modelling are stated in Table 3.2.

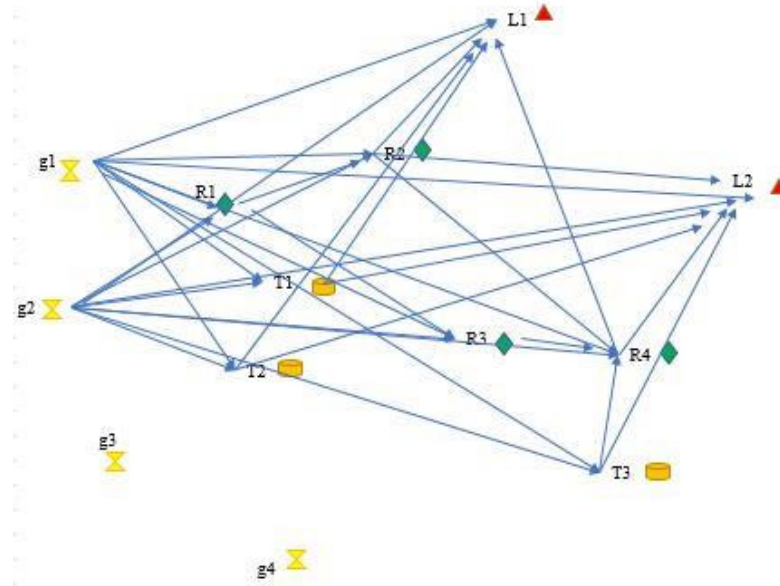
**Table 3.2** Notations used in the designed waste management framework

Index	Parameter	Value/unit	Description
t			Number of treatment facilities
r			Number of receiving facilities
s			Number of generation nodes (source)
l			Number of landfills
	Vsol	40,000 m <sup>3</sup>	Truck capacity (solid waste)
	Vliq	60,000 m <sup>3</sup>	Vacuum truck capacity (liquid waste)
	TR	10%	Treatment rate at solid treatment facilities
	cc	5 CAD/km.tonne	Transportation cost
	TCt	750 tonne/day	Capacity of treatment facility number t



RCr	1200 tonne/day	Capacity of receiving facility number r
LCr	Inf	Capacity of landfill facility number l
DIStr	km	Distance between two nodes

As previously stated, the primary objective function of the model is to identify the most optimized path within a marine oily waste management network. Consequently, all feasible paths between each node for waste originating from a particular node until it reaches its designated destination are considered design variables (Figure 3.4). For instance, the volume of waste transferred from source 1 to treatment facility one is denoted by  $ZST(1,1)$ , as per the notation outlined in Table 3.3. Subsequently, additional decision variables are defined based on the number of generation nodes (sources), treatment plants, receiving facilities, and landfills.



**Figure 3.4** Schematic view of possible transportation paths between each two nodes in the framework

**Table 3.3** Description of the decision variables used in the designed waste management framework

Decision Variable	Description
ZST(1,1)	The volume of waste transferred from source 1 to treatment plant 1
ZST(1,2)	The volume of waste transferred from source 1 to treatment plant 2
...	...
ZST(1,t)	The volume of waste transferred from source 1 to treatment plant t
ZST(2,1)	The volume of waste transferred from source 2 to treatment plant 1
ZST(2,2)	The volume of waste transferred from source 2 to treatment plant 2
.....	...
ZST(s,t)	The volume of waste transferred from source s to treatment plant t
ZSR(1,1)	The volume of waste transferred from source 1 to receiving facility 1
....	...
ZSR(s,r)	The volume of waste transferred from the source s to the receiving facility r
ZSL(1,1)	The volume of waste transferred from source 1 to Landfill 1
...	...
ZSL(s,l)	The volume of waste transferred from source s to Landfill l
ZTR(1,1)	The volume of waste transferred from treatment plant 1 to receiving facility 1
...	...
ZTR(t,r)	The volume of waste transferred from the treatment plant t to the receiving facility r
ZTL(1,1)	The volume of waste transferred from treatment plant 1 to landfill 1
...	...
ZTL(t,l)	The volume of waste transferred from the treatment plant t to the landfill l
ZRL(1,1)	The volume of waste transferred from receiving facility 1 to landfill l
...	...
ZRL(r,l)	The volume of waste transferred from the receiving facility r to the landfill l

