TRAFFIC-CONFLICT-BASED MODELING OF COLLISION RISK IN PORT WATERS

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SUMMARY

Navigational collisions are one of the major safety concerns for many seaports. Traditionally port water collision risks are modeled using historical collision data. In most cases, this approach of modeling is hampered because of low number of observations. It is also an unethical and reactive safety management approach because of its reliance on collision data.

To overcome the problems, this research explores the use of non-collision data in collision risk modeling. Traffic conflicts are innovatively proposed as an alternative to the collisions and use of the conflicts in risk modeling is explored by developing mathematical models for measuring and predicting the risks. A risk measurement model is developed that quantitatively measures collision risk in individual interactions, statistically characterizes the risks collectively and obtains risk of collision in waterways by identifying the interactions with high potential of collision. Validity of the model is assessed by evaluating correlations between the measured risks and those perceived by pilots. For prediction of risks, a binomial logistic model with considerations for hierarchical data structure is formulated. The model explains the relationships between the risks and waterway characteristics by accounting for the correlations in risks at different time periods in a waterway.

The proposed traffic-conflict-based modeling technique is illustrated for Singapore port waterways. Examining the validity of the models, this research proves that collision risk can be evaluated in a fast, reliable and proactive manner by using traffic conflicts.

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LIST OF ABBREVIATIONS

AD	Anderson-Darling
AIC	Akaike Information Criteria
ARPA	Automatic Radar Plotting Aid
BLM	Binomial Logistic Model
BPM	Binomial Probit Model
CAS	Collision Avoidance System
CDF	Cumulative Distribution Function
CPA	Closest Point of Approach
CQS	Close Quarter Situation
DCPA	Distance at Closest Point of Approach
DR	Deceleration Rate
ET	Encroachment Time
ETA	Event Tree Analysis
FI	Frequency Index
FSA	Formal Safety Assessment
FTA	Fault Tree Analysis
GT	Gross Tonnage
HAZID	Hazard Identification
HR	High Risk
IAPE	Initially Attempted Post Encroachment Time
IMO	International Maritime Organization
IS	Injury Severity
LR	Low Risk
LWCS	Lloyds World Casualty Statistics

MHIDAS	Major Hazard Incident Data Service
MR	Moderate Risk
NB	Negative Binomial
NTC	Navigational Traffic Conflict
OR	Odds Ratio
ORM	Ordinary Regression Model
PDF	Probability Distribution Function
PET	Post Encroachment Time
PSD	Proportion of Stopping Distance
RIBLM	Random Intercept BLM
RTC	Road Traffic Conflict
SD	Ship Domain
SI	Severity Index
TA	Time to Accident
TCPA	Time to Closest Point of Approach
TCT	Traffic Conflict Technique
TET	Time-Exposed TTC
TIT	Time-Integrated TTC
TSS	Traffic Separation Scheme
TTC	Time to Collision
VC	Vessel Class
VHR	Very High Risk
VTIS	Vessel Traffic Information System

LIST OF SYMBOLS

α	The average intercept across all observation periods and all waterways in a RIBLM
$\boldsymbol{\beta}$	Vector of regression coefficients representing the effects of explanatory variables
β_{0w}	The intercept term that differs across waterways *w* in a RIBLM
$\boldsymbol{\beta}_1$	Vector of coefficients explaining effects of $\mathbf{X}_{1wt}$
$\boldsymbol{\beta}_2$	Vector of coefficients explaining effects of $\mathbf{X}_{2w}$
γ	Location parameter of a distribution
δ_i	A term representing the exponential of ε_i
ε_i	Regression error term
η	The linear predictor ($=\boldsymbol{\beta}\mathbf{X}$)
θ	Threshold parameter of a distribution
ℓ	Log-likelihood function
λ_m	Threshold value of category *m* in an ordered regression model
μ	The mean of a Poisson distribution
μ_i	The expected number of events of an observation unit *i* in a Poisson regression model
$\tilde{\mu}_i$	The expected number of events of an observation unit *i* in a NB regression model
μ_{wt}	The expected number of serious conflicts in waterway *w* at time period *t*
π_i	The probability of $y_i = 1$ in Binomial distribution
ρ^2_{adj}	Adjusted Log-likelihood ratio index

$\rho_{MR,PR}$	Pearson correlation coefficient of measured risk and perceived risk
σ_{MR}	The standard deviation of *MR*
$\sigma_{MR,PR}$	The covariance between *MR* and *PR*
σ_{PR}	The standard deviation of *PR*
σ_u^2	Variance of u_w
τ	A threshold value for separating the serious conflicts from the non-serious ones
τ_{vc}	The threshold value for vessel class *vc*
$\hat{\phi}$	The scale parameter in $\hat{B}_{MS}$
ψ	Dispersion statistics
a	Shape parameter of a distribution
AD^2	Test statistics of Anderson-Darling test
b	Scale parameter of a distribution
$\hat{B}_{MS}$	Score factor of modified sandwich variance matrix
$C(t)$	The risk of collision in an interaction at time *t*
$C_{\max}$	The maximum value of $C(t)$ in an interaction process
$C'_{\max}$	Measure of conflict severity $=(1/(1-C_{\max}))$
C_{SD}	A constant value (= 1) of $C'_{\max}$ at truncation point
D	Observation values sorted in ascending order in an Anderson-Darling test
e	The index for encounter observation
$E(\cdot)$	Expected value
$f(\cdot)$	Probability density function of a distribution

$F(\cdot)$	Cumulative distribution function of a distribution
$f_{C'_{\max}}(C'_{\max})$	Probability density function of $C'_{\max}$
$F_{C'_{\max}}(C'_{\max})$	Cumulative density function of $C'_{\max}$
$F_{\tau_{vc}}(\tau_{vc})$	Cumulative density function of τ_{vc}
G^2	Likelihood ratio statistics
i	The index for observation unit in regression model
j	The index for a set of proximity indicators
k	The number of parameters to be estimated in a regression model
$LL(0)$	Log-likelihood of a null model
$LL(\beta)$	Log-likelihood of a model at convergence
$LL(F)$	Log-likelihood of a fully-specified model
$Logit(p_{ewt})$	$\log(p_{ewt}/(1-p_{ewt}))$
M	Number of categories of y_i in an ordered regression model
MR	A random variable representing the measured risk of collision
M&Z R^2	McKelvey and Zavoina's R^2
N	The total number of observations
n_{wt}	The total number of encounters in waterway w at time period t
P_c	Measured risk of collision in a waterway
p_{ewt}	The probability of Y_{ewt} = 1 in Binomial distribution
p_{vc}	Probability mass function of vessel classes
$p(0)$	Probability mass function of non-conflict encounters
PI_j	The index for proximity indicators in observation unit j
PR	A random variable representing the perceived risk of collision

(r,s)	Coordinates of the position of a vessel
$(\dot{r},\dot{s})$	Components of vessel speed in (r,s) coordinates
RS_m	The probability of collision for risk level *m*
t	The index for observation period
T_w	The number of observation periods for waterway *w*
u_w	The unobserved random effects of waterway *w* in a RIBLM
v_1	The index for *vessel 1* in an interaction
v_2	The index for *vessel 2* in an interaction
V	The number of vessel classes
$\hat{V}_{MH}$	Modified sandwich variance matrix
$\hat{V}_H$	Hessian matrix
$V(\cdot)$	Variance
w	The index for waterway
$\mathbf{X}$	Vector of explanatory variables in a regression model
$\mathbf{X}_{1wt}$	Vector of explanatory variables related to waterway
$\mathbf{X}_{2w}$	Vector of explanatory variables related to observation period
$\mathbf{X}_{ewt}$	Vector of explanatory variables related to an encounter *e* in waterway *w* at time *t*
$\mathbf{X}_{PI}(t)$	Vector of proximity indicators
$\mathbf{X}_{PI\,j}$	Vector of independent variables representing proximity indicators for observation unit *j*
$\mathbf{x}_{wt}$	The row of the matrix **X** associated with the t^{th} observation for subject *w* in $\hat{B}_{MS}$

y_i	Dependent variable for observation unit *i* in a regression model
y_i^*	Latent dependent variable in regression model
y_{wt}	The number of serious conflicts in waterway *w* at time period *t*
Y_{ewt}	Observed dependent variable for an encounter *e* in waterway *w* at time *t*

CHAPTER ONE
INTRODUCTION

1.1 MOTIVATION AND BACKGROUND

1.1.1 COLLISION RISK IN PORT WATERS

Navigational safety is among the top-priority concerns in worldwide maritime developments and research, because it is coupled with shipping efficiency, distribution reliability, port operations, and loss prevention. Maritime governing bodies around the world have repeatedly recognized the assessment and management of safety in maritime transportation as an important problem (Goossens and Glansdorp, 1998; NRC, 1986, 1991, 1994, 2000; Pietrzykowski, 2008; Yip, 2008). Concerns for navigational safety have been increasing over time, because shipping traffic has been increasing rapidly over the past decades in order to meet the increasing demand of waterborne transport (Soares and Teixeira, 2001).

Since often cargoes contain hazardous materials, safe navigation is a prime requisite. A navigational accident can be catastrophic posing serious threats to life, property and environment. A survey on navigational accidents (IMO, 2005) revealed that 589 ships and 101 lives had been lost in the year 2004. Another study (Roberts and Marlow, 2005) have shown that the fatal accident rate in British merchant shipping between 1976 and 2002 was 27.8 times higher than in the general workplace in Britain. Carpenter (1988) further reported that a navigational accident approximately costs USD 545,000 on an average. In case of the accidents producing oil/chemical spillage, the consequences could be much higher. For example, a collision between two ships in

Singapore waters (MPA, 1997) resulted in a spill of 28,500 tonnes of heavy marine fuel oil, which involved about 650 personnel and 80 crafts for a 3 weeks time period to clean up. The threats related to the consequences of navigational accidents inevitably imply that ensuring safety in navigation is a concomitant necessity.

Risk of a navigational accident can be higher in port waters, compared to open sea, because of dense traffic movements, relatively insufficient sea-room and restricted depth of water in port waters (Akten, 2004). Consequently, the consequences of accidents can also be higher in such waters. It has been shown that navigational accidents occur mostly in or near port territorial waters (C.-P. Liu et al., 2006) and more importantly, frequency of accidents in port areas is increasing over time (Darbra and Casal, 2004). Therefore, for efficient operation of ports, maintaining smooth and safe traffic movement along port waterways is necessary.

Navigational collisions are one of the major safety concerns for many ports. Collisions account for a substantial portion of major shipping accidents in port waters, as reported in many studies (Akten, 2004; Darbra and Casal, 2004; Goossens and Glansdorp, 1998; C.-P. Liu et al., 2006; Q. Liu et al., 2006; Yip, 2008). Collisions are also identified as one of the most severe types of accidents (IMO, 1998). Furthermore, the increasing growth of world fleet (Soares and Teixeira, 2001) is likely to result in increased traffic movements within port waters, which in turn could increase risk of collision in these congested and restricted waters. The number of traffic movements on a busy fairway in port waters can be as high as 2000 per day (Yip, 2008) and the number is expected to be increasing with the continuing growth of navigational traffic. Such a high number of movements may result in more conflicts and collisions. More importantly, navigational traffic is increasing in size (Faulkner, 2003) resulting in higher number of large ships in port waters. The larger ships have reduced maneuverability and thus face consequent increase in risk of collision, especially in the restricted waters (Akten, 2004). This continually increasing safety concern warrants a comprehensive risk modeling method to ensure safe and collision-free traffic movements in port waters.

1.1.2 PROBLEMS IN EXISTING METHODS OF RISK MODELING

To model navigational collision risk, researchers and safety analysts have utilized a number of methods, which can be broadly categorized into three types: qualitative, semi-quantitative and quantitative. In general, the qualitative methods are easiest to apply and least resource demanding but provide the least degree of insight. In contrast, the quantitative methods are most demanding on resources and skills, but potentially deliver the most detailed understanding. The semi-quantitative methods lie in between these extremes.

The commonly used qualitative methods are the Hazard Identification (HAZID) technique and the risk matrix method. In a HAZID application, the hazards associated with a collision event are identified in a structured process by employing expert judgment (Molland, 2008). Its functionality is often extended for qualitative evaluation of the identified hazards' significance by employing a risk matrix, which expresses the categorized likelihoods and consequences of the hazards in different dimensions (see DS, 1996; IMO, 1997; ISO, 1999; Trbojevic and Carr, 2000).

While a risk matrix is easy to apply and understand, it suffers from several limitations. Firstly, it is difficult to explain a collision that produces multiple consequences within a particular category of consequence. Secondly, inconsistency among the judgments of different experts may lead to biased results. Thirdly, categorization of the likelihood and consequence is often non-transparent because of qualitative definitions of the categories. This may further increase the inconsistency among experts' judgments. Finally, since an important requirement of the HAZID process is to have experience of analyzing collisions in order to capture the lessons learnt in identifying the hazards (Veritas, 2001), the qualitative risk modeling methods may face difficulty in dealing with novel safety hazards.

Semi-quantitative methods produce qualitative results by employing techniques of quantitative modeling or produce quantitative results by using techniques of qualitative modeling. Several techniques which are primarily used for quantitative risk modeling, such as Fault Tree Analysis (FTA), Event Tree Analysis (ETA) and Bow Tie, are employed for qualitative risk modeling (see Trbojevic and Carr, 2000). In this approach, the generation process of a safety hazard is evaluated by employing expert judgment. This arrangement of safety analysis may be useful for evaluating hazards where quantification is not possible or undesirable. Sometimes, the techniques of qualitative modeling (i.e., HAZID, risk matrix) are employed to obtain some form of quantification in results. The Formal Safety Assessment (FSA) (Wang, 2001) process of the International Maritime Organization (IMO) employs the HAZID and risk matrix method for quantitative modeling of risk. Several studies (e.g., Hu et al., 2007; Wang, 2002) have employed this method, where the categories of likelihood and consequence in a risk matrix are defined quantitatively by using numerical indices in order to obtain an estimate of risk for a particular hazard. However, this approach suffers from some of the limitations of the qualitative methods, such as biased judgments of different experts and difficulties in dealing with multiple consequences and novel hazards.

The qualitative and semi-quantitative methods might be useful for some preliminary safety investigation purposes, but to attain a higher degree of insight researchers employ a quantitative method. Traditionally, similar to the qualitative and semi-quantitative methods, the quantitative methods have relied on navigational collision data. A number of studies have employed collision data to examine trends and causes of collisions (Akten, 2004; Darbra and Casal, 2004; Hashemi et al., 1995; Le Blanc et al., 2001; Le Blanc and Rucks, 1996; C.-P. Liu et al., 2006; Yip, 2008), whereas some have examined consequences (i.e., injuries and fatalities) by using these data (Darbra and Casal, 2004; Talley, 2002; Talley et al., 2005, 2006, 2008; Yip, 2008). Some studies (Degré, 2003; MARIN, 2009; Roeleven et al., 1995) have also focused on modeling probability and predicting frequency of collision by utilizing such data.

While modeling based on collision data may provide a detailed understanding of collision risk, this ‘collision-data-based approach’ is often hampered by several limitations. Firstly, to obtain statistically sound inferences from analysis of collision records it is necessary to have a database of sufficiently large number of collisions. Since a long time period is required to obtain such a database, this approach is not suitable for short-term safety assessment, where, for example, there is a need to evaluate the effectiveness of a particular type of safety measure at a specific location. Moreover, in case of evaluating safety in a particular location, the sample size (i.e., number of collisions in that location) becomes even smaller, thus it becomes more difficult to obtain statistical soundness in results. This may explain why statistical significances are not reported in many studies (e.g., Darbra and Casal, 2004; C.-P. Liu et al., 2006). The low sample problem also often restricts safety analysts from using robust statistical methods, such as regression techniques. Secondly, collision is an outcome of a complex process of interaction involving vessels, pilots, crews, port operators and marine environment. Therefore, it is sometimes difficult to investigate the main causes of collisions just from the numbers of the outcome (i.e., collision) of the process as collision records often omit details of the pre-collision process. Finally, this approach of safety analysis is reactive and unethical as it requires sufficiently large number of collisions to take place first, before any preventive or corrective measures are taken. This is particularly true for a new or upgraded traffic infrastructure where historical collision data are unavailable.

The problems stemming from the collision-data-based approach have prompted the need for an alternative approach of collision risk modeling. This need motivates this research to call for a better approach that would not rely on collision data for modeling collision risk in port waters.

1.2 OBJECTIVE AND SCOPE

1.2.1 OBJECTIVE OF THE RESEARCH

The objective of this research is to explore the use of non-collision information in modeling collision risk in port waters.

1.2.2 RESEARCH METHODOLOGY

To achieve the above objective, a measure of collision risk is proposed as an alternative to the historical collision data. This is achieved by critically reviewing the existing techniques of collision risk modeling. In particular, the advantages and disadvantages of the techniques are identified which leads to obtaining traffic conflicts as an alternative to the collisions. By using the conflicts, a systematic method for modeling the risks is developed. Following the two aspects of risk modeling (i.e., measuring the level of risk and understanding the characteristics of the risk) two models, namely the Risk measurement model and the Risk prediction model, are developed.

The risk measurement model measures collision risk in a waterway by analyzing critical traffic interactions. To obtain a quantitative estimate of risk, this model quantitatively measures risks of collision in individual interactions, statistically characterizes the measured risks in all interactions in a waterway and obtains risk of collision in a waterway by identifying the interactions with high potential of collision. Validity of the model is assessed by evaluating correlations between the risks measured by the model and those perceived by pilots.

The risk prediction model explains the relationships between the risks and the geometric, traffic and regulatory control characteristics of waterways. A systematic method of model formulation, calibration and validation is developed for this purpose. By taking the risks measured by the conflict model as input to this model, a binomial logistic regression model with considerations for hierarchical data structure is formulated, calibrated and validated through this method.

The modeling techniques are illustrated using traffic movement data of the different types of waterways (i.e., fairways, anchorages and intersections) in Singapore port.

1.2.3 SIGNIFICANCE OF THE RESEARCH

Successful development of the non-collision-data-based modeling approach would provide more insights into understanding and managing port water collision risks in a proactive manner. It would provide navigational safety analysts an ethically appealing alternative to the traditional collision-data-based approach for fast, reliable and effective safety evaluation. A better understanding of the relationships between collision risks and waterway characteristics may offer new possibilities for unprecedented rapid safety evaluation. Being innovative in the concepts of the risk modeling approach, its successful development would be a breakthrough in the discipline of navigational safety research.

1.2.4 SCOPE OF THE RESEARCH

While the proposed techniques of risk measurement and prediction modeling could be applied to all waterway types in any ports, in this research the techniques are illustrated for the waterways of Singapore port. For this purpose, traffic movement data of four hour time periods at day and night are sampled which are supposed to be representative of navigational conditions at day and night respectively. Since the calibrated models may have some embedded port-specific effects, it is advisable to check the transferability of the models before applying to waterways of other ports. However, the modeling techniques developed in this research should be easily applied to calibrate similar models in other ports.

1.3 ORGANIZATION OF THE THESIS

The thesis is organized into six chapters as structured in Figure 1.1.

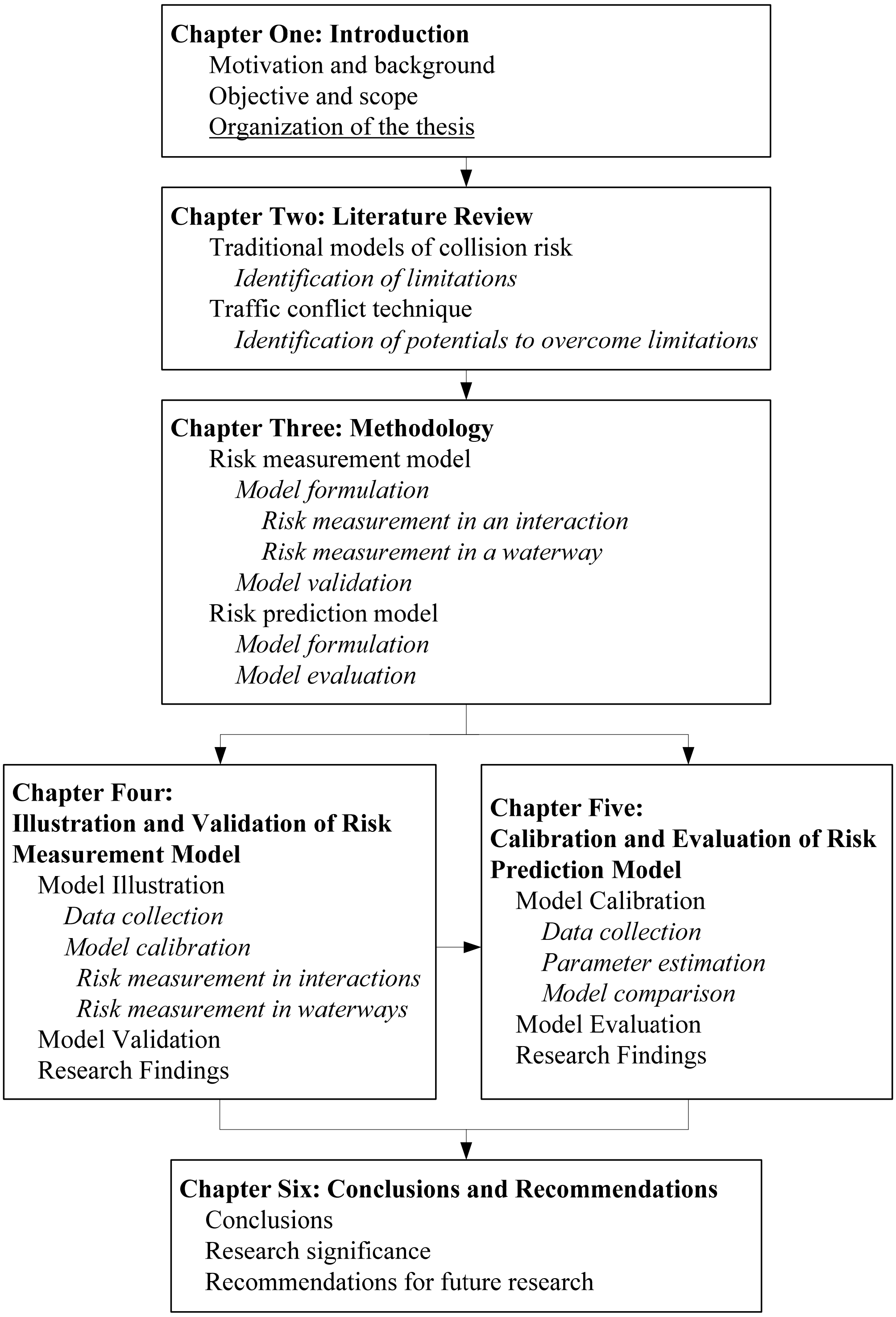

Figure 1.1 Structure of the Thesis

Chapter 2 provides a critical review of the existing techniques of collision risk modeling in order to search for an alternative approach of risk modeling. In particular, the advantages and disadvantages of the existing models are identified which leads to obtaining the Traffic Conflict Technique as an alternative approach to the existing models. The concepts and underlying theory of this technique are reviewed.

Chapter 3 describes the methodology of the thesis consisting of the two models proposed. The formulation and validation procedures of a risk measurement model are discussed first. This is followed by a description of the formulation, calibration and validation procedure of a risk prediction model.

Chapter 4 illustrates the proposed risk measurement model using traffic movement data of Singapore port. In addition, this chapter examines the validity of the model.

Chapter 5 describes an illustrative example of the risk prediction modeling technique for waterways in Singapore port.

Finally, chapter 6 summarizes the conclusions derived from this research. Significance of this research and directions for future research are also discussed.

CHAPTER TWO
LITERATURE REVIEW

2.1 INTRODUCTION

Traditionally, navigational collision risk modeling relies on expert judgments and historical collision data. Expert judgments are used for preliminary safety investigation purposes where collision data are not available or an in-depth safety analysis is not required. On the other hand, collision data are widely used to assess the level of risk and to investigate the causes and trends of collisions. However, these approaches of collision risk modeling suffer from several limitations. Modeling risk using expert judgments is often hindered by inconsistency among different expert's judgments. Risk modeling based on collision data is also often hampered by low number of observations, insufficiency in explaining collision causation and its reactive approach to safety. A promising alternative approach that could overcome these problems is the Traffic Conflict Technique (TCT), which relies on observations of critical traffic interactions as a surrogate of collisions. The TCT was primarily developed in the context of road traffic safety modeling and has been employed in an impressive number of studies to develop and refine its concepts, measurement methods, validity, and application issues. However, the TCT approach is yet to be implemented for modeling collision risks in port waters.

