RISK ASSESSMENT AND ACCIDENT FORECASTING FOR AN UNDERGROUND COAL MINE

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submitted by **MERVE MEVSİM** in partial fulfillment of the requirements for the degree of **Master of Science in Mining Engineering Department, Middle East Technical University** by,

Prof. Dr. Halil Kalıpçılar
Dean, Graduate School of **Natural and Applied Sciences** ____________________

Prof. Dr. Celal Karpuz
Head of Department, **Mining Engineering** ____________________

Prof. Dr. Celal Karpuz
Supervisor, **Mining Engineering Dept., METU** ____________________

Examining Committee Members:

Prof. Dr. Celal Karpuz
Mining Engineering Dept., METU ____________________

Assoc. Prof. Dr. Nuray Demirel
Mining Engineering Dept., METU ____________________

Assoc. Prof. Dr. Mehmet Ali Hindistan
Mining Engineering Dept., Hacettepe University ____________________

Date: 11.05.2018

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: Merve MEVSİM

Signature:

ABSTRACT

RISK ASSESSMENT AND ACCIDENT FORECASTING FOR AN UNDERGROUND COAL MINE

Mevsim, Merve

M.S., Department of Mining Engineering

Supervisor: Prof. Dr. Celal Karpuz

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In Turkey, underground coal mine accidents are commonly faced problems and cause loss of lives and money. In order to prevent these accidents, the hazards and risks specific to each mine should be assessed by both ordering the risk scores and building a statistical model for the future trend of accidents. In this study, past accident records of Üzülmez District of Turkish Hard Coal Enterprises is utilized. The risk scoring model is built by using Riskex Risk Score Calculator based on Fine-Kinney risk score equation. In accident forecasting, multiple linear regression and time series analysis techniques are utilized by the aid of the Minitab 17 software.

The data taken from Turkish Hard Coal Enterprises the Department of Labor Health, Safety and Education includes accident type, location, work shift, job, affected body part, age and experience for each recorded accident. Firstly, the scores of the risk of those seven category is found by utilizing Fine-Kinney method and the risks of each accident type, accident location, shift, job, body part affected after having an accident, age group and experience duration are ordered in order to find the relative seriousness of them. Secondly, expected number of accidents in future is forecasted with the aid of multiple linear regression and time series analysis. By performing multiple linear regression it is aimed to observe how the variables like raw coal production, total gallery advance, total number of workers, explosive consumption, and timber consumption effect number of accidents. By time series analysis, the number of accidents expected in future is determined which is thought to provide benefits to occupational health and safety managers in monitoring the performance of safety precautions. Time series model is found to be more reliable and practicable than multiple linear regression which uses just the monthly number of accidents as random variable. Research findings revealed that moving average time series model is the best fit model when the evaluation is made in terms of calculated accuracy values. However, quadratic trend model should be preferred when long term forecast horizon is needed.

Keywords: underground hard coal mine, risk analysis, multiple linear regression, time series analysis, moving average model, quadratic trend model

ÖZ

BİR YERALTI KÖMÜR MADENİ İÇİN RİSK DEĞERLENDİRMESİ VE KAZA TAHMİNİ

Mevsim, Merve
Yüksek Lisans, Maden Mühendisliği Bölümü
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Türkiye’de kömür madeni kazaları sıkça karşılaşılan bir problem olup insan ve para kaybına sebep olur. Bu kazaları önlemek için, her bir madene özgü tehlikeler ve riskler, hem risk puanları sıralanarak hem de gelecekteki kaza eğilimleri için istatistiksel bir model oluşturarak değerlendirilmelidir. Bu çalışmada, Türkiye Taşkömürü Kurumu Üzülmez Müessesei’ne ait geçmiş kaza kayıtları kullanılmıştır. Risk skorlama modeli, Fine-Kinney risk skoru denklemine dayalı Riskex Risk Puanı Hesaplayıcısı kullanılarak oluşturulmuştur. Kaza sayıları tahmininde ise, Minitab 17 yazılımının yardımı ile çoklu doğrusal regresyon ve zaman serisi analiz teknikleri kullanılmıştır.

Türkiye Taşkömürü Kurumu İş Sağlığı, Güvenliği ve Eğitim Daire Başkanlığından alınan veriler kayıt altına alınan her bir kaza için kaza tipi, kaza yeri, iş vardiyası, kazalının işi, etkilenen beden kısmı, yaş ve deneyim gibi bilgiler içermektedir. İlk olarak, Fine-Kinney yöntemini kullanarak bahsedilen yedi kategorinin her biri için risk skorları bulunmuş ve her bir kaza tipi, kaza yeri, vardiya, iş, kaza geçirdikten sonra etkilenen beden kısmı, yaş grubu ve deneyim süresinin göreceli ciddiyetini bulmak için puanlanan riskler sıralanmıştır. İkinci olarak, gelecekte beklenen kaza sayısı çoklu doğrusal regresyon ve zaman serileri analizi yöntemleriyle tahmin edilmiştir. Çoklu doğrusal regresyon gerçekleştirerek, tüvenan kömür üretimi, toplam galeri ilerlemesi, toplam işçi sayısı, patlayıcı tüketimi ve toplam direk sarfiyatının kaza sayısını nasıl etkilediğini gözlemlemek amaçlanmıştır. Zaman serileri analizi ile iş sağlığı ve güvenliği yöneticilerine güvenlik önlemlerinin performansının izlenmesinde fayda sağlayacağı düşünülen gelecekte beklenen kaza sayısı belirlenmiştir. Rassal değişken olarak sadece aylık kaza sayılarını kullanan zaman serisi modelinin doğrusal regresyondan daha güvenilir ve kullanışlı olduğu bulunmuştur. Araştırma bulguları, doğruluk değerleri açısından değerlendirmenin yapıldığı durumlarda, hareketli ortalama modelinin en uygun model olduğunu ortaya koymuştur. Ancak uzun vadeli tahmin ufku gerektiğinde kuadratik eğilim modeli tercih edilmelidir.