### 3.4.3 Objective Function and Constraints

As discussed in the previous section, the complexity of the problem involves numerous decision variables that cannot be readily solved. These issues fall under the Non-deterministic Polynomial-time hard (NP-hard) problems, which are computationally challenging and time-consuming to address using traditional algorithms. This challenge is exacerbated by the exponential growth rate of feasible solutions over time, a phenomenon known as combinatorial explosion (Hoang (2008)). Consequently, various meta-heuristic algorithms have been developed to tackle such optimization problems effectively.

One prominent meta-heuristic optimization approach is the Genetic Algorithm (GA), which has successfully addressed complex optimization challenges. Originating in 1975, GA is inspired by natural selection in biological evolution. In GA, a population of feasible solutions evolves through selection, recombination, and mutation, akin to genetic alterations aiming to enhance solution accuracy. The critical steps of a GA optimization problem are as follows:

- Initialization: A population of feasible solutions is randomly generated.
- Evaluation: Each solution is assessed against a fitness function, typically representing an error index quantifying its effectiveness in addressing the problem.
- Selection: A subset of solutions is chosen based on their fitness function values, expecting that subsequent generations will yield improved solutions.
- Recombination: Selected solutions undergo recombination operations such as crossover or mutation to generate a new population of solutions.

- Replacement and iteration: The new population replaces the previous one, repeating steps 2 to 5 for a specified number of generations or until a satisfactory solution is attained based on the fitness function.

GA's main advantage lies in its ability to handle many feasible solutions while remaining time-efficient. However, GA's performance heavily relies on the randomness of the initially generated solutions, underscoring the importance of running the model multiple times to achieve a robust solution.

In designing an optimized transportation framework, the primary objective function aims to minimize transportation costs and determine the optimal volume and path for waste generated from a predefined source location to the ultimate destination (landfills). The objective function can be formulated as follows:

$$\begin{aligned} Min(f_z) = & \sum_{s=1}^s \sum_{t=1}^t Z_{st} \times DIS_{st} \times cc + \sum_{s=1}^s \sum_{r=1}^r Z_{sr} \times DIS_{sr} \times cc + \sum_{s=1}^s \sum_{l=1}^l Z_{sl} \times DIS_{sl} \times cc + \\ & \sum_{t=1}^t \sum_{r=1}^r Z_{tr} \times DIS_{tr} \times cc + \sum_{t=1}^t \sum_{l=1}^l Z_{tl} \times DIS_{tl} \times cc + \sum_{r=1}^r \sum_{l=1}^l Z_{rl} \times DIS_{rl} \times cc \end{aligned} \quad \text{Eq. (3.5)}$$

$$Z_{Total} = Z_{s1} + Z_{s2} + \dots + Z_s \quad \text{Eq. (3.6)}$$

Where the variables and decision parameters are described in Table 3.2 and Table

3.3. The optimization model's constraints are outlined s follows:

1. Whenever a collection vehicle enters a node, it must exit it towards another destination.

2. Compatibility between wastes for transfer within a collecting vehicle is not a concern.
3. Waste types must align with the technology at treatment facilities and the types accepted by receiving facilities and landfills.
4. The quantity of waste allocated to a route and/or facility must be equal to or greater than zero.
5. The total waste volume across all directions must match the overall volume that needs to be managed, excluding considerations for waste type.
6. The volume of waste being transferred to a facility should be at most of the facility's capacity.
7. some waste residues can be directed to a receiving facility or a landfill following treatment.