This chapter aims to provide a critical review of the traditional techniques of modeling collision risk in order to identify the advantages and limitations of the models. In addition, the concepts and underlying theories of the TCT are discussed to examine its potentiality to overcome the limitations of the existing models.

2.2 MODELS OF COLLISION RISK

Safety in port water navigation is coupled with safety in port operations, offshore installations, and general loss prevention. For this reason, many of the navigational safety models are developed to have general applicability to any safety hazards in maritime domain. Efforts have also been devoted to develop models for analyzing specific safety problems, such as collision risk in port waters.

Safety models, which are applicable to port water collision risk modeling, are of two types: online models, and offline models. The online models deal with real-time traffic information for modeling collision avoidance in navigation. On the other hand, the offline models concern address issues related to modeling of collision risks using historical data (e.g., historical collision data) and expert judgments.

The online models have focused on different aspects of collision avoidance, such as development of collision avoidance systems (e.g., Chin and Debnath, 2009; Q. Liu et al., 2006), improvement on plotting performance of Automatic Radar Plotting Aid (ARPA) (e.g., Pedersen et al., 1999; Sato and Ishii, 1998), development of cone-shaped danger regions (Lenart, 1983), evaluation of display techniques (Pedersen et al., 2002a), evaluation of anti-collision maneuvers in collision avoidance systems (e.g., Kwik, 1989; Pedersen and Jacobsen, 2002; Pedersen et al., 2002b, 2003), application of kinetic Voronoi diagram in collision avoidance (Goralski et al., 2007), use of Automatic Identification System and VHF in collision avoidance (e.g., Harati-

Mokhtari, 2007; Harding, 2002; Harre, 1999; Norris, 2007; Pratt and Taylor, 2004; Stitt, 2003) and incorporation of collision avoidance capability in Vessel Traffic Service (Kao et al., 2007). A comprehensive review of the concepts, technologies and techniques of autonomous ship collision avoidance can be found in Statheros et al. (2008). Since the objective of this research is related to the offline models, the online models are not discussed in detail in this thesis.

The traditional offline models can be broadly categorized into three types – qualitative, semi-quantitative and quantitative models. In general, the qualitative models are easiest to apply and demands least resource, but provide the least degree of insight. In contrast, the quantitative models are most demanding on resources and skills, but potentially deliver the most in-depth understanding. The semi-quantitative models lie in between these extremes. These three types of safety models are discussed in subsequent sections.

2.1.1 QUALITATIVE MODELS

Qualitative safety models are used to identify possible hazards, to evaluate their significances, and to identify the measures for reducing the frequencies or consequences of the hazards. The commonly used models for a qualitative analysis include the Hazard Identification (HAZID) technique and the risk matrix method, which are discussed in this section.

HAZID is a structured process of identifying the hazards associated with a collision event (Molland, 2008). It involves a group of experts, who identifies the possible hazards through group interactions, so that the chance of overlooking any hazards is reduced. Though this method does not require historical collision data as input to the analysis, it relies on expert judgment and experience of analyzing collisions. To facilitate the hazard identification process, hazard checklists (i.e., a list of issues which are supposed to be considered in a HAZID process) are often used. A generic hazard checklist can be found in CMPT (1999).

To evaluate the significance of an identified hazard, risk matrices are usually employed. A risk matrix provides a traceable framework for explicit consideration of the frequency (i.e., 'likelihood' of the hazard occurrence) and consequence (i.e., 'severity' of the hazard's consequence) of a hazard. A typical matrix (see Figure 2.1) has rows representing categories of consequence severity (e.g., minor, significant, severe, catastrophic) and columns representing likelihood of the consequences (e.g., frequent, reasonable probable, remote, extremely remote).

CONSEQUENCE					INCREASING LIKELIHOOD				
Severity rating	People	Assets	Environment	Reputation	A	B	C	D	E
					Rarely occurred in E&P industry	Happened several times per year in industry	Has occurred in operating company	Happened several times per year in operating company	Happened several times per year in location
0	Zero injury	Zero damage	Zero effect	Zero impact	Negligible (Manage for continued improvement)				
1	Slight injury	Slight damage	Slight effect	Slight impact					
2	Minor injury	Minor damage	Minor effect	Limited impact					
3	Major injury	Local damage	Local effect	Considerable impact					
4	Single fatality	Major damage	Major effect	Major national impact	Intermediate (Incorporate risk reducing measures)				
5	Multiple fatality	Extensive damage	Massive effect	Major international impact			Intolerable		

Figure 2.1 A Typical Risk Matrix (ISO, 1997)

Upon identifying the hazards through a HAZID process, generally each hazard is qualitatively evaluated by defining different regions in a risk matrix. For example, the ISO risk matrix (ISO, 1999) uses three risk regions (see Trbojevic and Carr, 2000):

- Negligible (or broadly acceptable) – a hazard in this region indicates necessity of managing risk for continuous improvement.
- Intolerable – risk in this region is unacceptable.
- Intermediate region – this region lies in between the two extremes. Risks in this region have to be reduced to a level which is as low as reasonably practicable (HSWA, 1991).

While different risk matrix approaches are developed based on the general two-way matrix structure, inconsistency exists among the definitions of the categories of likelihood and consequence. For example, the ISO risk matrix (ISO, 1999) uses five categories of likelihood and six categories of consequence. The Defence Standard matrix (DS, 1996) categorizes the likelihood in six types and the consequence in four types. A 7 x 4 matrix configuration (likelihood x severity) is also found in IMO (1997). Furthermore, specifications of the risk regions also vary among different approaches. While the ISO risk matrix uses three risk regions, the Defence Standard matrix uses four. This lack of standardization among the categories of likelihood, consequence and risk regions may often cause confusion in risk matrix application.

A risk matrix is easy to apply and requires least resources and skills. However, it suffers from several potential limitations:

- In a risk matrix, it is difficult to explain a hazard that produces multiple consequences. Since risk matrix expresses severity of consequence by a single category, it may consider the most severe consequence only.

- Inconsistency among the judgments of different experts may lead to biased results. In general, different experts may have different judgments regarding a particular hazard. Furthermore, there may be variations in judgments of an individual expert. These variations may produce biased results.
- Categorization of likelihood and consequence of a hazard is often non-transparent because of qualitative definitions of the categories. This may further increase inconsistency among experts' judgments.
- It may be difficult to analyze a novel hazard by using a risk matrix. The HAZID process requires the experts to have past experience of analyzing hazards similar to the hazard in consideration so that the experts can capture the lessons learnt in identifying hazards (Veritas, 2001). Therefore, in case of a novel hazard, the HAZID and the risk matrix method becomes less useful.

2.1.2 SEMI-QUANTITATIVE MODELS

Semi-quantitative modeling of collision risk is achieved through two approaches:

1. Employ techniques of qualitative modeling, but produce quantitative results.
2. Employ techniques of quantitative modeling, but produce qualitative results.

The techniques of qualitative safety modeling (e.g., HAZID, risk matrices) are often employed to obtain some form of quantification in results. In this approach, the categories of likelihood and consequence in a risk matrix are defined quantitatively by using numerical indices (e.g., 1 to 5). By summing up the indices, a quantitative estimate of risk is obtained which allows prioritizing a set of hazards.

An example of this approach is the Risk Ranking matrix that is proposed in a revision of the IMO guidelines on Formal Safety Assessment (IMO, 1997). It uses seven Frequency Indices (FI) and four Severity Indices (SI) to define the categories of likelihood and consequence respectively. Risk of a hazard is expressed as

$$\text{Risk Index} = FI + SI \tag{2.1}$$

A different form of defining the FI and SI is proposed by Hu et al.(2007). In case of navigational accidents, they defined the FI as the ratio of the number of accidents (e.g., collision) to the number of shipping activities per unit time. The SI is defined as the ratio of the consequences to the number of accidents per unit time. It is obvious from the definitions that historical collision data are necessary to obtain the indices.

Due to incorporation of a risk matrix the Risk Ranking matrix approach suffers from some of the limitations of the qualitative modeling approach, such as biased judgments of different experts and difficulties in dealing with multiple consequences and novel hazards. While Hu et al. (2007) shows that a quantitative estimate of risk can be obtained by employing historical collision data instead of using expert judgments, this approach still suffers from the limitations of a risk matrix. Furthermore, safety analysis using collision data is often hampered by a number of drawbacks, which are discussed elaborately in Section 2.1.3.

The other semi-quantitative safety models employ techniques of quantitative modeling, such as Fault Tree Analysis (FTA), Event Tree Analysis (ETA) and Bow Tie, but do not actually quantify the estimate of risk. The FTA and ETA are used for analyzing the 'likelihood' and 'consequence' of a hazard, whereas a Bow Tie combines the two (see Trbojevic and Carr, 2000).

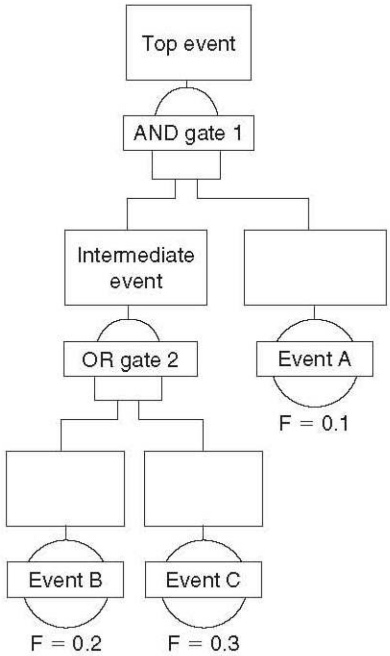

Figure 2.2 A Typical Fault Tree (Molland, 2008)

A FTA is a logical representation of a number of events and component failures that may contribute to cause one critical event, such as a collision. It is commonly used to quantify the likelihood of a critical event based on estimates of the failure rates of each component. A typical fault tree is shown in Figure 2.2. On the other hand, an ETA represents a number of events (consequences) that may result from an initiating event (component failure). As presented in Figure 2.3, it quantitatively estimates the probability of outcomes by using probabilities of preceding outcomes and the originating event. A comprehensive review of FTA and ETA, their applications, advantages and disadvantages can be found in Kristiansen (2005).

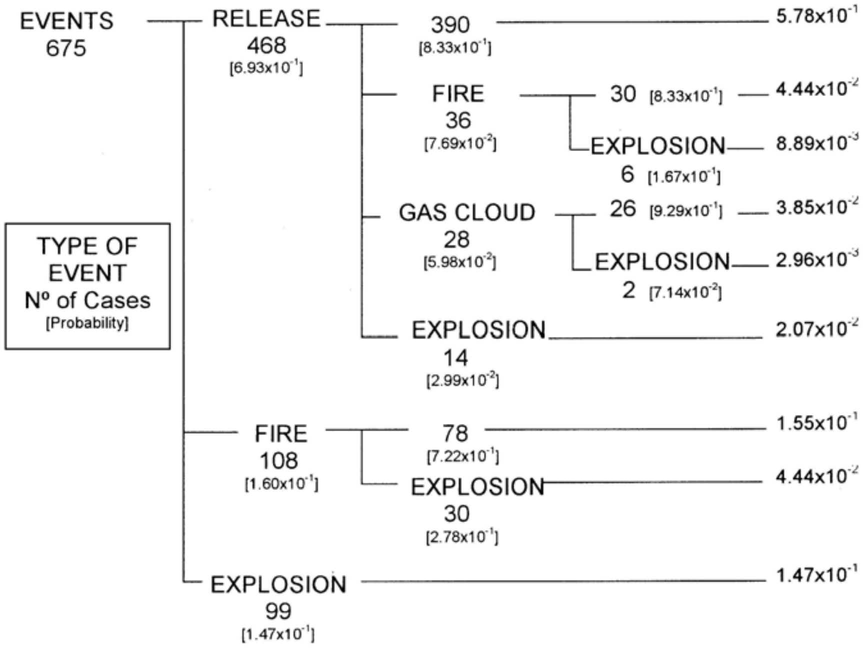

Figure 2.3 A Typical Event Tree of Ship-Ship Collision (Ronza et al., 2003)

While the FTA and ETA are usually used to quantify the probabilities of events and consequences, in semi-quantitative modeling they are employed to formulate the structure of the tree only. A team of experts identify the process of hazard generation and judge the adequacy of appropriate safety measures except quantifying the probabilities on the branches of the tree. This approach of safety modeling is useful for evaluating hazards where quantification is not possible or undesirable.

2.1.3 QUANTITATIVE MODELS

The qualitative and semi-quantitative models might be useful for some preliminary safety investigation purposes, but to attain a higher degree of insight a quantitative model is required. Quantitative models force all assumptions to be explicit and hence provide a better understanding of uncertainty than the models solely relying on expert judgments.

Traditionally, quantitative modeling of collision risk has relied on collision data. A number of studies have employed collision data to examine trends and causes of collisions (Akten, 2004; Darbra and Casal, 2004; Hashemi et al., 1995; Le Blanc et al., 2001; Le Blanc and Rucks, 1996; C.-P. Liu et al., 2006; Yip, 2008) whereas some have examined consequences (i.e., injuries and fatalities) by using the statistics (Darbra and Casal, 2004; Talley, 2002; Talley et al., 2005, 2006, 2008; Yip, 2008). Some studies (Degré, 2003; MARIN, 2009; Roeleven et al., 1995) have also focused on modeling probability and predicting frequency of collision by utilizing collision data. The studies are further discussed in detail in this section.

To analyze collision records, a number of mathematical tools have been employed, such as statistical models, FTA, and ETA. Among these tools, the statistical models are most commonly used which can be broadly categorized into two types: Descriptive models and Regression models. Collision risk modeling in view of these two types of models is discussed in the succeeding sections.

2.1.3.1 Descriptive Models

Statistics of collision frequency and casualties involved often used to represent the overall level of safety in port waters. A descriptive analysis of the statistics provides a simple and quick assessment of prevailed collision risk. To identify the level of risk, researchers used different indicators to represent frequency and consequences of collision records, such as

- Collision frequency: Number and percentage of collisions
- Collision consequences: Number and degree of injury and fatality, Injury and fatality rates, Degree of ship/cargo /property damage.

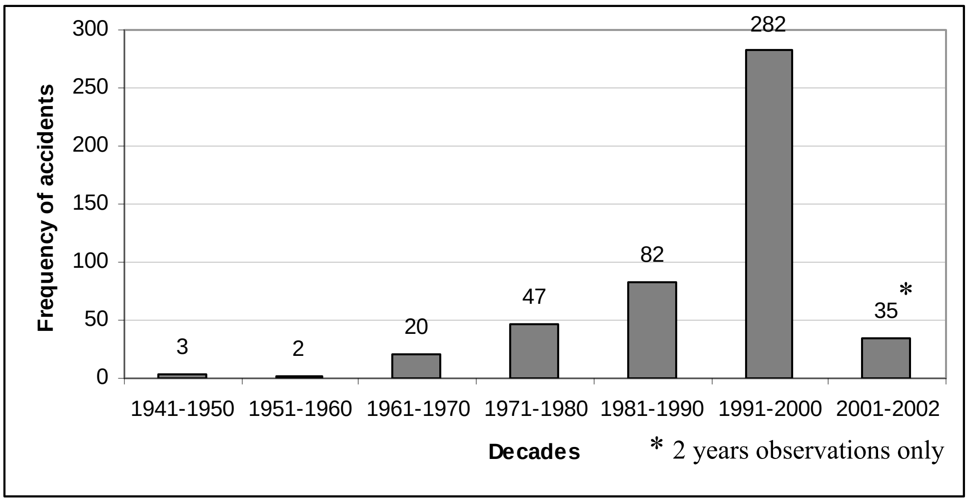

Figure 2.4 Distribution of Accidents (MHIDAS database) as a Function of Time (Darbra and Casal, 2004)

Darbra and Casal (2004) conducted a study on 471 accidents occurring in seaports in 1941 – 2002, which were obtained from the Major Hazard Incident Data Service (MHIDAS) (MHIDAS, 2002). They found that the number of accidents has increased spectacularly in recent decades (83% of the accidents have taken place in 1983 – 2002), as shown in Figure 2.4. Based on an observed increasing trend of accident occurrence and the notable growth in shipping traffic, they argued that the frequency of accidents in port areas will be increasing considerably in the next years. This study also showed that 56.5% of all accidents occurred during transport (i.e., involves moving ships), 65% involve an ocean going vessel (i.e., merchant vessels) and 26% are ship-ship collisions. These values imply that collision is a dominant safety hazard in port waters. Apart from the frequency analyses, this study examined injuries and fatalities resulted from the accidents by using accumulated frequency-number of deaths graph. They found that the probability of an accident with 10 or more deaths is seven times higher than that for an accident with 100 or more deaths.

In a study on the accidents in four commercial ports of Taiwan in years 1992 to 2003, C.-P. Liu et al. (2006) evaluated the safety levels in the ports. They reported that 23% of the accidents were caused by an impact (i.e., collision and contact). By analyzing accidents and utilizing expert judgments they identified several important navigational concerns, such as arbitrary anchoring of vessels, grounding and collision of heavily loaded vessels in complicated channels, failure to keep safe distance between neighboring berths, and reduced visibility of navigational aids. To mitigate the concerns, several strategies were suggested, such as enhancing vessel traffic management systems, maintenance and reinforcement of navigational aids, and conducting regular safety sessions among navigational personnel.

Akten (2004) analyzed the navigational accidents occurred in the Bosphorus in 1953 – 2002 and reported that 209 accidents (out of a total of 461) were collisions. The probability of a collision at night was found to be 2.1 times higher than that in day, which implies that collision occurrence is influenced by the navigational conditions at day and night. The other casual factors of accidents identified are dense traffic, sharp bends in fairways, improper conduct of vessels within Traffic Separation Scheme (TSS), and ships proceeding without a pilot. This study proved that TSS can be a significant measure of improving safety in dense and complicated fairways.

In a study of accidents in Hong Kong waters, Yip (2008) also showed that collision is the dominant type of accident in port waters. About 54% of all accidents reported in 2001 to 2005 were caused by collisions. Analyses of the collided vessel types revealed that 44% of the collisions took place between two cargo vessels. This implies that the consequences of a collision in port waters could be high because of the involvement of the vessels loaded with cargo.

Besides the above studies, some other (Hashemi et al., 1995; Le Blanc et al., 2001; Le Blanc and Rucks, 1996; Soares and Teixeira, 2001) also analyzed accident data descriptively and reported that collisions account for a substantial portion of major navigational accidents. Soares and Teixeria (2001) used the Lloyds World Casualty Statistics (LWCS) data (LWCS, 2009), whereas the others used accident database maintained by local authorities. Besides the descriptive statistics models, Hashemi et al. (1995) and Le Blanc et al. (2001) found that an artificial neural network is useful and accurate in predicting the type of vessel accidents that may occur under different combinations of navigating conditions.

2.1.3.2 Regression Models

While a descriptive statistics analysis uses a single variable model, a regression analysis uses a multi-variable model. A single variable model assumes that the effects of explanatory variables (if more than one) are independent of each other which would lead to obtaining biased effect estimates. On the other hand, a multi-variable model relaxes this assumption and estimates the effects of all explanatory variables together. For this reason, regression is often employed for a rigorous analysis.

Based on purposes of analysis, the regression models used for analyzing navigational accidents can be broadly categorized into two types, such as (1) Accident probability analysis and (2) Accident consequence analysis. The former type focuses on modeling accident frequency (or probability of occurrence), whereas the later focuses on modeling injuries and fatalities in an accident. These two types are discussed in the subsequent paragraphs.

Accident Probability Analysis:

Probability of accident is usually modeled as a binary variable, for example, an interaction between two vessels may take two possible forms: accident or no-accident. Binary logit/probit models are appropriate choice for modeling such a two-state dependent variable. The logit model uses a standard logistic distribution to explain the probability of accident, whereas the probit model uses a standard normal distribution. However, since these distributions are of similar shape, both models produce very similar results.

Roeleven et al. (1995) developed a binary logit model for modeling probability of collisions in restricted waters. In this model, the dependent variable *y* for i^{th} observation unit (i.e., an interaction) can only takes one of the two values: $y_i = 0$ (no-collision) or 1 (collision). A logistic transformation of $\pi_i = \Pr(y_i = 1)$ is interpreted as the logarithm of the odds of collision vs. no-collision. The binary logit model is obtained by treating the transformation as a link function in the generalized linear model framework,

$$\log\left(\frac{\pi_i}{1-\pi_i}\right) = \boldsymbol{X}_i\boldsymbol{\beta} \qquad (2.2)$$

Therefore, probability π_i is solved as

$$\pi_i = \frac{\exp(\boldsymbol{X}_i \boldsymbol{\beta})}{1 - \exp(\boldsymbol{X}_i \boldsymbol{\beta})} \tag{2.3}$$

where $\boldsymbol{X}_i$ is a vector of explanatory variables such as geometric, traffic, and situational factors, which are assumed to have effects on π_i. $\boldsymbol{\beta}$ is the effect coefficient vector of the explanatory variables.

Roeleven et al. (1995) found that probability of collision is significantly influenced by visibility, wind speed, ratio of navigable width to the width necessary for navigation, and bend radius of waterway. Apart from this study, Jin et al. (2002) and Jin and Thunberg (2005) have also employed a binary logit model for modeling probability of fishing vessel accidents.

Accident Consequence Analysis:

To analyze consequences of accidents (i.e., injuries and fatalities), researchers have employed a wide range of regression models. Injuries and fatalities are usually expressed in two forms: number of injuries and fatalities in an accident (count data) and categories of injury severities (ordered data). To model injury severity as count data, the Poisson and Negative Binomial (NB) models are used. On the other hand, ordered logit/probit models are used for modeling ordered data. Use of these regression models in navigational accident analyses are discussed in the succeeding paragraphs.

Poisson regression model has been used in modeling number of fatal and non-fatal injuries in ferry accidents (Talley, 2002), numbers of deaths and missing crews in freight ship accidents (Talley et al., 2005), number of missing crews in tugboat accidents (Talley et al., 2005), numbers of injuries, deaths and missing crews in tanker accidents (Talley et al., 2005), and numbers of deaths and missing occupants in passenger vessel accidents (Talley et al., 2006).

In a Poisson regression model, in order to ensure that the mean of a Poisson distribution (μ) is positive, a commonly used formulation is a log-linear relationship between the expected numbers of injuries or fatalities in an observation unit *i* (μ_i) and the covariates ***X,*** which is

$$\mu_i = E(y_i) = \exp(\boldsymbol{X}_i \boldsymbol{\beta}) \tag{2.4}$$

where $\boldsymbol{X}_i$ is a vector of covariates which describe the characteristics of a observation unit i and $\boldsymbol{\beta}$ is a vector of regression coefficients. If y_i is the observed number of injuries or fatalities in an observation unit *i*, the probability of observing y_i, when μ_i is given, can be expressed as

$$\Pr(y_i \mid \mu_i) = \frac{\exp(-\mu_i)\mu_i^{\,y_i}}{y_i!} \tag{2.5}$$

where μ_i is a deterministic function of $\boldsymbol{X}_i$ and randomness in the model comes from the Poisson specification for y_i.

The Poisson model assumes that the mean and variance of the dependent variable are equal. If this assumption is invalid, the standard errors will be biased and the test statistics derived from the model will be incorrect. To overcome this problem of over-dispersion, the NB regression model is employed instead of the Poisson model.

The NB regression model has been used in modeling numbers of injuries and deaths in port water accidents (Yip, 2008), numbers of injuries in freight ship accidents (Talley et al., 2005), number of injuries and deaths in tugboat accidents (Talley et al., 2005), and number of injuries in passenger vessel accidents (Talley et al., 2006).

In a NB regression model, the equality assumption between mean and variance is relaxed by introducing a stochastic component into the Poisson model. Mathematically,

$$\tilde{\mu}_i = \exp(\boldsymbol{X}_i \boldsymbol{\beta} + \varepsilon_i) \tag{2.6}$$

where ε is a random error that is assumed to be uncorrelated with $\boldsymbol{X}$. Hence, the relationship of $\tilde{\mu}$ and original μ in Poisson model follows readily $\tilde{\mu}_i = \exp(\boldsymbol{X}_i \boldsymbol{\beta}) \exp(\varepsilon_i) = \mu_{\mathrm{i}} \delta_i$. Assuming $E(\delta_i)$ equal to 1, $E(\tilde{\mu}_i)$ becomes μ_i, which imply that the expected count after adding the new source of variation is the same as it was for the Poisson model.