Anahtar Kelimeler: yeraltı taşkömürü madeni, risk analizi, çoklu doğrusal regresyon, zaman serileri analizi, hareketli ortalama modeli, kuadratik eğilim modeli

To my parents

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CHAPTER 1

INTRODUCTION

1.1 Background Information

Mining is an ancient occupation from the beginning of the civilization and has long jeopardized the workers' health and safety. Therefore, the safety concern has been an integral part of mining works. In Turkey, the first legislation related to occupational health and safety was introduced in coal mining sector, in 1865, called as Dilaver Paşa Articles. In other words, in Turkey, occupational health and safety concept arose from the problems of coal mining sector as in many countries.

According to International Labor Organization (ILO), each day, 6300 people decease because of occupational accidents or work-related illnesses and each year, 317 million accidents appear, causing substantial amount of workday loss. Some sectors and occupations such as construction, mining or ship-breaking are more hazardous than others and they require much more attention. As the amount of danger may change between sectors, it may change also within a sector. For example, when it is compared with surface mining, underground mining is a more dangerous sector as far as the safety and health of the workforce are concerned. Coal extraction is also much more prone to accidents and diseases compared to other mineral extractions.

The Turkish coal sector produces both hard coal (1.9 million tonnes in 2013) and lignite (63 million tonnes in 2013). Table 1.1 and Table 1.2 show the countries according to production rates of hard coal and lignite respectively. In Turkey, amount of lignite production is higher than hard coal production as can be inferred from Table

1.2 and Table 1.3. Main productor of lignite is TKİ (Turkish Coal Enterprise) whereas main productor of hard coal is TTK (Turkish Hard Coal Enterprise). Table 1.1, Table 1.2 and Table 1.3 summarize that Turkey seems to be out of the competition especially in hard coal mining production.

Table 1.1 Hard coal production of some countries and total world production (million tonnes) (Turkish Hard Coal Enterprise General Directorate Industry Report, 2016)

	2013	**2014**	**2015**
Australia	396.1	428.3	443.4
U.S.A.	833.6	846.1	748.7
India	565.7	609.2	648.0
South Africa	256.3	260.5	252.1
China	3748.5	3640.2	3527.2
Russia	252.3	264.0	276.1
Other	1088.1	1101.5	1005.8
TOTAL	7140.6	7113.8	6901.3

Table 1.2 Lignite production of some countries and total world production (million tonnes) (Turkish Hard Coal Enterprise General Directorate Industry Report, 2016)

	2013	**2014**	**2015**
Australia	62.3	60.5	65.4
Czech Republic	40.4	38.2	38.1
Germany	182.7	178.2	178.1
Greece	53.9	50.8	46.2
Poland	65.8	63.9	63.1
Turkey	57.5	62.6	50.4
U.S.A.	70.1	72.1	64.1
Russia	73.7	68.9	73.2
Other	277.6	220.7	228.8
TOTAL	834.0	815.9	807.4

Table 1.3 Hard coal production of Zonguldak basin (tonnes) (Turkish Hard Coal Enterprise General Directorate Industry Report, 2016)

	2014	**2015**	**2016**
TTK	1,300,154	948,573	911,002
Private Sector	488,187	486,309	404,968
Total Basin	1,788,341	1,434,882	1,315,970

According to ILO, around the world, mining sector employs about 30 million people which occupies one percent of the world's workforce and 10 million people out of this 30 million serve in coal mining sector. In Turkey, Social Security Instutition (SGK) is responsible for recording number of insured workers, number of workplaces as well as occupational accidents and diseases. According to Social Security Instutition 2014 Statistics of Workplace and Insured Person, under the activity code of 05 (coal and lignite extraction activity), there exists 717 workplaces and 41,058 insurees. Furthermore, Social Security Instutition 2014 Statistics of Work Accidents and Occupational Diseases states that under the activity code of 05, the number of deceased insurees is 335 as a result of work accidents and none as a result of occupational diseases. Coal and lignite extraction activity has the highest scores in terms of number of deceased persons. However, these statistics is not reliable due to covering only the insured workers. Thus it can be estimated that the number of occupational accidents and diseases are much greater than official statistics published.

Although Turkey's coal production amount is quite low compared to other countries, its accident frequency is quite high. From Table 1.4, it can be seen that between 1983-2014, there occured 22 mine accidents in which more than 3 workers die at the same time. All the accidents took place at underground coal mines except the one in Kastamonu. It can be inferred that underground coal mines have high risk potential which can lead to death of more than one worker in a single event.