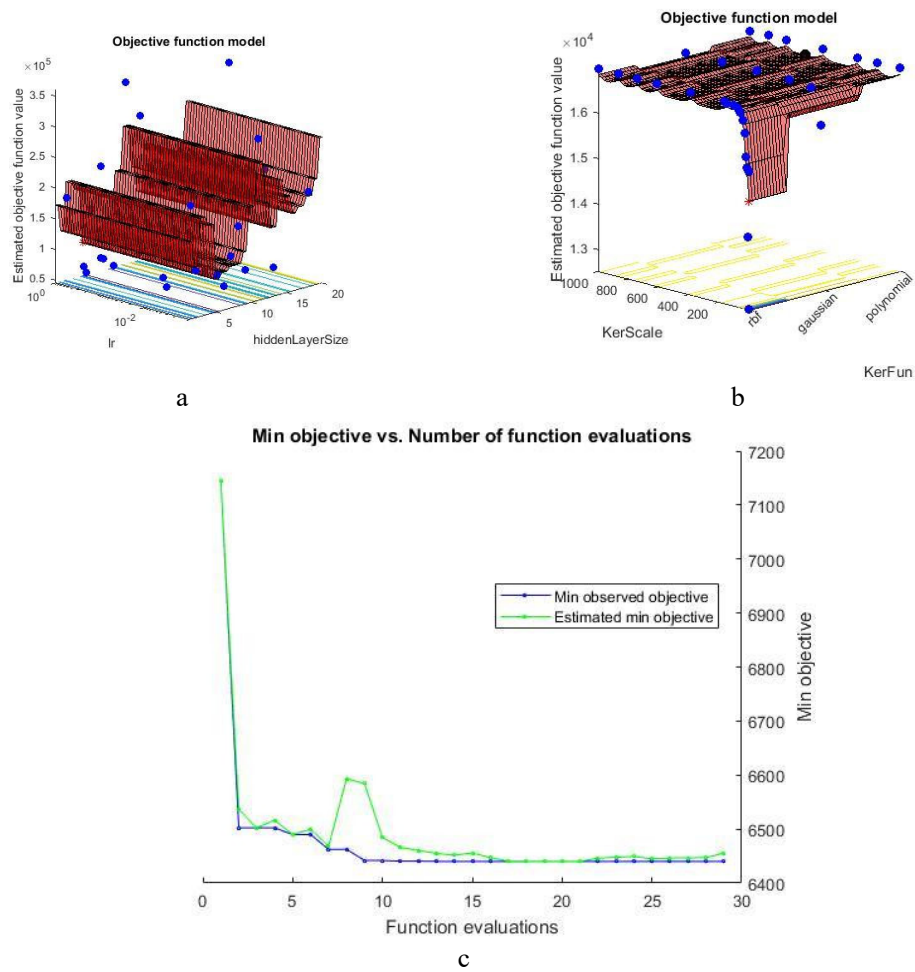
## CHAPTER 4 RESULTS and DISCUSSION

### 4.1 Hyperparameter Optimization

In this section, the optimized values for the hyperparameters of Artificial Neural Networks, Support Vector Regression, and Random Forest models are presented. As previously stated, this study aims to develop an estimation model for three types of oily waste: liquid, solid, and total solid and liquid waste. Bayesian optimization has been employed to fine-tune the hyperparameters of the estimation models listed in Table 3.1 to minimize the models' RMSE index. The scripts for all estimation models, including the hyperparameter optimization, were implemented in MATLAB. Figure 4.1 illustrates the results of Bayesian optimization for ANN, SVR, and RF models. Additionally, Tables 4.1, 4.2, and 4.3 provide detailed reports on the outcome of the optimization process and the best-determined values for the hyperparameters of ANN, SVR, and RF waste estimation models, respectively.

**Table 4.1** Optimized hyperparameters of ANN waste estimation model

Type of waste	Best Hidden layer size	Best Learning rate
Solid Waste	8	0.04087
Liquid Waste	8	0.03352
Total Waste	9	0.03156



**Figure 4.1** Results of Bayesian optimization for AI-based optimization models: a) ANN, b) SVR, and c) RF

**Table 4.2** Optimized hyperparameters of SVR waste estimation model

Type of waste	Best Kernel Function	Best Kernel scale
Solid Waste	RBF	1.127
Liquid Waste	RBF	1.127
Total Waste	RBF	1.127

**Table 4.3** Optimized hyperparameters of RF waste estimation model

Type of waste	Number of trees	Best max feature no.	Best split no.
Solid Waste	3270	6	5
Liquid Waste	112	3	13
Total Waste	259	1	6

