An Assessment of the Impacts of Climate Change on Freight Delivery Schedule Strategies on the Mackenzie River

by

Yunzhuang Zheng

A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in

TRANSPORTATION ENGINEERING

Department of Civil and Environmental Engineering
University of Alberta

Abstract

The Mackenzie River is a major freight transportation route serving many remote northern Canadian communities and mining sites. The river is only navigable during the summer and early fall months, when it is clear of ice. However, the water conditions of this river have changed significantly in recent years, and are expected to continue to do so into the future, resulting in increased uncertainty for waterway transport. This thesis discusses a climate change adaptation measure for freight schedule planning on the Mackenzie River. The purpose of this research is to provide some guidance to shipping companies, customers, and the government on how shipping patterns may need to evolve in order to efficiently adapt to future climate conditions.

In this research, we first analyse historical freight volume data and forecast the future volumes based on these data. Historical volumes are provided by Northern Transportation Company Limited (NTCL), a major shipping company on the Mackenzie River. Freight is categorized into two major classes according to historical volume data: fuel and dry cargos. Dry cargos include items such as construction materials and equipment, personal vehicles, etc. The seasonal Kendall trend test is applied to assess the monotonic trends (increase or decrease) existed in the freight volumes. Significant decreasing trends over time (from 2002 to 2015) at a 99% confidence level are identified in total freight volumes. Specifically, volume decreases after 2008 and in 2010 are found. One major reason for the volume decrease after 2008 is that since 2008 summer, another shipping company expanded their sealift services to Kitikmeot communities via the Northwest Passage, resulting in decreased volumes to Tuktoyaktuk and Arctic Region from NTCL. However, no documents were found to report reasons of the decrease in 2010. Checking historical water level data at Fort Good Hope, the water levels in 2010 were

found to be relatively lower compared to other years, which may be the reason for the decreased volumes in this year. Both decreases are modelled using transfer functions in the ARIMA model. However, based on parameter estimation results, the transfer function modelling the shock in 2010 is not remained in the final ARIMA model due to its low significant parameters. Future volumes for fuel and dry cargos are then predicted and applied in the numerical analysis as the base schedule, namely the schedule used when transport companies continue with “business as usual” in the future.

A generalized cost function is then developed to factor in the additional cost of rescheduling freight delivery to earlier dates as well as the benefit of utilizing better water conditions. Four cost components are included in this cost function, including handling cost, travel cost, rescheduling cost, and delay cost. A logistics cost optimization model is developed to minimize the total generalized cost to obtain optimal schedules. This model is applied in two scenarios in the numerical analysis, along with a sensitivity analysis. Numerical analysis results indicate that future waterway freight delivery capacities in September and October may be insufficient to transport freight originally assigned to those late-season months. In such a case, shipping companies can arrange a “tighter” schedule in June and July instead of starting the season earlier. However, under certain circumstances (e.g. unable to set up all equipment in May and June), shipping companies may still need to start delivery earlier than usual. Beginning the season earlier and arranging more deliveries in that early part of the season will have significant logistical impacts on customers, shipping companies will need to consult closely with their customers in adapting their operations to future climate conditions. As a result, this research also encourages customers to rethink their delivery needs, particularly the tradeoff of arranging earlier delivery for the advantage of greater delivery reliability. This research also identifies a need for government agencies to more closely monitor climate change and set up navigational aids and buoys in time to ensure shipping companies can start their delivery as they needed. Additionally, government agencies may also need to consider supporting further development of alternate modes of transport.

Overall, the results of this research may aid shipping companies, customers, and government agencies in rethinking current practices to more effectively respond to anticipated climate change impacts.

Keywords: Inland waterway transportation, climate change adaptation, freight delivery schedule planning, Northern Canada, optimization.

Dedicated to my parents

Acknowledgements

I would first like to thank my advisor, Dr. Amy Kim, whose devotion and dedication to research has deeply inspired me. Without her support, guidance, and patience, my thesis would have been impossible. I am fortunate to have her as my advisor. I would like to thank Dr. Tony Qiu and Dr. Yuntong She for being my thesis committee members. I would also like to thank Dr. Karim El-Basyouny.

I would like to thank the sponsor of this research, Transport Canada's NEXTAW (Network of Expertise on Transportation in Arctic Waters) initiative. I would also like to thank NTCL for providing freight volume data, the Government of the Northwest Territories for their enthusiastic and extensive support, and Dr. Thian Gan and members of his research group at the University of Alberta for providing the Mackenzie River stream flow simulation results.

Then, I want to thank all my colleagues, Yang (Naomi) Li, Qianqian Du, Kathy Hui, Matthew Woo, Kexin Ren, Danyang Sun, Jiangchen Li, Chenhao Wang, Yuwei Bie, Ai Teng, Can Zhang, Chen Qiu, Mudasser Seraj, Maged Gouda, Mostafa Tawfeek, and Suliman Gargoum for their support and help in the past two years. I also want to thank Aalyssa Atley for her assistances and advice in paper and thesis writing and editing.

Finally, special thanks to my family for their continuous encouragement, support, and love.

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Motivation and objective

The Mackenzie River serves as a major freight transportation route connecting remote communities in the Northwest Territories and parts of Nunavut to the southern Canada's freight network (Mariport Group Ltd., 2011a). However, in recent years, water conditions on the river have changed significantly, threatening this once highly reliable freight delivery route. According to William Smith, VP Logistics and Business Development at the Northern Transportation Company Limited (NTCL), a major shipping company operating on the Mackenzie River, water levels at the north end of the river from August 2014 to the end of the season were significantly lower than previous years (personal communication, December 4, 2015). Consequently, this severely impacted their tug-and-barge operations, such that deliveries planned to communities located towards the north end of the river did not occur. In order to adapt to these changing water conditions, shipping companies must consider changes to their delivery strategies and resulting scheduling. Although planning freight deliveries earlier in the season during good water conditions could improve reliability of delivery, there are significant internal and external costs to plan and implement such changes. Therefore, balancing the additional costs involved with planning new delivery schedules against the benefits of taking advantage of better water conditions is necessary for greater efficiency.

The purpose of this research is to provide guidance to shipping companies, customers, and the government on how freight delivery patterns may need to evolve in order to effectively adapt to future climate conditions. This thesis introduces a method that incorporates predicted water flow profile changes in waterway shipping companies' future delivery schedule planning and applies the method in two scenarios to assess how climate change may impact freight delivery schedule strategies on the Mackenzie River. Specifically, in this thesis, freight volumes delivered to communities via the Mackenzie River between January 2002 and July 2015 are first extracted from tow letters provided by NTCL. The seasonal Kendall trend test as well as ARIMA model and intervention analysis are then applied to assess the trends in the volume data and forecast future freight volume on the river. These forecasted volumes are used as the base schedule in the numerical analysis. The base schedule represents the anticipated bi-monthly freight delivery volumes when transport companies continue with "business as usual" in the future. A total generalized cost function that incorporates rescheduling costs and delay costs is developed to account for additional cost of rescheduling freight delivery as well as the benefit of utilizing better water conditions. This cost function is used as the objective function in the logistics cost optimization model. By minimizing the total generalized cost, the model can obtain the optimal solutions under certain water conditions on the Mackenzie River. This model is then applied in two scenarios in the numerical analysis to find new freight delivery scheduling strategies under anticipated climate change impacts, along with a sensitivity analysis to investigate the impacts of input parameter values to the optimization results.

1.2 Findings

In this research, we first analyse the trends in freight volume data and forecast future volumes using time series modeling. Significant decreasing trends over time (from 2002 to 2014) at a 99% confidence level are identified in the total freight volumes. One major reason may be that since 2008 summer, another shipping company expanded their sealift services to Kitikmeot communities via the Northwest Passage, resulting in decreased volumes to Tuktoyaktuk and Arctic Region from NTCL. This shock is modelled in the ARIMA model using a transfer function. Another volume decrease in 2010 is observed as well. However, transfer function that models this decrease is not included in the final ARIMA model, due to low statistically significant in parameter estimation results of the ARIMA model. The reason may be that this volume decrease is still caused by the shock events happened in 2008, and modeling the shock in 2008 is enough to represent the changings in volume data pattern.

A generalized cost function is developed to factor in the additional cost of rescheduling freight delivery to earlier dates as well as the benefit of utilizing better water conditions. Four cost components are included in this generalized cost function: handling cost, travel cost, rescheduling cost, and delay cost. A logistics cost optimization model is then developed using this cost function as the objective function to determine alternative marine shipping schedules that better align with predicted water conditions. This model is applied in two scenarios in the numerical analysis, and we also conduct a sensitivity analysis to investigate the influences of the model's key parameters on the optimal results. The numerical analysis results indicate that companies may need to consider changes to freight transport historically carried out towards the end of the summer delivery season (i.e. September and October) in order to decrease the likelihood of non-delivery (such as that experienced in 2014). Instead of starting delivery season earlier, shipping companies can arrange a "tighter" schedule to fully utilize capacities in July to ensure successful deliveries of freight originally assigned to late-season months. However, under certain situations (i.e. no enough equipment available in May and June), it may still be necessary for shipping companies to start the season earlier to ensure successful freight deliveries. The sensitivity analysis results indicate a need for more research on the difficulties of schedule planning under uncertain future demand and climate change impacts, and empirical studies on how to determine appropriate parameter values in total logistic transportation cost models.

1.3 Contributions

The results of this work can help shipping companies, customers, and the government better understand how current shipping practices may need to be revised, in effectively adapting to the impacts of climate change. In particular, this work highlights the need of shipping companies for more earlier-season planning of equipment and crew placement to take advantage of reliably better marine navigation conditions in earlier months, such as May and June, in future years. In that case, since beginning the season earlier and arranging more deliveries in early-season months (such as July) will have significant logistical impacts on the companies themselves as well as customers, shipping companies may need to consult closely with their customers in adapting their operations to future climate conditions. As a result, this research encourages customers to rethink their delivery needs as well, particularly the tradeoff of arranging earlier delivery (and possibly increasing storage costs) for the advantage of greater delivery reliability. Additionally, this work also highlights the need for government agencies to more closely monitor the impacts of climate change on freight transport operations and set up navigational aids and buoys in good time to begin the marine delivery season. Government agencies, such as the Department of Transportation in the NWT and Transport Canada, may also want to support further development of alternate modes of transport in case of unexpected failure of waterway freight deliveries in late-season months and hence, reduce non-deliveries of freight and financial losses for both waterway shipping companies and their customers.

1.4 Thesis organization

This thesis consists of seven chapters. Chapter 2 introduces the background information of the Northwest Territories (NWT), including the transportation network in the NWT, as well as the climate change and its influence on local transportation network operation. Chapter 3 contains brief literature reviews on the impacts of climate change on freight transportation costs for inland waterway and transportation schedules, time series analysis methods, and the total logistic transportation cost functions applied on freight transportation problems. Chapter 4 presents the waterway freight volume analysis and prediction. Chapter 5 describes the generalized cost function and the logistics cost optimization model developed based on this cost function to reschedule bi-monthly freight volumes based on projections of future water conditions, which is then applied in two scenarios in Chapter 6 along with a numerical analysis. The last chapter, Chapter 7, discusses the conclusions and contributions of this research and some recommendations for future work.

Chapter 2. Background on the Northwest Territories Transportation Network

The Northwest Territories (NWT) covers almost 1.2 million square kilometers land, about 13% of Canada’s land mass, and is home to over 41,000 people, among which more than 50% people are aboriginal people, living in 33 communities (Natural Resources Canada, GeoAccess Division, 2005; Statistics Canada, 2011). Within such vast land area, communities are sparsely distributed and many are located along the Mackenzie River and its tributaries, which is the largest and longest river system in Canada (Environment Canada, 2013). Among all these communities, the most populated community in the NWT is the capital city, Yellowknife, and about 50% people in the NWT are living in Yellowknife (City of Yellowknife, 2013). The total population in the NWT is increasing over years. Between 2001 and 2011, the population of the NWT expanded about 11% (Statistics Canada, 2001; Statistics Canada, 2011). Another important thing to note is that the Canadian Armed Forces (CAF) have operated in the NWT for more than a century to conduct routine sovereignty operations, regular surveillance, and security patrols (National Defence and the Canadian Armed Forces, 2014).

The NWT also contains abundant mineral resources (such as diamond, oil, and gas), leading to a large number of resource development activities. Over 30 mining sites were operated in NWT, 4 mining sites are operating at present, and 5 sites are under review (NRTEE, 2009). Besides, the NWT holds significant hydroelectric potential. It is believed that only less than 1% of its potential has been developed till now (NRTEE, 2009). In general, the NWT exhibits enormous economic potentials from the development of world-class diamond mines to the development of vast oil and gas reserves (Government of Canada, 2009).

However, there have been two major barriers for further economic developments in the NWT (and the Canadian Arctic, in general). First, lack of transportation infrastructure has been a major barrier (NRTEE, 2009). Due to sparse populations, highly remote geography, and extreme weather, the costs to construct, operate, and maintain infrastructure are much higher than in more southern regions of Canada (NRTEE, 2009). As a result, the current transportation infrastructure in the NWT does not provide most communities with year-round transportation access to the south (except by air) (Department of Transportation, GNWT, 2011a). Only one-third of the 1.2 million square kilometers of land area is within 100 kilometers of all-weather roads (Department of Transportation, GNWT, 2011a). Second, climate change, especially temperature increases, has and will continue to impact the NWT transportation network, particularly inland waterway transportation. Increased temperatures in the NWT is delaying river freeze-up in the fall (and the opening dates of winter roads) and changing local precipitation patterns (Environment and Natural Resources, GNWT, 2008). This has led to greater variability of waterway delivery season lengths and water conditions (Environment and Natural Resources, GNWT, 2008).

In this chapter, the NWT transportation infrastructure is introduced in 2.1; climate change in the NWT and its impacts on local transportation are presented in 2.2. In the last section, a summary is presented.

2.1 Transportation infrastructure in the NWT

Currently, three modes – roadway, marine, and air – are available for passenger, community resupply, and mining-related transportation in the NWT (see Figure 2-1). Roadway facilities consist of all-weather roads as well as winter roads, which are typically operated between mid or late December and early or mid-April next year (Department of Transportation, GNWT, 2016a). The Mackenzie River is one major marine transportation route to serve communities in the NWT, and Tuktoyaktuk is a transfer terminal where freight transported via the Mackenzie River will be transferred to ocean barges and transported to coastal communities (Northern Transportation Company Ltd., 2016). The NWT also has an extensive network of airports consisting of 27 government-operated airports (Department of Transportation, GNWT, 2016c). All three transportation modes are introduced in detail in the following sections.

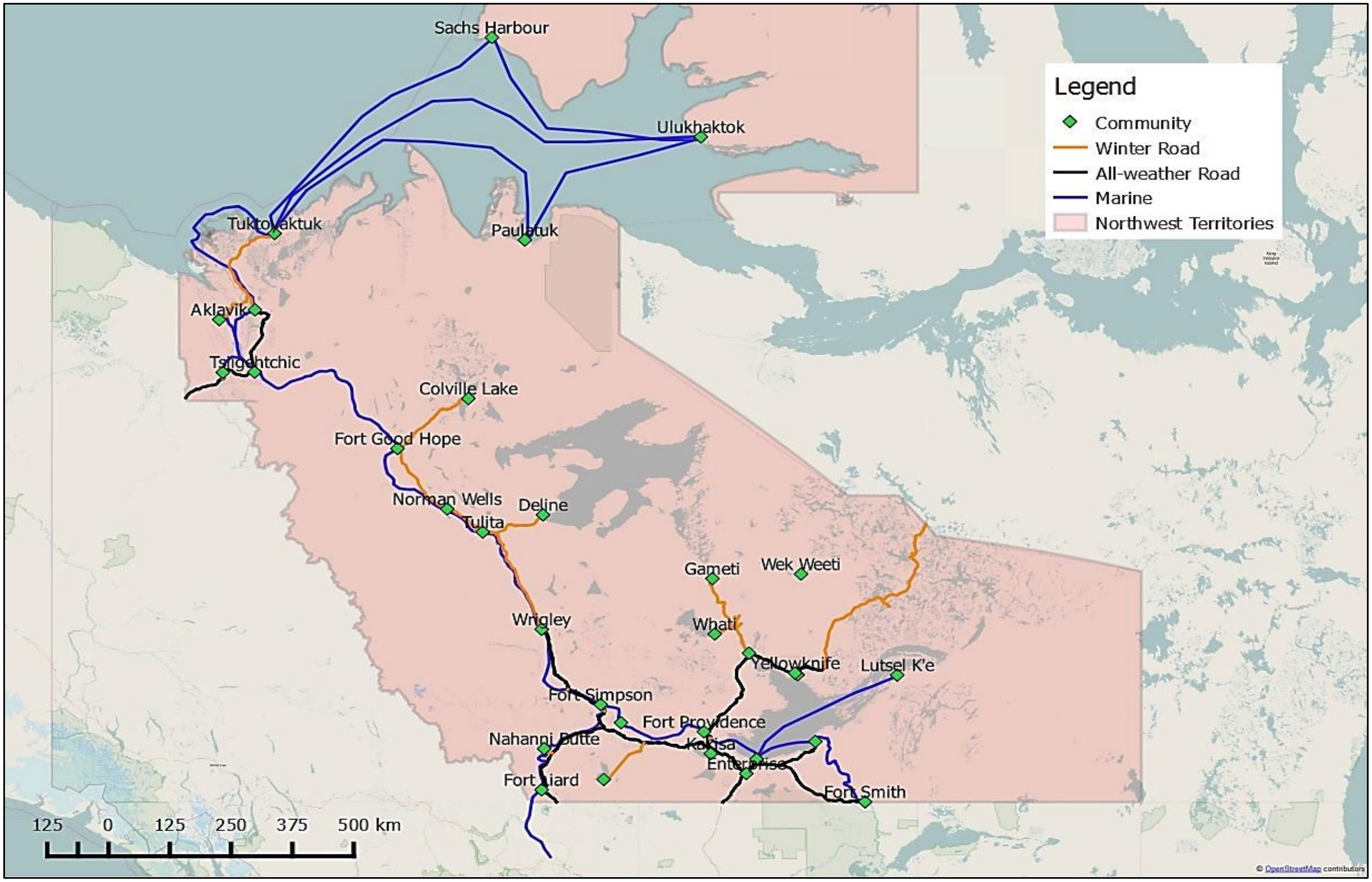


Figure 2-1 Transportation network connecting communities in the Northwest Territories[1]

---

[1] Taken from: (Department of Transportation, GNWT, 2016a; Department of Transportation, GNWT, 2016b)

2.1.1 All-weather road

All-weather roads provide year-round transportation access in the NWT. The total length of all-weather roads in the NWT is around 2,200 kilometers (NRTEE, 2009; Department of Transportation, GNWT, 2011a). Originally, there were five ferry/ice bridge crossings operated to link all-weather roads on different banks of rivers. In 2012, Deh Cho Bridge opened to provide all-season crossing of the Mackenzie River near Fort Providence (CBC News, 2012). After that, only four ferry/ice bridge crossings are currently operating (Department of Transportation, GNWT, 2016d). The four ferry/ice bridge crossings are: Lafferty ferry Liard river crossing, crossing Liard River near Fort Providence; the Johnny Berens ferry – N'duleh crossing, crossing the Mackenzie River near Wrigley; the Abraham Francis ferry, crossing the Peel River; and the Louis Cardinal ferry, crossing the Mackenzie River near Tsiigehtchic (Department of Transportation, GNWT, 2016b; Department of Transportation, GNWT, 2016d). The typical operation time for ferries is from late May or early June to late October or early November, and the typical operation time for ice bridges is between late December and late April (Department of Transportation, GNWT, 2013; Department of Transportation, GNWT, 2016d). The Government of Northwest Territories (GNWT) has been upgrading and expanding current transportation infrastructures, especially in roadway system, to provide better services for local communities and mining activities (Department of Transportation, GNWT, 2016e). An all-weather highway connecting Inuvik to Tuktoyaktuk is currently under construction, and another highway to connect Wrigley and Norman Wells is in the planning stages as well (Department of Transportation, GNWT, 2016f). Community resupply in the southern part of the NWT (such as Hay River, Yellowknife, Enterprise, Fort Providence, etc.) depends mainly on all-weather road. Dry cargo resupply for communities in the north Delta Region (such as Inuvik, Aklavik, Fort

McPherson, and Tsiigehtchic) is mainly served by all-weather road as well (Mariport Group Ltd., 2011b).

2.1.2 Winter road

A winter road is a road built over frozen lakes or along rivers to provide a temporary roadway in the winter months when ice thickness allows it (Department of Transportation, GNWT, 2015). Winter roads provide access to smaller, more remote communities in the NWT in the winter and help these communities better sustain themselves by reducing the cost of living as well as increasing connections to other communities (Department of Transportation, GNWT, 2016a). The total length of winter road in the NWT is 1,450 kilometers (NRTEE, 2009; Department of Transportation, GNWT, 2011a). Over 570 kilometers winter roads are constructed and owned by private companies for oil and gas development and mine resupply (NRTEE, 2009). The typical operation time is between mid or late December and early or mid-April next year (Department of Transportation, GNWT, 2016a).

Freight transportation costs via winter roads are significantly smaller than those for air transport, but much higher than marine (Mariport Group Ltd., 2011b). For example, the rates for freight transportation via winter road between Inuvik and Tukatoyaktuk would be at least twice marine delivery costs (Department of Transportation, GNWT, 2011b). However, for communities without marine access, winter road is still highly preferable to air because of the extremely high cost of air transport (Department of Transportation, GNWT, 2011b). For example, petroleum products for Colville Lake are typically stored in tankers at Fort Good Hope, waiting for transport when winter roads open (Mariport Group Ltd., 2011c).