Table 1.4 Major underground mine accidents that more than 3 workers die (Turkish Chamber of Mining Engineers, 2010) (This table is revised by adding accidents after 2010)

Location	**Date**	**Type**	**Fatalities**
TTK/ Armutçuk/coal	07.03.1983	Methane explosion	103
TTK/ Kozlu/coal	10.04.1983	Methane explosion	10
Yeni Çeltek/Amasya/coal	14.07. 1983	Methane explosion	5
TTK/ Kozlu/coal	31.01.1987	Roof fall	8
Yeni Çeltek/Amasya/coal	07.02. 1990	Methane explosion	68

Table 1.4 Major underground mine accidents that more than 3 workers die (continued) (Turkish Chamber of Mining Engineers, 2010)

Location	Date	Type	Fatalities
TTK/ Kozlu/coal	03.03.1992	Methane explosion	263
Yozgat/Sorgun/coal	26.03.1995	Methane explosion	37
Erzurum/ Aşkale/coal	08.08.2003	Methane explosion	8
Karaman/Ermenek/coal	22.11.2003	Methane explosion	10
Çorum/ Bayat/coal	09.082004	Methane explosion	3
Kastamonu/ Küre/metal	08.09.2004	Mine fire	19
Kütahya/ Gediz/coal	21.04.2005	Methane explosion	18
Balıkesir/Dursunbey/coal	02.06.2006	Methane explosion	17
Bursa/Mustafakemalpaşa/coal	10.12.2009	Methane explosion	19
Balıkesir/ Dursunbey /coal	23.02.2010	Methane explosion	17
TTK/ Karadon/coal	17.05.2010	Methane explosion	30
Edirne/ Küçükdoğanca/coal	07.07.2010	Roof fall	3
TTK/ Kozlu/coal	08.01.2013	Roof fall	8
Manisa/Soma/coal	13.05.2014	Mine fire	301
Şırnak/Kemerli/coal	11.06.2014	Roof fall	3
Karaman/Ermenek/coal	28.10.2014	Water inflow	18

1.2 Problem Statement

Employees working on some jobs face much more danger compared to others, often known as the "3D", dirty, difficult, and dangerous jobs. For example mining, especially coal extraction with underground production techniques is one of the most unsafe occupations. This type of occupations require much more right of priority concerning health and safety of the workers. Although occupational health and safety authorities concentrated heavily on mining safety, death and accident statistics prove that studies are insufficient. The accidents occurring in underground coal mining like explosions, fires, roof falls, inundations of dangerous gases, water or other free-flowing materials from old mine workings or geological faults and premature or improper detonation of explosives are generally catastrophic and they cost several lifes in a single event. In order to prevent these accidents the hazards and risks specific to each mine must be assessed. Accident type, location, work shift, job, affected body part, age, and experience that must be the most worthy of notice changes for each mine. For example, for the Mine Company A roof falls may be the most significant accidents that must be paid attention while for the Mine Company B mine fires may be the most significant accidents that must be paid attention. Likewise longwall face may be the most critical location for Mine Company X, whereas it is main transportation/haulage road that must be of top priority for Mine Company Y. Therefore forming a risk scoring model and grading each accident type, location, work shift, job, body part, age, and experience for each mine is crucial and provides prioritizing and managing the risks accordingly.

In Turkey, several site visits show that generally 5x5 risk matrix is used for underground coal mines risk assessment studies. In 5x5 risk matrix method, risk is defined by using two variables, namely, consequence (C) and probability (P). However, it is a well known fact that, risk does not arise without exposure. Therefore, risk assessment process should be taken to a more advanced level and definition of the risk should be revised by adding a new variable called exposure (E). Then, the prioritization of the risks could be more reliable and give more realistic results.

As well as prioritization of the risks, predicting the future trends of accidents is vitally important for an efficient risk analysis. In order to foresee future trend of accidents a statistical modelling should be built. The developed model can be used for monitoring the performance of safety precautions and the accuracy of the safety policy by evaluating the trend of number of accidents.

1.3 Objectives and Scope of the Study

The main objective of this research study is to determine the relative seriousness of all hazards by using Fine-Kinney method and order accident type, location, work shift, job, affected body part, age, and experience which bear risks for workers safety and to predict future trend of accidents in selected underground coal mine by utilizing multiple linear regression and time series analysis methods.

The scope of this research study is accident records of Turkish Hard Coal Enterprise Üzülmez district and covers the period of January 2003 to December 2013. The accidents included in the data are recorded under seven categories as accident type, location, work shift, job, body part, age, and experience. Accident types are classified due to their sources as roof fall, methane and other gases, electric, machine, material, transportation, explosive, and miscellaneous. Accident locations include longwall face, development headings, main transportation/haulage road, support maintanance/repair, electro mechanics shop, and miscellaneous. Jobs are categorized as longwall production worker, development headings worker, support maintanance worker, transportation worker, fireman, electrical technician, and mechanical technician. Affected body parts after accidents are foot-toe, leg, the lower part of the leg, calf, head, waist, neck, knee, fingers, chest, body, eye, hip, arm, shoulder, the back, face, whole body, respiratory, and other. This data is used for the risk prioritization. In accident forecasting, the data involving the six predictor variables which are raw coal production (tonnes), total gallery advance/daily wage (cm), total number of workers, explosive consumption/raw coal production (g/tonnes), and timber consumption/raw coal production (dm^3/tonnes) are used.