## 4.2 Waste Estimation Model

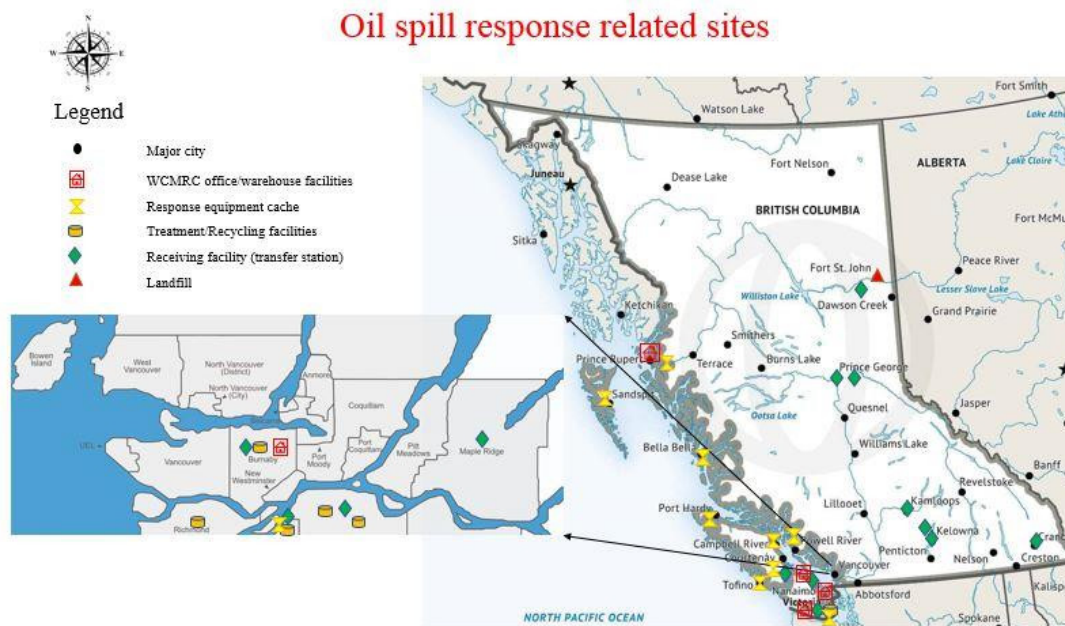
After optimizing the hyperparameters, the models were tested with the tuned settings, and the results of the estimation models are summarized in Table 4.4. It is observed that the error values decrease progressively from ANN to SVR and finally to RF. Notably, RF exhibits the lowest reported error indices (RMSE and RMAE) across all types of waste. Furthermore, RF demonstrates a higher correlation value (0.77) between the estimated and observed wastes compared to ANN and SVR, which average at 0.4 and 0.59, respectively. This superiority of RF can be attributed to its increased randomness and minimal risk of overfitting due to the large number of decision trees involved. Additionally, RF provides a more robust output estimation by ensuring low correlation among individual trees, achieved through diversification of the forest by limiting the number of input parameters for each tree. The RF-based model developed for oily waste estimation holds significant applicability to numerous oil spill incidents, as the database can be continuously updated, and the model will automatically adjust accordingly. This model is of immense value to oil spill response practitioners and waste disposal contractors by providing crucial insights for waste management planning.

**Table 4.4** Evaluation of the AI-based Waste Estimation Models

Model	Type of Waste	RMSE (tonne)	RMAE (%)	CC
ANN	Solid	9.98	4.86	0.39
	Liquid	9.98	4.88	0.39
	Total	9.98	4.80	0.41
SVR	Solid	3.69	5.32	0.61
	Liquid	3.69	6.09	0.55
	Total	3.69	5.32	0.61
RF	Solid	1.20	0.61	0.77
	Liquid	1.22	0.66	0.77
	Total	1.25	0.61	0.77

### 4.3 Waste Allocation Framework

The Bella Bella oil spill incident in British Columbia, Canada, serves as a case study to assess the proposed framework outlined in the methodology section. To this end, comprehensive details regarding treatment and receiving facilities, including their capacities and distances from one another, have been compiled and presented in Table 4.5. This data was acquired through numerous meetings with representatives and operation managers of Terrapure, the primary waste contractor on the West Coast. The geographical locations of each facility are indicated on the map depicted in Figure 4.2.