2.1.3 Marine

The NWT has an extensive hydrologic network, which includes Great Slave Lake, Great Bear Lake, and the longest river in Canada – the Mackenzie River. This marine transportation network is used broadly to serve communities in the lake areas, along the river and Western Arctic communities (Mariport Group Ltd., 2011a). There are three major water routes: two via ocean transit from either the Pacific or Atlantic Ocean, and one via the Mackenzie River (Mariport Group Ltd., 2011a). The ocean route from Atlantic mainly serves Eastern Arctic communities from Eastern Canada, the east coast of the U.S., and Europe (Mariport Group Ltd., 2011a). The operational window is limited due to the Arctic ice (Mariport Group Ltd., 2011a). The ocean route from Pacific is primarily used to serve Western Arctic communities from British Columbia, the west coast of the U.S., and Asia (Mariport Group Ltd., 2011a). The operational window is also limited due to the Arctic ice (Mariport Group Ltd., 2011a). The river route along the Mackenzie River is an important route to serve its adjacent communities and Western Arctic communities (The Water Transport Committee, 1978; Mariport Group Ltd., 2011a). The river is only navigable during the summer months when it is clear of ice, from mid-June until sometime in late-September to mid-October. Currently, several shipping companies provide freight delivery services on the Mackenzie River. Among them, the Cooper Barging Service Limited and Northern Transportation Company Limited (NTCL) are the two major shipping companies on the river. The Cooper Barging Service Limited is located in Fort Simpson and only provides delivery services to Tulita and Norman Wells. NTCL is located in Hay River and provides services to all communities along the river and most coastal communities which are mainly served using ocean barges transshipped at Tuktoyaktuk from river barges by NTCL. The

Mackenzie River once held a monopoly position to serve the NWT coastal communities until challenged by the ocean route via Atlantic since 2008 (Mariport Group Ltd., 2011a).

2.1.4 Air

The NWT has 27 government-operated airports, which provide year-round links to the outside world for local residents (Department of Transportation, GNWT, 2016c; PROLOG Canada & EBA Engineering Consultants Ltd., 2011). Air services in the NWT provide both passenger and cargo transportation. Communities are often served by combination aircraft where passengers and cargo are both carried on the main deck, separated by a moveable bulkhead (PROLOG Canada & EBA Engineering Consultants Ltd., 2010). For passenger services, government travel dominates passenger volumes, estimated to account for up to two-thirds of total traffic (PROLOG Canada & EBA Engineering Consultants Ltd., 2010). As for cargo delivery services, air cargo in the north are divided into three categories: perishable food and other essential items moving under the Nutrition North Program; general cargo that moves to communities as a co-product of scheduled passenger services; and air cargo support for natural resource development (PROLOG Canada & EBA Engineering Consultants Ltd., 2010). Freight delivery by air is the most expensive transportation option among all three available modes in the NWT (Department of Transportation, GNWT, 2011b). For example, the costs to transport one tonne of cargo from Yellowknife to Sachs Harbour is about 5 times the costs via roadway and about 10 times the costs via marine (Department of Transportation, GNWT, 2011b).

2.2 Climate change in the NWT and its impacts on local transportation

In recent years, conditions in northern Canada have changed significantly because of climate change. Due to complex feedback mechanisms in the atmosphere-ocean-ice system in high norther latitudes, the rate of temperature increase in circumpolar Arctic areas is at least twice that of other low altitude areas (IPCC, 2007; Environment and Natural Resources, GNWT, 2008). Compared to global average surface temperature increases, annual temperatures in Inuvik have increased an additional 2.25 Celsius over the past 100 years (Environment and Natural Resources, GNWT, 2008). In northern Canada, local governments and residents have observed the impacts of the warming climate on local transportation (Dillon Consulting Limited, 2007). The warming climate in northern Canada has delayed the Mackenzie River freeze-up in the fall, contributed to thinner ice and an earlier spring melt, and resulted highly variability of the amount and timing of precipitation events between different seasons (Environment and Natural Resources, GNWT, 2008). Because of changing precipitation patterns and spring run-off conditions, Aklavik and Fort Good Hope have experienced significant flooding events in recent years; while low water levels on the Mackenzie River at other times have restricted barge traffic and caused delays or cancellations of deliveries to communities (Environment and Natural Resources, GNWT, 2008). Specifically, in 2014, due to unusually low water levels in Fort Good Hope in September and October, NTCL had to cancel some shipments travelling by barge to the Northwest Territories' northern communities (CBC News, 2014). The warming climate also has impacts on the other transportation modes. The melting permafrost due to temperature increase can severely damage roadway and air system infrastructure (NRTEE, 2009). Permafrost is defined as frozen soil or rock at or below the freezing point of water, 0 Celsius, which provides a strong support for infrastructure such as roads, bridges, etc. (Environment and Natural Resources, GNWT, 2008) The melting permafrost can lead to gradual loss of structural integrity of all-weather road, bridges, and runways in the airports, and increases of infrastructure maintenance costs (NRTEE, 2009). Additionally, the operational season of the winter roads may become shorter due to the warming climate in the local area (Environment and Natural Resources, GNWT, 2008).

2.3 Summary

The NWT covers a massive land area, with only about 33 communities sparsely located in this vast area. Abundant mineral resources are found in the NWT, resulting in nowadays large number of resource development activities and vast development potentials in the future. Currently, three modes – roadway (including all-weather road and winter road), marine, and air – serve passengers and local freight transport needs, such as community resupply, mining support and supplies, etc., in the NWT. Among all three transportation modes, despite no year-round access, marine transportation is still the major freight transportation mode, considering its relatively low cost, historically high reliability, and good accessibility to remote communities (Statistics Canada, 2015). However, as a result of changing precipitation patterns and spring run-off conditions in the NWT, water conditions on the Mackenzie have changed significantly, threatening this once highly reliable mode of freight delivery. Due to unusually low water levels in Fort Good Hope in September and October in 2014, NTCL had to cancel some shipments travelling by barge to the Northwest Territories' northern communities, resulting in serious freight delivery delays and financial losses. The climate change adaptation measure for freight schedule planning on the Mackenzie River discussed in this research may help shipping companies on the river to increase their delivery reliability in their future freight deliveries.

Chapter 3. Literature Review

This chapter contains brief literature reviews on the impacts of climate change on freight transportation costs for inland waterway and transportation schedules, time series analysis methods, and the total logistic transportation cost functions applied on freight transportation problems.

3.1 Impacts of climate change on freight transportation cost (inland waterway) and transportation schedules

Many European and American researchers have studied the relationship between climate change, especially annual average temperature increase, and inland waterway freight transportation costs. Jonkeren et al. (2007) studied the impacts of climate change on inland water transport on the Rhine River, and found that there is a considerable negative effect of water levels on freight price per ton and a positive effect on load factor. In another article, Jonkeren et al. (2011) estimated that under extreme climate situations, a significant amount of freight would be transferred via modes other than waterway, including rails, roadways, etc. In addition, Olsen et al. (2005) believe that shipping costs on the Middle Mississippi River can be significant, due to the potential impacts of diminished river flows and even closures on waterway navigability. Hence, in their paper, they recommended water resources and transportation managers to monitor climate conditions for significant changes, and engineers to consider different climate change scenarios in navigation project feasibility studies.

Climate change may also impact transportation schedules. The impacts of climate and weather changes on transport schedules and resilience planning strategies to adapt climate and big weather events are broadly assessed in aviation systems. Robinson (1989) assessed the impact of fog, thunder, and snowstorms on aviation operations at the Atlanta Hartsfield International Airport. They found that all three weathers have big impacts on aviation operations and can cause significant airborne delays and cancellations of flights. They also mentioned that good weather forecasts can be very helpful for airlines in adjusting their schedules and reducing financial losses.

Two interesting points are found in those previous literatures. First, most research on climate change impacts on inland waterway transportation (cost) focuses on European and American rivers; research on Canada's inland waterways, particularly the Mackenzie River, is limited. Second, research on the impacts of climate change on waterway delivery schedules is also very limited, especially for rivers like the Mackenzie that are only available for a short season each year. This research has strived to fill these gaps. This research incorporates predicted water flow profile changes in shipping companies' future delivery schedule planning and factors in the benefits of taking advantage of better water conditions. Results of our research can help shipping companies on the Mackenzie River, such as NTCL, better understand the impacts of a changing environment on their business, and choose appropriate climate adaption measures in their future plans.

3.2 Time series data analysis and forecast

A time series dataset contains a collection of observations that are recorded sequentially through time (Chatfield, 2004). Analysis and forecasting methods of time series data can be divided into two types: qualitative methods and quantitative methods (O'Connell & Koehler, 2005).

Qualitative methods are usually used to predict historical time series data pattern changes (O'Connell & Koehler, 2005). Many quantitative methods cannot identify and account for data pattern changes on the basis of historical data series (O'Connell & Koehler, 2005). To better understand the data series and help to choose appropriate quantitative analysis and forecasting methods, trend tests are usually applied first to qualitatively determine whether upwards or downwards trends are existed in a subject dataset. For a linear trend test, simple linear regression is most commonly used. The slope can be used to determine the linear trend existed in the data series. Positive slope values indicate increasing trends over time, while negative values indicate decreasing trends. If the slope equals zero, the observation values remain constant. As for a non-linear trend test, Mann-Kendall test can be used to assess monotonic trend significance (Mann, 1945; Kendall, 1948). However, Mann-Kendall trend test does not account for seasonality (Hirsch, Slack, & Smith, 1982). Based on Mann-Kendall trend test method, Hirsch, Slack, and Smith proposed the seasonal Kendall trend test to analyze trends existed in monthly water quality data with obvious seasonality (Hirsch, Slack, & Smith, 1982).

The quantitative time series data analysis and forecasting techniques attempt to predict future values of a variable of interests based on historical data (O'Connell & Koehler, 2005). Box and Jenkins's *Time Series Analysis: Forecasting and Control* is considered to be an important milestone for time series analysis (Box & Jenkins, 1976; Tsay, 2000). This book presented a systematic approach that popularized the autoregressive integrated moving average (ARIMA) model and enabled practitioners to apply time series methods in forecasting (Box & Jenkins, 1976; Tsay, 2000). Seasonal ARIMA (SARIMA) models were also developed based on traditional ARIMA models to account for seasonality shown in the time series (Box & Jenkins, 1976). The ARIMA and SARIMA models have been applied in transportation and demand forecast in a lot of research. In 1992, Cullinane developed ARIMA models to predict the movement of the Baltic Freight Index, which provides an assessment of freight transport rates (Cullinane, 1992). Hunt applied SARIMA models to forecast freight on Estonian railways (Hunt, 2003). ARIMA models were also used to forecast future railway freight volumes in China based on historical freight volumes from 1978 to 2010 (Ma & Zhou, 2012).

In this research, significant seasonality is found in the waterway freight volumes, reflecting the seasonality of the Mackenzie River transport system. Hence, the seasonal Kendall trend test is chosen to identify whether a monotonic trend exists in the volume dataset, and then, appropriate SARIMA models are identified and estimated on the historical volume data series to forecast future waterway volumes.

3.3 Total logistic transportation cost function

The total logistic transportation cost function has been used widely in freight assignment models, as a tool to plan and evaluate the performance of freight transportation networks and delivery plans. In previous research, various cost components are included in the total logistic transportation cost function depending on purpose. Sheffi et al. included transportation costs, stationary inventory costs, and in-transit inventory costs in the total logistics cost function used in their research on transportation mode choice between a given origin and destination (Sheffi, Eskandari, & Koutsopoulos, 1988). Daganzo categorized freight transportation cost into three types: holding cost, transportation cost, and handling cost (Daganzo, 2005). Holding cost includes the rent for space, machinery needed for storage, and maintenance costs for the equipment. Transportation cost is the cost produced during transportation, including the driver wages, fuel consumption, etc. Handling cost is the cost for loading and unloading in the terminals. In 2013, Rodrigue et al. categorized total logistic cost into terminal cost, line-haul cost, and capital cost (Rodrigue, Comtois, & Slack, 2013). Loading, unloading, and transshipment costs are included in terminal costs; labour and fuel are included in the line-haul cost; for capital cost, the purchase of fixed assets and any enhancement of fixed assets are included. In general, handling costs at terminals, including the loading and unloading cost and the cost of equipment and maintenance, as well as travel costs, including fuel consumptions, labour, cost of time, etc., are considered as part of the overall freight transportation cost. In this research, asides from the handling and transportation costs that are generally included in total logistic transportation cost models, rescheduling and delay costs are introduced to account for the additional cost of implementing new schedules and the benefit of utilizing good water conditions.

3.4 Summary

Chapter 3 presents literature reviews on three topics: the impacts of climate change on freight inland waterway transportation costs and transportation schedules, time series analysis methods, and the total logistic transportation cost functions applied on freight transportation problems. It is found that research on impacts of climate change on marine freight transportation costs are mainly focused on the inland river transportations in Europe and the U.S.A, while related research on the Mackenzie River is very limited. Also, studies on impacts of climate change on waterway freight transportation schedules are fairly few, especially for rivers like the Mackenzie River that are only available for transportation for a short season each year. Additionally, in the previous literature, the seasonal Kendall trend test and SARIMA models are usually used to assess and forecast time series data with significant seasonality. As for total logistic transportation cost function, various cost components are included in the cost function depending on application purpose; however, handling and transportation costs are always included.

This research assesses the impacts of climate change on waterway freight delivery schedules on the Mackenzie River. This may help to make up the research gaps on climate change impacts on transportation costs and transportation schedules on the Mackenzie River. In addition, since significant seasonality is found in historical freight volume data, the seasonal Kendall trend test and SARIMA models are chosen to assess and forecast these volume data. A total generalized cost function is also developed in this research to account for additional cost of rescheduling freight delivery as well as the benefit of utilizing better water conditions. Based on previous literature on the total logistic transportation cost function reviewed in this chapter, asides from the handling and transportation costs that are generally modelled, rescheduling and delay costs are introduced in the cost function. This cost function is introduced in detail in 5.2.

Chapter 4. Waterway Freight Volumes Analysis

This chapter introduces analyses and forecasts of waterway freight volumes data. The data was provided by NTCL, which is one of the largest marine operators on the river (Transport Canada, 2012). The seasonal Kendall trend test is applied to test whether monotonic trends existed in freight data. Results of this test can provide guidance on choosing appropriate models for further forecast. ARIMA models and intervention analysis are then applied to estimate future freight volumes on the river. Those estimations are used in the numerical analysis presented in Chapter 6.

4.1 Data set

NTCL – one stakeholder of the project on which this research is based – provided tow letters from January 2002 and July 2015, consisting of freight volumes that they delivered to northern communities. The tow letters provided a rich set of information, including the following:

- Tug and barge departure dates from NTCL's southernmost and main terminal at Hay River;
- Barge numbers, fore draft, and after draft (in inches) for every barge;
- Delivery destinations;
- Type of freight carried, freight volumes (in tonnes and litres for petroleum products) for each barge;

The tow letters were provided as text documents, and as such, required manual entry into a spreadsheet. Annual total volumes delivered by NTCL are shown in Figure 4-1. Note that

Figure 4-1 shows volumes as a proportion of the historical maximum annual volume instead of absolute volumes, due to NTCL data confidentiality.

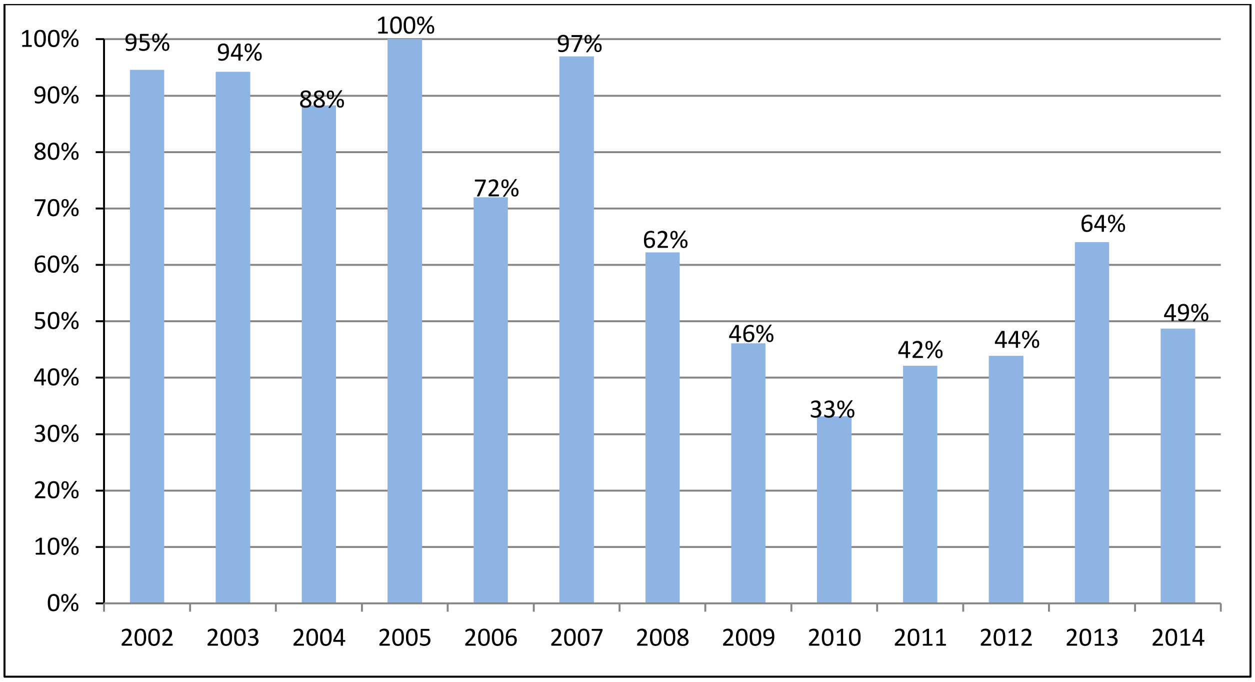
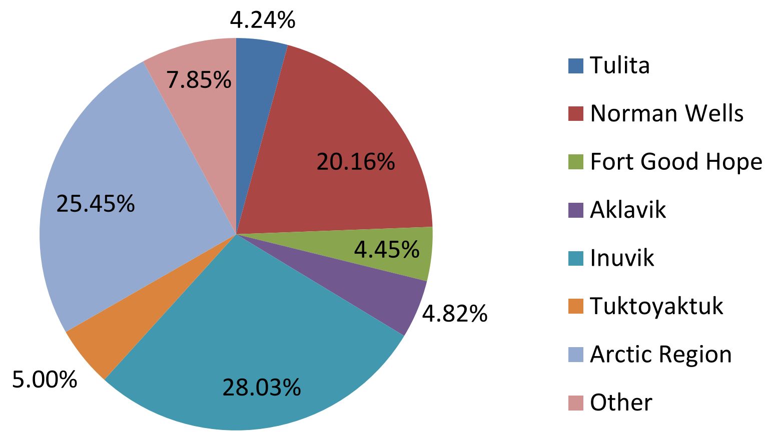


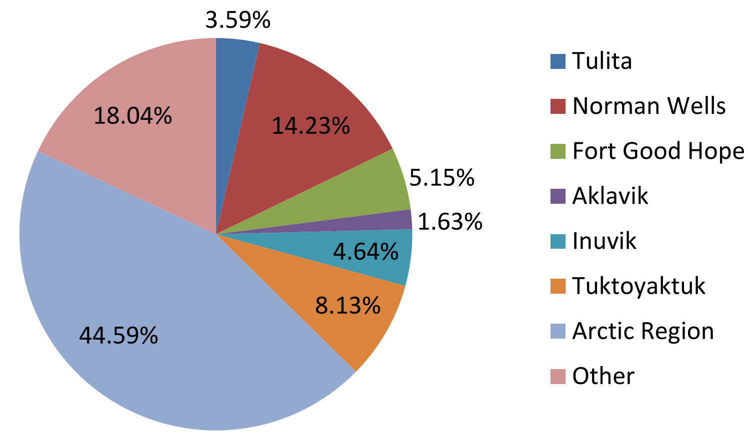
Figure 4-1 NTCL total freight volumes (as proportion of the maximum annual total volume)

It can be observed that there was a significant drop in volumes beginning in 2008 (although 2006 volumes had dropped as well). Also, volumes in 2010 are markedly lower than other years from 2008 to 2014. Reasons for those decreases are explored and discussed in Section 4.2.