Apart from the count models, researchers have employed ordered regression models to analyze injury severities in navigational accidents. Injury Severity (IS) may be described as an ordinal variable, such as no injury (IS = 0), non-fatal injury (IS = 1) and fatal injury (IS = 2). To model such ordinal dependent variable, ordered logit/probit models are used. Talley et al. (2008) have employed such an ordered probit model for modeling injury severities in cruise vessel accidents.

The ordered probit model is usually motivated in a latent variable framework:

$$y_i^* = \boldsymbol{X}_i \boldsymbol{\beta} + \varepsilon_i \tag{2.7}$$

$$y_i = m \quad \text{if } \lambda_{m\text{-}1} \le y^* < \lambda_m \qquad \text{for } m = 1 \text{ to } M \tag{2.8}$$

where y represents the injury severity and can be ordered in M severity levels, y^* is a continuous latent variable, $\boldsymbol{X}_i$ is a vector of explanatory variables, $\boldsymbol{\beta}$ is a vector of parameters to be estimated and ε_i is the error term.

The latent variable y_i^* ranging from $-\infty$ to $+\infty$ is mapped on to an observed ordinal variable y. The threshold values λ's are unknown parameters to be estimated which represent the boundaries of the severity levels. The ε is assumed to be normally distributed with mean 0 and variance 1, thus the predicted probability of any type of injury severity, m for given $\boldsymbol{X}_i$ is

$$\Pr\left(y_i = \mathrm{m} \mid \boldsymbol{X}_i\right) = F(\lambda_m - \boldsymbol{X}_i \boldsymbol{\beta}) - F(\lambda_{m-1} - \boldsymbol{X}_i \boldsymbol{\beta}) \tag{2.9}$$

Based on this formulation, injury severity is modeled to understand the relationships between injury severity and different explanatory variables.

Limitations of collision-data-based modeling approach:

The foregoing shows that traditionally quantitative modeling of collision risk rely mostly on collision data. It is natural to use collision data as measure of safety because of its common acceptability to researchers and practitioners. However, safety modeling relying on collision data is often hampered by several shortcomings, such as

- To obtain statistically sound inferences from analysis of collision records it is necessary to have a database of sufficiently large number of collisions. Since a long time period is required to obtain such a database, this collision-data-based approach is not suitable for short-term safety assessment, where, for example, there is a need to evaluate the effectiveness of a particular type of safety measure at a specific location. Moreover, in case of assessing safety in a particular location the sample size (i.e., number of collisions in that location) becomes even smaller, thus it becomes more difficult to obtain statistical soundness in results. This may explain why statistical significances are not reported in many studies (e.g., Darbra and Casal, 2004; C.-P. Liu et al., 2006).
- The low sample problem also restricts safety analysts from using robust statistical methods, such as regression techniques. As argued by Yip (2008), because of the complexity of extensive port activities, any database containing fewer than 1000 records might not be large enough to obtain statistically significant results. This might be a reason of using descriptive statistics analysis in many studies, instead of a rigorous regression analysis.
- The recorded data in navigational accident databases, such as MHIDAS (MHIDAS, 2002) and LWCS (LWCS, 2009), are often insufficient for an in-depth analysis (C.-P. Liu et al., 2006). Since the databases are maintained by

different authorities, the types of information stored also vary among them. This insufficiency and inconsistency problems may hinder safety analyses.

- Collision is an outcome of a complex process of interaction involving vessels, pilots, crews, port operators and marine environment. Therefore, it is sometimes difficult to investigate the main causes of collisions just from the numbers of the outcome (i.e., collision) of the process as collision records often omit details of the pre-collision process.
- The collision-data-based approach is also reactive and unethical as it requires sufficiently large number of collisions to take place first, before any preventive or corrective measures are taken. This is particularly true for a new or upgraded traffic infrastructure where historical collision data are unavailable.

The shortcomings of the collision-data-based approach warrant an alternative safety modeling approach which will not rely on collision data.

2.3 TRAFFIC CONFLICT TECHNIQUE

To overcome the shortcomings of safety modeling using accident data (i.e., collision in case of this research), researchers have looked for indirect (or surrogate) approaches of safety evaluation. Traffic conflict technique (TCT) is one of the most developed surrogate safety modeling approach which is a systematic method of analyzing traffic interactions for evaluating and compensating any potential sources of safety hazards. The most appealing aspect of the TCT is that a larger database can be obtained within a shorter period of time as traffic conflicts occur considerably more frequently than collisions. This advantage of the TCT solves the ethical problem associated with the need of long collision history and facilitates obtaining statistically sound results. Thus, this technique could be an ethically appealing alternative to the traditional approach of safety modeling using collision data.

The TCT has primarily been developed in the context of road traffic safety modeling with a long history of development. Though highway engineers have long been using the idea of traffic conflicts in identifying hazardous locations on highways (Baker, 1977), Perkins and Harris (1967) first formally stated this safety evaluation approach, which came to be called the TCT. The use of this technique generated immediate interest among safety researchers around the world who accepted this approach as supplement to, rather than replacement for, the traditional accident-data-based safety evaluation method. Increasing interest on this technique has refined its concepts and methods through several conferences, congresses and workshops with publications amounting no fewer than several hundreds. A survey on the literature on TCT (Kraay, 1983) lists as many as two hundred references. Further, due to technological advances (i.e., image processing technology) in the recent decades, developments and practices of the TCT has grabbed considerable attention of safety researchers in recent times. The concepts and definitions of traffic conflicts, the issues related to measurement and validity, and applicability of the technique has extensively been reviewed in literature (see Chin and Quek, 1997; Songchitruksa and Tarko, 2006; Williams, 1981).

To develop an alternative approach for modeling collision risks using non-collision information (e.g., traffic conflicts), it is necessary to understand the theories of TCT and the issues related to its application to road traffic safety modeling. A review of TCT is presented in this section.

2.3.1 CONCEPTS AND DEFINITIONS

In the landmark paper on TCT (Perkins and Harris, 1967), the approach adopted was to observe and record unsafe interactions between vehicles, determined by the use of evasive action to avoid a potential collision. Thus, conflicts were defined based on evasive actions which are readily observable in traffic stream. Chin and Quek (1997) argued that the insistence of regarding conflicts in terms of evasive actions may have resulted in a diversity of ways in defining, interpreting and identifying conflicts. They suggested that an exhaustive list of possible evasive actions in all traffic situations might be needed in order for conflict observers to understand what is to be observed. Although such a list was prepared in the user-manual for the US conflict technique (FHWA, 1989), observing the evasive actions in complicated traffic situations may be very difficult for observers which, in turn, may make them more prone to errors in conflict identification. More importantly, Chin and Quek (1997) argued that not all actions taken by drivers are ‘evasive’ in nature, some may be truly ‘precautionary’ as driving characteristics are likely to differ among drivers.

The First Workshop on Traffic Conflicts (Amundsen and Hyden, 1979) proposed a definition which does not rely on observed evasive actions. A conflict was defined as “an observable situation in which two or more road users approach each other in space and time to such an extent that there is a risk of collision if their movements remained unchanged”. This definition provides a common basis of thinking, but leaves some ambiguity with regard to what is ‘observable’ and what is a ‘sufficient’ level of risk to distinguish between conflict and non-conflict situations (Chin and Quek, 1997).

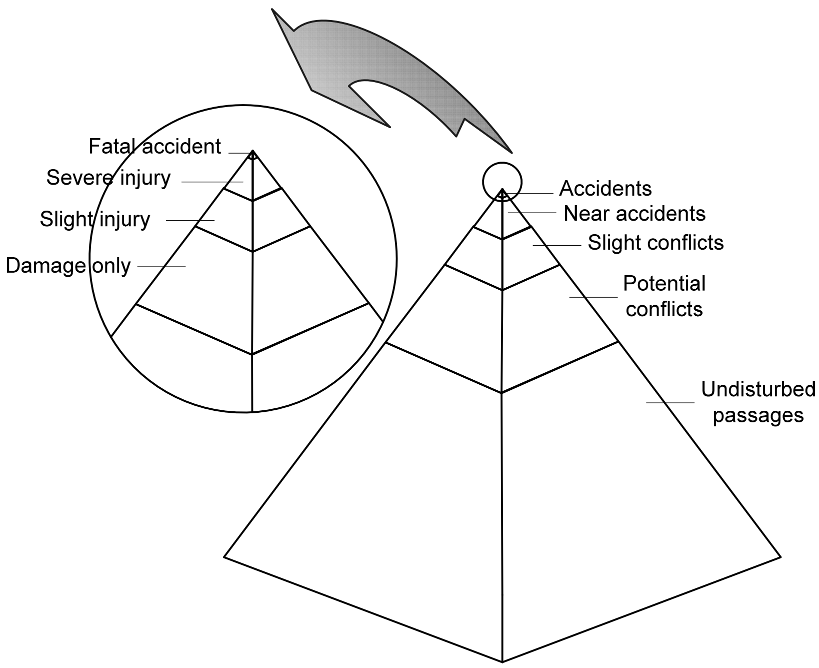

Figure 2.5 A Safety Pyramid of Road Traffic Events (Hyden, 1977)

To define conflicts more clearly, researchers proposed definitions of conflicts with stricter specifications. Some have defined conflicts by considering accident as a process preceded by conflicts which eventually has established a logical relationship between exposure, conflicts and accidents. Amundsen and Hyden (1979) described the relationship based on a set representation of traffic events (i.e., accidents are subset of conflicts, which are subset of a universal set of exposure), whereas some (Amundsen and Larsen, 1977; Baguley, 1982) represented it as an ordinal severity scale which ranges from slight conflicts to serious conflicts. Hyden (1977) defined the relationship as a safety pyramid, as shown in Figure 2.5. Another form of representation (see Figure 2.6), proposed by Glauz and Migletz (1980), is in the form of a frequency distribution of severity in terms of nearness to a collision. Although these representations describe the concept of TCT more clearly, still the severity levels of conflicts are not well-defined.

To define the severity levels more precisely, researchers (Guttinger, 1982; Hyden, 1977) concentrated on the more serious conflicts by setting a threshold value. However, Chin and Quek (1997) criticized this approach because ignoring the information of slight and moderate conflicts contradicts the main intention of TCT, which is aimed at using the more extensive information available in conflicts than in accident data.

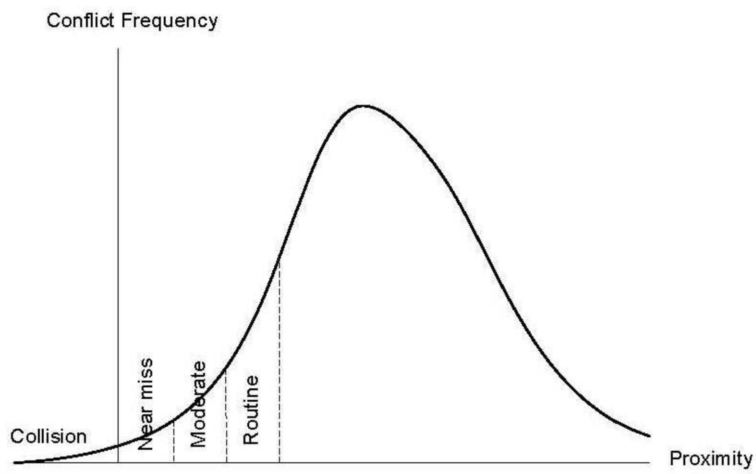

Figure 2.6 Frequency Distribution of Conflicts in terms of Nearness to Collision (Glauz and Migletz, 1980)

The distinction between serious and non-serious conflicts has also been a subject of debate. Conflicts were classified into the two classes qualitatively (Spicer, 1971) as well as quantitatively (Chin et al., 1991; Guttinger, 1982; Hyden, 1977). Time and distance thresholds were employed to separate the two types of conflicts. Chin et al. (1991) argued that classifying conflicts based on a single threshold value is not reasonable. They instead suggested using a distribution of thresholds in order to capture the variation in driving skills (e.g., response time) among different drivers.

2.3.2 PAST DEVELOPMENTS AND PRACTICES

The TCT has primarily been employed as a tool for diagnosing safety problems of road traffic systems. In particular, it has been applied to estimate the level of safety at intersections and roadway segments (e.g., merging area of expressway). Safety levels of different operating conditions (such as day and night conditions or dry or wet surface conditions) or different localities have also been compared by using TCT. In addition, TCT has often been used in evaluating before-after studies of safety countermeasures.

For a wide range or purposes, researchers have developed and implemented the TCT, including research on:

- Definitions of various types of conflicts (Amundsen and Hyden, 1979; Chin et al., 1991; FHWA, 2003; Parker and Zegeer, 1988; Perkins and Harris, 1967)
- Methods for collecting conflict data (Allen et al., 1978; Chin et al., 1991; FHWA, 1990; Fitzpatrick, 1991)
- Measures of conflict severity (Allen et al., 1978; Chin and Quek, 1997; Chin et al., 1991; FHWA, 2003; Hayward, 1972; Hyden, 1977; Minderhoud and Bovy, 2001)
- Establishing relationship between conflicts and accidents (FHWA, 1990; Migletz, 1985; Sayed and Zein, 1999; Spicer, 1971, 1973)
- Validity of the technique (Guttinger, 1979; Hauer, 1979; Hauer and Garder, 1986; Williams, 1981)

Traffic conflicts are analyzed and interpreted in different ways. One common way that was used at the early stage of TCT development is using number of observed conflicts.

To get more insights, sometimes number of serious conflicts is also used. Spicer (1971) used number of conflicts to study safety at a rural dual carriageway intersection. In another study (Spicer, 1973), he used serious conflict counts. Conflict rate (conflict counts normalized by traffic volume) was also used for this purpose (Campbell and Ellis King, 1970).

With development of the TCT, researchers focused on interpreting conflicts objectively. A number of quantitative measures of conflicts have been developed for this purpose (see Allen et al., 1978; Chin et al., 1991; FHWA, 2003; Hayward, 1972; Hyden, 1977). Some of the measures are discussed in the next section. Detailed analysis of conflicts, such as distribution and variation of the measures, was also achieved in some studies. Chin et al. (1991) measured risk of collision in an expressway merging process by considering a distribution of a quantitative measure – inverse of time to collision. They found that it follows a Weibull distribution. By identifying the serious conflicts from the tail end of the distribution, the probability of a near accident per merging event was computed.

2.3.3 MEASUREMENT OF CONFLICTS

The measurement method of traffic conflicts has been one of the major concerns in TCT development. A number of research efforts have been undertaken in order to develop methods for measuring conflicts in such a manner that the results are objective and repeatable based on the fact that the measurement methods in the early TCT studies are subjective.

In many of the early TCT studies, conflict measurement relies on subjective judgment of speed and distance by trained human observers. This subjectivity allows for possibility of unreliable measurement. Two aspects of unreliability in the measurement have been identified (Chin and Quek, 1997; Glauz and Migletz, 1980), which are

- Intra-rater variation or consistency problem: inconsistency in recording made by an individual.
- Inter-rater variation or repeatability problem: variability in interpretation and recording of a given situation between different observers.

The inconsistencies can be attributed to a number of factors including lack of training, inadequate definitions of the situations to be observed, fatigue, high number of conflicts, and the occurrence of complex conflict types (Chin and Quek, 1997; Older and Spicer, 1976). To overcome some of these problems, many manuals and training packages have been developed which aim at detailing various types of conflicts and observation procedures (see Chin and Quek, 1997 for a list of studies). Researchers often considered video recording of traffic interactions as an alternative of on-site observation. This attempt opened the door for more precise quantitative measurement of conflicts.

The reliability in conflict measurement can be improved by the use of objectively defined measures, for example, through measuring conflicts quantitatively. A number of quantitative measures, which express the severity of conflict in terms of space and time proximity, have been developed to measure road traffic conflicts.

Hayward (1972) suggested the use of *Time to Collision* (TTC), the time to collide with the leading vehicle if both vehicles continue in the same path without changing their speeds and directions. Chin et al. (1991) suggested the use of a reciprocal of TTC instead of TTC itself as the variation of the reciprocal of TTC get larger as the severity of conflict increases. Since the TTC can vary throughout an interaction process, different values of TTC at different points in an interaction process were also considered. The TTC at onset of breaking (also known as *Time to Accident*) (Hyden, 1977) and the minimum registered value of TTC or inverse of TTC in an interaction process (Chin et al., 1991) are the two most commonly used measures. Minderhoud and Bovy (2001) have proposed two measures of conflict to consider the occurrences of small TTC values of all traffic participants at any moment in a specified roadway. *Time-Exposed TTC* (TET) is the duration of exposure to safety critical TTC values over a specified duration. *Time-Integrated TTC* (TIT) is the integral of the TTC profile of drivers involved in traffic interactions in that duration.

Allen et al. (1978) proposed several measures of conflicts which include *Gap time*, *Post Encroachment Time* (PET), *Encroachment Time* (ET), *Initially Attempted Post Encroachment Time* (IAPE), *Proportion of Stopping Distance* (PSD) and *Deceleration Rate* (DR). *Gap time* is the time difference between the arrival times of the involved vehicles at the point of crossing if no evasive actions are taken. PET is the time lapse between the end of encroachment of a vehicle on a collision point and the time that the other vehicle actually arrives at that point. ET is defined as the time duration during which the turning of a vehicle infringes the right-of-way of the second vehicle. IAPE is the time lapse between the commencement of an encroachment by a turning vehicle plus the expected time for the other vehicle to reach a common conflict point, and the completion time of encroachment by the turning vehicle. PSD is the ratio of the remaining distance to the potential point of collision and the acceptable minimum stopping distance. DR is the highest rate at which a vehicle must decelerate to avoid a collision.

These quantitative measures of conflicts have widely been used for various purposes, such as diagnosing safety problems at intersections or roadway segments by measuring conflicts, comparison of safety levels between two roadway facilities, simulation of traffic events etc. However, research on how to measure conflicts is still ongoing so that the measures can fit in the purposes of TCT studies.

2.3.4 VALIDITY OF TRAFFIC CONFLICT TECHNIQUE

Validity of the TCT is traditionally judged by the adequacy in predicting number of accidents (Hauer and Garder, 1986) or by evaluating the magnitude of the correlation between conflict counts and accident counts (Chin and Quek, 1997). This approach of validation was considered particularly important in the early years of development in order to establish the TCT as an alternative to the accident data analysis.

The idea of predicting number of accidents is often criticized by many researchers (e.g., Chin and Quek, 1997; Hauer, 1979). Hauer (1979) who argued that the intention of a safety study should be to prevent accidents rather than to predict them. Chin and Quek (1997) further argued that the TCT should primarily be used as a diagnostic and evaluative tool rather than a predictive one, thus validating TCT based on its ability to predict accidents may be unnecessary.

Validating TCT by evaluating correlation between conflict counts and accident counts have also been a subject of intense debate as many TCT studies failed to show an acceptable level of correlation or, at best, produced inconsistent findings (see Williams, 1981 for a review of some TCT studies). The possible reasons of this inconsistency could be the problematic assumption of fixed conflict-accident proportionality, considerable measurement errors, and inaccuracy and under-reporting of accidents (Songchitruksa and Tarko, 2006; Williams, 1981). Glauz and Migletz (1980) identified a detailed list of the reasons why the TCT studies were unfruitful or misleading.

Hauer and Garder (1986) addressed the issue of validity more fundamentally rather than merely seeking a good statistical correlation between conflicts and accidents. They argued that the validity of the technique should be judged by comparing the variance of the estimates. It was suggested that the method producing the most unbiased estimate with the smallest amount of variance is that with the greatest degree of validity. Grayson and Hakkert (1987) further reasoned that validity should not only be confined to establishing a statistical relationship between conflict and accident. They proposed that construct validity should be established in relation to a common causation process that can lead to different outcomes for conflicts and accidents. Furthermore, Hauer (1979) argued that the numbers of expected (i.e., the true value) conflicts and accidents could be correlated, but not the observed ones.

Reviewing the attempts and arguments of validating TCT, Chin and Quek (1997) suggested that it may be a futile and unnecessary exercise to establish a statistically significant relationship between conflicts and accident to validate the TCT. They contended that a TCT study should be designed to diagnose safety problems as well as to evaluate safety and operational improvements in traffic system.

Relying on accident data to validate the TCT also contradicts TCT's proactive approach to safety. For example, to evaluate safety in a new or upgraded traffic infrastructure by using TCT, the technique cannot be validated due to absence of sufficient number of accident records. This dependence to accident data restricts the technique's use to safety diagnosis.

2.4 SUMMARY

This chapter provided a critical review of the traditional techniques of modeling collision risk and the traffic conflict technique. In particular, limitations of the traditional models were identified and how the traffic conflict technique may overcome the limitations was discussed.

Traditionally, the techniques of collision risk modeling rely on expert judgments and historical collision data. For qualitative or semi-quantitative evaluation of risk, models relying on expert judgments are employed. But, to attain higher degree of insight in risk modeling quantitative models are applied which rely mostly on collision data. The primary limitation of this approach is that a long waiting time is required to obtain large number of collisions, which is necessary for a statistically sound analysis. A potential alternative is to use traffic conflicts, instead of using collision data, because conflicts occur more frequently than collisions. This approach of safety modeling has been developed and implemented for road traffic systems and has shown great potential to evaluate safety in a proactive manner. But, it is yet to be implemented in navigational collision risk modeling. This research intends to use this approach for modeling collision risks in port waters.

CHAPTER THREE
METHODOLOGY

3.1 INTRODUCTION

In modeling collision risk in a port waterway, two major aspects need to be considered. Firstly, measuring the level of risk and secondly, understanding the characteristics of the risks, i.e., identifying the influential factors of the risks. To address these two aspects, two models are developed in this research, namely the Risk measurement model and the Risk prediction model.

The risk measurement model measures collision risk in a waterway by analyzing critical traffic interactions. This is accomplished by a two step procedure. In the first step, collision risk in an interaction is measured by developing a quantitative measure of conflicts. An ordered probit model of the risk of collision in an interaction is developed for this purpose. The second step involves developing a method for measuring collision risk in a waterway. This is accomplished by statistically characterizing all interactions in a waterway and identifying the interactions with high potential of collision. Validity of the risk measurement model is assessed by evaluating correlations between the measured risks and those perceived by pilots.

The risk prediction model explains the relationships between collision risks in waterways and the geometric, traffic, and regulatory control characteristics of waterways. A systematic method of model formulation, calibration and evaluation is developed for this purpose. In formulation of a predictive model, a binomial logistic regression model with considerations for hierarchical data structure is developed that accounts for the correlations in risks at different time periods in a waterway. Using maximum likelihood estimation method, the model is calibrated and its validity is evaluated by using several goodness-of-fit statistics.

This chapter discusses the two models. In particular, formulations of the models along with their validation and evaluation procedures are discussed.

3.2 RISK MEASUREMENT MODEL

To measure collision risk in a waterway, it is necessary to measure the conflict severities of all vessel interactions in that waterway. A suitable measure of conflict severity is then necessary to measure navigational traffic conflicts (NTC) quantitatively. After critically examining the suitability of conflict measures that were primarily developed to measure road traffic conflicts (RTC), a suitable measure is developed to measure NTC. With the measured conflict severities of all interactions in a waterway, risk of collision in that waterway can be measured by employing the risk measurement model. The formulation of the model is discussed in this section. An illustration of the modeling technique will be presented in Chapter 4.

3.2.1 METHOD OF MEASURING COLLISION RISK IN AN INTERACTION

As discussed in Chapter 2, RTC are found to be measured qualitatively or quantitatively. The former method relies on observers to identify and grade conflict severities by their judgments. It is criticized by many researchers (e.g., Chin and Quek, 1997; Glauz and Migletz, 1980; Guttinger, 1982) for its well recognized drawback of inconsistency in observers' subjective judgments. To overcome this drawback many researchers (e.g., Chin et al., 1991; Guttinger, 1982; Hyden, 1977) employed the quantitative measurement method, where conflicts are measured by using surrogate safety measures. This method is usually preferred as it is objective and provides a quantitative measure. In this research, we espouse this method to develop a suitable measure of NTC.

For quantitative measurement of conflicts, researchers have developed many surrogate measures in the context of road traffic. To employ these RTC measures for measuring NTC it is necessary to critically examine the measures' suitability in measuring NTC. Several RTC measures that may have potential in measuring NTC are examined in the context of navigational traffic in the succeeding paragraphs.