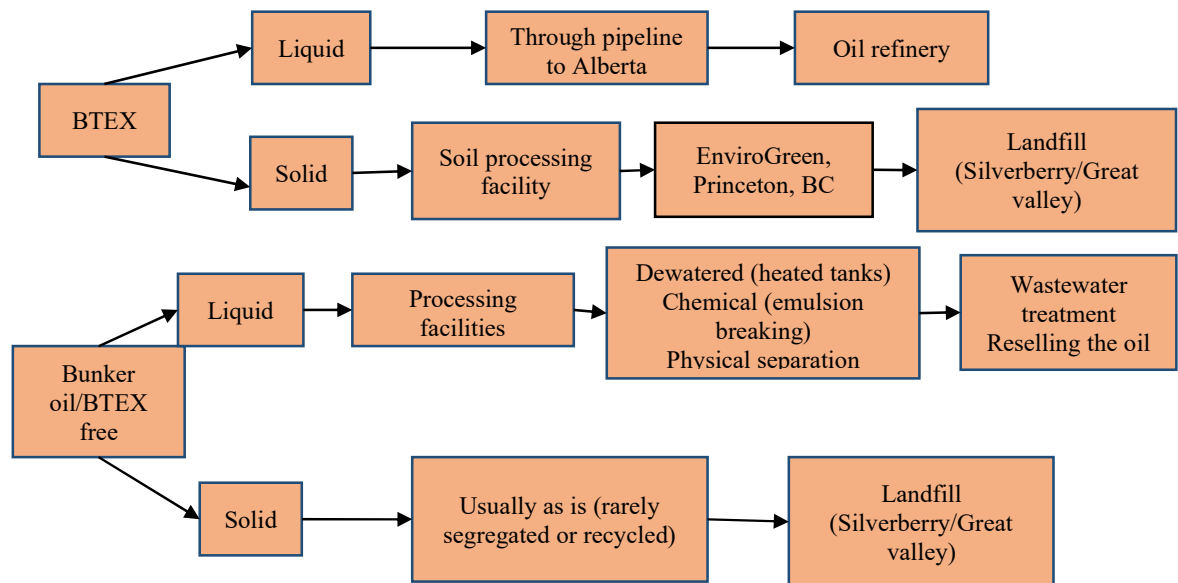
**Figure 4.2** The location of waste handling facilities in British Columbia

**Table 4.5** Name and location of currently operating facilities in British Columbia

Treatment/Recycle facilities	Receiving facilities (Transfer stations)
Safety Clean: Delta	Aveitas: Maple Ridge
Secure Energy: Richmond	GFL: Victoria, Nanaimo, Port Alberni, Surrey,
Sumas Environment: Burnaby	Cranbrook, Kelowna, Prince George
Stericycle: Surrey	Safety Clean: Delta
	Secure Energy: Richmond, Fort St. John
	Sumas Env: Burnaby, Kamloops
	Stericycle: Surrey

As depicted in Figure 4.2, most facilities are situated in the lower mainland area or on Vancouver Island, underscoring the importance of pre-established frameworks for waste

transport in the event of emergency incidents occurring in the central or northern regions of the province. Through research and discussions with the primary waste contractor for the province, it has been determined that the treatment path for generated oily waste varies depending on whether it contains a high concentration of BTEX or bunker oil, as illustrated in Figure 4.3. Liquid high BTEX oily waste is primarily transported to oil refineries in Alberta via pipelines. At the same time, its solid form can undergo processing within the province, being stabilized at a soil processing facility in Princeton before being transported to designated landfills. In cases where the generated solid waste stems from a bunker oil spill incident, it is typically transported directly to landfills without segregation. Conversely, the liquid waste undergoes treatment at specialized facilities, where processes such as dewatering, emulsion breaking, and physical separation are employed to separate oil from water. In many instances, the separated oil can subsequently be sold.