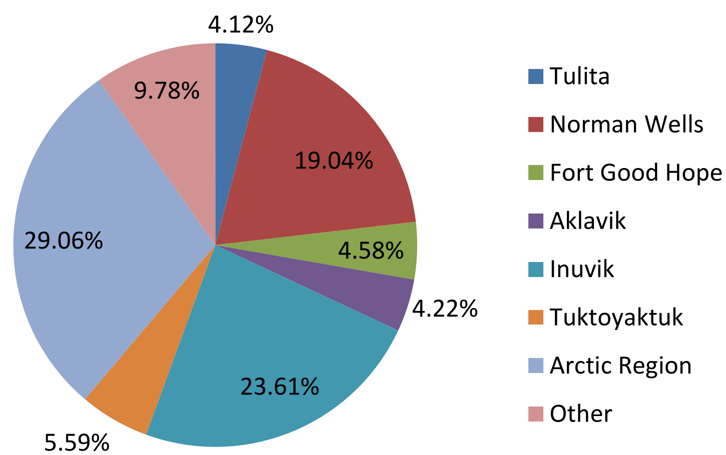
More than 70 destinations are identified in the NTCL tow letters, but many have very small delivery volumes; rather, there are a few major destinations that have the highest volumes. Based on total volumes for these destinations and their occurrence frequency between 2002 and 2015, 14 major destinations are identified, to which more than 90% of total freight volumes are destined. Six major communities are located along the Mackenzie River — Tulita, Norman Wells, Fort Good Hope, Aklavik, Inuvik, and Tuktoyaktuk. The rest (Sachs Harbour, Holman, Paulatuk, Kugluktuk, Roberts Bay, Cambridge Bay, Gjoa Haven, and Taloyoak) are in the north Inuvik region and Kitikmeot region and need to be delivered by ocean barges transshipped at Tuktoyaktuk from river barges. Since the major geographical scope of this research focuses on the Mackenzie River corridor, all major locations beyond the Mackenzie River are combined as one destination labeled “Arctic Region”. The freight recorded in the NTCL tow letters are categorized into two major classes: fuel and dry cargos. Dry cargos include items such as construction materials, mining equipment and gear, non-perishable food items, personal vehicles, etc. Figure 4-2 presents the fuel, dry, and total (fuel+dry) volumes (as a % of the total) destined to each major destination in the total volumes transported by NTCL from January 2002 to July 2015.



(a) Fuel



(b) Dry Cargo



(c) Total

Figure 4-2 Volumes to each major destination (June 2002 – July 2015) from NTCL tow letters

Figure 4-2 indicates that the total volumes destined to the major locations for both fuel and dry cargos contribute over 80% of the total volume. For fuel, volumes destined to Norman Wells, Inuvik, and Arctic Region contribute more than 70% of the total fuel volume, while volumes destined to other major locations make up about 20% of the total fuel volume. For dry cargos, volumes destined to Norman Wells and Arctic Region make up about 60% of the total dry cargo volume, while volumes to other major destinations contribute about 20% of the total dry cargo volume. For total (fuel+dry), it is clear that volumes to Norman Wells, Inuvik, and Arctic Region combined contribute the most significantly to freight volumes transported on the Mackenzie. The reason that those three destinations contribute such large amount of volumes is that Norman Wells and Inuvik are commercial and administrative centers for the Sahtu Region (including Norman Wells, Tulita, and Fort Good Hope) and the Mackenzie River Delta Region (including Inuvik, Aklavik, Tuktoyaktuk, etc.), respectively (Northern Transportation Company Ltd., 2016; GNWT, 2016a; GNWT, 2016b). The Arctic Region destinations are major coastal communities that can only be reached by water or airlift.

4.2 Seasonal Kendall trend test

This section presents the results of a seasonal Kendall trend test. The seasonal Kendall trend test is used to assess whether there is a statistically significant monotonic (increasing or decreasing) trend over time in a dataset. The results of this test can help us choose appropriate quantitative models to fit the data. Section 4.2.1 is a brief introduction on the seasonal Kendall trend test. The hypothesis and procedures to conduct this test are described in this section. Section 4.2.2 presents the test results and discusses indications based on the results.

4.2.1 Introduction

Trend tests are usually applied to determine whether upwards or downwards trends are present in a subject dataset. The results of such tests can provide guidance on choosing appropriate models for further analysis, such as ARIMA models. For a time-ordered dataset, the Mann-Kendall trend test can be used to assess whether there is a monotonic (increasing or decreasing) trend over time in this dataset within a certain level of significance. However, the traditional Mann-Kendall trend test does not account for seasonality (Hirsch, Slack, & Smith, 1982). Based on the Mann-Kendall trend test method, Hirsch, Slack, and Smith (1982) proposed the seasonal Kendall trend test to analyze trends in monthly water quality data. The seasonal Kendall trend test groups observations into different season groups (12 months, 52 weeks, etc.) and calculate trends in each subset over time separately.

The null hypothesis and alternative hypothesis of the seasonal Kendall test are as follows:

Null hypothesis, H_0: No monotonic trend over time.

Alternate hypothesis, H_1: For one or more seasons there is an increasing/decreasing monotonic trend over time.

If the absolute value of obtained score Z_{SK} is smaller than the standard score at confidence level α, Z_α, then the null hypothesis is accepted; otherwise, the null hypothesis is rejected. If Z_{SK} is larger than Z_α, it indicates that there is an increasing trend over time at a confidence level α. If Z_{SK} is smaller than $-Z_\alpha$, it indicates that there is a decreasing trend over time at a confidence level α.

There are six steps to a seasonal Kendall trend test (Hirsch, Slack, & Smith, 1982):

Step 1: Assign the data into different seasonal subsets. Since bi-monthly freight volume data from 2002-2015 were extracted from tow letters, our subsets can be set up as following.

$$X = (X_{Jan1}, X_{Jan2}, \dots, X_{Dec1}, X_{Dec2})$$

$$X_{Jan1} = \left(x_{Jan1,2002}, x_{Jan1,2003}, \dots, x_{Jan1,2015}\right)$$

$$X_{Jan2} = \left(x_{Jan2,2002}, x_{Jan2,2003}, \dots, x_{Jan2,2015}\right)$$

$$\vdots$$

$$X_{Dec2} = \left(x_{Dec2,2002}, x_{Dec2,2003}, \dots, x_{Dec2,2015}\right)$$

Where X represents our entire data set, X_i represents the subset for period i; and $x_{i,j}$ represents the observation of period i year j.

Step 2: Determine the sign of all $n_i(n_i - 1)/2$ possible differences $x_{i,j} - x_{i,k}$ for period i where $j > k$.

$$sign\left(x_{i,j} - x_{i,k}\right) = \begin{cases} 1 \ \ if \ x_{i,j} - x_{i,k} > 0 \\ 0 \ \ if \ \ x_{i,j} - x_{i,k} = 0 \\ -1 \ \ if \ \ x_{i,j} - x_{i,k} < 0 \end{cases} \qquad [1]$$

Step 3: Compute S score S_i and $Var(S_i)$ for every period.

$$S_i = \sum_{k=1}^{n_i-1} \sum_{j=k+1}^{n_i} sign\left(x_{i,j} - x_{i,k}\right) \qquad [2]$$

$$Var(S_i) = \frac{1}{18}\left[n_i(n_i - 1)(2n_i + 5) - \sum_{p=1}^{g_i} t_{ip}(t_{ip} - 1)(2t_{ip} + 5)\right] \qquad [3]$$

Where g_i is the number of tied groups for period i, (for every period, if there are more than two observations that are same and equal a certain value, we consider that these observations are in one tied group); t_{ip} is the number of observations in the pth tied group for period i.

For example, say we have a subgroup $X_i = (13,19,14,16,13,13,19,14)$. In total, there are three tied groups (13, 14, 19). Thus, $g_i = 3$. For tied value 13, because there are three observations equaling 13 in this subgroup, $t_{i1} = 3$. And for tied values 14 and 19, t_{i2} and t_{i3} equal 2.

Step 4: Compute overall S score S and $Var(S)$.

$$S = \sum_{i=1}^{m} S_i \quad [4]$$

$$Var(S) = \sum_{i=1}^{m} Var(S_i) \quad [5]$$

Where,m is the number of season groups. In our case, *m* is 24.

Step 5: Compute overall Z score Z_{SK}.

$$Z_{SK} = \begin{cases} \frac{(S-1)}{\sqrt{Var(S)}} \; if \; S > 0 \\ 0 \; if \; S = 0 \\ \frac{(S+1)}{\sqrt{Var(S)}} if \; S < 0 \end{cases} \quad [6]$$

Step 6: Compare Z_{SK} with Z_α to decide whether there is a monotonic trend.

4.2.2 Results

The seasonal Kendall trend test results for the freight volumes are shown in Table 4-1.

Table 4-1 The seasonal Kendall trend test results

Destinations	Z Score	Trends
Tulita	-1.69	No significant monotonic trend (95% confidence level)
Norman Wells	0.20	No significant monotonic trend (95% confidence level)
Fort Good Hope	-1.14	No significant monotonic trend (95% confidence level)
Aklavik	-1.87	No significant monotonic trend (95% confidence level)
Inuvik	-0.61	No significant monotonic trend (95% confidence level)
Tuktoyaktuk	-4.07	Significant decreasing trend (99% confidence level)
Arctic Region	-3.23	Significant decreasing trend (99% confidence level)
Total	-4.02	Significant decreasing trend (99% confidence level)

According to Table 4-1, total volumes transported via the river exhibited a statistically significant decreasing trend over time at a 99% confidence level. As for the major destinations, only volumes destined for Tuktoyaktuk and the Arctic Region showed a statistically significant decreasing trend at a 99% confidence level. One reason for the volume decrease of these two destinations is that since 2008 summer, another shipping company expanded their sealift services to Kitikmeot communities via the Northwest Passage (Nunatsiaq Online, 2008). According to Darren Locke from the Government of Northwest Territories' Department of Transportation (personal communication, November 24, 2015), new scheduled services from eastern Canada through the Northwest Passage are believed to have reduced NTCL's deliveries to these regions.

Based on Figure 4-1, another shock in the volumes was observed in 2010. No evidence was found to explain the reasons for this shock. However, historical water level data at Fort Good Hope (shown in Figure 4-3) indicate that water levels in 2010 (marked in red) were relatively low compared to other years, except 2014 (as mentioned in Section 1.1, water levels at the north end of the river were much lower than previous years from the beginning of September onwards through the rest of the season in 2014. As a result, much anticipated freight delivery to communities located at the north end of the river did not occur.) (Water Office, Government of Canada, 2014b). This could explain the sudden decrease of freight volumes in 2010. Monthly total volumes heading to major destinations were assessed, and the results indicate that there were decreases in freight volumes to Fort Good Hope and Arctic Region in 2010. This might also have resulted from poor water conditions at Fort Good Hope in 2010, contributing to the decline in total delivered freight volumes in 2010.

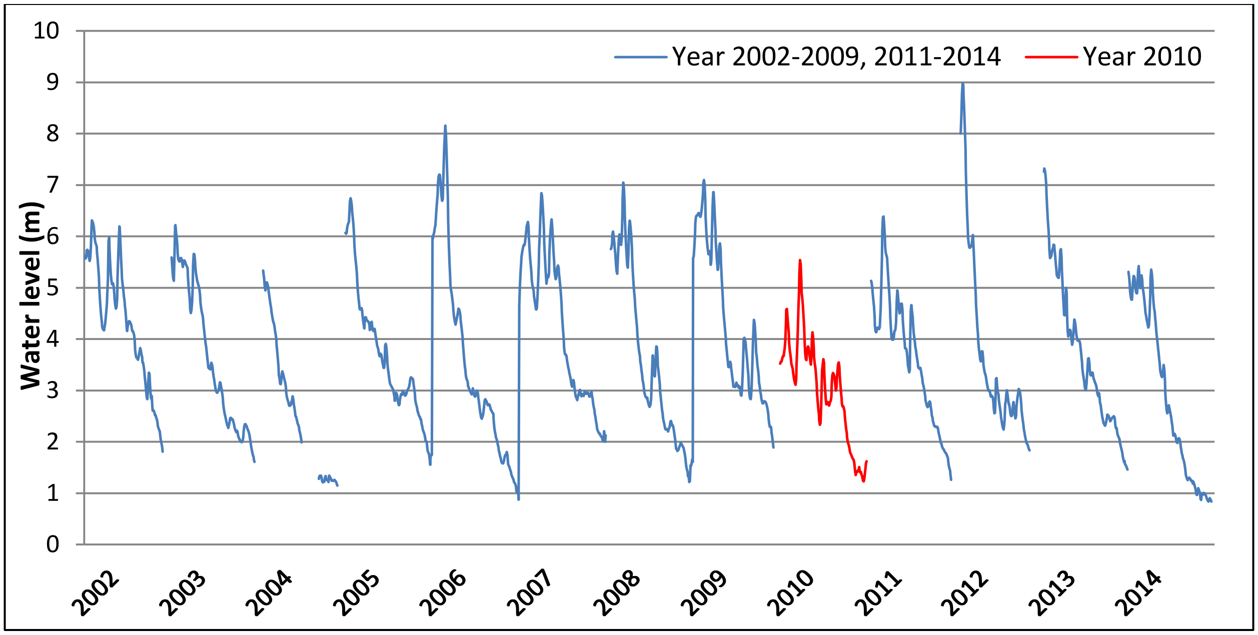


Figure 4-3 Historical water levels at Fort Good Hope (2002-2014) (Water Office, Government of Canada, 2014b)

Both shocks in 2008 and 2010 will be modelled in the intervention analysis in the following section.

4.3 ARIMA model and intervention analysis

ARIMA models and intervention analysis were applied to the historical NTCL freight volumes data to obtain an estimate of future freight volumes on the Mackenzie River. The model form was chosen based on the freight volumes plot, and autocorrelation and partial autocorrelation in the freight volume data. Then parameters in the chosen models were estimated based on historical freight volume series, and checked for statistical significance. The final model was then used to obtain the estimates of (future) freight volumes for 2025. These estimates are used in the numerical analysis presented in Chapter 6.

In this chapter, section 4.3.1 briefly introduces the ARIMA model and intervention analysis. Section 4.3.2 presents the model parameter estimation results and future waterway freight volume forecasts.

4.3.1 Model overview

The Autoregressive Integrated Moving Average (ARIMA) Model is used to model and forecast stationary time series. A stationary time series is a series with constant statistical properties (mean, variance, etc.) over time.

A non-stationary series needs to be transformed into a stationary series before applying ARIMA models (O'Connell & Koehler, 2005). A common way to transform a non-stationary series into a stationary series is differencing. First and second differences are usually enough for such transformation (O'Connell & Koehler, 2005), and their mathematic formulas are specified in Eq. 7 and Eq. 8 respectively:

$$z_t = y_t - y_{t-1}, t = 2,3, \dots, n \qquad [7]$$

Where, z_t is the new time series observation at time t; y_t is the original time series observation at time t.

$$z_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) = y_t - 2y_{t-1} + y_{t-2}, t = 3,4, \dots, n \qquad [8]$$

In ARIMA model, two factors are considered to influence the values of observations: autocorrelation and white noise. Autocorrelation describes that values of previous observations will influence the value of current observation. And white noise accounts for the randomness existed in the data set.

To account for both autocorrelation and white noise, ARIMA model integrated two types of model: autoregressive (AR) model and moving average (MA) model. AR models are used to represent the correlation between previous observations and current observation, and an AR model with order p is specified in Eq. 9:

$$z_t = \delta + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_p z_{t-p} + a_t \qquad [9]$$

Where, z_t is the observation at time t in a stationary time series; δ is a constant; $\varphi_1 \dots \varphi_p$ are parameters of AR model; a_t is the white noise at time t, $a_t \sim N(0, \sigma^2)$.

MA models account for randomness, and a MA model with order q is specified in Eq. 10:

$$z_t = \delta + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \quad [10]$$

Where $\theta_1 \dots \theta_q$ are estimated parameters.

Therefore, a typical ARIMA model includes three terms(p, d, q), where p represents the order of AR term; d represents the number of differences to obtain a stationary series in case of non-stationary series; q is the order of MA term.

If a time series shows significant seasonality, seasonal ARIMA terms should be considered. Besides (p, d, q) in the ARIMA model, three extra terms $(P, D, Q)_s$ are included in the seasonal ARIMA model as well, where s is the number of seasons until same pattern shows again, P is the order of AR term in the seasonal part, Q is the order of MA term in the seasonal part, and D represents the number of differences with lag s. The mathematic form of a general seasonal ARIMA model can then be specified in Eq. 11.

$$\left(1 - \varphi_1 B^1 - \varphi_2 B^2 - \cdots - \varphi_p B^p\right)\left(1 - \varphi_{1,s} B^s - \varphi_{2,s} B^{2s} - \cdots - \varphi_{P,s} B^{Ps}\right)(1 - B)^d (1 - B^s)^D y_t = (1 - \theta_1 B^1 - \theta_2 B^2 - \cdots - \theta_q B^q)(1 - \theta_{1,s} B^s - \theta_{2,s} B^{2s} - \cdots - \theta_{Q,s} B^{Qs}) a_t \quad [11]$$

Where, B is the backward shift operator, defined as $B^k y_t = y_{t-k},\ k = 1,2, \dots, t-1$; y_t is the original observation at time t; a_t is the white noise at time t, $a_t \sim N(0, \sigma^2)$; $\varphi_1 \dots \varphi_p, \theta_1 \dots \theta_q$ are the parameters in non-seasonal part; $\varphi_{1,s} \dots \varphi_{P,s}, \theta_{1,s} \dots \theta_{Q,s}$ are the parameters in seasonal part.

Since shocks in 2008 and 2010 are identified in the trend test and obvious decreases in the total volumes after 2008 and in 2010 are observed, transfer functions are added in the

ARIMA model to represent the impacts of these shocks. The transfer function to model those sudden drops is specified in Eq. 12.

$$TC = \omega I_t \qquad [12]$$

Where, ω is the intervention parameter, representing the expected changes of mean in one period before and after the intervention; I_t is a step function specified in Eq. 13.

$$I_t = \begin{cases} 0, & \text{if } t < T \\ 1, & \text{if } t \geq T \end{cases} \qquad [13]$$

Where T is the year of intervention.

For the shock in 2008, since the total volumes showing a sudden drop in 2008 and the impacts of this drop lasted after 2008, the transfer function is built as below.

$$TC_1 = \omega_1 I_{t1} \qquad [14]$$

Where, I_{t1} is a step function specified in Eq. 15.

$$I_{t1} = \begin{cases} 0, & \text{if } t1 \text{ is before year 2008} \\ 1, & \text{if } t1 \text{ is after year 2008} \end{cases} \qquad [15]$$

The shock in 2010 only influenced the volumes for 2010 alone. Hence, the transfer function is built as Eq. 16 and Eq. 17.

$$TC_2 = \omega_2 I_{t2} \qquad [16]$$

Where, I_{t2} is a step function.

$$I_{t2} = \begin{cases} 0, & \text{if } t2 \text{ is in year 2010} \\ 1, & \text{if } t2 \text{ is not in year 2010} \end{cases} \qquad [17]$$

As described in 4.1, freight is categorized as fuel or dry cargo. Seasonal ARIMA models are applied on both bi-monthly total fuel volumes and total dry cargo volumes transported by NTCL via the river. Freight volume data are extracted and organized bi-monthly; as a result, each year is divided into 24 periods, from the first half of January to the second half of December, such that $s = 24$. A set of possible ARIMA model forms were selected according to information provided by a plot of the freight volumes, sample autocorrelation, and partial sample autocorrelation. The Akaike's Information Criterion (AIC) was calculated, as shown in Table 4-2. In general, for a set of ARIMA model forms, the one with the lowest AIC is considered to best fit the data set and be most appropriate to apply (O'Connell & Koehler, 2005).

Table 4-2 ARIMA model evaluation

Model form	**AIC**	
	Fuel	**Deck**
$(1,1,0)(1,1,0)_{24}$	5755.08	4894.83
$(0,1,0)(1,1,0)_{24}$	5833.94	4959.40
$(1,0,0)(1,1,0)_{24}$	5644.57	4888.04
$(0,0,0)(1,1,0)_{24}$	5593.67	4774.59

Hence, model $ARIMA\,(0,0,0)(1,1,0)_{24}$ is finally chosen for both fuel and deck data series. The integration of ARIMA model and transfer function is thus specified as Eq. 18.

$$y_t = \varphi(y_{t-24} - y_{t-48}) + y_{t-24} + a_t + \omega_1 I_{t1} + \omega_2 I_{t2} \quad [18]$$

Where, y_t is the original observation at time period t; a_t is the white noise at time t, $a_t \sim N(0, \sigma^2)$; φ is the parameter in the seasonal AR model.

4.3.2 Parameter estimation results

Estimates of parameters φ, ω_1, and ω_2 for fuel and dry cargo volume ARIMA models are presented in Table 4-3.

Table 4-3 Parameter estimation results of ARIMA model and transfer function

	Fuel		Dry Cargos	
	Value	***p*-Value**	**Value**	***p*-Value**
φ	-0.464	<0.0001	-0.577	<0.0001
ω_1	-830.14	0.1010	-314.75	0.0094
ω_2	-441.76	0.3319	-174.17	0.1249

The p-value of ω_1 for fuel volume data is 0.1010, indicating that this parameter is statistically significant just below the 90% confidence level. Despite this somewhat marginal significance, we retain this term in the following forecasting process. However, ω_2 estimates for fuel and dry cargos are not statistically significant according to their p-value. A reason for this may be that although volumes in 2010 are observed to be lower than other years after 2008, it may still be one consequence of the sudden decrease after 2008. Hence, in the ARIMA model, the transfer function that models the 2010 shock is not included due to its statistical insignificance. Also, ω is negative, indicating that there is a drop on the mean of data series before and after the intervention. The absolute values of ω_1 for both fuel and dry cargo indicate that the fuel volume decreased about 830 tons per half month on average after 2008, while the dry cargos dropped about 315 tons per half month. The new ARIMA models applied to forecast fuel and dry cargo volumes are presented in Eq. 19.

$$y_t = \varphi(y_{t-24} - y_{t-48}) + y_{t-24} + a_t + \omega_1 I_{t1} \quad [19]$$

Based on the chosen ARIMA model, fuel and dry cargo volumes forecast for 2025 were obtained and shown in Figure 4-4. Note that Figure 4-4 only shows volumes from June to October since volumes in other periods are zero. Also, Figure 4-4 shows volumes as a proportion of the historical maximum annual volume instead of absolute volumes, due to NTCL data confidentiality issues. The SAS codes used to implement these models are shown in Appendix A.