The most commonly used temporal RTC measure is the *Time to Collision* (TTC) (Hayward, 1972), which is defined as the expected time for two vessels to collide if course and speeds of both vessels remain unchanged. To measure TTC, a prerequisite is that collision course must exist between the vessels involved. Therefore, it is incapable of measuring conflicts, where a collision course does not exist. However, vessels could pass each other with a narrow space/time margin, which may be a safety concern. Since TTC can vary throughout an interaction process, researchers considered different points at which TTC should be measured (Horst, 1990). The most commonly used measure is the minimum registered value of TTC in an interaction process (Chin et al., 1991) and the TTC at the onset of taking evasive actions, which is termed as *Time to Accident* (TA) (Hyden, 1977). A prerequisite of measuring TA is that the evasive actions must be observable. However, measuring conflicts depending on observable evasive actions could be misleading (Chin and Quek, 1997). More importantly, it would be difficult to observe such actions in the context of navigational traffic. Based on the TTC concept, Minderhoud and Bovy (2001) proposed two more explorative measures – *Time Exposed TTC* (TET) and *Time Integrated TTC* (TIT). These two measures do not rely on observable evasive actions, but suffer from the limitation of collision course existence criterion. Moreover, they are highly data-intensive and attainable only in simulation environment. Although the other measures of the TTC family are easy to measure and apply, they may not be appropriate to measure NTC due to the limitations.

Researchers (Allen et al., 1978) proposed another temporal measure – *Post Encroachment Time* (PET) that overcomes the major limitations of the TTC family. The PET is the time lapse between end of encroachment of a vessel on a potential collision point and the time that the other vessel actually arrives at that point. It is especially suitable for measuring conflicts in which two vessels pass over a common spatial point or area with a temporal difference, regardless of the collision course existence criterion. Although it overcomes this limitation of TTC, it suffers from a couple of major drawbacks. Firstly, only the conflicts involving vessels with transversal trajectories can be measured by PET. Conflicts involving vessels with similar or nearly opposite trajectories cannot be measured because of the absence of any point of collision. Secondly, to measure PET a fixed projected point of collision is required, rather than one that changes with dynamics of vessel interactions. Several derivatives of the PET measure were also proposed by Allen et al. (1978), such as *Gap time*, *Encroachment time*, *Initially attempted PET*. However, these measures are also constrained by one/both of the limitations of PET. Since NTC can be of several types (such as meeting/head-on, overtaking, crossing, and hitting a stationary vessel) and PET is capable of measuring the crossing type only, the PET measure family losses its suitability for measuring NTC.

Besides the time-based measures, some other measures that explain spatial or kinematic characteristics of vessel interactions were proposed for measuring RTC. A spatial measure, the *Proportion of Stopping Distance* (PSD) represents the ratio of the distance available for maneuvering to that of the necessary stopping distance to a projected point of collision (FHWA, 2003). A kinematic measure, the *Required Deceleration Rate* (RDR) is the maximum uniform rate at which a vessel must decelerate to avoid a collision. These two measures are particularly suitable for measuring RTC as the maneuvering space on road is very limited. For measuring NTC, these may not be suitable enough due to availability of considerably higher maneuvering space in navigation, compared to road driving, which allows pilots to alter course and/or slacken speed in order to avoid collisions, instead of stopping.

The foregoing shows that the RTC measures are not suitable for measuring NTC, mainly because of a dimensional difference between the two types of conflicts. The RTC is often measured in one-dimension, whereas the NTC is required to be measured two-dimensionally. Conceptually, the measures of TTC family are incapable of measuring the NTC in which collision course does not exist between the involved vessels. Although the PET measure and its derivatives can overcome this limitation, use of them are limited to measuring crossing type of conflicts only. The PSD and RDR are capable of measuring all types of NTC, but they do not match the characteristics of navigational traffic. Therefore, to measure NTC correctly it is necessary to develop a measure that would suit the two-dimensional traffic characteristics. Measuring NTC spatially as well as temporally would be useful for this purpose.

3.2.1.1 Development of Conflict Measure

A quantitative measure of NTC is developed which expresses risk of collision in an interaction by employing two proximity indicators. These indicators, *Distance at Closest Point of Approach* (DCPA) and *Time to Closest Point of Approach* (TCPA), represent spatial and temporal closeness between a pair of vessels. DCPA and TCPA are respectively the probable distance between a vessel pair at their *Closest Point of Approach* (CPA) and the time required to reach CPA, given that the course and speed of both vessels remain unchanged. Both indicators are independent of collision course existence criteria and are capable of measuring all types of NTC. Furthermore, the indicators can easily be calculated from vessels' position and speed vectors.

The proximity indicators have been employed in on-board navigation and navigational research for many years. Navigators make use of these parameters in order to assess collision risk in on-board navigation. These are also used in navigational studies of different aspects, such as development and evaluation of navigational support systems (Q. Liu et al., 2006; Pedersen et al., 2003; Sato and Ishii, 1998), traffic density analysis (Merrick et al., 2003) and ship domain analysis (Szlapczynski, 2006; Zhu et al., 2001). Being used in navigation and navigational studies, the indicators have general acceptability to navigators and researchers.

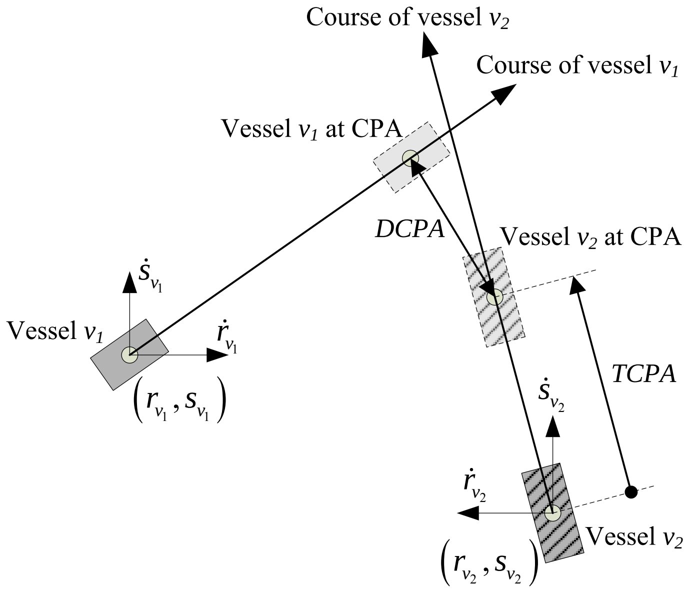

Figure 3.1 A Typical Interaction showing Spatial and Temporal Proximity Indicators

To derive DCPA and TCPA in a vessel interaction (see Figure 3.1), let vessels v_1 and v_2 are approaching each other from their current positions (r_{v_1}, s_{v_1}) and (r_{v_2}, s_{v_2}) at speeds of $(\dot{r}_{v_1}, \dot{s}_{v_1})$ and $(\dot{r}_{v_2}, \dot{s}_{v_2})$ respectively at time *t*. If they maintain their speeds and courses, they will reach at CPA after a time period equal to TCPA. By making use of this condition, DCPA and TCPA can be derived in terms of the vessels' current positions and speeds as

$$DCPA(t) = \sqrt{\left[\left(s_{v_2} - s_{v_1}\right) + \left(\dot{s}_{v_2} - \dot{s}_{v_1}\right) \times TCPA\right]^2 + \left[\left(r_{v_2} - r_{v_1}\right) + \left(\dot{r}_{v_2} - \dot{r}_{v_1}\right) \times TCPA\right]^2} \tag{3.1}$$

$$TCPA(t) = \frac{-\left[\left(s_{v_2} - s_{v_1}\right)\left(\dot{s}_{v_2} - \dot{s}_{v_1}\right) + \left(r_{v_2} - r_{v_1}\right)\left(\dot{r}_{v_2} - \dot{r}_{v_1}\right)\right]}{\left(\dot{s}_{v_2} - \dot{s}_{v_1}\right)^2 + \left(\dot{r}_{v_2} - \dot{r}_{v_1}\right)^2} \tag{3.2}$$

In general, vessels would keep changing their speeds and courses throughout an interaction process while taking some evasive actions to avoid collision or just taking some precautionary actions. Consequently, the values of DCPA and TCPA would be changing with time, but not necessarily simultaneously increasing or decreasing. Therefore, to express the risk of collision in an interaction at a particular time *t*, it is necessary to develop a relationship between the risk and the two proximity indicators,

$$C(t) = f(\mathbf{X}_{PI}(t)) \tag{3.3}$$

where $C(t)$ is the risk of collision in an interaction at time *t* and $\mathbf{X}_{PI}(t)$ is a vector of the proximity indicators. The maximum of $C(t)$ in an interaction process, $C_{\max}$, is taken to represent the conflict severity of that interaction. A method of developing the relationship between collision risk in an interaction and the proximity indicators is discussed in the succeeding section.

3.2.1.2 Modeling Collision Risk in an Interaction

A relationship between collision risk in an interaction and the proximity indicators can be obtained by employing expert judgments on collision risks. It is reasonable to assume that the perception of pilots reflects the actual risks of collision in different interactions, because pilots are very familiar with the characteristics of port waterways from their years of experience and they are the only group of people who assess and mitigate the risks in navigation. Expert judgments on collision risks can be collected through a risk perception survey on harbor pilots, where pilots can be asked to rate collision risks in different vessel interactions, which are explained by the two proximity indicators. Intensity of risk can be expressed by a scale categorizing risk into five levels, as shown in Table 3.1.

Since the risk levels used in the scale are ordered in nature, an ordered categorical analysis will be most appropriate to treat such data. Two possible regression models may be employed: the ordered probit or ordered logit models. The models differ in the assumption of the distributions of regression errors. The probit model assumes a normal distribution of errors with mean 0 and variance 1, whereas the logit model assumes a standard logistic distribution with mean 0 and variance $\pi^2/3$. The ordered probit model is selected for this research though the choice matters little as both models produce very similar results.

Table 3.1 Scale of Perceived Collision Risk in an Interaction

Risk level	Level of actions necessary to avoid collision	Risk level indicator, m
Very high (VHR)	Collision imminent, cannot be avoided	1
High (HR)	Immediate actions needed	2
Moderate (MR)	Take precautionary actions, communicate with other ship	3
Low (LR)	Keep safe navigational watch	4
Safe	No actions necessary	5

The ordered probit model is usually formulated as a latent (i.e., unobserved) variable framework. The structural model specification is

$$y_i^* = \boldsymbol{\beta}\mathbf{X}_{PI\,i} + \varepsilon_i \tag{3.4}$$

where y_i^* is a continuous latent variable measuring perceived collision risk for the i^{th} set of $\mathbf{X}_{PI}$; $\mathbf{X}_{PI\,i}$ is the vector of independent variables (i.e., DCPA and TCPA); $\boldsymbol{\beta}$ is the vector of regression coefficients; ε_i is the random error term.

The latent variable is mapped on to an observed ordinal variable *y*, which represents the risk levels used in the scale, as

$$y_i = m \text{ if } \lambda_{m-1} \le y_i^* < \lambda_m \text{; for } m = 1 \text{ to M} \tag{3.5}$$

where M is number of ordinal categories (as indicated in Table 3.1) and the threshold values (λ) are unknown parameters describing the boundaries of risk levels.

Based on the normality assumption of the error term, the probability of risk level *m* for given $\mathbf{X}_{PI}$ can be predicted as

$$\hat{\Pr}\left(y = m \middle| \mathbf{X}_{PI}\right) = F\left(\hat{\lambda}_m - \hat{\boldsymbol{\beta}}\mathbf{X}_{PI}\right) - F\left(\hat{\lambda}_{m-1} - \hat{\boldsymbol{\beta}}\mathbf{X}_{PI}\right); \quad \sum_{m=1}^{M} \hat{\Pr}\left(y = m \middle| \mathbf{X}_{PI}\right) = 1 \tag{3.6}$$

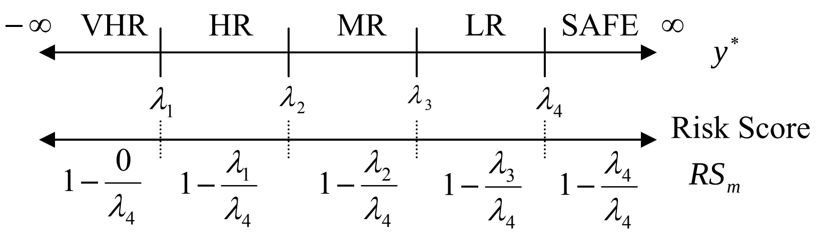

Figure 3.2 Risk Scores for Collision Risk Levels

Once the probabilities of each risk level are predicted, the associated collision risk in an interaction can be computed. To do so, risk scores (RS_m) are assigned to each risk level based on the thresholds, as shown in Figure 3.2. The RS_m represents the probability of collision for risk level *m*. Using the proposed risk scale, risk scores for VHR and Safe levels are assigned values of 1 and 0 respectively. The VHR level refers to vessel interactions where collision cannot be avoided, which represents the probability of collision as 1. On the other hand where no action is required under the Safe level, the probability of collision is zero. Therefore, the λ values are normalized to a probability value with the range [0, 1]. Collision risk in an interaction can then be computed as

$$C(t)|\mathbf{X}_{PI} = \sum_{m=1}^{M} RS_m \times \hat{\Pr}(y = m|\mathbf{X}_{PI}); \; 0 \leq C(t) \leq 1 \tag{3.7}$$

In order to examine the significance of $\mathbf{X}_{PI}$ **'**s included in model the z-test is employed and to evaluate if the model have sufficient explanatory and predictive power several goodness-of-fit (gof) measures found in Long and Freese (2006) are used. The likelihood ratio statistics is used to examine the overall gof of the model by testing the global null hypothesis that all coefficients except the intercept are zero. The McKelvey and Zavoina's R^2 is also used to measure the predictive power of the model.

The risk of collision in any vessel interaction may vary with the size of vessels involved. Perez and Clemente (2007) have shown that maneuverability and ease in speed adjustments diminishes as vessel size increases and for this reason, vessels of different sizes would produce different levels of risk in an interaction. Consequently, the risks perceived by pilots may also vary. In order to consider the effects of vessel sizes in modeling the risks, vessels may be clustered into several vessel classes (VC) according to Gross Tonnage (GT).

As the perceived risk is influenced by the pilot's experience in a particular vessel class, both experience and VC need to be considered together in a perception survey. In general, pilots with more experience are authorized to operate VC with higher GT, a positive association between experience and VC will exist. Hence, modeling the risks separately for each VC is necessary.

Furthermore, navigation is affected by the environment, and in particular, in day and night settings (see Akten, 2004). Therefore, perceived risks would also be different for day and night conditions. Hence, the risks need to be modeled separately for day and night conditions.

3.2.1.3 Perception Survey on Collision Risk in an Interaction

To calibrate the parameters of the ordered probit model, perceptions of collision risks under different vessel interaction situations need to be obtained from pilots. Perceived risk data can be collected by employing two experimental methods: simulation or survey. The former is an exercise which can be carried out using ship-handling simulators, where pilots are asked to navigate vessels in a specified navigational environment and to judge collision risks at various stages of the navigation. The difficulty in a simulation exercise is the amount of resources needed for a sufficiently large number of pilots to ensure a sound statistical analysis. On the other hand, the survey method involves conducting questionnaires among pilots by generating a suitable platform for them to judge collision risk. In this case, the proximity indicators would be used to define the navigational conditions, and pilots would specify the level of their perceived risk under various conditions of DCPA and TCPA. The survey method allows a high amount of respondents to be obtained easily for a proper statistical analysis. Therefore, the survey method is employed in this research.

To collect perceived risk data, it is necessary to develop a two-way risk matrix, defined by different values of the proximity indicators. The appropriate values of DCPA and TCPA used in classifying the different navigational situation were determined based on the expert input of several experienced pilots in a preliminary survey. Based on the outcome of the preliminary survey, a 5 x 5 risk matrix is formulated, representing five threshold values of TCPA $\in (1,3,5,10,20)$ minutes and five values of DCPA $\in (1,2,5,7,10)$ cables length[1]. Pilots are asked to indicate their level of perceived risk of collision in terms of Safe, Low Risk, Moderate Risk, High Risk and Very High Risk, for each of the 25 combinations of DCPA and TCPA. The perceived risk are needed to be collected separately for the day and night conditions. A copy of the designed survey is shown in Appendix A.

3.2.2 METHOD OF MEASURING COLLISION RISK IN A WATERWAY

The preceding section shows the method of obtaining the $C_{\max}$ value in an interaction. To measure collision risk in a waterway, $C_{\max}$ values of all interactions in the waterway need to be obtained for a specified time period. Since the $C_{\max}$ values are obtained from continuous measurement of $C(t)$, it is necessary to truncate the measurement at some point in order to eliminate the interactions which do not produce

[1] 1 cable length = 0.1 nautical mile

any significant risk of collision. The truncation point can be defined by employing the concept of Ship Domain (SD), which is the surrounding effective waters around a vessel that a pilot wants to keep clear of other vessels (Goodwin, 1975). It means that a pilot senses there is a risk of collision only if another vessel penetrates his vessel's domain. Therefore only the interactions, where one vessel is within the SD of the other, are considered for conflict analysis. These interactions are termed as 'encounter' throughout this thesis.

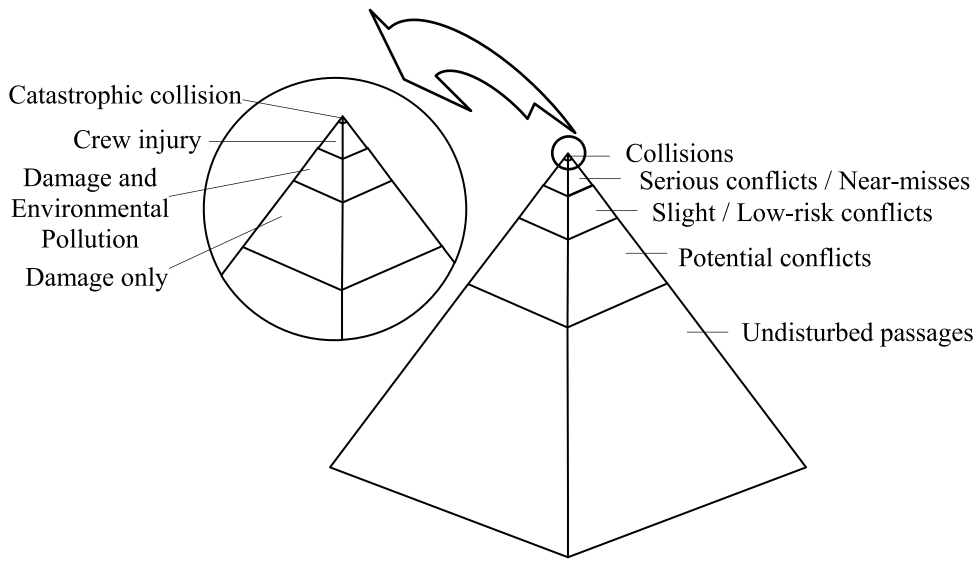

Figure 3.3 A Safety Pyramid of Navigational Traffic Events

To characterize the conflict severities of the encounters in a waterway, a probability distribution function (PDF) of C_{max} can be obtained. Since the C_{max} values are truncated at SD in each encounter, a set of truncated distributions need to be chosen to examine their fitness with the observed C_{max} values. Based on the traffic safety pyramid proposed by Hyden (1987), the frequency distribution of conflict severity observations would be skewed to the right, i.e., higher frequencies for smaller C_{max} values (lower risk) and vice versa. A similar safety pyramid for navigational traffic is presented in Figure 3.3. The right skewed distribution pattern of conflict severity observations is also found in Chin et al. (1991). To obtain a similar distribution, the measure of conflict severity can be used as $C'_{max} = (1/(1 - C_{max}))$. Since C_{max} ranges from 0 (safe, obtained at SD boundary) to 1 (extreme collision risk), the distribution of C'_{max} is left-truncated at $C'_{max} = 1$ and is asymptotic towards right. Therefore, for the distribution fitting exercise the following truncated distributions can be prescribed: negative exponential, gamma, weibull, lognormal, and loglogistic. Table 3.2 presents the cumulative distribution functions (CDF) of the distributions.

Table 3.2 Cumulative Distribution Functions of Proposed Distributions

Truncated Distributions	Cumulative distribution functions, $F_{C'_{max}}(C'_{max})$
Negative exponential	$p(0) + [1 - p(0)] \left[1 - e\left\{-\frac{C'_{max} - \theta}{b}\right\}\right]$
Gamma	$p(0) + [1 - p(0)] \int_{\theta}^{\tau} \frac{1}{\Gamma a \times b^{a}} (q - \theta)^{a-1} e^{\frac{-(q-\theta)}{b}} dq$
Weibull	$p(0) + [1 - p(0)] \left[1 - \exp\left\{-\left(\frac{C'_{max} - \theta}{b}\right)^{a}\right\}\right]$
Lognormal	$p(0) + [1 - p(0)] \int_{\theta}^{\tau} \frac{1}{\sqrt{2\pi}\ b(q - \theta)} \exp\left[-\frac{(\ln(q - \theta) - \gamma)^2}{2b^2}\right] dq$
Loglogistic	$p(0) + [1 - p(0)] \left[\frac{1}{1 + \exp\left[-\left\{\frac{\ln(C'_{max} - \theta) - \gamma}{b}\right\}\right]}\right]$

To examine which distribution fits the observed data best, the Anderson-Darling (AD) test can be employed. The test statistics (AD^2) measures how well the data follow a particular distribution (see Stephens, 1974). The statistics is obtained as

$$AD^2 = \sum_{n=1}^{N} \frac{1-2n}{N} \left[\ln\left(F\left[D_n\right]\right) + \ln\left(1 - F\left[D_{N+1-n}\right]\right) \right] - N \tag{3.8}$$

where N is the number of observations; $F(\cdot)$ is the CDF of the tested distribution; and D is the observation values sorted in ascending order. The statistics is compared against its critical values at specified significance level in order to examine fitness of the distributions (see Stephens, 1974).

Once the PDF of $C'_{\max}$, $f_{C'_{\max}}(C'_{\max})$ is obtained, its CDF $F_{C'_{\max}}(C'_{\max})$ can be obtained by considering the proportions of non-conflict and conflict encounters. The non-conflict encounters, where vessels have diverging trajectories although one vessel is within the SD of the other, correspond to negative TCPA values and are represented by a probability mass function (PMF) $p(0)$. In contrast, the conflict encounters, where the measured TCPA is non-negative, are represented by $f_{C'_{\max}}(C'_{\max})$. Therefore, the area under the $f_{C'_{\max}}(C'_{\max})$ is equal to $[1 - p(0)]$, which yields

$$F_{C'_{\max}}(C'_{\max}) = p(0) + [1 - p(0)] \int_{C_{SD}}^{C'_{\max}} f_{C'_{\max}}(q)\,dq \tag{3.9}$$

where C_{SD} is a constant value (= 1) of $C'_{\max}$ at truncation point (i.e., at SD).

Since $C'_{\max}$ represents the severity of conflict, the area under the tail end of $f_{C'_{\max}}(C'_{\max})$ (as shown in Figure 3.4) can be employed to measure collision risk in terms of probability of serious conflict per encounter. This can be accomplished by setting a threshold value (τ) of $C'_{\max}$ which will separate the serious conflicts from the non-serious ones (see Chin and Quek, 1997). A serious conflict corresponds to an encounter that may pose risk of a certain collision. Therefore, the risk of collision in a waterway can be expressed as

$$P_c = p(C'_{\max} > \tau) = 1 - F_\tau(\tau) \tag{3.10}$$

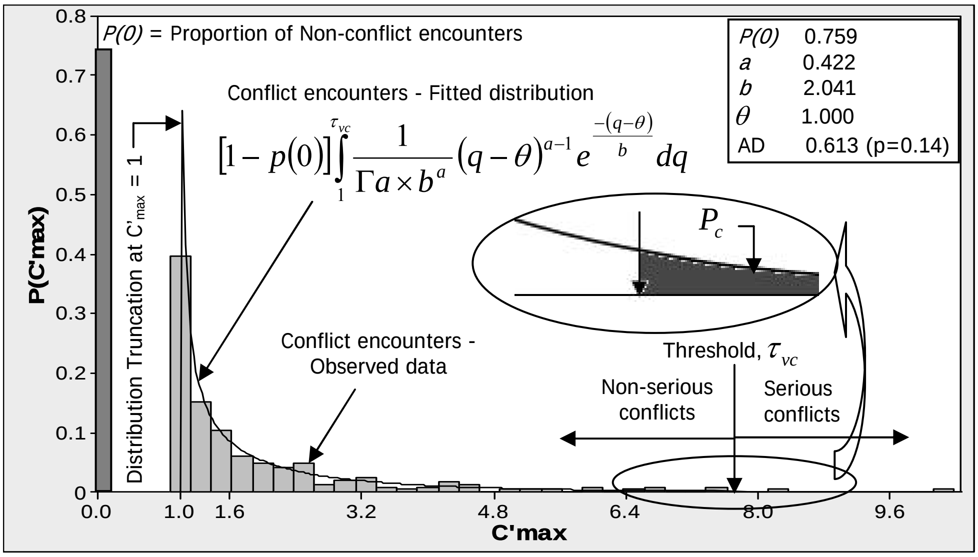

Figure 3.4 A Typical PDF of $C'_{\max}$ showing Distribution Truncation and Serious Conflict Threshold

As discussed in Section 3.2.1.2, the risk of collision in any vessel interaction may vary with the size of vessels involved. In order to consider the effects of vessel sizes in computing collision risk, it is necessary to consider a distribution of threshold values instead of a single threshold. The distribution may be obtained by clustering vessels into several vessel classes (VC). The risk of collision is then expressed as

$$P_c = p\left(C'_{\max} > \tau_{VC}\right) = \sum_{vc=1}^{V} \left[1 - F_{\tau_{vc}}\left(\tau_{vc}\right)\right] \times p_{vc} \tag{3.11}$$

where p_{vc} is the PMF of VCs, τ_{vc} is the threshold value for vessel class *vc*, *V* is the number of VCs.

