RISK ANALYSIS

OF TRANSIT VESSEL TRAFFIC IN THE STRAIT OF ISTANBUL[1]

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ABSTRACT

The Strait of Istanbul, the narrow waterway separating Europe from Asia, holds a strategic importance in maritime transportation as it links the Black Sea to the Mediterranean. It is considered one of the world's most dangerous waterways to navigate. Over 50,000 transit vessels pass through the Strait annually, 20% of which carry dangerous cargo.

In this research, we have developed a mathematical risk analysis model to analyze the risks involved in the transit vessel traffic system in the Strait of Istanbul. In the first step of the risk analysis, the transit vessel traffic system is analyzed and a simulation model is developed to mimic and study the system behavior. In addition to vessel traffic and geographical conditions, the current vessel scheduling practices are modeled using a scheduling algorithm. This algorithm is developed through discussions with the Turkish Straits Vessel Traffic Services (VTS) to mimic their decisions on sequencing vessel entrances as well as coordinating vessel traffic in both directions. Furthermore, a scenario analysis is performed to evaluate the impact of several parameters on the system performance.

Risk analysis is performed by incorporating a probabilistic accident risk model into the simulation model. A mathematical model is developed based on probabilistic arguments and historical data and subject matter expert opinions. We have also performed a scenario analysis to evaluate the characteristics of the accident risk. This analysis allows us to investigate how various factors impact risk. These factors include vessel arrivals, scheduling policies, pilotage, overtaking, and local traffic density. Policy indications are made based on results.

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1 INTRODUCTION

Peter Gilles, a French humanist writing in the 16th century, described the Bosporus as a "strait that surpasses all straits, because with one key it opens and closes two worlds, two seas" according to [Freely, 1996]. The two seas that he refers to are the Aegean and the Black Sea, and the two worlds are Europe and Asia, since the Bosporus and the Dardanelles have throughout history been the major crossing-places between the two continents.

The Turkish Straits, which consist of the Strait of Istanbul (Bosporus), the Strait of Çanakkale (the Dardanelles) and the Sea of Marmara, have for centuries been one of the world's most strategic waterways. As the Black Sea's sole maritime link to the Mediterranean and the open ocean beyond, they are a vital passageway not just for trade but for the projection of military and political power.

The Turkish Straits are distinct among the waterways of the world in their morphological structure and oceanographic characteristics; leading to navigational hazards that are unique to this passageway. The most difficult part of this challenging passage is the Bosporus, which is defined by its extreme narrowness, winding contour and densely populated shores.

Perhaps no other waterway is as fabled as the Bosporus. The earliest myths date back to the second millennium BC. One of these stories tells the myth of Zeus and Io, his mistress whom he changed into a heifer, to hide her from his wife Hera. When Hera found out about the affair, she pursued Io with a relentless gadfly, forcing her to swim the Strait. Thenceforth, the Strait bore the name Bosporus, or "Cow's Ford", commemorating Io.

Jason and the Argonauts, in their quest for the Golden Fleece, barely sailed through the Clashing Rocks, a part of the Bosporus, before the Strait closed behind them. Darius I, the Persian emperor, used pontoons to cross the Bosporus and attack the Greeks. The

Byzantine and Ottoman empires were governed from the shores of the Bosporus for over 1,600 years. Today, this narrow passage runs through the heart of Istanbul, home to over 12 million people and some of the world's most celebrated ancient monuments.

The Strait of Istanbul is approximately 31 km long, with an average width of 1.5 kilometers. At its narrowest point between Kandilli and Bebek, it measures a mere 698m. It takes several sharp turns, forcing the ships to alter course at least 12 times, sometimes executing turns of up to 80 degrees. Navigation is particularly treacherous at the narrowest point, as the vessels approaching from opposite directions cannot see each other around the bends.

In addition to its winding contour, the unpredictable countervailing currents that may reach 7 knots pose significant danger to ships. Surface currents in the Strait flow from the Black Sea to the Sea of Marmara, but submarine currents 50 feet below the surface run in the opposite direction. Within bays and near point bars, these opposing currents lead to turbulence. The unpredictable climate brings about further danger. During storms with strong southerly winds, the surface currents weaken or reverse in some places, making it even harder to navigate. Not surprisingly, all these elements can easily cause vessels transiting the Strait to veer off course, run aground or collide.

The current international legal regime governing the passage of vessels through the Turkish Straits is the 1936 Montreux Convention. Although this instrument provides full authority over the straits to the Turkish government, it asserts that in time of peace, merchant vessels are free to navigate the straits without any formalities [Montreux Conv., 1937]. When the Convention was put in place, less than 5,000 vessels used to pass through the Strait of Istanbul annually. Today, the changes in the shipping and navigational circumstances have led to a ten-fold increase in the maritime traffic through the Strait.

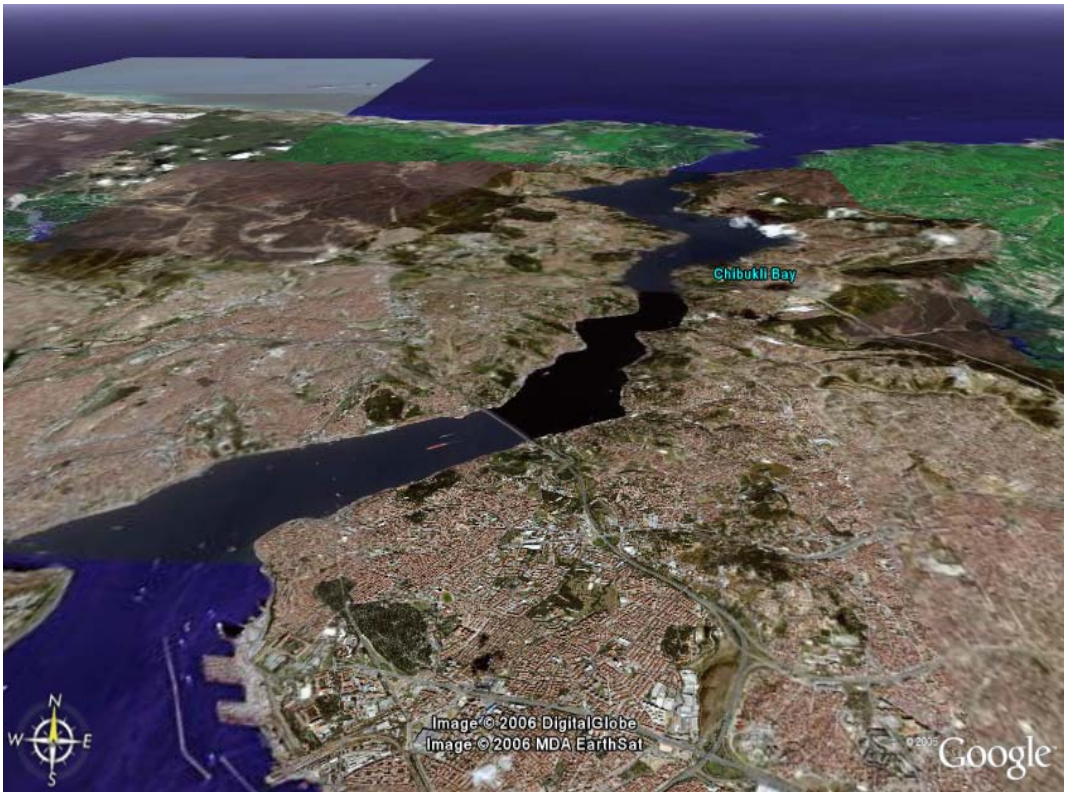

Figure 1.1 Strait of Istanbul

Several reasons contributed to this immense increase. The Turkish Straits provide the only maritime link between the Black Sea riparian states and the Mediterranean, forcing these states to rely heavily on the straits for foreign trade. The opening of the Main-Danube canal has linked the Rhine to the Danube, linking the North Sea and Black Sea. Traffic originating from the Volga-Baltic and Volga-Don waterways has also increased in the recent years.

Still, the most alarming increase in traffic is observed in the number of vessels carrying dangerous cargoes. The fall of the Soviet Union in 1991 has led to the emergence of newly independent energy-rich states along the Caspian Sea. Currently, the oil and gas from Azerbaijan, Turkmenistan and Kazakhstan reach the western markets through the Turkish Straits. The maritime traffic will increase substantially since the production is expected to double by 2010. In addition, Russian oil companies are setting new records for production and export. Analysts predict that Russia could be pumping 10 million barrels of crude oil daily by the end of the decade, a significant portion of which is expected to pass through the straits.

During the 1930s, when the Montreux Convention went into force, transport of hazardous materials posed little concern due to the infrequent passages and small vessel sizes. However, the increases in traffic and vessel sizes have raised the likelihood and the severity of accidents. The unusual characteristics of the Bosporus and its climate, coupled with the failure to request pilotage in this treacherous waterway, have led to over 200 accidents in the past decade.

The first major hazardous cargo accident occurred in 1960 when the Greek-flagged M/T World Harmony collided with the Yugoslavian-flagged M/T Peter Zoranic, leading to the death of 20 crew members, severe oil pollution and fire that lasted several weeks, suspending the transit traffic. In 1979, Romanian-flagged Independenta and the Greek freighter M/V Evriyalı collided at the southern entrance of the Strait. 43 crew members died, 64,000 tons of crude oil spilled into the sea and 30,000 tons burned into the atmosphere. In yet another catastrophe, the Greek Cypriot vessels M/T Nassia and M/V Shipbroker collided in the Strait. 29 officers and crewmen perished and 20,000 tons of crude oil burned for five days, suspending the traffic for a week. A potential disaster was averted only because the accident occurred just north of the city.

In order to ensure the safety of navigation, life, property and to protect the environment, the Turkish government adopted unilaterally the 1994 Maritime Traffic Regulations for the Turkish Straits and Marmara Region. Four years later, the rules were revised and the 1998 Reviewed Regulations were adopted. These regulations include extensive provisions for facilitating safe navigation through the straits in order to minimize the likelihood of accidents and pollution. The provisions aim to monitor the vessels with hazardous cargoes, regulate the patterns of ship traffic by establishing new procedures for passage in the straits, and attempt to account for dangerous meteorological and oceanographic conditions by restricting traffic under certain situations.

Even though the number of accidents decreased after the adoption of the regulations, the vulnerability of the straits was evident once again in an incident in 1999. Voganeft-248, a Russian tanker, ran aground and broke apart at the Sea of Marmara entrance of the Strait. Over 800 tons of oil spilled into the sea, and clean-up efforts lasted several months.

The navigational hazards of the Strait of Istanbul are real and well known. Although strengthening transit restrictions and safety precautions have decreased the danger, accidents will happen. In 2005, almost 55,000 vessels passed through the Strait, an increase of 16% over the previous year. Inevitably, as the number of vessels transiting the Strait increases dramatically, so will the likelihood of accidents and environmental catastrophes, endangering the only city in the world that stands astride two continents, and its 12 million inhabitants. Therefore, determining accident risks and measures to mitigate these risks becomes of utmost importance. In this dissertation, this is achieved through probabilistic risk analysis.

The goal of this research is to analyze the risks involved in the transit vessel traffic system in the Strait of Istanbul. We have developed a detailed mathematical risk analysis model to be used in a risk mitigation process to improve safety in the Strait. In the first step of the risk analysis process, the transit vessel traffic system in the Strait of Istanbul is thoroughly analyzed and a simulation model is developed to mimic and study the system. In addition to transit vessel traffic through the Strait and geographical conditions, the current vessel scheduling practices are modeled using a scheduling algorithm. This algorithm is developed through discussions with the Turkish Straits Vessel Traffic Services (VTS) to mimic their decisions on sequencing vessel entrances as well as giving way to vessel traffic in either direction. Furthermore, a scenario analysis is performed to evaluate the impact of several policies and practices on the system performance.

Risk analysis of the Strait is performed by incorporating a probabilistic accident risk model into the simulation model. This mathematical model is developed based on probabilistic arguments and utilizes historical accident data and subject matter expert opinions. We have also performed a scenario analysis to evaluate the characteristics of accident risk. This analysis allows us to investigate how changes in various factors impact risk. These factors include vessel arrival rates, scheduling policies, pilotage, overtaking, and local traffic density.

2 RISK ANALYSIS OF THE TRANSIT VESSEL TRAFFIC IN THE STRAIT OF ISTANBUL

2.1 INTRODUCTION

The concepts of risk analysis, assessment and management are becoming more important as the future becomes less predictable in today's chaotic society. Numerous papers and books have been written on the subject in the last 15 years (see [Ansell and Wharton, 1992], [Steward *et al*., 1997], [Koller, 1999, 2000], [Wang and Rousch, 2000], [Bedford and Cooke, 2001], [Aven, 2003], [Ayyub, 2003], and [Modarres, 2006].

[Rausand and Høyland, 2004] defines *risk* as an expectation of an unwanted consequence, which combines both the severity and the likelihood of the consequence. [Kaplan and Garrick, 1981] and [Kaplan, 1997] provide a quantitative definition of risk. The authors argue that in order to define risk one must answer three questions:

i. What can go wrong?
ii. How likely is that to happen?
iii. If it does happen, what are the consequences?

To answer these questions, a list of scenarios is constructed as shown in Table 2-41. Let s_i be the ith scenario, and p_i and x_i be its probability and consequence, respectively.

Table 2-1 List of scenarios

Scenario	Probability	Consequence
s_1	p_1	x_1
s_2	p_2	x_2
$\vdots$	$\vdots$	$\vdots$
s_N	p_N	x_N

Thus, the triplet $\langle s_i, p_i, x_i \rangle$ represents an answer to the above questions. Consequently, risk is defined as the complete set of triplets including all possible scenarios.

$$R = \{\langle s_i, p_i, x_i \rangle\}, \qquad i = 1, \ldots, N$$

The scenarios are sorted in an increasing order of severity of consequence such that $x_1 \le x_2 \le \cdots \le x_N$.

Table **2-2** is obtained by adding a column representing the cumulative probabilities calculated starting with the most severe scenario s_N.

Table 2-2 List of scenarios with Cumulative Probability

Scenario	Probability	Consequence	Cumulative Probability
s_1	p_1	x_1	$P_1 = P_2 + p_1$
s_2	p_2	x_2	$P_2 = P_3 + p_2$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
s_i	p_i	x_i	$P_i = P_{i+1} + p_i$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
s_{N-1}	p_{N-1}	x_{N-1}	$P_{N-1} = P_N + p_{N-1}$
s_N	p_N	x_N	$P_N = p_N$

By plotting the consequence versus cumulative probability, a *risk curve* can be obtained as depicted in Figure 2.1.

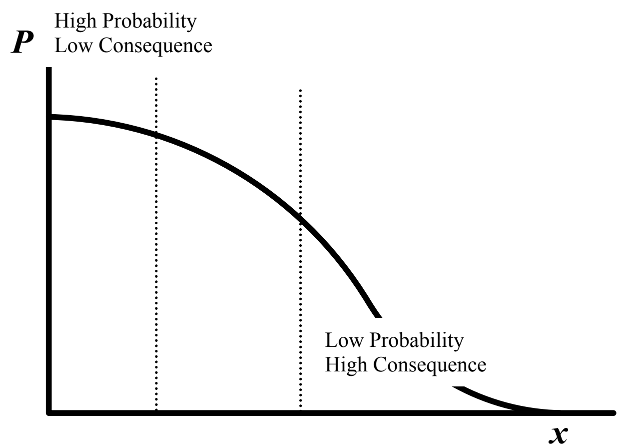

Figure 2.1 Risk curve

The Society for Risk Analysis, on the other hand, defines risk as "the potential for realization of unwanted, adverse consequences to human life, health, property, or the environment" [SRA, 2007], whereas [Ayyub, 2003] provides a quantitative engineering definition of risk as follows:

$$R = \text{Probability}(E) \times \text{Consequence Impact}(E)$$

where E is an unwanted event.

Risk analysis can be defined as "a detailed examination … performed to understand the nature of unwanted negative consequences to human life, health, property, or the environment" [SRA, 2007]. However, *risk management* builds on the risk analysis process by seeking answers to a set of three questions [Haimes, 1991]:

i. What can be done and what options are available to mitigate risks?
ii. What are the associated tradeoffs in terms of all costs, benefits, and risks?
iii. What are the impacts of current management decisions on future options?

The steps of risk analysis and management are presented in Figure 2.2.

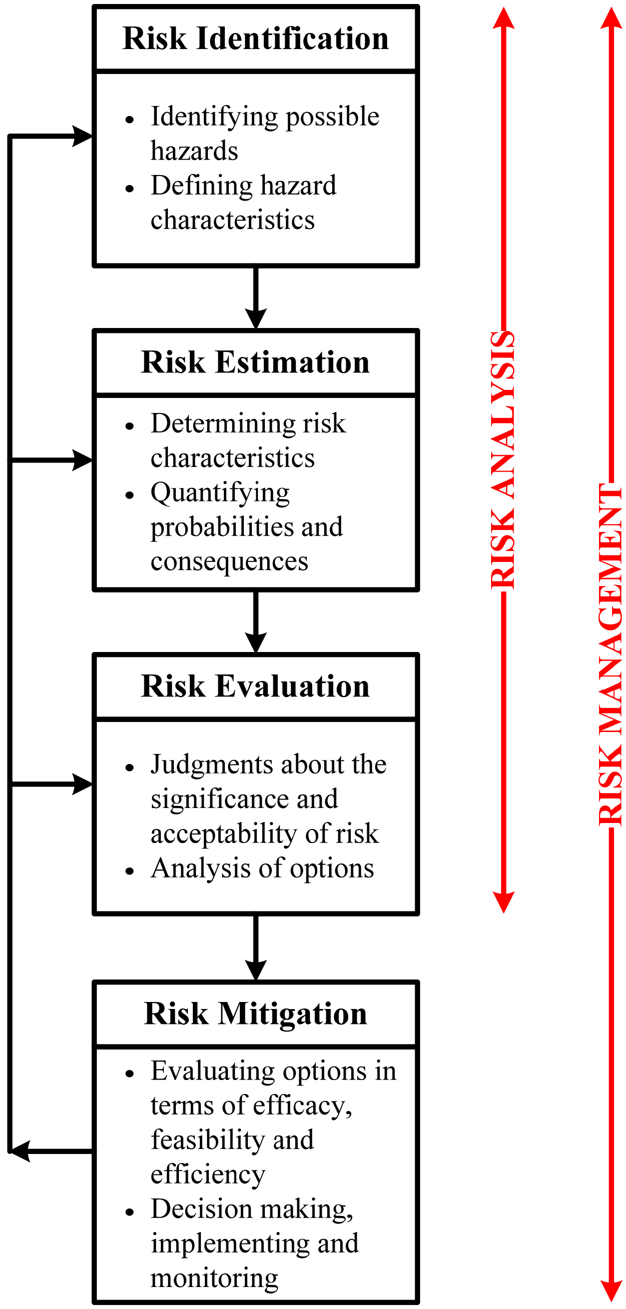

Figure 2.2 Risk analysis and management

Furthermore, *probabilistic risk analysis (PRA)* is a risk analysis method, which uses experimental and actual data to quantify risks in a system. It is also referred to as *quantitative risk analysis (QRA)* or *probabilistic safety analysis (PSA)* depending on the field.

Even though the concepts of risk analysis and management are relatively new, the thinking on the topic of risk was initiated by the notion of insurance, a risk management tool that reduces risk for a person or a party by sharing potential financial burdens with others. Insurance has roots that reach back to 1800 B.C. when it was used to help finance sea expeditions. An early form of life insurance was provided by trade and craft guilds in Greece and Rome. As trade expanded in the Middle Ages, new forms of insurance were used to protect farmers and traders from droughts, floods, and other disasters.

Risk has also been an integral part of money markets and financial services. Options, a financial instrument that allows individuals to buy and sell goods from one another at pre-arranged prices, were traded in the U.S. in the 1790s in what would later become the New York Stock Exchange. Futures, in use in Europe since medieval times, were another type of financial instrument that helped reduce risk for farmers and commodity buyers. Futures on products such as grain and copper have been sold on the Chicago Board of Trade starting in 1865. Between the 1970s and the 1990s, derivatives, financial contracts that derive their value from one or more assets, became popular among individuals and organizations [Vesper, 2006].

Since the Industrial Revolution, the nature of risk has changed. Hazardous agents have increased significantly in size such as bridges, airplanes, oil tankers and skyscrapers. They have also gotten smaller, e.g. pesticides and biological weapons.

In recent years, risk analysis has been utilized in numerous industries, leading to the improvement of existing methodologies as well as the development of new ones. Probabilistic risk analysis originated in the aerospace industry. One of the earliest studies was launched after the fire in the Apollo flight AS-204 in 1967, in which three astronauts were killed. In 1969, the Space Shuttle Task Group was created. [Colglazier and Weatherwas, 1986] conducted a probabilistic risk analysis of shuttle flights. Since the

Challenger accident in 1986, NASA has instituted various programs of quantitative risk analysis to assure safety during the design and operations phases of manned space travel [Bedford and Cooke, 2001]. Examples of such risk analyses include the SAIC Shuttle Risk Assessment [Fragola, 1995] and the risk assessment of tiles of the space shuttle orbiter [Paté-Cornell and Fischbeck, 1993].

In the nuclear industry, the focus has always been on reactor safety. The first risk analysis study was the Reactor Safety Study [NRC, 1975] published by the US Nuclear Regulatory Commission (NRC). This study was criticized by a series of reviews: American Physical Society [APS, 1975], Environmental Protection Agency [EPA, 1976], [Union of Concerned Scientists, 1977], and [Lewis *et al*., 1979]. However, two independent analyses of the Three Mile Island accident, [Kemeny *et al*., 1979] and [Rogovin and Frampton, 1980], re-emphasized the need for conducting probabilistic risk analysis. The US NRC released *The Fault Tree Handbook* [Vesely *et al*., 1981] in 1981 and the *PRA Procedures Guide* [NRC, 1983] in 1983, which standardized the risk assessment methodology.

Probabilistic risk analysis has been applied to study a variety of natural disasters. These studies include predicting earthquakes [Chang *et al*., 2000], floods [Voortman *et al*., 2002], [Mai and Zimmermann, 2003], [Kaczmarek, 2003], and environmental pollution [Slob and Pieters 1998], [Moore *et al*., 1999]. A large number of studies focus on waste disposal and environmental health [Sadiq *et al*., 2003], [Cohen, 2003], and [Garrick and Kaplan, 1999].

In the 1990s, the U.S. Food and Drug Administration (FDA) began requiring manufacturers of certain types of foods to use a risk management method called hazard analysis and critical control points (HACCP) to identify, control, and monitor risks. The U.S. Department of Agriculture also requires that meat and poultry processing plants use HACCP as a risk management process [Vesper, 2006].

In health care, probabilistic risk analysis has focused on analyzing the causes of unwanted events such as medical errors or failure mode and effect analysis of near catastrophic events [Bonnabry *et al*., 2005]. PRA is also utilized in the pharmaceutical industry to make decisions on new product development [Keefer and Beccue, 2001]. Further, the FDA is expanding use of risk analysis and risk management within the industry.

Risk analysis and management has also become important in maritime transportation industry. The National Research Council identified it as an important problem domain [NRC, 1986]. The grounding of the *Exxon Valdez*, the capsize of the *Herald* of Free Enterprise and the Estonia passenger ferries are some of the most widely known accidents in maritime transportation. [Merrick and Van Dorp, 2006] states that the consequences of these accidents ranged from severe environmental and property damage to high casualties. These and other similar accidents have led researches to focus on maritime risk analysis. Early work concentrated on risk assessment of structural designs using reliability engineering tools. The studied structures included nuclear powered vessels [Pravda and Lightner, 1966], vessels transporting liquefied natural gas [Stiehl, 1977] and offshore oil and gas platforms [Paté-Cornell, 1990]. Recently, researchers have applied Probabilistic Risk Analysis to maritime transportation. A detailed literature review on this topic is provided in Section 2.3.

The application of risk analysis to terrorism is new. In terrorism, risk is defined as "the result of a *threat* with negative effects to a *vulnerable* system" [Haimes, 2004, 2006]. Here, the threat refers to "the intent and capability to cause harm or damage to the system by negatively changing its states". [Taylor *et al*., 2002] has applied probabilistic risk analysis in cyber terrorism risk assessment. Other works have suggested the use of these techniques in assessment of terrorism [Apostolakis and Lemon, 2005], [Haimes and Longstaff, 2002]. [Willis, 2007] studies on risk-based resource allocation and compares terrorism risk with other risk management decisions to emphasize the difficulty in terrorism risk management. He uses results of Risk Management Solutions' (RMS) Probabilistic Terrorism Model. The model calculates risk as a function of threat, vulnerability and consequences by using expert judgments. The details of the model is explained in [Willis *et al*., 2005] and [Willis *et al*., 2007]. [Paté-Cornell and Guikema, 2002] present a model that sets priorities among countermeasures and threats for different scenarios. They use probabilistic risk analysis, decision analysis and game theory to set priorities and calculate disutility of a successful attack. As terrorism risk differs from accidental or natural calamities and probability is not enough to calculate it, [Major, 2002] uses game theory to model terrorism risks.

In this chapter, we will focus our attention to the risk analysis of the maritime transit traffic in the Strait of Istanbul.

2.2 BACKGROUND INFORMATION

The Strait of Istanbul is among the world's busiest waterways. The heavy traffic through the Strait of Istanbul presents substantial risks to the local environment. Various reasons including the increase in maritime traffic and the number of vessels carrying dangerous and hazardous cargo, the unpredictable weather conditions, the unusual characteristics of the Strait of Istanbul and the failure to request pilotage have led to over 500 accidents in the last decade alone.

The first major accident occurred in 1960 when the Greek-flagged M/T World Harmony collided with the Yugoslavian-flagged M/T Peter Zoranic. 20 crew members, including both shipmasters, died; the resulting oil pollution and fire lasted several weeks, suspending the traffic in the Strait.

Although numerous catastrophic accidents have occurred in the Strait, some incidents should especially be mentioned because of their magnitude, both in terms of damage they caused, and their impact on the Turkish psyche:

- In 1960, Yugoslavian flagged tanker Petar Zoranić collided with the Greek tanker World Harmony at Kanlıca. 50 members of the crew died. 18,000 tons of oil spilled into the sea, causing severe pollution. Fire lasted for some weeks, suspending transit traffic in the Strait. Petar Zoranić's wreck led to more accidents. In 1964, Norwegian flagged vessel Norborn crashed into the wreck, causing fire and pollution.

- In March 1966, two Soviet flagged vessels M/T Lutsk and M/T Cransky Oktiabr collided at Kızkulesi. 1,850 tons of oil spilled into the fire. The resulting fire burned down the Karaköy ferry terminal and a ferry.

- In July 1966, the ferry Yeni Galatasaray collided with the Turkish coaster Aksaray. 13 people died in the fire.

- In November 1966, the ferry Bereket hit the Romanian flagged Ploesti. 8 people drowned.

- In 1979, Greek freighter M/V Evriyalı collided with Romanian-flagged Independenta near Haydarpasa, at the southern entrance. The Romanian tanker sank and 43 members of the crew died. 64,000 tons of oil spilled into the sea, while 30,000 tons of oil burned into the atmosphere. An area of 5.5 kilometers in diameter was covered with thick tar, and the mortality rate of the marine life was estimated at 96 percent according to [Oguzülgen, 1995]. The incident was ranked as the 10th worst tanker accident in the world.

- In 1988, Panama-flagged M/T Blue Star carrying ammonium chloride collided with Turkish tanker M/T Gaziantep. 1,000 tons of the corrosive chemical spilled into the sea, causing severe pollution.

- In March 1990, Iraqi tanker M/T Jambur and Chinese bulk carrier M/V Da Tong Shan collided in the Strait. About 2,600 tons of oil spilled into the sea as Jambur ran aground after the collision. The cleaning efforts lasted several weeks.

- In 1991, the Turks witnessed yet another incident involving improper navigation, when Phillippine-flagged bulk carrier M/V Madonna Lily and Lebanese live stock carrier Rabunion 18 collided in November. Three members of the Rabunion 18 crew died as the ship sank with its cargo of 21,000 sheep.

- In yet another catastrophe in March 1994, the Greek Cypriot vessels M/T Nassia and M/V Shipbroker collided in the Strait, just north of Istanbul. 29 people died; over 20,000 tons of crude oil burned for five days, suspending the traffic in the Strait for a week.

- The Russian tanker Volganeft-248 ran aground and split in two at the southern entrance of the Strait of Istanbul in December 1999. 1,500 tons of oil spilled into the sea, polluting both the water and the shores. Clean-up efforts lasted for several months.

- In October 2002, Maltese-flagged M/V Gotia ran into the Emirgan pier in the Strait, damaging its fuel tank. 18 tons of oil spilled into the sea.

- Georgian-flagged cargo carrier M/V Svyatov Panteleymon ran aground and broke apart while navigating the Strait of Istanbul in November 2003. Its fuel spilled into the sea, polluting a strip of about 600 meters of the shore.

- In February 2004, severe weather caused Cambodian-flagged M/V Hera to sink in the Black Sea, just a few miles off the northern entrance of the Strait. None of the 19 members of the crew survived.

- Just a few days after the M/V Hera incident, North-Korean flagged Lujin-1 carrying scrap iron ran aground while entering the Strait, damaging its hull. It took several days to rescue the ship's 15 crewmembers and months to salvage the ship.

As indicated in the above examples, the heavy traffic through the Strait undoubtedly presents substantial risks. The impact of heavy tanker traffic is already evident in the ecology of the marine life. Though a potential major spill could bring immediate environmental catastrophe, a key problem caused by the presence of large tankers is the day to day release of contaminated water as the ships ballast their holds and discharge their bilge water.

The Strait of Istanbul possesses features that make heavy volumes of traffic dangerous. Over the last few decades as the magnitude of traffic has increased, accidents in the Strait have become common. With the increase in oil production projected as a result of the exploitation of Central Asian oil fields, the traffic through the Strait is expected to increase significantly, putting both the local environment and the inhabitants of Istanbul at risk of a major catastrophe. In addition to claiming lives, destroying the historical heritage and polluting the environment, a major accident in the Strait could cause significant economic problems for the Black Sea littoral states in the event of a prolonged suspension of traffic.

2.3 LITERATURE REVIEW ON MARITIME RISK ANALYSIS

The existing risk assessment studies in maritime systems may be categorized in two main groups: risk assessment of the structural design using the tools of reliability engineering, and the probabilistic risk analysis of the system as a whole.

[Guedes Soares and Teixeira, 2001] provides a review of the studies that have been published on the structural design risk assessment in maritime systems. It concentrates on the global assessment of risk levels and its differentiation in ship types and main types of ship losses.

In our research, we consider the vessel traffic system as a whole instead of concentrating only on the vessel failures. In our risk analysis methodology, we utilize probabilistic risk analysis tools and simulation modeling. Therefore, we concentrate on the work that has been done in the second category.

[Atallah and Athens, 1984] provides general guidelines for the application of risk assessment methodology to existing or proposed marine terminal operations. The proposed methodology includes four consecutive stages: identification of potential hazards, quantification of risks, evaluation of risk acceptability; and reduction of unacceptable risks. Specifically, the authors focus on the accidental releases of hazardous flammable and/or toxic cargoes in or near harbors and inland waterways.

[Haya and Nakamura, 1995] proposes a quantitative risk evaluation procedure that systematically combines various simulation techniques. Also, the degree of collision risk of a ship felt by the shiphandler is incorporated in the risk evaluation procedure using a method introducing Subjective Judgment values as indexes expressing the subjective degree of danger felt by the shiphandler.

[Amrozowicz, 1996] and [Amrozowicz *et al*., 1997] focus on the first level of a proposed three-level risk model to determine the probability of oil tanker grounding. The approach utilizes fault trees and event trees and incorporates the Human Error Rate Prediction data to quantify individual errors. The high-leverage factors are identified in order to determine the most effective and efficient use of resources to reduce the probability of grounding. The authors present results showing that the development of the Electronic Chart Display and Information System incorporated with the International Safety Management Code can significantly reduce the probability of grounding.

[Dougligeris *et al*., 1997] provides a methodology of analyzing, quantifying and assigning risk cost estimates in maritime transportation of petroleum products. The objective of the risk analysis, as stated in the paper, is to identify shipping routes that minimize a function of transportation and risk cost while maintaining an equitable distribution of risk. In addition, the proposed methodology is implemented in a case study involving the oil transportation in the Gulf of Mexico during the 1990-1994 time periods.

Similarly, [Iakovou, 2001] considers the maritime transportation of crude oil and petroleum products. The paper presents the development of a strategic multi-objective network flow model, allowing for risk analysis and routing, with multiple commodities, modalities and origin-destination pairs. The authors demonstrate the development of an interactive solution methodology and its implementation via an Internet-based software package. The objective is to facilitate the government agencies to determine how regulations should be set to derive desirable routing schemes.

[Slob, 1998] presents a study for the purpose of optimizing the combating and disposing of spills on the Dutch inland waterways. A system is developed for the determination of risks on inland waters and to classify the inland waterways into four risk-classes. The study also determines per location whether the amount of preparation of combating acute spills measures the risks of these locations. Finally, standard contingency plans are developed for combating spills for the different relevant locations in the Netherlands.

[Harrald *et al*., 1998] describes the modeling of human error related accident event sequences in a risk assessment of maritime oil transportation in Prince William Sound, Alaska. A two stage human error framework and the conditional probabilities implied by this framework are obtained from system experts such as tanker masters, mates, engineers, and state pilots. A dynamic simulation to produce the risk analysis results of the base case is also discussed.

[Merrick *et al*., 2000] and [Merrick *et al*., 2002] present the detailed model of the Prince William Sound oil transportation system, using system simulation, data analysis, and expert judgment. The authors also propose a systems approach to risk assessment and management by a detailed analysis of the sub-systems and their interactions and dependencies.

[Merrick *et al*., 2001] explains the Washington State Ferries Risk Assessment. A modeling approach that combines system simulation, expert judgment and available data is used to estimate the contribution of risk factors to accident risk. A simulation model is utilized to capture the dynamic environment of changing risk factors, such as traffic interactions, visibility or wind conditions.

[Van Dorp *et al*., 2001] describes a study that has been carried out to assess the sufficiency of passenger and crew safety in the Washington state ferry system, estimate the level of risk present, and develop recommendations for prioritized risk reduction measures. As a supplement to [Merrick *et al*., 2001], the potential consequences of collisions are modeled to determine the requirements for onboard and external emergency response procedures and equipment. In addition, potential risk reduction measures are evaluated and various risk management recommendations are resulted.

[Merrick and Van Dorp, 2006] combines a Bayesian simulation of the occurrence of situations with accident potential and a Bayesian multivariate regression analysis of the relationship between factors describing these situations and expert judgments of accident risk for two case studies. The first is an assessment of the effects of proposed ferry service expansions in San Francisco Bay. The second is an assessment of risk of the Washington State Ferries, the largest ferry system in the United States.

[Kuroda *et al*., 1982] proposes a mathematical model for estimating the probability of the collision of ships passing through a uniform channel. The model takes into account traffic characteristics such as traffic volume, ship size distribution, and sailing velocity distribution, as well as channel conditions such as width, length and centerline. The proposed model is examined on the basis of collision statistics for some channels and straits in Japan and it is concluded that the model gives a good estimation of the collision risk of a channel.

[Kaneko, 2002] considers probabilistic risk assessment methods applied to ships. The author presents a holistic methodology for risk evaluation and a method used in the process of estimating the probability of collision. In addition, he examines a method to reduce the number of fire escalation scenarios and demonstrates a trial risk evaluation of cabin fire.

Whereas the above literature utilizes probabilistic risk assessment techniques and simulation modeling, there are other studies on risk assessment that are based on statistical analysis of the data. These are performed through modeling accident probabilities and casualties using statistical estimation methods and time-series analysis of the past data as discussed below.

[Fortson *et al.*, 1973] proposes a methodological approach and task plan for assessing alternative methods of reducing the potential risk caused by the spill of hazardous cargo as the result of vessel collisions and groundings.

[Van der Tak and Spaans, 1976] explains the research conducted by Navigation Research Centre of the Netherlands Maritime Institute to develop a “maritime risk criterium number” for a certain sea area. The main purpose is to calculate the criterium number for different traffic alternatives in a certain area to find the best regulatory solution for the overall traffic situation.

[Maio *et al.*, 1991] develops a regression model as part of a study by the U.S. Department of Transportation for the U.S. Coast Guard's Office of Navigation Safety and Waterway to estimate the waterway casualty rate depending on the type of waterway, average current velocity, visibility, wind velocity, and channel width.

[Roeleven *et al.*, 1995] describes the fitting procedures in order to obtain the model that forecasts the probability of accidents as function of waterway attributes and circumstances. The authors use Generalized Linear Models (GLM), which do not require the assumption that the accident probability is normally distributed. Therefore, the binomial approach is used instead. The authors conclude that the circumstances such as visibility and wind speed are more explanatory with respect to the probability of accidents than the waterway characteristics.

While [Talley, 1995a] analyzes the cause factors of accident severity to evaluate the policies for reducing the vessel damage and the subsequent oil spillage of tanker accidents, [Talley, 1995b] investigates the causes of accident passenger-vessel damage cost.

In addition, [Anderson and Talley, 1995] uses a similar approach to study the causal factors of the oil cargo spill, and tanker barge vessel accidents, and [Talley, 1996] investigates the main factors of the risk and the severity of cargo of containership accidents by using vessel accident data.

Similarly, [Psaraftis *et al*., 1998] presents an analysis on the factors that are important determinants of maritime transportation risk. The purpose of the analysis is to identify technologies and other measures to improve maritime safety.

[Le Blanc and Rucks, 1996] describes the cluster analysis performed on a sample of over 900 vessel accidents that occurred on the lower Mississippi River. The objective is to generate four groups that are relatively unique in their respective attribute values such as type of accident, river stage, traffic level, and system utilization. The four groups resulting from the cluster analysis are characterized as Danger Zone, Bad Conditions for Good Navigators, Probably Preventable, and Accidents That Should Not Have Happened.

[Kite-Powell *et al*., 1998] explains the Ship Transit Risk project. The developed physical risk model is based on the assumption that the probability of an accident depends on a set of risk factors, which include operator skill, vessel characteristics, traffic characteristics, topographic and environmental difficulty of the transit, and quality of operator's information about the transit. The objective is to investigate the relationship between these factors.

In [Le Blanc *et al*., 2001], the authors use a neural network model to build logical groups of accidents instead of the cluster analysis. The groups generated in [Le Blanc and Rucks, 1996] and in this paper are compared and found to be radically different in terms of the relative number of records in each group and the descriptive statistics describing each comparable set of groups.

[Degre *et al*., 2003] describes the general principles of risk assessment models, the nature of input data required and the methods used to collect certain category of these data. It then describes more deeply the SAMSON model developed in the Netherlands. Finally, the authors show how the concepts used in these models may be generalized in order to assign a dynamic risk index to certain types of ships.

[Yudhbir and Iakovou, 2005] presents the development of an oil spill risk assessment model. The goal of this model is to first determine and assign risk costs to the links of a maritime transportation network, and then to provide insights on the factors contributing to the spills.

[Moller *et al*., 2005] reviews the current status of the government-industry partnerships for dealing with oil spills as the result of maritime transportation. The main factors of oil spill risk are identified, analyzed, and discussed in relation to the oil transportation pattern of each region. These are compared to the data on major oil pollution incidents. The authors also consider priorities and activities in different regions, and the implications for oil spill response before estimating the capabilities for increasing effective spill response measures in different regions at the end.

Our research specifically involves the risk analysis of the traffic in the Strait of Istanbul. The early work in this area is somewhat limited.

[Kornhauser and Clark, 1995] used the regression model developed by [Maio *et al*., 1991] to estimate the vessel casualties resulting from additional oil tanker traffic through the Strait of Istanbul.

A physics based mathematical model is developed in [Otay and Özkan, 2003] to simulate the random transit maritime traffic through the Strait of Istanbul. The developed model estimates the probability distribution of vessel casualties using the geographical characteristics of the Strait. Risk maps showing the expected number of accidents in different sections of the Strait are also presented for different vessel sizes and casualty types including collision, ramming and grounding.

[Tan and Otay, 1998] and later [Tan and Otay, 1999] present a physics-based stochastic model to investigate casualties resulting from tanker accidents in the narrow waterway. The authors demonstrate a state-space model developed to represent the waterway and the location of vessels at a given time. By incorporating the drift probabilities and random arrival of vessels into a Markov chain model they obtain the probability of casualty at a given location and also the expected number of casualties for a given number of vessels arriving per unit time.

[Or and Kahraman, 2002] investigates possible factors contributing to accidents in the Strait of Istanbul using Bayesian analysis and simulation modeling. The Bayesian analysis is used to obtain estimates for conditional maritime accident probabilities in the Strait. The resulting probabilities are then combined with the Strait's characteristics and traffic regulations in the simulation model. Simulation results indicate the significant impact of transit traffic arrivals, local traffic density, and the meteorological conditions on the number of accidents in the Strait of Istanbul.

[Örs and Yılmaz, 2003] and [Örs, 2005] study the oil spill development in the Strait of Istanbul. The developed model is based on a flow field computed by finite element analysis of the shallow water equations. A stochastic Lagrangian particles cluster tracking approach is adopted for the simulation of the oil movement. The results of the study show that the timescale of a major spill is as little as a few hours.

2.4 MODELING RISK

2.4.1 FRAMEWORK

In this chapter, our objective is to determine operational policies that will mitigate the risk of having an accident that will endanger the environment, the residents of Istanbul and impact the economy, while maintaining an acceptable level of vessel throughput.

We will start by defining the events that may trigger an accident as *instigators*. Various instigators include human error, rudder failure, propulsion failure, communication and/or navigation equipment failure, and mechanical and/or electrical failure. The *1st tier accident* types occurring as a result of instigators include collision, grounding, ramming, and fire and/or explosion. The *2nd tier accident* types that may occur following 1st tier accidents include grounding, ramming, fire and/or explosion, and sinking. The potential consequences of such accidents include human casualty, property and/or infrastructure damage, environmental damage and traffic effectiveness. These represent consequences of both the 1st and 2nd tier accidents. Note that in some instances, there may not be a 2nd tier accident following a 1st tier one.

The first step of a risk analysis process is the identification of the series of events leading to an accident and its consequences. An accident is not a single event, but the result of a series of events. Figure 2.3 shows the classification of different risk elements in the transit vessel traffic system in the Strait of Istanbul.

In addition to identifying different types of instigators, accidents, and consequences, risk analysis includes the estimation of the probabilities of these events and the evaluation of the consequences of different degrees of severity. This assessment establishes the basis of our mathematical risk model.