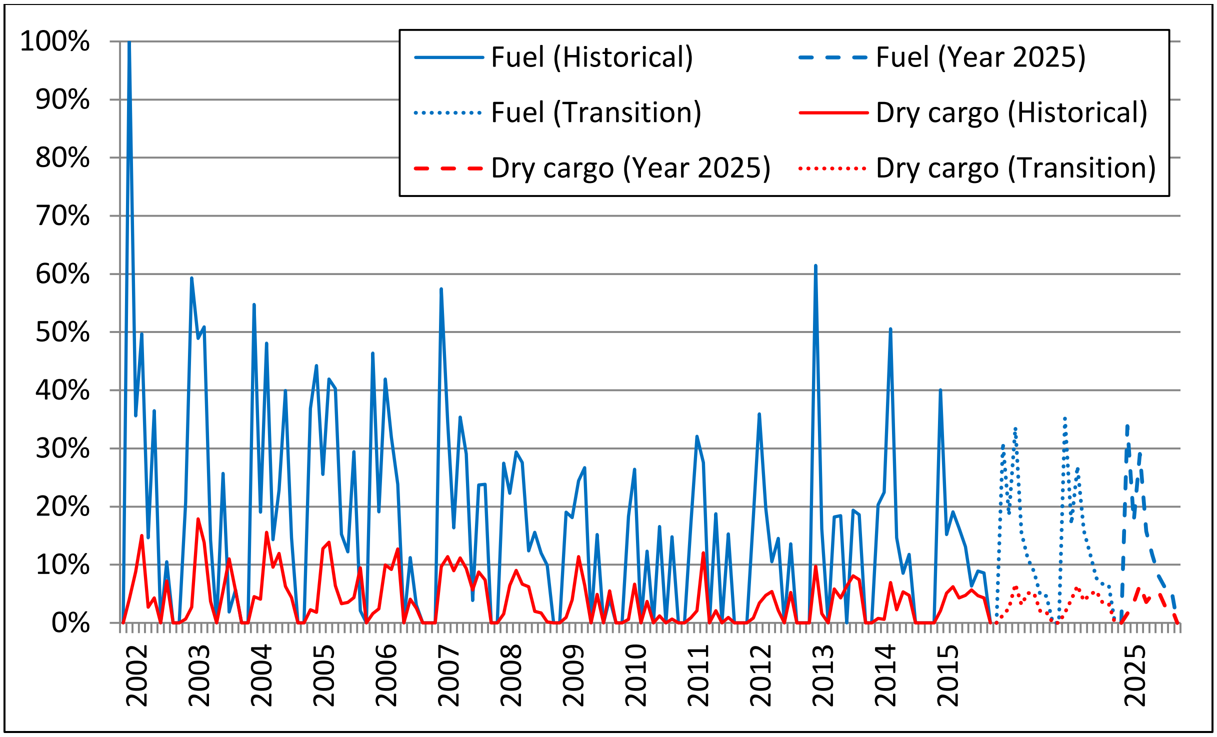


Figure 4-4 Forecast of fuel and dry cargo volumes in 2025

In Figure 4-4, it can be observed that the forecast volumes are relative lower than the volumes in 2002 to 2007, due to the impacts of the shock happened in 2008. Also, the volumes are expected to peak in late June and July in 2025. These forecasted volumes for 2025 are used as the base schedule in the scheduling planning model and numerical analysis (Chapter 6). The base schedule represents the anticipated bi-monthly freight delivery volumes when transport companies continue with "business as usual" in the future.

4.4 Summary

This chapter presents analyses and forecasts on waterway freight data. The freight data are extracted from tow letters provided by NTCL. More than 70 destinations are identified in the tow letters. However, based on the total volumes to these destinations and their occurrence frequency since 2002 to 2015, seven major destinations are identified, to which more than 90 percent of total freight volumes are destined. In addition, freight transported by NTCL via the

Mackenzie River can be categorized into two major classes: fuel and dry cargos. Bi-monthly volumes heading to every major destination and total volumes delivered to all destinations are collected from the tow letters by type. Obvious drops in volumes after 2008 and in 2010 are observed in this data. Both shocks are assessed for statistical significant using a trend test, and accounted for accordingly in ARIMA models and intervention analysis.

The seasonal Kendall trend test is chosen to test whether monotonic trends existed in freight data. Significant decreasing trends over time (from 2002 to 2014) at a 99% confidence level are identified in total freight volumes, volumes to Tuktoyaktuk, and volumes to Arctic Region. One major reason may be that since 2008 summer, another shipping company expanded their sealift services to Kitikmeot communities via the Northwest Passage, resulting in decreased volumes to Tuktoyaktuk and Arctic Region from NTCL. As for the shock in 2010, although no documents were found to report reasons of this shock, checking historical water level data at Fort Good Hope, the water levels in 2010 were found to be relatively low compared to other years, which may be the reason for the decreased volumes in this year.

ARIMA models and intervention analysis are then applied to estimate future freight volumes on the river. Both shocks in 2008 and 2010 are modelled using transfer functions. However, according to parameter estimation results, the 2010 transfer function shock parameter was not found to be statistically significant. Therefore, in the ARIMA model, the transfer function for the 2010 shock is not retained. The forecast of fuel and dry cargo volumes in 2025 were obtained using the new ARIMA models. It can be observed that the forecasted volumes are lower than the volumes in 2002 to 2007 due to impacts of the shock in 2008, and the volumes are expected to peak in late June and July. These forecast volumes are then used in numerical analysis presented in Chapter 6.

Chapter 5. Generalized Cost Function and Future Schedule Planning Model

In this chapter a generalized cost function is developed to account for the additional cost of rescheduling freight delivery to earlier dates as well as the benefit of utilizing better water conditions. Four cost components are included in this generalized cost function: handling cost, travel cost, rescheduling cost, and delay cost. Then, a schedule planning model is developed based on this cost function to determine alternative schedules that better align with predicted water conditions. As discussed in Chapter 1, the purpose of this model is not focused on obtaining specific schedules to adapt to potential climate change, but providing guidance based on its results on how shipping patterns may need to evolve in the context of future climate conditions. We then apply this model in two scenarios in the numerical analysis (see Chapter 6) to assess how climate change may impact delivery schedules on the Mackenzie River. In addition, based on the optimal schedules obtained via applying the model in the numerical analysis, we intend to provide some guidance to shipping companies, customers, and the government in developing their future delivery planning and scheduling strategies on the river.

In 5.1, freight type and important variables are defined. The generalized cost function and the future schedule planning model are introduced in 5.2 and 5.3 respectively. In the last section, the summary of this chapter is presented.

5.1 Model setup

According to William Smith of NTCL (personal communication, December 4, 2015), fuel and contracted dry cargo (for mining and other industrial operations) deliveries are often planned well in advance of the season (six months to a year). However, delivery requests for personal dry cargos, such as personal vehicles, residential building materials, etc., are variable and often not known in advance, making early planning difficult. Therefore, for our modeling purposes, we have assumed three types of freight: fuel, contracted dry cargo, and "unscheduled" dry cargo. In this model, we use q to represent freight types (q=1 is fuel; q=2 is contracted dry cargo; q=3 is "unscheduled" dry cargo). Since deliveries of the first two types are planned in advance, we assume here that it would be easier (and therefore, cheaper) for a shipping company to "reschedule" these freight types compared to the last. Demands for delivery of "unscheduled" dry cargo are usually quite small compared to fuel and contracted dry cargos (William Smith, NTCL, personal communication, December 4, 2015). Thus, we have also assumed for this research that 90% of all dry cargo is contracted while 10% is "unscheduled", and that this remains true in 2025 (of course this depends heavily on the future of mining and oil & gas explorations in the Northwest Territories).

The model is built on an abstracted and simplified network, with only one origin and destination, connected by a single waterway route. In this model, we define variable $d_{i,j}^{q}$ to represent the volume (in tons) of freight q "rescheduled" from time period j to period i, and denote the delayed volume (volume not successfully transported within required time period) of freight q in time period i as l_i^q. If the capacity for q $\left(C_i^q\right)$ is larger than the total volume requiring transport in this period i (including volumes assigned to this period, $\sum_j d_{i,j}^{q}$, and delayed volumes in the preceding period, l_{i-1}^{q}), l_i^q should be zero, as all freight demanding transport in this period is satisfied; otherwise, l_i^q equals total volume requiring transport minus the capacity (actual volume transported). Let us assume that l_0^q equals zero, meaning that the season does not start with freight undelivered from the previous year, and l_i^q can be defined mathematically as Eq. 20.

$$l_i^q = \begin{cases} 0, \quad if\ l_{i-1}^q + \sum_j d_{i,j}^q \le C_i^q \\ l_{i-1}^q + \sum_j d_{i,j}^q - C_i^q, \ \ if\ \ l_{i-1}^q + \sum_j d_{i,j}^q > C_i^q \end{cases} \ (i = 1, .., I) \quad [20]$$

Where I is the final time period (half-month duration) of a year, such that $I = 24$. (Period 1 represents the first half month in January, and period 2 represents the second half month in January, and so on so forth).

Since the total volume requiring transport may either be transported during assigned period or delayed to a subsequent one, the summation of delayed volume (l_i^q) and transported volume (denoted as v_i^q) in period i always equals the total volume requiring transport in this period ($l_{i-1}^q + \sum_j d_{i,j}^q$). Then, v_i^q can be defined as Eq. 21.

$$v_i^q = l_{i-1}^q + \sum_j d_{i,j}^q - l_i^q \quad [21]$$

5.2 Generalized cost function

A total generalized cost function is developed with the variables defined in 5.1 and used as the objective function in the future schedule planning model (5.3). There are four cost components to consider in this model, including:

- Handling costs (C_H): this is meant to aggregately represent costs associated with activities at terminals, such as freight loading and unloading, equipment utilization and maintenance, and etc. The shipping companies are most impacted by this cost, since they are the ones to conduct such activities;
- Travel cost (C_T): fuel consumption, labour, transport time, etc. This type of cost also impacts the shipping companies most, since it is the shipping companies who directly pay for the fuel and labour during the transportation;

- Direct costs associated with scheduling freight delivery volumes to a different time period (C_R): major components consists of actions required to schedule freight to other periods, such as extra freight storage and inventory, rearranging tows and barges to accommodate new plans, modifying customer contracts and logistics plans. This type of cost not only influences the shipping company but also the customers. "Rescheduling" freight delivery to another period will not only impact the schedule plans of shipping companies but also the plans of the customers and may also add pressure on the customers' storage capacities if the freight is delivered earlier;
- Delay costs (C_D): costs associated with dealing with delayed freight (i.e. delivered in a time period later than the one originally intended) and non-delivery by the end of the summer marine delivery season. For this type of cost, the customers will be most impacted, since the customers need to pay for the losses associated with delayed freight and freight not successfully delivered to the destinations.

The total cost can be expressed as follows:

$$C = C_H + C_T + C_R + C_D \qquad [22]$$

Since handling time and travel time are usually several days on the Mackenzie River, we quantify them in days. Hence, the unit for the generalized cost and all four cost components in this model is chosen as day·tons.

The benefits of delivering freight in good water conditions can be reflected in two aspects of the cost function. First, if water levels on the river decrease faster over the summer delivery season in the future, it is likely that water levels in late September and early October will be poor for tug and barge operations (if not making operations entirely impossible), and therefore, freight intended to be transported at this time would possibly experience high delays and potential non-delivery by end of season. The costs of delays and non-delivery can be very high, despite that delivery plans may be adjusted throughout the season in response to changing water conditions. By rethinking delivery of these late-season deliveries to an earlier time in the season, the costs of delays and non-deliveries may be significantly reduced. Second, the travel time of a tow in good water conditions (i.e. high water levels) is likely to be smaller than in less-ideal conditions. According to the Canadian Coast Guard (CCG), container ships with vessel beam[1] not exceeding 24 meters may travel on the St. Lawrence River at speeds under 7 knots if the under-keel clearance[2] is 0.79 meters. However, allowable speeds are up to 15 knots if the under-keel clearance is greater than 2.17 meters (Canadian Coast Guard, 2013). For vessels with beam larger than 24 meters, the requirements for under-keel clearance are even higher for the same speeds. Although there is no specific under-keel clearance guidance for vessel transportation on the Mackenzie River, according to operation companies on the Mackenzie River, vessel operation speeds are also constrained by low water levels. Hence, the St. Lawrence River clearance requirements can be used as a reference regarding safe marine transportation operations on the Mackenzie River. Another major reason for longer travel times in low water conditions is that barges must be anchored and pushed one by one through hazard sections in the river, including rapids and ramparts (Mulder & Williams, 2006).

In our model, the handling cost is a linear function of the total volume transported within the delivery season (v_i^q) for each freight type, while travel cost is a linear function of the total

[1] Vessel beam is ship's width at the widest point as measured at the ship's nominal waterline.
[2] Under-keel clearance (UKC) refers the minimum clearance between the deepest point on the vessel and the bottom in still water.

travel time in each period. Handling cost and travel cost are shown in Eq. 23 and Eq. 24 respectively.

$$(C_H)_i^q = \alpha^q \cdot v_i^q \; (i = 1,2, \dots I) \tag{23}$$

Where α^q is the time cost at terminals to handle freight q (i.e. loading/unloading, average waiting time before transportation, etc., unit is days), and v_i^q is the volume of freight q delivered in time period i, defined as Eq. 21 (unit is tons).

$$(C_T)_i^q = v_i^q \cdot t_i \; (i = 1,2, \dots I) \tag{24}$$

Where t_i is the round-trip travel time in time period i (unit of days).

Rescheduling cost is considered to be related not only to the volume of freight "rescheduled" from other time periods, but also the amount of time (i.e. number of periods) that freight is moved earlier compared to optimal schedule (Eq. 25).

$$(C_R)_i^q = \vartheta^q \cdot \sum_j \left(t_{i,j} \cdot d_{i,j}^q\right) \; (i = 1,2, \dots I) \tag{25}$$

Where ϑ^q is a parameter representing the demand uncertainty of freight q (the higher the value, the more costly it is to "reschedule"). Usually, the uncertainty for fuel and contracted cargos are low since they are always planned out in advance, while the uncertainty for "unscheduled" cargo is high. Parameter $t_{i,j}$is the time difference between period i and period j, and to make sure that the units for C_R is consistent with other terms (C_H, C_T, C_D) and the generalized cost, C, the unit for $t_{i,j}$ is defined in days.

There are two types of costs within the delay cost component defined previously. First, before the last feasible time period for river delivery of freight q, typically the second half month of September or the first half month of October nowadays, if some freight cannot be delivered by the end of the assigned period, it can still be arranged for delivery in following delivery periods.

The cost for this type of delay is specified in the first part of Eq. 26. If there is remaining freight not transported by the end of the delivery season, it cannot be successfully delivered during the current summary delivery season. Therefore, the cost of this non-delivery is defined in the second part of Eq. 26. To avoid double counting the costs associated with non-deliveries, this delay cost will be only taken into account and calculated once at the last time period, I, in the model. Therefore, for time periods between the last feasible time period for summer river delivery and period $I - 1$, we define delay cost as zero, as shown in the third part of Eq. 26.

$$(C_D)_i^q = \begin{cases} \varphi_1 \cdot \Delta_i \cdot l_i^q, & (i = 1, \dots, n-1) \\ \varphi_2 \cdot l_i^q, & (i = I) \\ 0, & (i = n, \dots, I-1) \end{cases} \quad [26]$$

Where l_i^q is the volumes of freight type q that are not delivered in time period i, defined as Eq. 20, and the unit is tons; parameters φ_1, φ_2 represent the unit cost of delays and non-deliveries (the higher the values, the higher the cost attributed to delays and non-deliveries); parameter Δ_i is the delay of a ton of some freight q that cannot be delivered in period $i - 1$ and needs to wait to be transported in period i, and on average we assume freight has been delayed for a time of $\frac{L_i}{2}$, where L_i is the length of time period i, and the unit is days; and n represents the last feasible time period within the delivery season, for example, currently, it is usually the second half month in September or the first half month in October.

Two binary parameters are introduced to reformulate the piece-wise function for C_D (shown in Eqs. 27, 28, and 29) into a form that can be easily represented and solved using optimization software. Parameter a_i is the weighting parameter on the delay costs for transport delay. Hence, if the delivery time period is prior to the last time period within delivery season ($i = n$), a_i equals 1; otherwise, a_i equals 0 (see Eq. 28). Parameter b_i is the weight on delay cost for non-deliveries. Therefore, only when the time period is the last time period of the year's marine delivery season ($i = I$), b_i equals 1; otherwise, b_i equals 0 (see Eq. 29). This definition ensures that in this delay cost function, all non-delivery costs will not be double-counted.

$$(C_D)_i^q = a_i \cdot \varphi_1 \cdot \Delta_i \cdot l_i^q + b_i \cdot \varphi_2 \cdot l_i^q \qquad [27]$$

Where

$$a_i = \begin{cases} 1, \text{ if } i = 1, \dots, n-1 \\ 0, \text{ if} i = n, \dots, I \end{cases} \qquad [28]$$

$$b_i = \begin{cases} 1, \text{ if } i = I \\ 0, \text{ if } i = 1, \dots, I-1 \end{cases} \qquad [29]$$

Based on above definitions of each type of cost, the total generalized cost function can then be written as in Eq. 30.

$$C = \sum_q \sum_i (\alpha^q \cdot v_i^q + t_i \cdot v_i^q + \vartheta^q \cdot \sum_j (t_{i,j} \cdot d_{i,j}^q) + a_i \cdot \varphi_1 \cdot \Delta_i \cdot l_i^q + b_i \cdot \varphi_2 \cdot l_i^q) \qquad [30]$$

Where l_i^q and v_i^q are defined as Eq. 20 and Eq. 21 separately.

5.3 Future schedule planning model

The model introduced in this section outputs a future revised freight delivery schedule by minimizing the total cost introduced in 5.2. These optimal revised delivery schedules may provide guidance to local government and shipping companies on how future Mackenzie River freight delivery plans may be reassessed and revised to adapt to future climate conditions. Capacities have been estimated for fuel and dry cargo (the latter which includes both contracted and "unscheduled" cargos). Hence, we use Q to represent either fuel (indicated as a value of 1) or dry cargo (indicated as a value of 2) for delayed volumes $\left(l_i^Q\right)$ and delivery capacities $\left(C_i^Q\right)$. The model is shown as below.

$$\text{Min } C = \sum_q \sum_i ((C_H)_i^q + (C_T)_i^q + (C_R)_i^q + (C_D)_i^q) \quad [31]$$

Subject to:

$$d_{i,j}^q \geq 0, \forall i = 1, \dots, I, j = 1, \dots, I, q \quad [32]$$

$$\sum_i d_{i,j}^q = p_j^q, \forall j = 1, \dots, I, q \quad [33]$$

$$l_0^Q = 0, \forall Q \quad [34]$$

$$l_i^Q = max\left(0, l_{i-1}^Q + \sum_j d_{i,j}^Q - C_i^Q\right), Q = 1, \forall i = 1, \dots, I \quad [35]$$

$$l_i^Q = max\left(0, l_{i-1}^Q + \sum_{q=2}^3 \sum_j d_{i,j}^q - C_i^Q\right), Q = 2, \forall i = 1, \dots, I \quad [36]$$

Where, p_j^q represents predicted volume of freight q in period j; and C_i^Q represents delivery capacity of freight Q in period i.

Eq. 32 stipulates that volumes "rescheduled" from period j to period i should be non-negative. Eq. 33 specifies that in the new schedule all freight "rescheduled" from period j (even if divided up and "rescheduled" to multiple periods) should still add up to the total volume originally assigned to period j in the base schedule. Eq. 34 ensures that l_0^Q is always zero, meaning that the season does not start with undelivered dry cargo or fuel. Eqs. 35 and 36 specify that l_i^q is always the largest of 0 or the total volume requiring transport $(l_{i-1}^Q + \sum_q \sum_j d_{i,j}^q)$ minus the delivery capacity (C_i^Q) for all Q in each i.

Since there is a recursive function in the definition of delayed volume, l_i^q, this optimization problem is not a typical linear programming (LP) problem, whose objective function and constraints are represented by linear relationships, and cannot be solved using traditional methods for LP problems. This research uses the dynamic search method in CPLEX 12.6.1.0 Studio to find the optimal solution. The optimization solving software, CPLEX 12.6.1.0 Studio, and the dynamic search method will be introduced in detail in Chapter 6.

5.4 Summary

This chapter introduced a generalized cost function and future schedule planning (optimization) model based on the cost function.

Modeled freight is categorized into three types: fuel, contracted dry cargo, and "unscheduled" dry cargo. Fuel and contracted dry cargo deliveries are often planned well in advance of the season (six months to a year), but demand for "unscheduled" dry cargo is more flexible, and scheduling this type freight to earlier dates is assumed to be more difficult than the other two types. This feature was accounted for in the model by setting a larger value of demand uncertainty of "unscheduled" dry cargo (ϑ^3), and this will be introduced in detail later in 6.1. The freight type category is used when building future schedule planning model.