The goal of this study will be achieved through the following objectives:

- Probability, severity, and exposure analysis of accidents with the previous accident data in order to determine the relative seriousness of all hazards by Fine-Kinney method
- Future accident estimation by using multiple linear regression and time series analysis methods

1.4 Research Methodology

The research methodology includes five main stages. These stages are listed as:

- Pre-processing and sorting the accident data according to titles, namely; accident type, location, work shift, job, affected body part, age, and experience
- Determination of probabilities and severities of accidents at each title by using Microsoft Excel
- Determination of the exposures to each title by using Minitab 17 software
- Interpreting the findings related to exposures, probabilities, and severities in Riskex Risk Score Calculator
- Multiple Linear Regression by Minitab 17 software
- Time Series Anlaysis by Minitab 17 software

1.5 Expected Scientific and Industrial Contributions of the Study

This research offers the application of a new approach to the existing risk assessment studies carried on underground coal mines. The first contribution of the study is that it is the first application of a comprehensive quantitative risk analysis method in a specific mine site by using Fine-Kinney method together with Time Series Analysis.

The current researches lack information related to the application of Fine-Kinney Method in quantitative risk analysis of an underground coal mine. Risk is usually defined by using two variables, namely, consequence (C) and probability (P) but the effect of exposure (E) on risk score is ignored. In this study, the effect of exposure (E) on risk score is taken into consideration. With this aspect, this study is first in its field.

Predicting the future trend of accidents is vitally important for an efficient risk analysis. Building a model to see the future trend of accidents helps the safety managers to monitor the performance of safety precautions and the accuracy of the safety policy by examining descents and ascents in number of accidents. The main expected industrial contribution of this study is that it brings a new approach to risk analysis practices by both ordering the risk scores and building a statistical model for the future trend of accidents at the same time.

1.6 Outline of the Thesis

This thesis comprises of six chapters. After the introduction chapter, the literature is reviewed extensively in the second chapter. This chapter begins with a brief introduction to safety performance of the mining sector. Then the general occupational health and safety terminology is scrutinized. After that, the capacity and safety performance of Turkey and world coal mining is compared. Later the most common hazards and risk assessment methods in underground coal mines are discussued.

In Chapter 3 information about the data handled and research area is given. Chapter 4 presents a general information on risk score modelling firstly. Then, probabability, exposure, and consequence factors for each accident type, location, work shift, job, affected body part, age, and experience are assessed and compiled under Fine-Kinney risk score equation by using Riskex Risk Score Calculator. At the last part of this chapter, calculated risk score values are sorted by magnitude and prioritization of risk is performed.

In order to foresee future trend of accidents by utilizing multiple linear regression and time series analysis method, prediction models are built and discussed in Chapter 5. By performing multiple linear regression how variables like raw coal production, total gallery advance, total number of workers, total energy consumption, explosive consumption, and timber consumption affect the number of accidents is examined. By time series analysis the number of accidents expected in next months is determined. Finally, in the sixth chapter the results of risk score model and forecasting models are rewieved. Furthermore, primary conclusions drawn from the thesis and recommendations for the future researches are explained.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

Each day, 6300 people die due to occupational accidents or work-related diseases which make more than 2.3 million deaths per year (ILO, 2016). In order to make a comparison, it is good to take a glance at road traffic fatality numbers. According to World Health Organization, 1.24 million people were killed on the world's roads in 2010 (WHO, 2013). Although deaths due to occupational accidents are pretty much than the deaths due to traffic accidents, occupational accidents do not gain attention on public opinion as traffic accidents. A world embracing consciousness about the importance of workplace accidents is crucial. Health and safety of all employees must be regarded by the governments and employers as well as employees. In addition to human cost, there is a monetary point of view. According to ILO, the financial effect of poor occupational safety and health practices come out at 4 per cent of global Gross Domestic Product each year (ILO, 2016).

Fatality numbers related to occupational health and safety may change for different sectors and different countries.

> *"For example, in China more fatal accidents occur in the mining sector while in Indonesia there are more fatalities in the manufacturing sector. In the UK, the construction sector accounts for more fatal accidents than any other sector and in Poland the agriculture sector claims more lives due to fatal accidents."* (Pearson, 2009).

In view of Turkey's fatality numbers, most deadly sector varies with years. For example, when the most recent data collected by SGK is evaluated, it is deduced that mining of coal and lignite accounts for more fatal accidents for the year 2014 due to 301 fatalities in Soma and 18 fatalities in Ermenek whereas construction of buildings accounts for more fatal accidents for the year 2013. Figure 2.1 and Figure 2.2 shows top ten deadly sectors of Turkey for 2014 and 2013, respectively.