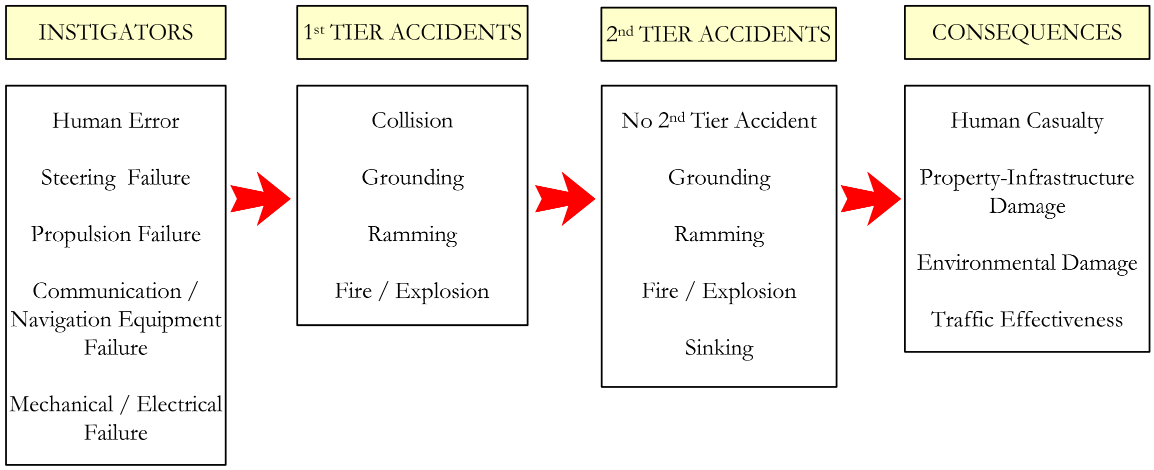

Figure 2.3 The framework of the risk model

2.4.2 A MATHEMATICAL RISK MODEL

The accidents that occurred in the Strait of Istanbul in the last 58 years have varied in frequency and severity. Some of them were high probability and low consequence accidents whereas others were low probability and high consequence ones. Specifically, the existence of the latter leads to difficulties in the risk analysis process. Due to the rare occurrence of such accidents, there is a lack of available data to determine the contribution of various situational attributes to accident risks. Therefore, we constructed a risk model, which incorporates vessel traffic simulation and available data as well as subject matter expert judgments in order to quantify accident risks through the estimation of the contribution of situational attributes to accident risk.

While a transit vessel navigates in the Strait of Istanbul, there is a possibility that something could go wrong. For example, there can be a mechanical failure in the vessel or the pilot can make an error. We have called these events that may trigger an accident as *instigators*. The occurrence of an instigator depends on the *situation*, which is the vector of situational attributes. Obviously, some system states are more “risky” than others. For instance, a vessel navigating on a clear day is at lower “risk” than a vessel navigating in a poor visibility situation.

An instigator may lead to an accident. For example, a short-circuit problem in a vessel may cause a fire. Here, the probability of a fire occurring after a short-circuit depends on the situational attributes. For example, short-circuit occurrence on an LNG carrier is more "risky" than on a container vessel.

Similarly, the consequence of an accident and its impact depends not only on the accident itself but also on the vessels themselves as well as a number of attributes of the Strait. For instance, a fire on an oil tanker would have a bigger impact on the human life and the environment than a fire on a dry cargo vessel.

Since the system state influences the risk of an accident at every step starting from the occurrence of an instigator up to the consequences of the accident, we utilize Probabilistic Risk Assessment (PRA) to emphasize the effect of the dynamic nature of the vessel traffic system on the risk.

To clarify the effect of different situational attributes on the various steps of the risk model shown in Figure 2.3, we divide the situational attributes into two categories: attributes influencing accident occurrence and attributes influencing consequences and their impact. These two categories are listed in Figure 2.4 and Figure 2.5.

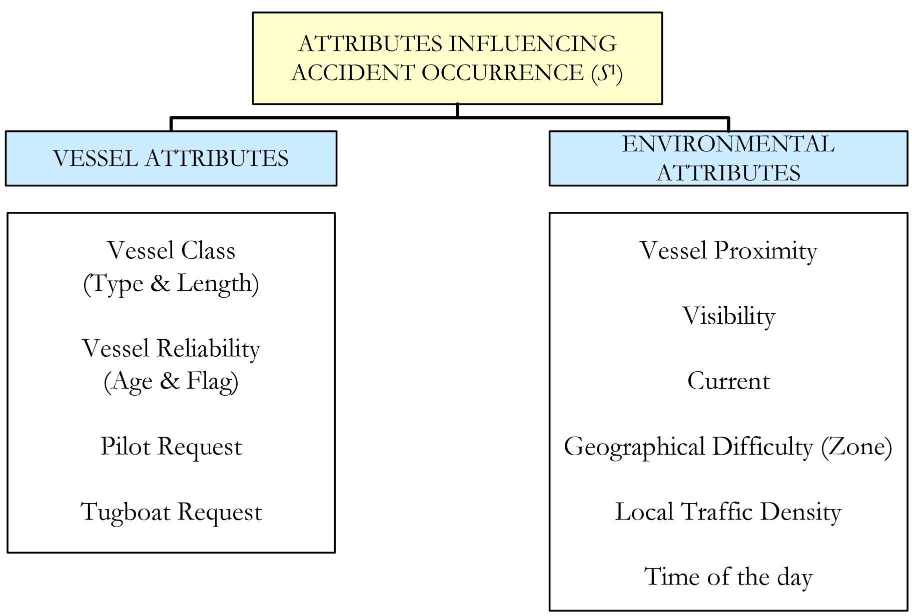

Figure 2.4 Situational attributes influencing accident occurrence

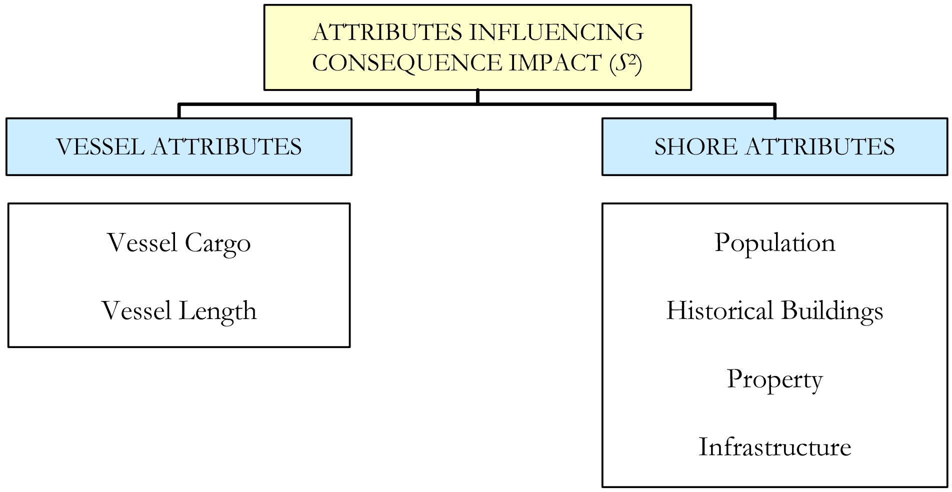

Figure 2.5 Situational attributes influencing the consequences

In order to quantify the risk, we need to answer the following questions:

- How often do the various situations occur?
- For a particular situation, how often do instigators occur?
- If an instigator occurs, how likely is an accident?
- If an accident occurs, what would the damage to human life, property, environment and infrastructure be?

In this study, risks are quantified based on historical data, expert judgment elicitation and a high-fidelity simulation model of the transit vessel traffic in the Strait of Istanbul. We have obtained a detailed vessel/traffic data from the VTS and meteorological data from various resources. The simulation model mimics arrivals of various types of cargo vessels in various lengths as shown in **Error! Reference source not found.,** scheduling their entrances, their pilotage and transit travel (with details such as speeds and overtaking), and their exit from the Strait along with all the relevant local traffic, weather and water dynamics. The scheduling algorithm was developed through a close cooperation with the VTS to mimic their decisions on sequencing vessel entrances in days and nights as well as giving way to vessel traffic in either direction. The model was tested through a validation process and the results were more than satisfactory.

Table 2-3 Vessel types in the Strait of Istanbul

<table>
<tr><th></th><th></th><th colspan="5">Type</th></tr>
<tr><th>Length (m.)</th><th>Draft (m.)</th><th>Tanker</th><th>Carrying Dangerous Cargo</th><th>LNG-LPG</th><th>Dry Cargo</th><th>Passenger Vessels</th></tr>
<tr><td>< 50</td><td>< 15</td><td rowspan="2" colspan="2">Class E</td><td rowspan="3">Class B</td><td rowspan="3">Class D</td><td rowspan="6">Class P</td></tr>
<tr><td>50 - 100</td><td>< 15</td></tr>
<tr><td>100 - 150</td><td>< 15</td><td rowspan="2" colspan="2">Class C</td></tr>
<tr><td>150 - 200</td><td>< 15</td><td></td><td rowspan="3">Class C</td></tr>
<tr><td>200 - 250</td><td>< 15</td><td rowspan="2" colspan="3">Class A</td></tr>
<tr><td>250 - 300</td><td>> 15</td></tr>
<tr><td>> 300</td><td>> 15</td><td colspan="5">Class T6</td></tr>
</table>

In the model, the Strait of Istanbul is divided into 21 slices (each 8 cables long, where 1 cable = 1.09 miles) for risk analysis purposes as depicted in Figure 2.6. The risk at slice s, R_s, is calculated based on the snapshot of the traffic in that slice every time a vessel enters it. This includes all the vessels entering the slice in either direction. The observing vessel entering the slice first calculates its own contribution to the slice risk and then calculates the contribution of each vessel navigating in the slice.

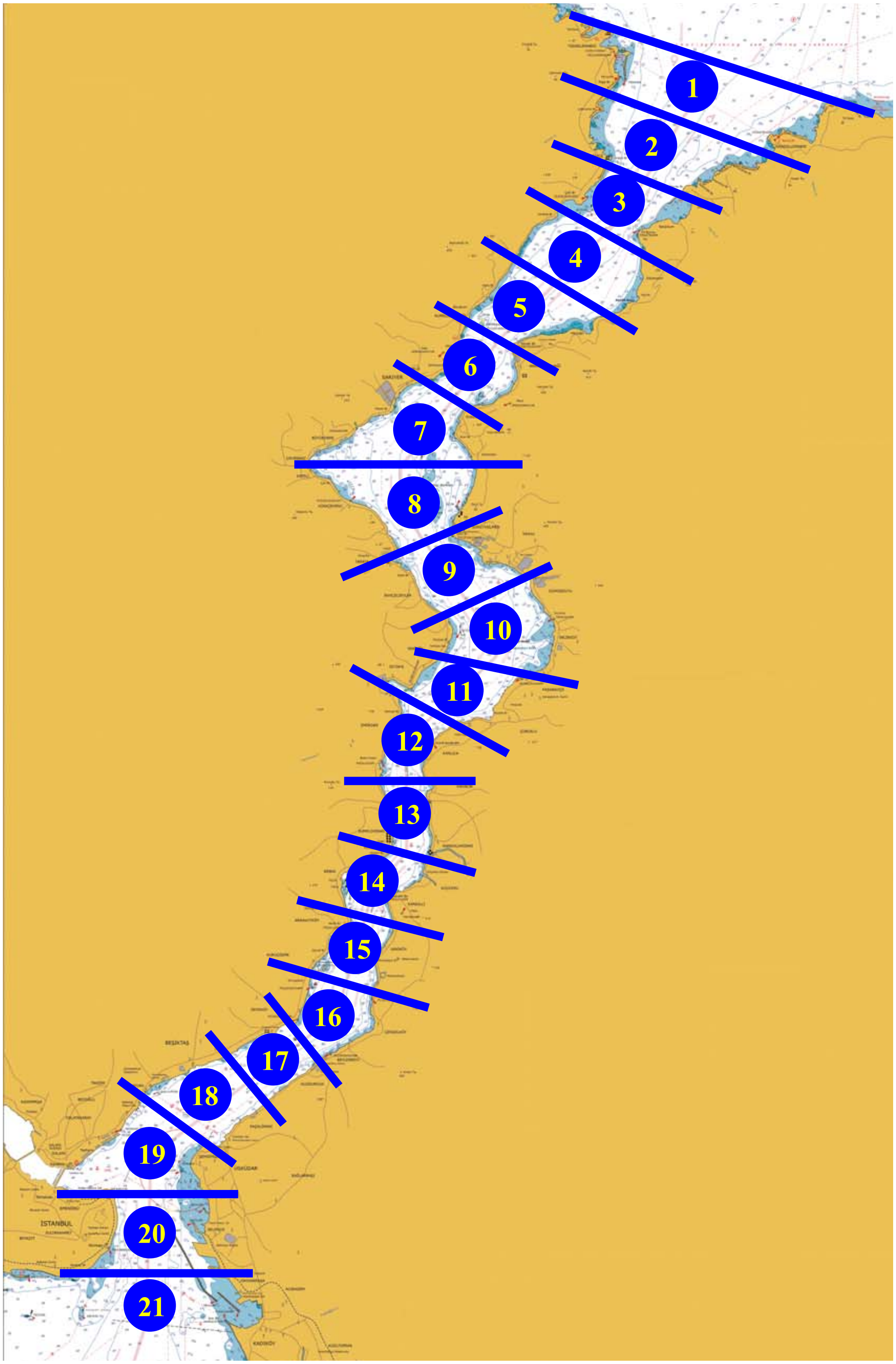

Figure 2.6 Risk Slices

The risk at slice s, R_s, is defined by

$$R_s = \sum_{r \in \mathcal{V}_s} \sum_{m \in \mathcal{A}^1} \sum_{i \in \mathcal{A}_m^2} \left(\sum_{j \in \mathcal{C}_m} E\left[C_{jmrs} \middle| A_{mrs}^1 \right] \times \Pr\left(A_{mrs}^1 \right) + \sum_{j \in \mathcal{C}_i} E\left[C_{jirs} \middle| A_{irs}^2 \right] \times \Pr\left(A_{irs}^2 \right) \right) \quad (2.1)$$

where

A_{mrs}^1 : 1st tier accident type m at slice s involving vessel r

A_{irs}^2 : 2nd tier accident type i at slice s involving vessel r

$\mathcal{A}^1$: Set of 1st tier accident types

$\mathcal{A}_m^2$: Set of 2nd tier accident types that may be caused by 1st tier accident type m as indicated in Table 2-4.

C_{jmrs} : Consequence type j of 1st tier accident type m at slice s contributed by vessel r

C_{jirs} : Consequence type j of 2nd tier accident type i at slice s contributed by vessel r

$\mathcal{C}_i$: Set of consequence types of accident type i as indicated in Table 2-5

$\mathcal{V}_s$: Set of vessels navigating at slice s as seen by an observing vessel entering the slice

Note: In the case where there are no 2nd tier accidents, the first term in (2.1) equals zero.

Table 2-4 Causal relationship between 1st and 2nd tier accident types

		No 2nd Tier Accident	**2nd Tier Accident Type**			
			Grounding	Ramming	Fire / Explosion	Sinking
1st Tier Accident Type	Collision	✓	✓	✓	✓	✓
	Grounding	✓			✓	✓
	Ramming	✓	✓		✓	✓
	Fire / Explosion	✓	✓	✓		✓

(Information presented in this table can be interpreted as: collision may either not cause a 2nd tier accident or it may cause grounding, ramming, fire/explosion, or sinking as a 2nd tier accident)

Table 2-5 Set of accident consequences

Accidents Types		Consequences			
		Property / Infrastructure Damage	Human Casualty	Environmental Damage	Traffic Effectiveness
	Collision		✓	✓	✓
	Grounding			✓	✓
	Ramming	✓	✓	✓	✓
	Fire/Explosion	✓	✓	✓	✓
	Sinking	✓	✓	✓	✓

The probability of 1st tier accident type *m* at slice *s* involving vessel *r* is defined by

$$\Pr\left(A^1_{mrs}\right) = \sum_{k \in \mathcal{J}_m} \sum_{l \in \mathcal{S}^1} \Pr\left(A^1_{mrs} \middle| I_{ks}, S^1_{ls}\right) \times \Pr\left(I_{ks} \middle| S^1_{ls}\right) \times \Pr\left(S^1_{ls}\right) \tag{2.2}$$

where

I_{ks} : Instigator type *k* at slice *s*

$\mathcal{J}_m$: Set of instigator types that may cause accident type *m* as indicated in

Table 2-6

S^1_{ls} : Situation *l* influencing accident occurrence at slice *s*

$\mathcal{S}^1$: Set of situations influencing accident occurrence.

Table 2-6 Set of instigators that may cause an accident

		1st Tier Accidents			
		Collision	Grounding	Ramming	Fire / Explosion
Instigators	Human Error	✓	✓	✓	✓
	Steering Failure	✓	✓	✓	
	Propulsion Failure	✓	✓	✓	
	Communication/Navigation Equipment Failure	✓	✓	✓	
	Mechanical/Electrical Failure				✓

The probability of 2nd tier accident type *i* at slice *s* involving vessel *r* is calculated by

$$\Pr\left(A_{irs}^{2}\right) = \sum_{m \in \mathcal{A}_i^1} \Pr\left(A_{irs}^{2} \middle| A_{mrs}^{1}\right) \times \Pr\left(A_{mrs}^{1}\right) \tag{2.3}$$

The expected value of consequence *j* at slice *s* given *n*th tier accident type *i* is defined by

$$E\left[C_{jirs} \middle| A_{irs}^{n}\right] = \sum_{h \in \mathcal{L}_{ij}} \sum_{l \in S^2} C_{jirs}\left(h\right) \times \Pr\left(C_{jirs}\left(h\right) \middle| A_{irs}^{n}, S_{ls}^{2}\right) \times \Pr\left(S_{ls}^{2}\right) \tag{2.4}$$

where

$\mathcal{L}_{ij}$: Set of impact levels of consequence *j* of accident type *i*

S^2_{ls} : Situation *l* influencing consequence at slice *s*

$\boldsymbol{S}^2$: Set of situations influencing consequence impact

C_{jirs} : Consequence type *j* of nth tier accident type *i* at slice *s* contributed by vessel *r*.

The methodology used to calculate each component of the risk expression, R_s , is explained in the following section.

2.4.3 METHODOLOGY

In this section, we demonstrate how to obtain various conditional probabilities and expected consequences used in (2.1) - (2.4). The concept and the approach to obtain each type of conditional probability and expected consequences are presented focusing on one of them, namely the collision probability and human error. Below we start with the conditional probability of a first tier accident which is followed by the probability of a second tier accident and the expected consequences.

2.4.3.1 FIRST TIER ACCIDENT PROBABILITY

In order to calculate the probability of a first tier accident, one needs to evaluate (2.2) involving probability of a first tier accident given an instigator and a situation, probability of an instigator given a situation and probability of a situation. . In addition to these evaluations, a calibration process needs to be carried out to make sure that the long-run accident probabilities are legitimate.

2.4.3.1.1 PROBABILITY OF A 1ST TIER ACCIDENT GIVEN AN INSTIGATOR AND A SITUATION

Once an instigator has occurred, the probability of a 1st tier accident is affected by the situation, which represents the system condition. Due to lack of data to determine the contribution of various situational attributes to accident risks, the estimation of the probability of an accident given an instigator requires elicitation of expert judgments.

There are a number of elicitation methods available as noted in [Cooke, 1991], and we are using a paired comparisons elicitation method in this research. Our decision to use this method is based on the observation that experts are more comfortable making paired comparisons rather than directly assessing a probability value for a given situation. The specific paired comparison elicitation method used in this research was also used in [Merrick *et al*., 2001], [Merrick and Van Dorp, 2006] and [Szwed *et al*., 2006].

Similar to the Analytical Hierarchy Process (AHP) the paired comparison approach focuses on the functional relationship between situational attributes $\underline{S}^1 = (X_1, X_2, \ldots, X_p)^T$ and an accident probability rather than a value function. The probability of a 1st tier accident given an instigator can be defined as

$$\Pr\left(A^1 \middle| I, \underline{S}^1\right) = P_0 \exp\left(\underline{\beta}^T \underline{S}^1\right) \tag{2.5}$$

where $\underline{S}^1$ represents a column vector of situational attributes describing a situation during which an instigator has occurred, $\underline{\beta}$ is a vector of parameters and P_0 is a calibration constant. The accident probability model (2.5) was proposed in [Roeleven *et al*., 1995], [Merrick *et al*., 2000] and [Van Dorp *et al*., 2001]. It is based on the proportional hazards model originally proposed by [Cox, 1972], which assumes that accident probability behaves exponentially with changes in covariate values.

The probability of an accident, defined by (2.5) where $\underline{S}^1 \in [0,1]^p$, $\underline{\beta} \in R^p$ and $P_0 \in [0,1]$, is assumed to depend on the situational attributes listed in Table 2-7. The situational attributes X_i, $i = 1,\ldots,p$ are normalized so that $X_i = 1$ describes the "worst" case scenario while $X_i = 0$ describes the "best" case scenario. For example, for the 11th attribute, that is time of the day, $X_{11} = 1$ represents the nighttime, while $X_{11} = 0$ represents the daytime.

Unfortunately, sorting the possible values of situational attributes from worst to best as it relates to an accident probability is not an easy task. Also, the accident probability behaves much like a value function. That is, not only the order amongst different values of a situational attribute is important, but also their relative differences. Therefore, a scale is needed to rank especially the lesser evident situational attributes. The possible values of situational attributes and their scales were obtained through discussions with the VTS. The possible values of the situational attributes influencing accident occurrence ($\underline{S}^1$) are listed in Table 2-7 while their normalized scale values are given in Appendix A.

Among the situational attributes, the reliability of a vessel is difficult to measure. Thus, we define it in terms of vessel age and flag type. The age of a vessel is categorized as new, middle age or old. Additionally, the flag of a vessel may be used as an indicator of the education and experience of the captain and crew as well as the technology and maintenance level of the equipment. The flag of a vessel may be defined as low, medium or high risk depending on the flag state. Consequently, the reliability of a vessel is defined as the combination of age and flag and is represented through nine possible values.

Table 2-7 Possible values of situational attributes influencing accident occurrence S^1

Variable	Attribute Name	Number Possible Values	Description
X_1	1st Interacting Vessel Class	9	1-3, 6-11 (see Table 2.8)
X_2	2nd Interacting Vessel Class	11	1-11 (see Table 2.8)
X_3	1st Vessel Tugboat Request	2	Yes, No
X_4	1st Vessel Pilot Request	2	Yes, No
X_5	Nearest Transit Vessel Proximity	9	same direction 0-4 cables, same direction 4-8 cables; same direction >8 cables, 1 knot/hr speed difference overtaking lane, 2 knots/hr speed difference overtaking lane, 3 knots/hr speed difference overtaking lane, 4 knots/hr speed difference overtaking lane, opposite direction normal lane, opposite direction overtaking lane

X_6	Visibility	3	<0.5 mile, 0.5-1 mile , >1 mile
X_7	Current	8	0-2 knots/hr same direction with 1st vessel, 2-4 knots/hr same direction with 1st vessel, 4-6 knots/hr same direction with 1st vessel, > 6 knots/hr same direction with 1st vessel, 0-2 knots/hr opposite to 1st vessel, 2-4 knots/hr opposite to 1st vessel, 4-6 knots/hr opposite to 1st vessel, > 6 knots/hr opposite to 1st vessel
X_8	Local Traffic Density	3	1-2, 3-5, >5
X_9	Zone	12	Anadolu Feneri-Sarıyer SB, Anadolu Feneri-Sarıyer NB, Sarıyer-Beykoz SB, Sarıyer-Beykoz NB, Beykoz-Kanlıca SB, Beykoz-Kanlıca NB, Kanlıca-Vaniköy SB, Kanlıca-Vaniköy NB, Vaniköy-Üsküdar SB, Vaniköy-Üsküdar NB, Üsküdar-Kadıköy SB, Üsküdar-Kadıköy NB
X_{10}	Vessel Reliability	9	Age (New, Middle Age, Old) x Flag Category (Low Risk, Medium Risk, High Risk)
X_{11}	Time of the Day	2	Daytime, Nighttime

The grouping of vessel age into the three categories (i.e. new, middle age or old) within each vessel type is determined through an age survey collected from experts. In addition, each flag is assigned to one of the three flag categories (i.e. low, medium or high risk) based on the 2006 Shipping Industry Flag State Performance Table [MISS, 2006]. The performance table includes measures such as the annual reports of Port State Control Organizations (i.e. Paris MOU, Tokyo MOU and US Cost Guard), convention ratifications, age information, STCW and ILO (International Labor Organization) reports, and IMO meeting attendance. An importance factor for each measure is determined through the interviews with the experts. These factors and the information in the Flag State Performance Table are then used to calculate a mathematical performance measure for each flag state. Finally, the mathematical value is transformed to one of the three flag categories mentioned earlier using a scale.

Table 2-8 Possible values for 1st and 2nd Interacting Vessel Class (X_1, X_2)

<table>
<tr><th></th><th colspan="6">Vessel Type</th></tr>
<tr><th>Length(m)</th><th>Tanker</th><th>LNG-LPG</th><th>Dry Cargo</th><th>Passenger</th><th>Local ferry</th><th>Local others</th></tr>
<tr><td>0 - 100</td><td colspan="3">1</td><td rowspan="2">3</td><td>4</td><td>5</td></tr>
<tr><td>100 - 150</td><td colspan="3">2</td><td colspan="2" rowspan="5"></td></tr>
<tr><td>150 - 200</td><td colspan="3">6</td><td rowspan="3">9</td></tr>
<tr><td>200 - 250</td><td colspan="3">7</td></tr>
<tr><td>250 -300</td><td colspan="3">8</td></tr>
<tr><td>300-350</td><td colspan="3">11</td><td>10</td></tr>
</table>

For the situational attribute X_9, Strait of Istanbul is divided into 12 different zones as depicted in Figure 2.7 and listed in

Table **2-9**. Each zone is unique in terms of population, historical buildings, property, and infrastructure located on its shores, as well as its geographical difficulty, and local traffic density. These zones are determined through our discussions with the VTS.

Table 2-9 List of zones

Zone Number	Zone Name
1	Anadolu Feneri - Sarıyer Southbound
2	Anadolu Feneri - Sarıyer Northbound
3	Sarıyer - Beykoz Southbound
4	Sarıyer - Beykoz Northbound
5	Beykoz - Kanlıca Southbound
6	Beykoz - Kanlıca Northbound
7	Kanlıca -Vaniköy Southbound
8	Kanlıca -Vaniköy Northbound
9	Vaniköy -Üsküdar Southbound
10	Vaniköy -Üsküdar Northbound
11	Üsküdar - Kadıköy Southbound
12	Üsküdar – Kadıköy Northbound

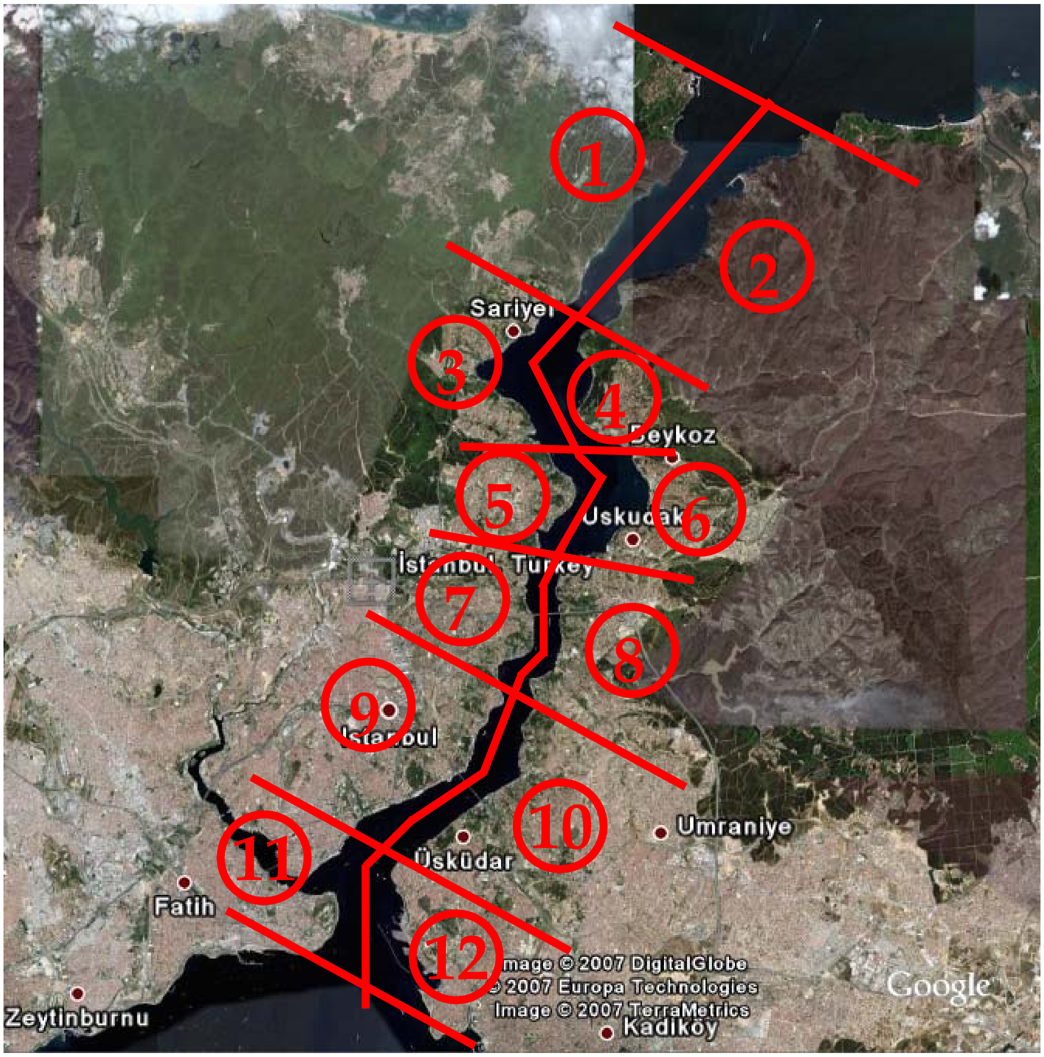

Figure 2.7 Risk zones

In addition to the individual situational attributes listed in Table 2-7, attributes describing interaction effects are included in the model. For example, $X_{12} = X_1 \cdot X_9$ represents the interaction between the 1st interacting vessel class and the zone. The objective is to model the combined impact of certain key attributes on the accident probability. There are 12 interaction attributes as seen in Table 2-10. Again, these interaction attributes are determined through interviews with authorities at the VTS.

Table 2-10 Interaction attributes

	Interaction	Description
X_{12}	$X_1 \cdot X_9$	1st Interacting Vessel Class x Zone
X_{13}	$X_4 \cdot X_7$	1st Vessel Pilot Request x Current
X_{14}	$X_4 \cdot X_9$	1st Vessel Pilot Request x Zone
X_{15}	$X_3 \cdot X_9$	1st Vessel Tugboat Request x Zone
X_{16}	$X_3 \cdot X_7$	1st Vessel Tugboat Request x Current
X_{17}	$X_5 \cdot X_6$	Nearest Transit Vessel Proximity x Visibility
X_{18}	$X_5 \cdot X_7$	Nearest Transit Vessel Proximity x Current
X_{19}	$X_7 \cdot X_9$	Current x Zone
X_{20}	$X_6 \cdot X_8$	Visibility x Local Traffic Density
X_{21}	$X_6 \cdot X_9$	Visibility x Zone
X_{22}	$X_9 \cdot X_8$	Zone x Local Traffic Density
X_{23}	$X_{10} \cdot X_4$	Time of the Day x 1st Vessel Pilot Request

To assess the accident probability given an instigator, subject matter experts were asked to compare two situations $\underline{S}_1^1$ and $\underline{S}_2^1$. Figure 2.8 provides a sample question appearing in one of the accident probability questionnaires used in the risk analysis of the transit vessel traffic in the Strait of Istanbul. The questionnaires were answered by numerous experts with different backgrounds (e.g. pilots, captains, VTS authorities, academia, etc.) In each question, compared situations differ only in one situational attribute. If the expert thinks that the likelihood of an accident is the same in situations 1 and 2, then he/she circles "1". If the expert thinks that it is more likely to have an accident in one situation than other, then he/she circles a value towards that situation. For example, if "5" is circled towards Situation 2, then the expert thinks that it is 5 times more likely to have an accident in Situation 2 than Situation 1. The experts don't have to select one of the values on the given scale. They can also enter other values as they see fit.

QUESTION 1

Situation 1	Situational Attribute	Situation 2
1	1st Interacting Vessel Class	11
1	2nd Interacting Vessel Class	-
Yes	1st Vessel Tugboat Request	-
Yes	1st Vessel Pilot Request	-
Same direction >8 cables	Nearest Transit Vessel Proximity	-
>1 mile	Visibility	-
0-2 knot/hr opposite to 1st vessel	Current	-
1-2	Local Traffic Density	-
Anadolu Feneri - Sarıyer Northbound	Zone	-
Daytime	Time of the Day	-

HUMAN ERROR		
Other: ____	**9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9**	**Other:** ____
STEERING FAILURE		
Other: ____	**9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9**	**Other:** ____
PROPULSION FAILURE		
Other: ____	**9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9**	**Other:** ____
COMMUNICATION/NAVIGATION EQUIPMENT FAILURE		
Other: ____	**9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9**	**Other:** ____
COLLISION is more likely in Situation 1	⟵⟶	**COLLISION is more likely in Situation 2**

Figure 2.8 A sample accident probability question

A separate questionnaire is prepared for each 1st tier accident. The experts are asked to compare situations for each instigator type in a given question as seen in Figure 2.8. Note that the instigators specified in the questionnaires are assumed to take place in the 1st interacting vessels. We ask 4 questions per situational attribute, one question representing the worst case scenario, one representing the best case, and two others corresponding to ordinary cases. Since not all accident types are influenced by every situational attribute, the total number of questions differs from one questionnaire to another.

Consider two situations defined by the situational attribute vectors $\underline{S}_1^1$ and $\underline{S}_2^1$. The relative probability is the ratio of the accident probabilities as defined by

$$\frac{\Pr\left(A^1 \middle| I, \underline{S}_1^1\right)}{\Pr\left(A^1 \middle| I, \underline{S}_2^1\right)} = \frac{P_0 \exp\left(\underline{\beta}^T \underline{S}_1^1\right)}{P_0 \exp\left(\underline{\beta}^T \underline{S}_2^1\right)} = \exp\left(\underline{\beta}^T \left(\underline{S}_1^1 - \underline{S}_2^1\right)\right) \tag{2.6}$$

where $(\underline{S}_1^1 - \underline{S}_2^1)$ denotes the difference vector of the two situations. Therefore, the relative probability of an accident given an instigator in two situations depends only on the difference vector $(\underline{S}_1^1 - \underline{S}_2^1)$ and the parameter vector $\underline{\beta}$. Since the experts are asked to assess the above ratio in (2.6), the parameter vector $\underline{\beta}$ can be estimated without determining the accident probability itself.

Let $z_{l,j}$ be the response of expert l ($l = 1, \ldots, m$) to question j ($j = 1, \ldots, n$). To aggregate the expert responses, their geometric mean is taken as follows:

$$\overline{z}_j = \left(\prod_{l=1}^{m} z_{l,j}\right)^{\frac{1}{m}}. \tag{2.7}$$

The geometric mean is thought to be appropriate since the responses represent ratios of probabilities. Using (2.6) and (2.7), we have

$$\overline{z}_j = \frac{\Pr\left(A^1 \middle| I, \underline{S}_{1j}^1\right)}{\Pr\left(A^1 \middle| I, \underline{S}_{2j}^1\right)} = \exp\left(\underline{\beta}^T \left(\underline{S}_{1j}^1 - \underline{S}_{2j}^1\right)\right) \tag{2.8}$$

which makes the basis for a regression equation used to determine the relative effect of the situational attributes on the accident probability. This equation is

$$y_j = \underline{\beta}^T \left(\underline{S}_{1j}^1 - \underline{S}_{2j}^1\right) + \varepsilon_j \tag{2.9}$$

where $y_j = \ln(\overline{z}_j)$ and ε_j is the residual error term. Since in each question, compared situations differ only in one situational attribute, the difference vector has all "0" except a "1" term.

Under the assumption that ε is normally distributed ($\varepsilon_j \sim i.i.d\ N(0,\sigma^2)$), this equation can be explained as a standard multiple linear regression equation. The aggregate expert response is the dependent variable, $(\underline{S}_{1j}^1 - \underline{S}_{2j}^1)$ is the vector of independent variables and $\underline{\beta}$ is a vector of regression parameters. Subsequently, the $\tilde{\underline{\beta}}$ vector is estimated using a standard linear regression analysis. The results of the regression analysis for each accident probability questionnaire are given in Appendix B.

Below we present the next type of conditional probability in (2.2) of instigators, which is the probability of an instigator given a situation.

2.4.3.1.2 PROBABILITY OF AN INSTIGATOR GIVEN A SITUATION

Among the instigators, human error has a unique place due to lack of data. Therefore it is handled differently than the other instigators. Expert judgment is used to arrive at the conditional human error probabilities whereas accident data is used for the others. Below we first present how the human error conditional probability is obtained. Clearly, probability of human error is affected by the particular vessel attributes as well as environmental attributes. We have estimated its conditional probability using the paired-comparison approach described in section 2.4.3.1.1. Thus the probability of human error is defined as

$$\Pr\left(\text{Human Error}\middle|\underline{S}^1\right) = P_0^1 \exp\left(\underline{\beta}^{1T}\underline{S}^1\right) \tag{2.10}$$

where P_0^1 is the calibration constant and $\underline{\beta}^1$ is the parameter vector for the human error probability. To assess the human error probability, experts were asked to make a number of paired $(\underline{S}_1^1, \underline{S}_2^1)$ comparisons. Figure 2.9 provides a sample question appearing in the human error questionnaire, which consists of 40 questions.

QUESTION 34

Situation 1	Situational Attribute	Situation 2
10	1st Interacting Vessel Class	-
2	2nd Interacting Vessel Class	-
Yes	1st Vessel Pilot Request	-
2 knots/hr speed difference overtaking lane	Nearest Transit Vessel Proximity	-
0.5 - 1 mile	Visibility	-
4-6 knots/hr opposite to 1st vessel	Current	-
3-5	Local Traffic Density	-
Sariyer - Beykoz Northbound	Zone	-
New & High Risk	Vessel Reliability	Medium Age x Low Risk
Daytime	Time of the Day	-
Other: ____	9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9	**Other:** ____
HUMAN ERROR is more likely in Situation 1	⟵ ⟶	**HUMAN ERROR is more likely in Situation 2**

Figure 2.9 A sample human error question

The regression equation describing the relative effect of situational attributes on the human error probability is given by

$$y_j = \underline{\beta}^{1T}\left(\underline{S}_{1j}^{1} - \underline{S}_{2j}^{1}\right) + \varepsilon_j \tag{2.11}$$

where ε is the residual error term. Under the assumption that ε is normally distributed, (2.11) becomes a multiple linear regression equation. Therefore, the estimate parameter vector $\underline{\tilde{\beta}}^{1}$ is obtained using a linear regression analysis. The results of the regression analysis for the human error questionnaire are given in Appendix C.

Human error appears to have a larger marginal probability of occurrence when compared to rest of the instigators. Therefore, we have used the above expert judgment based approach to evaluate the human error conditional probability. For the remaining instigators, we have incorporated the process of finding their conditional probabilities into a calibration process based on historical data. This reduced the need to generate further questionnaires for elicitation hopefully without losing much accuracy.

Below we discuss marginal probabilities of situations.

2.4.3.1.3 PROBABILITY OF A SITUATION

Probabilities of situations are used in calculating accident probabilities and expected consequences to evaluate accident risks. As an example, consider the probability of collision that can be written as

$$
\begin{aligned}
\Pr(\text{Collision}) = & \sum_{l \in S^1} \Pr\left(\text{Collision} \middle| \text{Human Error}, S_{ls}^1\right) \times \Pr\left(\text{Human Error} \middle| S_{ls}^1\right) \times \Pr\left(S_{ls}^1\right) \\
& + \sum_{l \in S^1} \Pr\left(\text{Collision} \middle| \text{Steering Fail}, S_{ls}^1\right) \times \Pr\left(\text{Steering Fail} \middle| S_{ls}^1\right) \times \Pr\left(S_{ls}^1\right) \\
& + \sum_{l \in S^1} \Pr\left(\text{Collision} \middle| \text{Propulsion Fail}, S_{ls}^1\right) \times \Pr\left(\text{Propulsion Fail} \middle| S_{ls}^1\right) \times \Pr\left(S_{ls}^1\right) \\
& + \sum_{l \in S^1} \Pr\left(\text{Collision} \middle| \text{Comm/Nav Fail}, S_{ls}^1\right) \times \Pr\left(\text{Comm/Nav Fail} \middle| S_{ls}^1\right) \times \Pr\left(S_{ls}^1\right)
\end{aligned}
\tag{2.12}
$$

where each term of the summation represents the joint probability of collision and an instigator such as

$$
\Pr(\text{Collision,Human Error}) = \sum_{l \in S^1} \Pr\left(\text{Collision} \middle| \text{Human Error}, S_{ls}^1\right) \times \Pr\left(\text{Human Error} \middle| S_{ls}^1\right) \times \Pr\left(S_{ls}^1\right). \tag{2.13}
$$

Combining (2.5) and (2.10), we obtain

$$
\begin{aligned}
\Pr(\text{Collision}) = & \sum_{l \in S^1} P_0^2 \exp\left(\sum_{i=1}^{p} \beta_i^2 x_i + \beta_0^2\right) \times P_0^1 \exp\left(\sum_{i=1}^{p} \beta_i^1 x_i + \beta_0^1\right) \times \Pr\left(S_{ls}^1\right) \\
& + \sum_{l \in S^1} P_0^3 \exp\left(\sum_{i=1}^{p} \beta_i^3 x_i + \beta_0^3\right) \times \Pr\left(\text{Steering Fail} \middle| S_{ls}^1\right) \times \Pr\left(S_{ls}^1\right) \\
& + \sum_{l \in S^1} P_0^4 \exp\left(\sum_{i=1}^{p} \beta_i^4 x_i + \beta_0^4\right) \times \Pr\left(\text{Propulsion Fail} \middle| S_{ls}^1\right) \times \Pr\left(S_{ls}^1\right) \\
& + \sum_{l \in S^1} P_0^5 \exp\left(\sum_{i=1}^{p} \beta_i^5 x_i + \beta_0^5\right) \times \Pr\left(\text{Comm/Nav Fail} \middle| S_{ls}^1\right) \times \Pr\left(S_{ls}^1\right)
\end{aligned}
\tag{2.14}
$$

In the simulation model, situations regarding the vessel attributes as well as the environmental (natural) conditions such as daytime, current, visibility etc., are generated using corresponding random variate generations. Therefore, while evaluating the collision probability at time t (and other accident probabilities similarly) using (2.14), the situation probabilities are replaced by their associated indicator functions as shown below.

$$
\begin{aligned}
\Pr(\text{Collision}) = & \sum_{l \in S^1} P_0^2 \exp\left(\sum_{i=1}^{p} \beta_i^2 x_i + \beta_0^2\right) \times P_0^1 \exp\left(\sum_{i=1}^{p} \beta_i^1 x_i + \beta_0^1\right) \times \mathbf{I}_{S_{ls}^1} \\
& + \sum_{l \in S^1} P_0^3 \exp\left(\sum_{i=1}^{p} \beta_i^3 x_i + \beta_0^3\right) \times \Pr\left(\text{Steering Fail} \middle| S_{ls}^1\right) \times \mathbf{I}_{S_{ls}^1} \\
& + \sum_{l \in S^1} P_0^4 \exp\left(\sum_{i=1}^{p} \beta_i^4 x_i + \beta_0^4\right) \times \Pr\left(\text{Propulsion Fail} \middle| S_{ls}^1\right) \times \mathbf{I}_{S_{ls}^1} \\
& + \sum_{l \in S^1} P_0^5 \exp\left(\sum_{i=1}^{p} \beta_i^5 x_i + \beta_0^5\right) \times \Pr\left(\text{Comm/Nav Fail} \middle| S_{ls}^1\right) \times \mathbf{I}_{S_{ls}^1}
\end{aligned}
\tag{2.15}
$$

where $\mathbf{I}_{S_{ls}^1}$ is defined by $\mathbf{I}_{S_{ls}^1} = \begin{cases} 1 & S_{ls}^1 \text{ represents the current situation} \\ 0 & \text{Otherwise} \end{cases}$ and (?) $\sum_{l \in S^1} \mathbf{I}_{S_{ls}^1} = 1$.