A generalized cost function is developed to account for the additional cost of rescheduling freight delivery to earlier dates as well as the benefit of utilizing better water conditions. Four cost components are included in this generalized cost function: handling cost, travel cost, rescheduling cost, and delay cost. Additional cost of rescheduling freight delivery to earlier dates is represented in the rescheduling cost component in the function. While benefits of delivering freight in good water conditions (i.e. high water levels and stream flows) are reflected in two aspects in the cost function. First, rescheduling volumes to earlier dates can reduce the delayed volumes, contributing to reduced delay costs and, therefore, total costs. Second, shipping in good water conditions can reduce the shipping time, due to higher operational speed, contributing to reduced travel cost and, hence, total costs. This generalized cost function is used as the objective function in future schedule planning model.

Future schedule planning model is then developed and intends to minimize total generalized cost to obtain optimal schedules. In this model, due to a recursive function in the definition of delayed volume, l_i^q, the optimization model is not a typical linear programming (LP) problem, and cannot be solved using traditional methods for LP problems. This research uses CPLEX 12.6.1.0 Studio and dynamic search method to solve it. The optimal schedules obtained from this model may help provide some guidance and help shipping companies to decide their future delivery plans. This model is applied in two scenarios in Chapter 6 to assess how current scheduling strategies may be changed to adapt to potential climate change.

Chapter 6. Numerical Analysis

In this chapter, we assess how a company may rethink their freight delivery scheduling strategy under anticipated climate change impacts via applying the model introduced in 5.3 in two scenarios. Also, a sensitivity analysis is applied to assess how changings of key parameter values impact the optimal results.

These numerical examples were solved in CPLEX 12.6.1.0. CPLEX is an optimization software package developed by International Business Machines Corporation (IBM) to solve linear programming (LP) and related problems (International Business Machines Corporation (IBM), 2014). In Eq. 20, there is a recursive function (we are using the value of delayed volume in period $i-1$, l_{i-1}^{q}, to calculate the value of delayed volume in period i, l_i^q) when defining the delayed volume in each period. Since it is difficult to directly define variables with recursive definitions in CPLEX, this recursive function was then added to constraints. We specify that l_0^q is always zero for all freight types, indicating that the season does not start with freight undelivered from the previous year. Also, we constrained that l_i^q always equals the largest value in 0 and $l_{i-1}^{q} + \sum_j d_{i,j}^{q} - C_i^q$ for all freight types in period i. The values of l_i^q chosen during the optimization process under this constraint are equivalent to the values decided by the piece-wise definition function, Eq. 20. The CPLEX codes are shown in Appendix B.

Inputs and assumptions applied in this sensitivity analysis are introduced in the first section. In Section 6.2, the estimation method for period capacities is introduced and the estimate results are presented. Section 6.3 presents the estimation results and conclusions based on the results. Section 6.4 presents the sensitivity analysis results and discussions on these results.

Section 6.5 introduces the alternative scenario, along with the optimal results under this scenario and discussions on the results. Finally a summary is presented in the last section.

6.1 Inputs and assumptions

The values of all parameters used in this numerical analysis are shown in Table 6-1.

Table 6-1 Parameter value table

Parameter	**Value**
α^q $(q = 1,2,3)$	4
ϑ^1	1
ϑ^2	1
ϑ^3	2
φ_1	2
φ_2	150

Parameter α^q is chosen to be 4 days because loading/unloading time is typically 1-2 days at each terminal (one each at the origin and destination). Parameter ϑ^q reflects the demand uncertainty of freight q; the higher the value, the more costly it is to "reschedule" the freight volumes. Since "unscheduled" dry cargo is considered more difficult to "reschedule" than fuel and contracted dry cargo, we assume $\vartheta^1$and ϑ^2 are 1, while ϑ^3 is 2. Due to a lack of information for populating appropriate values for $\varphi_1$and φ_2, they are assumed to be 2 and 150 respectively to indicate that 1) the consequences of delays are severe and therefore costly, and 2) the consequences of non-delivery within the shipping season are far more severe than delays.

We know that with worse water conditions (i.e. lower water level and stream flow), safe travel speed limits are lower, resulting in longer trip travel times (Canadian Coast Guard, 2013). However, there is a lack of information on relationships between stream flows and vessel travel speeds. Here, we assume that if the difference between maximum stream flow and forecasted period stream flow is larger than 3000 m^3/s, travel times will increase 15% to reflect the impacts of water conditions on travel time.

6.2 Estimates of capacity

Future delivery capacities in each time period (as dictated by water conditions) are estimated using historical freight volumes, the historical stream flow profile, and 2025 predicted stream flow profile. We assume that the tug-and-barge delivery capacities are restricted by water conditions, and adequate equipment can be available and ready at any time during the summer delivery season. Also, since in the tow letters from NTCL, dry cargo is always labeled as deck cargo, we assume that the dry cargo can only be placed on the deck and the capacities of fuel and dry cargo are independent, meaning that the capacity of one freight type will not be influenced by the capacities of other freight types. Therefore, in this section, we estimate future capacities for fuel and dry cargo separately.

Historical stream flows and stream flows projected for the year 2025, provided by Dr. Thian Gan's research group at the University of Alberta, are presented in Figure 6-1 (Jan.1 and Jan.2 represent the first and second half months in January respectively, and so on). From the NTCL tow letters combined with historical stream flow data (2002-2014) at Fort Simpson (Water Office, Government of Canada, 2014a), we observed that no deliveries occurred when stream flow was smaller than 6000 m^3/s. As predicted stream flows for September and October 2025 are lower than 6000 m^3/s (as shown in Figure 6-1), we assume that deliveries cannot be made at these times. In addition, it can be observed that the average stream flow in the second half of August (Aug.2), is also quite low at 6277 m^3/s, which is very close to the minimum stream flow historically observed to be transporting freight.

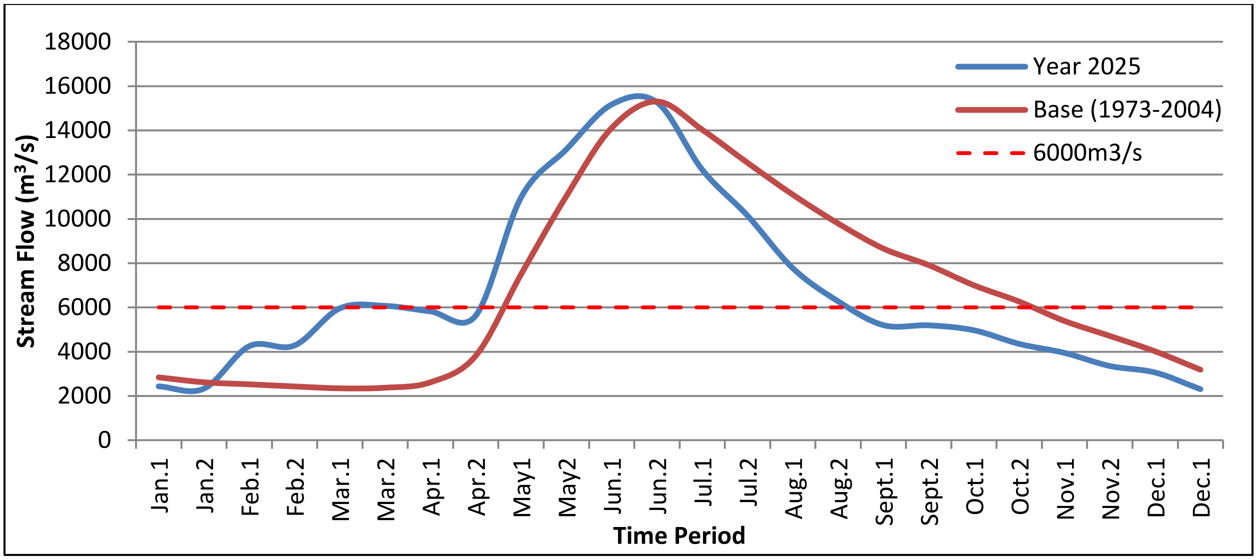


Figure 6-1 Predicted and historical stream flows at Fort Simpson in the Mackenzie River (from Dr. Thian Gan (2016))

In Figure 6-1, the 2025 predicted stream flow profile is observed to increase and decrease about half a month earlier than the historical profile. Also, we assume that the capacities increase with higher stream flows, and vice versa. Based on stream flow profile characteristics and assumed stream flow-capacity relationship, we define here the ratio of future capacity in period m for freight q, C_m^q, over the predicted stream flow in this period, P_m, equals the ratio of historical capacity in period $m+1$ for freight q, V_{m+1}^q, over the historical stream flow in period $m+1$, H_{m+1}. This relationship is presented in Eq. 36.

$$\frac{C_m^q}{P_m} = \frac{V_{m+1}^q}{H_{m+1}} \qquad [36]$$

Thus, estimated delivery capacity for freight q in period m can be estimated using following equation.

$$C_m^q = \frac{P_m}{H_{m+1}} \cdot V_{m+1}^q \qquad [37]$$

Capacity is usually a stochastic variate following a distribution function, and the average, median, or values in certain percentile of the distribution can be chosen to represent the capacity value (Minderhoud, Botma, & Bovy, 1997). Here, historical bi-monthly volumes in the 85th percentile are assumed as the historical capacities, in order to remove outliers and reflect typical situations. Here, to avoid use of extreme situations in the calculation of freight capacity based on water levels, historical bi-monthly fuel and dry cargo volumes in the 85th percentile are assumed as the historical capacities, and shown in Figure 6-2. Figure 6-2 (where Jun.1 and Jun.2 represent the first and second half months of June respectively, and so on) only displays results from Jun.1 to Oct.2, since waterway delivery capacities in other periods are zero. Note that Figure 6-2 shows volumes as a proportion of the historical maximum 85th percentile volume instead of absolute volumes, to protect NTCL data confidentiality.

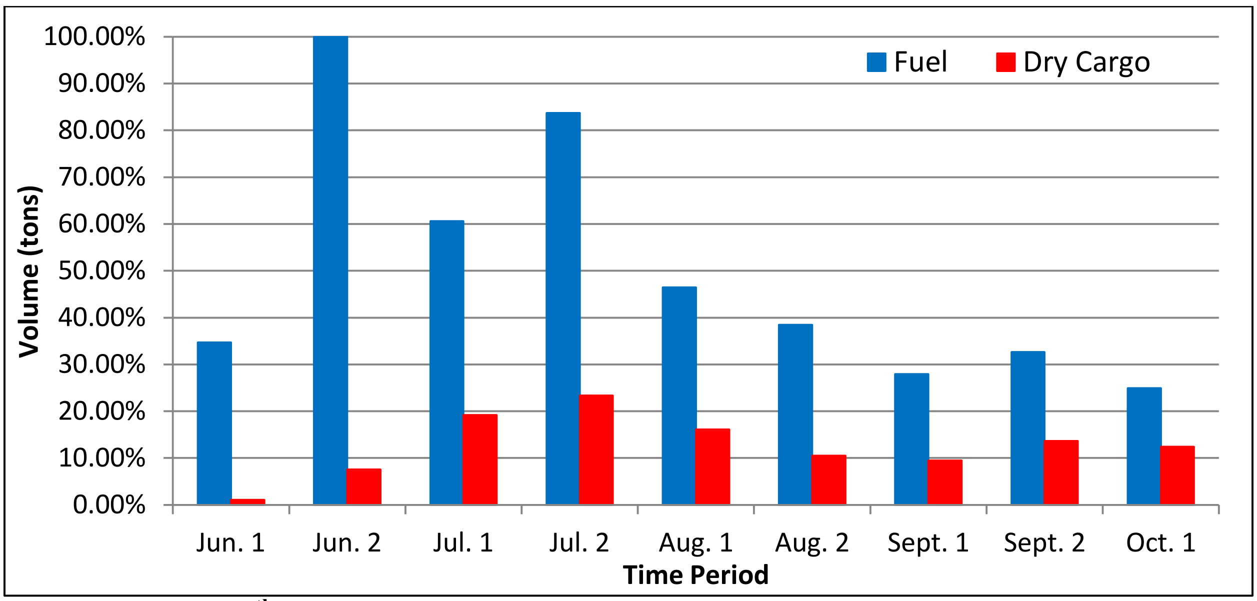


Figure 6-2 85th percentile volumes for fuel and dry cargos from 2002 to 2014 (as a proportion of the historical maximum 85th percentile volume)

The predicted capacities for fuel and dry cargos from May2 to Aug.2 are then calculated using Eq. 37 and are shown in Figure 6-3.

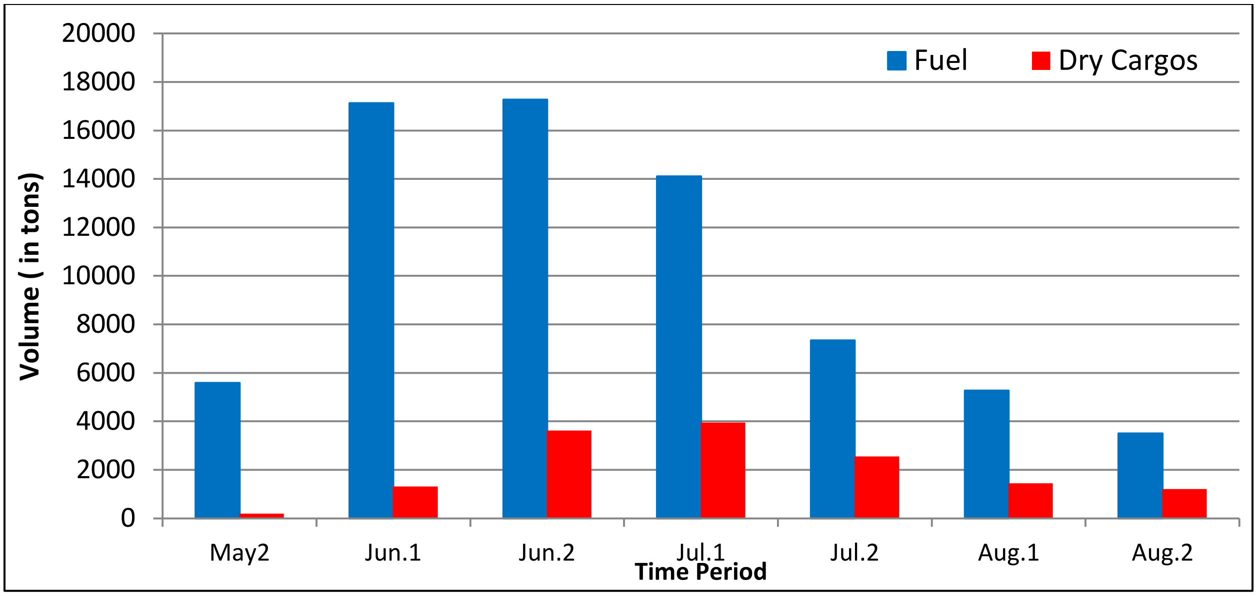


Figure 6-3 Predicted capacities for fuel and dry cargos in 2025

6.3 Results

This section presents the results of the optimization obtained under the inputs introduced in 6.1 and estimated delivery capacities presented in 6.2. The rescheduling results are discussed in 6.3.1, along with a comparison between total generalized costs for base and new delivery plans in 6.3.2. In the last subsection, summary of this section is presented.

6.3.1 Optimization results

The optimization problem of Eqs. 31-36 was solved using CPLEX 12.6.1.0. As mentioned in 5.3, this optimization problem is not a typical linear programming (LP) problem, and cannot be solved using traditional methods for LP problems. According to *ILOG CPLEX Optimization Studio 12.6.1: CPLEX User's Manual* (International Business Machines Corporation (IBM), 2014), CPLEX provides branch-and-cut algorithm, which is designed mainly to solve mixed integer programming (MIP) problem, to solve optimization problems like the optimization problem in our numerical analysis. Branch-and–cut procedure manages a goal tree consisting of nodes, which represent LP and quadratic programming (QP) sub-problems. If one node has not yet been processed, this node is an active node. CPLEX will continue to processes active nodes in the goal tree until no more active nodes existed or some limit has been reached. In addition to a robust branch-and-cut algorithm, CPLEX offers a new and innovative algorithmic approach for MIP problems in CPLEX 11.0 and later versions (International Business Machines Corporation (IBM), 2007). The dynamic search, same as branch-and-cut, consists of four building blocks: LP relaxation, branching, cuts, and heuristics. For many models, a dynamic search can find optimal solutions more quickly than a conventional branch-and-cut algorithm. CPLEX will choose between dynamic search and branch-and-cut based on characteristics it finds in the optimization models. While solving our optimization problem, CPLEX choose the dynamic search method to find solutions. The Engine Log for solving our optimization problem is shown in Appendix C.

Before showing the optimized results, I would like to mention one note about the solution of our optimization model. In our optimization model, the results obtained for the volumes of freight type q "rescheduled" from time period j to period i (d_{ij}^{q}) may not be unique, but when aggregating the results into bi-monthly freight volume level in the new schedule, these results are unique. For example, suppose we want to "reschedule" m tons freight from period x to earlier periods, but in period $x-1$, it is only capable to deliver extra n tons (where, $n<m$) freight, and therefore, $m-n$ tons freight needs to be delivered in period $x-2$. Although the "rescheduled" result is always the same (delivering extra n tons in period $x-1$ and extra $m-n$ tons in period $x-2$), there can be several assignment methods to obtain this result. One way to do this is to "reschedule" n tons freight from period x to period $x-1$ and then $m-n$ tons from period x to period $x-2$ (then, $d_{(x-1)(x)}^{q}=n$, $d_{(x-2)(x)}^{q}=m-n$, and $d_{(x-2)(x-1)}^{q}=0$). But we can also "reschedule" m tons freight from period x to period $x-1$ and then $m-n$ tons from period

$x-1$ to period $x-2$ (then, $d^q_{(x-1)(x)} = m$, $d^q_{(x-2)(x)} = 0$, and $d^q_{(x-2)(x-1)} = m-n$). In this thesis, one solution for the volumes of freight type q "rescheduled" from time period j to period i (d^q_{ij}) is presented.

The volumes (in tons) of freight type q "rescheduled" from time period j to period i, d^q_{ij}, where q is fuel, contracted dry cargo, "unscheduled" dry cargo, and dry cargo as a whole (contracted dry cargo + "unscheduled" dry cargo), are presented in Table 6-2 to Table 6-5 respectively. The first and second half months in January are represented as Jan.1 and Jan.2 respectively in these tables, and so on. The last columns (highlighted in yellow) in these tables present the base schedules, while rows marked in orange present new schedules and delivery capacities in every period. The remaining (white) values of the matrix show values for d^q_{ij}. For example, in Table 6-2, the value in row Sept.2 column Aug.2 is 1780, indicating that 1780 tons of fuel are "rescheduled" from Sept.2 in the base schedule to Aug.2 in the new schedule. Summaries of the final rescheduling results for all freight are presented in Figure 6-4. It can be observed that freight originally delivered in September and October has been "rescheduled" to earlier periods in the future schedule. However, due to limited capacity in late July and August as a result of low stream flow, some of this freight must be "rescheduled" to even earlier periods (late June or early July) to ensure successful delivery. According to Table 6-2 and Table 6-5, freight volumes in the Jul.2, Aug.1, and Aug.2 reach delivery capacity (as determined by stream flow). In Figure 6-4, freight volumes in early July are significantly higher than in other periods during the delivery season. In addition, since the "unscheduled" dry cargos are more difficult to "reschedule" than the contracted dry cargos, "unscheduled" dry cargos originally assigned to September and October were first arranged for transportation in the last period available for transportation (See Table 6-4). To ensure that the capacity of dry cargos in this period will not be exceeded, some of the contracted dry freight originally assigned to this period is “rescheduled” to an even earlier period (See Table 6-3). Also, in Figure 6-4, we can observe that in the future (optimized) schedule, the delivery season starts in Jun.2, just as it has historically. This indicates that it may not be necessary to start the season earlier in the future; instead, shipping companies can retain the same season start date but arrange for a more intense delivery season. However, limited equipment and crew availability (which is explored in Section 6.5), as well as customers’ storage and warehousing limitations, may require companies to actually begin their season earlier in order to reduce their overall logistics costs.