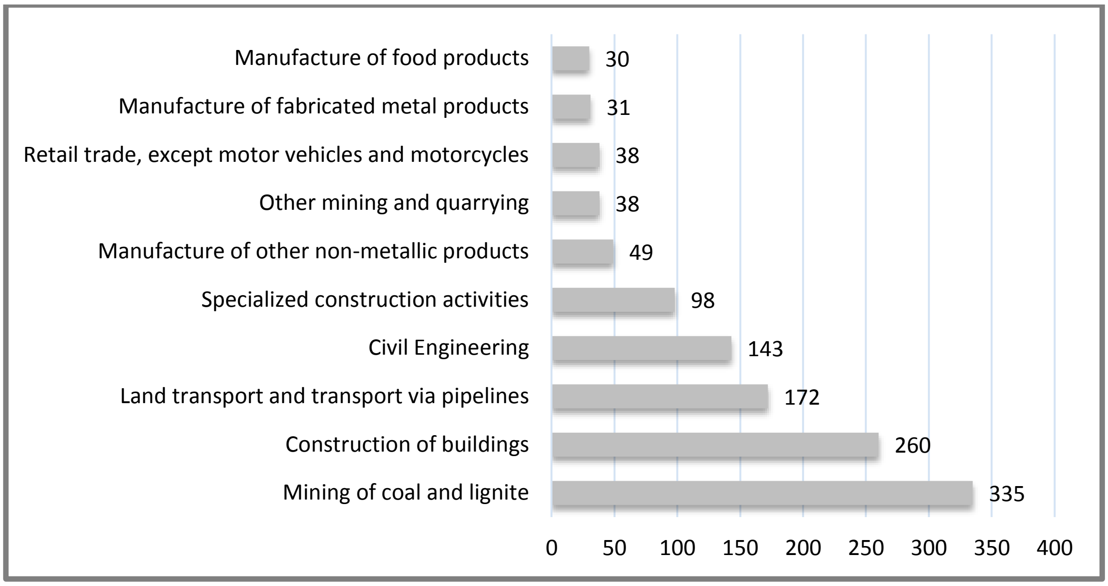


Figure 2.1 Top ten fatality intensive sector of Turkey in 2014 (SGK 2014 Work Accidents and Occupational Diseases Statistics)

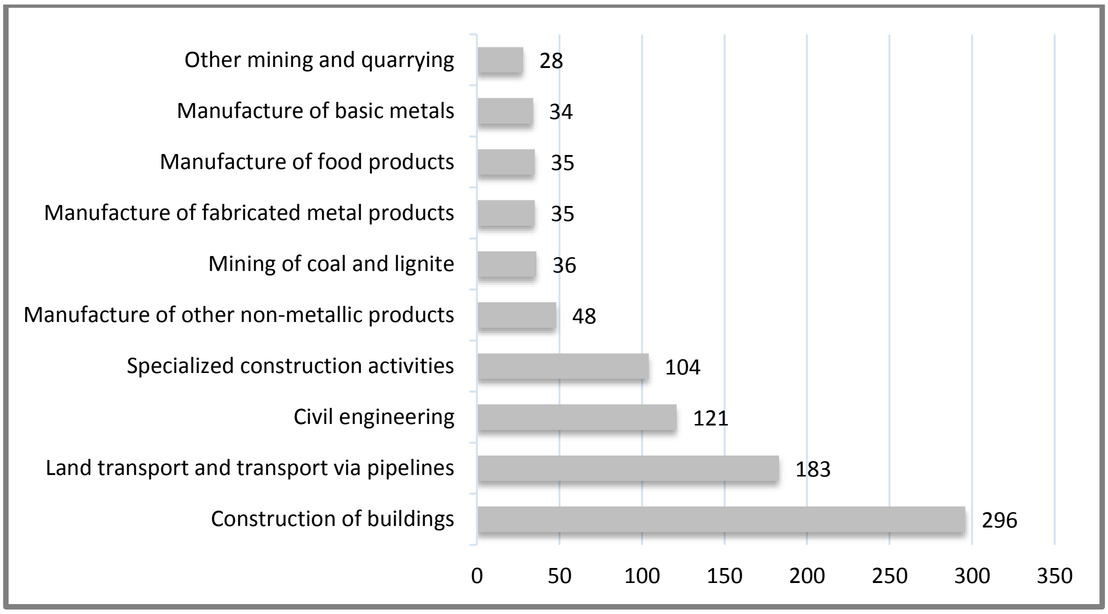


Figure 2.2 Top ten fatality intensive sector of Turkey in 2013 (SGK 2013 Work Accidents and Occupational Diseases Statistics)

In Turkey, two economic activities under the codes of “05” and “41” which are called as “mining of coal and lignite” and “construction of buildings” respectively, are usually in the top ten hazardous occupations in terms of fatality numbers. This situation forces the academicians and experts to study on occupational health and safety of the workers of these fields and drives legislators to make regulations. In many countries of the world as well as in Turkey, mining and construction sector came to minds while thinking over occupational health and safety issues.

Although high fatality rates at coal mining sector is a disincentive factor in performing this job, coal is essential to the functioning of our society and has to be produced (Margolis, 2009). As can be appeared in ILO Code of Practice on Safety and Health in Underground Coalmines,

> *“Industrialization was and continues to be fuelled by coal. Internationally, coal is the most widely used energy source in electricity generation and an essential input to most steel production; consequently, it is of great importance for many countries economies.*” (ILO Code of Practice on Safety and Health in Underground Coalmines, 2006).

It is not possible for a country who wants to develop, to abstain from producing coal, especially when it has got producible reserves. For this reason, it is vital for governments, employers and workers of mining sector to cooperate and to improve occupational health and safety and as a result reduce the workplace hazards and injuries and diseases.