The P_c represents collision risk in terms of probability of serious conflict per encounter at a specific time period in a waterway. It could be used as an indicator of the state of safety in that waterway. For this reason, it may be directly employed to compare safety among waterways or time periods, or to evaluate a before-and-after study of navigational facilities.

3.2.3 METHOD OF MODEL VALIDATION

As discussed in Section 2.3.4, it may be a futile exercise to validate the proposed conflict model based on correlations of measured conflicts and observed collisions. Therefore, it is attempted to validate the model by evaluating correlations between the measured risks of collision in waterways and those perceived by pilots. This approach of model validation does not need to rely on observed collision records, thus retains the proactive nature of the modeling technique. Moreover, conceptually it is sensible to compare the measured and perceived risks as pilots are very familiar with port waterways, and thus have sufficient knowledge regarding the actual risks in waterways. By analyzing pilot's perceived risks in fairways, Debnath and Chin (2009) have also concluded that pilots seem to have reasonable grasp of the characteristics of collision risks in fairways.

To compute the correlations between measured collision risks and pilots' perceived risks, the Pearson correlation coefficient (see Long and Freese, 2006) can be employed. The coefficient is given by

$$\rho_{MR,PR} = \frac{\sigma_{MR,PR}}{\sigma_{MR}\sigma_{PR}} \tag{3.12}$$

where *MR* and *PR* are two random variables representing the measured risk and the perceived risk respectively; σ_{MR} is the standard deviation of *MR*; σ_{PR} is the standard deviation of *PR*; $\sigma_{MR,PR}$ is the covariance between *MR* and *PR*.

The correlation is 1 in the case of an increasing linear relationship, −1 in the case of a decreasing linear relationship, and some value in between in all other cases, indicating the degree of linear dependence between the variables. The closer the coefficient is to either −1 or 1, the stronger the correlation between the variables.

To gain information on pilot's perceived risks in waterways, it is necessary to conduct a risk perception survey. The design process of the survey is discussed in the following section.

3.2.3.1 Perception Survey on Collision Risk in a Waterway

To facilitate the perception process of pilots a five-point scale is developed based on the 'likelihood of a close quarter situation (CQS) in a waterway', as presented in Table 3.3. A CQS is a critical incident that poses risk of collision but not necessarily involve a collision. Conceptually, it is similar to a serious conflict. Since pilots are more familiar with the term 'CQS', it is used in this survey. It is reasonable to assume that the risk of collision is higher when the likelihood of CQS is higher.

In this survey, a total of 15 fairway sections, 9 anchorage clusters and 5 intersections in Singapore port are considered. These waterways are further described in Section 4.2. Pilots are asked to indicate their level of perceived risk of collision in terms of the five risk levels used in the scale. To obtain representative risks for navigation in day and night, the perceived risks are needed to be collected separately for day and night conditions. A copy of the survey form (showing a set of waterways) is presented in Appendix A.

Table 3.3 Scale of Perceived Collision Risk in a Waterway

Score	Risk level	Likelihood of a close quarter situation in a waterway
1	Safe	Very unlikely
2	Low risk	Unlikely
3	Moderate risk	Moderate chance
4	High risk	Likely
5	Very high risk	Very likely

In designing the survey, considerations need to take into account potential biases in perceived risks. Four general sources of biases, identified by Weinstein (1987) and Fischhoff et al. (1993), are carefully examined in the design process. The first is 'unwarranted optimism bias', which indicates that people tend to be excessively optimistic and overconfident while judging likelihood of own involvement in risky events. This could lead pilots to overrate their pilotage skills and to consider themselves as less likely to be involved in risky events. To avoid this bias in this survey, the pilots are asked to perceive risks in such a way that it does not relate to the risk of their own involvement. They are asked to perceive the overall risks in waterways so that these could reflect the actual risks in the waterways.

The second is 'anchoring bias' in which respondents tend to anchor their risk estimates around some known values of actual risk (e.g., from collision statistics). In this survey, no statistics are provided so that pilots will not make biased responses.

The third is 'availability bias' and this is the bias that could result from collision experiences or disproportionately available information regarding collisions in media, such as highlighted news which are easily remembered. Therefore, a pilot, who has experienced a collision in a particular waterway or read/seen news regarding collisions in media, could rate higher collision risk in that waterway, compared to a pilot who has no such experience or information. In order to avoid this potential source of bias, pilots are asked to perceive risks from their judgments regarding likelihood of CQSs in waterways. The reason of using the CQSs, instead of collisions, is that the CQSs are likely to occur considerably more frequently than collisions. This increases the probability of having CQS experiences for all pilots, whereas their chance of having collision experiences is very low. Thus, most of the pilots could have CQS experience, resulting in a uniform bias in their perceptions. Moreover, CQS are usually not reported in media, thus reducing the chances of obtaining disproportionately available information.

The fourth bias is the tendency of respondents to overestimate the risk of very rare events and to underestimate the risks of events that occur very frequently. Since collisions are very rare events, using them as basis in risk perception could result is biased perceptions. On the other hand, the CQSs do not occur very frequently so that the perceptions could be biased due to underestimation. Thus, using the CQS as basis in risk perception could reduce this bias.

3.3 RISK PREDICTION MODEL

Risk of collision in a waterway can be expressed in different ways for various purposes. Some studies represented the risk of collision based on collision frequencies, whereas some used the consequences of collisions (i.e., injuries and fatalities) to represent it. However, as discussed in Chapter 2, this collision-data-based approach suffers from several serious limitations. The major limitation is that it is difficult to obtain statistically sound inferences from analysis of collision records due to the very infrequent nature of collision occurrence leading to low number of observations. To overcome this limitation, a possible way of expressing collision risk is to focus on conflict occurrence, instead of relying on collision occurrence. As shown in Section 3.2, risk of collision can be expressed as the probability of serious conflict per vessel encounter. In other words, collision risk in a waterway is the proportion of the number of serious conflicts and the number of total encounters in that waterway.

As reviewed in Chapter 2, a binomial logit/probit model is an appropriate choice to model a binary or proportional response variable. Taking risk of collision at different time periods in a waterway as response variable, these models consider each 'waterway'-'time period' combination as a unit of observation. An underlying assumption of such a model is that all the observation units are independent of each other. However, this assumption is not valid because collision risks at different time periods in a particular waterway are likely to be correlated due to the fixed characteristics of waterway over the time periods (e.g., geometric and regulatory control characteristics). In order to take the correlated data structure into consideration in predictive modeling of collision risk, a hierarchical regression model can be useful.

A hierarchical regression model allows potential correlation among observation units within a panel (i.e., hierarchical data structure) to be correctly specified and estimated (Snijders and Bosker, 1999). A good number of applications of this modeling technique can be found in sociological research disciplines. In traffic safety research, Jones and Jorgensen (2003) presented a good exploration and discussion on the potential applications of this technique.

To develop a prediction model of collision risks at day and night time periods in different waterways, a model with properly specified hierarchical data structure is necessary. A binomial logistic model is proposed that could account for the correlations among within panel observations. A systematic procedure of evaluating the model is employed in order to assess the existence of overdispersion and the fitness of a best-fitted model, which is obtained through a process of model comparison by using Akaike Information Criteria. In this section, the formulation of the model is discussed. An illustration of the modeling technique will be presented in Chapter 5.

3.3.1 MODEL FORMULATION

A Binomial Logistic Model (BLM) is appropriate to use when the response variable is a dichotomy (an event occurred or not) or a proportion (number of events occurred with a particular outcome divided by total number of events). In this research, the response variable, which expresses the risk of collision in a waterway as the probability of a serious conflict in an encounter, is proportional in nature.

An encounter *e* at time *t* in waterway *w* can have two possible forms: serious conflict (Y_{ewt} = 1) and non-serious conflict (Y_{ewt} = 0). The probability that a serious conflict will occur is $p_{ewt} = \Pr(Y_{ewt} = 1)$, which follows a binomial distribution. Since the p_{ewt} is restricted within the range $[0, 1]$, the probability is transformed into the logarithm of the odds, $Logit(p_{ewt}) = \log(p_{ewt}/(1 - p_{ewt}))$, which ranges from $-\infty$ (p_{ewt} = 0) to ∞ (p_{ewt} = 1). The BLM is obtained by treating the logit transformation as a link function in the generalized linear model framework (see Hardin and Hilbe, 2007 for a detailed description of such models),

$$\log\left(\frac{p_{ewt}}{1 - p_{ewt}}\right) = \boldsymbol{\beta}\mathbf{X}_{ewt} \tag{3.13}$$

where $\mathbf{X}_{ewt}$ is a vector of explanatory variables and $\boldsymbol{\beta}$ is the vector of unknown parameters explaining effects of the explanatory variables.

The probability that a serious conflict will occur is then expressed as

$$p_{ewt} = \frac{\exp(\boldsymbol{\beta}\mathbf{X}_{ewt})}{1+\exp(\boldsymbol{\beta}\mathbf{X}_{ewt})} \tag{3.14}$$

The BLM can also be applied to model a proportional response variable. Suppose, in a waterway w at time period t, y_{wt} is the number of serious conflicts and n_{wt} is the total number of encounters. The y_{wt} follows a binomial distribution, $f(y_{wt}; n_{wt}, p_{ewt})$. Therefore, the expected number of serious conflicts in waterway w at time period t is

$$E(y_{wt}) = n_{wt}\, p_{ewt} \tag{3.15}$$

The proportional response variable, y_{wt}/n_{wt} , is then equivalent to p_{ewt} as

$$E(y_{wt}/n_{wt}) = p_{ewt} \tag{3.16}$$

As shown in Equation 3.14, the p_{ewt} can be modeled by employing a BLM. Therefore, the BLM can be employed to model the proportional response variable as well.

An alternative to the BLM is the Binomial Probit Model (BPM) that uses a standard cumulative normal distribution function to explain the p_{ewt}. Since the normal and the logistic distribution have similar shapes, the models produce very similar results. Although theoretically there is no compelling reason to prefer one model over another, in practice, the BLM is chosen for this research because it allows interpreting the effects of explanatory variables as Odds Ratio (O.R.).

In order to interpret the effects of explanatory variables, the exponential of the regression coefficients, i.e., $\exp(\beta)$ can be calculated to obtain O.R.. This provides a basic interpretation for the magnitude of β: if O.R. is less than 1.0, a unit increase in an explanatory variable will reduce the odds of a serious conflict by a multiplicative effect of $\exp(\beta)$ and vice versa. In case of categorical variables, $\exp(\beta_a - \beta_b)$ can be calculated which represents the O.R. between two categories, a and b for comparison purpose.

3.3.2 CONSIDERATIONS FOR HIERARCHICAL DATA

In the presence of within-panel correlation in response variable, models without appropriately considering the hierarchical data structure may yield biased results. The correlation of the observations within a panel violates the assumption in an Ordinary Regression Model (ORM), such as the BLM, that all observations across all panels are independent. When this assumption is violated, the ORM underestimates the standard errors of the regression coefficients. This underestimation results in obtaining falsely significant results (Allison, 1999). A hierarchical model, on the other hand, takes into consideration the correlated structure of observations in estimation of the standard errors.

Risks of collision at different time periods (i.e., day and night) in a particular waterway are likely to be correlated. This is because of the fixed characteristics of the waterway over the time periods (e.g., geometric and regulatory control characteristics). To account for this within-waterway correlation, two possible formulations of the BLM can be proposed: Random intercept BLM and BLM with modified sandwich variance matrix. These formulations are discussed in the subsequent sections.

3.3.2.1 Random Intercept Binomial Logistic Model

In a Random Intercept BLM (RIBLM), the intercept of the model is allowed to differ across clusters (i.e., fairways), whereas the intercept is kept constant in a BLM. Thus, the structural form of a BLM can be modified to obtain a RIBLM as (see Snijders and Bosker, 1999 for detailed description of such models):

$$\log\left(\frac{p_{wt}}{1-p_{wt}}\right) = \beta_{0w} + \boldsymbol{\beta}_1 \mathbf{X}_{1wt} + \boldsymbol{\beta}_2 \mathbf{X}_{2w} \tag{3.17}$$

where p_{wt} is the probability of serious conflict in waterway *w* at time *t*, β_{0w} is the intercept that differs across clusters *w*, $\mathbf{X}_{1wt}$ and $\mathbf{X}_{2w}$ are vectors of explanatory variables related to waterway (level-2) and time periods (level-1) respectively, $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are the corresponding vectors of unknown parameters explaining effects of explanatory variables.

In the RIBLM, the within-fairway correlation is specified as

$$\beta_{0w} = \alpha + u_w \tag{3.18}$$

where α is the average intercept across all time periods and all waterways, and u_w is the unobserved random effects of waterway *w* assumed to follow normal distribution with mean zero and variance σ_u^2, as suggested by Snijders and Bosker (1999).

While a RIBLM specifies the correlated data structure correctly, there is a tradeoff of using this model. A RIBLM requires more complex computations, and consequently longer time to converge, in comparison with a BLM. In addition, if a large set of explanatory variables is included in the model with low numbers of panels and within-panel observations, model convergence may not be achieved.

3.3.2.2 Binomial Logistic Model with Modified Sandwich Variance Matrix

Another possible and simpler approach of taking into consideration the within-waterway correlations is to employ a BLM while specifying the hierarchical data structure for computation of standard errors. Instead of including a random effect parameter in the model, the standard errors are computed separately from model estimation in this approach. The key idea is that since an ordinary BLM underestimates standard errors in a correlated data structure, this approach computes the standard errors by treating the correlations and keeps the other computations similar to an ordinary BLM. Thus, this configuration of the BLM produces the same estimates of the coefficients as are estimated by an ordinary BLM, but the standard errors and confidence intervals are estimated by considering the within-waterway correlations.

In this approach, a BLM uses a modified sandwich (also known as Clustered Robust or Clustered Huber) variance matrix to find the maximum likelihood estimates while treating the correlated data structure (see Hardin and Hilbe, 2007 for details). The matrix has a score factor, $\hat{B}_{MS}$, sandwiched between two copies of Hessian matrix, which is usually used in estimating parameters of an ordinary BLM, as

$$\hat{V}_{MH} = \hat{V}_H^{-1} \hat{B}_{MS} \hat{V}_H^{-1} \tag{3.19}$$

where if each panel w (i.e., waterway) contains T_w observations (i.e., time periods), $\mathbf{x}_{wt}$ refers to the row of the matrix **X** associated with the t^{th} observation for subject w, $\hat{\phi}$ is the scale parameter, η is the linear predictor = $\boldsymbol{\beta}\mathbf{X}$, and μ_{wt} is the expected number of serious conflicts in waterway w at time period t (= $n_{wt}\, p_{ewt}$), the score factor is given as

$$\hat{B}_{MS} = \sum_{w=1}^{W} \left\{ \sum_{t=1}^{T_w} \mathbf{x}_{wt}^{\mathrm{T}} \frac{y_{wt} - \hat{\mu}_{wt}}{\mathrm{V}(\hat{\mu}_{wt})} \left(\frac{\partial \mu}{\partial \eta} \right)_{wt} \hat{\phi} \right\} \left\{ \sum_{t=1}^{T_w} \frac{y_{wt} - \hat{\mu}_{wt}}{\mathrm{V}(\hat{\mu}_{wt})} \left(\frac{\partial \mu}{\partial \eta} \right)_{wt} \hat{\phi} \mathbf{x}_{wt} \right\} \tag{3.20}$$

The Hessian matrix is expressed as

$$\hat{V}_H = \left(- \frac{\partial^2 \ell}{\partial \beta\, \partial \beta^{\mathrm{T}}} \right)^{-1} \tag{3.21}$$

where $\ell = \sum_{w=1}^{W} \sum_{t=1}^{T_w} \left\{ y_{wt} \ln\left(\frac{\mu_{wt}}{1 - \mu_{wt}} \right) + n_{wt} \ln(1 - \mu_{wt}) + \ln\binom{n_{wt}}{y_{wt}} \right\}$ is the log likelihood function of the model.

In maximum likelihood estimation method, the regression coefficients of the BLM are estimated by maximizing the log likelihood function, and the sandwich variance matrix is used to estimate the standard errors and confidence intervals of the coefficients. The main advantages of using this configuration of the BLM are that it is a less complex method and model convergence can be achieved with a smaller number of panels and observations, compared to a RIBLM.

3.3.3 MODEL EVALUATION

An important part of statistical modeling is evaluating the appropriateness and fitness of a model by employing various hypothesis tests and goodness-of-fit statistics. The tests and statistics used in this research are discussed in this section.

3.3.3.1 Overdispersion Assessment

Overdispersion is a primary problem in modeling discrete response variable. It generally occurs when the variance of the response variable is greater than the nominal variance. The problem with overdispersion is that it may cause underestimation of standard errors of the regression coefficients which will lead to obtaining falsely significant results. Therefore, it is necessary to assess if a discrete-response model is overdispersed.

Existence of overdispersion can be identified by observing the value of the dispersion statistics (Hardin and Hilbe, 2007),

$$\psi = \frac{-2\phi\left(LL(\beta) - LL(F)\right)}{N - k} \tag{3.22}$$

where ϕ is the scale parameter (equal to 1 for a binomial variance model), $LL(\beta)$ is the log-likelihood of the model in consideration, $LL(F)$ is the log-likelihood of a fully-specified model (a model with as many independent parameters as observations), N is the total number of observations and k is the number of parameters to be estimated. A value of ψ greater than 1.0 indicates existence of overdispersion. As suggested by Hardin and Hilbe (2007), a small amount of overdispersion is of little concern. However, if ψ greater than 2.0, then an adjustment to the standard errors is necessary.

3.3.3.2 Model Comparison

Selecting the most parsimonious model among a set of competing models is one of the objectives of statistical modeling. The general principle is that the best model is the one with least complexity among various models with different number of parameters. Since increasing complexity is accompanied by a better fit, models are compared by trading off these two quantities. A common procedure of comparing models is using the Akaike Information Criteria (AIC), developed by Akaike (1973). The AIC statistics is given by

$$AIC = -2LL(\beta) + 2k \tag{3.23}$$

where $LL(\beta)$ is the log-likelihood value of the candidate model at convergence and k is the number of parameters to be estimated. The better model will result in a smaller AIC value (Joshua and Garber, 1990). Starting with a full set of explanatory variables, a systematic procedure to eliminate the insignificant variables one at a time may be employed by comparing the different AIC values. The resulting model with minimum AIC value may be considered the best-fitted and most parsimonious model.

3.3.3.3 Model Fitness Assessment

Another important step of model evaluation is to examine the significance of the explanatory variables obtained in the best-fitted model. To test whether an estimated regression coefficient is significantly different from zero or not, the z-test is usually employed. Furthermore, to evaluate if the best-fitted model have sufficient explanatory and predictive power, several goodness-of-fit statistics are used (see Long and Freese, 2006 for a list of such statistics).

To measure the overall goodness-of-fit, the likelihood ratio statistics (G^2) is used. This statistics is given by

$$G^2 = 2[LL(\beta) - LL(0)] \tag{3.24}$$

where $LL(\beta)$ and $LL(0)$ are the log-likelihoods of the best-fitted model and the null model respectively. Since G^2 follows a χ^2 distribution, it is compared against a critical value of a χ^2 distribution at a specified level of significance. A value of G^2 higher than the critical value rejects the global null hypothesis that all coefficients except the intercept of the model are zero.

To examine the predictive power of the model, the log-likelihood ratio index, a measure of statistical fitness used for an indication of the additional variation of an obtained model compared to a null model, can be employed. However, it has an undesirable characteristic that for the same data set, it will increase whenever new variables are added to the model (Ben-Akiva and Lerman, 1985). To overcome this problem, the adjusted log-likelihood ratio index is used which is expressed as

$$\rho_{adj}^2 = 1 - \frac{LL(\beta) - k}{LL(0)} \tag{3.25}$$

3.4 SUMMARY

This chapter presented the methodology of this research. Two models were formulated for measuring the level of collision risk in a waterway and understanding the relationships between the risks and waterway characteristics.

A risk measurement model was formulated that measures risk of collision in a waterway by analyzing critical traffic interactions. In the formulation, a method of measuring collision risk in an interaction was developed first which employs an ordered probit model to model the risks as a function of two proximity indicators. A perception survey was designed for calibration of the ordered model. A method of measuring collision risk in a waterway was developed next that statistically characterizes the measured risks collectively. Several statistical distributions including the negative exponential, gamma, weibull, lognormal and loglogistic were proposed for characterizing the risks. Anderson Darling test was employed to examine the goodness-of-fit of the distributions. To validate the risk measurement model, a framework was developed that evaluates the correlations between the measured risks and those perceived by pilots. To collect the perceived risk data, another perception survey was designed. The technique of risk measurement modeling is illustrated later in Chapter 4.

For explaining the relationships between the risks of collision in waterways and the geometric, traffic and regulatory control characteristics of waterways, a risk prediction model was proposed. A systematic method of model formulation, calibration and evaluation was developed for this purpose. In the formulation, a binomial logistic model with considerations for hierarchical data structure was developed that accounts for the potential correlations in risks at different time periods in a waterway. For evaluating model fitness, predictive power and existence of overdispersion, several goodness-of-fit statistics were employed. The modeling technique is illustrated later in Chapter 5.

CHAPTER FOUR
ILLUSTRATION AND VALIDATION OF RISK MEASUREMENT MODEL

4.1 INTRODUCTION

A model for measuring collision risks in port waterways was presented in Chapter 3. In this chapter, the modeling technique is illustrated and validated using Singapore port data. Following a description of the waterways (i.e., fairways, anchorages and intersections) in Singapore port waters, the collection and preparation procedure of the data necessary for the model is discussed first. The results of risk measurement in an interaction is presented then, followed by the results of measured risks in the waterways. The risk measurement model is validated afterwards before providing a summary of this chapter.

4.2 DESCRIPTION OF SINGAPORE PORT WATERS

The port of Singapore is a mega transshipment hub and one of the busiest sea ports in the world. Every year it receives calls from about 130,000 vessels totaling about 1.5 billion gross tonnage. Use of modern facilities in port operations and traffic management has consistently helped it to achieve top ratings among competitive ports.

Singapore port waters constitute three typical types of waterways – fairways, anchorages and intersections. These waterway types form the traffic network of the port. The fairways serve as links in the network, while the intersections are the nodes. The anchorages provide facilities for anchoring the vessels calling to port terminals or waiting for bunkers. According to the operational definitions of the waterway types (MPA, 2006), the traffic network is composed of 12 fairways and 5 intersections. In addition, a total of 34 anchorages serve the traffic depending on anchoring purposes.

For modeling risks of collision in the waterways, it is necessary to divide them into sections. The fairways can be divided into sections by using two approaches: fixed-length sections or homogeneous sections (see Miaou et al., 1991 for a discussion on dividing roadways). Since fairways and roadways are similar from their functional point of view, the two approaches could be useful in dividing the fairways. Using fixed-length sections, it may be difficult to divide the fairways due to diversity in fairway lengths. In contrast, the concept of homogeneous sections (i.e., sections with approximately uniform geometric and traffic control characteristics) would be useful for this purpose. From operational definitions of fairways, the fairways are divided into 15 approximately homogeneous sections. A map showing the fairway sections (hatched) is presented in Figure 4.1.