Table 6-2 Fuel volumes "rescheduled" from period *j* to period *i*

j \ *i*	Jan. 1	Jan. 2	Feb 1	Feb 2	Mar. 1	Mar. 2	Apr. 1	Apr. 2	May 1	May 2	Jun. 1	Jun. 2	Jul. 1	Jul. 2	Aug. 1	Aug. 2	Sept. 1	Sept. 2	Oct. 1	Oct. 2	Nov. 1	Nov. 2	Dec. 1	Dec. 2	Base
Jan. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Jan. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Feb. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Feb. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Mar. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Mar. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Apr. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Apr. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
May 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
May 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Jun. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Jun. 2	0	0	0	0	0	0	0	0	0	0	0	**9852**	**0**	**0**	**0**	**0**	0	0	0	0	0	0	0	0	**9852**
Jul. 1	0	0	0	0	0	0	0	0	0	0	0	**0**	**5090**	**0**	**0**	**0**	0	0	0	0	0	0	0	0	**5090**
Jul. 2	0	0	0	0	0	0	0	0	0	0	0	**0**	**6259**	**2289**	**0**	**0**	0	0	0	0	0	0	0	0	**8548**
Aug. 1	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**1654**	**2936**	**0**	0	0	0	0	0	0	0	0	**4590**
Aug. 2	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**3398**	**0**	**0**	0	0	0	0	0	0	0	0	**3398**
Sept. 1	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**0**	**628**	**1717**	0	0	0	0	0	0	0	0	**2345**
Sept. 2	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**0**	**0**	**1780**	0	0	0	0	0	0	0	0	**1780**
Oct. 1	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**0**	**1711**	**0**	0	0	0	0	0	0	0	0	**1711**
Oct. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Nov. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Nov. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Dec. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Dec. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Optimal	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**9852**	**11349**	**7341**	**5275**	**3497**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	
Capacity	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**5592**	**17127**	**17277**	**14111**	**7341**	**5275**	**3497**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	

Table 6-3 Contracted dry cargo volumes "rescheduled" from period *j* to period *i*

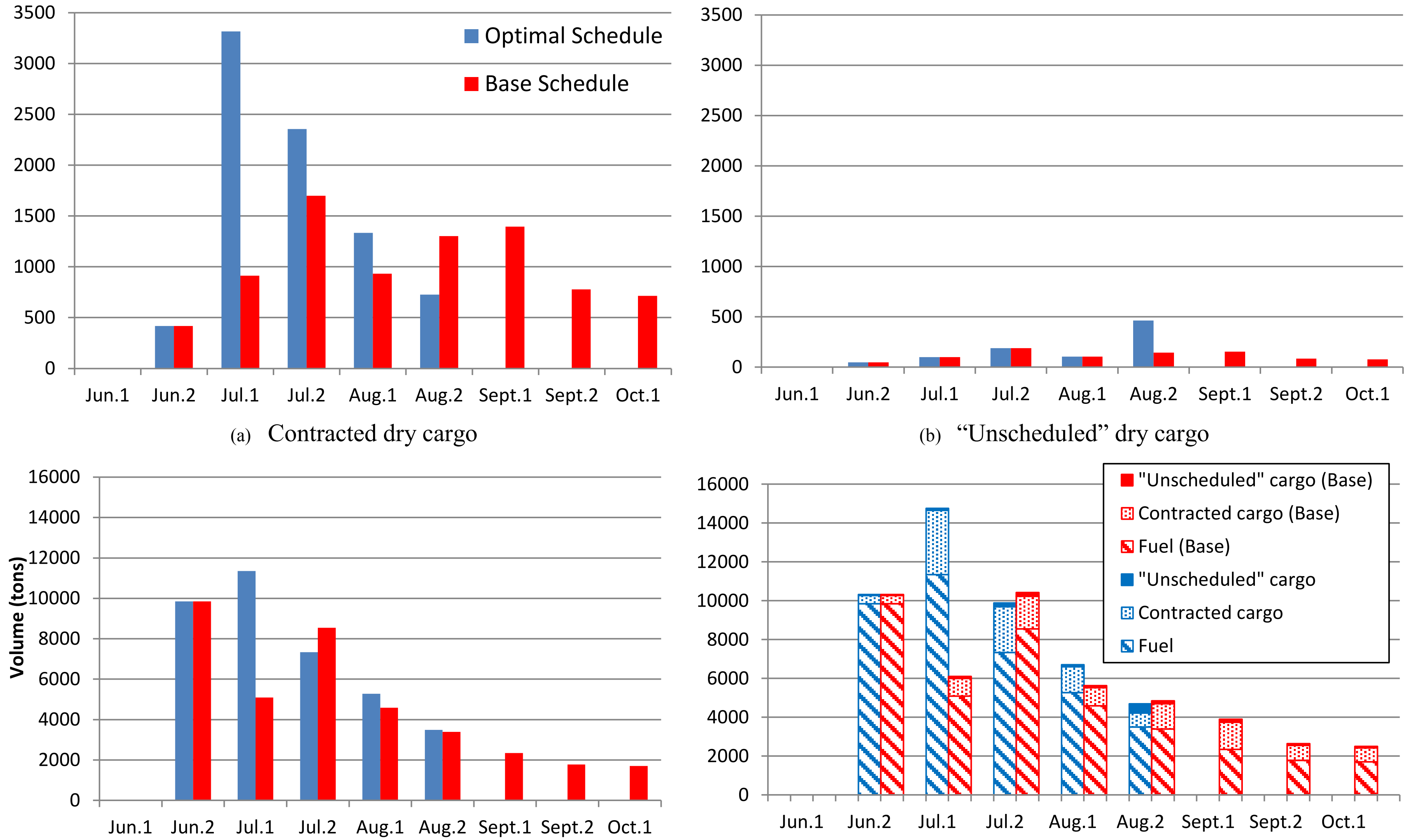
j \ *i*	Jan. 1	Jan. 2	Feb 1	Feb 2	Mar. 1	Mar. 2	Apr. 1	Apr. 2	May 1	May 2	Jun. 1	Jun. 2	Jul. 1	Jul. 2	Aug. 1	Aug. 2	Sept. 1	Sept. 2	Oct. 1	Oct. 2	Nov. 1	Nov. 2	Dec. 1	Dec. 2	Base
Jan. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jan. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Feb. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Feb. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mar. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mar. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Apr. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Apr. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
May 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
May 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jun. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jun. 2	0	0	0	0	0	0	0	0	0	0	0	419	0	0	0	0	0	0	0	0	0	0	0	0	419
Jul. 1	0	0	0	0	0	0	0	0	0	0	0	0	913	0	0	0	0	0	0	0	0	0	0	0	913
Jul. 2	0	0	0	0	0	0	0	0	0	0	0	0	1471	227	0	0	0	0	0	0	0	0	0	0	1698
Aug. 1	0	0	0	0	0	0	0	0	0	0	0	0	932	0	0	0	0	0	0	0	0	0	0	0	932
Aug. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	1302	0	0	0	0	0	0	0	0	0	0	1302
Sept. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	112	1283	0	0	0	0	0	0	0	0	0	1395
Sept. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51	727	0	0	0	0	0	0	0	0	778
Oct. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	714	0	0	0	0	0	0	0	0	0	0	714
Oct. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nov. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nov. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Dec. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Dec. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Optimal	0	0	0	0	0	0	0	0	0	0	0	419	3316	2355	1334	727	0	0	0	0	0	0	0	0	

Table 6-4 “Unscheduled” dry cargo volumes “rescheduled” from period *j* to period *i*

j \ *i*	Jan. 1	Jan. 2	Feb 1	Feb 2	Mar. 1	Mar. 2	Apr. 1	Apr. 2	May 1	May 2	Jun. 1	Jun. 2	Jul. 1	Jul. 2	Aug. 1	Aug. 2	Sept. 1	Sept. 2	Oct. 1	Oct. 2	Nov. 1	Nov. 2	Dec. 1	Dec. 2	Base
Jan. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Jan. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Feb. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Feb. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Mar. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Mar. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Apr. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Apr. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
May 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
May 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Jun. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Jun. 2	0	0	0	0	0	0	0	0	0	0	0	**47**	**0**	**0**	**0**	**0**	0	0	0	0	0	0	0	0	**47**
Jul. 1	0	0	0	0	0	0	0	0	0	0	0	**0**	**101**	**0**	**0**	**0**	0	0	0	0	0	0	0	0	**101**
Jul. 2	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**189**	**0**	**0**	0	0	0	0	0	0	0	0	**189**
Aug. 1	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**0**	**104**	**0**	0	0	0	0	0	0	0	0	**104**
Aug. 2	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**0**	**0**	**145**	0	0	0	0	0	0	0	0	**145**
Sept. 1	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**0**	**0**	**155**	0	0	0	0	0	0	0	0	**155**
Sept. 2	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**0**	**0**	**86**	0	0	0	0	0	0	0	0	**86**
Oct. 1	0	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**0**	**0**	**79**	0	0	0	0	0	0	0	0	**79**
Oct. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Nov. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Nov. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Dec. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Dec. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Optimal	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**47**	**101**	**189**	**104**	**465**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	

Table 6-5 Dry cargo (contracted + "unscheduled") volumes "rescheduled" from period *j* to period *i*

j \ *i*	Jan. 1	Jan. 2	Feb 1	Feb 2	Mar. 1	Mar. 2	Apr. 1	Apr. 2	May 1	May 2	Jun. 1	Jun. 2	Jul. 1	Jul. 2	Aug. 1	Aug. 2	Sept. 1	Sept. 2	Oct. 1	Oct. 2	Nov. 1	Nov. 2	Dec. 1	Dec. 2	Base
Jan. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jan. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Feb. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Feb. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mar. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mar. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Apr. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Apr. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
May 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
May 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jun. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jun. 2	0	0	0	0	0	0	0	0	0	0	0	466	0	0	0	0	0	0	0	0	0	0	0	0	466
Jul. 1	0	0	0	0	0	0	0	0	0	0	0	0	1014	0	0	0	0	0	0	0	0	0	0	0	1014
Jul. 2	0	0	0	0	0	0	0	0	0	0	0	0	1471	416	0	0	0	0	0	0	0	0	0	0	1887
Aug. 1	0	0	0	0	0	0	0	0	0	0	0	0	932	0	104	0	0	0	0	0	0	0	0	0	1036
Aug. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	1302	0	145	0	0	0	0	0	0	0	0	1447
Sept. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	112	1283	155	0	0	0	0	0	0	0	0	1550
Sept. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51	813	0	0	0	0	0	0	0	0	864
Oct. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	714	0	79	0	0	0	0	0	0	0	0	793
Oct. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nov. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nov. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Dec. 1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Dec. 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Optimal	0	0	0	0	0	0	0	0	0	0	0	466	3417	2544	1438	1192	0	0	0	0	0	0	0	0	
Capacity	0	0	0	0	0	0	0	0	0	176	1297	3610	3941	2544	1438	1192	0	0	0	0	0	0	0	0	



(a) Contracted dry cargo

(b) "Unscheduled" dry cargo

(c) Fuel

(d) Total

Figure 6-4 2025 Freight rescheduling results summary

Since the purpose of our research is not to find specific schedules to adapt to future climate change, the results are not meant to provide scheduling strategies that can be adopted directly in the future to adapt to climate change. Rather, the results are meant to provide guidance to shipping companies and their customers to plan their freight demand and delivery as early as possible, and wait until the late months in the season as infrequently as possible. Specifically, the results reveal that future waterway freight transportation capacities in September and October – as determined by Mackenzie River stream flow predictions – are insufficient to transport freight volumes currently assigned to that time in the delivery season due to changing climate conditions. Shipping companies can either begin their delivery season at the same time as is currently done, and instead arrange a "tighter" delivery schedule, or vice versa, to accommodate the lack of water in the early fall months. Shipping companies may want to fully utilize high water levels (and therefore, shipping capacities) in July to ensure successful deliveries of freight originally assigned to late-season months. In addition, since the "unscheduled" dry cargo is harder to "reschedule", the volumes originally assigned to September and October intend to be "rescheduled" to the nearest period that is available for freight delivery, which is Aug.2 in our case. This spike in Aug.2 does not indicate that this is the best operational way for shipping companies to respond to the anticipated unsatisfactory water conditions in September and October in the future. Rather, it urges the shipping companies and their customers to consider planning their freight demand and deliveries as early as possible. As for government agencies, such as Department of Transportation in the NWT and Transport Canada, they may also consider supporting further development of alternate modes of transport in case of unexpected failure of waterway freight deliveries in late-season months and reduce both non-deliveries of freight and financial losses.

6.3.2 *Cost comparison between base and optimal schedules*

The generalized costs calculated for both the optimal schedule scenario and base schedule, based on the generalized cost function of Eq. 22, are compared. The results are shown in Table 6-6.

Table 6-6 Different cost components calculated for base and optimal schedules

	Handling & Travel costs	Rescheduling costs	Delay Costs		Total Costs
			First Type	Second Type	
Base Schedule	4.24×10^5	0	2.10×10^5	1.44×10^6	2.07×10^6
Optimal Schedule	5.30×10^5	6.56×10^5	0	0	1.20×10^6

According to Table 6-6, the total generalized cost calculated for the optimal schedule is about 40% lower than that of the base schedule. When we break down the total cost components, the handling and travel costs of the optimal schedule are about 25% larger than those of the base schedule because more freight are delivered in the optimal schedule (in the base, much of this freight is left undelivered at the end of season due to reduced capacities in September and October). Compared to the total costs, however, the differences in handling costs and rescheduling costs between the optimal and base schedule are quite insignificant. Since rescheduling costs are incurred due to freight delivery in earlier time periods in the optimal schedule (compared to the base schedule), the rescheduling cost in the base schedule is always 0. The major differences between the total costs of the base versus optimal schedule are due to delay costs. Because all freight volumes can be delivered on time and successfully in the optimal schedule, the delay cost is 0. However, the base schedule delay costs are high due to the high volumes of freight that are delivered later in the season than intended and also not delivered at all during the summer delivery season. About 20% freight is assigned for delivery in September and October in the base schedule. Because the future Mackenzie River stream flow projection at Fort

Simpson are quite low in September and October, rendering this time unsuitable for freight transport, at least 20% of freight assigned to these two months cannot be delivered. Additionally, low stream flows in August also result in low delivery capacities at this time, exacerbating the problem of late season deliveries and causing total delay costs to skyrocket in the base schedule.

6.3.3 Summary

Freight assigned to September and October in the base schedule has been "rescheduled" to earlier periods due to a lack of delivery capacities in these periods. Additionally, "unscheduled" dry cargos originally assigned to September and October are first arranged for delivery in Aug.2, the last period available for waterway transportation, due to higher difficulties to "reschedule" this type of freight. In order to meet the capacity of dry cargos in Aug.2, some contracted dry cargos originally assigned to this period have to be "rescheduled" to an earlier period. The total generalized cost of this optimal schedule is about 1.20×10^6 tons·days, about 40% less than the total cost of the base schedule. These results reveal that future waterway freight transportation capacities in September and October may be insufficient to transport freight expected for delivery in those late-season months. This indicates a need to change freight volume transport schedules so that there is a higher probability that all freight can be successfully delivered if low water conditions occur in September and October. Instead of starting delivery season earlier, optimization results indicate that shipping companies can arrange a "tighter" schedule to fully utilize capacities in July to ensure successful deliveries of freight originally assigned to late-season months. However, shipping freight earlier with a "tighter" schedule will have significant logistical impacts on customers. Hence, shipping companies may need to consult closely with their customers to finally decide the new schedules. In addition, this research also encourages customers to rethink their delivery needs, particularly the tradeoff of arranging earlier delivery for the advantage of greater delivery reliability. As for government agencies, the results indicate a need for them to consider supporting further development of alternate modes of transport and increase the investment on local transportation infrastructure if needed in case of unexpected failures of waterway freight delivery in late-season months.

6.4 Sensitivity analysis

A sensitivity analysis is conducted to assess how the demand uncertainty of "unscheduled" dry cargo (ϑ^3), cost parameter for transport delay (φ_1), and cost parameter for non-delivery (φ_2), impact the schedule optimization results. Since the demand uncertainty for fuel (ϑ^1) and contracted dry cargo (ϑ^2) are set at 1 (representing low difficulty to "reschedule") in the previous numerical analysis, the same parameter for "unscheduled" dry cargo should be larger than 1 to reflect the greater difficulty associated with rescheduling "unscheduled" dry cargos. Therefore, ϑ^3 values from 2 to 25 are investigated. In addition, the overall range of φ_1 parameter values tested is 0.2 to 10, using a step size of 0.2 between values 0.2 and 2, and a step size of 2 between values 2 to 10. The overall range of φ_2 parameter values is 10 to 1500, with a step size of 10 from values 10 to 300, and a step size 50 for values between 300 and 1500.

Figures 6-5 to 6-7 show the sensitivity analysis results for total generalized costs, rescheduling costs, and delay costs, respectively. It can be observed that rescheduling and delay costs change little as the cost parameter for transport delay changes, indicating that optimal scheduling solutions are not very sensitive to this parameter. In Figures 6-5 and 6-6, it can be observed that when the cost parameter for non-delivery is larger than 80, the results begin to differ for the various ϑ^3 values and hence, one can observe the different "layers". Some layers level out, indicating no further changes to total generalized cost and rescheduling cost, as cost parameters for transport delay and non-delivery increase. It can be observed that darker layers (higher values for demand uncertainty of "unscheduled" dry cargo (ϑ^3)) level out at a larger critical cost parameter for non-delivery. The reason is that, in our model, the larger the demand uncertainty of the "unscheduled" dry cargo, the greater the rescheduling cost, and hence, the greater the benefits needed to compensate these costs. The cost benefits are primarily from the cost savings of delivering volumes that were previously undelivered at the end of the season. Moreover, if the benefits of rescheduling volumes (i.e. not incurring the non-delivery cost) in this period are greater than the rescheduling costs, rescheduling this freight is beneficial. As shown in Figure 6-7, at a certain critical value of cost parameter for non-delivery, the benefits of rescheduling certain types of freight begin to surpass the rescheduling costs, at which point, it becomes cost-effective to "reschedule" the transport of all (or portions) of the volume for this freight type to another available period (or multiple periods, depending on the capacity of the new periods). This results in a significant drop to delay costs.