2.4.3.1.4 CALIBRATION

Since the expert responses are used to estimate relative comparisons of paired scenarios, these relative results are then calibrated into probability values using calibration constants P_0^i. These calibration constants can be obtained using historical accident data.

In order to calibrate the joint probabilities, we first let $P_0^1 = P_0^2 = \cdots = P_0^5 = 1$ and $\Pr\left(\text{Steering Fail} \middle| S_{ls}^1\right) = \Pr\left(\text{Propulsion Fail} \middle| S_{ls}^1\right) = \Pr\left(\text{Comm/Nav Fail} \middle| S_{ls}^1\right) = 1$ in (2.15). One can take the long-run average of each component of the summation in (2.15) considering all the possible situations to obtain joint probabilities of accident types and instigators in the simulation model. We then compare these values with their counterparts (e.g. $\Pr(\text{Collision, Human Error})$, etc.) obtained from the historical data

On the other hand, we have

$$\Pr(\text{Collision,Human Error}) = \Pr(\text{Human Error} | \text{Collision}) \times \Pr(\text{Collision}) \tag{2.16}$$

Using historical data, we can estimate $\Pr(\text{Human Error}|\text{Collision})$ and $\Pr(\text{Collision})$ using

$$\Pr(\text{Human Error}|\text{Collision}) = \frac{\text{Number of collisions due to human error}}{\text{Total number of collisions}} \tag{2.17}$$

and the probability that a vessel is involved in collision is;

$$\Pr(\text{Collision}) = \frac{\text{Total number of collisions}}{\text{Total number of vessels}} \tag{2.18}$$

Thus, using (2.16) – (2.18) we can estimate $\Pr(\text{Collision,Human Error})$. The joint probabilities obtained from the historical data are given in Table 2-11.

Table 2-11 Pr (1st tier Accident, Instigator) obtained from accident data

		Instigator				
		Human Error	Steering Failure	Propulsion Failure	Comm/Nav Eq. Failure	Mech/Elec Failure
1st tier Accident	Collision	0.000293584	0.000008720	0	0	
	Ramming	0.000152593	0.000026227	0.000023843	0	
	Grounding	0.000167023	0.000038396	0.000019198	0	
	Fire/Explo	0.000063801				0.000079751

Let G_1 be the long run average of $\sum_{l \in S^1} P_0^2 \exp\left(\sum_{i=1}^{p} \beta_i^2 x_i + \beta_0^2\right) \times P_0^1 \exp\left(\sum_{i=1}^{p} \beta_i^1 x_i + \beta_0^1\right) \times \mathbf{I}_{S_{ls}^1}$ in (2.15), which can also be expressed as $P_0^1 P_0^2 C_1$ where $C_1 \in R$. Thus, the comparison of G_1 with its counterpart (e.g. $\Pr(\text{Collision,Human Error})$) obtained from the historical data shown in Table 2-11, will provide an estimate for the product of calibration constants $P_0^1 P_0^2$ using

$$P_0^1 P_0^2 = \frac{\Pr(\text{Collision,Human Error})}{C_1} \tag{2.19}$$

Similarly, for the remaining conditional instigator probabilities, we have

$$P_0^3 \times \Pr\left(\text{Steering Fail}\middle|S_{ls}^1\right) = \frac{\Pr\left(\text{Collision,Steering Fail}\right)}{C_2} \tag{2.20}$$

$$P_0^4 \times \Pr\left(\text{Propulsion Fail}\middle|S_{ls}^1\right) = \frac{\Pr\left(\text{Collision,Propulsion Fail}\right)}{C_3} \tag{2.21}$$

and

$$P_0^5 \times \Pr\left(\text{Comm/Nav Fail}\middle|S_{ls}^1\right) = \frac{\Pr\left(\text{Collision,Comm/Nav Fail}\right)}{C_4}. \tag{2.22}$$

Therefore, we do not need to estimate the individual probability of human error or any other instigator probability if or calibrating the probabilities obtained via elicitation or simulation. The particular values of the aforementioned expressions obtained from simulation are shown in Table 2-12.

Table 2-12 Calibration expressions for joint accident probabilities

Expression	**Value**
$P_0^1 P_0^2$	4.58692E-08
$P_0^3 \times \Pr(\text{Steering Fail})$	1.52547E-09
$P_0^4 \times \Pr(\text{Propulsion Fail})$	0
$P_0^5 \times \Pr(\text{Comm/Nav Fail})$	0
$P_0^1 P_0^6$	1.01135E-07
$P_0^7 \times \Pr(\text{Steering Fail})$	4.05626E-08
$P_0^8 \times \Pr(\text{Propulsion Fail})$	1.29715E-08
$P_0^9 \times \Pr(\text{Comm/Nav Fail})$	0
$P_0^1 P_0^{10}$	5.28376E-08
$P_0^{11} \times \Pr(\text{Steering Fail})$	6.03708E-08
$P_0^{12} \times \Pr(\text{Propulsion Fail})$	5.20445E-08
$P_0^{13} \times \Pr(\text{Comm/Nav Fail})$	0
$P_0^1 P_0^{14}$	6.11866E-06
$P_0^{15} \times \Pr(\text{Mech/Elec Fail})$	2.73693E-05

It is guaranteed that the long-run accident probabilities are legitimate probabilities due to the calibration process.

Now that the calibration process is over one is ready to calculate conditional as well as marginal accident, instigator, situation probabilities (as described in subsections 2.4.3.1.1 – 2.4.3.1.3), and obtained the probability of a first tier accident. Next, will demonstrate how to obtain probability of a second tier accident.

2.4.3.2 SECOND TIER ACCIDENT PROBABILITY

The conditional probability of a 2nd tier accident given a 1st tier accident occurs in (2.3) is estimated using the historical accident data as shown below

$$\Pr\left(A_i^2 \middle| A_m^1\right) = \frac{\text{Number of type } m \text{ 1}^{\text{st}} \text{ tier accidents that lead to a type } i \text{ 2}^{\text{nd}} \text{ tier accident}}{\text{Total number of type } m \text{ 1}^{\text{st}} \text{ tier accidents}} \tag{2.23}$$

Values of $\Pr\left(A_i^2 \middle| A_m^1\right)$ for the Strait are given in Table 2-13.

Table 2-13 Values for Pr (2nd tier Accident|1st tier Accident)

		2nd tier Accident				
		No 2nd Tier Accident	Grounding	Ramming	Fire / Explosion	Sinking
1st tier Accident	Collision	0.8737	0.0289	0.0000	0.0158	0.0816
	Grounding	0.9794			0.0041	0.0165
	Ramming	0.8325	0.1218		0.0102	0.0355
	Fire / Explosion	0.9355	0.0081	0.0000		0.0565

At this point, we are able to calculate all of the accident probabilities. Below, we present the approach to calculate the expected consequences of various accidents.

2.4.3.3 EXPECTED CONSEQUENCE GIVEN AN ACCIDENT

2.4.3.3.1 PROBABILITY OF A CONSEQUENCE GIVEN AN ACCIDENT

Due to the lack of any sort of consequence data, we rely on the expert judgment to estimate the probability of a consequence. We assume that the probability of a consequence depends on the accident type and the situational attributes. The list of the situational attributes influencing consequence impact (including interaction attributes) and their possible values are given in Table 2-14.

Table 2-14 Possible values of situational attributes influencing consequence impact S^2

Variable	Attribute Name	Number of Possible Values	Description
W_1	1st Interacting Vessel Type	6	LNG-LPG, Tanker, Empty LNG-LPG, Empty Tanker; Passenger, other vessel
		2	Passenger vessel, other vessel
		3	Loaded LNG-LPG and Tanker, Passenger, other vessel
W_2	2nd Interacting Vessel Type	6	LNG-LPG, Tanker, Empty LNG-LPG, Empty Tanker; Passenger, other vessel
		2	Passenger vessel, other vessel
		3	Loaded LNG-LPG and Tanker, Passenger, other vessel
W_3	1st Interacting Vessel Length	2	0-150m., 150-300m.
W_4	2nd Interacting Vessel Length	2	0-150m., 150-300m.
W_5	Zone	6	Anadolu Feneri-Sarıyer, Sarıyer-Beykoz, Beykoz-Kanlıca, Kanlıca-Vaniköy, Vaniköy-Üsküdar, Üsküdar-Kadıköy
W_6	$W_1 \cdot W_2$		1st Interacting Vessel Type x 2nd Interacting Vessel Type
W_7	$W_3 \cdot W_4$		1st Interacting Vessel Length x 2nd Interacting Vessel Length
W_8	$W_1 \cdot W_5$		1st Interacting Vessel Type x Zone
W_9	$W_3 \cdot W_5$		1st Interacting Vessel Length x Zone

As seen in Table 2-14, the 1st interacting vessel type has three different sets for different consequence-accident type pairs. For example, for (environmental damage, collision), 1st Interacting Vessel Type is categorized in five possible values in terms of cargo type and amount. However, for (human casualty, collision) pair, it is categorized in three values based on the number of people in the vessel.

We estimate this probability using the paired comparison approach described in section 2.4.3.1.1. Thus the probability of a consequence given an accident and situation is defined by

$$\Pr\left(C_j\left(h\right)\middle|A^n,\underline{S}^2\right)=P_0\exp\left(\underline{\beta}^T\underline{S}^2\right) \tag{2.24}$$

where P_0 is the calibration constant and $\underline{\beta}$ is the parameter vector. To assess the probability of a consequence given an accident, experts were asked to compare two situations $\underline{S}_1^2$ and $\underline{S}_2^2$. Figure 2.10 provides a sample question appearing in the consequence questionnaire given a (fire/explosion, human casualty). A separate questionnaire is prepared for each (consequence, accident type) pair. The experts are asked to compare situations for each consequence impact level in a given question as seen in Figure 2.10. We ask 4 questions per situational attribute, one question representing the worst case scenario, one representing the best case, and two others corresponding to ordinary cases. Since not all (consequence, accident type) pairs are influenced by every situational attribute, the total number of questions differs from one questionnaire to another.

QUESTION 5 - FIRE/EXPLOSION

Situation 1	Situational Attribute	Situation 2
General Cargo Vessel	1st Interacting Vessel Class	-
≤150m.	Length of the 1st Interacting Vessel	>150m.
Anadolu Feneri - Sarıyer	Zone	-
Other: ____	9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9	Other: ____
LOW SEVERITY HUMAN CASUALTY is more likely in Situation 1	⟵⟶	**LOW SEVERITY HUMAN CASUALTY is more likely in Situation 2**
Other: ____	9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9	Other: ____
MEDIUM SEVERITY HUMAN CASUALTY is more likely in Situation 1	⟵⟶	**MEDIUM SEVERITY HUMAN CASUALTY is more likely in Situation 2**
Other: ____	9 8 7 6 5 4 3 2 1 2 3 4 5 6 7 8 9	Other: ____
HIGH SEVERITY HUMAN CASUALTY is more likely in Situation 1	⟵⟶	**HIGH SEVERITY HUMAN CASUALTY is more likely in Situation 2**

Figure 2.10 A sample consequence question

The regression equation used to determine the relative effect of situational attributes on the probability of a consequence given an accident is

$$y_j = \underline{\beta}^T \left(\underline{S}_{1j}^2 - \underline{S}_{2j}^2 \right) + \varepsilon_j \tag{2.25}$$

where ε_j is the residual error term. The results of the regression analysis for the consequence questionnaires are given in Appendix D.

Since the expert responses are used to estimate relative comparisons, these relative results are then calibrated into probability values using the calibration constant P_0. The calibration constants are obtained using accident data. As an example, consider the probability of low casualty given collision, which is evaluated using

$$\begin{aligned} \Pr\left(\text{Casualty}\left(\text{Low}\right)\middle|\text{Collision}\right) &= \sum_{l \in S^2} \Pr\left(\text{Casualty}\left(\text{Low}\right)\middle|\text{Collision}, S_{ls}^2\right) \times \Pr\left(S_{ls}^2\right) \\ &= \sum_{l \in S^2} P_0^{20} \exp\left(\sum_{i=1}^{q} \beta_i^{20} x_i + \beta_0^{20} \right) \times \Pr\left(S_{ls}^2\right) \end{aligned} \tag{2.26}$$

In the simulation model, the low casualty probability given collision at time *t* is evaluated using the following expression:

$$\Pr\left(\text{Casualty}\left(\text{Low}\right)\middle|\text{Collision}\right) = \sum_{l \in S^2} P_0^{20} \exp\left(\sum_{i=1}^{q} \beta_i^{20} x_i + \beta_0^{20}\right) \times \mathbf{I}_{S_{ls}^2} \qquad (2.27)$$

where $\mathbf{I}_{S_{ls}^2}$ is the indicator function and $\mathbf{I}_{S_{ls}^2} = \begin{cases} 1 & S_{ls}^2 \text{ represents the current situation} \\ 0 & \text{Otherwise} \end{cases}$ and (?) $\sum_{l \in S^2} \mathbf{I}_{S_{ls}^2} = 1$.

In order to calibrate the joint probabilities, we first let $P_0^{20} = 1$. We then take the long-run average of the conditional probability expression in (2.27) considering all the possible situations in the model. We then compare these values with their counterparts (e.g. $\Pr\left(\text{Casualty}\left(\text{Low}\right)\middle|\text{Collision}\right)$, etc.) obtained from the accident data using

$$\Pr\left(\text{Casualty}\left(\text{Low}\right)\middle|\text{Collision}\right) = \frac{\text{Number of collisions with low casualty}}{\text{Total number of collisions}} \qquad (2.28)$$

The conditional probability values obtained from the historical accident data for each (consequence, accident pair) are given in Table 2-15, Table 2-16, Table 2-17 and Table 2-18

Table 2-15 Pr (Human Casualty|Accident) obtained from accident data

	Human Casualty		
	Low	Medium	High
Collision	0.9579	0.0421	
Ramming	0.9695	0.0305	
Grounding			
Fire/Explo	0.9248	0.0376	0.0376
Sinking	0.8241	0.1759	

Table 2-16 Pr (Property/Infrastructure Damage|Accident) obtained from accident data

	Property/Infrastructure Damage		
	Low	Medium	High
Collision			
Ramming	0.6497	0.3503	
Grounding			
Fire/Explo	0.8195	0.1579	0.0226
Sinking	0.2222	0.7778	

Table 2-17 Pr (Environmental Damage|Accident) obtained from accident data

	Environmental Damage		
	Low	Medium	High
Collision	0.9763	0.0237	
Ramming	0.9797	0.0203	
Grounding	0.9928	0.0072	
Fire/Explo	0.9474	0.0226	0.0301
Sinking	0.9537	0.0463	

Table 2-18 Pr (Traffic Effectiveness|Accident) obtained from accident data

	Traffic Effectiveness		
	Low	Medium	High
Collision	0.9737	0.0263	
Ramming	0.9695	0.0305	
Grounding	0.9857	0.0143	
Fire/Explo	0.9398	0.0226	0.0376
Sinking	0.9815	0.0185	

Let G_{20} be the long-run average of $\sum_{l \in S^2} P_0^{20} \exp\left(\sum_{i=1}^{q} \beta_i^{20} x_i + \beta_0^{20}\right) \times \mathbf{I}_{S_{ls}^2}$ in (2.27), which can be represented by $P_0^{20} C_{20}$ where $C_{20} \in R$ and obtained from simulation. Thus, the comparison of G_{20} with its counterpart (e.g. $\Pr\left(\text{Casualty}\left(\text{Low}\right)\middle|\text{Collision}\right)$) from the historical data shown in Table 2-15, will provide an estimate for the calibration constant P_0^{20} using

$$P_0^{20} = \frac{\Pr\left(\text{Casualty}\left(\text{Low}\right)\middle|\text{Collision}\right)}{C_{20}} \tag{2.29}$$

The calibration constants for all (consequence impact, accident) pairs are calculated similarly. The values of these calibration constants are shown in

Table **2-19**.

Table 2-19 Calibration constants of conditional consequence probabilities

Calibration Constant	**Value**
P020	0.080896
P021	0.003151
P022	0.228763
P023	0.006421
P024	0.088635
P025	0.003153
P026	0.001873
P027	0.129700
P028	0.022069
P029	0.106948
P030	0.001634
P031	0.273184
P032	0.001239
P033	0.204376
P034	0.003266
P035	0.170421
P036	0.003201
P037	0.000164
P038	0.152176
P039	0.004361
P040	0.008278
P041	0.000121
P042	0.042430
P043	0.000236
P044	0.025447
P045	0.000324
P046	0.014419
P047	0.000101
P048	0.000078
P049	0.060872
P050	0.000121
P051	0.162954
P052	0.041665
P053	0.037044
P054	0.004607
P055	0.000389
P056	0.188596
P057	0.098551
P058	0.080896
P059	0.003151
P060	0.106948
P061	0.001634

P062	0.008278
P063	0.000121

Similar to section 2.4.3.1, the calibration constants do not ensure that the instantaneously calculated conditional probabilities of consequences given accidents are legitimate probabilities. Thus, we normalize these conditional probabilities so that $\sum_{h \in \mathcal{L}_{ij}} \Pr\left(C_{ji}\left(h\right)\middle|A_i^n\right) = 1$.

2.4.3.3.2 CONSEQUENCE

We have assumed that the quantitative values of impact levels (such as low, medium, high) of a consequence type j of an accident type i at slice s contributed by vessel r, $C_{jirs}(h)$, are uniformly distributed within their associated scales. Their parameters are given in Table 2.20 for different levels of consequence impact. These values do not represent the actual consequence of an accident in a specific unit (e.g. dollars or number of casualties). Instead, we utilize index values representing the user's perception of a low, medium and high consequence. Therefore, the calculated risk values are meaningful when compared to each other in a given context. For example, comparing risk at different slices helps to determine high and low risk zones.

Table 2-20 Consequence impact levels

Impact Level	Value
Low	Uniform(0-1,000)
Medium	Uniform(4,000-6,000)
High	Uniform(8,000-10,000)

2.4.3.3.3 PROBABILITY OF A SITUATION

Probabilities of situations can be calculated in a similar manner to the ones presented in Section 2.4.3.1.3.

Then conditional expectation of consequences are obtained using (2.4), which in turn allows us to calculate the expected total consequence that is nothing but the risk we have been striving to calculate from the very beginning .

2.4.3.4 QUESTIONNAIRE DESIGN

The linear regression function in (2.9) with p coefficients (situational attributes), the intercept β_0, and n data points (number of questions) with $n \geq (p+1)$ allows us to construct the following:

$$\mathbf{Y} = \mathbf{X} \cdot \underline{\beta} + \underline{\varepsilon} \tag{2.30}$$

which can be written in the following matrix format.

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}_{n\times 1} = \begin{bmatrix} 1 & \left(x_{1,1}^1 - x_{1,1}^2\right) & \left(x_{2,1}^1 - x_{2,1}^2\right) & \cdots & \left(x_{p,1}^1 - x_{p,1}^2\right) \\ 1 & \left(x_{1,2}^1 - x_{1,2}^2\right) & \left(x_{2,2}^1 - x_{2,2}^2\right) & \cdots & \left(x_{p,2}^1 - x_{p,2}^2\right) \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & \left(x_{1,n}^1 - x_{1,n}^2\right) & \left(x_{2,n}^1 - x_{2,n}^2\right) & \cdots & \left(x_{p,n}^1 - x_{p,n}^2\right) \end{bmatrix}_{n\times(p+1)} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{bmatrix}_{(p+1)\times 1} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}_{n\times 1} \tag{2.31}$$

where $x_{i,j}^1$ is the scale value of situational attribute i in Situation 1 of question j and $x_{i,j}^1 - x_{i,j}^2$ is the difference of the scale values.

Therefore, the estimated values of the parameters can be obtained using

$$\hat{\underline{\beta}} = \left(\mathbf{X}^T\mathbf{X}\right)^{-1}\mathbf{X}^T\mathbf{Y} \tag{2.32}$$

where $\mathbf{X}^T$ is the questionnaire matrix and $\mathbf{X}^T\mathbf{X}$, which is a $(p+1)\times(p+1)$ matrix and is called the design matrix $\mathbf{D}$ of the questionnaire. Note that the questionnaire needs to be designed in a manner such that the resulting matrix $\mathbf{D}$ is nonsingular to be able to obtain the estimated values of the parameters, $\hat{\underline{\beta}}$

2.4.4 NUMERICAL RESULTS

We have incorporated the risk analysis model described above into the simulation model developed to mimic the transit vessel traffic in the Strait of Istanbul. We then performed a scenario analysis to evaluate the characteristics of accident risk in the Strait. This analysis has provided us with the ability to investigate how changes in various policies and practices impact risk. These include vessel arrival rates, scheduling policies, pilotage, overtaking, and local traffic density.

In the scenario analysis, the base scenario represents the present system with all the current regulations and policies in place. The simulation results of each scenario are compared to the results of the base scenario. The findings are presented below.

2.4.4.1 IMPACT OF ARRIVAL RATES

We start our analysis by focusing on the impact of arrival rates of some of the vessels. In Scenario 1, we increase the arrival rates of dangerous cargo vessels (Class A, B, C, and E) 10%. As a result, the average risk in most of the slices increases as seen in Table 2-21. In those slices where the average risk decreases, the observed change in percentage is very small.

On the other hand, when we decrease the arrival rates of dangerous cargo vessels 20% in Scenario 2, the average risk decreases in most of the slices.

Thus, the average slice risk is directly proportional to the vessel arrival rates. However, vessel arrivals have a small impact on the accident risk since the scheduling policy to take vessels into the Strait and subsequently the required time gap between vessels do not change. In order to obtain a significant impact on the accident risks, the change in the arrival rates must be substantial.

Table 2-21 Average Slice Risk in Scenarios 1 and 2 compared to the Base Scenario

	BASE SCENARIO		SCENARIO 1			SCENARIO 2		
Slice	Average	Half Width (95% CI)	Average	Half Width (95% CI)	% Increase in Average	Average	Half Width (95% CI)	% Increase in Average
1	1.3748	0.34	1.3932	0.32	1.34%	1.2815	0.26	-6.79%
2	1.6021	0.63	1.6279	0.61	1.61%	1.461	0.45	-8.81%
3	1.5105	0.35	1.5078	0.26	-0.18%	1.3895	0.23	-8.01%
4	1.4257	0.30	1.4255	0.24	-0.01%	1.3309	0.23	-6.65%
5	1.4322	0.19	1.4315	0.22	-0.05%	1.3626	0.28	-4.86%
6	1.4484	0.26	1.4386	0.17	-0.68%	1.402	0.32	-3.20%
7	1.1723	0.08	1.1863	0.06	1.19%	1.1276	0.10	-3.81%
8	1.1943	0.08	1.2193	0.10	2.09%	1.1408	0.08	-4.48%
9	1.2002	0.09	1.2313	0.12	2.59%	1.1486	0.10	-4.30%
10	1.1972	0.10	1.2175	0.11	1.70%	1.1489	0.12	-4.03%
11	1.185	0.09	1.2003	0.07	1.29%	1.139	0.09	-3.88%
12	1.3361	0.07	1.343	0.06	0.52%	1.2767	0.06	-4.45%
13	1.2676	0.06	1.2822	0.06	1.15%	1.2228	0.07	-3.53%
14	1.36	0.06	1.3788	0.06	1.38%	1.313	0.06	-3.46%
15	1.3427	0.05	1.3581	0.07	1.15%	1.2955	0.08	-3.52%
16	1.3462	0.06	1.367	0.08	1.55%	1.3021	0.08	-3.28%
17	1.3794	0.07	1.3956	0.10	1.17%	1.3316	0.08	-3.47%
18	7.0459	0.15	6.9457	0.06	-1.42%	7.1591	0.13	1.61%
19	25.441	0.60	24.8969	0.41	-2.14%	26.4149	0.30	3.83%
20	6.9067	0.09	6.8969	0.18	-0.14%	7.2625	0.07	5.15%
21	4.4412	0.10	4.5107	0.10	1.56%	4.5574	0.07	2.62%

The maximum risks observed at different slices are displayed in Figure 2.11. The overall maximum risk value in Scenario 1 and Scenario 2 decreases 11% and 4%, respectively compared to the maximum value observed in the Base Scenario. However, note that the maximum risk values do not necessarily reflect the impact of a given factor on the overall risk. They are contingent upon the occurrence of a random situation at an instance.

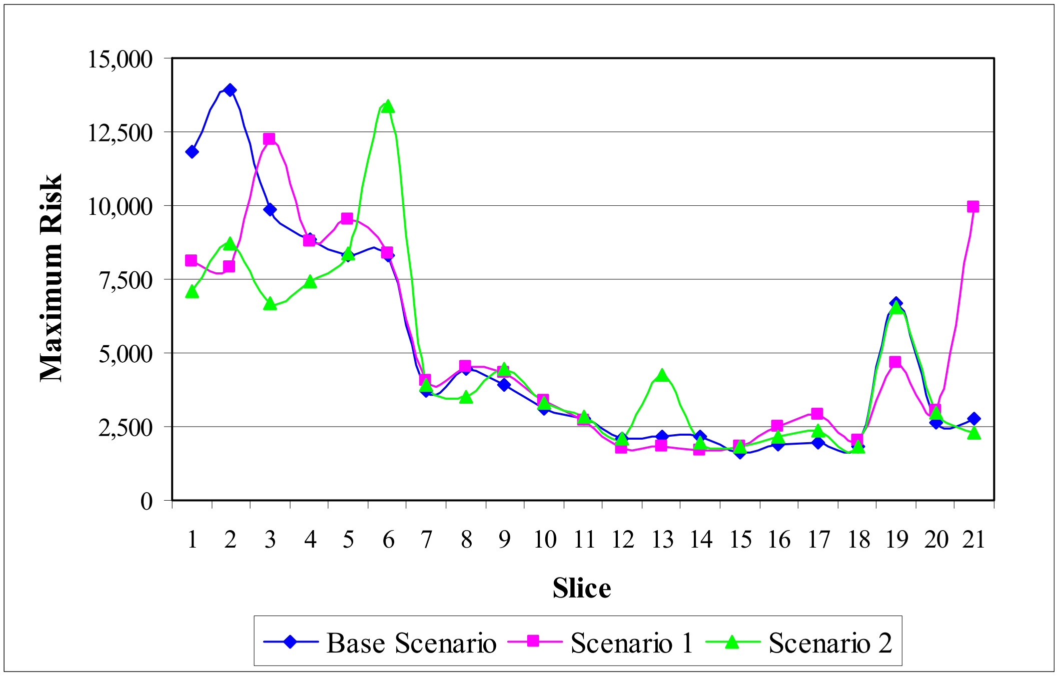

Figure 2.11 Maximum Slice Risk in Scenarios 1 and 2 compared to the Base Scenario

In the simulation model, the maximum slice risk observed by a vessel throughout its passage is recorded. The distributions of maximum risk as observed by vessels in each scenario are displayed in Figure 2.12. The patterns are very similar in all scenarios and the majority of the observations result in low maximum risk values. Note that Scenario 2 provides a lower number of observations with high maximum risk values compared to the other scenarios.

Additionally, the distributions for the maximum risk values that are greater than 50 are shown in Figure 2.13. The distributions for all scenarios are very similar at the higher values of risk as well.

Further, while recording the maximum slice risk as observed by a vessel, we also record the slice at which the vessel observes this value. The resulting histograms representing the distribution of slices at which the maximum risk is observed are given in Figure 2.14. In all scenarios, the slice distributions are identical. Also, the majority of the vessels observe the maximum risk at slice 19. Slice 19 is the area between Beşiktaş and Üsküdar, which has a very heavy local traffic.

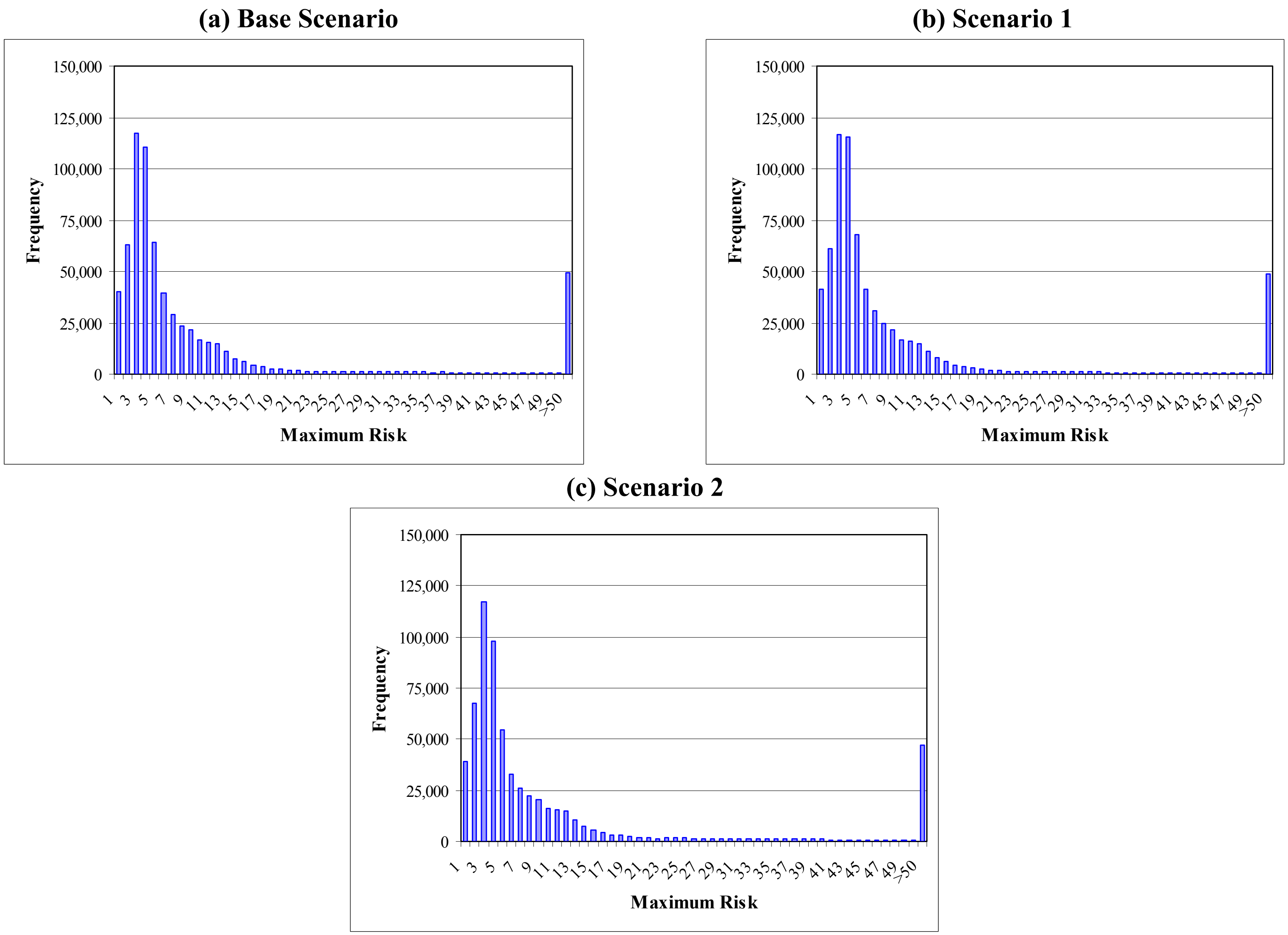

Figure 2.12 Maximum risk distribution as observed by vessels in Scenarios 1 and 2 compared to the Base Scenario

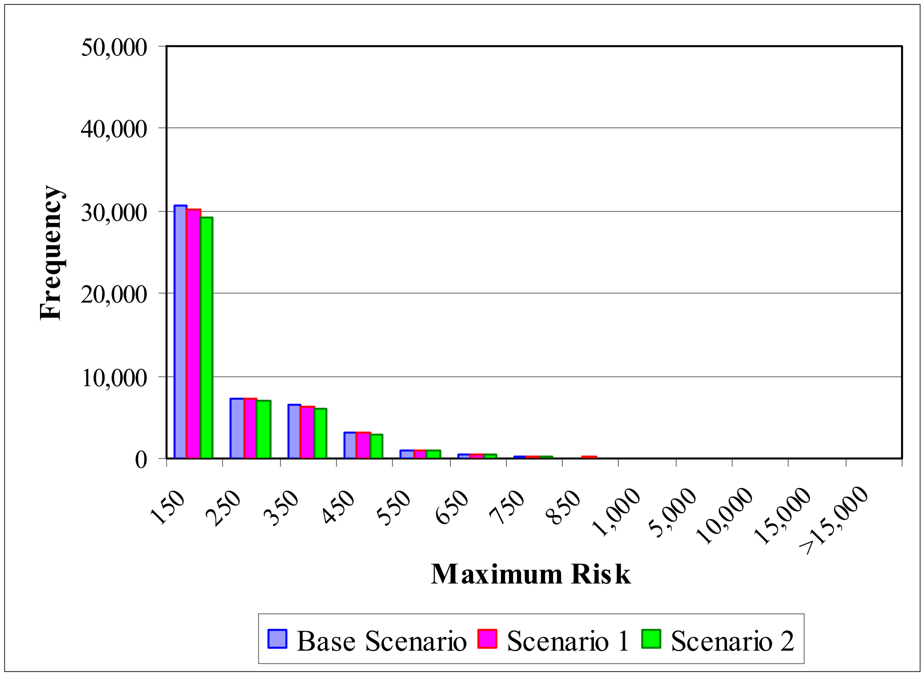

Figure 2.13 Maximum risk distribution as observed by vessels in Scenarios 1 and 2 compared to the Base Scenario for values >50

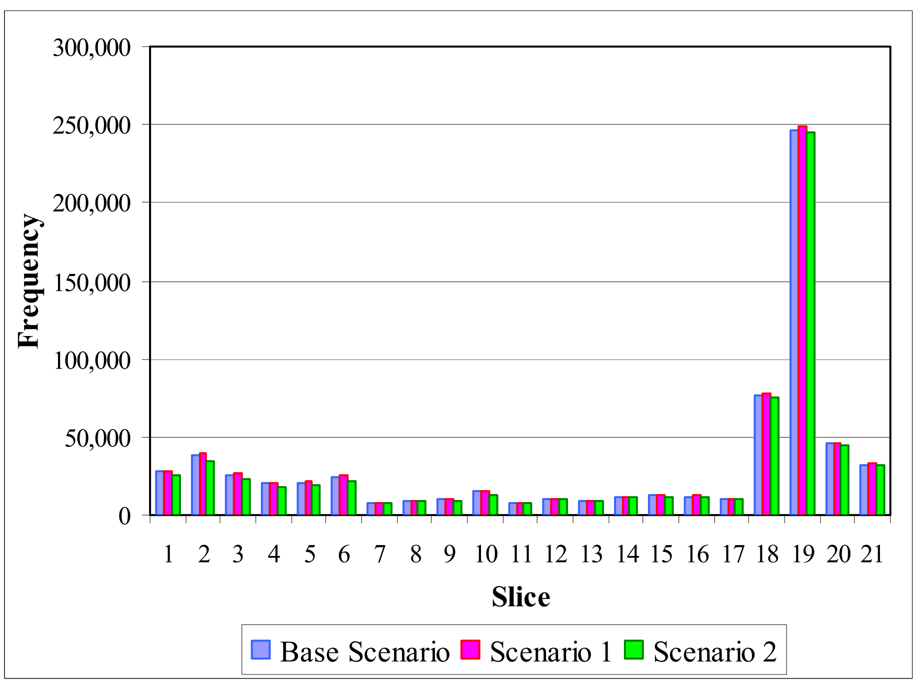

Figure 2.14 Distribution of slices at which maximum risk is observed in Scenarios 1 and 2 compared to the Base Scenario

As seen in Table 2-22, the vessel waiting times increase (decrease) in general as we increase (decrease) the arrival rates. Only class B vessels behave differently due to their special circumstances in scheduling.

Table 2-22 Waiting Times (in minutes) in Scenarios 1 and 2 compared to the Base Scenario

	BASE SCENARIO		**SCENARIO 1**			**SCENARIO 2**		
Class (Direction)	**Average**	**Half Width (95% CI)**	**Average**	**Half Width (95% CI)**	**% Increase in Average**	**Average**	**Half Width (95% CI)**	**% Increase in Average**
A	1,987.15	1,564.30	2,488.50	1,469.88	25.23%	1,157.18	169.59	-41.77%
A(N)	2,127.69	1,642.60	2,696.50	1,664.47	26.73%	1,211.58	181.23	-43.06%
A(S)	1,847.74	1,479.95	2,281.79	1,276.72	23.49%	1,098.75	159.52	-40.54%
B	492.48	19.55	474.40	21.53	-3.67%	562.46	28.61	14.21%
B(N)	500.55	20.51	485.08	21.97	-3.09%	568.33	19.65	13.54%
B(S)	459.77	44.04	427.13	23.89	-7.10%	532.30	23.39	15.78%
C	684.42	112.21	1,067.01	154.54	55.90%	430.23	39.92	-37.14%
C(N)	609.80	110.12	947.54	130.45	55.39%	371.22	30.46	-39.12%
C(S)	754.87	115.01	1,179.56	177.15	56.26%	486.08	40.34	-35.61%
D	172.48	29.67	190.26	29.14	10.31%	144.52	22.25	-16.21%
D(N)	151.75	29.14	163.02	29.45	7.43%	121.53	23.29	-19.91%
D(S)	192.53	30.89	216.61	30.07	12.51%	166.69	22.53	-13.42%
E	180.19	19.37	197.55	17.41	9.63%	142.09	12.96	-21.14%
E(N)	194.60	23.56	216.12	22.66	11.06%	148.96	12.27	-23.45%
E(S)	165.93	15.56	179.36	12.45	8.09%	135.34	13.86	-18.44%
P	77.93	10.07	82.82	4.22	6.27%	67.13	6.15	-13.86%
P(N)	73.86	11.61	78.47	1.81	6.25%	62.25	6.03	-15.72%
P(S)	81.90	9.26	87.23	8.16	6.51%	72.00	6.38	-12.09%

Policy Indication 1: In the wake of an increase in arrival rates, the scheduling regime should be kept as is to maintain the risks at the current levels. A 10% increase in the dangerous cargo vessel arrival rates results in rather acceptable waiting times at the entrance. However, further increases in vessel traffic may result in discouraging ships away from the Strait due to excessive waiting times.

2.4.4.2 IMPACT OF SCHEDULING POLICIES

2.4.4.2.1 SCHEDULING MORE VESSELS

In scenarios 3, 4, 5, and 6, we decrease the required time gap between vessels, thereby scheduling more vessels within a given time frame. Specifically, in Scenario 3, we schedule Class C and Class D vessels every 15 and 5 minutes, respectively, without changing the required time gap between Class A and Class B vessels as seen in Figure 2.15. This allows us, for instance, to schedule 5 Class C and 12 Class D vessels between consecutive northbound Class A vessels as opposed to 2 Class C and 6 Class D vessels in the Base Scenario.

On the other hand, we schedule Class C and Class D vessels every 25 and 6.25 minutes, respectively, in Scenario 4 as depicted in Figure 2.16. This time, we increase the required time gap between consecutive northbound Class A vessels to 100 minutes, thereby scheduling 3 Class C and 12 Class D vessels.

In Scenario 5, we change the time gap between Class C and Class D vessels from 30 and 10 to 20 and 10 minutes, respectively, as shown in Figure 2.17. We also schedule northbound and southbound Class A vessels every 100 and 80 minutes, respectively, instead of 90 and 75 minutes. Finally, in Scenario 6, we combine the scheduling policy in Scenario 3 with the 10% arrival rate increase in Scenario 1.

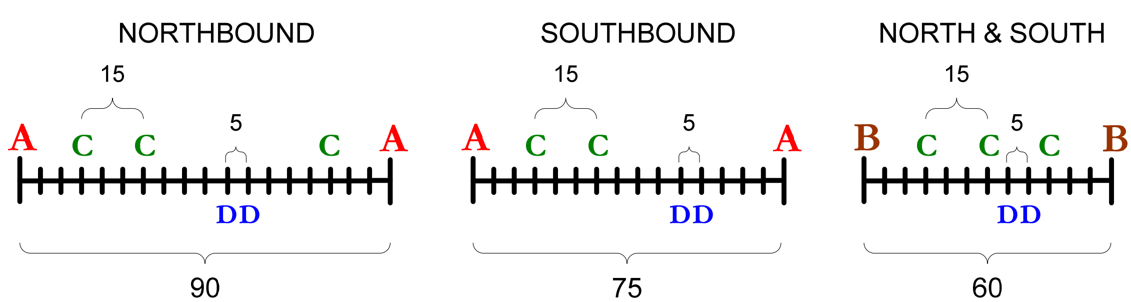

Figure 2.15 Scheduling Policy in Scenario 3

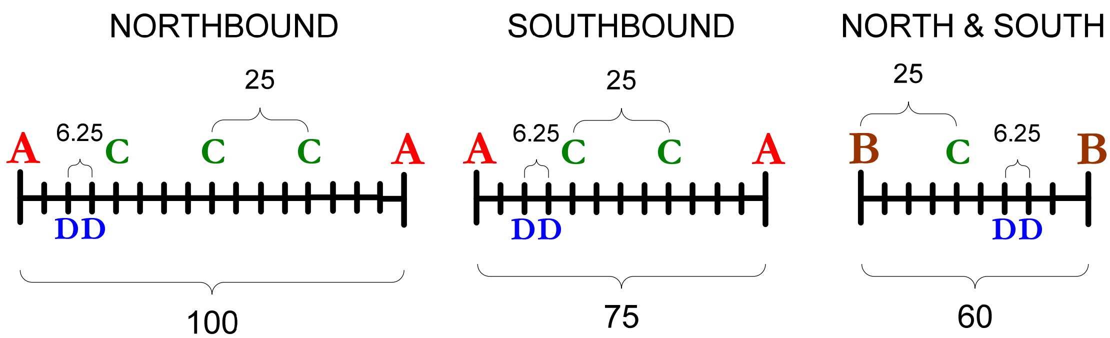

Figure 2.16 Scheduling Policy in Scenario 4

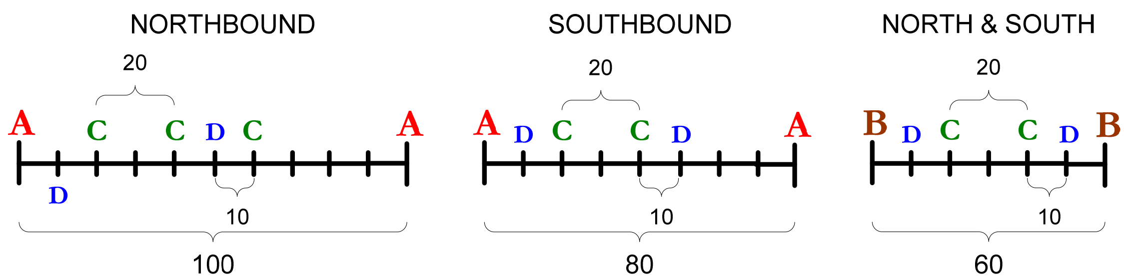

Figure 2.17 Scheduling Policy in Scenario 5

The average risk at each slice for all scenarios is listed in Table 2-23. We observe that the average slice risk increases as the required time gap between consecutive vessels decreases. The greatest increase in average risk is detected in Scenario 6, where both the vessel arrival rates and the number of scheduled vessels are increased. The combined effect of these factors results in a greater increase in average risk.