**Figure 4.3** The common practice of oily waste management in British Columbia



Considering the heterogeneous nature of oily wastes, it is imperative to consider waste-waste compatibility. Furthermore, the transportation of each waste type necessitates specific types of trucks and treatment facilities. To address these requirements, comprehensive details regarding all operational facilities have been compiled and are presented in Table 4.6.

**Table 4.6** The detailed information on oily waste handling facilities in British Columbia

ID	Name	Type	City
S1	Bella Bella	Oil Spill Incident	Bella Bella
T1	GFL	Treatment Facility	Victoria
T2	GFL		Surrey
T3	Safety Clean		Delta
T4	Secure Energy		Richmond
T5	Sumas		Burnaby
	Environmental		
T6	Stericycle		Surrey
R1	Aveitas	Receiving Facility	Maple
			Ridge
R2	Safety Clean		Delta
R3	Secure Energy		Richmond
R4	Secure Energy		Fort St. John
R5	Sumas		Burnaby
	Environmental		
R6	Sumas		Kamloops
	Environmental		
R7	Stericycle		Surrey

R8	GFL		Victoria
R9	GFL		Nanaimo
R10	GFL		Port Alberney
R11	GFL		Surrey
R12	GFL		Cranbrook
R13	GFL		Kelowna
R14	GFL		Prince George
L1	Silverberry	Landfill	Fort St. John
L2	Great Valley		

As outlined in the methodology section, the optimization of decision variables surpasses the cognitive capacity of human processing, classifying these issues as NP-hard problems that are nearly insurmountable without computational aid. GA emerges as a robust solution for optimizing decision variables involved in waste transfer processes, effectively integrating the capacities of diverse handling facilities into the model without necessitating intricate programming. This accelerates processing time and enhances the model's practicality, which is a critical consideration in emergency scenarios. The real-world application of this methodology is exemplified through the analysis of the Bella Bella oil spill incident in British Columbia, where estimated solid waste volume and associated cleanup costs serve as pivotal parameters. However, detailed information regarding the incident volume is private. Therefore, based on the most recent study published on the estimated solid waste in the Bella Bella oil spill incident, the volume of generated solid waste is estimated to be  $13.8 \times 10^3$  tonnes. According to the published articles, the cleanup costs of the Bella Bella oil spill incident amount to around \$2.7 million. The cost breakdown is reported as follows:

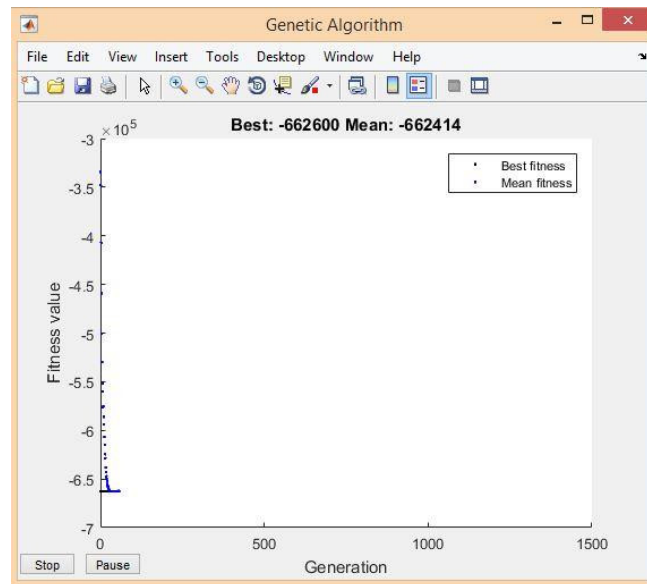
- Cleanup costs: \$2.7 million
- Fines for non-compliance: \$500,000
- Environmental testing during spill: \$50,000
- Labor expenses: \$500,000
- Office equipment, boats, etc.: \$100,000
- Hidden costs: \$100,000
- Transportation and disposal expenses: \$1.45 million
- Disposal fee (approx.): \$100/tonne of solid waste
- Total transportation cost: Approximately \$1 million

After running the model, the transportation cost was minimized, as shown in Table 4.7. The optimization process took approximately 30 minutes, resulting in a total minimized cost of 662,600 CAD. Figure 4.4 illustrates the trial-and-error process of the algorithm to achieve the lowest transportation cost for waste disposal from the source to the landfill. It is evident from the analysis that utilizing the model would yield savings of 337,400 CAD.