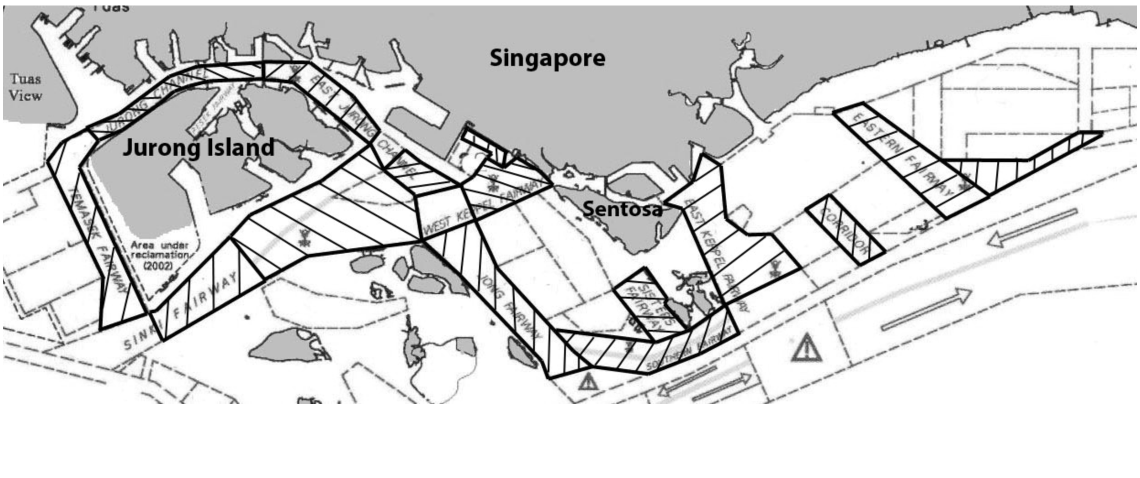

Figure 4.1 Fairways in Singapore Port Waters

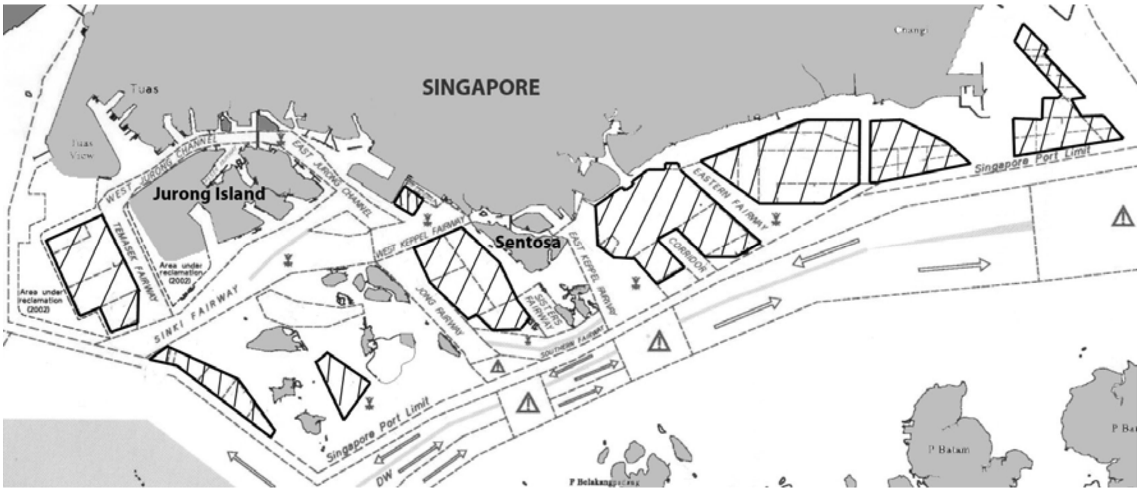

Figure 4.2 Anchorages in Singapore Port Waters

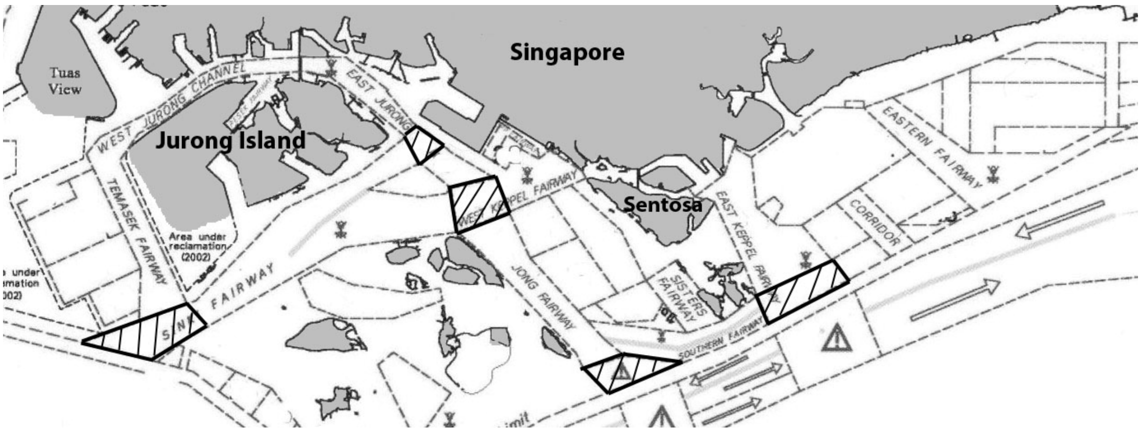

Figure 4.3 Intersections in Singapore Port Waters

Dividing anchorages and intersections is pretty straightforward because of the uniformity in their characteristics. Anchorages are usually well defined on maps and sometimes bounded by navigational aids (i.e., buoys). In general, the anchorages serving similar purposes are clustered together. Therefore, the clusters could be a useful basis of dividing anchorages. A total of 9 clusters are defined (shown in Figure 4.2 as hatched areas). The intersections are defined on the basis of traffic interactions. Cross traffic interactions are allowed only at intersections. Following the directions of traffic movements in the fairways, the water areas attributing cross-traffic interactions are identified. A total of 5 intersections are found, as shown in Figure 4.3 as hatched areas.

4.3 DATA COLLECTION AND PREPARATION

To obtain an overall representative measure of collision risk in a waterway, it is necessary to measure collision risks separately for day and night conditions. This is because navigation is affected by the environment, and in particular, in day and night settings (see Akten, 2004). Furthermore, sufficiently large numbers of conflict observations are necessary in order to obtain a statistically fitted distribution of $C'_{\max}$. Uncertainties in the estimated parameters of the distributions proposed in Section 3.2.2 could be reduced with increased number of observations. Based on a preliminary analysis, traffic movement data of four hour time periods in day and night conditions are taken for the analysis.

Traffic movement data, obtained from the Vessel Traffic Information System (VTIS) database of Singapore port, are analyzed to measure risks of collision in waterways. This data include vessels' positions in coordinates, speeds, headings, and their numeric identities. The kinematic information is usually updated at time intervals of few seconds depending on traffic characteristics, thus the data provides detailed trajectories of vessels. An initial challenge in using the data was to unscramble the VTIS system data as the data is stored in a compact format, which is unrecognized by general computers. A computer program was developed to unscramble the VTIS system data into a computer readable format. Using the developed program, a database of vessels' trajectories is obtained in which the trajectories are chronologically listed in segments of update cycles. The structure of the unscrambled database is shown in Appendix B.

To measure the proximity indicators of encounters and associated risks of collisions, another computer program is necessary for analyzing the unscrambled database. A block diagram showing the steps of a developed program is presented in Figure 4.4.

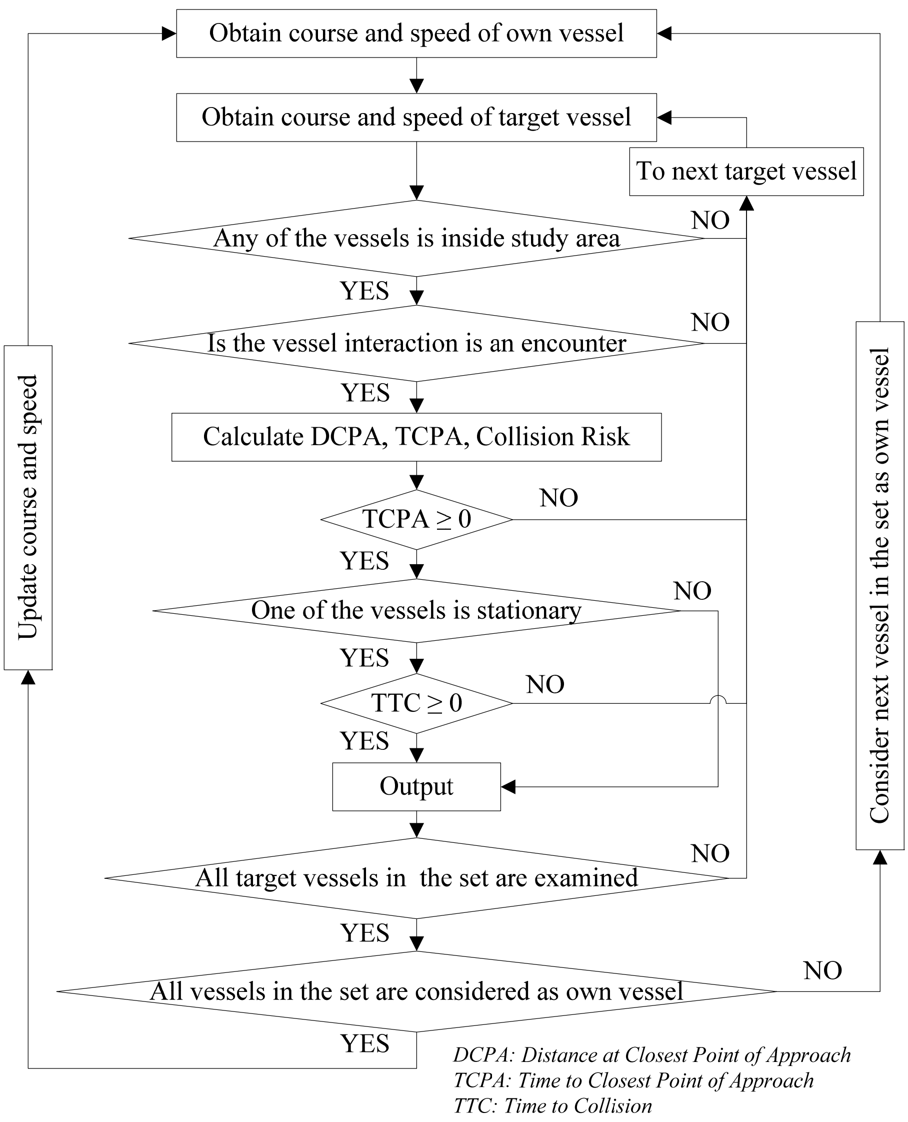

Figure 4.4 Block Diagram of Conflict Analysis

The input information necessary for the analysis are the positions, speeds and bearings of vessels plying in and around a waterway in consideration. By utilizing the input data, the proximity indicators and *C(t)* values are calculated for all possible vessel pairs in a waterway in consideration. To form the pairs, the first vessel in the first update-cycle segment of the database is kept as own vessel, while the rest are considered as target vessel one after another.

Before proceeding to analysis, it is necessary to check whether any of the vessels are inside the waterway as the database contains vessel trajectories whole over the port waters. Further, it is necessary to check if the interaction between the vessels is an encounter which is accomplished by comparing distance between the vessels with the larger vessel's SD radius. From results of a survey conducted on Singapore port pilots (discussed later in Section 4.4), SD radii of four vessel classes[2] are presented in Table 4.1.

Table 4.1 Vessel Categories and Ship Domain in Day and Night Conditions

Vessel category	Description	SD in Day (NM)	SD in Night (NM)
VC 1	If $300 \le GT \le 12000$	1.869	2.308
VC 2	If $12000 < GT \le 20000$	1.889	2.389
VC 3	If $20000 < GT \le 75000$	2.700	3.150
VC 4	If $GT > 75000$	2.947	3.316

NM = Nautical Mile

For encounters involving a stationary vessel, it is important to assess whether the dynamic vessel is likely to hit the stationary one or not. This is because often vessels are anchored near fairway boundary and the fairway vessel may deliberately pass the anchored vessel with a small distance margin while not heading towards the anchored vessel. Such an encounter, which is indicated by a negative TTC, needs to be excluded from the analysis as it may produce false risk of collision. By considering these

[2] Vessels of different sizes would produce different levels of risk in an interaction. In order to consider the effects of vessel sizes on risk of collision, it is necessary to cluster vessels in several classes. The classification based on Singapore port regulations is used in this research.

criteria, *C(t)* value is obtained for a vessel pair. The procedure of obtaining *C(t)* values from the proximity indicators is illustrated in the succeeding section.

Following a similar analysis, the *C(t)* values are obtained for all vessel pairs in all the update-cycle segments within a time period.

4.4 MEASUREMENT OF COLLISION RISK IN AN INTERACTION

To obtain the *C(t)* value in an encounter, it is necessary to develop a relationship between the *C(t)* and the proximity indicators. For this purpose, an ordered probit model was formulated in Section 3.2.1.2. To calibrate this model, a risk perception survey (described in Section 3.2.1.3) was conducted on Singapore port pilots. This section describes the collected perception data, followed by the results of the ordered probit model calibration and evaluation.

4.4.1 RISK PERCEPTION DATA COLLECTION

A total of 160 pilots were given the survey forms. Participation was voluntary and the response is anonymous. A total of 70 respondents completed the survey giving a return rate of 44%. The age of the respondents ranges from 28 to 61 years with a mean and standard deviation of 43.0 years and 9.8 years respectively. The experience of the respondents as harbor pilot exhibits a mean and standard deviation of 11.3 years and 10.9 years respectively, ranging from 3 months to 40 years. The wide range of age and experience in the sample gave quite a good representative picture of the population.

The collected data contains pilots' perceived risk levels for different combinations of the proximity indicators. From the 70 respondents, a total of 1750 data points are obtained. These data are used for calibrating the ordered probit model.

4.4.2 RESULTS OF MODEL CALIBRATION AND EVALUATION

The ordered probit model was calibrated using the maximum likelihood method for each of the vessel class and separately for day and night conditions. Table 4.2 shows the estimated parameters and goodness-of fit statistics of all models.

Table 4.2 Estimates of the Ordered Probit Model

		Ordered probit regression models							
		VC 1		VC 2		VC 3		VC 4	
		Day	Night	Day	Night	Day	Night	Day	Night
Regression estimates of explanatory variables									
DCPA (cables length)									
	Coef.	0.2660	0.2179	0.5611	0.6502	0.2641	0.2710	0.2431	0.2088
	Std. Err.	0.0221	0.0202	0.0487	0.0523	0.0248	0.0248	0.0123	0.0117
	Z-stat	12.01*	10.77*	11.51*	12.44*	10.65*	10.93*	19.82*	17.85*
TCPA (minutes)									
	Coef.	0.1168	0.0902	0.3278	0.2637	0.1151	0.1181	0.1013	0.0892
	Std. Err.	0.0108	0.0096	0.0288	0.0230	0.0119	0.0117	0.0058	0.0056
	Z-stat	10.80*	9.35*	11.39*	11.48*	9.70*	10.07*	17.42*	16.02*
Thresholds									
λ_1	$\hat{\lambda}_1$	0.2716	0.3271	0.7505	1.3021	0.3212	0.5363	0.3732	0.4457
	Std. Err.	0.1489	0.1402	0.2578	0.2364	0.1674	0.1659	0.0833	0.0808
λ_2	$\hat{\lambda}_2$	1.0468	1.2946	2.5342	3.3943	1.5432	1.8126	1.4135	1.5219
	Std. Err.	0.1504	0.1486	0.2743	0.3088	0.1805	0.1857	0.0891	0.0898
λ_3	$\hat{\lambda}_3$	2.1088	1.9947	4.6098	5.9758	2.3581	2.7565	2.3464	2.4159
	Std. Err.	0.1738	0.1627	0.4031	0.4776	0.2039	0.2147	0.1029	0.1027
λ_4	$\hat{\lambda}_4$	3.1519	3.0112	6.9348	8.5806	3.4408	3.9437	3.3680	3.2375
	Std. Err.	0.2058	0.1912	0.5655	0.6476	0.2390	0.2602	0.1200	0.1154
Summary statistics									
# of Obs.		325	325	225	225	250	250	950	950
$LL(0)$		-500.5	-518.4	-334.0	-343.3	-395.0	-395.0	-1510.9	-1505.6
$LL(\beta)$		-378.8	-424.5	-153.9	-150.7	-300.0	-294.4	-1193.9	-1242.7
G^2 (2 df)		243.4	187.8	360.2	385.0	190.1	201.1	634.0	525.7
M&Z R^2		0.583	0.471	0.894	0.887	0.578	0.591	0.527	0.456

* significant at 99% significance level

The likelihood ratio statistics of all models (e.g., 243.4 and 187.8 for VC1-Day and VC1-Night models respectively) are well above the critical value for significance at 99% level of significance, which implies that the models have reasonable good fit. The McKelvey and Zavoina's R^2 values (e.g., 0.58 and 0.47 for VC1-Day and VC1-Night models respectively) also indicate sufficient predictive power for all models.

Both DCPA and TCPA show significant positive association with the latent variable in all models (e.g., for VC1-Day model: β_{DCPA} = 0.27, p < 0.001; β_{TCPA} = 0.12, p < 0.001). This indicates that collision risk decreases if DCPA and TCPA increase.

Table 4.3 Estimated Risk Level Probabilities and Collision Risks (at DCPA = 1 cable length, TCPA = 2 minutes)

Vessel class	Day						Night					
	Predicted probability from model estimates					Col. risk	Predicted probability from model estimates					Col. risk
	VHR	HR	MR	LR	SAFE		VHR	HR	MR	LR	SAFE	
VC1	0.4099	0.2981	0.2383	0.0498	0.0040	0.858	0.4716	0.3433	0.1298	0.0507	0.0045	0.869
VC2	0.3205	0.5857	0.0935	0.0003	0.0000	0.902	0.5495	0.4372	0.0133	0.0000	0.0000	0.928
VC3	0.4313	0.4216	0.1159	0.0296	0.0016	0.887	0.5116	0.3925	0.0836	0.0120	0.0003	0.900
VC4	0.4711	0.3623	0.1379	0.0269	0.0017	0.881	0.5233	0.3484	0.1070	0.0191	0.0022	0.901

VHR: Very High Risk; HR: High Risk; MR: Moderate Risk; LR: Low Risk

Table 4.4 Risk Scores for Risk Levels

Vessel class	Day			Night		
	RS_{HR}	RS_{MR}	RS_{LR}	RS_{HR}	RS_{MR}	RS_{LR}
VC1	0.9138	0.6679	0.3309	0.8914	0.5701	0.3376
VC2	0.8918	0.6346	0.3353	0.8483	0.6044	0.3036
VC3	0.9066	0.5515	0.3147	0.8640	0.5404	0.3010
VC4	0.8892	0.5803	0.3033	0.8623	0.5299	0.2538

RS_{HR}: Risk score for High Risk level; RS_{MR}: Risk score for Moderate Risk level; RS_{LR}: Risk score for Low Risk level

By utilizing the regression estimates in Equation 3.7, risk of collision in an interaction can be obtained. This is illustrated for DCPA = 1 cable length and TCPA = 2 minutes, as shown in Table 4.3. A comparison of the risks with the scores of the risk levels (presented in Table 4.4) of all models shows that the risks fall in the HR range (e.g., for VC1-Day model: risk = 0.86 < RS_{HR} = 0.91), which is expected for such small values of DCPA and TCPA. Risks in night conditions are also found to be higher than those in the day, e.g., the risk in night increases by 1.3% for VC1. It is sensible to observe higher risk in night because of the restricted visibility and lack of visual perception in the night condition.

4.5 MEASUREMENT OF COLLISION RISKS IN WATERWAYS

By using the calibrated ordered probit model, the *C(t)* values are obtained for all vessel pairs in all the update-cycle segments. By taking the maximum of *C(t)* values over a time period (i.e., day or night periods) the corresponding $C'_{\max}$ values are extracted. Having extracted $C'_{\max}$ values for all vessel pairs in a waterway, the PDF of $C'_{\max}$ is obtained by examining fitness of the proposed distributions with observed values of $C'_{\max}$. It is obtained through a two step procedure. Firstly, parameters of the proposed distributions are estimated by utilizing the observed data. Secondly, to find the best-fitted distribution, goodness-of-fit of the proposed distributions are examined by using AD test.

Results of the distribution fitting exercise show that a truncated gamma distribution consistently gives the best fit for all waterways in day and night conditions. The $F_{C'_{\max}}(C'_{\max})$ (Equation 3.9) can then be rewritten as

$$F_{C'_{\max}}\left(C'_{\max}\right) = p(0) + \left[1 - p(0)\right]\int_{\theta}^{\tau_{vc}} \frac{1}{\Gamma a \times b^{a}}(q-\theta)^{a-1} e^{\frac{-(q-\theta)}{b}} dq \tag{4.1}$$

where a and b are the estimated shape and scale parameters of the gamma distribution respectively; θ is the threshold parameter representing the truncation value (= 1). A PDF for a typical set of $C'_{\max}$ was shown in Figure 3.4.

Having estimated the parameters in $F_{C'_{\max}}(C'_{\max})$, risk of collision is measured for all waterways in day and night conditions. In this research, the thresholds of serious conflicts for the four vessel classes are defined based on the specifications of the risk levels used in the proposed scale of perceived collision risk in an interaction. Since a serious conflict coincides with the transition from the High Risk level to Very High Risk level, the risk scores of the former level are employed to obtain the thresholds as $1/(1 - RS_{HR})$. By utilizing the thresholds (presented in Table 4.5) in Equation 3.11, risks of collision in the waterways are computed.

Table 4.5 Thresholds for Separating Serious and Non-Serious Conflicts

Vessel Category	Day	Night
VC 1	11.6049	9.2057
VC 2	9.2402	6.5898
VC 3	10.7123	7.3535
VC 4	9.0247	7.2630

The probability of a serious conflict in the fairways is found to vary from 1 in 1 000 000 to 5 in 1 000 encounters in the day condition, while that in the night vary from 1 in 10 000 to 2 in 100 encounters. In the anchorages, the probability varies from 8 in 100 000 000 to 1 in 100 in the day condition, and 1 in 100 000 to 3 in 100 in the night condition. At the intersections, the probability ranges from 8 in 100 000 to 1 in 1 000 and 2 in 1 000 to 7 in 1 000 in the day and night conditions respectively.

Measured risks show that the probability of serious conflict per encounter is higher in night condition, compared to day. In daytime, because of better visibility pilots can readily judge speeds, distances between vessels and even any change of courses in order to perceive risk of collision and mitigate it. On the other hand, in nighttime they need to rely on navigational lights, which could make the perception-mitigation process difficult. This may lead vessels to come closer before taking any evasive actions, resulting in higher collision risks in night.

Measured risks could be employed to compare safety in different waterways and time periods. To further extract meaningful inferences from the risks, measured values for different navigational scenarios can be compared to evaluate safety at those scenarios. For example, if one is interested in evaluating safety in a waterway before and after some changes in its physical or regulatory characteristics, then it can be accomplished by comparing the measured risks for the two scenarios. Modern navigational facilities (e.g., Full-bridge simulator, Electronic chart display and information system simulator) could be useful for such a before-and-after study.

4.6 MODEL VALIDATION

To validate the risk measurement model, correlations between the measured risks and the perceived risks in the waterways for day and night conditions are evaluated. For this purpose, the perception survey (described in Section 3.2.3.1) was conducted on Singapore port pilots in order to collect pilots' perceived risks in the waterways. The respondents of this survey and those of the 'perception survey on collision risk in an interaction' were the same as the two surveys were conducted together.