Table 2-23 Slice Risk in Scenarios 3, 4, 5, and 6 compared to the Base Scenario

	BASE SCENARIO		SCENARIO 3			SCENARIO 4			SCENARIO 5			SCENARIO 6		
Slice	Average	Half Width (95% CI)	Average	Half Width (95% CI)	% Increase in Average	Average	Half Width (95% CI)	% Increase in Average	Average	Half Width (95% CI)	% Increase in Average	Average	Half Width (95% CI)	% Increase in Average
1	1.3748	0.34	1.3826	0.27	0.57%	1.388	0.34	0.96%	1.4055	0.34	2.23%	1.4524	0.34	5.64%
2	1.6021	0.63	1.6453	0.58	2.70%	1.6558	0.61	3.35%	1.6056	0.53	0.22%	1.6809	0.54	4.92%
3	1.5105	0.35	1.6257	0.41	7.63%	1.6293	0.35	7.86%	1.5200	0.28	0.63%	1.6198	0.25	7.24%
4	1.4257	0.30	1.4788	0.37	3.72%	1.4793	0.30	3.76%	1.4227	0.22	-0.21%	1.4793	0.24	3.76%
5	1.4322	0.19	1.4664	0.31	2.39%	1.5075	0.34	5.26%	1.4495	0.25	1.21%	1.4724	0.21	2.81%
6	1.4484	0.26	1.4588	0.24	0.72%	1.5278	0.33	5.48%	1.4651	0.23	1.15%	1.4989	0.23	3.49%
7	1.1723	0.08	1.1928	0.09	1.75%	1.2355	0.12	5.39%	1.2046	0.11	2.76%	1.2362	0.11	5.45%
8	1.1943	0.08	1.2216	0.11	2.29%	1.2592	0.13	5.43%	1.2180	0.09	1.98%	1.2587	0.11	5.39%
9	1.2002	0.09	1.2128	0.10	1.05%	1.2527	0.12	4.37%	1.2330	0.13	2.73%	1.2419	0.08	3.47%
10	1.1972	0.10	1.1961	0.09	-0.09%	1.2442	0.13	3.93%	1.2192	0.11	1.84%	1.2282	0.07	2.59%
11	1.185	0.09	1.2033	0.09	1.54%	1.2410	0.11	4.73%	1.2173	0.12	2.73%	1.2306	0.07	3.85%
12	1.3361	0.07	1.3971	0.07	4.57%	1.4059	0.08	5.22%	1.3524	0.07	1.22%	1.4173	0.04	6.08%
13	1.2676	0.06	1.2968	0.06	2.30%	1.3320	0.07	5.08%	1.2881	0.06	1.62%	1.3303	0.06	4.95%
14	1.36	0.06	1.4086	0.07	3.57%	1.4423	0.08	6.05%	1.3817	0.06	1.60%	1.4463	0.05	6.35%
15	1.3427	0.05	1.3898	0.08	3.51%	1.4247	0.09	6.11%	1.3666	0.07	1.78%	1.4168	0.06	5.52%
16	1.3462	0.06	1.3893	0.08	3.20%	1.4354	0.09	6.63%	1.3700	0.08	1.77%	1.4322	0.07	6.39%
17	1.3794	0.07	1.4172	0.08	2.74%	1.4630	0.09	6.06%	1.3973	0.09	1.30%	1.4533	0.06	5.36%
18	7.0459	0.15	8.8172	0.15	25.14%	8.4584	0.23	20.05%	7.0167	0.17	-0.41%	8.9337	0.17	26.79%
19	25.441	0.60	34.0901	0.52	34.00%	31.9745	0.58	25.68%	25.3566	0.47	-0.33%	34.6849	0.92	36.33%
20	6.9067	0.09	9.2728	0.32	34.26%	8.8498	0.14	28.13%	7.0728	0.32	2.40%	9.496	0.21	37.49%
21	4.4412	0.10	5.9615	0.13	34.23%	5.7542	0.22	29.56%	4.5270	0.12	1.93%	6.1129	0.25	37.64%

Based on the results in Figure 2.18, the maximum risks observed at the middle slices are similar across all four scenarios. Yet they vary at the first six and the last three slices. Note that the last three slices constitute the southern entrance of the Strait where the local traffic is very heavy.

The maximum slice risk observed in all four scenarios is lower than the one observed in the Base Scenario. Scenario 5 provides the lowest maximum risk value. The highest variance in the maximum risk is observed in slices 2 and 20. Finally, Scenario 3 deviates the most from the Base Scenario.

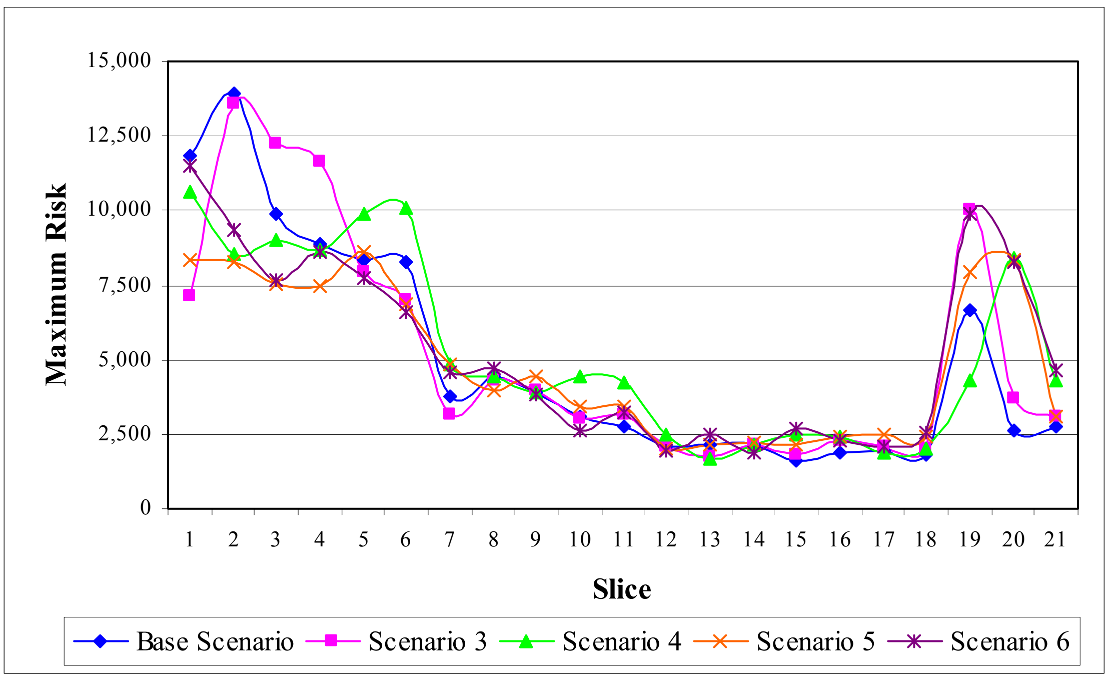

Figure 2.18 Maximum Slice Risk in Scenarios 3, 4, 5, and 6 compared to the Base Scenario

The distributions of maximum risk as observed by vessels in the Base Scenario and scenarios 3, 4, 5, and 6 are displayed in Figure 2.19. The results observed in Scenario 5 are very similar to the Base Scenario. However, scenarios 3, 4, and 6 differ from the Base Scenario in that they result in a greater number of observations with high maximum risk values.

Moreover, the distributions for the maximum risk values that are greater than 50 are shown in Figure 2.20. The distributions for all four scenarios are very similar at the higher values of risk as well. The only exception is that Scenario 5 provides a greater number of high maximum risk values.

The histograms representing the distribution of slices at which vessels observe the maximum risk are given in Figure 2.21. In all scenarios, the distributions of slices are very similar. Once again, the majority of the vessels observe the maximum risk at slice 19.

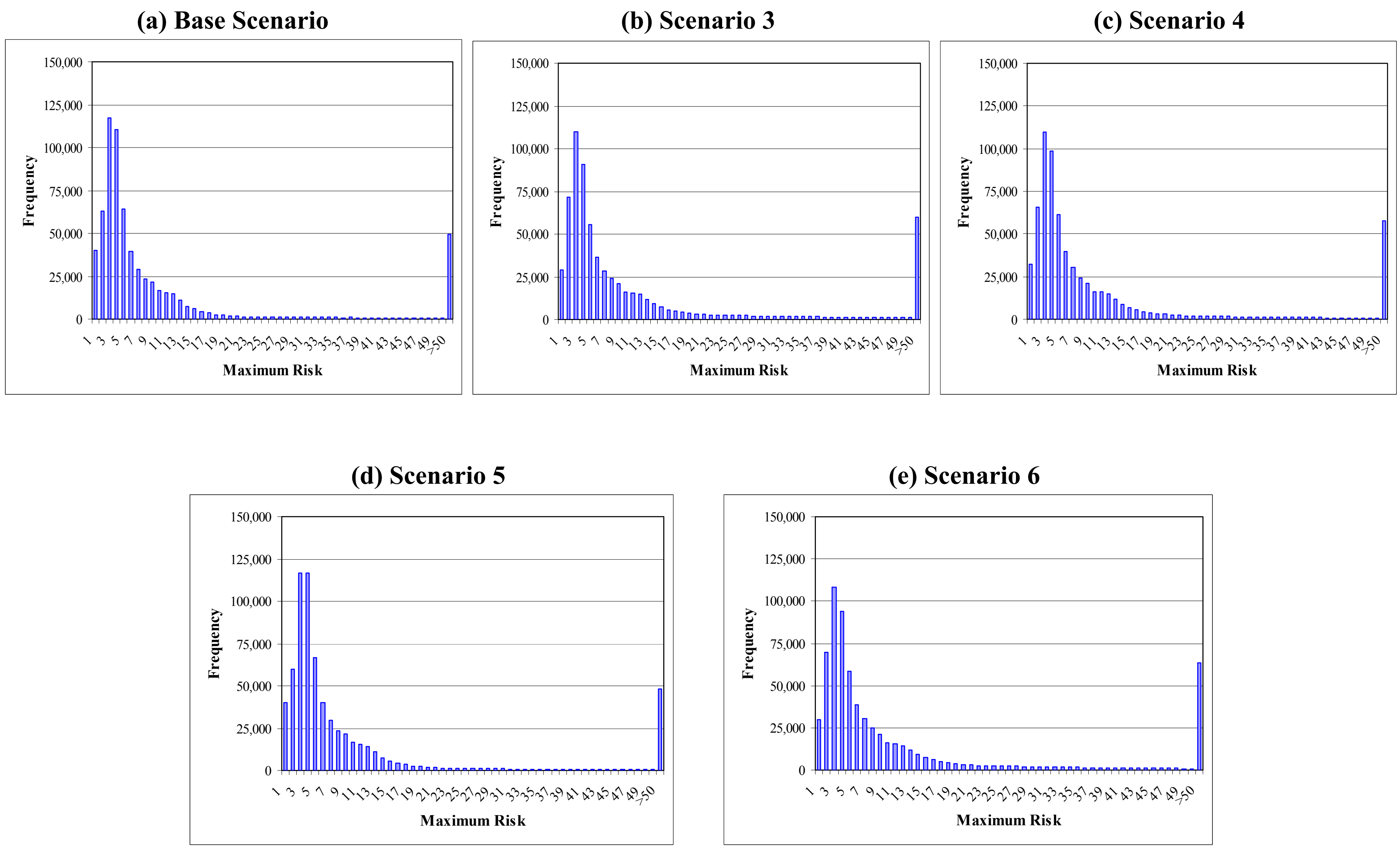

Figure 2.19 Maximum risk distribution as observed by vessels in Scenarios 3, 4, 5, and 6 compared to the Base Scenario

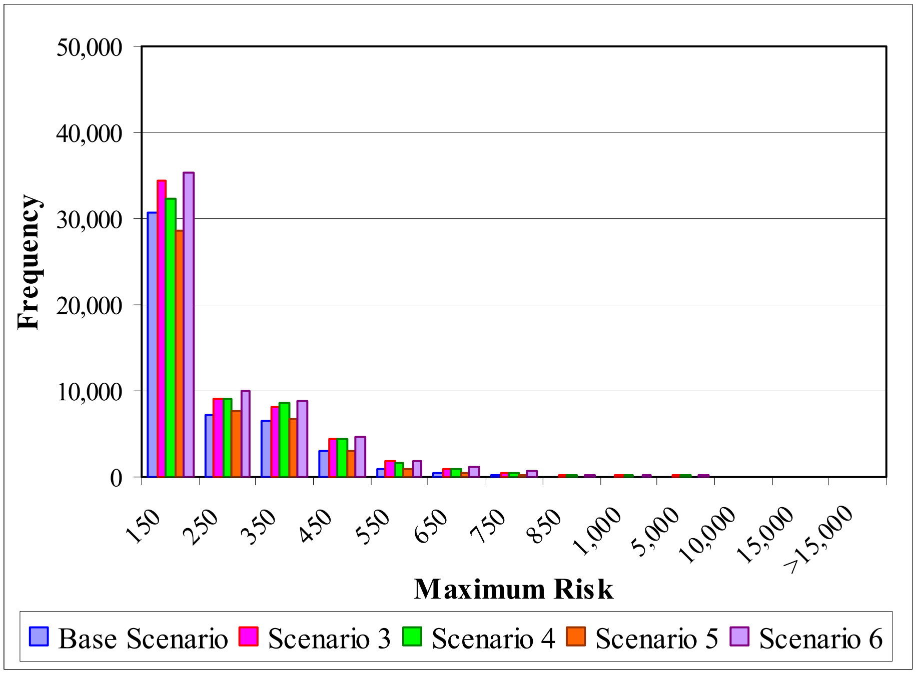

Figure 2.20 Maximum risk distribution as observed by vessels in Scenarios 3, 4, 5, and 6 compared to the Base Scenario for values >50

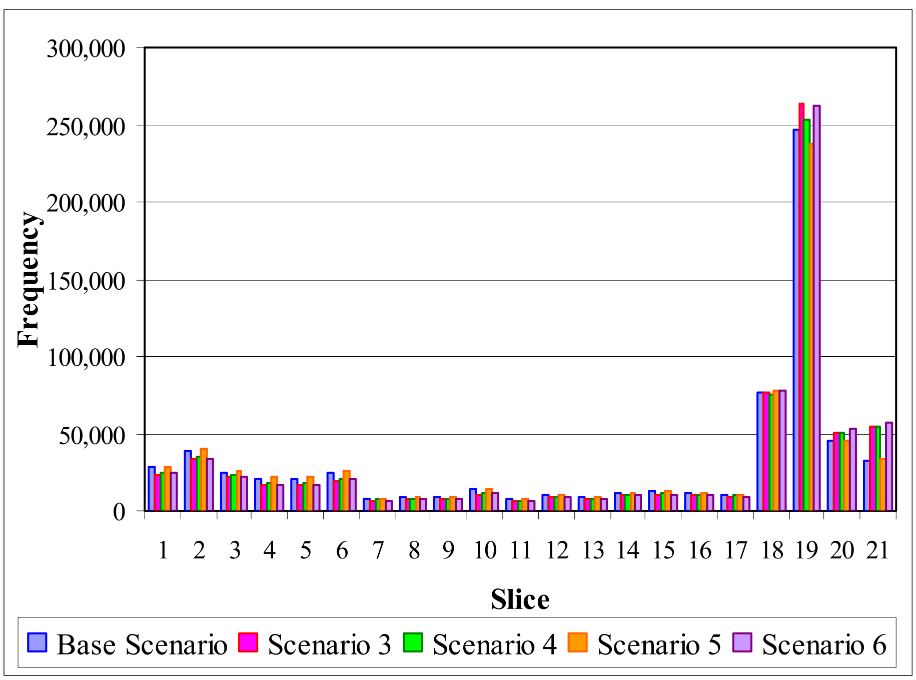

Figure 2.21 Distribution of maximum risk observations per slice in Scenarios 3, 4, 5, and 6 compared to the Base Scenario

In all four scenarios, Class C, D, E, and P vessels are scheduled more frequently compared to the Base Scenario. Thus, the average waiting times of these vessel classes decrease in all of them as seen in Table 2-24.

We also observe a high increase in the average waiting time of Class A vessels in scenarios 4 and 5 since we increase the required time gap between consecutive Class A vessels.

Policy Indication 2: Scheduling changes that are made to reduce vessel waiting times increase risks in the Strait. Thus, scheduling decisions to balance out delays vs. risks should be made based on extensive experimentation with the model developed in this study.

Table 2-24 Waiting Times (in minutes) in scenarios 3, 4, 5, and 6 compared to the Base Scenario

	BASE SCENARIO		SCENARIO 3			SCENARIO 4			SCENARIO 5			SCENARIO 6		
Class (Direction)	**Average**	**Half Width (95% CI)**	**Average**	**Half Width (95% CI)**	**% Increase in Average**	**Average**	**Half Width (95% CI)**	**% Increase in Average**	**Average**	**Half Width (95% CI)**	**% Increase in Average**	**Average**	**Half Width (95% CI)**	**% Increase in Average**
A	1,987.15	1,564.30	2,160.80	915.57	8.74%	3,911.61	1,619.54	96.85%	7,843.32	2,794.68	294.70%	3,265.44	1,726.58	64.33%
A(N)	2,127.69	1,642.60	2,251.54	914.17	5.82%	4,124.65	1,693.80	93.86%	8,200.43	2,900.44	285.41%	3,384.67	1,750.81	59.08%
A(S)	1,847.74	1,479.95	2,071.68	917.17	12.12%	3,702.12	1,539.97	100.36%	7,488.01	2,680.75	305.25%	3,149.85	1,700.74	70.47%
B	492.48	19.55	699.37	30.18	42.01%	621.12	78.32	26.12%	680.05	46.51	38.09%	699.59	24.35	42.05%
B(N)	500.55	20.51	710.53	35.94	41.95%	627.37	19.39	25.34%	690.11	43.47	37.87%	706.08	16.72	41.06%
B(S)	459.77	44.04	644.56	67.69	40.19%	592.37	20.27	28.84%	636.55	62.2	38.45%	669.80	64.36	45.68%
C	684.42	112.21	273.29	21.1	-60.07%	391.18	29.06	-42.85%	323.79	25.53	-52.69%	281.13	21.93	-58.92%
C(N)	609.80	110.12	217.80	15.16	-64.28%	315.69	27.95	-48.23%	252.79	25.99	-58.55%	227.39	13.40	-62.71%
C(S)	754.87	115.01	326.06	28.53	-56.81%	463.25	28.60	-38.63%	389.82	26.92	-48.36%	331.89	35.58	-56.03%
D	172.48	29.67	94.53	9.20	-45.19%	114.53	32.30	-33.60%	201.56	24.44	16.86%	100.28	7.12	-41.86%
D(N)	151.75	29.14	88.99	12.01	-41.36%	101.72	10.67	-32.97%	171.99	22.63	13.34%	94.43	9.09	-37.77%
D(S)	192.53	30.89	99.90	7.76	-48.11%	126.90	11.85	-34.09%	230.27	27.01	19.60%	105.94	7.76	-44.97%
E	180.19	19.37	103.25	8.85	-42.70%	130.26	14.26	-27.71%	169.02	16.59	-6.20%	109.69	10.44	-39.13%
E(N)	194.60	23.56	101.78	11.91	-47.70%	128.99	16.07	-33.72%	167.85	17.99	-13.75%	109.87	13.68	-43.54%
E(S)	165.93	15.56	104.65	6.88	-36.93%	131.49	13.38	-20.76%	170.14	15.34	2.54%	109.52	8.30	-34.00%
P	77.93	10.07	72.54	7.04	-6.91%	80.74	5.50	3.61%	88.07	6.81	13.01%	77.88	4.36	-0.07%
P(N)	73.86	11.61	68.77	7.44	-6.89%	72.56	5.10	-1.76%	82.63	7.21	11.88%	73.75	4.62	-0.14%
P(S)	81.90	9.26	76.35	7.50	-6.78%	89.10	7.09	8.79%	93.78	8.09	14.50%	81.98	6.63	0.09%

2.4.4.2.2 SCHEDULING FEWER VESSELS

In scenarios 7, 8, and 9, we increase the required time gap between vessels, thereby scheduling fewer vessels within a given time frame. Specifically, in Scenario 7, we schedule Class C and Class D vessels every 35 and 10 minutes, respectively, while changing the required time gap between Class A and Class B vessels to 105 and 70 minutes, respectively, as seen in Figure 2.22.

On the other hand, in Scenario 8 we schedule northbound Class A, southbound Class A and Class B vessels every 105, 75 and 70 minutes, respectively as shown in Figure 2.23. We keep the required time gaps between Class C and Class D vessels at 35 and 10 minutes, respectively.

Finally, in Scenario 9, we combine the scheduling policy in Scenario 8 with the 20% arrival rate decrease in Scenario 2.

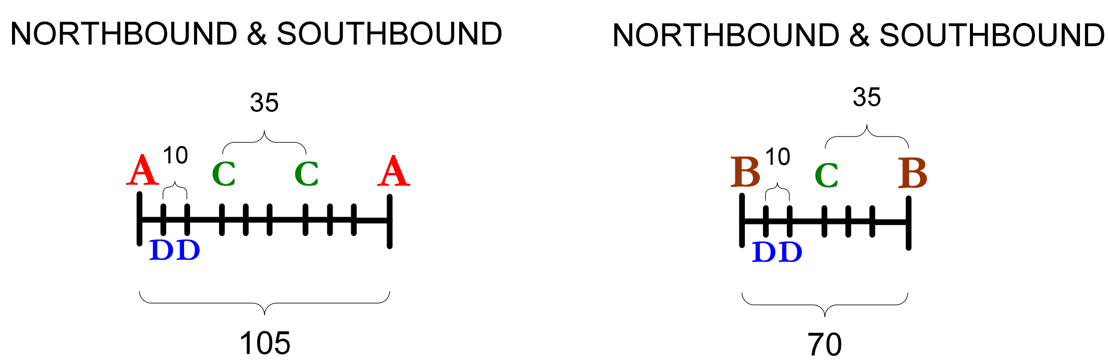

Figure 2.22 Scheduling Policy in Scenario 7

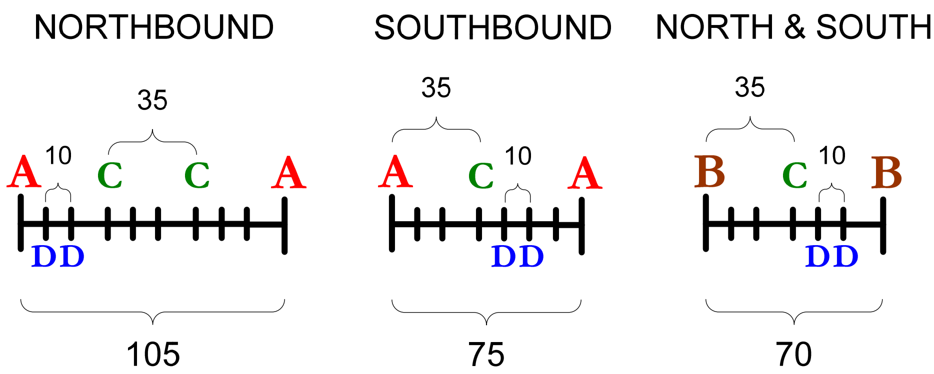

Figure 2.23 Scheduling Policy in Scenario 8

The average risk at each slice for all scenarios is listed in Table 2-25. We observe that the average slice risk decreases in general as the required time gap between consecutive vessels increases. The greatest decrease in average risk is detected in Scenario 9, where both the vessel arrival rates and the number of scheduled vessels are decreased. The combination of these factors results in a greater decrease in average risk.

Table 2-25 Slice Risk in Scenarios 7, 8, and 9 compared to the Base Scenario

	BASE SCENARIO		SCENARIO 7			SCENARIO 8			SCENARIO 9		
Slice	Average	Half Width (95% CI)	Average	Half Width (95% CI)	% Increase in Average	Average	Half Width (95% CI)	% Increase in Average	Average	Half Width (95% CI)	% Increase in Average
1	1.3748	0.34	1.4522	0.26	5.63%	1.3683	0.22	-0.47%	1.2889	0.21	-6.25%
2	1.6021	0.63	1.6536	0.45	3.21%	1.6018	0.54	-0.02%	1.4420	0.33	-9.99%
3	1.5105	0.35	1.5664	0.26	3.70%	1.5057	0.29	-0.32%	1.3557	0.10	-10.25%
4	1.4257	0.30	1.4765	0.20	3.56%	1.4264	0.25	0.05%	1.3005	0.11	-8.78%
5	1.4322	0.19	1.4846	0.21	3.66%	1.4336	0.26	0.10%	1.3201	0.14	-7.83%
6	1.4484	0.26	1.4874	0.17	2.69%	1.4552	0.27	0.47%	1.3531	0.18	-6.58%
7	1.1723	0.08	1.2158	0.06	3.71%	1.1776	0.10	0.45%	1.1165	0.07	-4.76%
8	1.1943	0.08	1.2231	0.04	2.41%	1.1917	0.08	-0.22%	1.1404	0.09	-4.51%
9	1.2002	0.09	1.2362	0.06	3.00%	1.1965	0.09	-0.31%	1.1433	0.09	-4.74%
10	1.1972	0.10	1.2306	0.07	2.79%	1.1934	0.10	-0.32%	1.1442	0.10	-4.43%
11	1.1850	0.09	1.2270	0.08	3.54%	1.1855	0.09	0.04%	1.1338	0.09	-4.32%
12	1.3361	0.07	1.3746	0.05	2.88%	1.3295	0.06	-0.49%	1.2743	0.06	-4.63%
13	1.2676	0.06	1.3015	0.05	2.67%	1.2634	0.05	-0.33%	1.2153	0.05	-4.13%
14	1.3600	0.06	1.3927	0.05	2.40%	1.3500	0.05	-0.74%	1.3064	0.06	-3.94%
15	1.3427	0.05	1.3743	0.05	2.35%	1.3384	0.05	-0.32%	1.2878	0.05	-4.09%
16	1.3462	0.06	1.3823	0.07	2.68%	1.3388	0.06	-0.55%	1.2916	0.06	-4.06%
17	1.3794	0.07	1.4069	0.06	1.99%	1.3685	0.08	-0.79%	1.3243	0.07	-3.99%
18	7.0459	0.15	6.4746	0.05	-8.11%	6.6342	0.12	-5.84%	6.8381	0.14	-2.95%
19	25.4410	0.60	22.1711	0.21	-12.85%	23.3101	0.50	-8.38%	24.6535	0.41	-3.10%
20	6.9067	0.09	6.3464	0.07	-8.11%	6.5582	0.11	-5.05%	6.8424	0.14	-0.93%
21	4.4412	0.10	4.0757	0.07	-8.23%	4.2196	0.10	-4.99%	4.3661	0.18	-1.69%

Based on the results in Figure 2.24, maximum risk observed at each slice varies across the scenarios. The maximum slice risks observed in Scenario 8 and Scenario 9 are lower than the one observed in the Base Scenario, with Scenario 8 providing the lowest maximum risk.

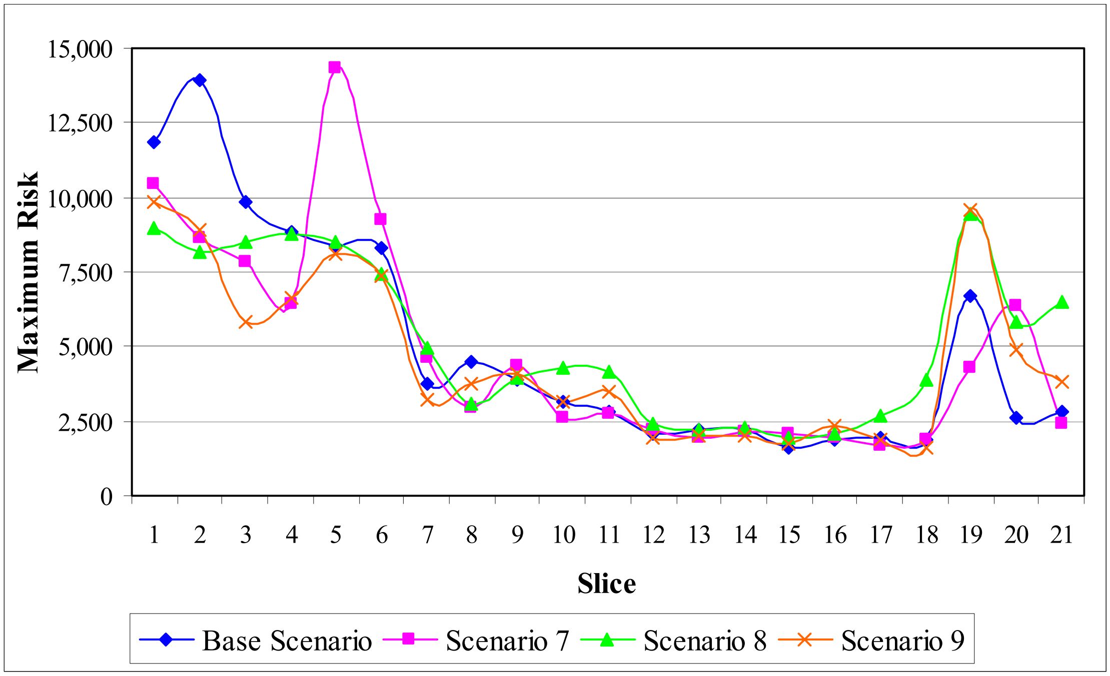

Figure 2.24 Maximum Slice Risk in Scenarios 7, 8, and 9 compared to the Base Scenario

The distributions of maximum risk as observed by vessels in the Base Scenario and scenarios 7, 8, and 9 are displayed in Figure 2.25. The results observed in all three scenarios are similar to the Base Scenario. The only exception is that scenarios 8 and 9 provide fewer observations with high maximum risk values.

The distributions for the maximum risk values for all three scenarios are very similar for higher values of risk as seen in Figure 2.26.

As seen in Figure 2.27, in all three scenarios the distributions of slices at which the maximum risk is observed are very similar to the Base Scenario, with slice 19 having the greatest number of observations.

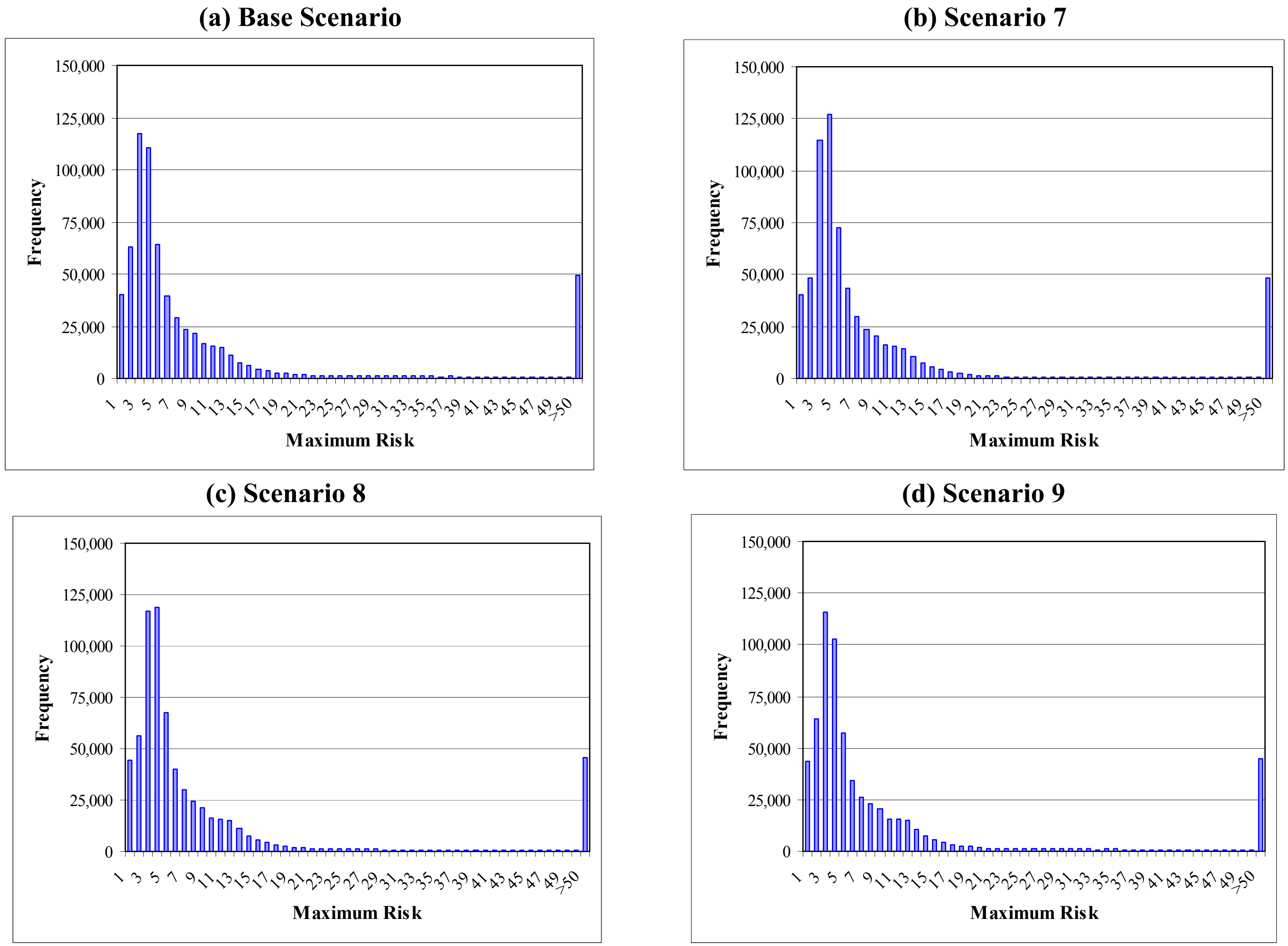

Figure 2.25 Maximum risk distribution as observed by vessels in Scenarios 7, 8, and 9 compared to the Base Scenario

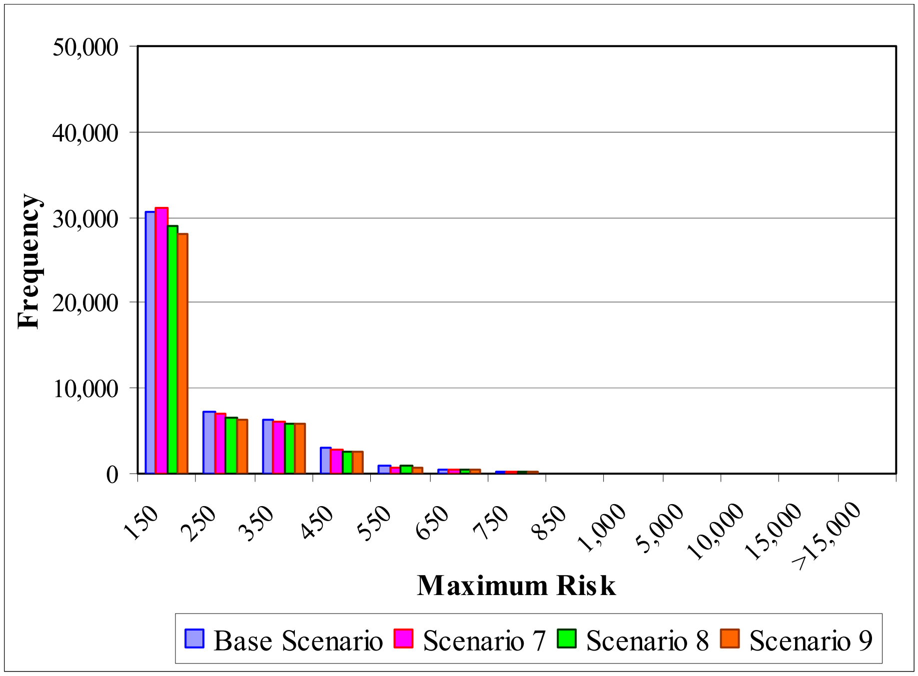

Figure 2.26 Maximum risk distribution as observed by vessels in Scenarios 7, 8, and 9 compared to the Base Scenario for values >50

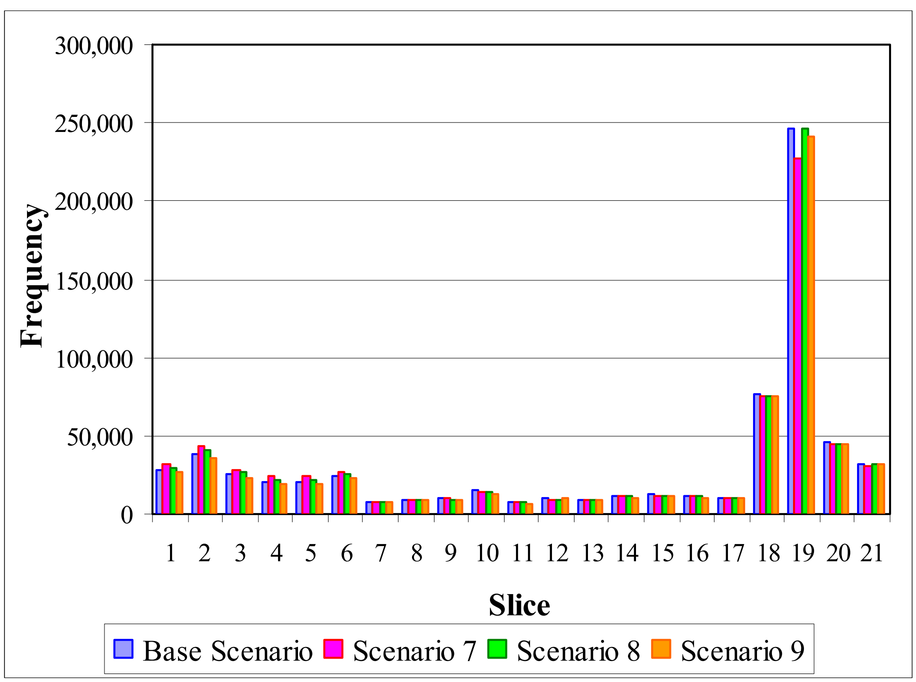

Figure 2.27 Distribution of maximum risk observations per slice in Scenarios 7, 8, and 9 compared to the Base Scenario

Table 2-26 shows that the average waiting times of all vessel classes increase substantially in all three scenarios compared to the Base Scenario, since the vessels are scheduled less frequently. The resulting increases observed in Scenario 7 and Scenario 8 are unacceptable. Therefore, these scenarios are rendered infeasible even though they result in lower average slice risks. On the other hand, Scenario 9, in which vessel arrivals are decreased 20%, provides acceptable waiting times coupled with lower average and maximum slice risks, clearly at the expense of 20% lesser traffic.

Policy Indication 3: In the current situation, scheduling policy changes that are made to reduce risks cause major increases in average vessel waiting times. The benefits obtained in risks do not justify the resultant waiting times. In case of future major decreases in dangerous cargo traffic may occur due to alternative transport modes such as pipelines and other routes. In this case, scheduling changes can be made to take lesser number of vessels into the Strait and can still be justified due to the resultant insignificant increases in delays.

Table 2-26 Waiting Times (in minutes) in Scenarios 7, 8, and 9 compared to the Base Scenario

	BASE SCENARIO		**SCENARIO 7**			**SCENARIO 8**			**SCENARIO 9**		
Class (Direction)	**Average**	**Half Width (95% CI)**	**Average**	**Half Width (95% CI)**	**% Increase in Average**	**Average**	**Half Width (95% CI)**	**% Increase in Average**	**Average**	**Half Width (95% CI)**	**% Increase in Average**
A	1,987.15	1,564.30	16,696.04	16,696.04	740.20%	4,610.02	2,187.49	131.99%	1,841.05	271.95	-7.35%
A(N)	2,127.69	1,642.60	17,193.56	18,192.67	708.09%	4,988.77	2,271.92	134.47%	1,997.02	275.45	-6.14%
A(S)	1,847.74	1,479.95	16,208.59	17,636.09	777.21%	4,236.06	2,108.72	129.26%	1,678.78	273.99	-9.14%
B	492.48	19.55	486.00	457.65	-1.32%	477.36	477.36	-3.07%	509.69	23.13	3.49%
B(N)	500.55	20.51	483.13	458.08	-3.48%	485.25	485.25	-3.06%	518.28	20.19	3.54%
B(S)	459.77	44.04	499.34	455.74	8.61%	445.26	445.26	-3.16%	475.31	41.72	3.38%
C	684.42	112.21	62,129.49	38,085.47	8977.68%	35,522.74	13,222.85	5090.20%	621.01	103.53	-9.26%
C(N)	609.80	110.12	63,268.26	38,199.69	10275.25%	35,758.80	13,523.03	5764.02%	559.02	113.13	-8.33%
C(S)	754.87	115.01	61,056.72	23,179.62	7988.38%	35,297.09	12,940.10	4575.92%	679.82	97.68	-9.94%
D	172.48	29.67	321.67	47.10	86.50%	279.17	44.24	61.86%	204.72	27.77	18.69%
D(N)	151.75	29.14	298.35	49.92	96.61%	202.20	38.01	33.25%	162.91	36.3	7.35%
D(S)	192.53	30.89	344.26	48.98	78.81%	353.80	53.82	83.76%	245.39	22.77	27.46%
E	180.19	19.37	266.54	22.87	47.92%	252.51	21.07	40.14%	188.71	17.11	4.73%
E(N)	194.60	23.56	288.83	30.43	48.42%	267.09	24.43	37.25%	198.61	20.2	2.06%
E(S)	165.93	15.56	244.76	16.89	47.51%	238.20	17.81	43.55%	179.06	14.73	7.91%
P	77.93	10.07	104.39	7.09	33.95%	92.05	8.39	18.12%	79.47	4.99	1.98%
P(N)	73.86	11.61	106.73	6.17	44.51%	82.91	9.33	12.26%	70.65	8.32	-4.34%
P(S)	81.90	9.26	102.03	12.42	24.57%	101.29	7.95	23.67%	88.51	5.04	8.07%

2.4.4.3 IMPACT OF OTHER FACTORS

In Scenario 10, we turn the pilotage option off. That is, none of the vessels request pilots for their passage through the Strait. Scenario 11 represents the case where overtaking is not allowed within the Strait. Finally, local traffic density in the Strait is decreased by 50% in Scenario 12.

Table 2-27 reveals that the average risk increases at each slice when pilotage is not available. The resulting average increase is 50% across all slices.