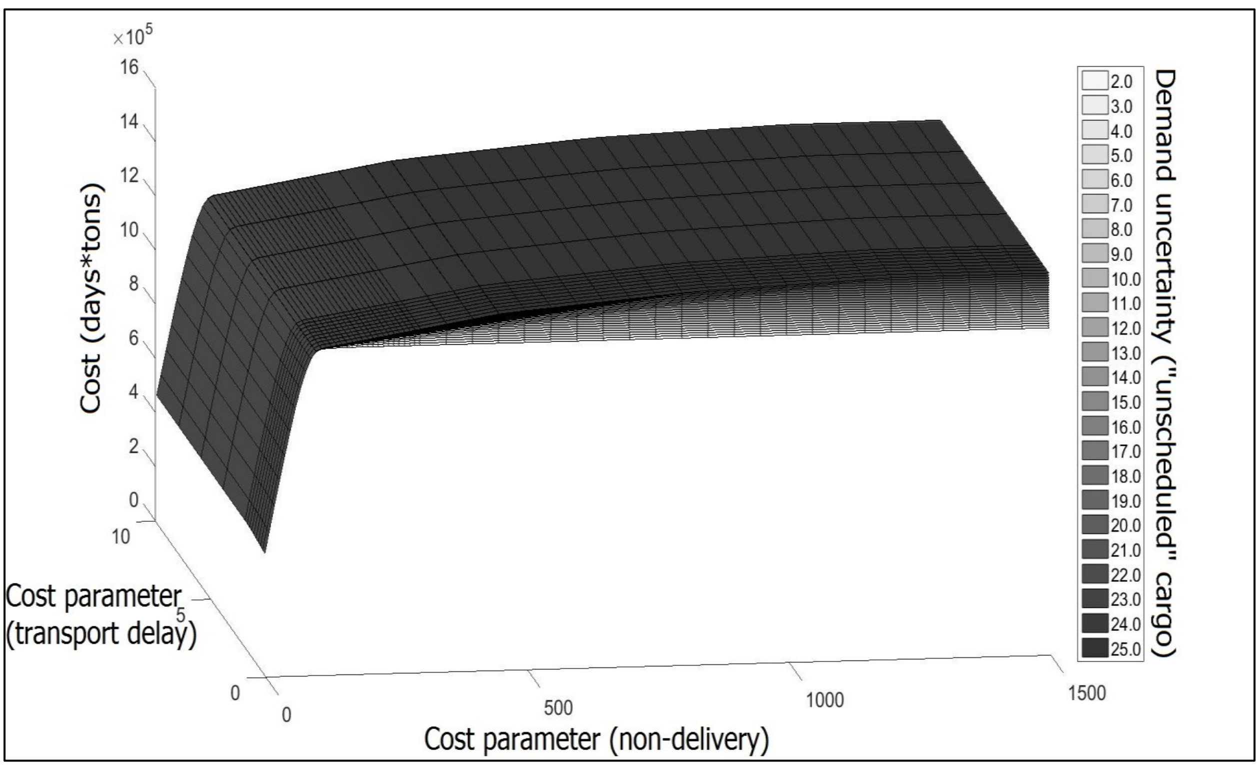


Figure 6-5 Sensitivity analysis results for total generalized costs

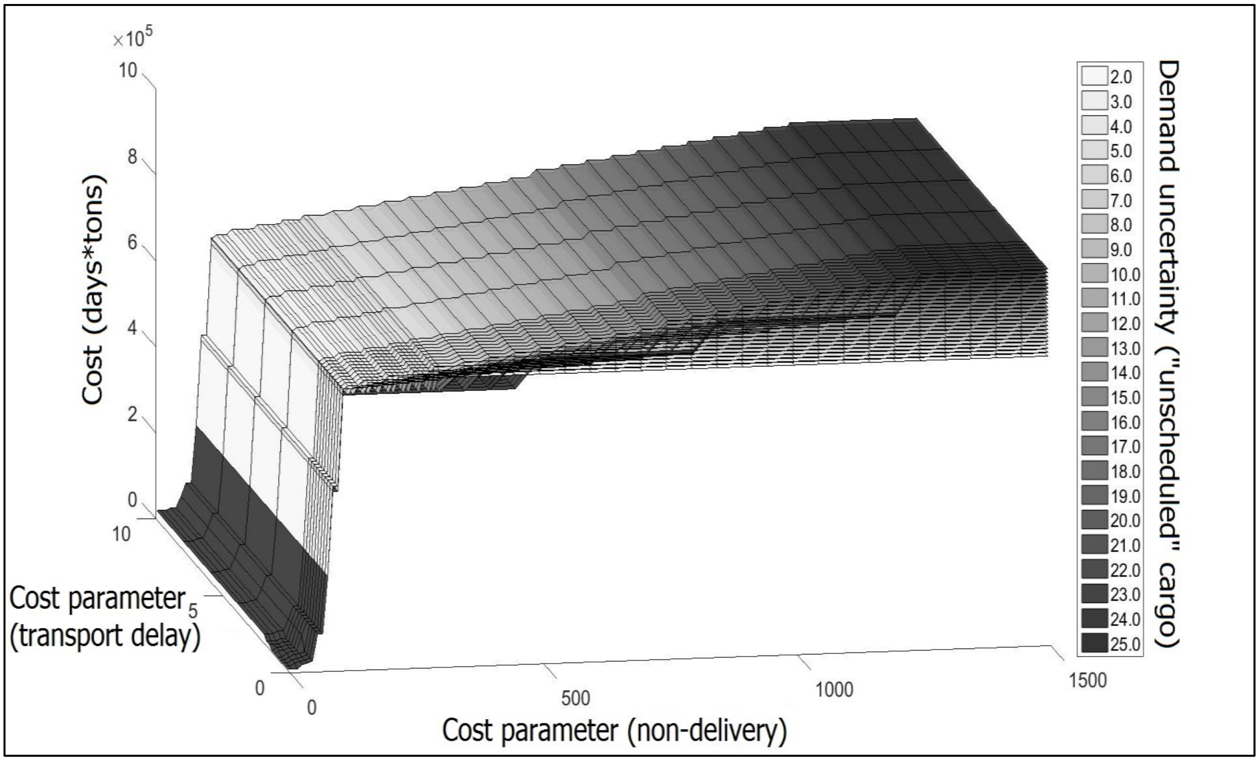


Figure 6-6 Sensitivity analysis results for rescheduling costs

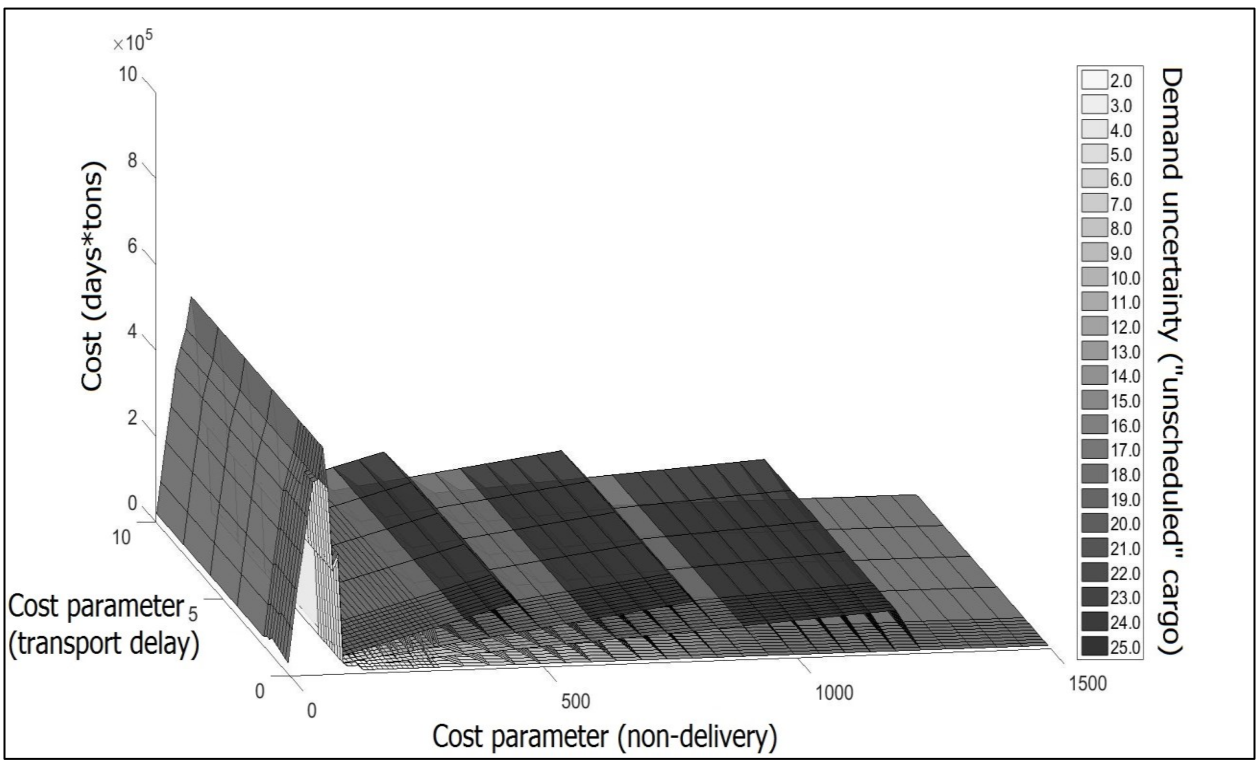


Figure 6-7 Sensitivity analysis results for delay costs

In summary, this sensitivity analysis has indicated the following:

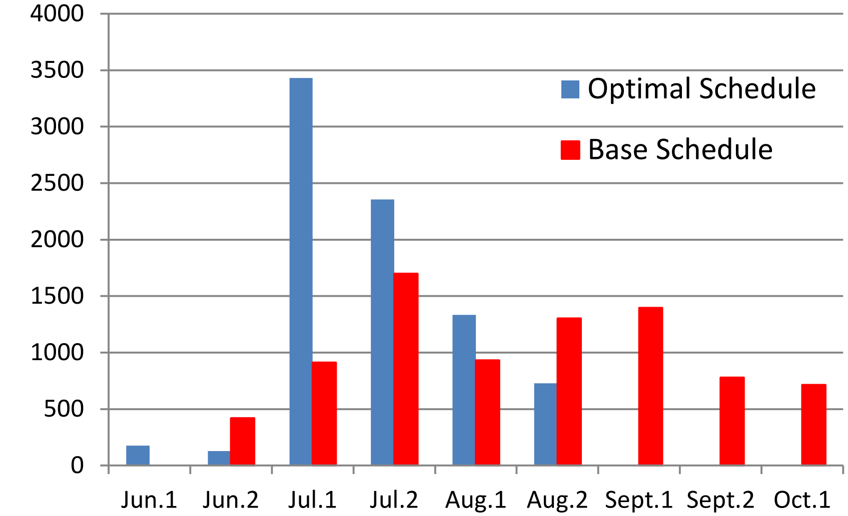
1. Optimal solutions are not very sensitive to costs associated with transport delays;
2. The larger the "unscheduled" cargo demand parameter (ϑ^3), the larger the benefits required to compensate for rescheduling "unscheduled" cargo; and
3. Delay costs drop discretely rather than continually as the cost parameter for non-delivery increases.

The results have highlighted a need for more research on the difficulties of schedule planning under uncertain future demand and climate change impacts, and empirical studies on how to determine appropriate parameter values in total logistic transportation cost models.

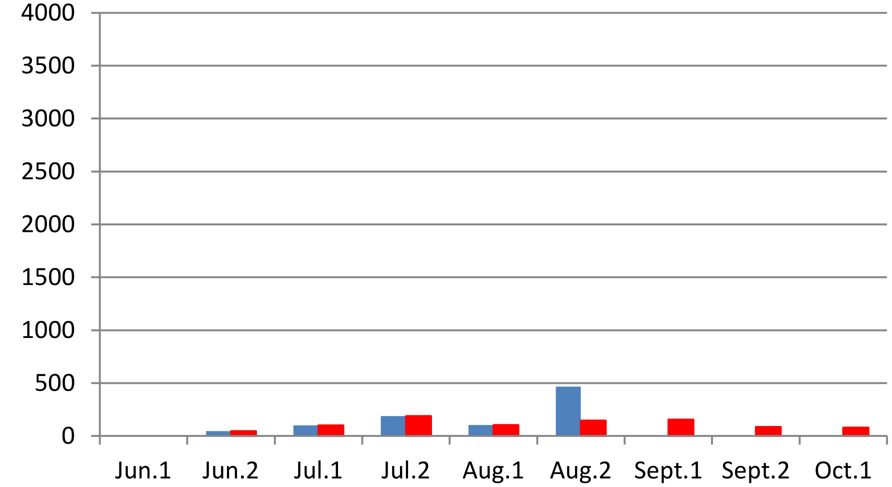
6.5 Alternative scenario

In the previous scenario, we set delivery capacities only on water conditions alone, assuming adequate equipment is available at any period time. As a result, the fuel delivery capacities in June are high. However, it is highly plausible that delivery capacities dictated by water conditions are not what actually limit freight delivery capacity, but rather, the availability of company equipment and crew. This may be particularly true at the beginning of the delivery season. Here we explore an alternate scenario where we assume that delivery capacities earlier in the summer shipping season are restricted by equipment limitations rather than water conditions. In this scenario, we assume that the delivery capacities in June are limited by equipment and crew availability, and such that the (half month) capacities equal that of May2 (see Figure 6-3). Capacities in all remaining periods of the season remain the same as those in the previous scenario.

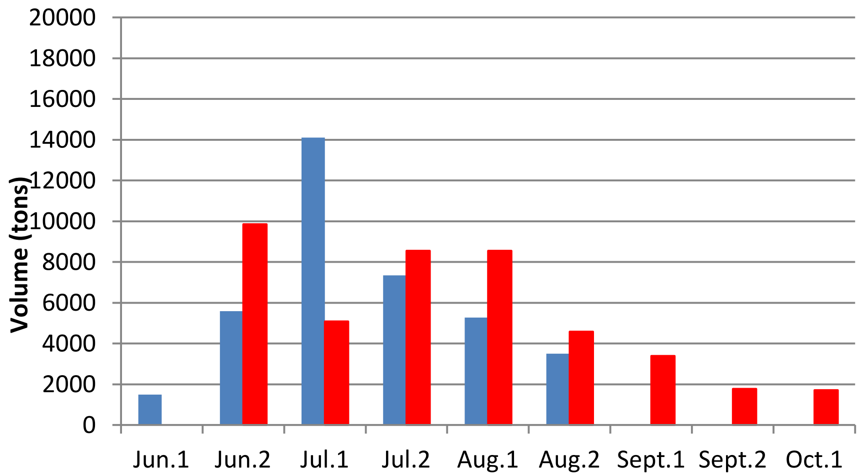
The total generalized cost of the optimal schedule under this equipment and crew capacity restricted scenario is about 106% of the total cost of the optimal schedule in the previous scenario; the results are shown in Figure 6-8. In Figure 6-8, "unscheduled" dry cargo assignment remains the same as in the previous scenario due to the difficulty (and therefore, high cost) of rescheduling. As for fuel and contracted dry cargo, since Jun.2 delivery capacities are reduced in this scenario, some volumes originally assigned to this period in the previous scenario are "rescheduled" to other periods in this restricted capacity scenario, resulting in more volumes assigned to Jul.1. Note that Jun.1 has not typically seen freight delivery activity in historical shipping schedules; the season typically begins in the second half of June (Jun.2).



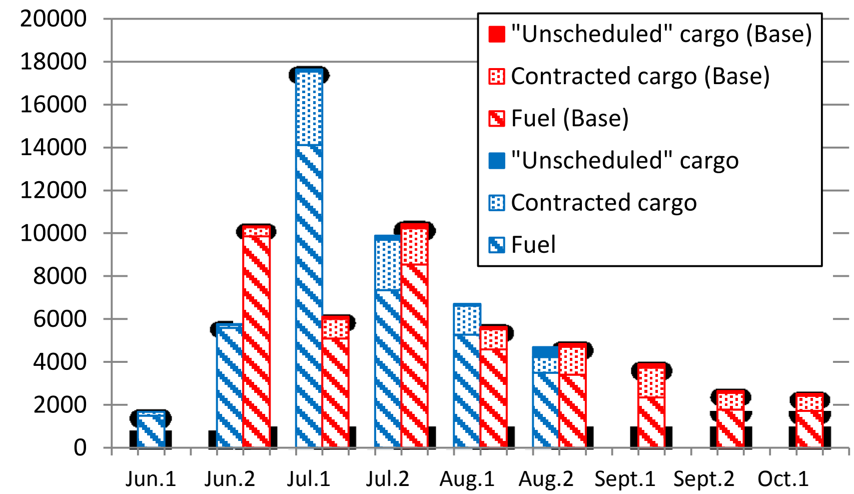
(a) Contracted dry cargo



(b) “Unscheduled” dry cargo



(c) Fuel



(d) Total

Figure 6-8 2025 Freight rescheduling results in the alternative scenario

The results suggest that shipping companies may need to increase their equipment and crew availability at the beginning of the delivery season (May and June), to handle volumes "rescheduled" from later in the season to earlier due to low water conditions. Also, shipping companies may see a need to begin deliveries prior to their typical start in mid-June, which was not necessary in the previous modeled scenario of 6.3. However, according to William Smith from NTCL (personal communication, December 4, 2015), the season start date depends on when the Canadian Coast Guard completes installation of the navigational buoys on all waterways. Hence, these results may indicate a need for the Canadian Coast Guard to set up navigational aids and buoys earlier, depending on, of course, ice break up, to ensure shipping companies are able to take advantage of good water conditions to begin operations as soon as possible.

6.6 Summary

This chapter describes the application of the future schedule planning optimization model to two scenarios, and the results of a sensitivity analysis of the key cost model parameters.

In the first scenario, we assume that the tug-and-barge delivery capacities are restricted only by water conditions, with the implicit assumption that adequate equipment and crew is available and ready at any time during the summer delivery season. Hence, the delivery capacities are estimated with historical volume data, historical stream flow profile, and predicted stream flow profile for 2025. The optimal schedule obtained under this scenario indicates that future water conditions in September and October may not be suitable for freight delivery and may lead to serious delays and non-deliveries in the late-season periods. Freight originally scheduled to these late-season periods is suggested to be "rescheduled" to earlier periods. Shipping companies can either begin their delivery season at the same time as is currently done, and instead arrange a "tighter" delivery schedule, or vice versa, to accommodate the lack of water in the early fall months. Specifically, shipping companies may want to fully utilize high water levels in July to ensure successful deliveries of freight originally assigned to late-season months. Since shipping freight earlier with a "tighter" schedule will have significant logistical impacts on customers, shipping companies may want to consult with their customers when deciding the new schedules. Customers may also need to rethink their delivery needs, and consider delivering their freight as early as possible, to avoid expected low water conditions in late-season months and reduce the risk of unsuccessful delivery. Additionally, the results in this scenario also indicate a need for government agencies to consider supporting further development of alternate freight transportation modes in case of unexpected failures of waterway freight delivery in late-season months and hence, reduce non-deliveries and financial losses.

A sensitivity analysis is conducted under first scenario to investigate how the demand uncertainty of "unscheduled" dry cargo (ϑ^3), cost parameter for transport delay (φ_1), and cost parameter for non-delivery (φ_2) impact schedule optimization. This sensitivity analysis has revealed that 1) optimal solutions are not very sensitive to cost parameter for transport delay (φ_1); 2) the larger the "unscheduled" cargo demand parameter (ϑ^3), the larger the benefits required to compensate for rescheduling "unscheduled" cargo; and 3) delay costs drop discretely rather than continually with respect to increases in the non-delivery cost parameter. Results of this analyse indicate a need for more research on the difficulties of schedule planning under uncertain future demand and climate change impacts, and empirical studies on how to determine appropriate parameter values in total logistic transportation cost models.

Different to the first scenario, in the alternative scenario, we assume that equipment is not fully available and ready in May and June. Hence, we assume that the delivery capacities in

Jun.1 and Jun.2 in this scenario equal the capacities in May2, the first feasible period for transportation in the first scenario. Results of this scenario indicate that, under certain situations (i.e. no enough equipment and crew available in May and June), the capacities in the current delivery season that NTCL operates in reality are not enough to transport all freight volumes and starting the season earlier is necessary to ensure successful freight deliveries. Therefore, shipping companies may need to increase their equipment and crew availability at the beginning of the delivery season (May and June), to handle volumes “rescheduled” from later in the season. Since the season open time depends on when the Canadian Coast Guard finishes installing navigational buoys every year, the results may also encourage government to more closely monitor climate change and set up navigational aids and buoys in time to ensure shipping companies can start their delivery as they needed.

Chapter 7. Conclusions

This chapter summarizes the key findings and major conclusions of this research and presents the research contributions as well as research limitations and recommended future work. Thesis overview is presented in 7.1. Major findings are introduced in 7.2. Then, contributions of this research are discussed in 7.3. In the last section, research limitations and future work are introduced.

7.1 Thesis overview

This research provided an assessment on how the climate change may impact the shipping schedule strategies on the Mackenzie River in the future and also provided some guidance and suggestions to shipping companies, customers, and the government on how shipping patterns may need to evolve in order to efficiently adapt to future climate conditions. The major research question that has been addressed in this thesis is how to balance the additional cost of implementing new delivery plans against the cost benefits of utilizing good water conditions in future delivery schedule planning that adapts to climate change impacts. Based on future water condition projections from climate simulation models, this research aims to account for anticipated climate change impacts in the marine freight schedule planning process and determine alternative schedule strategies that may better align with predicted water conditions.

To achieve this objective, the following work was conducted:

1) An assessment of how forecasted future freight volumes along the Mackenzie River might be modified to account for the impacts of climate change on water conditions.

2) Development of a generalize cost function to account for potential climate change. The cost function applied in this study factors in the additional cost of rescheduling freight delivery to earlier dates as well as the benefit of utilizing better water conditions. This cost function is used as the objective function in future schedule planning model. By minimizing the total generalized cost, this model can determine more cost-effective (costs as defined in Chapter 5.2) transport plans, which take better advantage of future anticipated water conditions and therefore, provide a higher likelihood of successful delivery.

3) Construction and application of a future schedule planning model in two capacity scenarios, to assess how to rethink the freight delivery scheduling strategy under anticipated climate change impacts. A sensitivity analysis is also applied to assess how changings of parameters impact the optimal results.

7.2 Findings

In time series analysis, volume decreases after 2008 and in 2010 are found in the historical freight volume data. One major reason for the volume decrease after 2008 is that since 2008 summer, another shipping company expanded their sealift services to Kitikmeot communities via the Northwest Passage, resulting in decreased volumes to Tuktoyaktuk and Arctic Region from NTCL. As for shock in 2010, checking historical water level data at Fort Good Hope, the water levels in 2010 were found to be relatively lower compared to other years, and this may be the reason for the decreased volumes in this year. Both shocks are modelled using transfer functions in the ARIMA model. However, parameter estimation results indicate that parameters in the transfer function that models the shock in 2010 are not statistically significant. A reason for this may be that although volumes in 2010 are observed to be lower than other years after 2008, it may still be one consequence of the sudden decrease after 2008.

Hence, modelling the shock after 2008 is enough for representing the changes in freight volume pattern in the ARIMA model.

Numerical analysis results suggest that freight deliveries in the late-season months, specifically in September and October, will be significantly affected, if stream flows start to increase and drop earlier every year. Due to a lack of delivery capacity in these periods, freight assigned for delivery in September and October in the optimal schedule has to be "rescheduled" to earlier periods. This will result in "tighter" schedules that fully utilize the delivery capacities in July. In addition, since the "unscheduled" dry cargos are more difficult to "reschedule" than contracted dry cargos, "unscheduled" dry cargos originally assigned to September and October are first arranged for transportation in the last period available for transportation. To ensure that the capacity of dry cargos in this period will not be exceeded, some of the contracted dry cargo originally assigned to this period is "rescheduled" to an earlier period. These results indicate a need to change freight delivery schedules to adapt to potential climate change. Instead of starting the season earlier than current schedules, shipping companies can arrange a "tighter" schedule to fully utilize capacities in July to ensure successful deliveries of freight originally assigned to late-season months. However, if equipment is not available and set up ready in May and June, the capacities in the current delivery season that NTCL operates in reality may be insufficient to transport all freight volumes and hence, starting the season earlier is necessary to ensure successful freight deliveries.

The sensitivity analysis results reveal a need for future studies on the difficulties of planning for "unscheduled" dry cargo, and what the specific costs are for non-deliveries when deciding values for demand uncertainty of "unscheduled" dry cargo (ϑ^3), as well as the cost parameter for non-delivery (φ_2), since the rescheduling results are quite sensitive to these parameters.

7.3 Contributions

Our results can help shipping companies, customers, and the government better understand how current shipping practices may need to be revised in order to effectively adapt to the impacts of climate change. Several indications and suggestions from our results may help them to decide their future freight delivery planning strategies in the context of potential climate change:

- Instead of starting delivery season earlier, shipping companies can arrange a "tighter" schedule to fully utilize capacities in July to ensure successful deliveries of freight originally assigned to late-season months.
- Under certain situations (i.e. no enough equipment available in May and June), besides arranging "tighter" schedule, shipping companies may still need to start the season earlier to ensure successful freight deliveries.
- Shipping companies may need to increase their equipment and crew availability at the beginning of the delivery season (May and June), to handle volumes "rescheduled" from later in the season to earlier due to low water conditions.
- Shipping companies may also need to consult with their customers to finally decide the new schedules, since shipping freight earlier with a "tighter" schedule may increase the pressure on customers' storage capacity.
- The customers may want to consider rethinking how they plan their own operations (i.e., when they need their deliveries), and particularly consider making their deliveries earlier in the season in order to increase delivery reliability, by

taking advantage of better water conditions and ensuring successful and on time deliveries of their freight.