2.2 Occupational Safety and Health Terminology- Risk, Hazard, Risk Management, Risk Analysis, Risk Evaluation, Risk Assessment

All businesses regardless of their activity, size or structure; must assess risks related to occupational health and safety to meet legal obligations of Occupational Health and Safety Law (Law No, 6331). Actually, the terms like “risk”, “hazard” and “risk assessment” are not comprehended by even occupational health and safety professionals. The descriptions of these terms in Occupational Health and Safety Law (Law No, 6331) are as follows:

Risk:	*Probability of loss, injury or other harmful result arising from hazard.*
Risk assessment:	*Activities required for identifying hazards which are existing in or may arise from outside the workplace, analyzing and rating the factors causing these hazards to turn into risks and the risks caused by hazards and determining control measures.*
Hazard:	*Potential which exists at the workplace or may arise from outside the workplace to cause harm or damage which could affect the worker or the workplace.*

"Risk management", "risk assessment" and "risk evaluation" terms are generally confused with each other and they are used like all means the same. However, their differences and relations should be well known before developing a basic understanding. Lev M. Klyatis and Eugene Klyatis stated these terms as following:

Risk management:	*The systematic and iterative optimization of the project, resources, performed according to the established project risk management policy.*
Risk evaluation:	*Procedure based on the **risk analysis** to determine whether the tolerable risk has been achieved.*
Risk assessment:	*Overall process comprising a **risk analysis** and a risk evaluation.*

In addition to these definitions, OSHA's definition for the risk assessment is more related with occupational health and safety and is as follows:

"Risk assessment is the process of evaluating risks to workers' safety and health from workplace hazards. It is a systematic examination of all aspects of work that considers:

- what could cause injury or harm
- whether the hazards could be eliminated and, if not,
- what preventive or protective measures are, or should be, in place to control the risks."

European Commission has also defined these terms in Risk Assessment and Mapping Guidelines for Disaster Management as follows:

Risk assessment:	*The overall process of risk identification, risk analysis, and risk evaluation (ISO 31010).*
Risk identification:	*The process of finding, recognizing and describing risks (ISO 31010).*
Risk analysis:	*The process to comprehend the nature of risk and to determine the level of risk (ISO 31010).*
Risk evaluation:	*The process of comparing the results of risk analysis with risk criteria to determine whether the risk and/or its magnitude is acceptable or tolerable (ISO 31010).*

In order to better understand risk analysis, risk evaluation, risk assessment and risk management concepts, it could be very useful to have look at Australian standard having the code of AS/NZS 4360:2004 which explains the risk management process clearly. It presents a detailed logical framework for a risk management process in order not to overlook any significant risks (Figure 2.3).

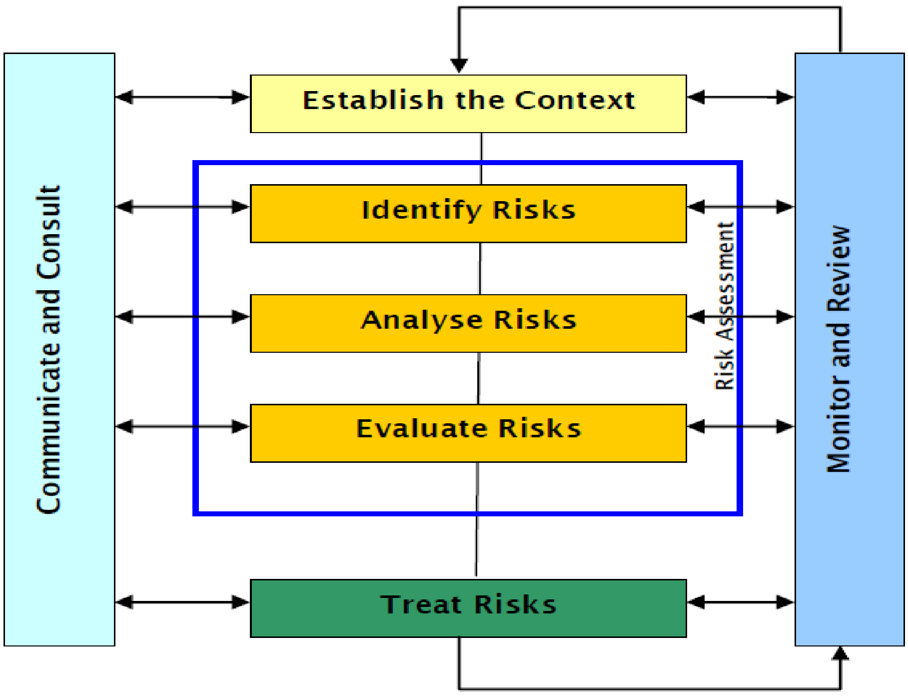


Figure 2.3 The phases of the risk management process (Standards Australia, 2004, Risk Management, AS/NZS 4360:2004)

2.3 Workplace Hazards in Underground Coal Mines

Coal mining business is full of potential hazards leading to catastrophic disasters due to its multidimensional nature of dangers originating from materials, equipment, human resources and environment (Sarı *et al.*, 2004). Each coal mine enterprise has its own characteristics and this multivariate structure preclude the standardization of hazards related to underground coal mines.