Surprisingly, the average risk also increases in Scenario 11 when overtaking is not allowed. This is a result of expert opinions stating that two vessels following each other in a normal traffic lane creates a riskier situation than a vessel overtaking another.

Finally, the average slice risk decreases in Scenario 12. The 50% decrease in local traffic density results in a 50% average decrease in slice risk.

Table 2-27 Slice Risk in Scenarios 10, 11, and 12 compared to the Base Scenario

	BASE SCENARIO		SCENARIO 10			SCENARIO 11			SCENARIO 12		
Slice	Average	Half Width (95% CI)	Average	Half Width (95% CI)	% Increase in Average	Average	Half Width (95% CI)	% Increase in Average	Average	Half Width (95% CI)	% Increase in Average
1	1.3748	0.34	1.7581	0.27	27.88%	1.5762	0.64	14.65%	1.3416	0.34	-2.41%
2	1.6021	0.63	1.7584	0.25	9.76%	1.8805	1.05	17.38%	1.5689	0.63	-2.07%
3	1.5105	0.35	1.7985	0.28	19.07%	1.817	0.81	20.29%	1.4746	0.35	-2.38%
4	1.4257	0.30	1.8366	0.32	28.82%	1.6895	0.68	18.50%	1.3885	0.30	-2.61%
5	1.4322	0.19	1.8711	0.30	30.65%	1.665	0.60	16.25%	1.3835	0.29	-3.40%
6	1.4484	0.26	1.9207	0.29	32.61%	1.6843	0.59	16.29%	1.3826	0.26	-4.54%
7	1.1723	0.08	1.5367	0.12	31.08%	1.2864	0.18	9.73%	1.0880	0.08	-7.19%
8	1.1943	0.08	1.5792	0.12	32.23%	1.3052	0.19	9.29%	1.1039	0.08	-7.57%
9	1.2002	0.09	1.5951	0.17	32.90%	1.3182	0.23	9.83%	1.1156	0.09	-7.05%
10	1.1972	0.10	1.5883	0.15	32.67%	1.2846	0.16	7.30%	1.1106	0.10	-7.23%
11	1.1850	0.09	1.5688	0.14	32.39%	1.2913	0.17	8.97%	1.0850	0.09	-8.44%
12	1.3361	0.07	1.8574	0.11	39.02%	1.4573	0.16	9.07%	1.1069	0.07	-17.15%
13	1.2676	0.06	1.7249	0.13	36.08%	1.4035	0.17	10.72%	1.1114	0.06	-12.32%
14	1.3600	0.06	1.8699	0.14	37.49%	1.5082	0.15	10.90%	1.1204	0.05	-17.62%
15	1.3427	0.05	1.8483	0.13	37.66%	1.477	0.14	10.00%	1.1186	0.06	-16.69%
16	1.3462	0.06	1.8236	0.14	35.46%	1.4944	0.17	11.01%	1.1222	0.06	-16.64%
17	1.3794	0.07	1.8642	0.14	35.15%	1.4995	0.15	8.71%	1.1303	0.08	-18.06%
18	7.0459	0.15	11.6996	0.20	66.05%	8.0102	0.17	13.69%	1.6180	0.06	-77.04%
19	25.4410	0.60	45.3467	0.69	78.24%	30.3149	0.15	19.16%	5.0426	0.08	-80.18%
20	6.9067	0.09	11.9161	0.30	72.53%	8.3434	0.23	20.80%	1.3933	0.05	-79.83%
21	4.4412	0.10	7.2117	0.22	62.38%	5.3849	0.18	21.25%	1.3170	0.06	-70.35%

Based on Figure 2.28, Scenario 12 provides maximum risk values similar to the Base Scenario at each slice except slices 19, 20 and 21. These slices are affected by local traffic density the most. In addition, the highest maximum risk observed in Scenario 12 is identical to the Base Scenario.

On the other hand, the highest maximum risk values observed in scenarios 10 and 11 are lower than the Base Scenario. However, as stated before, the maximum risk values do not necessarily reflect the impact of a given factor on the overall risk. They are contingent upon the occurrence of a random situation at an instance. Thus, we need to consider the maximum risk distribution.

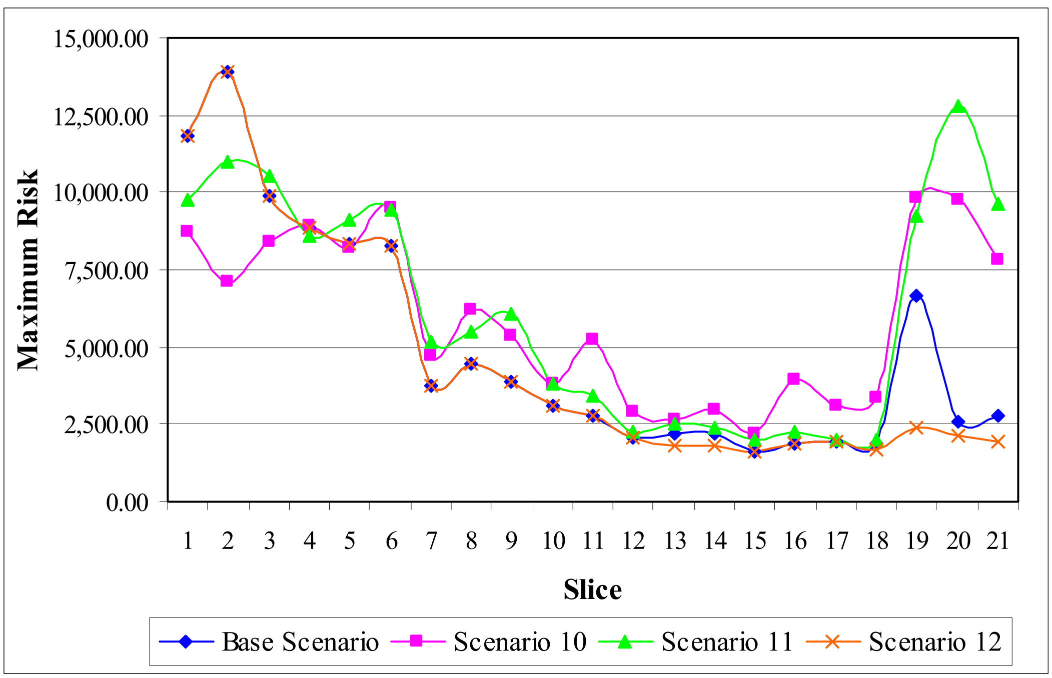

Figure 2.28 Maximum Slice Risk in Scenarios 10, 11, and 12 compared to the Base Scenario

As seen in Figure 2.29, the maximum risk distributions observed in Scenario 11 are very similar to the Base Scenario. On the other hand, Scenario 10 results in a substantially greater number of observations with high maximum risk values while Scenario 12 provides a significantly greater number of low maximum risk values. These phenomena are also observed in Figure 2.30.

The histograms representing the distribution of slices at which the maximum risk is observed are given in Figure 2.31. In scenarios 10 and 11, the distributions of slices are very similar to the Base Scenario. However, in Scenario 12 the observations are more evenly distributed across all slices. This is due to the fact that the discrepancies in observations in the Base Scenario are caused by heavier local traffic density in the last four slices. Thus, decreasing the local traffic density 50% in Scenario 12 dampens this effect.

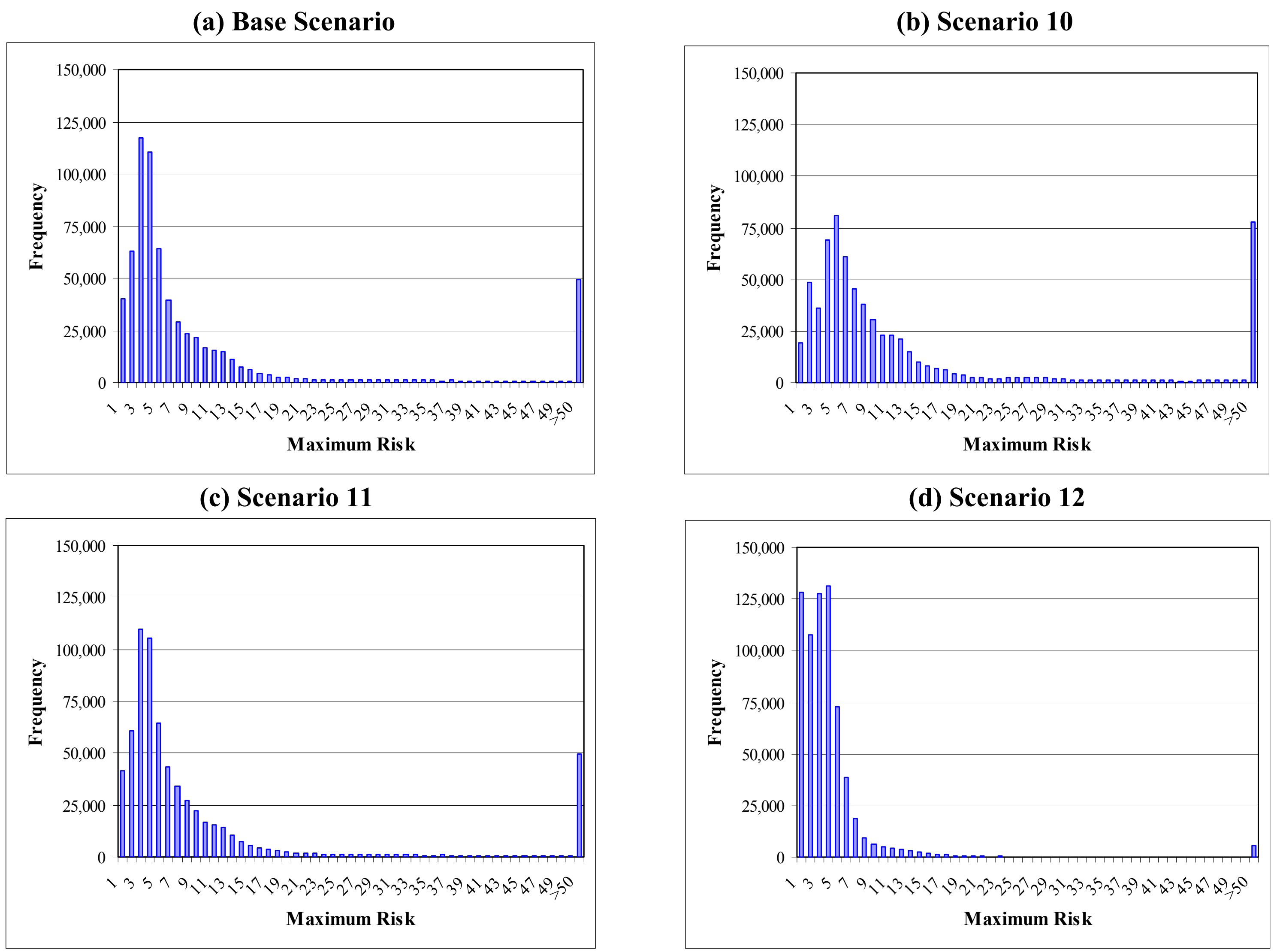

Figure 2.29 Maximum risk distribution as observed by vessels in Scenarios 10, 11, and 12 compared to the Base Scenario

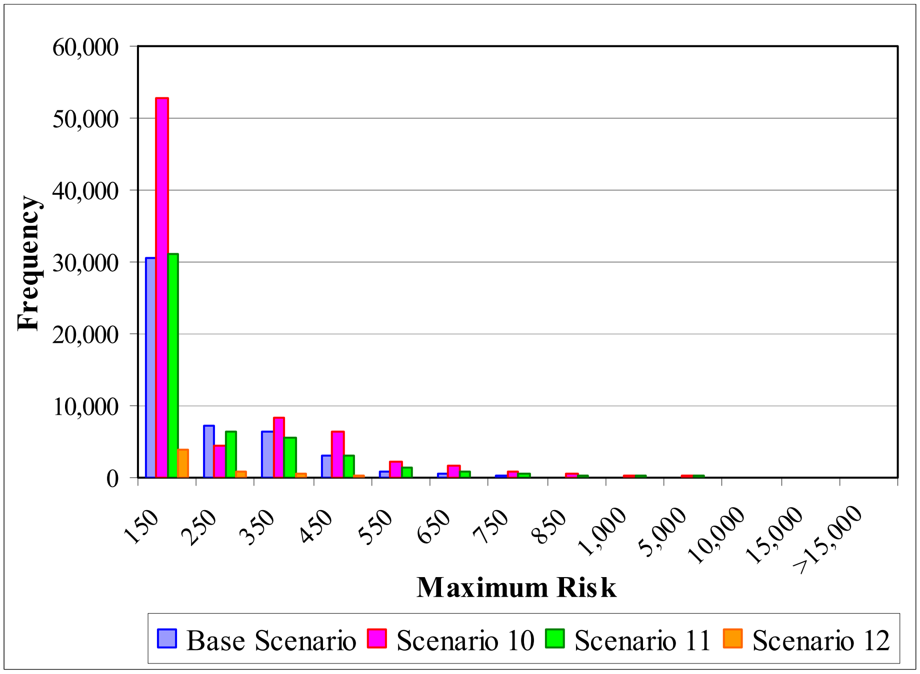

Figure 2.30 Maximum risk distribution as observed by vessels in Scenarios 10, 11, and 12 compared to the Base Scenario for values >50

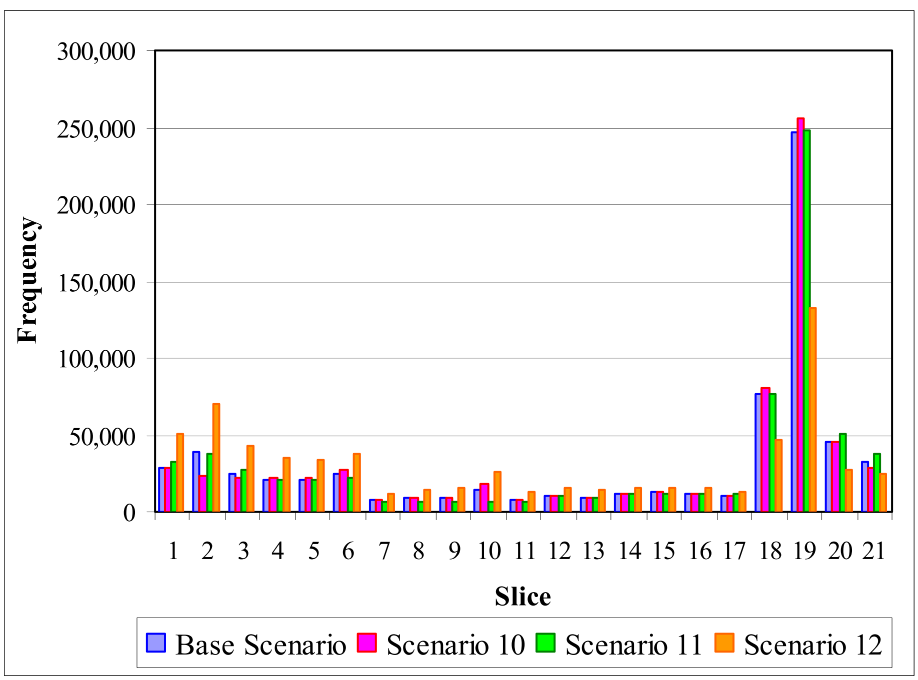

Figure 2.31 Distribution of maximum risk observations per slice in Scenarios 10, 11, and 12 compared to the Base Scenario

The average vessel waiting times in scenarios 10, 11 and 12 are displayed in Table 2-28. When we turn the pilotage option off in Scenario 10, the average waiting times decrease in general as the vessels do not have to wait for the next available pilot.

We observe that the average vessel waiting times decrease slightly when overtaking is not allowed. Although overtaking does not have a direct effect on scheduling, the observed decrease in waiting times is a result of changing event sequences in the simulation due to variability.

On the other hand, the average waiting times in Scenario 12 are identical to the ones in the Base Scenario since local traffic density has no effect on scheduling.

Policy Indication 4: The model indicates that pilots are of utmost importance for safe passage, and lack of pilotage significantly increases the risks in the Strait. In the current practice, vessels greater than 300 m. in length are mandated to take a pilot, and it is voluntary for the rest. Thus, we recommend mandatory pilotage for vessels greater than 150 m. in length.

Policy Indication 5: Even though current regulations do not allow overtaking anywhere in the Strait, the risk model indicates that overtaking a vessel is less risky as opposed to slowing down behind it. Therefore, in the areas where the width of the Strait tolerates it (except between Kanlıca and Vaniköy), overtaking proves to be a safe practice as confirmed by the expert opinion.

Policy Indication 6: The most significant contributor to the risk appears to be the juxtaposition of the transit and local traffic. To reduce risk significantly, the scheduling procedure should be revised to move more of the dangerous cargo vessels to nighttime traffic. This requires further research on what kind of modifications can be done to the nighttime scheduling practice to control vessel delays.

Table 2-28 Waiting Times (in minutes) in Scenarios 10, 11, and 12 compared to the Base Scenario

	BASE SCENARIO		SCENARIO 10			SCENARIO 11			SCENARIO 12		
Class (Direction)	**Average**	**Half Width (95% CI)**	**Average**	**Half Width (95% CI)**	**% Increase in Average**	**Average**	**Half Width (95% CI)**	**% Increase in Average**	**Average**	**Half Width (95% CI)**	**% Increase in Average**
A	1,987.15	1,564.30	1,845.96	827.24	-7.11%	1,820.49	699.20	-8.39%	1,987.15	1,564.30	0.00%
A(N)	2,127.69	1,642.60	1,967.03	878.73	-7.55%	1,944.66	759.58	-8.60%	2,127.69	1,642.60	0.00%
A(S)	1,847.74	1,479.95	1,727.09	774.69	-6.53%	1,698.94	640.07	-8.05%	1,847.74	1,479.95	0.00%
B	492.48	19.55	493.16	13.15	0.14%	493.47	16.38	0.20%	492.48	19.55	0.00%
B(N)	500.55	20.51	502.31	11.85	0.35%	501.75	13.96	0.24%	500.55	20.51	0.00%
B(S)	459.77	44.04	452.30	32.83	-1.62%	456.70	33.55	-0.67%	459.77	44.04	0.00%
C	684.42	112.21	664.54	143.31	-2.90%	688.43	105.91	0.59%	684.42	112.21	0.00%
C(N)	609.80	110.12	577.92	118.51	-5.23%	606.51	89.57	-0.54%	609.80	110.12	0.00%
C(S)	754.87	115.01	746.70	169.56	-1.08%	766.30	122.94	1.51%	754.87	115.01	0.00%
D	172.48	29.67	169.55	26.72	-1.70%	170.37	24.91	-1.22%	172.48	29.67	0.00%
D(N)	151.75	29.14	147.96	27.36	-2.50%	150.69	29.93	-0.70%	151.75	29.14	0.00%
D(S)	192.53	30.89	190.42	28.40	-1.10%	189.46	20.66	-1.59%	192.53	30.89	0.00%
E	180.19	19.37	176.26	18.37	-2.18%	176.93	16.40	-1.81%	180.19	19.37	0.00%
E(N)	194.60	23.56	191.42	23.53	-1.63%	191.22	20.62	-1.74%	194.60	23.56	0.00%
E(S)	165.93	15.56	161.27	13.79	-2.81%	162.94	12.41	-1.80%	165.93	15.56	0.00%
P	77.93	10.07	74.86	7.94	-3.95%	76.90	8.88	-1.33%	77.93	10.07	0.00%
P(N)	73.86	11.61	69.96	6.76	-5.28%	71.94	11.84	-2.59%	73.86	11.61	0.00%
P(S)	81.90	9.26	79.73	9.78	-2.65%	81.99	6.43	0.11%	81.90	9.26	0.00%

3 CONCLUSION

Istanbul is the only city in the world that stands astride two continents. Europe is separated from Asia by the Strait of Istanbul in the northwestern corner of Turkey. It holds a strategic importance as it links the states of Black Sea to the Mediterranean and the world beyond.

The Strait of Istanbul is considered not only one of the world's most dangerous waterways to navigate but also one of the most congested maritime traffic regions in the world. More than 50,000 transit vessels pass through the Strait annually, 20% of which are tankers, dangerous cargo vessels, and LNG-LPG carriers. Currently, the oil and gas from the newly independent energy-rich states along the Caspian Sea reach the western markets through the Strait of Istanbul. Consequently, more than 3 million barrels of oil pass through the Strait every day.

The nature of the global economy dictates that the tanker traffic in the Strait of Istanbul cannot be eliminated. Nonetheless, the economic aspirations and environmental awareness need not to be mutually exclusive goals in the Strait as stated in [Joyner and Mitchell, 2002]. The risk involving the transit traffic can be mitigated by operational policies and restrictions that adequately regulate the transit vessel traffic while maintaining the freedom of passage. Until then, the environment, the priceless historical monuments and the health and safety of the city's residents will be at jeopardy.

In this research, we have developed a mathematical risk analysis model to analyze the risks involved in the transit vessel traffic system in the Strait of Istanbul. In the first step of the risk analysis, the transit vessel traffic system was analyzed and a simulation model was developed to mimic and study the system. In addition to vessel traffic and geographical conditions, the current vessel scheduling practices were modeled using a scheduling algorithm. This algorithm was developed through discussions with the

Turkish Straits Vessel Traffic Services (VTS) to mimic their decisions on sequencing vessel entrances as well as coordinating vessel traffic in both directions.

Risk analysis was performed by incorporating a probabilistic accident risk model into the simulation model. The framework of this risk model was established taking into account the attributes that influence the occurrence of an accident as well as the consequences and their impact. The mathematical accident risk model was developed based on probabilistic arguments and utilized historical accident data and subject matter expert opinions.

We have also performed a scenario analysis to understand and evaluate the characteristics of the accident risk. This analysis allowed us to investigate how various factors impact risks in the Strait. These factors include vessel arrivals, scheduling policies, pilotage, overtaking, and local traffic density.

The numerical results showed that local traffic density and pilotage are the two main factors that affect slice risk the most. A 50% decrease in local traffic density results in an average of 50% decrease in slice risk. The importance of the local traffic density is also highlighted by the fact that the majority of the vessels observe the maximum risk at slice 19, which has a heavier local traffic density than other slices. Moreover, changing the local traffic density does not impact the vessel waiting times. Therefore, to reduce risk significantly, the scheduling procedure should be revised to move more of the dangerous cargo vessels to nighttime traffic. This requires further research on what kind of modifications can be done to the nighttime scheduling practice to control vessel delays.

Moreover, the model indicates that pilots are of utmost importance for safe passage and lack of pilotage significantly increases the risks in the Strait. In the current practice, vessels greater than 300 m. in length are mandated to take a pilot and it is voluntary for the rest. Thus, we recommend mandatory pilotage for vessels greater than 150 m. in length.

Conversely, changing the scheduling policy by increasing the required time gaps between consecutive vessels, thereby reducing the number of scheduled vessels decreases the average slice risk. However, in such scenarios the resulting average vessel waiting times are unacceptable. Therefore, they are rendered infeasible even though they result in lower average slice risks. On the other hand, in the future major decreases in dangerous cargo traffic may occur due to alternative transport modes such as pipelines and other routes. In this case, scheduling changes can be made to take lesser number of vessels into the Strait and can still be justified due to the resultant insignificant increases in delays. Additionally, scheduling decisions to balance out delays vs. risks should be made based on extensive experimentation with the model developed in this study.

Even though vessel arrival rates are directly proportional to the average slice risk, they have a small impact as long as the scheduling policies are not changed. Thus, the change in the arrival rates must be substantial in order to obtain a significant impact. In the wake of increase in arrival rates, the scheduling regime should be kept as is to maintain the risks at the current levels. A 10% increase in the dangerous cargo vessel arrival rates results in rather acceptable waiting times at the entrance. However, further increases in vessel traffic may result in discouraging shippers away from the Strait due to excessive waiting times.

Note that in the scenario where both the vessel arrival rates and the number of scheduled vessels are decreased, the combination of the two factors results in a greater decrease in average and maximum slice risks. This scenario also provides acceptable waiting times.

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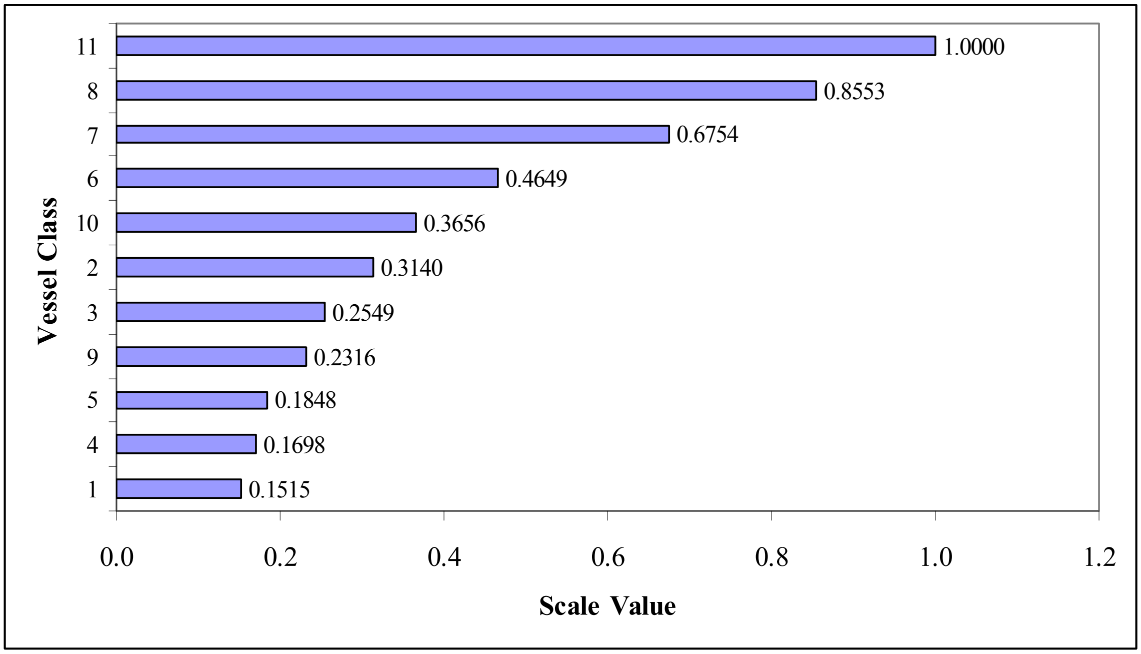
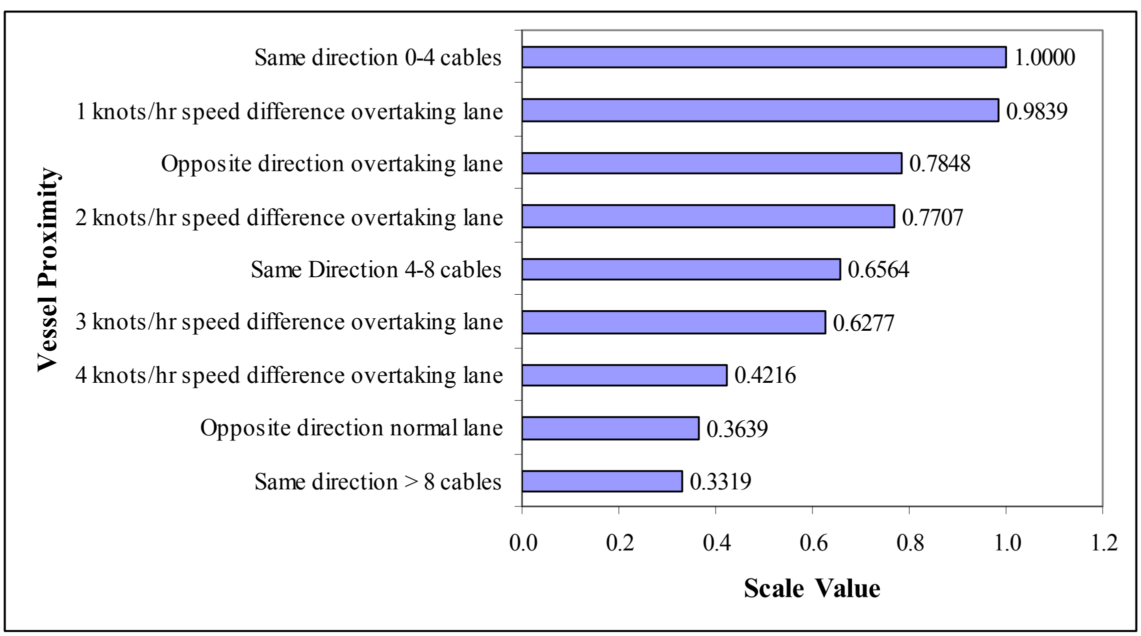
APPENDIX A: Scale Values of Situational Attributes Influencing Accident Occurrence

In this appendix, we provide scale values of situational attributes influencing accident occurrence obtained from the experts.

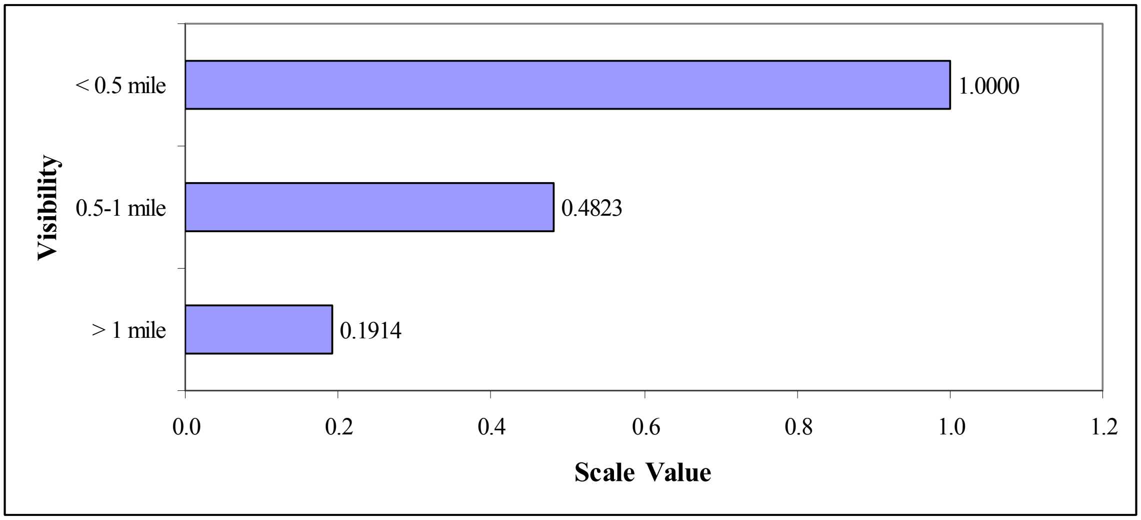
x_1 : 1st Interacting Vessel Class - x_2 : 2nd Interacting Vessel Class



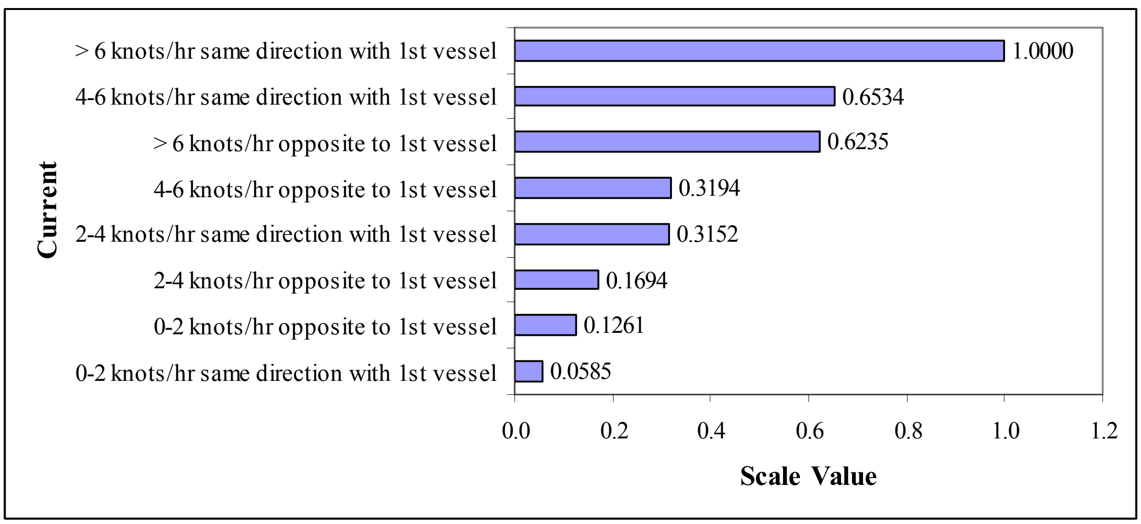
x_5 : Nearest Transit Vessel Proximity



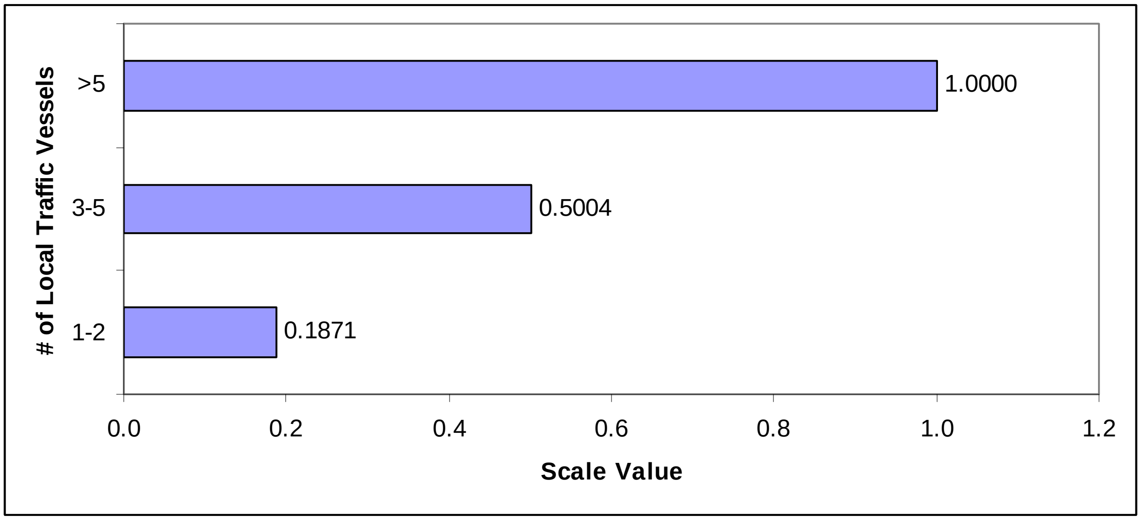
x_6 : **Visibility**



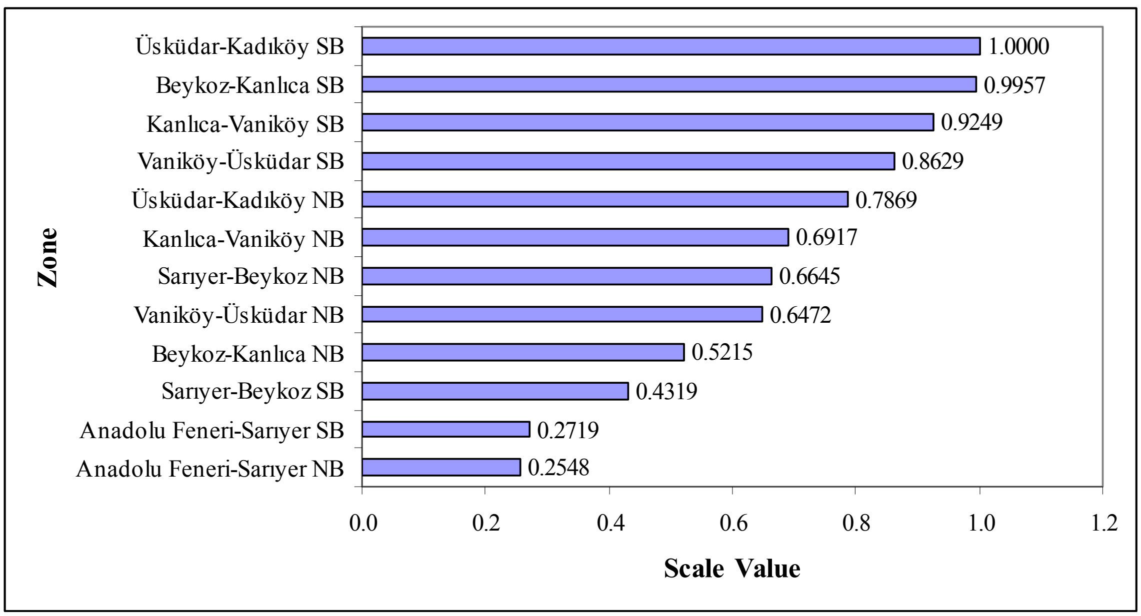
x_7 : **Current**



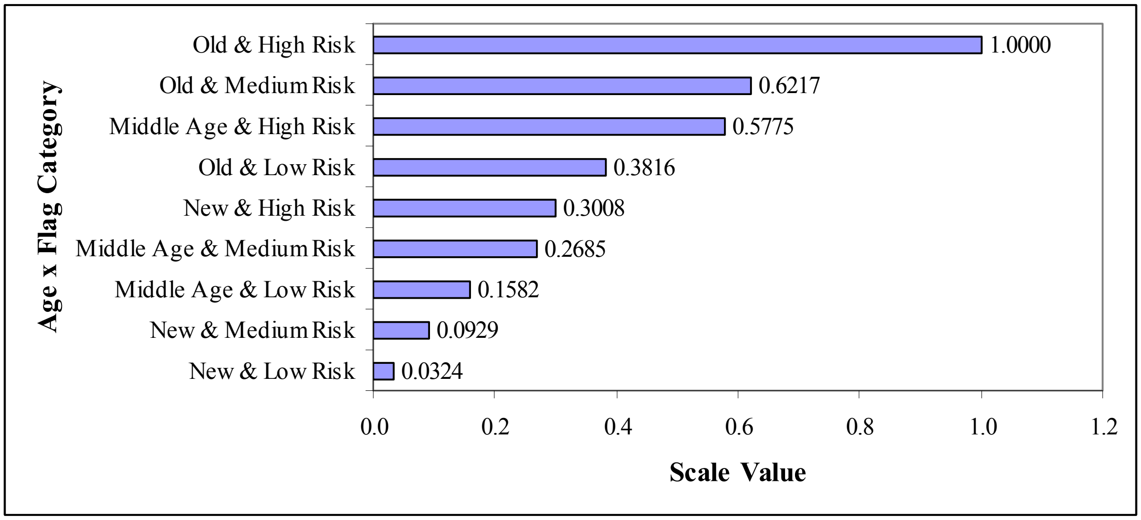
x_8 : **Local Traffic Density**



x_9 : **Zone**



x_{10} **: Vessel Reliability**



APPENDIX B: Regression Results of the Accident Probability Questionnaires

$\Pr\left(\text{Collision} \middle| \text{Human Error}, \underline{S}^{1}\right)$

Summary

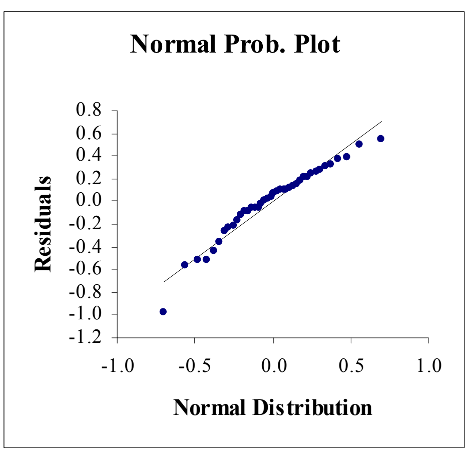
R^2	R	Adj. R^2	S.E. of Estimate
0.934	0.966	0.893	0.400

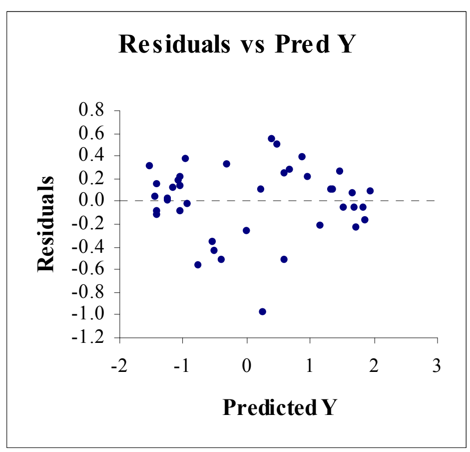
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	54.336	15	3.622	22.601	0.000
Residual	3.847	24	0.160		
Total	58.182	39			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.216	0.080		0.052	0.380	2.721	0.012
X1	1.726	0.322	0.281	1.062	2.390	5.361	0.000
X2	2.046	0.318	0.338	1.390	2.702	6.435	0.000
X3	1.680	0.597	0.435	0.447	2.912	2.813	0.010
X4	1.633	0.204	0.423	1.212	2.055	8.004	0.000
X5	1.401	0.338	0.217	0.703	2.099	4.142	0.000
X6	1.415	0.649	0.239	0.076	2.754	2.181	0.039
X7	3.430	0.936	0.492	1.498	5.363	3.663	0.001
X8	1.244	0.633	0.211	-0.062	2.551	1.966	0.061
X10	1.255	0.204	0.325	0.834	1.676	6.151	0.000
X15	-2.564	1.301	-0.490	-5.249	0.121	-1.971	0.060
X16	2.410	0.947	0.442	0.455	4.364	2.545	0.018
X19	-3.937	1.537	-0.547	-7.109	-0.764	-2.561	0.017
X20	-3.842	1.347	-0.617	-6.621	-1.062	-2.853	0.009
X21	4.264	1.380	0.621	1.415	7.113	3.089	0.005
X22	4.201	1.383	0.584	1.346	7.056	3.037	0.006





$\Pr\left(\text{Collision}\,\middle|\,\text{Steering Failure}, \underline{S}^1\right)$

Summary

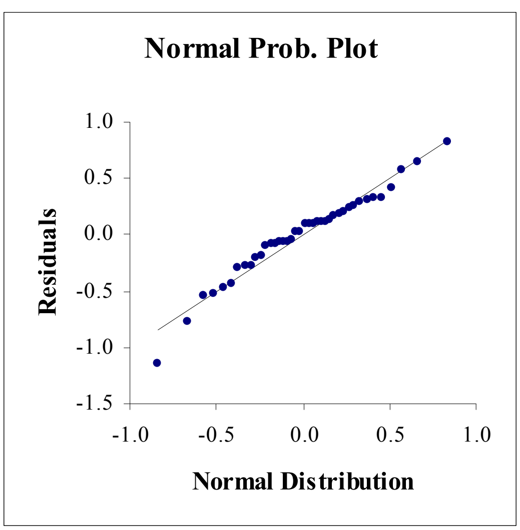
R^2	R	Adj. R^2	S.E. of Estimate
0.928	0.964	0.888	0.470