The model's high level of customization is evident in its ability to adjust capacities for different facilities, preventing traffic congestion in smaller plants. Furthermore, the model accommodates diverse treatment rates and relevant costs across facilities, contributing to a more cost-effective waste allocation strategy. The model's adaptability is a key highlight, enabling rapid adjustments in response to emergencies, such as the malfunction of a treatment plant, ensuring an optimized flow of waste transportation.

**Table 4.7** The identified path from source to landfill with volume based on the Bella Bella oil spill incident in British Columbia

ID	Path	Volume (tonne)	Description
26	Zs1l1	7.28	Volume of waste from source 1 to landfill 1
58	Zs1r1	6.4	Volume of the waste from source 1 to receiving facility 1
59	Zr1l1	6.4	Volume of waste from receiving facility 1 to landfill 1



**Figure 4.4** Genetic Algorithm minimization cost graph

The model's capacity to consider multiple generation nodes reflects its applicability to real-world scenarios where waste transfer involves intricate networks. The reported daily transfer of 60 tonnes of non-marine oily waste in British Columbia underscores the

significance of such a comprehensive approach. Moving beyond immediate applications, the study offers valuable insights for decision-makers regarding future facility expansions and strategic placements. It serves as an evaluative tool, providing feedback on the current performance of facilities and proposing a holistic optimization of the waste management system. The model's versatility extends to different geographical areas, making it a valuable tool for calculating distances based on the coordinates of new facilities or potential oil spill sources.

## **CHAPTER 5            CONCLUSION AND RECOMMENDATIONS**

### **5.1 Conclusion**

In conclusion, this research represents a significant step forward in the field of Oily waste management, offering an in-depth exploration of estimation models and allocation frameworks. The study systematically examined three prominent models – Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Random Forest (RF) – and found that RF stands out as the most adept in accurately predicting volumes of oily waste. Incorporating Bayesian optimization in hyperparameter tuning enhanced the precision and adaptability of the estimation model, rendering it a potent tool for practical applications in diverse scenarios.

Utilizing the Genetic Algorithm (GA), the waste allocation framework emerged as a robust solution to the intricate challenges of transporting varied types of oily waste to treatment and disposal facilities. Its flexibility enables decision-makers to tailor the framework to specific needs, accounting for facility capacities, waste compatibility, and real-time conditions. This research showcased its practical efficacy by applying the framework to the Bella Bella oil spill incident in British Columbia, highlighting its pivotal role in facilitating informed decision-making during emergencies.

Beyond its theoretical contributions, this research holds practical implications for waste management practitioners, environmental authorities, and response teams. The rigorous evaluation and validation of the proposed models and frameworks establish a solid foundation for enhancing waste management practices in offshore environments. As the offshore industry evolves, integrating artificial intelligence and optimization techniques becomes imperative for developing sustainable and efficient waste management strategies.

The models and frameworks introduced in this study address current challenges and set the stage for future innovations in the field, emphasizing the continual need for advancements in off-shore waste management.

The success of the waste allocation framework lies in its adaptability, providing decision-makers with the ability to customize the model based on facility capacities, waste compatibility, and real-world constraints. Furthermore, applying the Genetic Algorithm enables quick adjustments to the network in response to emergencies, ensuring that the optimized flow of waste transportation can be identified promptly. The model's capacity to handle multiple generation nodes and provide insights into facility performance and potential expansions further strengthens its utility in practical waste management scenarios.

In summary, this research underscores the pivotal role of advanced modelling and optimization techniques in addressing the complexities of off-shore oily waste management. The presented models and frameworks advance our understanding of waste estimation and allocation and offer tangible tools for improving decision-making in the face of environmental emergencies. As the industry progresses, integrating these innovations will be essential in shaping sustainable practices and minimizing the ecological impact of off-shore activities.

The summary of advantages and disadvantages of the incorporated models in this study are presented as follows:

**Strengths:**

- **Precision in Waste Estimation:** Bayesian optimization enhances the precision of waste estimation models, ensuring accurate predictions.
- **Optimized Waste Allocation:** Genetic Algorithm-based waste allocation framework optimizes transportation routes and minimizes the costs.