Leigh *et al*. (1990) collected the factors leading to accidents under two title:

- Personal and behavioral factors: factors associated with the injured worker
- Environmental factors: agencies instrumental in causing injury and circumstances surrounding the injury

According to Donoghue (2004), mining is an interdisciplinary business, benefiting from various professions and occupational health hazards in mining can be outlined as:

- Physical hazards: noise, heat, humidity, whole body vibration, hand–arm vibration, solar ultraviolet exposures in surface mining operations, high barometric pressure in deep underground mines and low barometric pressure in high altitude mines,
- Chemical hazards: Coal dust, methane gas, carbon dioxide, and hydrogen sulphide gas in underground coal mines, diesel particulate exposures in underground mines because of diesel powered mobile equipment, crystalline silica dust, arsenic (sometimes a contaminant of metal ores), metal ores including those of lead, cadmium, manganese, platinum, and cobalt, mercury in some gold mining operations,
- Biological hazards: tropical diseases such as malaria and dengue fever at some remote mining locations, leptospirosis, and ankylostomiasis due to rats
- Ergonomic hazards: cumulative trauma disorders due to low mechanization and high manual handling, shoulder disorders due to overhead work during ground support, fatigue in relation to shiftwork
- Psychosocial hazards: drug and alcohol abuse, due to remote locations mine employees separated from their families and communities during work periods, impact of fatal and severe traumatic injuries on colleagues' morale.

ILO Code of Practice on Safety and Health in Underground Coalmines defines safety risks as well as health risks:

- mine explosions and mine fires
- falls of the mine roof, face and sides (ribs)
- disabling and deadly lung diseases caused by the inhalation of respirable coalmine dust
- noise-induced hearing loss
- crushing of a miner between machinery or machinery and the coal sides in confined spaces
- shock, burns, and electrocution

- ignitions of methane which can explode during coal cutting
- inundations of dangerous gases, water or other free-flowing materials from old mine workings or geological faults
- outbursts of rock, coal or gases released from the earth under extreme pressure
- premature or improper detonation of explosives
- exposure to harmful chemicals and harmful agents used in mines

In addition to the list above, ILO Code of Practice on Safety and Health in Underground Coalmines defines numerous other hazards in coalmines that can result in injury, illness or death as:

- slips, trips and falls
- handling materials
- unguarded machinery
- falls from heights
- excessive temperatures/heat
- vibration
- ergonomics

Kurnia and Mujumdar (2012), identify hazards in underground coal mining as:

I. Structural/geological hazards
   i. Rib/roof failure
   ii. Failure of supported ground
   iii. Pillar failure or collapse
II. Mine gases hazards
   i. Oxygen depletion
   ii. Methane
   iii. Carbon monoxide, etc…
III. Chemical hazards
   i. Coal dust
   ii. Crystalline silica
IV. Machinery/equipment hazards
V. Physiological hazards

2.4 Accident Types Examined in This Study

Underground coal mining activity has always contained dangers within itself and lead to many accidents. According to Brnich and Kowalski (2010), in U.S. underground coal mines, hundreds of disasters leading to thousands of miner deaths have occurred since 1900s (Table 2.1).

Table 2.1 Number of underground coal mine worker fatalities by type of disaster, 1900 through 2008

Type of incident	Number of Events	Number of Fatalities
Explosion	420	10,390
Fire	35	727
Haulage	21	145
Ground fall/Bump	14	92
Inundation	7	62
Other	17	199

It is a fact that when the history of the underground coal mine disasters are examined, explosions, fires, haulage incidents, ground falls and inundations took place on the top. In the handled data most of these have not been observed except haulage incidents and ground falls. The available data classifies accidents in eight categories as roof fall, methane and other gases, electric, machine, material, transportation, explosive, and miscellaneous.

2.4.1 Roof Fall

Roof falls are usually ranking first in underground coal mine accidents occurred in Turkey. In the area of investigation roof falls come first and caused 42% of all the accident cases. According to MSHA's classification of mine accidents, fall of roof or back is defined as:

> "*Underground accidents which include falls while barring down or placing props; also pressure bumps and bursts*".

In order to prevent roof fall accidents, causes of them must be scrutinized. Geologic defects in the roof rock, moisture degradation of shales, extreme loading conditions under high cover, multiple seam mining and inadequate support can give rise to a roof fall (Molinda and Mark, 2010). In order to avoid roof falls, a proper roof support taking account of the conditions of the mine and possible causes of roof fall must be designed and installed. However, roof falls can occur even in supported areas. Therefore, roof support systems must be monitored periodically. According to MSHA accident database, in 2005, small rocks falling from between permanent roof supports and roof skin fall resulted in much more injury compared to massive roof fall (Compton et al., 2008).

2.4.2 Methane and Other Gases

Accidents related to methane and other gases are rarely seen events compared to other type of accidents; however, if they are seen they result in disasters and many fatalities. In the area of investigation, during a period of January 2003 to December 2013, only 3 accidents out of 4731 accidents have occured due to methane and other gases. One of them led to death due to asphyxia, while the other two led to burn injuries.

Explosions and fires due to methane and other mine gases may lead catastrophic loss of life, property and mineral resource. Methane is a suffocative gas and may lead suffocations even if it does not form an explosible atmosphere. In order to prevent accidents related to methane and other mine gases, they have to be controlled properly. The basic steps for efficient methane control are moving a sufficient quantity of intake air from the end of the tubing or curtain to the face, mixing intake air with methane gas liberated at the face and moving methane contaminated air away from the face (Taylor et al., 2010).

Methane control in underground coal mines varies according to current situation of the mine. Pre-mining drainage may be applicable before excavation while fresh air ventilation, water spray, inert ventilation, scrubber ventilation techniques are practicible during excavation. After excavation, inertisation and post-mining drainage are practised generally (Kurnia and Mujumdar, 2012).

2.4.3 Electrical Accidents

With the advancement of technology in underground coal mines, the use of electric power tools increased. Although the use of electric power tools has provided numerous advantages, it has also brought some disadvantages and gave rise to electrical accidents.