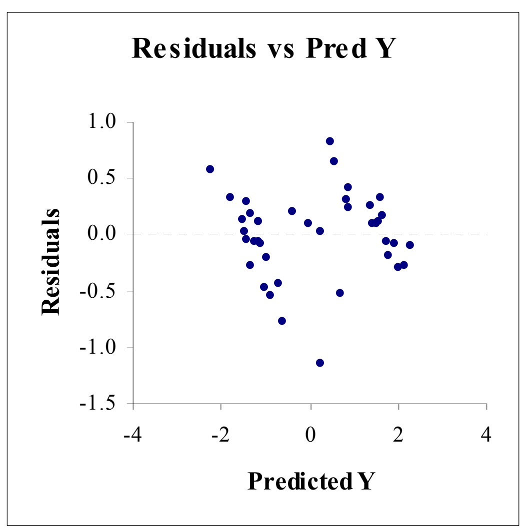
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	71.591	14	5.114	23.159	0.000
Residual	5.520	25	0.221		
Total	77.111	39			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.243	0.091		0.055	0.430	2.661	0.013
X1	1.976	0.378	0.280	1.197	2.754	5.228	0.000
X2	2.384	0.373	0.342	1.615	3.153	6.387	0.000
X3	2.105	0.616	0.473	0.835	3.374	3.414	0.002
X4	1.328	0.526	0.299	0.245	2.411	2.525	0.018
X5	1.655	0.397	0.223	0.837	2.473	4.169	0.000
X6	2.200	0.365	0.323	1.449	2.952	6.029	0.000
X7	2.645	0.697	0.330	1.210	4.081	3.795	0.001
X8	1.911	0.364	0.281	1.162	2.661	5.254	0.000
X9	2.306	0.799	0.208	0.660	3.952	2.886	0.008
X10	1.388	0.239	0.312	0.895	1.881	5.801	0.000
X13	-1.994	0.886	-0.315	-3.818	-0.169	-2.250	0.033
X14	2.046	1.016	0.355	-0.047	4.139	2.013	0.055
X15	-2.115	1.259	-0.351	-4.708	0.478	-1.680	0.105
X16	1.506	0.912	0.240	-0.373	3.385	1.650	0.111





$\Pr\left(\text{Collision} \middle| \text{Propulsion Failure}, \underline{S}^1\right)$

Summary

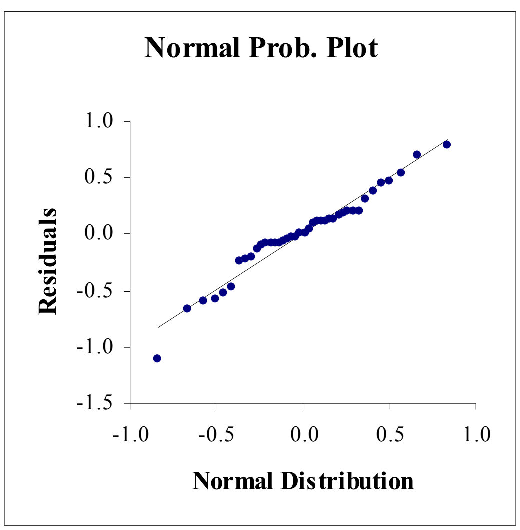
R^2	R	Adj. R^2	S.E. of Estimate
0.928	0.963	0.883	0.474

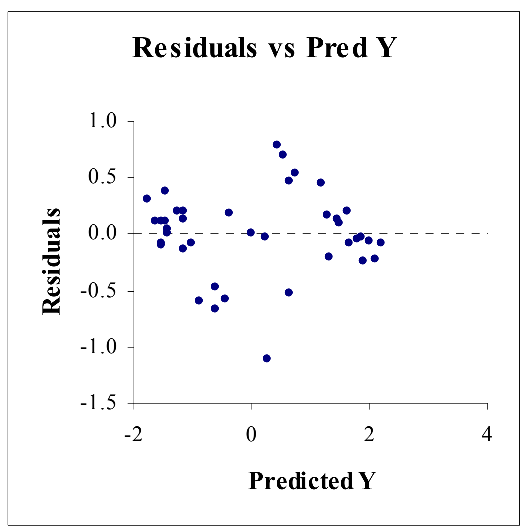
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	69.451	15	4.630	20.566	0.000
Residual	5.403	24	0.225		
Total	74.854	39			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.231	0.094		0.036	0.425	2.448	0.022
X1	1.938	0.382	0.279	1.150	2.725	5.079	0.000
X2	2.344	0.377	0.341	1.566	3.122	6.219	0.000
X3	2.341	0.708	0.534	0.880	3.801	3.308	0.003
X4	1.772	0.242	0.404	1.273	2.271	7.325	0.000
X5	1.548	0.401	0.212	0.721	2.376	3.862	0.001
X6	1.641	0.769	0.244	0.054	3.227	2.134	0.043
X7	4.161	1.110	0.526	1.871	6.452	3.749	0.001
X8	1.466	0.750	0.219	-0.082	3.014	1.954	0.062
X10	1.383	0.242	0.316	0.884	1.882	5.717	0.000
X15	-3.139	1.542	-0.529	-6.322	0.043	-2.036	0.053
X16	2.477	1.122	0.400	0.160	4.793	2.207	0.037
X19	-4.512	1.822	-0.553	-8.272	-0.752	-2.476	0.021
X20	-4.596	1.596	-0.651	-7.890	-1.302	-2.879	0.008
X21	4.886	1.636	0.627	1.510	8.263	2.987	0.006
X22	4.895	1.639	0.600	1.511	8.278	2.986	0.006





$\Pr\left(\text{Collision} \middle| \text{Communication/Navigation Equipment Failure}, \underline{S}^1\right)$

Summary

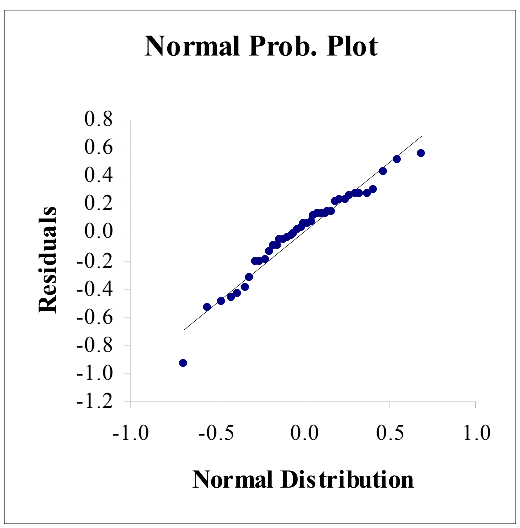
R^2	R	Adj. R^2	S.E. of Estimate
0.936	0.968	0.901	0.383

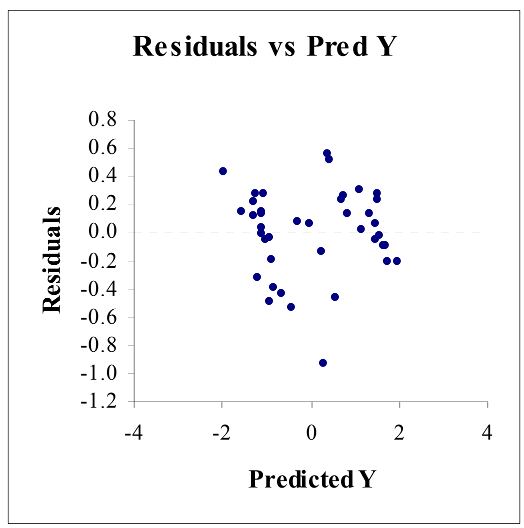
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	54.008	14	3.858	26.322	0.000
Residual	3.664	25	0.147		
Total	57.672	39			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.208	0.074		0.055	0.361	2.797	0.010
X1	1.570	0.308	0.257	0.936	2.204	5.101	0.000
X2	1.754	0.304	0.291	1.128	2.380	5.769	0.000
X3	1.602	0.502	0.417	0.568	2.637	3.190	0.004
X4	1.156	0.429	0.301	0.273	2.039	2.697	0.012
X5	1.380	0.323	0.215	0.714	2.047	4.268	0.000
X6	2.174	0.297	0.369	1.561	2.786	7.311	0.000
X7	2.138	0.568	0.308	0.968	3.307	3.764	0.001
X8	1.766	0.296	0.300	1.156	2.377	5.959	0.000
X9	2.022	0.651	0.211	0.681	3.363	3.105	0.005
X10	1.321	0.195	0.344	0.920	1.723	6.777	0.000
X13	-1.602	0.722	-0.293	-3.089	-0.116	-2.220	0.036
X14	1.740	0.828	0.349	0.035	3.446	2.102	0.046
X15	-1.554	1.026	-0.298	-3.667	0.558	-1.515	0.142
X16	1.229	0.743	0.226	-0.302	2.760	1.653	0.111





$\Pr\left(\text{Grounding} \middle| \text{Human Error}, \underline{S}^1\right)$

Summary

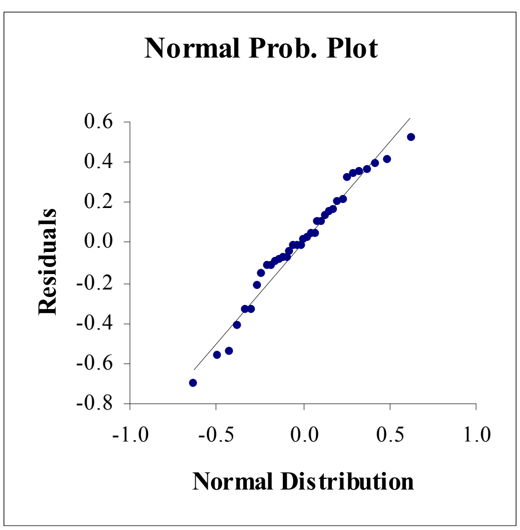
R^2	R	Adj. R^2	S.E. of Estimate
0.933	0.966	0.877	0.389

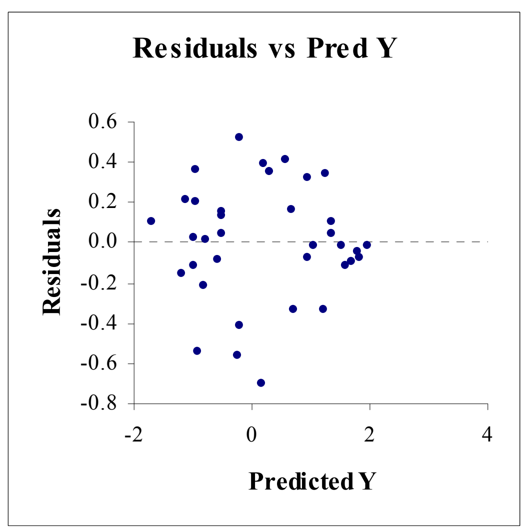
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	40.103	16	2.506	16.585	0.000
Residual	2.871	19	0.151		
Total	42.974	35			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.383	0.091		0.192	0.574	4.197	0.000
X1	1.847	0.313	0.351	1.193	2.502	5.909	0.000
X3	2.311	0.605	0.695	1.044	3.577	3.818	0.001
X4	0.943	0.465	0.284	-0.030	1.916	2.028	0.057
X5	1.193	0.328	0.215	0.505	1.880	3.631	0.002
X6	1.124	0.637	0.221	-0.209	2.456	1.765	0.094
X7	3.236	0.920	0.540	1.310	5.163	3.516	0.002
X8	1.433	0.628	0.282	0.118	2.748	2.281	0.034
X10	0.881	0.200	0.265	0.463	1.299	4.413	0.000
X13	-1.300	0.803	-0.275	-2.980	0.380	-1.619	0.122
X14	1.806	0.902	0.420	-0.081	3.694	2.003	0.060
X15	-3.807	1.345	-0.842	-6.622	-0.993	-2.831	0.011
X16	2.819	0.956	0.599	0.818	4.821	2.948	0.008
X19	-3.150	1.609	-0.509	-6.518	0.218	-1.958	0.065
X20	-3.253	1.377	-0.607	-6.134	-0.371	-2.363	0.029
X21	3.621	1.416	0.613	0.659	6.584	2.558	0.019
X22	3.220	1.426	0.520	0.235	6.204	2.258	0.036





$\Pr\left(\text{Grounding} \middle| \text{Steering Failure}, \underline{S}^1\right)$

Summary

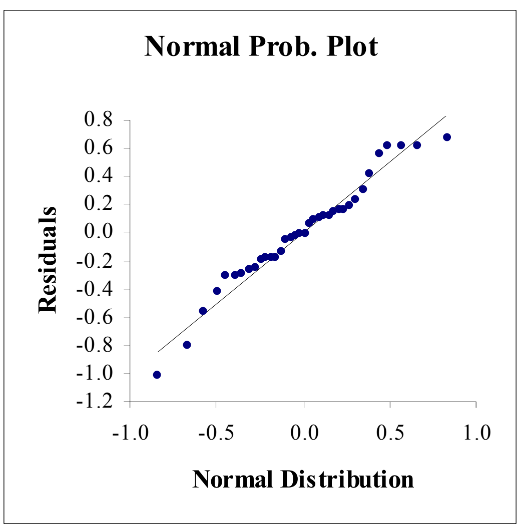
R^2	R	Adj. R^2	S.E. of Estimate
0.913	0.955	0.867	0.473

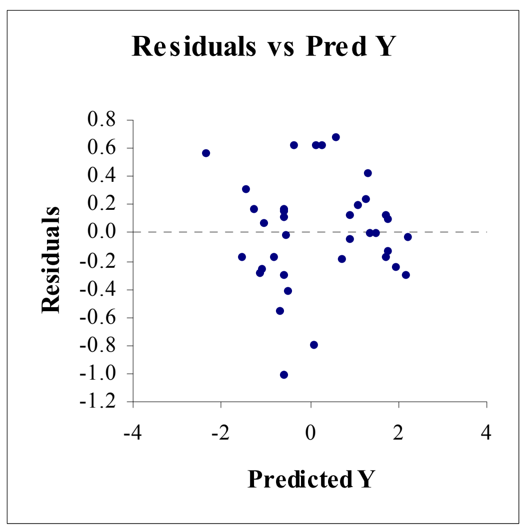
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	53.663	12	4.472	20.028	0.000
Residual	5.136	23	0.223		
Total	58.799	35			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.366	0.097		0.165	0.568	3.761	0.001
X1	2.210	0.380	0.358	1.424	2.996	5.816	0.000
X3	2.534	0.608	0.652	1.276	3.792	4.167	0.000
X5	1.420	0.399	0.219	0.594	2.246	3.556	0.002
X6	1.991	0.367	0.334	1.232	2.750	5.426	0.000
X7	2.564	0.695	0.366	1.127	4.001	3.692	0.001
X8	1.718	0.366	0.289	0.961	2.474	4.694	0.000
X9	1.751	0.789	0.181	0.120	3.383	2.221	0.036
X10	0.949	0.241	0.244	0.450	1.448	3.932	0.001
X13	-2.782	0.895	-0.504	-4.633	-0.931	-3.109	0.005
X14	4.138	0.724	0.822	2.639	5.636	5.712	0.000
X15	-3.419	1.228	-0.647	-5.960	-0.879	-2.784	0.011
X16	2.303	0.888	0.418	0.466	4.140	2.593	0.016





$\Pr\left(\text{Grounding} \middle| \text{Propulsion Failure}, \underline{S}^1\right)$

Summary

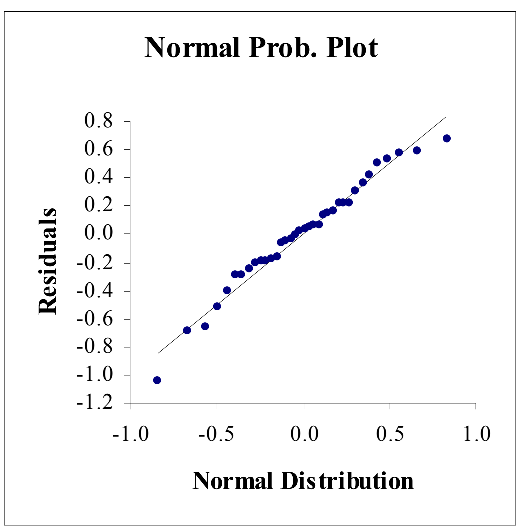
R^2	R	Adj. R^2	S.E. of Estimate
0.916	0.957	0.867	0.481

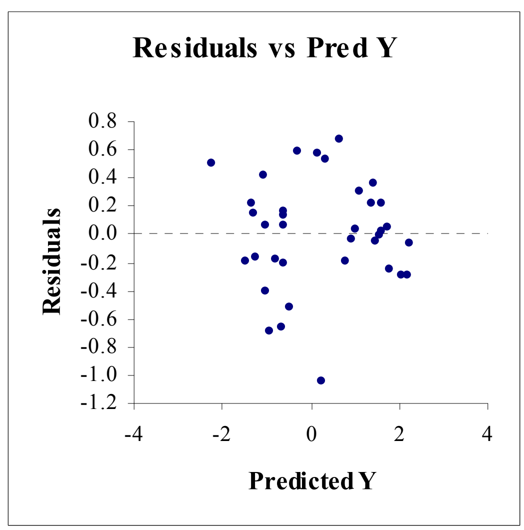
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	55.603	13	4.277	18.475	0.000
Residual	5.093	22	0.232		
Total	60.697	35			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.396	0.101		0.186	0.606	3.909	0.001
X1	2.190	0.387	0.350	1.387	2.992	5.659	0.000
X3	2.330	0.636	0.590	1.010	3.650	3.661	0.001
X4	0.852	0.540	0.216	-0.269	1.972	1.577	0.129
X5	1.440	0.407	0.219	0.597	2.283	3.543	0.002
X6	2.073	0.374	0.343	1.298	2.848	5.548	0.000
X7	2.908	0.715	0.408	1.425	4.390	4.067	0.001
X8	1.720	0.373	0.285	0.947	2.492	4.615	0.000
X9	1.854	0.821	0.188	0.152	3.556	2.259	0.034
X10	1.013	0.246	0.256	0.503	1.523	4.121	0.000
X13	-2.622	0.918	-0.467	-4.525	-0.718	-2.857	0.009
X14	3.001	1.042	0.587	0.839	5.162	2.879	0.009
X15	-2.743	1.303	-0.511	-5.446	-0.040	-2.105	0.047
X16	1.772	0.936	0.317	-0.169	3.713	1.893	0.072





$\Pr\left(\text{Grounding} \middle| \text{Communication/Navigation Equipment Failure}, \underline{S}^1\right)$

Summary

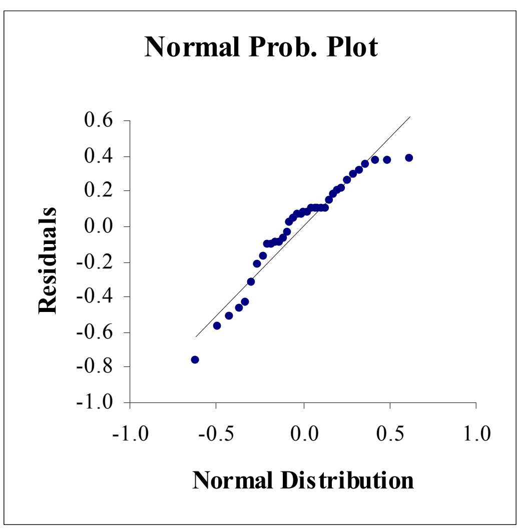
R^2	R	Adj. R^2	S.E. of Estimate
0.929	0.964	0.887	0.358

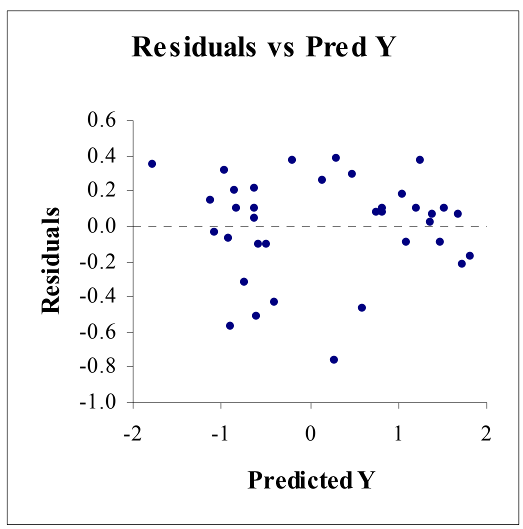
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	36.633	13	2.818	22.046	0.000
Residual	2.812	22	0.128		
Total	39.445	35			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.314	0.075		0.158	0.470	4.168	0.000
X1	1.625	0.288	0.322	1.028	2.221	5.651	0.000
X3	1.503	0.473	0.472	0.523	2.484	3.179	0.004
X4	0.836	0.401	0.262	0.003	1.668	2.082	0.049
X5	1.094	0.302	0.206	0.468	1.721	3.622	0.002
X6	1.759	0.278	0.361	1.183	2.334	6.334	0.000
X7	2.194	0.531	0.382	1.092	3.296	4.130	0.000
X8	1.431	0.277	0.294	0.857	2.005	5.170	0.000
X9	1.503	0.610	0.189	0.238	2.767	2.464	0.022
X10	0.939	0.183	0.295	0.560	1.317	5.138	0.000
X13	-1.707	0.682	-0.377	-3.122	-0.293	-2.503	0.020
X14	2.081	0.774	0.505	0.475	3.687	2.687	0.013
X15	-1.684	0.968	-0.389	-3.692	0.325	-1.738	0.096
X16	1.235	0.696	0.274	-0.208	2.677	1.775	0.090





$\Pr\left(\text{Ramming} \middle| \text{Human Error}, \underline{S}^{1}\right)$

Summary

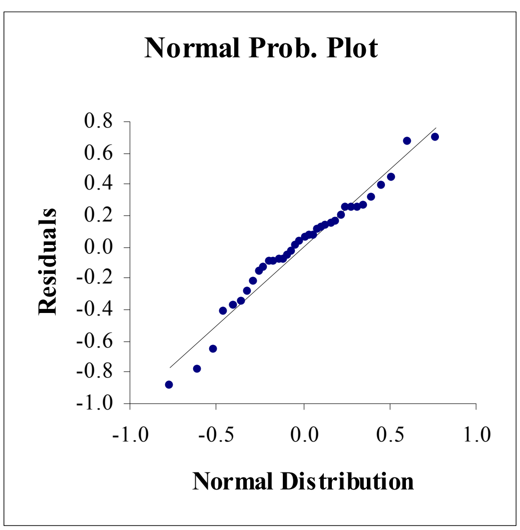
R^2	R	Adj. R^2	S.E. of Estimate
0.923	0.961	0.877	0.440

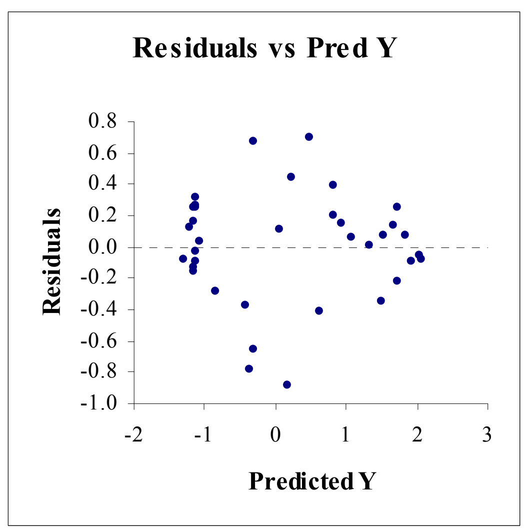
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	50.787	13	3.907	20.173	0.000
Residual	4.260	22	0.194		
Total	55.047	35			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.278	0.096		0.079	0.478	2.890	0.009
X1	1.853	0.354	0.311	1.119	2.587	5.236	0.000
X3	2.180	0.661	0.580	0.810	3.551	3.299	0.003
X4	1.440	0.225	0.383	0.973	1.907	6.395	0.000
X6	1.518	0.619	0.264	0.235	2.801	2.453	0.023
X7	3.496	0.842	0.515	1.749	5.242	4.150	0.000
X8	1.165	0.641	0.203	-0.166	2.495	1.816	0.083
X10	1.391	0.225	0.370	0.924	1.858	6.176	0.000
X15	-3.766	1.528	-0.736	-6.934	-0.597	-2.464	0.022
X16	3.037	1.126	0.570	0.702	5.372	2.697	0.013
X17	5.829	1.521	0.959	2.675	8.984	3.833	0.001
X18	-4.522	1.587	-0.728	-7.812	-1.231	-2.850	0.009
X20	-5.118	1.606	-0.844	-8.448	-1.788	-3.188	0.004
X22	5.990	1.526	0.854	2.826	9.154	3.926	0.001





$\Pr\left(\text{Ramming} \middle| \text{Steering Failure}, \underline{S}^1\right)$

Summary

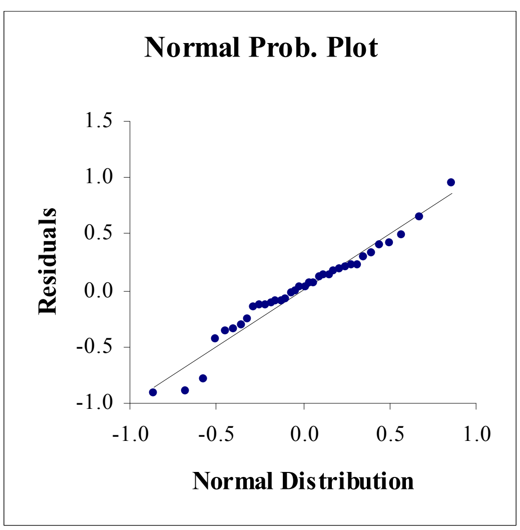
R^2	R	Adj. R^2	S.E. of Estimate
0.919	0.959	0.871	0.492

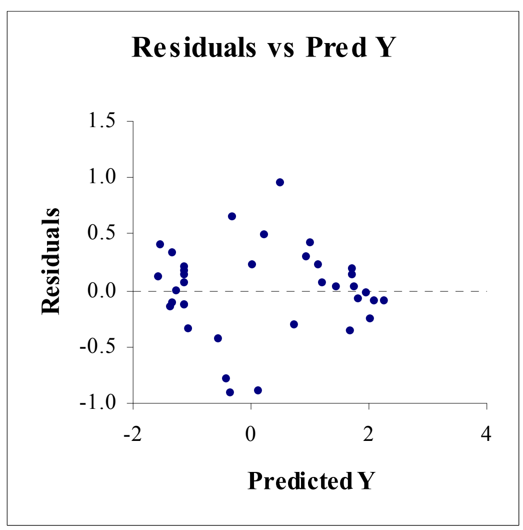
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	60.463	13	4.651	19.222	0.000
Residual	5.323	22	0.242		
Total	65.786	35			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.302	0.108		0.079	0.526	2.806	0.010
X1	1.974	0.396	0.303	1.154	2.794	4.990	0.000
X3	2.833	0.739	0.689	1.301	4.365	3.834	0.001
X4	1.414	0.252	0.344	0.891	1.936	5.614	0.000
X6	1.795	0.692	0.285	0.360	3.229	2.594	0.017
X7	4.434	0.942	0.598	2.481	6.387	4.709	0.000
X8	1.445	0.717	0.230	-0.042	2.932	2.015	0.056
X10	1.436	0.252	0.349	0.913	1.958	5.702	0.000
X15	-4.734	1.708	-0.846	-8.276	-1.191	-2.771	0.011
X16	3.637	1.258	0.624	1.027	6.247	2.890	0.009
X17	7.243	1.700	1.089	3.717	10.769	4.260	0.000
X18	-5.810	1.774	-0.856	-9.488	-2.132	-3.276	0.003
X20	-6.829	1.795	-1.030	-10.551	-3.107	-3.805	0.001
X22	7.282	1.705	0.950	3.746	10.819	4.270	0.000





$\Pr\left(\text{Ramming} \middle| \text{Propulsion Failure}, \underline{S}^{1}\right)$

Summary

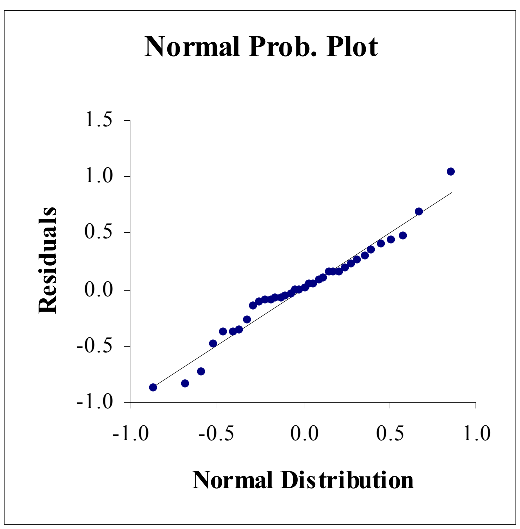
R^2	R	Adj. R^2	S.E. of Estimate
0.921	0.960	0.874	0.495

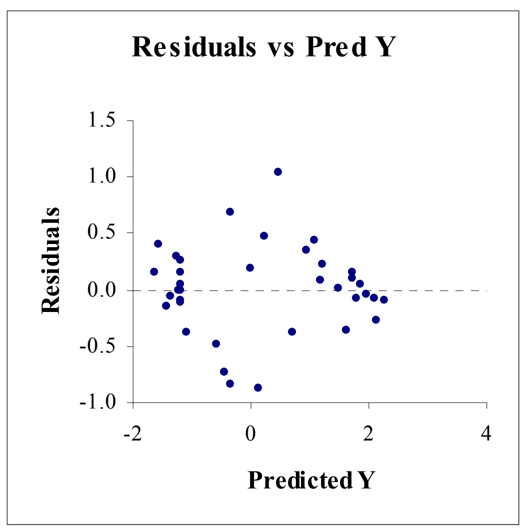
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	62.698	13	4.823	19.662	0.000
Residual	5.396	22	0.245		
Total	68.094	35			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.269	0.108		0.044	0.493	2.476	0.021
X1	2.010	0.398	0.303	1.184	2.836	5.048	0.000
X3	2.767	0.744	0.661	1.224	4.310	3.720	0.001
X4	1.462	0.253	0.349	0.936	1.988	5.768	0.000
X6	1.698	0.696	0.265	0.254	3.142	2.438	0.023
X7	4.468	0.948	0.592	2.502	6.434	4.713	0.000
X8	1.321	0.722	0.207	-0.176	2.818	1.829	0.081
X10	1.458	0.253	0.349	0.933	1.984	5.753	0.000
X15	-4.483	1.720	-0.788	-8.050	-0.917	-2.607	0.016
X16	3.593	1.267	0.606	0.966	6.221	2.836	0.010
X17	7.255	1.712	1.073	3.705	10.805	4.238	0.000
X18	-5.759	1.786	-0.834	-9.462	-2.056	-3.225	0.004
X20	-6.705	1.807	-0.994	-10.452	-2.958	-3.711	0.001
X22	7.269	1.717	0.932	3.708	10.830	4.233	0.000





$\Pr\left(\text{Ramming} \middle| \text{Communication/Navigation Equipment Failure}, \underline{S}^{1}\right)$

Summary

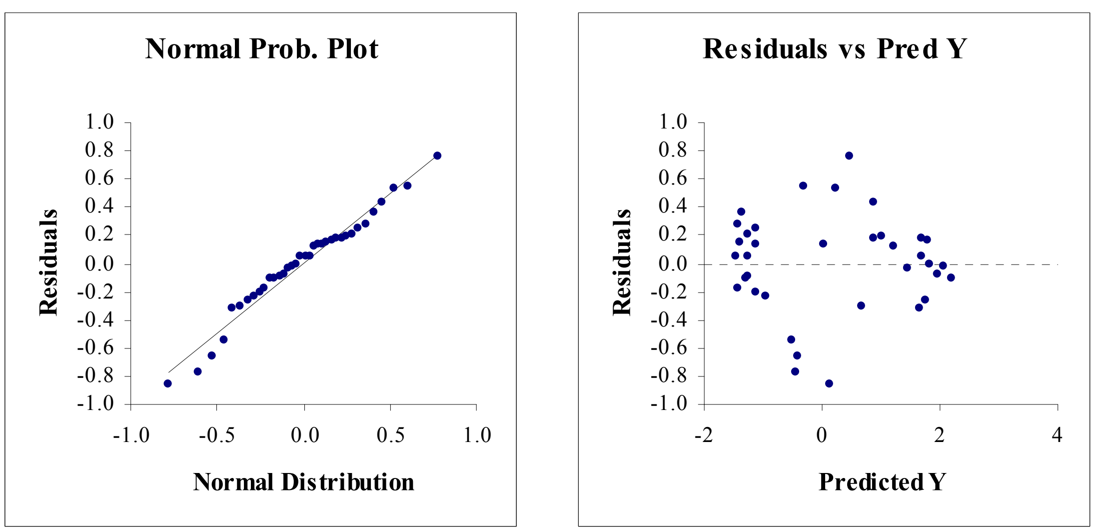
R^2	R	Adj. R^2	S.E. of Estimate
0.931	0.965	0.891	0.445

ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	59.077	13	4.544	22.934	0.000
Residual	4.359	22	0.198		
Total	63.436	35			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.280	0.097		0.077	0.482	2.868	0.009
X1	1.847	0.358	0.288	1.105	2.590	5.160	0.000
X3	2.567	0.669	0.636	1.181	3.954	3.840	0.001
X4	1.405	0.228	0.348	0.932	1.877	6.166	0.000
X6	2.077	0.626	0.336	0.779	3.375	3.319	0.003
X7	3.971	0.852	0.545	2.204	5.738	4.660	0.000
X8	1.547	0.649	0.251	0.201	2.893	2.384	0.026
X10	1.532	0.228	0.379	1.059	2.004	6.722	0.000
X15	-4.353	1.546	-0.793	-7.559	-1.148	-2.817	0.010
X16	3.282	1.139	0.574	0.920	5.643	2.882	0.009
X17	6.639	1.539	1.017	3.448	9.829	4.315	0.000
X18	-5.197	1.605	-0.779	-8.525	-1.868	-3.238	0.004
X20	-6.338	1.624	-0.974	-9.706	-2.970	-3.903	0.001
X22	6.855	1.543	0.911	3.655	10.056	4.442	0.000



$\Pr\left(\text{Fire/Explosion} \middle| \text{Human Error}, \underline{S}^1\right)$

Summary

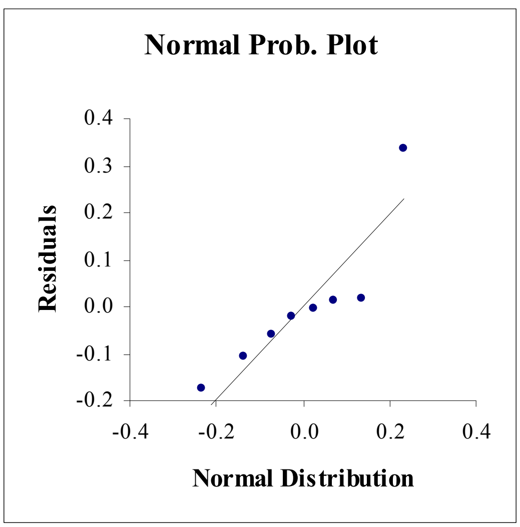
R^2	R	Adj. R^2	S.E. of Estimate
0.963	0.981	0.948	0.179

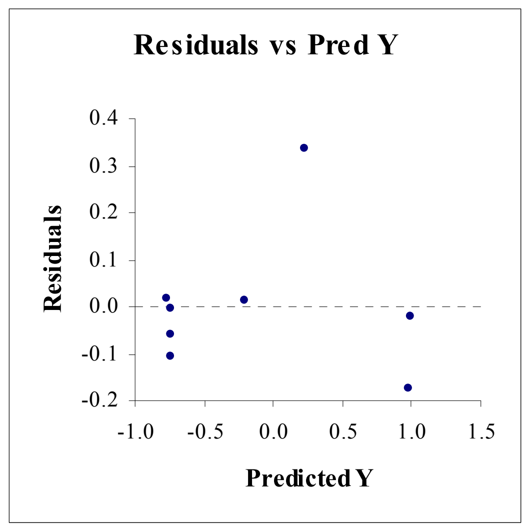
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	4.171	2	2.085	65.186	0.000
Residual	0.160	5	0.032		
Total	4.331	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.116	0.068		-0.058	0.290	1.710	0.148
X1	1.043	0.144	0.623	0.673	1.413	7.243	0.001
X10	0.859	0.096	0.772	0.613	1.105	8.980	0.000





$\Pr\left(\text{Fire/Explosion} \middle| \text{Mechanical/Electrical Failure}, \underline{S}^1\right)$

Summary

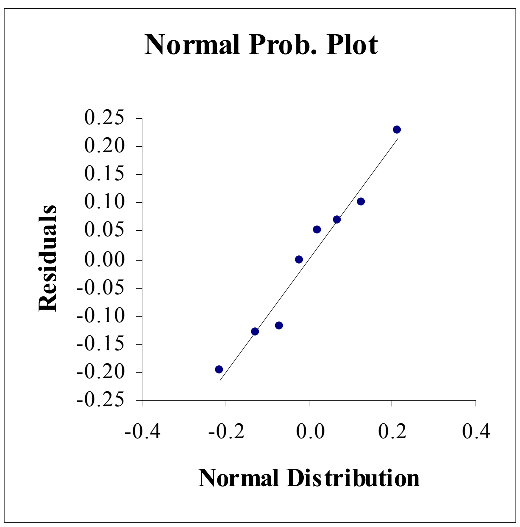
R^2	R	Adj. R^2	S.E. of Estimate
0.971	0.985	0.959	0.166

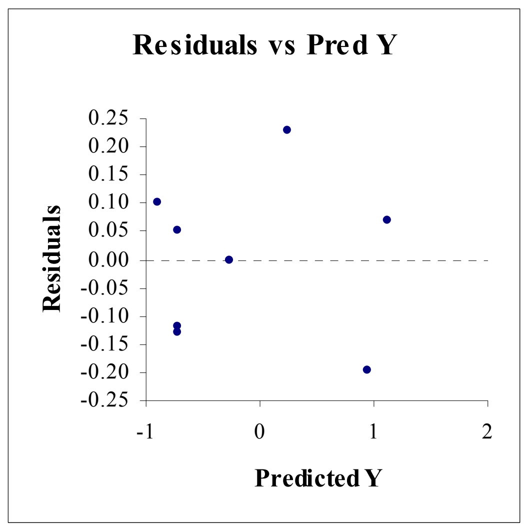
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	4.547	2	2.274	82.313	0.000
Residual	0.138	5	0.028		
Total	4.685	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.113	0.063		-0.048	0.275	1.801	0.132
X1	1.191	0.134	0.683	0.847	1.535	8.898	0.000
X10	0.838	0.089	0.724	0.610	1.067	9.432	0.000





APPENDIX C: Regression Results of the Human Error Probability Questionnaire

Summary

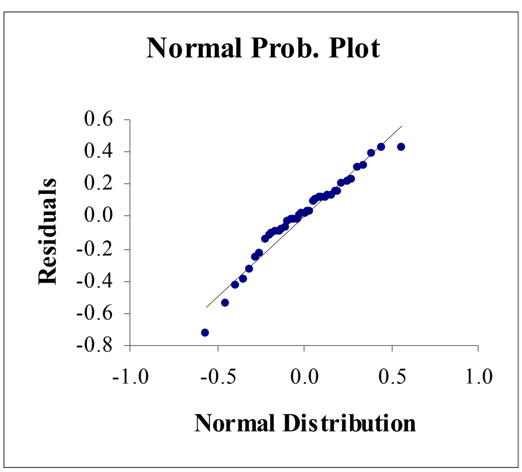
R^2	R	Adj. R^2	S.E. of Estimate
0.756	0.870	0.634	0.308

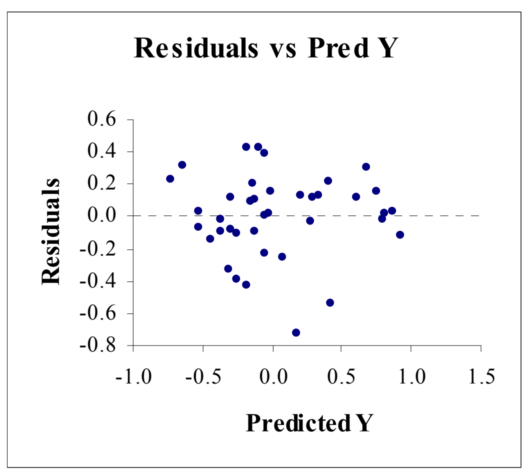
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	7.634	13	0.587	6.207	0.000
Residual	2.460	26	0.095		
Total	10.094	39			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	-0.045	0.061		-0.171	0.081	-0.733	0.470
X2	0.292	0.244	0.116	-0.211	0.794	1.194	0.243
X3	0.595	0.415	0.370	-0.257	1.448	1.435	0.163
X6	0.462	0.418	0.187	-0.398	1.322	1.105	0.279
X7	0.657	0.403	0.287	-0.171	1.484	1.630	0.115
X10	0.324	0.173	0.201	-0.031	0.678	1.875	0.072
X12	0.375	0.328	0.138	-0.300	1.051	1.143	0.263
X15	-2.411	0.927	-1.174	-4.317	-0.505	-2.600	0.015
X16	2.545	0.704	1.160	1.097	3.993	3.613	0.001
X17	3.291	0.958	1.265	1.321	5.260	3.434	0.002
X18	-2.305	0.983	-0.915	-4.324	-0.285	-2.346	0.027
X20	-2.617	1.002	-1.009	-4.676	-0.557	-2.612	0.015
X22	3.179	0.944	1.172	1.238	5.120	3.367	0.002
X23	0.650	0.249	0.282	0.139	1.161	2.616	0.015





APPENDIX D: Regression Results For Consequence Questionnaires

$\Pr\left(\text{Human Casualty}\left(\text{Low Impact}\right)\middle|\text{Collision}, \underline{S}^2\right)$

Summary

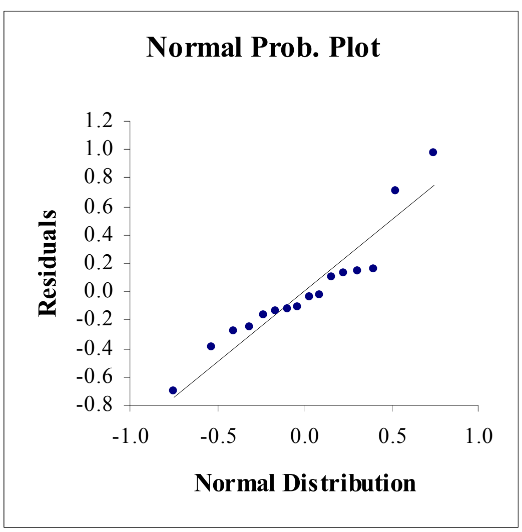
R^2	R	Adj. R^2	S.E. of Estimate
0.751	0.867	0.661	0.466