- According to William Smith from NTCL (personal communication, December 4, 2015), NTCL has complete control over the time to stop their transport operation every year, but they have little control over the start time of the delivery season, because the open time depends on when the Canadian Coast Guard finishes installing navigational buoys after the ice breaks up. Hence, government agencies may need to more closely monitor climate change and set up navigational aids and buoys in time to ensure shipping companies can start their delivery as they needed.
- Government agencies, such as Department of Transportation in the NWT and Transport Canada, have responsibilities to help facilitate reliable and efficient freight transportation in the NWT through the setting of appropriate policies and regulations. These agencies may need to consider supporting further development of alternate modes of freight and increase investment on local transportation infrastructure if needed to respond to unexpected failures of waterway freight delivery in late-season months and therefore, reduce the delays and financial losses.

7.4 Research limitations and future work

There are several limitations in this research that may be addressed in future studies.

First, the modeling work can be improved through application of a network-level model that considers multiple destinations.

Second, the optimization model in this research is a deterministic model, so in the future, a stochastic optimization model may be developed to account for variations in inputs and shipping conditions.

Third, more consultation and cooperation with companies such as NTCL will be helpful in setting a cost model that more realistically reflects real operational considerations and challenges.

Forth, since there has been very limited research on transportation issues in the Mackenzie River corridor, transport-related data is quite limited, resulting in that many parameters can only be estimated based on experience or research on waterways in other areas. Future research may focus on analysing the freight transportation operations in the Mackenzie River corridor, and provide more accurate estimations of the parameters, such as the cost parameters for transport delays (φ_1) and non-deliveries (φ_2), needed in the model.

Finally, the methods to estimate delivery capacities with predicted stream flow profiles may be refined through an interdisciplinary effort between transportation and water resource engineers to provide more accurate estimations of delivery capacities under certain water conditions.

References

Box, G. E., & Jenkins, G. M. (1976). *Time Series Analysis: Forecasting and Control, revised ed.* Holden-Day.

Canadian Coast Guard. (2013, 4 1). *Under-Keel Clearance Table for Container Ships (St. Lawrence Rive, Quebec to Montreal)*. Retrieved from Canadian Coast Guard: http://www.marinfo.gc.ca/en/Publications/Table_PC.asp

CBC News. (2012, 11 06). *Deh Cho Bridge to open Nov. 30*. Retrieved from CBC News: http://www.cbc.ca/news/canada/north/deh-cho-bridge-to-open-nov-30-1.1147024

CBC News. (2014, September 25). *NTCL cancels barge to Fort Good Hope, Inuvik, Tuktoyaktuk*. Retrieved from CBC News: http://www.cbc.ca/news/canada/north/ntcl-cancels-barge-to-fort-good-hope-inuvik-tuktoyaktuk-1.2777444

Chatfield, C. (2004). *The Analysis of Time Series: An Introduction, 6th ed.* Boca Raton: CPC Press Company.

City of Yellowknife. (2013). *Demographics and Statistics*. Retrieved from City of Yellowknife: https://www.yellowknife.ca/en/doing-business/demographics-and-statistics.asp

Cullinane, K. (1992). A short-term adaptive forecasting model for Biffex speculation: A Box-Jenkins approach. *Maritime Policy & Management 19(2)*, 91-114.

Daganzo, C. F. (2005). Cost. In C. F. Daganzo, *Logistics System Analysis* (pp. 15-31). Springer Science & Business Media.

Department of Transportation, GNWT. (2011a, Novemnber). *On Track - Status, Challenges, and Initiatives of the Department of Transportation, Goverment of the Northwest Territories.* Retrieved from Department of Transportation, Government of the Northwest Territories:

http://www.dot.gov.nt.ca/media/fe4a05fb-4720-4c92-9afd-52ea6e19febc/9o6P0g/Projects/PDF/On%20Track%20Final%20Document.pdf.

Department of Transportation, GNWT. (2011b). *Community Re-supply Options and Costs.* Yellowknife: Department of Transportation, Government of Northwest Territories.

Department of Transportation, GNWT. (2013). *Northwest Territories Highway Traffic, 2013.* Yellowknife: Department of Transportation, Government of Northwest Territories.

Department of Transportation, GNWT. (2015). *Guidelines for Safe Ice Construction 2015.* Retrieved from Department of Transportation, GNWT: http://www.dot.gov.nt.ca/media/bfca0a67-4fc1-4a7c-9530-48dacc399d25/8I1bsw/Projects/PDF/0016-001%20Norex%20Ice%20Road%20Constr._WEB.pdf

Department of Transportation, GNWT. (2016a). *Winter Roads*. Retrieved from Department of Transportation, Government of Northwest Territories: http://www.dot.gov.nt.ca/Highways/Winter-Roads

Department of Transportation, GNWT. (2016b). *Highway System*. Retrieved from Department of Transportation, Government of Northwest Territrories: http://www.dot.gov.nt.ca/Highways/Highway_System

Department of Transportation, GNWT. (2016c). *Airports*. Retrieved from Department of Transportation, Government of Northwest Territories: http://www.dot.gov.nt.ca/Airports/Airports

Department of Transportation, GNWT. (2016d). *Ferry Schedules*. Retrieved from Deparment of Transportation, Government of Northwest Territories: http://www.dot.gov.nt.ca/Highways/Ferry

Department of Transportation, GNWT. (2016e). *Current Projects*. Retrieved from Department of Transportation, GNWT: http://www.dot.gov.nt.ca/Projects/Current-Projects

Department of Transportation, GNWT. (2016f). *Mackenzie Valley Highway*. Retrieved from Department of Transportation, Government of Northwest Territories: http://www.dot.gov.nt.ca/Projects/Future_Projects/Mackenzie-Valley-Highway

Dillon Consulting Limited. (2007). *Climate Change and Transportation in the NWT - Final Report.*

Environment and Natural Resources, GNWT. (2008). *NWT Climate Change Impacts and Adaptation Report.* Yellowknife: Environment and Natural Resources, Government of Northwest Territories.

Environment Canada. (2013, 7 22). *Water sources: Rivers.* Retrieved 11 26, 2014, from http://ec.gc.ca/eau-water/default.asp?lang=En&n=45BBB7B8-1#canada

GNWT. (2016a). *About ITI, Regional Offices, Sahtu*. Retrieved from Government of Northwest Territories: http://www.iti.gov.nt.ca/en/sahtu

GNWT. (2016b). *About ITI, Regional Offices, Beafort Delta*. Retrieved from Government of Northwest Territories: http://www.iti.gov.nt.ca/en/beaufort-delta

Government of Canada. (2009). *Canada's Northern Strategy: Our North, Our Heritage, Our Future*. Retrieved from Government of Canada: http://www.northernstrategy.gc.ca/cns/cns-eng.asp

Hirsch, R. M., Slack, J. R., & Smith, R. A. (1982). Techniques of trend analysis for monthly water quality data. *Water resources research*, pp. 107-121.

Hunt, U. (2003). Forecasting of railway freight volume: Approach of Estonian railway to arise efficiency. *Transport 18(6)*, 255-258.

International Business Machines Corporation (IBM). (2007). *11.0 User's manual.* Mountain View: EUA.

International Business Machines Corporation (IBM). (2014). *ILOG CPLEX Optimization Studio 12.6.1: CPLEX User's Manual.* Retrieved from IBM Knowledge Center: http://www.ibm.com/support/knowledgecenter/SSSA5P_12.6.1/ilog.odms.studio.help/pdf/usrcplex.pdf

IPCC. (2007). *Climate Change 2007: Synthesis Report.* Geneva: Intergovernmental Panel on Climate Change.

Jonkeren, O., Jourquin, B., & Rietveld, P. (2011). Modal-split effects of climate change: The effect of low water levels on the competitive position of inland waterway transport in the river Rhine area. *Transportation Research Part A: Policy and Practice*, 1007-1019.

Jonkeren, O., Rietveld, P., & Ommeren, J. (2007). Climate change and inland waterway transport: welfare effects of low water levels on the river Rhine. *Journal of Transport Economics and Policy*, 387-411.

Kendall, M. G. (1948). *Rank correlation methods.* London: Griffin.

Ma, S., & Zhou, Q. (2012). Research on China railway freight econometric analysis and modeling. *ICLEM 2012: Logistics for Sustained Economic Development - Technology and Management for Efficiency* (pp. 462-468). ASCE.

Mann, H. B. (1945). Nonparametric tests against trend. *Econometrica: Hournal of the Econometric Society*, 245-259.

Mariport Group Ltd. (2011a). *Western Arctic access routes.*

Mariport Group Ltd. (2011b). *Community Re-supply Options and Costs.*

Mariport Group Ltd. (2011c). *Source Locations and Delivery Costs for Petroleum Products to Service Western Arctic Communities.*

Minderhoud, M., Botma, H., & Bovy, P. (1997). Assessment of roadway capacity estimation methods. *Transportation Research Record: Journal of the Transportation Research Board*(1572), 59-67.

Mulder, C., & Williams, P. (2006). Improving the Performance of Shallow Draft Tugs in Northern Canada. *SNAME Transactions*, *114*, p. 16.

National Defence and the Canadian Armed Forces. (2014, 11 14). *Operations in the North*. Retrieved from National Defence and the Canadian Armed Forces: http://www.forces.gc.ca/en/operations-canada-north-america/north.page

Natural Resources Canada, GeoAccess Division. (2005, 2 5). *Land and freshwater area, by province and territory*. Retrieved from Statistics Canada: http://web.archive.org/web/20110524063547/http://www40.statcan.gc.ca/l01/cst01/phys01-eng.htm

Northern Transportation Company Ltd. (2016). *Communities We Serve*. Retrieved from Northern Transportation Company Ltd.: http://www.ntcl.com/community-cargo-resupply/communities-we-supply/

NRTEE. (2009). *True North: Adapting Infrastructue to Climate Change in Northern Canada.* Ottawa: National Round Table on the Environment and the Economy.

Nunatsiaq Online. (2008). *Around Nunavut*. Retrieved 11 6, 2015, from Nunatsiaq Online: http://www.nunatsiaqonline.ca/archives/2008/803/80328/news/nunavut/80328_1054.html

O'Connell, R. T., & Koehler, A. B. (2005). *Forecasting, time series, and regression: An applied approach. Vol. 4.* South-Western Pub.

Olsen, R. J., Zepp, L. J., & Dager, C. A. (2005). Climate impacts on inland navigation. *World Water and Environmental Resources Congress*, (pp. 15-19).

PROLOG Canada & EBA Engineering Consultants Ltd. (2010). *The Northern Transportation System Assessment, Phase 1 Report: Northern Transportation Demand Assessment.* Transport Canada.

PROLOG Canada & EBA Engineering Consultants Ltd. (2011). *The Northern Transportation System Assessment, Phase 2 Report: Infrastructure Needs Assessment.* Transport Canada.

Robinson, P. J. (1989). The influence of weather on flight operations at the Atlanta Hartsfied international Airport. *Weather and Forecasting 4(4)*, 461-468.

Rodrigue, J.-P., Comtois, C., & Slack, B. (2013). Transportation and the economy. In J.-P. C. Rodrigue, *The geography of transport systems* (pp. 226-254). Routledge.

Sheffi, Y., Eskandari, B., & Koutsopoulos, H. N. (1988). Transportation mode choice based on total logistics costs. *Jornal of Business Logistics*, 137-154.

Statistics Canada. (2001). *Age and Sex, 2001 Counts for Both Sexes, for Canada, Provinces and Territories - 100% Data*. Retrieved from Statistics Canada: http://www12.statcan.ca/english/census01/products/highlight/AgeSex/Page.cfm?Lang=E&Geo=PR&View=1&Code=0&Table=1a&StartRec=1&Sort=2&B1=Counts&B2=Both

Statistics Canada. (2011). *Population and Dwelling Count Highlight Tables, 2011 Census*. Retrieved from Statistics Canada: http://www12.statcan.gc.ca/census-recensement/2011/dp-pd/hlt-fst/pd-pl/Table-Tableau.cfm?LANG=Eng&T=101&SR=1&S=3&O=D

Statistics Canada. (2015, 11 27). *Transportation in the North*. Retrieved from Statistics Canada: http://www.statcan.gc.ca/pub/16-002-x/2009001/article/10820-eng.htm

The Water Transport Committee. (1978). *Examination of the Water Transportation Industry with Respect to the Mackenzie River and to All Other Navigable Waters of the Northerwest Territories.*

Transport Canada. (2012, 7 18). *Marine Transportation*. Retrieved 6 12, 2016, from Transport Canada: https://www.tc.gc.ca/eng/policy/anre-menu-3019.htm

Tsay, R. S. (2000). Time Series and Forecasting: Brief History and Future Research. *Journal of the American Statistical Association*, 638-643.

Water Office, Government of Canada. (2014a, 06). *Daily Discharge Graph for MACKENZIE RIVER AT FORT SIMPSON (10GC001)*. Retrieved 2 5, 2016, from Water Office, Government of Canada: http://wateroffice.ec.gc.ca/report/report_e.html?type=h2oArc&stn=10GC001

Water Office, Government of Canada. (2014b, 6). *Monthly Water Level Graph for MACKENZIE RIVER AT FORT GOOD HOPE (10LD001)*. Retrieved from Water Officie, Government of Canada: http://wateroffice.ec.gc.ca/report/report_e.html?stn=10LD001&mode=Graph&type=h2oArc&dataType=Monthly&year=2014&y1Max=1&y1Min=1

Appendix A SAS Codes for ARIMA Model

```
* Model ARIMA(0,0,0)(1,1,0)12 for fuel data;
```

```
proc arima data=WORK.Halfmonth_Fuel;
    identify var=volume(24) crosscor=(S1(24) S2(24));
    estimate p=(24) Input=(S1 S2) noconstant method=ml
        printall maxit=30 backlim=-3 plot;
    forecast lead=850;
run;
```

```
* Model ARIMA(0,0,0)(1,1,0)12 for dry cargo data;
```

```
proc arima data=WORK.Halfmonth_drycargo;
    identify var=volume(24) crosscor=(S1(24) S2(24));
    estimate p=(24) Input=(S1 S2) noconstant method=ml
        printall maxit=30 backlim=-3 plot;
    forecast lead=850;
run;
```

Appendix B CPLEX Codes for Future Schedule Planning Model in Rescheduling Analysis

```
/*********************************************
 * OPL 12.6.1.0 Model
 * Author: Yunzhuang Zheng
 * Creation Date: Apr 14, 2016 at 11:46:39 AM
 *********************************************/

 // parameters
 int n=...;//number of cargo types
 int m=...;//number of time slots

 range cargo=1..n;
 range time_slots=1..m;
 range cap_range=1..n-1; /* since in our model, only fuel and dry cargo
                          capacities are identified, the number of
                          freight types in capacity is n-1, namely 2.*/

 range leftover_range = 1..m+1; /* since in our model, the delayed
                                 volume for period 0 is defined as 0 to
                                 represent that the season does not
                                 start with freight undelivered from
                                 the previous year.*/

 int t[time_slots][time_slots]=...; /* the time difference between
                                     period i and period j.*/

 float p[time_slots][cargo]=...; /* projected volume for each type of
                                 freight in each period.*/

 float para[cargo]=...; /* the factor to reflect the unpredictability
                         of each freight to be "rescheduled" to another
                         time period.*/

 float cap[time_slots][cap_range]=...; /* capacity for each type of
                                        freight in each period.*/

 float tt[time_slots]=...; // travel time in each period.
 float t_delay[time_slots]=...; /* the average delay of a ton of
                                freight that cannot be delivered in
                                period i-1 and needs to wait to be
                                transported in period i.*/

 float a[time_slots]=...; // parameter a.
 float b[time_slots]=...; // parameter b.
 float c[time_slots]=...; /* CPLEX may use very small values to
                          represent values close to zero, say 10^(-13).
```

```
                              Since we assume the travel time for periods
                              that are not available for freight delivery
                              is an extreme value, 10^27, the travel cost
                              value for some period should be zero could
                              be a large value, say 10^(-13)*10^27 is
                              10^14. This will surely impact the final
                              results. Thus, this parameter c is used to
                              assure that there is no travel cost during
                              the periods that are not available for
                              freight delivery (c[i] equals to 1 if period
                              i is within the delivery season, otherwise,
                              c[i] equals 0).*/

 float VOM=...; /* the parameter to measure the time cost before and
                 after the transportation, say loading/unloading,
                 average waiting time before transportation.*/
 float phi[1..2]=...; //parameters for delay costs.

 //variables
 dvar float+ x[time_slots][time_slots][cargo];
 dvar float+ l[leftover_range][cap_range];

//expressions
dexpr float allo_new [i in time_slots][q in cargo] = sum(j in
time_slots) x[i][j][q];
dexpr float HC_TC[i in time_slots] = c[i]*(VOM+tt[i])*(l[i][1]-
l[i+1][1]+l[i][2]-l[i+1][2]+sum(q in cargo) allo_new[i][q]);
dexpr float RC[i in time_slots] = (sum(q in cargo, j in time_slots)
(para[q]*t[i][j])*x[i][j][q]);
dexpr float DC[i in time_slots] =
((a[i]*t_delay[i]*phi[1]+b[i]*phi[2])*(l[i+1][1]+l[i+1][2]));


dexpr float obj = sum(i in time_slots) (HC_TC[i]+RC[i]+DC[i]);

 //model

 minimize obj;

 subject to{
     forall(q in cargo, j in time_slots){
          /* Constraint 1: the total volume originally scheduled in
             period j should equal to the projected volume in period
             j*/
          demand_cons:
          sum(i in time_slots) x[i][j][q] == p[j][q];
     }

     forall (q in cap_range){
          /* Constraint 2:  the delayed volume for period 0 is always
             equal 0, meaning that the season does not start with
             freight undelivered from the previous year.*/
```

```
            leftover_cons_01:
            l[1][q] == 0;
      }

      forall (i in time_slots){
            /* Constraint 3: the definition of delayed volume in period
               i, where i>1 for fuel.*/
            leftover_cons_02:
            l[i+1][1] == maxl(0,(l[i][1]-cap[i][1]+sum(j in time_slots)
x[i][j][1]));
      }

      forall (i in time_slots){
            /* Constraint 4: the definition of delayed volume in period
               i, where i>1 for dry cargo.*/
            leftover_cons_03:
            l[i+1][2] == maxl(0,(l[i][2]-cap[i][2]+sum(j in time_slots)
(x[i][j][2]+x[i][j][3])));
      }
      }


/*********************************************
 * OPL 12.6.1.0 Data
 * Author: Yunzhuang Zheng
 * Creation Date: Apr 14, 2016 at 11:46:39 AM
 *********************************************/

 n=3;
 m=24;

SheetConnection my_sheet("Input_Max_2025_M2.xlsx");

VOM from SheetRead(my_sheet,"VOM");
t from SheetRead(my_sheet,"tij");
p from SheetRead(my_sheet,"pj");
para from SheetRead(my_sheet,"paramaters");
cap from SheetRead(my_sheet,"Cap");
tt from SheetRead(my_sheet,"tti");
t_delay from SheetRead(my_sheet,"t_delay");
a from SheetRead(my_sheet,"a");
b from SheetRead(my_sheet,"b");
c from SheetRead(my_sheet,"c_1");
phi from SheetRead(my_sheet,"phi");
```

Appendix C CPLEX Solution Engine Log

Found incumbent of value 3530330.400000 after 0.00 sec. (0.11 ticks)
Tried aggregator 2 times.
MIP Presolve eliminated 196 rows and 1205 columns.
Aggregator did 142 substitutions.
Reduced MIP has 120 rows, 768 columns, and 1390 nonzeros.
Reduced MIP has 96 binaries, 0 generals, 0 SOSs, and 96 indicators.
Presolve time = 0.00 sec. (2.27 ticks)
Probing fixed 0 vars, tightened 139 bounds.
Probing time = 0.01 sec. (1.31 ticks)
Tried aggregator 2 times.
MIP Presolve eliminated 81 rows and 603 columns.
Aggregator did 9 substitutions.
Reduced MIP has 30 rows, 156 columns, and 274 nonzeros.
Reduced MIP has 14 binaries, 0 generals, 0 SOSs, and 14 indicators.
Presolve time = 0.00 sec. (0.98 ticks)
Probing fixed 0 vars, tightened 23 bounds.
Probing time = 0.00 sec. (0.07 ticks)
Tried aggregator 1 time.
Reduced MIP has 30 rows, 156 columns, and 274 nonzeros.
Reduced MIP has 14 binaries, 0 generals, 0 SOSs, and 14 indicators.
Presolve time = 0.00 sec. (0.13 ticks)
Probing fixed 0 vars, tightened 8 bounds.
Probing time = 0.00 sec. (0.06 ticks)
Clique table members: 7.
MIP emphasis: balance optimality and feasibility.
MIP search method: dynamic search.
Parallel mode: deterministic, using up to 8 threads.
Root relaxation solution time = 0.00 sec. (0.06 ticks)

	Node	Nodes Left	Objective	IInf	Best Integer	Cuts/ Best Bound	ItCnt	Gap
*	0+	0			2265468.4500	855308.6500		62.25%
	0	0	1382145.3500	4	2265468.4500	1382145.3500	31	38.99%
*	0	0	integral	0	1382145.3500	Impl Bds: 4	35	0.00%
	0	0	cutoff		1382145.3500	1382145.3500	35	0.00%

Elapsed time = 0.03 sec. (9.52 ticks, tree = 0.00 MB, solutions = 2)

Implied bound cuts applied: 2

Root node processing (before b&c):
Real time = 0.03 sec. (9.61 ticks)
Parallel b&c, 8 threads:

Real time = 0.00 sec. (0.00 ticks)
Sync time (average) = 0.00 sec.
Wait time (average) = 0.00 sec.

Total (root+branch&cut) = 0.03 sec. (9.61 ticks)