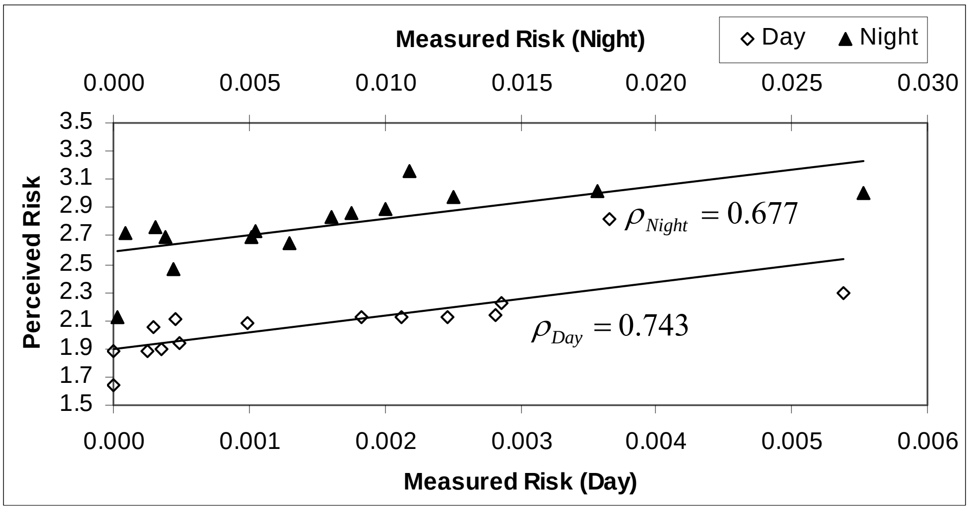

Figure 4.5 Correlations between Measured Risks and Perceived Risks in Fairways

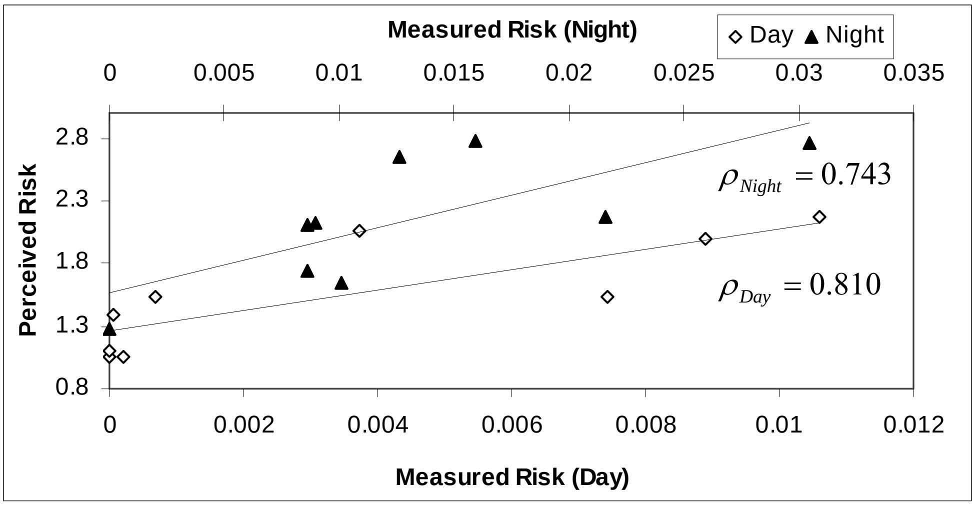

Figure 4.6 Correlations between Measured Risks and Perceived Risks in Anchorages

The correlations between the measured risks and the average perceived risks in the fairways, anchorages and intersections are shown graphically in Figure 4.5, Figure 4.6 and Figure 4.7 respectively. Results show that the $\rho_{MR,PR}$ values for day and night conditions in the fairways are 0.74 (p = 0.002) and 0.68 (p = 0.006) respectively. For anchorages, the coefficients are found as 0.81 (p = 0.008) and 0.74 (p = 0.022) in day and night conditions respectively. The corresponding coefficients for intersections are found as 0.85 (p = 0.068) and 0.83 (p = 0.079). The reasonably high correlations with acceptable statistical significance imply that the risk measurement model is valid for all of the three types of waterways.

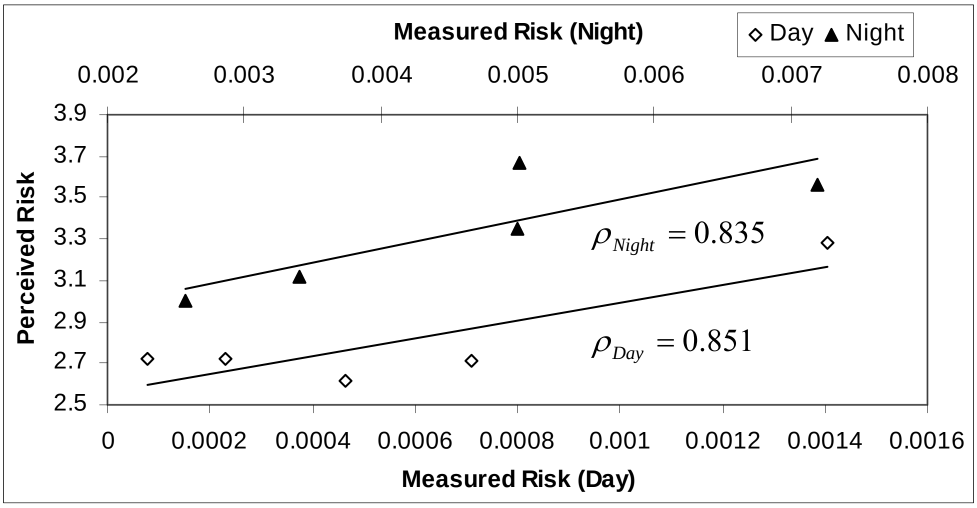

Figure 4.7 Correlations between Measured Risks and Perceived Risks at Intersections

4.7 SUMMARY

The proposed risk measurement was illustrated and validated by using Singapore port data. The illustrative results were presented in this chapter.

To illustrate the risk measurement model, traffic movement data of Singapore port were collected and prepared. Using these data risk of collision in an interaction was measured by employing an ordered probit model. Calibration results of the ordered probit model showed reasonable goodness-of-fit and predictive power. By utilizing the measured collision risks in all interactions in a waterway collectively, the risk of collision in the waterway was measured. To assess the validity of the risk measurement model, correlations between the measured risks and those perceived by pilots were evaluated. Results indicated that the model is valid and could be used for measuring or comparing the levels of collision risks in different waterways. It also indicated that a useful alternative of the historical collision data is the traffic conflicts.

CHAPTER FIVE
CALIBRATION AND EVALUATION OF RISK PREDICTION MODEL

5.1 INTRODUCTION

To develop a model for predicting collision risks in waterways, a Binomial Logistic Model (BLM) with considerations for hierarchical data structure was developed in Chapter 3. In this chapter, the modeling technique is illustrated for Singapore port waterways. Following a description of the input datasets of the models for different waterway types (i.e., fairways, anchorages and intersections), model calibration and evaluation results are presented. Based on the model estimates, the significant explanatory variables are identified and discussed before providing a summary of the chapter.

5.2 DATASET FOR ANALYSIS

To calibrate the BLM, the measured collision risks in fairways, anchorages and intersections of Singapore port (presented in Chapter 4) are used as response variable. Separate datasets are prepared for the three types of waterways. The explanatory variables include the geometric, traffic and regulatory control characteristics of the waterways and a time indicator. These data are collected from various sources, such as navigational charts, tables and the Singapore port traffic database. The explanatory variables of the model for fairways, anchorages and intersections are discussed in the subsequent sections.

5.2.1 FAIRWAYS

A total of 20 explanatory variables, which are hypothesized to relate to risk of collision in fairway, are considered in the model. A correlation matrix of the variables is examined to identify and avoid multi-collinearity. For the highly correlated variables, only the most significant variable is retained in the analysis. Through this process, three correlated variables are omitted from the dataset. The definitions of the remaining variables, together with their means and standard deviations (S.D.), are presented in Table 5.1.

Table 5.1 Summary of Explanatory Variables in Fairway Model

Explanatory variables	Description	Mean	S.D.
Fairway characteristics			
Fairway boundary			
Shoreline	1 if present, else 0	0.200	0.407
Intersection	1 if present, else 0	0.600	0.498
Anchorage	1 if present, else 0	0.733	0.450
Confined water	1 if present, else 0	0.667	0.479
Local fairway	1 if present, else 0	0.867	0.346
International fairway	1 if present, else 0	0.400	0.498
Water depth	Controlling water depth of navigation (meters)	17.987	9.078
Fairway width	Average width of fairway (meters)	1224.171	693.810
Degree of bend	Cumulative fairway centerline deflections (degrees)	35.200	34.098
Pilot B/D ground	1 if present, else 0	0.400	0.498
Traffic separation scheme	1 if present, else 0	0.133	0.346
Cardinal mark	Number of cardinal marks	0.933	1.552
Isolated danger mark	Number of isolated danger marks	0.133	0.346
Traffic characteristics			
Dynamic ship density	Avg. dynamic ship density in fairway (ships/sq NM)	1.714	1.206
Stationary ship density	Avg. stationary ship density in fairway (ships/sq NM)	1.016	1.565
Operating speed	Average operating speed in fairway (knots)	6.097	3.586
Time variable			
Day/Night	1 if night, 0 if day	0.500	0.509

Since risk of collision in a fairway is likely to be influenced by traffic in its boundary waters, it is necessary to consider the boundary effects. The waters around a fairway are described by six types of boundaries, such as shoreline, intersection, anchorage, confined water, local fairway and international fairway. Confined waters comprise the port terminal berth areas and the low depth waters with scattered land obstacles. The fairways inside port waters are referred to as local fairway, while those outside port waters are referred to as international fairways. The others are defined according to their standard definitions. The boundary waters are defined as binary variables in the model based on their presence.

Geometric characteristics of fairways include the water depth of navigation, average navigable width, the degree of bend (described by the sum of all angular deflection from a straight line extended from the straight fairway section prior to a bend), the presence of pilot boarding/disembarkation ground, the type of traffic (one-way or both way) and whether the traffic separation scheme (TSS) is enforced. Pilot boarding/disembarkation grounds are defined as the waters used by pilots to board or disembark an ocean-going vessel. Presence of TSS represents if traffic streams in a fairway are separated by some between space margins. Due to multi-collinearity, the *type of traffic* is omitted from the analysis.

Characteristics of navigational aids (e.g., navigational buoys/lights) in fairways are represented by four types of such facilities, as specified in the IALA Maritime Buoyage System (IALA, 1980). The types include lateral mark, cardinal mark, isolated danger mark and safe water mark. A lateral mark is used to indicate the navigation channels, particularly to distinguish the preferred channel at the points where a channel divides. A cardinal mark indicates the deepest water side around the mark. An isolated danger mark is used to indicate danger of small area which has navigable water all around it. A safe water mark is used particularly to represent mid channel or landfall marks, where navigable waters are present all around the mark. Lateral marks are represented based on their presence, while the others are described as the number of marks present in fairways. Due to multi-collinearity, the *lateral mark* and the *safe water mark* variables are omitted.

Traffic characteristics of fairways are obtained from the vessel traffic information system database of Singapore port. These include traffic densities, and operating speeds of the fairways. Traffic density is described as the average number of dynamic vessels per square nautical mile and the average number of stationary vessels per square nautical mile, while operating speed represents the average speed of vessels navigating in fairways. The average values are obtained for both the day and night situations. Furthermore, to account for the effects of differences in navigational characteristics at day and night a binary variable representing the two time periods are considered.

5.2.2 ANCHORAGES

A total of 15 explanatory variables, which are hypothesized to relate to risk of collision in anchorage, are considered in the model. Among these variables, three are omitted from the dataset due to multi-collinearity. The definitions of the remaining variables, together with their means and standard deviations (S.D.), are presented in Table 5.2.

The waters around an anchorage are described by five types, such as shoreline, intersection, confined water, local fairway and international fairway, which are defined as binary variables in the model based on their presence. Since *local fairway* and *confined water* are found to be highly correlated, the former one is not considered in the analysis.

Geometric characteristics include the controlling water depth of navigation, presence of pilot boarding/disembarkation ground and the ratio of area to perimeter of anchorage. The *area-perimeter ratio* is preliminarily considered to examine if there is any effect of anchorage shape on collision risk, but it is omitted due to multi-collinearity. In addition, the variable representing presence of pilot boarding/disembarkation ground is omitted from the analysis.

Table 5.2 Summary of Explanatory Variables in Anchorage Model

Explanatory variables	Description	Mean	S.D.
Anchorage characteristics			
Anchorage boundary			
Shoreline	1 if present, else 0	0.667	0.485
Intersection	1 if present, else 0	0.667	0.485
Confined water	1 if present, else 0	0.333	0.485
International fairway	1 if present, else 0	0.667	0.485
Water depth	Controlling water depth of navigation (meters)	16.389	4.164
Cardinal mark	Number of cardinal marks	0.333	0.970
Isolated danger mark	Number of isolated danger marks	0.333	0.485
Traffic characteristics			
Dynamic ship density	Avg. dynamic ship density in anchorage (ships/sq NM)	1.194	0.818
Stationary ship density	Avg. stationary ship density in anchorage (ships/sq NM)	2.693	2.257
Operating speed	Average operating speed in anchorage (knots)	2.419	2.032
Time variable			
Day/Night	1 if night, 0 if day	0.500	0.514

Characteristics of navigational aids are represented by cardinal mark, isolated danger mark and safe water mark. Due to multi-collinearity, the *safe water mark* variable is omitted.

Traffic characteristics include the average density of dynamic ships, the average density of stationary ships and the mean operating speed in anchorages. A binary variable indicating day and night time is also considered to represent the navigational characteristics in the time periods.

5.2.3 INTERSECTIONS

A total of 12 explanatory variables, which are hypothesized to relate to risk of collision in intersections, are considered in the model. Five of these variables are omitted from the analysis due to multi-collinearity. The definitions of the remaining variables, together with their means and standard deviations (S.D.), are presented in Table 5.3.

Table 5.3 Summary of Explanatory Variables in Intersection Model

Explanatory variables	Description	Mean	Std. Dev.
Intersection characteristics			
Intersection boundary			
Anchorage	1 if present, else 0	0.600	0.516
Confined water	1 if present, else 0	0.600	0.516
Lateral mark	1 if present, else 0	0.400	0.516
Cardinal mark	Number of cardinal marks	0.400	0.516
Traffic characteristics			
Dynamic ship density	Avg. dynamic ship density in intersection (ships/sq NM)	1.522	1.130
Operating speed	Average operating speed in intersection (knots)	7.065	0.675
Time variable			
Day/Night	1 if night, 0 if day	0.500	0.527

The boundary waters of an intersection are described by three types, such as anchorage, confined water and international fairway, which are defined as binary variables in the model based on their presence. Due to multi-collinearity, the *international fairway* variable is not considered in the analysis.

Geometric characteristics of an intersection include the controlling water depth of navigation, proportion of two-way approaches and proportion of approaches attributing traffic separation scheme. However, the variables are subjected to the problem of multi-collinearity.

Characteristics of navigational aids are represented by lateral mark, cardinal mark, and precautionary mark. A precautionary mark in an intersection is considered to be present if the intersection is marked with a precautionary sign on navigation chart, while the others follow the previously stated definitions. Due to multi-collinearity, the *precautionary mark* variable is not considered in the analysis.

Traffic characteristics include the average density of dynamic ships and the mean operating speed in intersections. In addition, a binary variable representing day and night periods is considered to represent the navigational characteristics in the time periods.

5.3 RESULTS OF MODEL CALIBRATION AND EVALUATION

The parameters of the BLM were derived using the maximum likelihood estimation method. To avoid excess complexity in the model as the large set of explanatory variables used, the correlations among observations within a waterway panel were modeled using the modified sandwich variance matrix approach, as explained in Section 3.3.2.2.

Starting with a saturated model that includes the full set of explanatory variables, a backward elimination procedure was employed to obtain the most parsimonious model by minimizing the value of AIC. The insignificant variables were omitted one after another starting with the most insignificant one. Estimates of the BLM along with the fitness statistics for the fairway, anchorage and intersection models are presented in Table 5.4, Table 5.5 and Table 5.6 respectively.

Table 5.4 BLM Estimates of Collision Risks in Fairways

Explanatory variables	Effect estimates		Odds ratio	Z-stat	P-value
	Coefficient	S.E.			
Fairway characteristics					
Fairway boundary					
Shoreline	3.0292	0.2905	20.681	10.43	0.000
Intersection	1.1429	0.1526	3.136	7.49	0.000
Confined water	-1.5875	0.2889	0.204	-5.50	0.000
Local fairway	-1.8804	0.1479	0.153	-12.71	0.000
International fairway	3.7602	0.2785	42.956	13.50	0.000
Water depth	-0.1308	0.0121	0.877	-10.78	0.000
Degree of bend	0.0101	0.0012	1.010	8.55	0.000
Cardinal mark	0.1445	0.0399	1.155	3.62	0.000
Isolated danger mark	1.6545	0.2819	5.230	5.87	0.000
Traffic characteristics					
Dynamic ship density	0.4412	0.1479	1.555	2.98	0.003
Stationary ship density	-0.3595	0.1999	0.698	-1.80	0.072
Operating speed	-0.1641	0.0218	0.849	-7.54	0.000
Time variable					
Day/Night	2.2992	0.3357	9.966	6.85	0.000
Model statistics					
Intercept	-7.7939	0.8197		-9.51	0.000
Log-likelihood (null)	-156.375				
Log-likelihood (model)	-34.032				
Likelihood ratio statistics	244.686				
Adj. LL ratio index	0.693				
AIC	96.064				
Dispersion parameter	0.513				

The resulting BLM yields AIC value of 96.1 (fairway), 63.9 (anchorage) and 32.9 (intersection). The corresponding values of the dispersion statistics are 0.51, 0.83 and 0.22 respectively, which indicate that adjustments to the standard errors are not necessary. The likelihood ratio statistics of the models (fairway: 244.7, $p < 0.001$; anchorage: 231.3, $p < 0.001$; intersection: 20.8, $p < 0.001$) are well above their critical values for significance at 95% level of significance, which implies that the models have reasonably good fit. The adjusted log-likelihood ratio index values for the fairway, anchorage and intersection models (0.69, 0.77 and 0.21 respectively) also indicate that the models have sufficient explanatory and predictive power.

Table 5.5 BLM Estimates of Collision Risks in Anchorages

Explanatory variables	Effect estimates		Odds ratio	Z-stat	P-value
	Coefficient	S.E.			
Anchorage characteristics					
Anchorage boundary					
Shoreline	5.5156	0.4307	248.543	12.80	0.000
Confined water	-5.5356	0.4768	0.004	-11.61	0.000
International fairway	3.8023	0.4997	44.803	7.61	0.000
Isolated danger mark	-4.3017	0.6901	0.014	-6.23	0.000
Traffic characteristics					
Operating speed	-0.4991	0.1689	0.607	-2.95	0.003
Time variable					
Day/Night	2.0819	0.8520	8.020	2.44	0.015
Model statistics					
Intercept	-9.8153	0.6148		-15.96	0.000
Log-likelihood (null)	-140.621				
Log-likelihood (model)	-24.962				
Likelihood ratio statistics	231.318				
Adj. LL ratio index	0.773				
AIC	63.924				
Dispersion parameter	0.825				

Table 5.4, Table 5.5 and Table 5.6 also show the significant explanatory variables that are strongly associated with risk of collision in the three types of waterways. On fairways, the presence of *shoreline*, *intersection*, *confined water*, *local fairway* and *international fairway* at fairway boundary, *water depth*, *degree of bend*, number of *cardinal mark* and *isolated danger mark*, *density of dynamic ships*, *operating speed* and *night time* are found to be significant. For anchorages, the presence of *shoreline*, *confined water* and *international fairway* at anchorage boundary, number of *isolated danger mark*, *operating speed* and *night time* are found to be significantly associated with collision risk. At intersections, presence of *anchorage* at intersection boundary,

presence of *lateral mark*, number of *cardinal mark*, *operating speed* and *night time* are found to be significant.

Table 5.6 BLM Estimates of Collision Risks at Intersections

Explanatory variables	Effect estimates		Odds ratio	Z-stat	P-value
	Coefficient	S.E.			
Intersection characteristics					
Intersection boundary					
Anchorage	0.4578	0.0672	1.581	6.81	0.000
Lateral mark	-0.7526	0.3297	0.471	-2.28	0.022
Cardinal mark	0.4716	0.1476	1.603	3.20	0.001
Traffic characteristics					
Operating speed	-0.1405	0.0357	0.869	-3.93	0.000
Time variable					
Day/Night	1.7180	0.3184	5.573	5.40	0.000
Model statistics					
Intercept	-6.4324	0.5852		-10.99	0.000
Log-likelihood (null)	-20.840				
Log-likelihood (model)	-10.429				
Likelihood ratio statistics	20.822				
Adj. LL ratio index	0.212				
AIC	32.858				
Dispersion parameter	0.221				

The odds ratios of the significant variables are presented in respective tables of the waterway types, and discussed in the succeeding section.

5.4 DISCUSSION ON SIGNIFICANT EXPLANATORY VARIABLES

Presence of Shoreline at Waterway Boundary

Risk of collision is found to be significantly associated with presence of shoreline at fairway boundary (beta = 3.03, $p < 0.001$) and at anchorage boundary (beta = 5.52, $p < 0.001$). In fairways, the odds of a serious conflict are 19.7 times higher if it is attached to shoreline. This type of fairways are usually narrower and likely to have land activities (e.g., terminals, berths) along the shoreline, which could further reduce the effective navigational width of the fairways. Pilots may have less flexibility in taking evasive actions in these narrow fairways because navigating closer to shoreline will increase the risk of grounding. Risk of collision could be higher due to the reduced flexibility in maneuvering. On the other hand, anchorages attached to shoreline shows 247 times higher odds of a serious conflict. Vessels have restricted access to this type of anchorages due to the presence of shoreline. Hence, vessels anchored near the shoreline need to navigate through the other anchored vessels in order to move out of the anchorage. This implies greater interaction between vessels and, possibly, more conflicts.

Presence of Intersection at Fairway Boundary

Intersection attached to fairways shows significant positive effect (beta = 1.14, $p < 0.001$) on collision risks in fairways with 214% higher odds of a serious conflict. Number of vessel movements is high in these waters as vessels from different fairways approach towards intersection for crossing purpose. Risk of collision could rise due to the cross traffic interactions.

Presence of Anchorage at Intersection Boundary

Risk of collision at intersections attached to anchorages are found to be increased (beta = 0.46, $p < 0.001$), correspondingly increasing the odds of a serious conflict by 58%. While the numbers of crossing interactions are high in the intersections, other types of traffic interactions (e.g., merging, diverging) are also very common in such waters. Safety can be improved by providing dedicated navigational management service, such as monitoring and assisting pilots by providing relevant information regarding vessels plying in such waters so that pilots can better manage the complicated interactions.

Presence of Confined Water at Waterway Boundary

Risk of collision is found to be decreased in the fairways (beta = -1.59, $p < 0.001$) and the anchorages (beta = -5.54, $p < 0.001$) bounded by confined water. Results show that the corresponding odds of a non-serious conflict are 4.9 times higher in fairways, whereas in anchorages it is 250 times higher. Confined water characterizes low density and slow speed vessel movements in the berth areas, and only the small vessels (e.g., pilot boats, speed boats) operate in the low depth waters. For these reasons, risks in attached fairways and anchorages could be lower.

Presence of International Fairway at Waterway Boundary

Risk of collision significantly increases if an international fairway is present at fairway boundary (beta = 3.76, $p < 0.001$) and at anchorage boundary (beta = 3.8, $p < 0.001$). Pilot boarding/disembarkation grounds are usually located near the international fairways. These grounds are used by pilots to go onboard the vessels calling to port or to disembark the vessels intending to leave the port. The boarding and disembarkation process is a safety critical event in navigation (SOLAS, 1974) and it often requires vessels to slacken speeds for making the process safer. This speed reduction could impede the through traffic in international fairways and, possibly, result in more number of conflicts. In addition, interactions of pilot boats with the existing traffic may pose additional risk of collision. Results show that the odds of a serious conflict are about 42 times and 44 times higher if international fairway is present at fairway boundary and at anchorage boundary respectively.

Presence of Local Fairway at Fairway Boundary

The presence of local fairway shows significant negative effect on collision risks in fairways (beta = -1.88, $p < 0.001$) with a corresponding decrease of 84.7% in the odds of a serious conflict. Two local fairways can be attached if there is no intersections between them and the fairways differ only in their geometric and/or regulatory control characteristics (e.g., width, presence of TSS). While the presence of an intersection increases collision risks in fairways (shown earlier), its absence will reduce the risks as no cross traffic interactions take place in such waters.

Controlling Water Depth of Navigation

The navigable water depth is found to have a negative association (beta = -0.13, $p < 0.001$) with collision risks in fairways. This result is expected because pilots do not need to worry about under keel clearance, squat effects, or monitoring echo-sounder while navigating in deeper waters, which may allow taking risk mitigating actions at an early stage. Debnath and Chin (2009) have also reported that perceived risks decrease if water depth is higher.

Degrees of Bend

Increasing degrees of deflection is found to positively influence (beta = 0.01, $p < 0.001$) collision risks in fairways. This finding is consistent with that of Roeleven et al. (1995) who reported that decreasing bend radius (i.e., increasing degree of deflection) gives rise to the probability of collision. Debnath and Chin (2009) have also reported that pilots perceive higher risks in fairways having sharper bends. This is generally expected as vessels need larger navigation room for course alteration in case of sharper bends (Sarioz et al., 2000) and traffic interactions are more complicated at bends, compared to straight sections. Furthermore, rear and forward views could be restricted prior to and during course alternation at bends due to presence of land obstacles, which could impede the timely evasive action taking process. Interestingly results show that the odds of a serious conflict increases by 1% for a unit increment in degree of deflection. While this may be obvious, increasing sight distance by managing land obstacles could improve safety at bends.