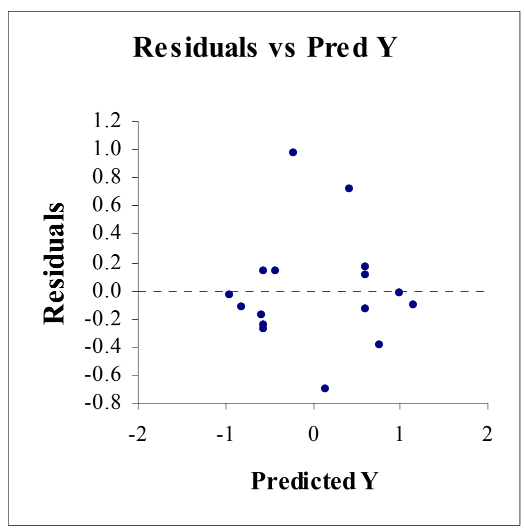
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	7.200	4	1.800	8.305	0.002
Residual	2.384	11	0.217		
Total	9.584	15			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.098	0.125		-0.178	0.373	0.782	0.451
W1	1.848	0.531	0.524	0.680	3.015	3.482	0.005
W2	1.595	0.548	0.438	0.389	2.802	2.910	0.014
W3	0.657	0.241	0.411	0.126	1.187	2.724	0.020
W4	0.509	0.241	0.319	-0.021	1.040	2.114	0.058





$$\Pr\left(\text{Human Casualty}\left(\text{Medium Impact}\right)\middle|\text{Collision}, \underline{S}^2\right)$$

Summary

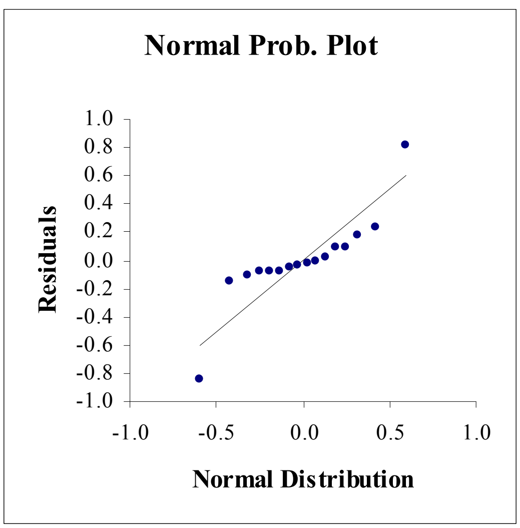
R^2	R	Adj. R^2	S.E. of Estimate
0.837	0.915	0.778	0.374

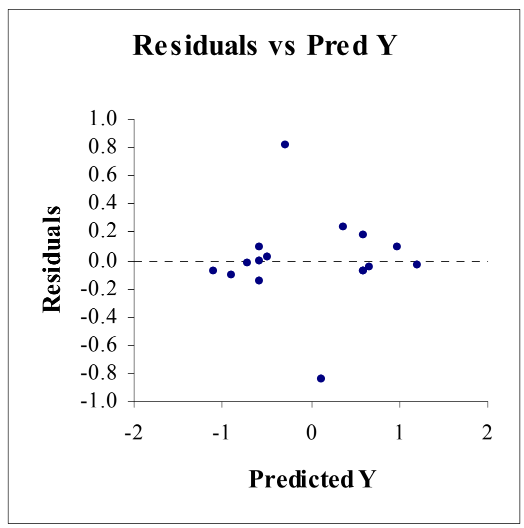
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	7.885	4	1.971	14.129	0.000
Residual	1.535	11	0.140		
Total	9.420	15			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.053	0.100		-0.167	0.274	0.533	0.605
W1	2.044	0.426	0.585	1.107	2.981	4.801	0.001
W2	1.653	0.440	0.457	0.684	2.621	3.757	0.003
W3	0.623	0.193	0.393	0.197	1.049	3.222	0.008
W4	0.539	0.193	0.340	0.113	0.964	2.785	0.018





$\Pr\left(\text{Human Casualty}\left(\text{Low Impact}\right)\middle|\text{Ramming}, \underline{S}^2\right)$

Summary

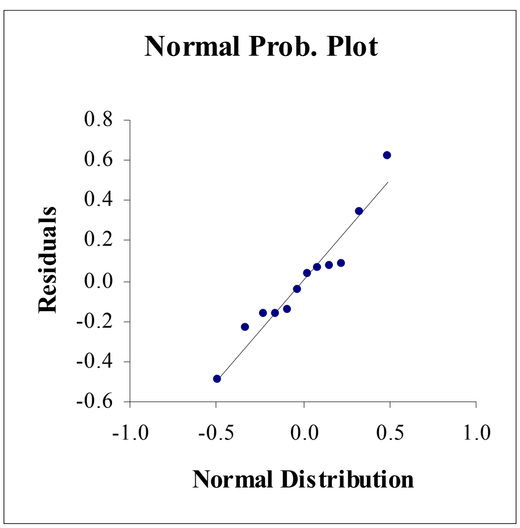
R^2	R	Adj. R^2	S.E. of Estimate
0.767	0.876	0.679	0.333

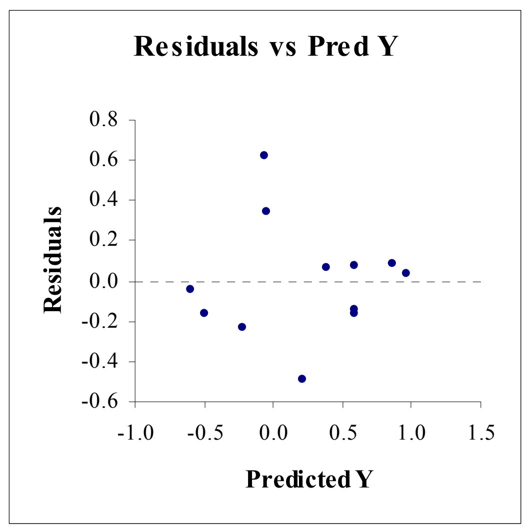
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	2.913	3	0.971	8.754	0.007
Residual	0.887	8	0.111		
Total	3.801	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.181	0.101		-0.051	0.414	1.804	0.109
W1	1.198	0.404	0.507	0.267	2.129	2.967	0.018
W3	0.404	0.174	0.397	0.003	0.805	2.323	0.049
W5	0.867	0.253	0.587	0.285	1.450	3.433	0.009





$\Pr\left(\text{Human Casualty}\left(\text{Medium Impact}\right)\middle|\text{Ramming}, \underline{S}^2\right)$

Summary

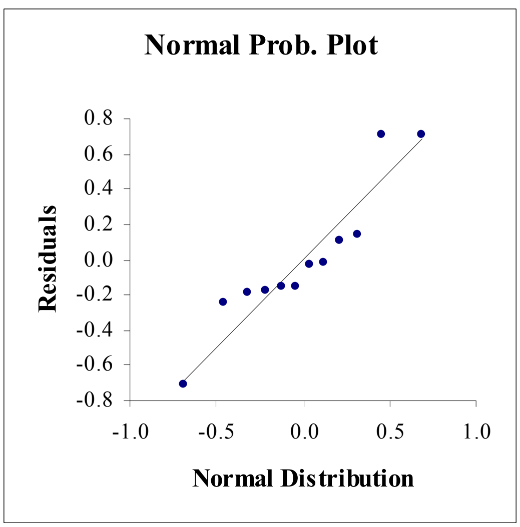
R^2	R	Adj. R^2	S.E. of Estimate
0.683	0.827	0.564	0.464

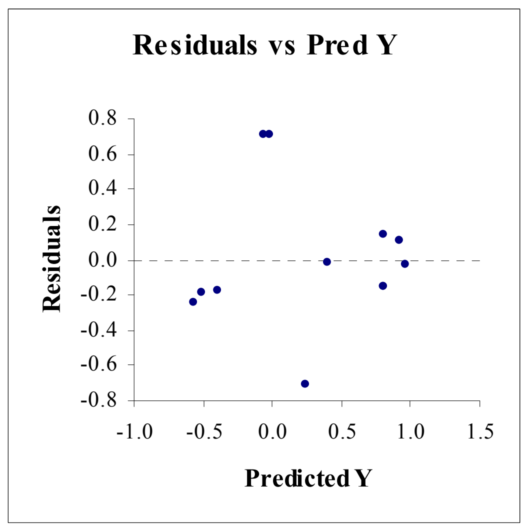
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	3.716	3	1.239	5.750	0.021
Residual	1.723	8	0.215		
Total	5.439	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.203	0.140		-0.120	0.526	1.448	0.186
W1	1.262	0.563	0.447	-0.035	2.560	2.243	0.055
W3	0.602	0.242	0.495	0.043	1.161	2.485	0.038
W5	0.849	0.352	0.480	0.038	1.661	2.413	0.042





$\Pr\left(\text{Human Casualty}\left(\text{Low Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

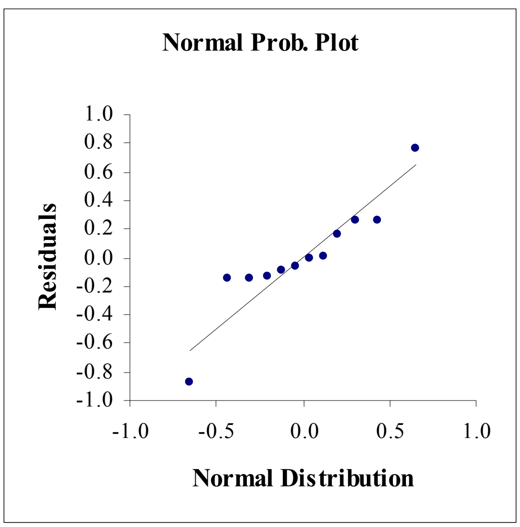
R^2	R	Adj. R^2	S.E. of Estimate
0.818	0.904	0.749	0.444

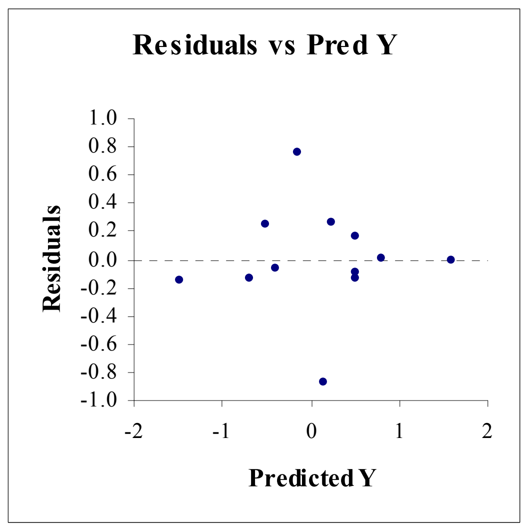
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	7.081	3	2.360	11.949	0.003
Residual	1.580	8	0.198		
Total	8.661	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.056	0.134		-0.254	0.365	0.415	0.689
W1	2.731	0.539	0.765	1.488	3.973	5.067	0.001
W3	0.452	0.232	0.294	-0.083	0.988	1.948	0.087
W5	0.826	0.337	0.370	0.048	1.603	2.449	0.040





$\Pr\left(\text{Human Casualty}\left(\text{Medium Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

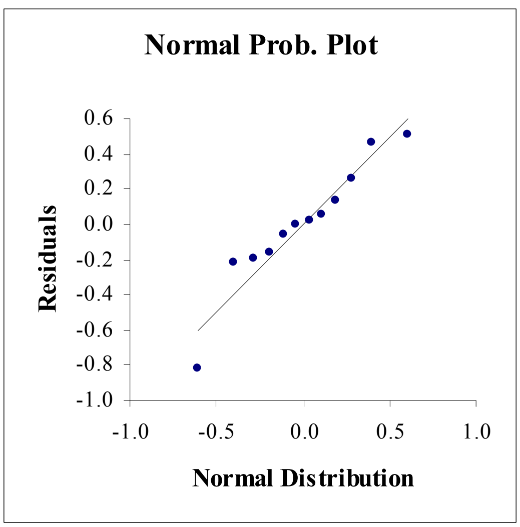
R^2	R	Adj. R^2	S.E. of Estimate
0.842	0.918	0.783	0.410

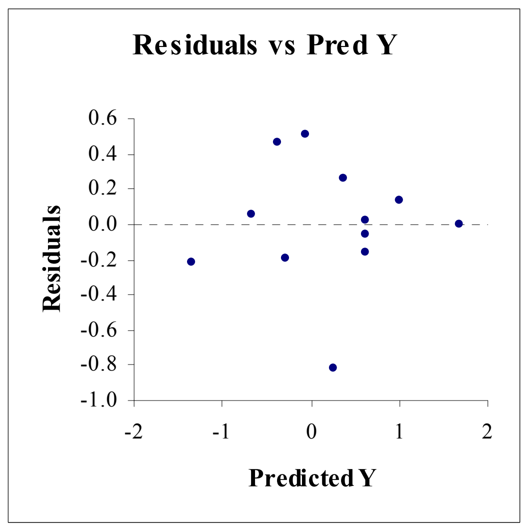
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	7.162	3	2.387	14.196	0.001
Residual	1.345	8	0.168		
Total	8.507	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.171	0.124		-0.114	0.457	1.383	0.204
W1	2.678	0.497	0.758	1.532	3.825	5.387	0.001
W3	0.444	0.214	0.291	-0.050	0.938	2.072	0.072
W5	0.925	0.311	0.418	0.208	1.642	2.974	0.018





$\Pr\left(\text{Human Casualty}\left(\text{High Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

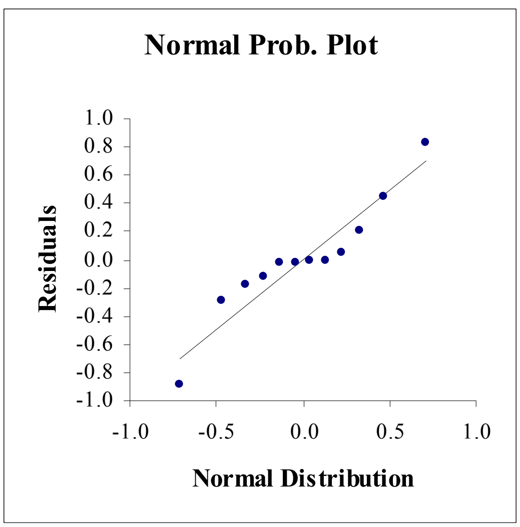
R^2	R	Adj. R^2	S.E. of Estimate
0.849	0.921	0.792	0.479

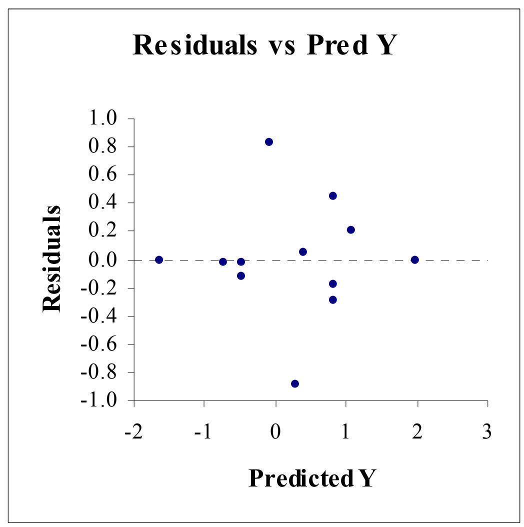
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	10.319	3	3.440	14.976	0.001
Residual	1.837	8	0.230		
Total	12.156	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.177	0.145		-0.157	0.511	1.225	0.256
W1	3.200	0.581	0.757	1.861	4.540	5.508	0.001
W3	0.639	0.250	0.351	0.062	1.216	2.552	0.034
W5	0.998	0.363	0.377	0.160	1.836	2.745	0.025





$\Pr\left(\text{Human Casualty}\left(\text{Low Impact}\right)\middle|\text{Grounding}, \underline{S}^2\right)$

Summary

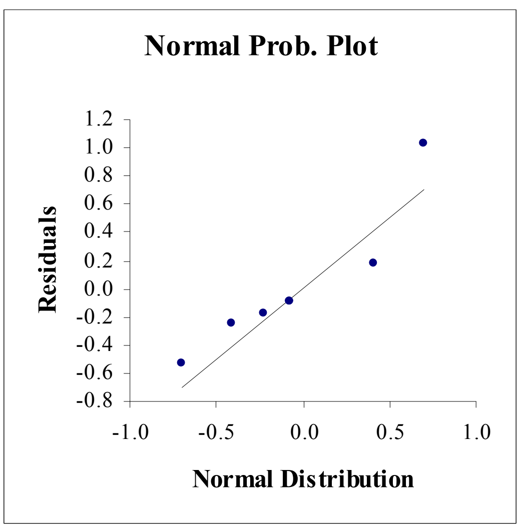
R^2	R	Adj. R^2	S.E. of Estimate
0.634	0.796	0.488	0.542

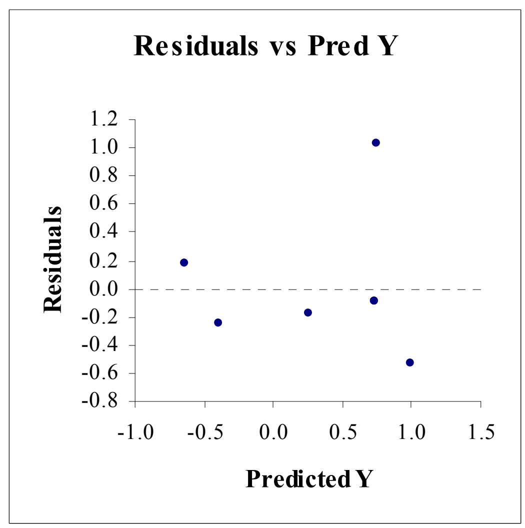
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	2.549	2	1.274	4.335	0.081
Residual	1.470	5	0.294		
Total	4.019	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.174	0.209		-0.362	0.711	0.835	0.442
W1	2.452	1.051	0.633	-0.250	5.154	2.333	0.067
W3	0.567	0.291	0.529	-0.180	1.314	1.952	0.108





Summary

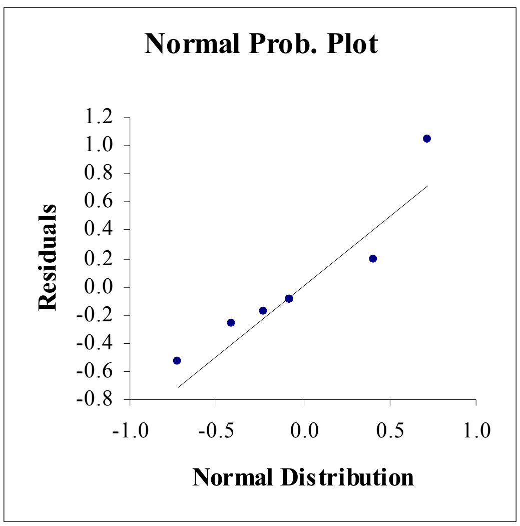
R^2	R	Adj. R^2	S.E. of Estimate
0.670	0.818	0.537	0.555

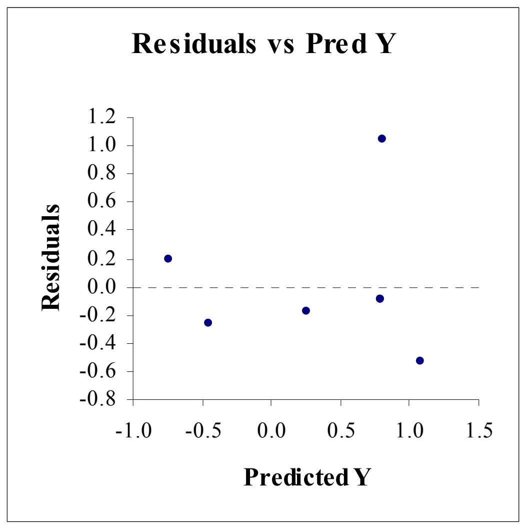
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	3.121	2	1.560	5.067	0.063
Residual	1.540	5	0.308		
Total	4.661	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.173	0.214		-0.376	0.722	0.810	0.455
W1	2.736	1.076	0.655	-0.029	5.501	2.543	0.052
W3	0.620	0.297	0.537	-0.145	1.384	2.084	0.092





$\Pr\left(\text{Environmental Damage}\left(\text{Low Impact}\right)\middle|\text{Collision}, \underline{S}^2\right)$

Summary

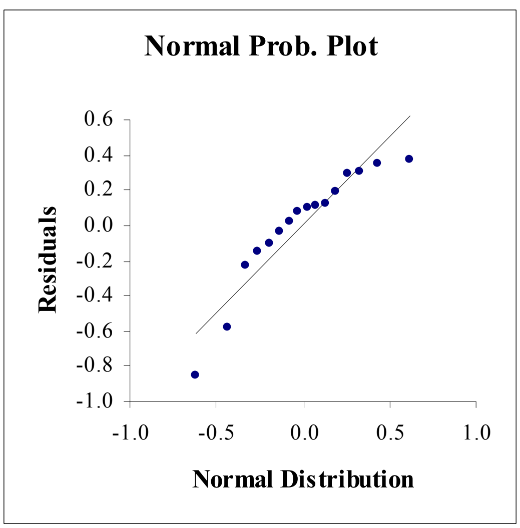
R^2	R	Adj. R^2	S.E. of Estimate
0.928	0.963	0.902	0.388

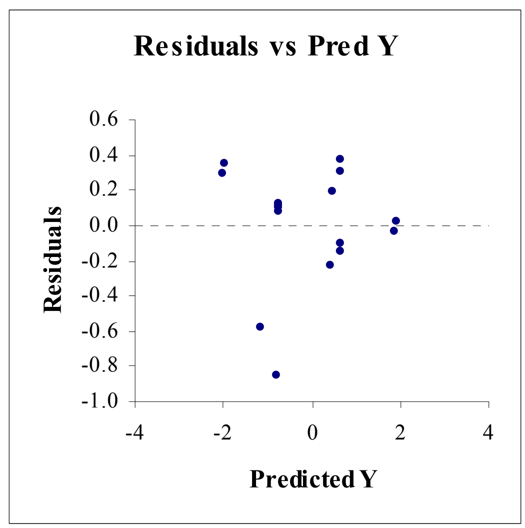
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	21.286	4	5.321	35.437	0.000
Residual	1.652	11	0.150		
Total	22.938	15			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	-0.038	0.104		-0.266	0.191	-0.363	0.724
W1	2.448	0.330	0.601	1.722	3.174	7.422	0.000
W2	2.492	0.320	0.630	1.788	3.196	7.789	0.000
W3	0.712	0.201	0.288	0.270	1.153	3.548	0.005
W4	0.689	0.201	0.278	0.247	1.130	3.433	0.006





$\Pr\left(\text{Environmental Damage}\left(\text{Medium Impact}\right)\middle|\text{Collision}, \underline{S}^2\right)$

Summary

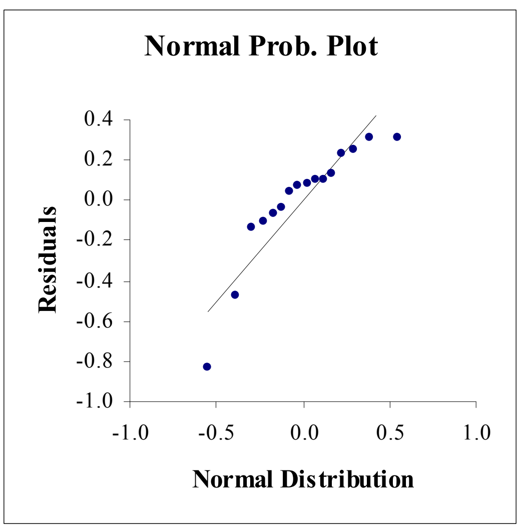
R^2	R	Adj. R^2	S.E. of Estimate
0.956	0.978	0.940	0.345

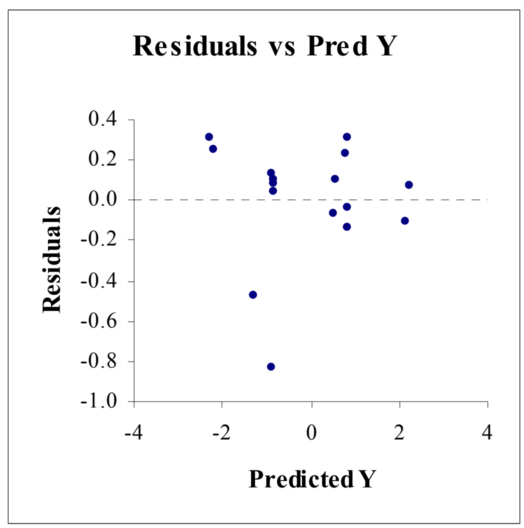
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	28.375	4	7.094	59.436	0.000
Residual	1.313	11	0.119		
Total	29.688	15			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	-0.026	0.092		-0.229	0.178	-0.279	0.785
W1	2.754	0.294	0.594	2.106	3.401	9.365	0.000
W2	2.874	0.285	0.639	2.247	3.502	10.078	0.000
W3	0.825	0.179	0.293	0.432	1.219	4.615	0.001
W4	0.876	0.179	0.311	0.482	1.269	4.896	0.000





$\Pr\left(\text{Environmental Damage}\left(\text{Low Impact}\right)\middle|\text{Grounding}, \underline{S}^2\right)$

Summary

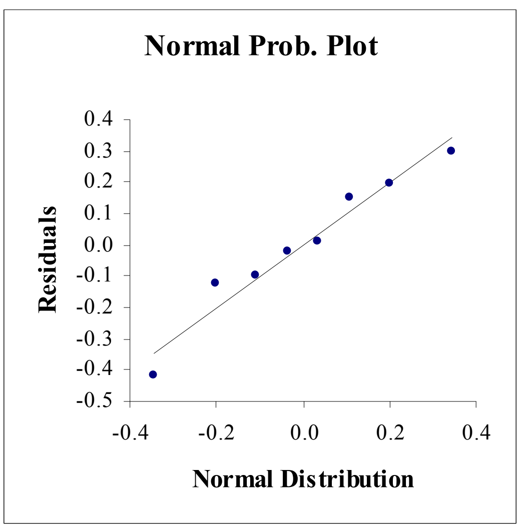
R^2	R	Adj. R^2	S.E. of Estimate
0.961	0.980	0.945	0.266

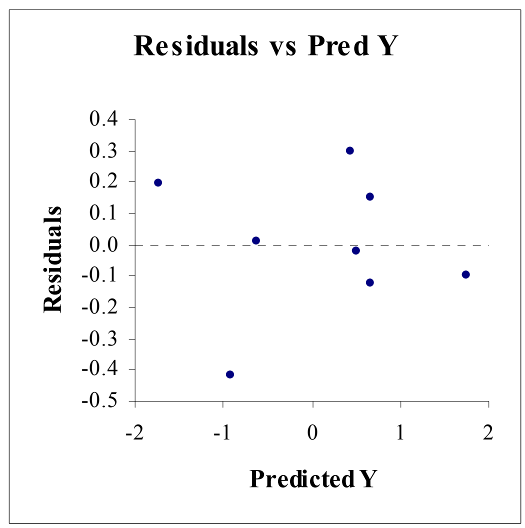
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	8.633	2	4.316	61.086	0.000
Residual	0.353	5	0.071		
Total	8.986	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.012	0.100		-0.244	0.269	0.123	0.907
W1	2.223	0.221	0.893	1.655	2.790	10.062	0.000
W3	0.645	0.149	0.385	0.263	1.027	4.337	0.007





$\Pr\left(\text{Environmental Damage}\left(\text{Medium Impact}\right)\middle|\text{Grounding}, \underline{S}^2\right)$

Summary

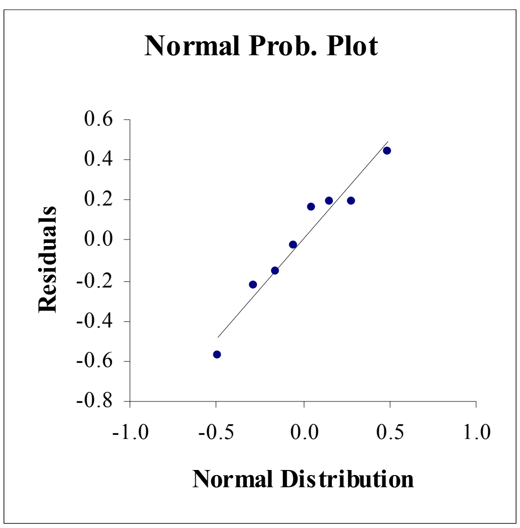
R^2	R	Adj. R^2	S.E. of Estimate
0.951	0.975	0.931	0.376

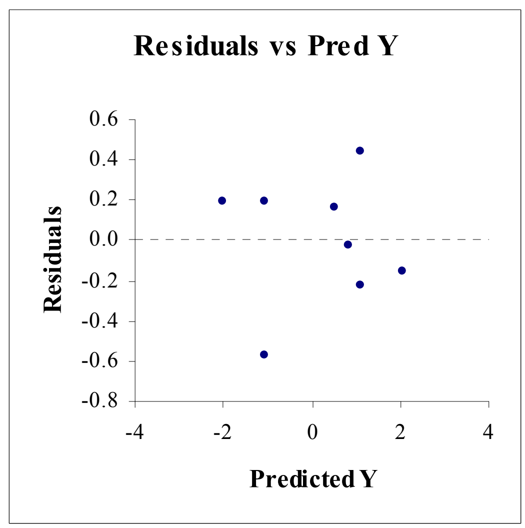
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	13.679	2	6.840	48.495	0.001
Residual	0.705	5	0.141		
Total	14.384	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.012	0.141		-0.350	0.375	0.088	0.933
W1	2.574	0.312	0.817	1.772	3.377	8.250	0.000
W3	1.089	0.210	0.513	0.549	1.629	5.184	0.004





$\Pr\left(\text{Environmental Damage}\left(\text{Low Impact}\right)\middle|\text{Ramming}, \underline{S}^2\right)$

Summary

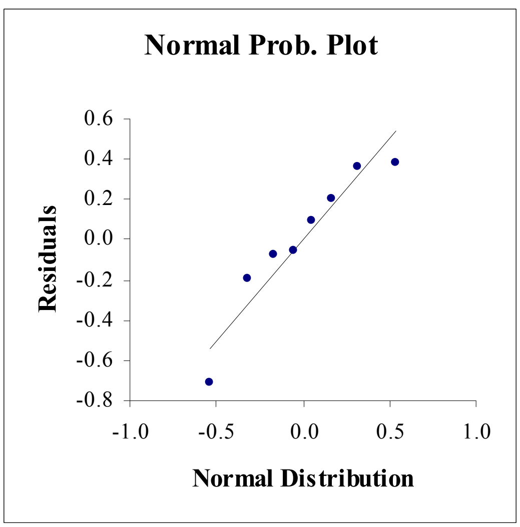
R^2	R	Adj. R^2	S.E. of Estimate
0.927	0.963	0.898	0.419

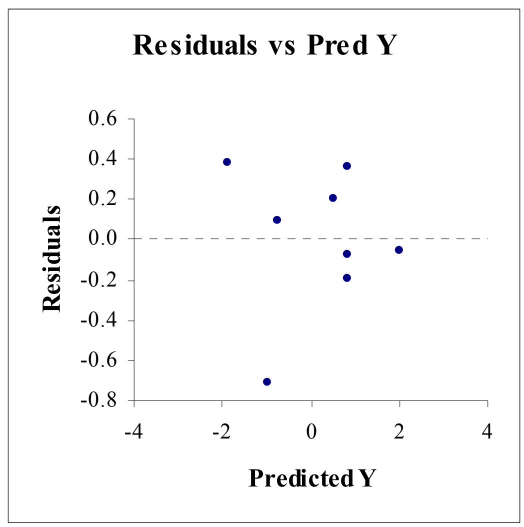
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	11.212	2	5.606	31.926	0.001
Residual	0.878	5	0.176		
Total	12.090	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.058	0.159		-0.350	0.466	0.365	0.730
W1	2.462	0.348	0.853	1.567	3.358	7.072	0.001
W3	0.793	0.224	0.427	0.217	1.369	3.540	0.017





$\Pr\left(\text{Environmental Damage}\left(\text{Medium Impact}\right)\middle|\text{Ramming}, \underline{S}^2\right)$

Summary

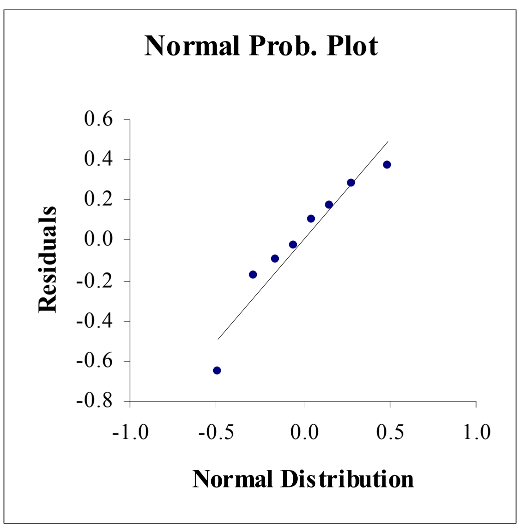
R^2	R	Adj. R^2	S.E. of Estimate
0.955	0.977	0.936	0.378

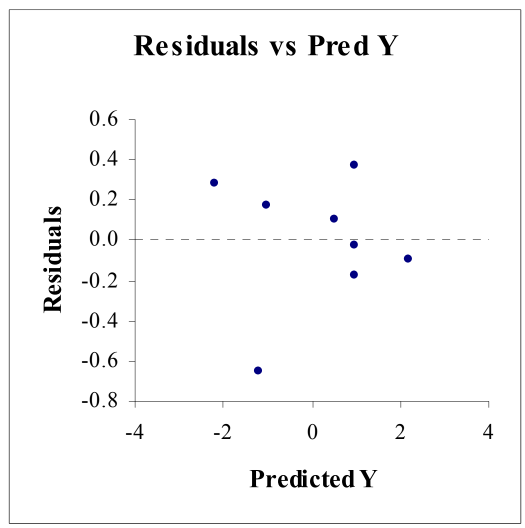
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	15.018	2	7.509	52.496	0.000
Residual	0.715	5	0.143		
Total	15.733	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	-0.022	0.143		-0.391	0.346	-0.156	0.882
W1	2.783	0.314	0.845	1.975	3.591	8.856	0.000
W3	0.996	0.202	0.470	0.477	1.516	4.927	0.004





$\Pr\left(\text{Environmental Damage}\left(\text{Low Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

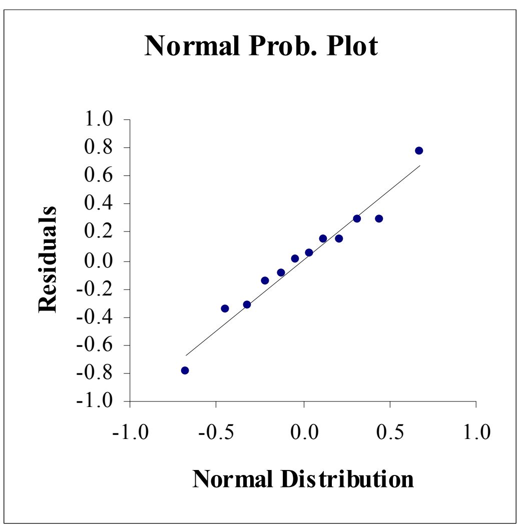
R^2	R	Adj. R^2	S.E. of Estimate
0.883	0.939	0.856	0.432

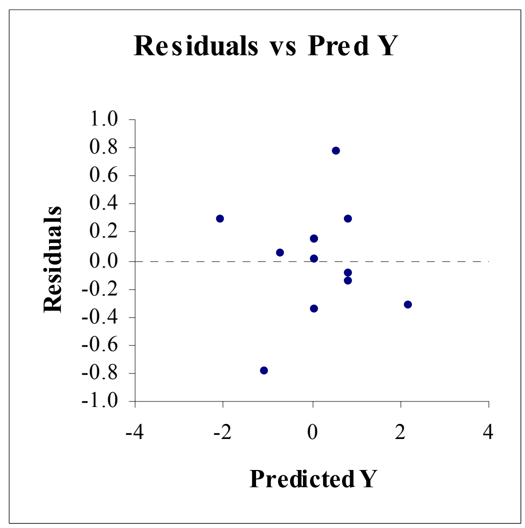
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	12.634	2	6.317	33.812	0.000
Residual	1.681	9	0.187		
Total	14.316	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.070	0.131		-0.226	0.365	0.534	0.606
W1	2.675	0.359	0.852	1.863	3.487	7.454	0.000
W3	0.756	0.226	0.383	0.246	1.267	3.350	0.009





$\Pr\left(\text{Environmental Damage}\left(\text{Medium Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

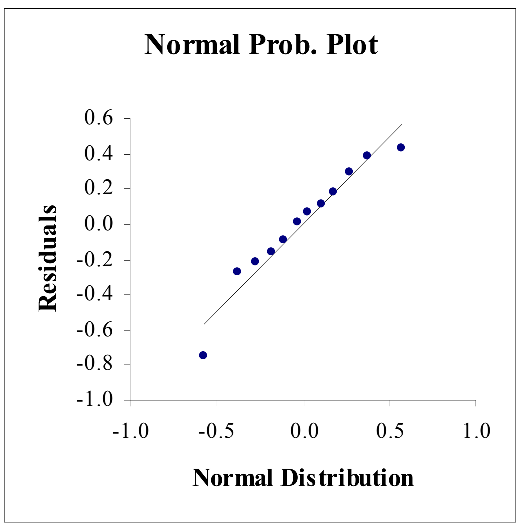
R^2	R	Adj. R^2	S.E. of Estimate
0.927	0.963	0.911	0.364

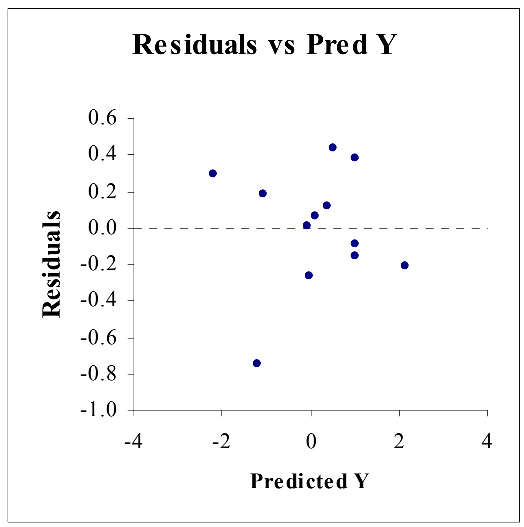
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	15.174	2	7.587	57.375	0.000
Residual	1.190	9	0.132		
Total	16.364	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	-0.023	0.112		-0.277	0.231	-0.206	0.842
W1	2.750	0.302	0.819	2.067	3.433	9.108	0.000
W9	1.430	0.262	0.490	0.837	2.023	5.454	0.000





$\Pr\left(\text{Environmental Damage}\left(\text{High Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

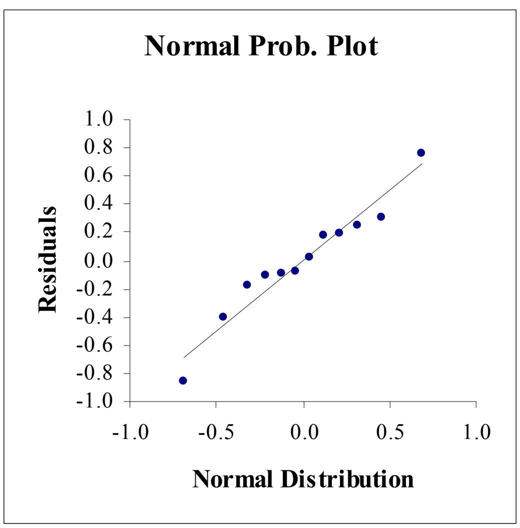
R^2	R	Adj. R^2	S.E. of Estimate
0.928	0.963	0.900	0.465

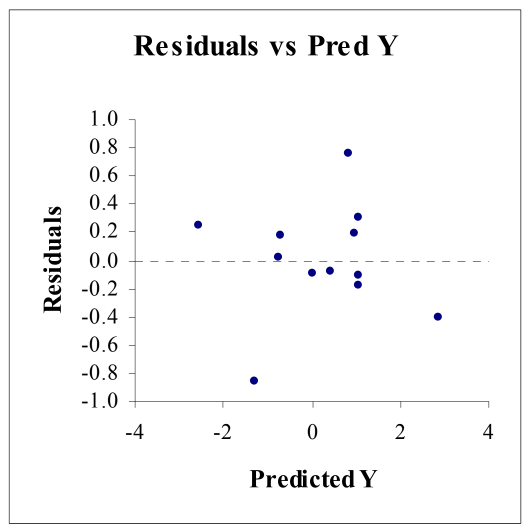
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	22.143	3	7.381	34.147	0.000
Residual	1.729	8	0.216		
Total	23.873	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.152	0.141		-0.172	0.476	1.085	0.310
W1	3.463	0.386	0.854	2.573	4.353	8.973	0.000
W3	0.909	0.243	0.356	0.349	1.469	3.745	0.006
W5	3.049	1.162	0.250	0.371	5.728	2.625	0.030





$\Pr\left(\text{Environmental Damage}\left(\text{Low Impact}\right)\middle|\text{Sinking}, \underline{S}^2\right)$

Summary

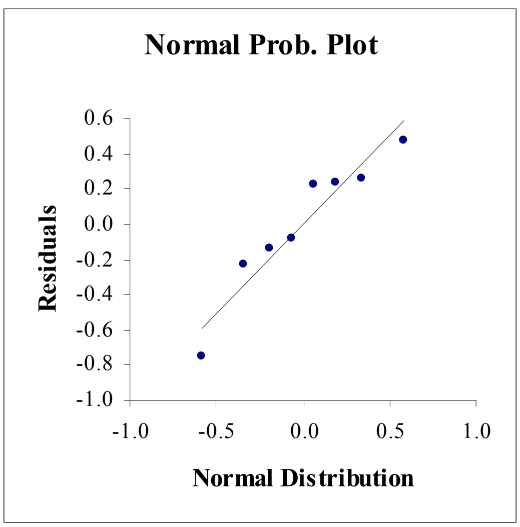
R^2	R	Adj. R^2	S.E. of Estimate
0.933	0.966	0.906	0.454

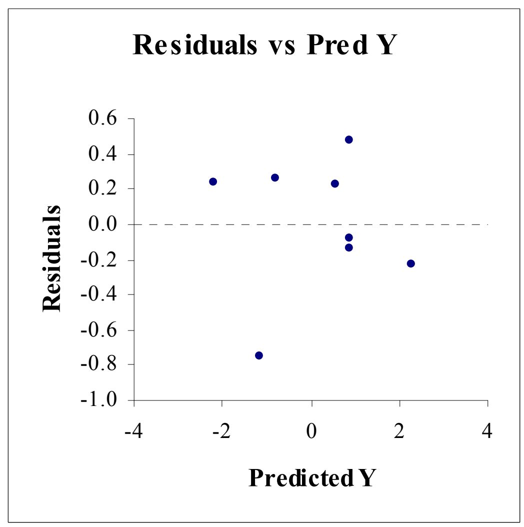
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	14.290	2	7.145	34.693	0.001
Residual	1.030	5	0.206		
Total	15.320	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.037	0.172		-0.405	0.479	0.218	0.836
W1	2.832	0.377	0.871	1.862	3.801	7.509	0.001
W3	0.828	0.243	0.396	0.205	1.452	3.414	0.019





$\Pr\left(\text{Environmental Damage}\left(\text{Medium Impact}\right)\middle|\text{Sinking}, \underline{S}^2\right)$