- **Model Adaptability:** The waste allocation framework is highly customizable, allowing adjustments based on real-time conditions and facility capacities.
- **Practical Efficacy:** Application of the framework in the Bella Bella oil spill incident demonstrates its practical efficacy in real-world emergencies.
- **Flexibility for Decision-Makers:** Decision-makers can tailor the waste allocation framework to specific needs, considering waste compatibility and facility capacities.
- **Quick Network Modifications:** Genetic Algorithm enables adjustments to the waste transportation network in response to emergencies or facility malfunctions.
- **Handling Multiple Generation Nodes:** The model can consider multiple generation nodes, addressing the complexity of waste transfers to various facilities.
- **Insights for Facility Expansion:** Provides insights into the performance of existing facilities, aiding in strategic decisions for future expansions.
- **Feedback Mechanism:** The model acts as a feedback mechanism for the performance of present facilities, allowing for continuous improvement.
- **Applicability in Different Areas:** The model's ability to calculate distances by entering geographical coordinates makes it applicable in diverse geographical locations.

#### **Weaknesses:**

- **Limited Public Data:** Lack of publicly available data for actual incidents, such as the Bella Bella oil spill incident, limits the accuracy of model validation.
- **Complexity of NP-Hard Problems:** Waste allocation problems are NP-hard, making manual handling impractical due to the extensive number of decision variables.
- **Dependency on Initial Solutions (GA):** The performance of the Genetic Algorithm is highly dependent on the randomness of the initial generated solutions.



- **Incomplete Information for Bella Bella Oil Spill Incident:** Limited information on the volume of the Bella Bella oil spill incident waste hinders precise modelling and validation.
- **Challenges in Modeling Waste-Waste Compatibility:** Incorporating waste-waste compatibility in the models is challenging due to the heterogeneous nature of oily wastes.
- **Specificity of Truck and Facility Requirements:** Shipping each type of waste requires specific trucks and treatment facilities, adding complexity to the waste allocation problem.
- **Continuous Model Improvement:** The model's performance depends on frequent updates and adjustments based on evolving waste management practices.
- **Resource-Intensive Bayesian Optimization:** Bayesian optimization, while effective, can be resource-intensive, requiring significant computational power.
- **Inherent Uncertainties in Oil Spill Incidents:** The unpredictable nature of oil spill incidents introduces uncertainties that may affect the accuracy of waste estimation.
- **Need for Real-Time Data Integration:** Real-time data integration is crucial for the models, and its absence may impact the adaptability and accuracy of waste allocation.

## 5.2 Recommendations

Given the strengths and weaknesses outlined in the previous section, broadening the study by integrating various approaches or components will contribute to a more thorough evaluation of off-shore oily waste estimation. The suggested viewpoints are summarized below:

- **Integration of Real-Time Data:** Developing methods for real-time data integration to enhance the adaptability and accuracy of waste management models.
- **Enhanced Validation Processes:** Implementing comprehensive validation processes, including creating realistic scenarios, to overcome data limitations for incident-specific models.
- **Exploration of Advanced Optimization Algorithms:** Investigating the application of advanced optimization algorithms beyond Genetic Algorithms for waste allocation to improve efficiency.
- **Incorporation of Waste-Waste Compatibility Models:** Developing models that explicitly consider waste-waste compatibility, addressing the challenges posed by the heterogeneous nature of oily wastes.
- **Dynamic Facility Capacity Updates:** Implementing mechanisms for dynamic updates of facility capacities, allowing for real-time adjustments in waste allocation frameworks.
- **Human-Computer Interaction:** Conducting studies on human-computer interaction to enhance the user-friendliness of waste allocation frameworks for decision-makers.
- **Integration of Machine Learning for Incident Volume Estimation:** Investigating the use of machine learning techniques for more accurate estimation of incident volumes, considering the complexities of real-world incidents.
- **Environmental Impact Assessment:** This includes an environmental impact assessment component in future studies to evaluate the sustainability of waste management practices proposed by optimization models.

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