Lateral Mark

Presence of lateral mark significantly reduces collision risks at intersections (beta = -0.75, p = 0.022) with 52.9% lower odds of a serious conflict. Lateral mark indicates the boundary of navigation channel which may help the pilots to form queues in a safer manner while approaching an intersection.

Cardinal Mark

The number of cardinal mark is found to have positive association with collision risks both in fairways (beta = 0.14, p < 0.001) and at intersections (beta = 0.47, p = 0.001), correspondingly increasing the odds of a serious conflict by 16% and 60% respectively. A cardinal mark is used to indicate the deepest water side (i.e., safe side to pass a danger) around the mark. It is also used to mark the locations featuring a bend, an intersection or a bifurcation (MPA, 2006). Risks of collision in these locations are usually high, which may be a reason of observing the positive association between number of cardinal mark and risk.

Isolated Danger Mark

The number of isolated danger mark is found to have significant association with collision risks in fairways (beta = 1.65, $p < 0.001$) and anchorages (beta = -4.30, $p < 0.001$). An isolated danger mark increases the odds of a serious conflict by 423% in fairways, whereas in anchorages the odds decrease by 98.6%. The difference in the effects of isolated danger mark could be due to the fact that operating speed is higher in fairways. At high speed, it is necessary to take risk mitigating actions at an early stage. Failing to do so may increase the risk of collision. In addition, pilots need to take care of avoiding danger of grounding at locations marked by the marks, which may further influence collision risk positively. On the other hand, vessels operate at lower speeds in anchorages, thus allowing earlier risk mitigating actions. At low speed, it is also easier to guide vessels on a planned track.

Density of Dynamic Ships

The risk of collision in a fairway increases with increased density of dynamic ships (beta = 0.44, $p = 0.003$). Results show that the odds of a serious conflict increase by 55.5% for a unit increment in the density. This result is expected because increased density implies greater interaction between vessels and possibly results in more multi-vessel conflicts. Risk of collision will therefore increase because of greater exposure.

Operating Speed

Operating speed shows significant negative association with collision risk in all waterway types. An increase of 1 knot reduces the odds of a serious conflict by 15.1% in fairways (beta = -0.16, $p < 0.001$), 39.3% in anchorages (beta = -0.50, $p = 0.003$) and 13.1% at intersections (beta = -0.14, $p < 0.001$). The result can be explained by the fact that in order to take evasive actions, pilots may slacken speed while being involved in an encounter producing significant collision risk. For this reason, the negative association could be observed.

Time Effects

Risk of collision is found to be higher in night condition for all waterway types: fairways (beta = 2.30, $p < 0.001$), anchorages (beta = 2.08, $p = 0.015$) and intersections (beta = 1.72, $p < 0.001$). Results show that the corresponding odds of a serious conflict in fairways, anchorages and intersections are 9.0, 7.0 and 4.6 times higher, than in the day condition. This could be because during the day the speeds, distances between vessels and even any change of courses can be judged readily than at the night. At nighttime, pilots need to rely on navigational aids (e.g., radar, navigational lights), which makes the risk perception and mitigation process difficult. Furthermore, naturally visibility deteriorates at night which could hinder the watchkeeping process leading to confusions in navigation. Effectiveness of navigational lights can also be reduced at night due to bright background lights on shore and from nearby islands (Akten, 2004; C.-P. Liu et al., 2006). A number of studies (Chin and Debnath, 2009; Debnath and Chin, 2009) have also reported that pilots perceive higher collision risks at night.

5.5 SUMMARY

A traffic-conflict-based modeling technique for predicting collision risks in port waterways (presented in Chapter 3) was illustrated for Singapore port waterways in this chapter. A BLM of collision risks in different types of waterways, i.e., fairways, anchorages and intersections were separately calibrated and evaluated for this purpose.

All three models showed reasonable goodness-of-fit and sufficient explanatory and predictive power. The BLM also identified several significant relationships between collision risks and the geometric, traffic and regulatory control characteristics of waterways. Results imply that for predicting collision risk in a waterway, the developed modeling technique can be employed effectively. Results also indicate that a predictive model of collision risk can be obtained by using traffic conflicts as an alternative to the traditional collision-data-based approach.

CHAPTER SIX
CONCLUSIONS AND RECOMMENDATIONS

A summary of the research findings, conclusions and recommendations for future research are presented in this final chapter.

6.1 CONCLUSIONS AND SIGNIFICANCE OF RESEARCH

Traditionally collision data are used to assess the level of collision risk and to investigate the causes and trends of collisions in port waters. Since a large number of collision observations are necessary in order to obtain statistically sound inferences from analysis of collision records, risk modeling relying on collision data is often hampered by low number of observations. This collision-data-based modeling approach is also an unethical and reactive approach to safety because of its reliance on collision data.

To overcome these problems, this research aimed to explore the use of non-collision information in modeling collision risks in port waters. Traffic conflicts were innovatively proposed as an alternative to the collisions and use of the conflicts in collision risk modeling was explored by developing mathematical models for measuring and predicting the risks. The models proved that traffic conflicts are a useful alternative of the collisions and port water collision risks can be evaluated in a fast, reliable and efficient manner by using the conflicts.

The traffic-conflict-based approach has a great potential in navigational safety discipline. This approach allows safety analysts to diagnose safety deficiencies in a proactive manner, which, consequently, has potential for managing collision risks efficiently. It also provides safety analysts an ethically appealing alternative to the traditional collision-data-based approach for fast, reliable and proactive safety evaluation.

The modeling techniques of the developed models for measuring and predicting risks were illustrated for Singapore port waters. Summaries of the two models are presented in the subsequent sections.

6.1.1 RISK MEASUREMENT MODEL

To measure the level of collision risk in a waterway, this research innovatively developed a risk measurement model that measures collision risk by analyzing traffic conflicts. Results of an illustrative example of the modeling technique proved that the model can be used effectively for measurement of collision risks.

In formulation of the risk measurement model, a two step procedure was employed. In the first step, collision risk in an interaction was measured by developing a quantitative measure of conflicts. An ordered probit model was developed for this purpose, where collision risk in an interaction was modeled as a function of two proximity indicators representing the spatial and temporal closeness between a pair of vessels. In the second step, a method for measuring risk of collision in a waterway was developed that statistically characterizes the measured risks for all interactions in a waterway. Several statistical distributions including the negative exponential, gamma, weibull, lognormal and loglogistic were employed for this purpose. Anderson Darling test was employed to examine the goodness of fit of the distributions. To validate the risk measurement model, a framework was developed that evaluates the correlations between the measured risks and those perceived by pilots.

Using traffic movement data of Singapore port waterways, the illustrative results showed that the risk measurement model is valid. Pearson correlation coefficients of 0.74 ($p = 0.002$) and 0.68 ($p = 0.006$) were found between measured and perceived risks in fairways for day and night conditions respectively. For anchorages, the coefficients were found as 0.81 ($p = 0.008$) and 0.74 ($p = 0.022$) in day and night conditions respectively. The corresponding coefficients for intersections were found as 0.85 ($p = 0.068$) and 0.83 ($p = 0.079$). The reasonably high correlations with acceptable statistical significance imply that the risk measurement model is valid for all of the three types of waterways.

6.1.2 RISK PREDICTION MODEL

To develop predictive models of collision risks in port waterways, this research developed a binomial logistic model (BLM) that explains the relationships between the measured risks (i.e., proportion of serious conflicts in encounters in a waterway) and the geometric, traffic and regulatory control characteristics of waterways. To account for the correlations in risks at different time periods in a waterway, the ordinary BLM is improved to properly specify the hierarchical data structure. A systematic procedure of evaluating the model is developed in order to assess the existence of overdispersion and the fitness of a best-fitted model, which is obtained through a process of model comparison by using Akaike information criteria. The likelihood ratio statistics and the adjusted log likelihood ratio index were employed to assess the fitness and predictive power of the model respectively.

Using the measured risks in the fairways, anchorages and intersections in Singapore port waters, the corresponding risk prediction models identified statistically significant relationships between the risks and waterway characteristics with reasonable model fitness. The likelihood ratio statistics of the models (fairway: 244.7, $p < 0.001$; anchorage: 231.3, $p < 0.001$; intersection: 20.8, $p < 0.001$) are well above the critical value for significance at 5% level of significance. It means that the models have reasonably good fit. The adjusted log-likelihood ratio index values for the fairway, anchorage and intersection models (0.69, 0.77 and 0.21 respectively) also indicate that the models have sufficient explanatory and predictive power. The results indicate that for predicting collision risks in waterways, the traffic-conflict-based modeling technique can be employed effectively.

Results showed that the presence of shoreline, intersection and international fairway at fairway boundary, higher degree of bend, lower depth of water, higher numbers of cardinal marks and isolated danger marks, higher density of dynamic ships, lower operating speed, and night condition are associated with higher risks of collision in fairways. On the other hand, the presence of confined water and local fairway at fairway boundary were found to be negatively associated with collision risks in fairways. Risks of collision in anchorages were found to be positively associated with the presence of shoreline and international fairway at anchorage boundary, lower number of isolated danger marks, lower operating speed, and night condition. The presence of confined water at anchorage boundary was found to associate with lower risks of collision in anchorages. At intersections, the presence of anchorage at intersection boundary, absence of lateral marks, higher number of cardinal marks, lower operating speed, and night condition were found to be positively associated with risks of collision at intersections.

6.2 RECOMMENDATIONS FOR FUTURE RESEARCH

The modeling techniques of collision risk measurement and prediction have great potential for future extensions as well as application for future research in navigational safety discipline. Three major directions are outlined in the subsequent sections.

6.2.1 EXTENSIONS OF RISK MEASUREMENT MODEL

While this research illustrated the modeling technique of the risk measurement model for the waterways in Singapore port by considering aggregate effects for day and night navigation conditions, the effects for smaller time intervals may also be examined. Examining the disaggregate effects may provide more insights into understanding the nature of collision risks at particular sites. However, such a study may need to take special considerations on choosing the time segments because a smaller time segment will yield a smaller number of conflict observations. This may hamper fitting the distribution of the observations in a sound statistical manner. A possible strategy to obtain a statistically fitted distribution may be by selecting time segments of unequal length in such a way that there is sufficient number of observations in each segment.

Furthermore, the modeling technique may be applied to examine the effects of weather factors (e.g., tide, current, visibility) on collision risks. Again, the main difficulty in such a study is to obtain a very large database of traffic movements. Since the weather factors follow a cyclic pattern, it is necessary to obtain movement data of a month at least. Besides managing such a large database, another difficulty is to obtain suitable time segments so that the weather factors vary over the segments. In addition, ensuring sufficient number of observations in each segment may lead to a more complicated analysis.

6.2.2 EVALUATION OF BAYESIAN PRIORS IN RISK PREDICTION MODELING

While in this research, the risk prediction modeling technique was developed in the classical frequentist paradigm (i.e., maximum likelihood estimation), the modeling technique may also be developed in the Bayesian paradigm. Inference in maximum likelihood estimation is based on the likelihood of the model calibration data alone, whereas in Bayesian models two sources of data are used: prior beliefs and the likelihood of model calibration data. This allows using existing information or prior experience combined with the observed data in prediction modeling. Use of the Bayesian models has acquired impressive attention of safety researchers (especially in the context of road traffic) in recent time.

In Bayesian models, the likelihood of observed data y given parameters β is used to modify the prior beliefs $\pi(\beta)$ and the updated knowledge is summarized as posterior information $\pi(\beta|y)$. In case of developing a predictive model of collision risks in waterways, the measured (i.e., observed) risks could be used as observed data, and the risks in waterways perceived by pilots could be used as prior beliefs. This will provide a blend of expert judgments and observed traffic data in explaining the relationships between the observed risks and the geometric, traffic and regulatory control characteristics of waterways.

This arrangement of prior beliefs and observed data will also allow using 'informative' priors in Bayesian modeling. In general, 'non-informative' or 'flat' priors have been used in road traffic safety research because of the absence of any existing knowledge. Using expert judgments as prior beliefs would relax this constraint and may significantly improve model fitness and predictive power.

6.2.3 USE OF PERCEPTUAL MODELS IN COLLISION AVOIDANCE

To develop a relationship between the risk of collision in an interaction and the proximity indicators (i.e., DCPA and TCPA), this research derived an ordered probit model. By utilizing risks perceived by pilots, it was calibrated to obtain perceptual models of pilots. These perceptual models have great potential to be applied in collision avoidance.

In the traditional arrangement of collision avoidance, pilots assess and mitigate collision risk by combining data obtained from collision avoidance systems (CAS) with information obtained by visual watch-keeping. The most widely CAS used on most merchant vessels is the Automatic Radar Plotting Aid (ARPA). It allows pilots to track a number of target vessels within the radar detection range and triggers alarms to alert the pilots of collision risk. In the ARPA system, collision risk is treated as a discrete variable. However, to better help pilots in decision making in encounters, collision risk should be considered as a continuous variable. Furthermore, as the performance and judgment in encounter vary from one pilot to another, it is also necessary to consider the probabilistic aspects of defining risk. Moreover, other factors such as vessel size and the environment play an important role in influencing navigational risk. These factors are not considered in the existing CAS.

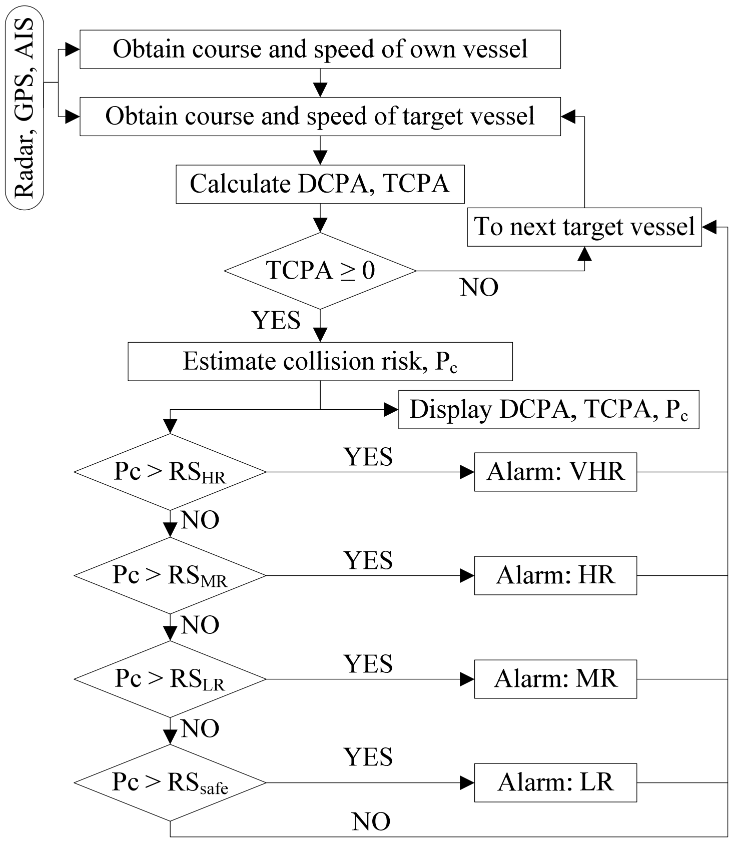

Figure 6.1 Block Diagram of Collision Avoidance System

To overcome the identified limitations of the existing CAS, the ordered probit model developed in this research could be useful. Results of the model calibration and evaluation showed that the calibrated models have reasonable predictive power. This implies that the regression estimates can be used effectively to develop a CAS. A framework of risk assessment in CAS that utilizes the estimates to predict collision risk in an interaction is proposed (see Figure 6.1) and discussed in detail in Chin and Debnath (2009). By assessing collision risk probabilistically, this framework produces alarms for different levels of risk. It also enables prioritizing interacting vessels according to the level of risk involved. Following the proposed framework, a real-time CAS can be developed and its effectiveness in collision avoidance can be evaluated in future research.

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APPENDICES

APPENDIX A

This appendix presents the risk perception survey form indicated in Chapter 3.

<u>Harbor Pilot Perception Survey on Collision risk</u>

We, researchers of the National University of Singapore, are conducting this survey to gather information about harbor pilots' perception of vessel collision risk in port waters. Findings of this survey will help researchers and engineers to examine such risk and mitigate it. Your participation is greatly appreciated. **All information collected is strictly confidential and will be used for research purposes only.**

<u>Part A.</u> Risk Perception of Shipping Interactions

In this part, we want you to provide us your judgment of collision risk for vessel interactions. Please use the Risk Scale (given below) for this part.

<u>Risk Scale:</u>

Risk Level	Risk Score	Level of actions necessary to avoid collision
Safe	**0**	No actions necessary
Low Risk	**1**	Keep monitoring
Moderate Risk	**2**	Take precautionary actions, communicate with other ship
High Risk	**3**	Immediate actions needed
Very High Risk	**4**	Collision imminent, cannot be avoided

Q1. Suppose you are involved in a two-ship interaction. The interaction is described by values of Distance at Closest Point of Approach (DCPA) and Time to CPA (TCPA). **What is the Collision Risk for each set of DCPA and TCPA** (given below in tables)**?** Consider average ship sizes that you operate frequently.

*Please fill up the tables with **Risk Scores (0-4):***

During **Day time** navigation:

	TCPA (Minutes)				
DCPA (Cables)	***1***	***3***	***5***	***10***	***20***
1					
2					
5					
7					
10					

During **Night time** navigation:

	TCPA (Minutes)				
DCPA (Cables)	***1***	***3***	***5***	***10***	***20***
1					
2					
5					
7					
10					

Q2. While channeling, usually when you would start monitoring other ships?

Ans.: 1. At Day time: when other ships are _____ (nautical mile) away from my ship.

2. At Night time: when other ships are ____ (nautical mile) away from my ship.

Part B. Background Information

Please tell us about yourself:

1. Age: _________ years.

2. Number of years on-board as harbor pilot: _________ years.

3. Pilot grade: [1] Trainee [2] C [3] B [4] A 3 [5] A 2 [6] A 1

4. Last time I did technical training (e.g., crisis management or equipment operations):

[1] 1 month ago [2] 2 – 6 months ago [3] 6 – 12 months ago [4] Above 1 year [5] Never

5. Range of vessel tonnage that I operate: ___________ GT to ___________ GT.

Part C. Risk Perception of Waterways

In the last part, we want you to provide us your expert judgment about collision risk in several waterways of Singapore port. **Please use the Risk Scale (given below) for this part.** This scale describes collision risks according to the probability of experiencing a close-quarter situation (CQS) in a waterway, i.e., **the chance of involving in a CQS when you guide a ship through a particular waterway.**

Risk Scale:

Risk Level	Score	Likeliness of experiencing a close-quarter situation at an interaction in a waterway
Safe	**0**	Very Unlikely
Low Risk	**1**	Unlikely
Moderate Risk	**2**	Moderate chance
High Risk	**3**	Likely
Very High Risk	**4**	Very Likely

Please proceed to next page…

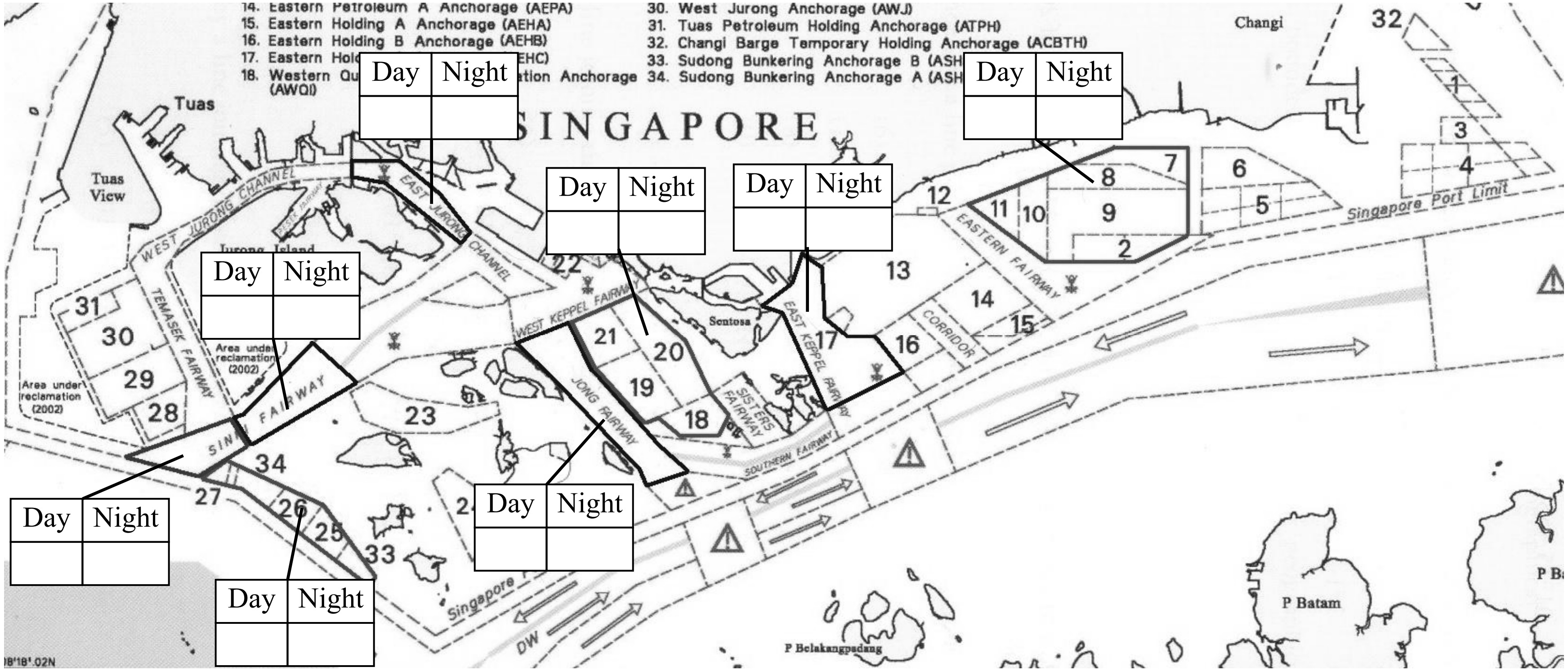
Q. What is the collision risk in waterways marked on the map?

Please provide Risk Scores (0-4) for each waterway in corresponding table:

Risk Level	Score	Likeliness of experiencing a CQS at an encounter in a waterway
Safe	**0**	Very Unlikely
Low Risk	**1**	Unlikely
Moderate Risk	**2**	Moderate chance
High Risk	**3**	Likely
Very High Risk	**4**	Very Likely

Example to fill-up:

Risk at **Day**	Risk at **Night**
1	3



END OF SURVEY – THANK YOU

APPENDIX B

This appendix presents the structure of the prepared database, which contains the unscrambled VTIS data, for analyzing traffic conflicts. The data structure is shown in Table B.1.

Table B.1 Structure of Database Containing Unscrambled VTIS Data

		Ship's position		Ship's speed		Ship's attributes			
Time	ID of Ship	in hor. axis	in vert. axis	in hor. axis	in vert. axis	Gross Tonnage	Length overall	Height	Draft
T	1	-	-	-	-	-	-	-	-
T	2	-	-	-	-	-	-	-	-
T	3	-	-	-	-	-	-	-	-
T	.	-	-	-	-	-	-	-	-
T	.	-	-	-	-	-	-	-	-
T	.	-	-	-	-	-	-	-	-
T	N	-	-	-	-	-	-	-	-
T+1	1	-	-	-	-	-	-	-	-
T+1	2	-	-	-	-	-	-	-	-
T+1	3	-	-	-	-	-	-	-	-
T+1	.	-	-	-	-	-	-	-	-
T+1	.	-	-	-	-	-	-	-	-
T+1	.	-	-	-	-	-	-	-	-
T+1	N	-	-	-	-	-	-	-	-
T+2	1	-	-	-	-	-	-	-	-
T+2	2	-	-	-	-	-	-	-	-
T+2	3	-	-	-	-	-	-	-	-
T+2	.	-	-	-	-	-	-	-	-
T+2	.	-	-	-	-	-	-	-	-
T+2	.	-	-	-	-	-	-	-	-
T+2	N	-	-	-	-	-	-	-	-
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2000 – 2005 B.Sc. in Civil Engineering, Bangladesh University of Engineering and Technology.

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List of Publications

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