Summary

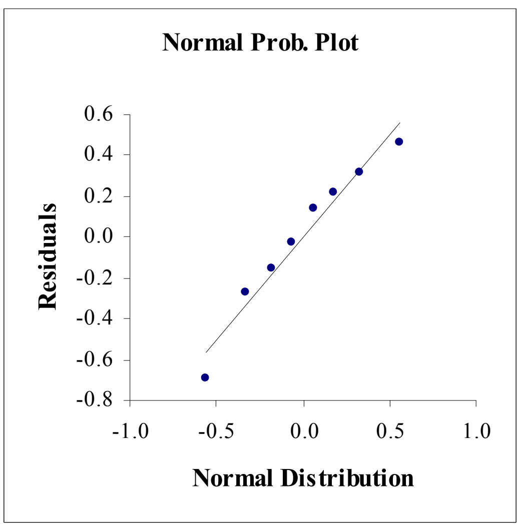
R^2	R	Adj. R^2	S.E. of Estimate
0.957	0.978	0.940	0.436

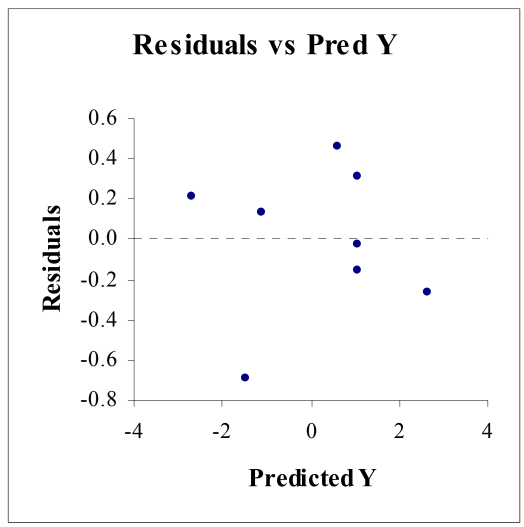
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	21.192	2	10.596	55.776	0.000
Residual	0.950	5	0.190		
Total	22.142	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	-0.023	0.165		-0.448	0.402	-0.139	0.895
W1	3.381	0.362	0.865	2.450	4.312	9.334	0.000
W3	1.096	0.233	0.436	0.497	1.695	4.704	0.005





$\Pr\left(\text{Traffic Effectiveness}\left(\text{Low Impact}\right)\middle|\text{Collision}, \underline{S}^2\right)$

Summary

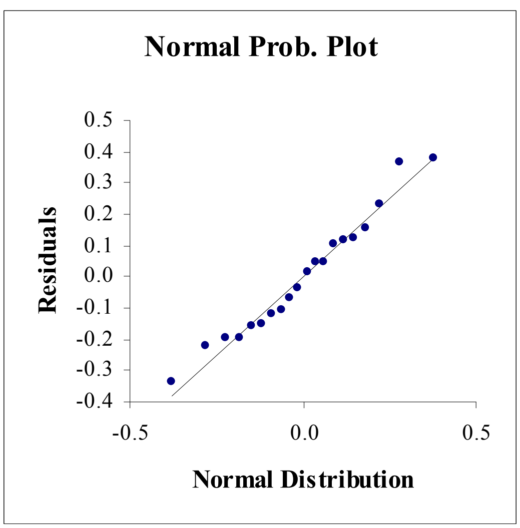
R^2	R	Adj. R^2	S.E. of Estimate
0.956	0.978	0.936	0.235

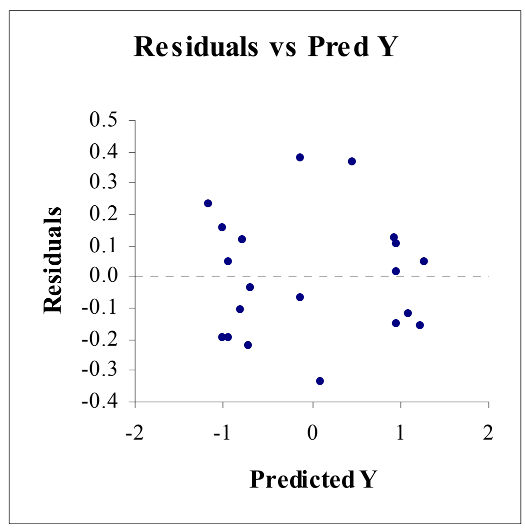
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	15.722	6	2.620	47.390	0.000
Residual	0.719	13	0.055		
Total	16.441	19			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.137	0.061		0.006	0.268	2.255	0.042
W1	2.120	0.255	0.483	1.568	2.671	8.305	0.000
W2	2.025	0.255	0.462	1.474	2.577	7.936	0.000
W3	1.918	0.404	0.922	1.045	2.791	4.747	0.000
W4	0.834	0.121	0.401	0.572	1.097	6.872	0.000
W5	2.069	0.410	0.561	1.184	2.954	5.052	0.000
W9	-1.110	0.442	-0.548	-2.065	-0.155	-2.511	0.026





$\Pr\left(\text{Traffic Effectiveness}\left(\text{Medium Impact}\right)\middle|\text{Collision}, \underline{S}^2\right)$

Summary

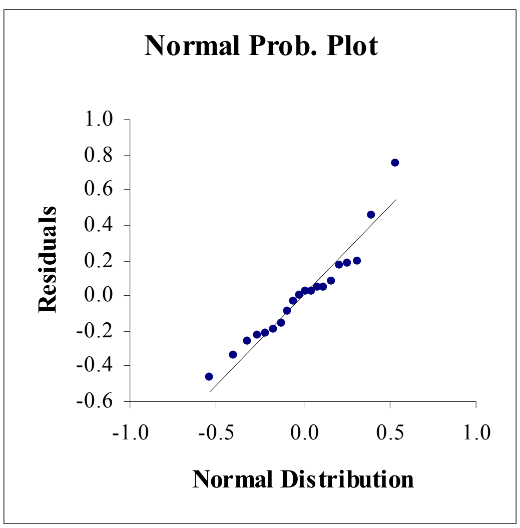
R^2	R	Adj. R^2	S.E. of Estimate
0.945	0.972	0.925	0.321

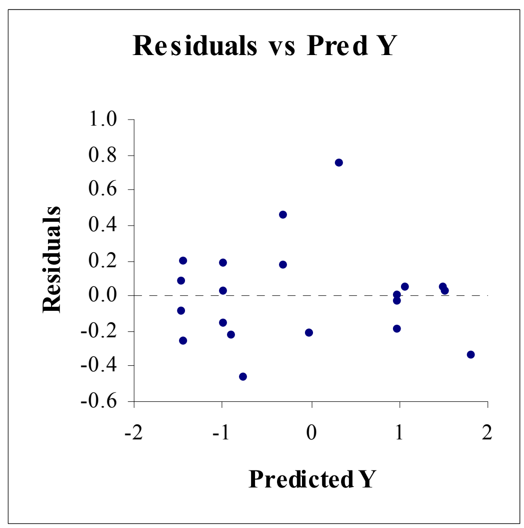
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	24.693	5	4.939	47.812	0.000
Residual	1.446	14	0.103		
Total	26.139	19			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.044	0.079		-0.125	0.213	0.563	0.582
W1	2.740	0.348	0.496	1.993	3.487	7.868	0.000
W2	2.783	0.348	0.503	2.036	3.530	7.990	0.000
W3	1.031	0.165	0.393	0.677	1.386	6.234	0.000
W4	0.939	0.165	0.358	0.584	1.294	5.676	0.000
W5	1.775	0.293	0.381	1.146	2.403	6.056	0.000





$\Pr\left(\text{Traffic Effectiveness}\left(\text{Low Impact}\right)\middle|\text{Grounding}, \underline{S}^2\right)$

Summary

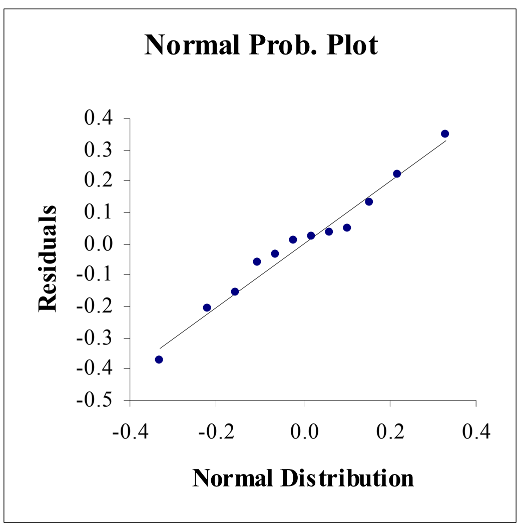
R^2	R	Adj. R^2	S.E. of Estimate
0.946	0.973	0.926	0.224

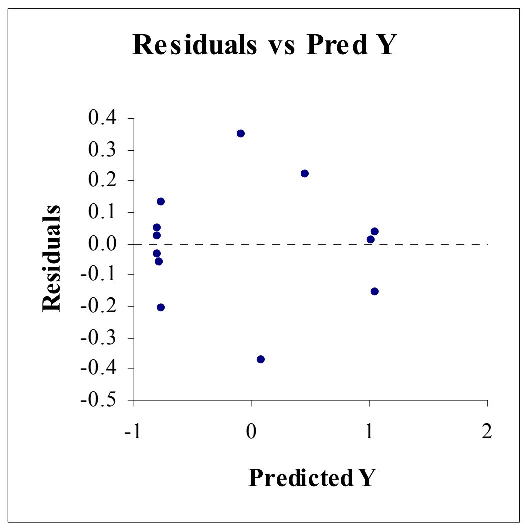
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	7.031	3	2.344	46.643	0.000
Residual	0.402	8	0.050		
Total	7.433	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.131	0.069		-0.029	0.291	1.893	0.095
W1	1.662	0.245	0.559	1.097	2.227	6.782	0.000
W3	0.924	0.117	0.649	0.653	1.194	7.873	0.000
W5	2.033	0.341	0.490	1.246	2.819	5.960	0.000





$\Pr\left(\text{Traffic Effectiveness}\left(\text{Medium Impact}\right)\middle|\text{Grounding}, \underline{S}^2\right)$

Summary

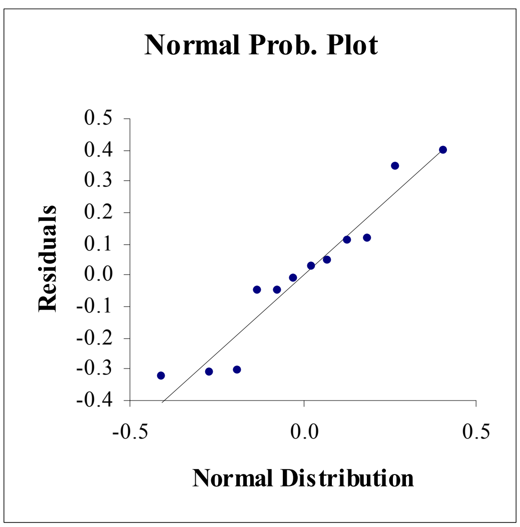
R^2	R	Adj. R^2	S.E. of Estimate
0.952	0.976	0.934	0.275

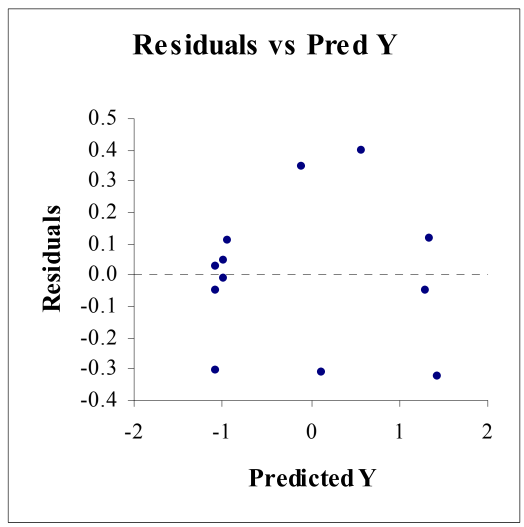
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	12.011	3	4.004	52.965	0.000
Residual	0.605	8	0.076		
Total	12.616	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.180	0.085		-0.016	0.376	2.114	0.067
W1	2.162	0.300	0.558	1.469	2.855	7.195	0.000
W3	1.257	0.144	0.678	0.925	1.589	8.734	0.000
W5	2.485	0.418	0.460	1.521	3.450	5.941	0.000





$\Pr\left(\text{Traffic Effectiveness}\left(\text{Low Impact}\right)\middle|\text{Ramming}, \underline{S}^2\right)$

Summary

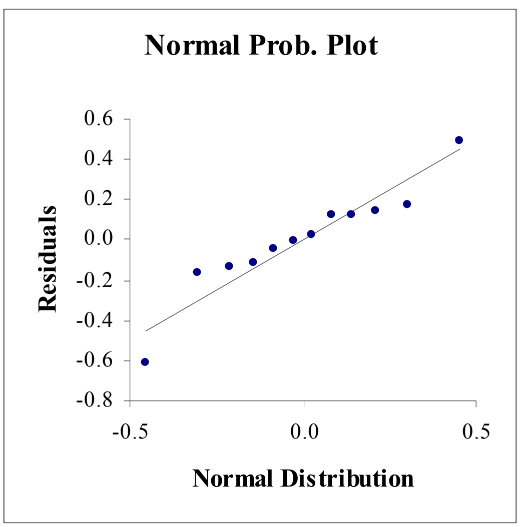
R^2	R	Adj. R^2	S.E. of Estimate
0.921	0.960	0.892	0.308

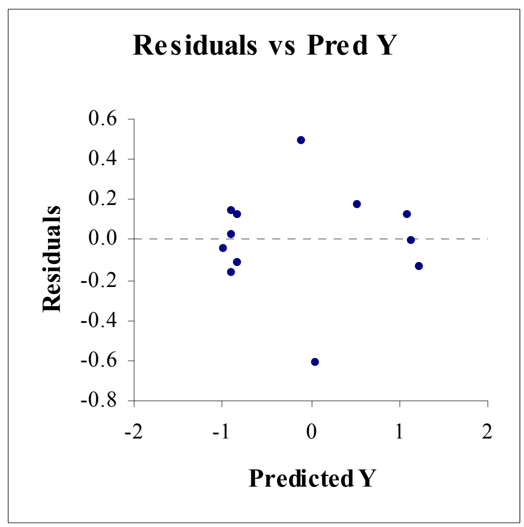
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	8.858	3	2.953	31.210	0.000
Residual	0.757	8	0.095		
Total	9.615	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.127	0.095		-0.093	0.346	1.332	0.220
W1	1.795	0.336	0.531	1.020	2.570	5.340	0.001
W3	1.015	0.161	0.627	0.644	1.387	6.308	0.000
W5	2.449	0.468	0.519	1.370	3.529	5.234	0.001





$$\Pr\left(\text{Traffic Effectiveness}\left(\text{Medium Impact}\right)\middle|\text{Ramming}, \underline{S}^2\right)$$

Summary

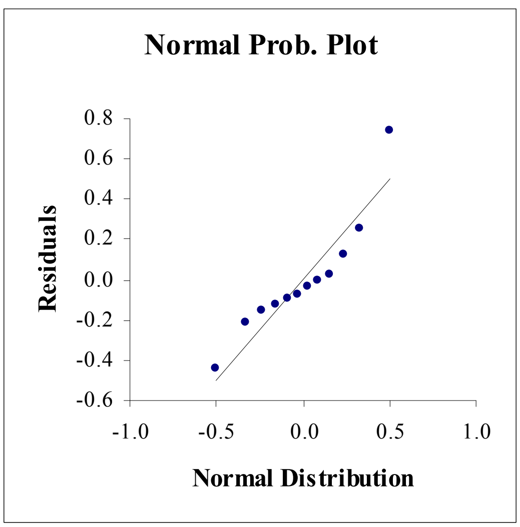
R^2	R	Adj. R^2	S.E. of Estimate
0.934	0.967	0.910	0.340

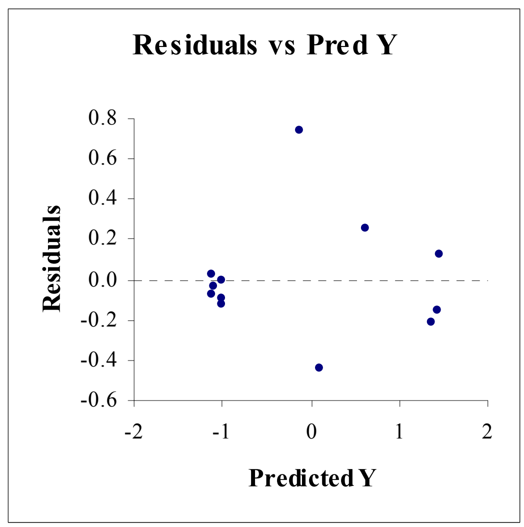
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	13.123	3	4.374	37.924	0.000
Residual	0.923	8	0.115		
Total	14.046	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.176	0.105		-0.066	0.418	1.677	0.132
W1	2.409	0.371	0.589	1.553	3.265	6.489	0.000
W3	1.192	0.178	0.609	0.782	1.602	6.704	0.000
W5	2.814	0.517	0.494	1.622	4.005	5.445	0.001





$\Pr\left(\text{Traffic Effectiveness}\left(\text{Low Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

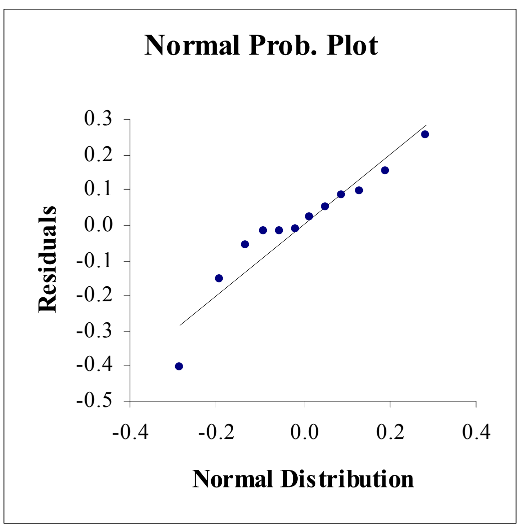
R^2	R	Adj. R^2	S.E. of Estimate
0.967	0.984	0.955	0.193

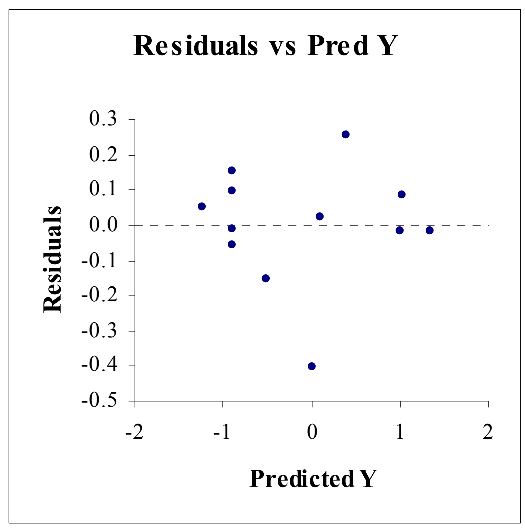
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	8.858	3	2.953	79.018	0.000
Residual	0.299	8	0.037		
Total	9.157	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.061	0.059		-0.074	0.196	1.036	0.331
W1	2.894	0.295	0.627	2.214	3.574	9.812	0.000
W3	0.959	0.101	0.607	0.726	1.192	9.497	0.000
W5	2.117	0.294	0.460	1.438	2.795	7.197	0.000





$\Pr\left(\text{Traffic Effectiveness}\left(\text{Medium Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

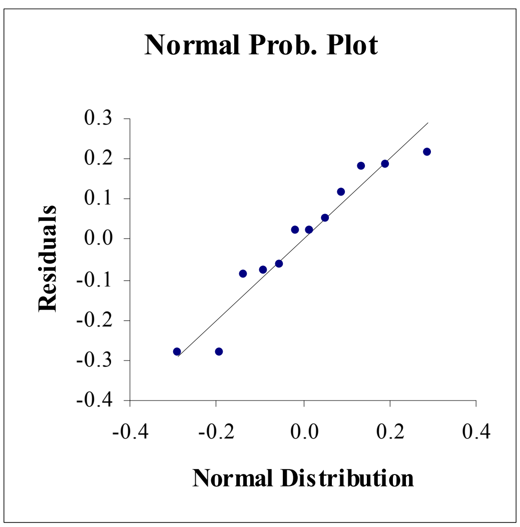
R^2	R	Adj. R^2	S.E. of Estimate
0.975	0.987	0.965	0.196

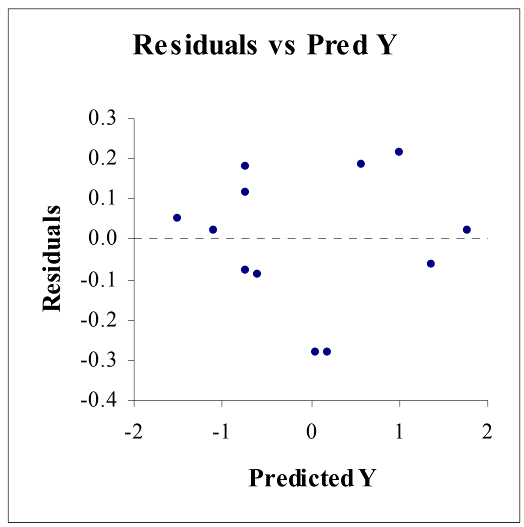
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	11.903	3	3.968	103.505	0.000
Residual	0.307	8	0.038		
Total	12.210	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.135	0.059		-0.002	0.272	2.279	0.052
W1	3.715	0.299	0.697	3.027	4.404	12.436	0.000
W3	0.874	0.102	0.479	0.638	1.110	8.541	0.000
W5	2.729	0.298	0.514	2.042	3.416	9.163	0.000





$\Pr\left(\text{Traffic Effectiveness}\left(\text{High Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

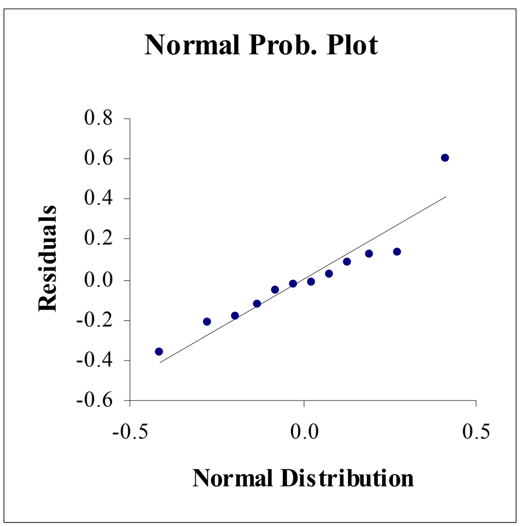
R^2	R	Adj. R^2	S.E. of Estimate
0.962	0.981	0.948	0.280

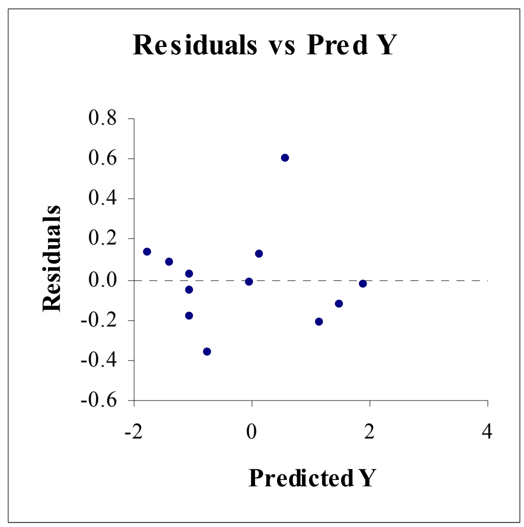
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	16.061	3	5.354	68.089	0.000
Residual	0.629	8	0.079		
Total	16.690	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.057	0.085		-0.139	0.253	0.666	0.524
W1	4.119	0.428	0.661	3.133	5.106	9.627	0.000
W3	1.106	0.147	0.518	0.768	1.444	7.549	0.000
W5	3.172	0.427	0.510	2.188	4.156	7.435	0.000





$\Pr\left(\text{Traffic Effectiveness}\left(\text{Low Impact}\right)\middle|\text{Sinking}, \underline{S}^2\right)$

Summary

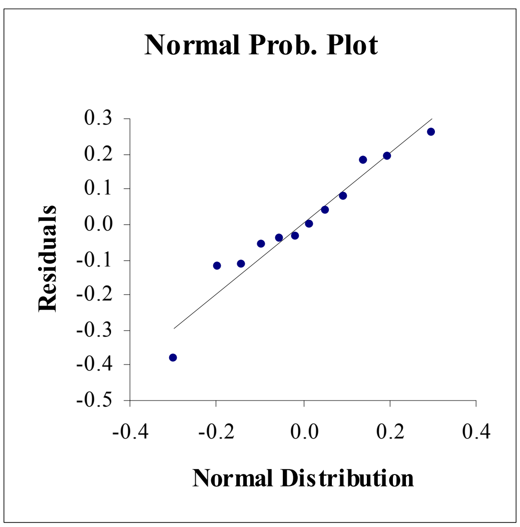
R^2	R	Adj. R^2	S.E. of Estimate
0.943	0.971	0.922	0.202

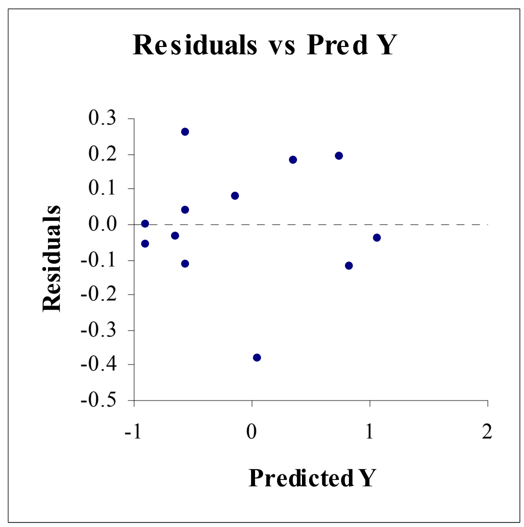
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	5.404	3	1.801	44.347	0.000
Residual	0.325	8	0.041		
Total	5.729	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.091	0.062		-0.052	0.235	1.467	0.181
W1	1.833	0.220	0.702	1.325	2.341	8.323	0.000
W3	0.656	0.105	0.525	0.413	0.899	6.219	0.000
W5	1.648	0.307	0.453	0.940	2.355	5.373	0.001





$\Pr\left(\text{Traffic Effectiveness}\left(\text{Medium Impact}\right)\middle|\text{Sinking}, \underline{S}^2\right)$

Summary

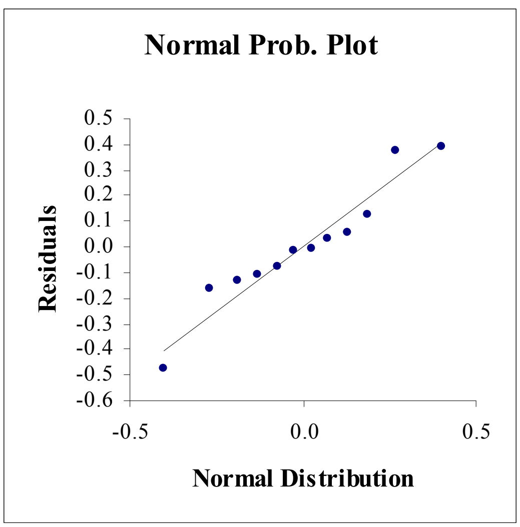
R^2	R	Adj. R^2	S.E. of Estimate
0.962	0.981	0.948	0.273

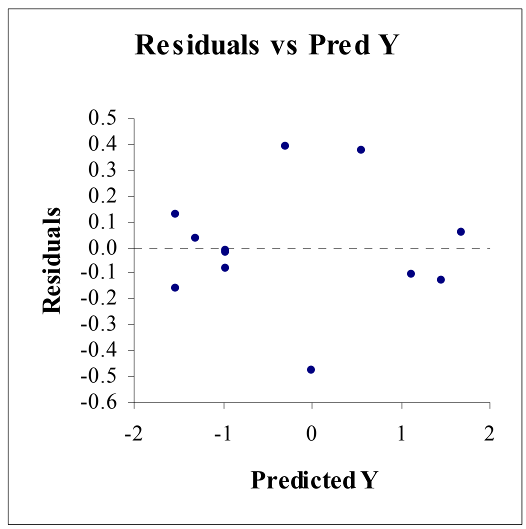
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	15.163	3	5.054	67.742	0.000
Residual	0.597	8	0.075		
Total	15.760	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.078	0.084		-0.117	0.273	0.925	0.382
W1	3.006	0.299	0.694	2.317	3.694	10.068	0.000
W3	1.040	0.143	0.502	0.711	1.370	7.276	0.000
W5	3.047	0.416	0.505	2.089	4.005	7.332	0.000





$\Pr\left(\text{Property/Infrastructure Damage}\left(\text{Low Impact}\right)\middle|\text{Ramming}, \underline{S}^2\right)$

Summary

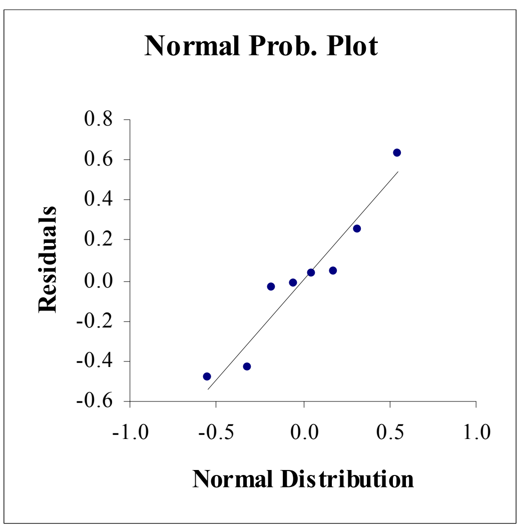
R^2	R	Adj. R^2	S.E. of Estimate
0.825	0.908	0.755	0.420

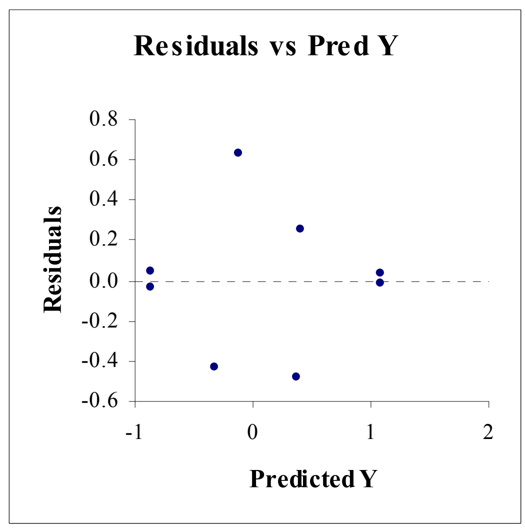
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	4.163	2	2.082	11.798	0.013
Residual	0.882	5	0.176		
Total	5.046	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.109	0.149		-0.273	0.491	0.731	0.497
W1	1.258	0.362	0.650	0.328	2.188	3.477	0.018
W5	1.146	0.338	0.634	0.277	2.015	3.389	0.019





$\Pr\left(\text{Property/Infrastructure Damage}\left(\text{Medium Impact}\right)\middle|\text{Ramming}, \underline{S}^2\right)$

Summary

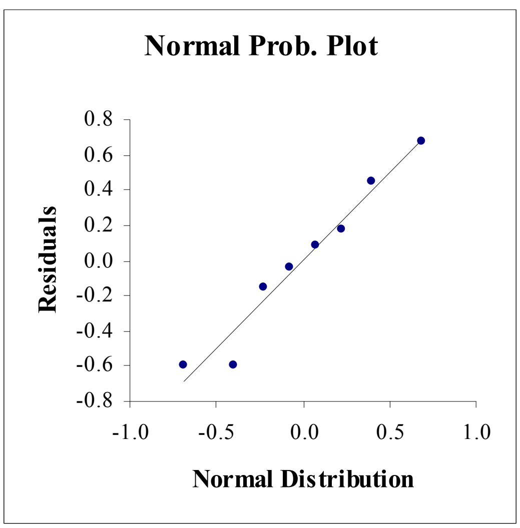
R^2	R	Adj. R^2	S.E. of Estimate
0.869	0.932	0.817	0.534

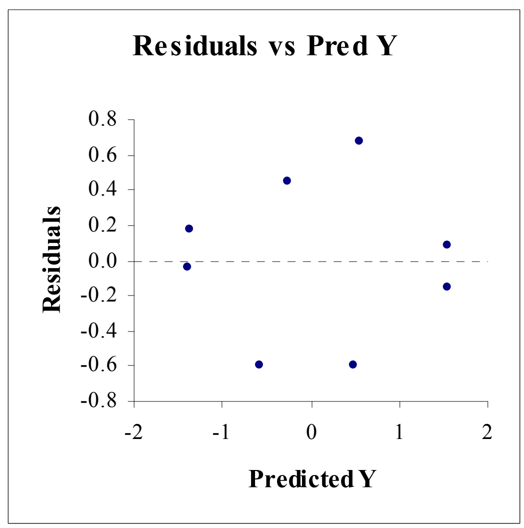
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	9.464	2	4.732	16.610	0.006
Residual	1.424	5	0.285		
Total	10.888	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.082	0.189		-0.403	0.568	0.436	0.681
W1	1.890	0.460	0.665	0.709	3.071	4.113	0.009
W5	1.734	0.430	0.653	0.629	2.838	4.035	0.010





$\Pr\left(\text{Property/Infrastructure Damage}\left(\text{Low Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

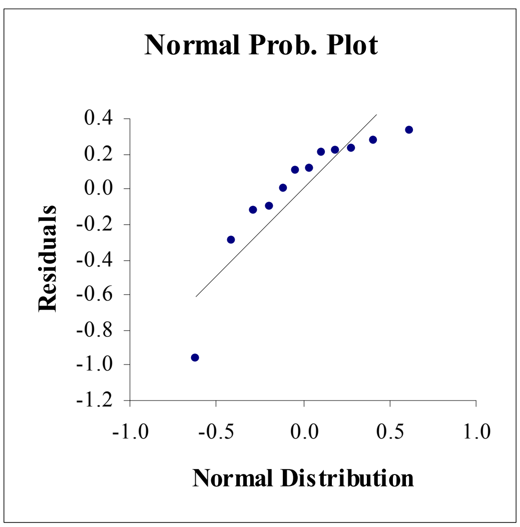
R^2	R	Adj. R^2	S.E. of Estimate
0.929	0.964	0.902	0.416

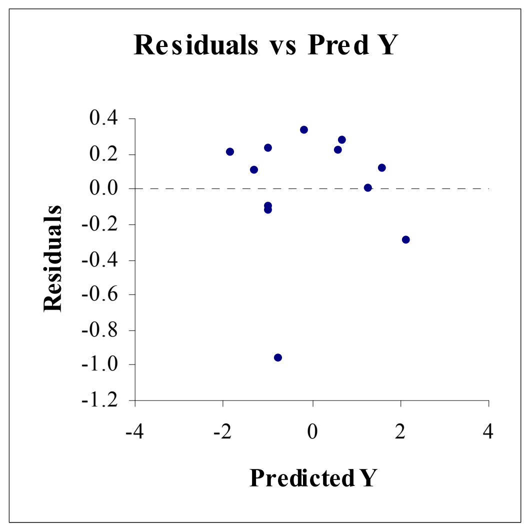
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	17.982	3	5.994	34.687	0.000
Residual	1.382	8	0.173		
Total	19.365	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.156	0.125		-0.134	0.445	1.241	0.250
W1	2.567	0.358	0.678	1.742	3.392	7.172	0.000
W3	1.117	0.217	0.486	0.617	1.618	5.146	0.001
W5	1.724	0.335	0.487	0.952	2.495	5.151	0.001





$\Pr\left(\text{Property/Infrastructure Damage}\left(\text{Medium Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

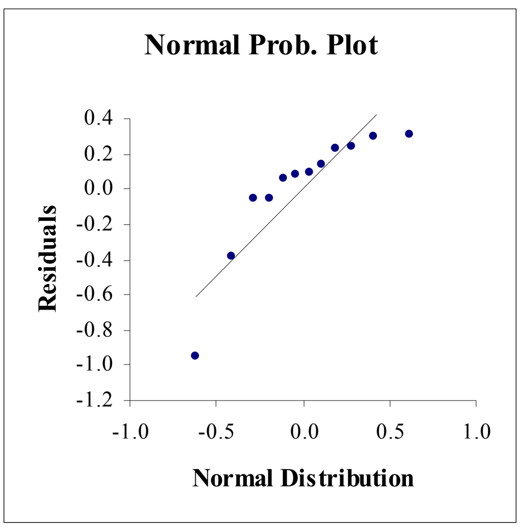
R^2	R	Adj. R^2	S.E. of Estimate
0.939	0.969	0.917	0.415

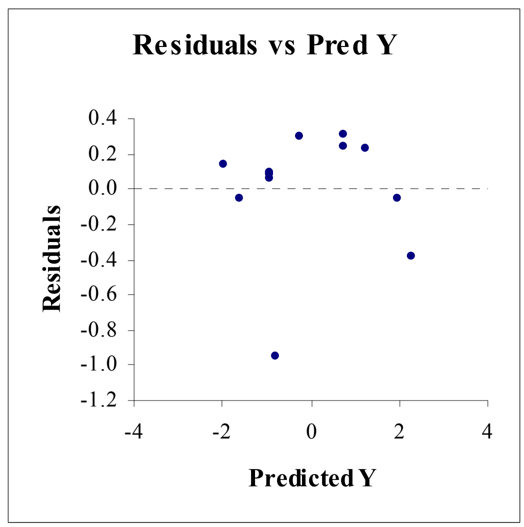
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	21.409	3	7.136	41.354	0.000
Residual	1.381	8	0.173		
Total	22.790	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.164	0.125		-0.125	0.453	1.311	0.226
W1	2.779	0.358	0.676	1.954	3.603	7.769	0.000
W3	1.074	0.217	0.431	0.574	1.574	4.950	0.001
W5	2.103	0.334	0.547	1.332	2.874	6.289	0.000





$\Pr\left(\text{Property/Infrastructure Damage}\left(\text{High Impact}\right)\middle|\text{Fire/Explosion}, \underline{S}^2\right)$

Summary

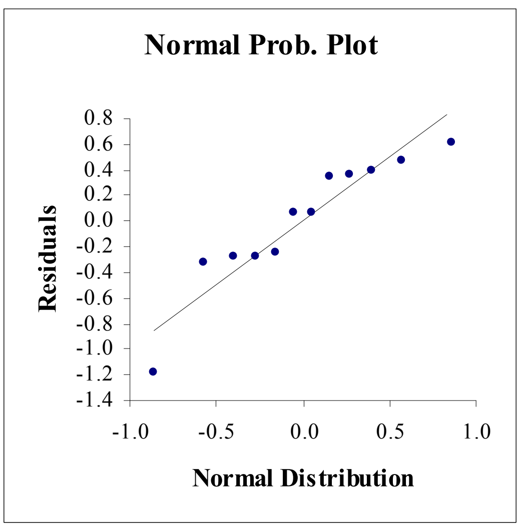
R^2	R	Adj. R^2	S.E. of Estimate
0.909	0.953	0.875	0.583

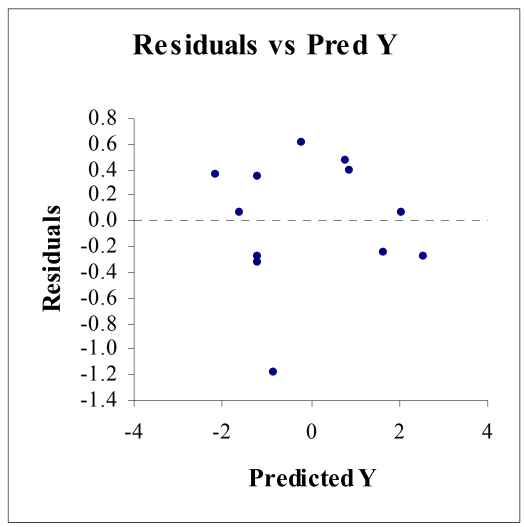
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	27.148	3	9.049	26.650	0.000
Residual	2.717	8	0.340		
Total	29.865	11			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.216	0.176		-0.189	0.622	1.231	0.253
W1	3.051	0.502	0.648	1.894	4.207	6.081	0.000
W3	1.435	0.304	0.503	0.733	2.137	4.715	0.002
W5	2.151	0.469	0.489	1.070	3.233	4.586	0.002





$$\Pr\left(\text{Property/Infrastructure Damage}\left(\text{Low Impact}\right)\middle|\text{Sinking}, \underline{S}^2\right)$$

Summary

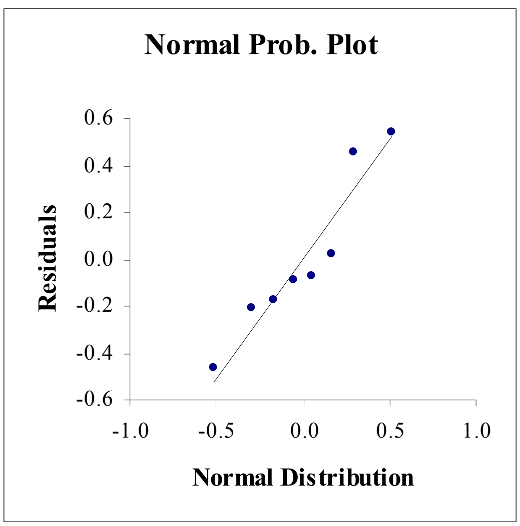
R^2	R	Adj. R^2	S.E. of Estimate
0.838	0.915	0.811	0.366

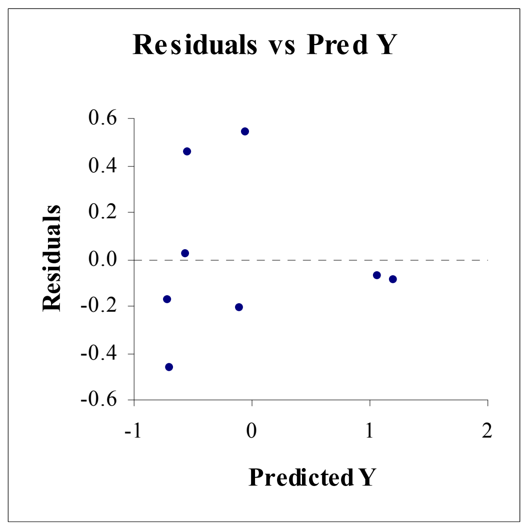
ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	4.155	1	4.155	31.045	0.001
Residual	0.803	6	0.134		
Total	4.958	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	-0.338	0.139		-0.679	0.002	-2.430	0.051
W8	1.817	0.326	0.915	1.019	2.615	5.572	0.001





$$\Pr\left(\text{Property/Infrastructure Damage}\left(\text{Medium Impact}\right)\middle|\text{Sinking}, \underline{S}^2\right)$$

Summary

R^2	R	Adj. R^2	S.E. of Estimate
0.960	0.980	0.943	0.283

ANOVA

Source	Sum Sq.	D.F.	Mean Sq.	F	Prob.
Regression	9.527	2	4.764	59.387	0.000
Residual	0.401	5	0.080		
Total	9.928	7			

Regression Coefficients

Source	Coefficient	Std Error	Std Beta	-95% C.I.	+95% C.I.	t	Prob.
Intercept	0.016	0.100		-0.242	0.274	0.161	0.879
W1	1.931	0.244	0.712	1.304	2.558	7.918	0.001
W5	1.706	0.228	0.672	1.120	2.292	7.482	0.001