According to MSHA's classification of mine accidents, electrical accident is defined as *"Accidents in which electric current is most directly responsible for the resulting accident."*

U.S. Mine Safety and Health Administration (MSHA) statistics shows electrical fatality rates for the mining industry as 1.36 deaths per 100,000 workers from 2000 to 2009. These statistics prove mining to be among the most hazardous industries with respect to electrical hazards (Homce and Cawley, 2013). Between the years 2000 and 2009, 39 fatal electrical accidents have occurred and 21 of them took place in coal mining, with 12 in underground operations and nine at surface operations. The most frequent type of power system components or equipment involved in accidents resulting to electrical injuries were electrical switchgear, trailing cables, batteries used in battery-powered underground mobile equipment, power cable plugs and couplers and surface equipment engine-starter batteries. The electrical injuries mostly occurred due to no or inadequate lock out and tagging, failure of power system components and contact of overhead electrical power lines by mobile equipment (Homce and Cawley, 2013).

2.4.4 Mechanical Accidents

Mechanisation has also been ascended with the development of technology in underground coal mines which gave rise to an increasement in the number of accidents due to machinery. According to Homce and Cawley (2013), in U.S., machine related accidents were the 3rd most common cause of injuries in the mining between the years 2000 and 2009. Ruff et al. (2011) indicated that these type of accidents include workers entangled in rotating machinery, struck by moving machine components or run over by mobile equipment. During 2000-2007, in U.S., the most common machinery involved in these accidents are rock or roof bolting machines, load-haul-dump, scoop trams, conveyors and shuttle cars (Ruff et al., 2011).

Machine related accidents may be seen both during the operation and maintenance or repair. Between the years 2000 and 2007, 46% of the accidents occurred during the operation of the machine and 25% occurred during maintenance or repair (Ruff et al., 2011).

2.4.5 Material Related Accidents

In the area of investigation, of all the 4731 accidents, 597 occurred due to material handling and hand tools and these type of accidents are 3rd most common seen accidents. Between the years 2000 and 2009, material handling ranks 1st and hand tools rank 4th in the causes of accidents in U.S. mines (Homce and Cowley, 2013).
Between June 1998 and the end of December 2002, loading and unloading supplies and materials, handling coal rock and waste, machine maintenance and repair and moving power cables are the most causing operations leading to material related accidents. In order to prevent materials handling injuries, behavior modifications and mechanical solutions must be proposed. Behavior modifications involve the development of a series of articles on safety solutions and training materials that focus on common lifting tasks while mechanical solutions involve the mobile manipulator system and the in-mine hoist system (Stewart et al., 2007).

2.4.6 Accidents Related to Transportation

Transportation and haulage operations in an underground coal mine covers transportation of personel, coal, waste rock, several supplies such as materials for ventilation, roof support and explosives. Underground coal mine haulage is comprised of face haulage (at the production section or panel), intermediate haulage, (where production from several sections are transported) and mainline haulage (transportation for the entire mine). An accident in the mainline haulage can affect the entire production of the mine as well as the safety of the miners (Lineberry and Bise, 2013). According to MSHA injury data, between 2003-2012, 52 (or 28%) of the fatalities and 2564 (or 11%) of the lost-time injuries in underground coal mines were due to haulage machines like shuttle cars, scoops, conveyors, elevators, load-haul-dumps, mine cars, underground trucks, and tractors (Randolph and Trackemas, 2014).

2.4.7 Accidents Related to Explosives

Blasting operations in an underground coal mine is a very important issue in terms of miners' health and safety. In U.S. mining industry, between 1978 and 2003, 1131 blasting-related injuries have occured (Bajpayee et al., 2005). These injuries have arised due to blast area security, premature blast, flyrock, misfires, and fumes, transportaion and disposal of explosives. In underground mines creating a secure blast area is much more complicated than surface mines. Ventilation, roof characteristics, and the roof control plan of the mine must be scrutinized before a blasting operation in an underground coal mine. Blasting could give rise to ground fall in adjacent entries and exposure to smoke, dust or toxic fumes. All workers must be threw away from such adjacent entries or other affected airways (Bajpayee et al., 2005). In most of the mines blasting operations are made at the shifts when there is no worker. Bajpayee et al. (2005) indicate that the principles for creating a secure blast area are accurate determination of the bounds of the blast area, clearing employees from the blast area, effective access control, use of adequate blasting shelters, efficient communications, and training.

2.5 Risk Analysis Methods in Underground Coal Mines

Depending on the circumstances, risk analysis techniques could be qualitative, semi-quantitative or quantitative or a combination of these. Complexity and costs of these analyses is highest in quantitative, then semi-quantitative and qualitative, sequentially. When the likelihood and the severity of the mining hazard is assessed by qualitative analysis a word form or descriptive scales are used generally. However, though the number allocated to each description does not have to bear any accurate relationship to the actual magnitude of the severity or likelihood, in semi-quantitative analysis, qualitative scales are given values. In quantitative analysis, numerical values (rather than descriptive scales used in qualitative and semi-qualitative analysis) are used for both the severity and likelihood utilizing data from a variety of sources. Risk matrix, risk monogram and SPEAR matrix are the examples for qualitative risk analysis (Risk Management Manual for the Australian Coal Mining Industry, 2007).

More advanced risk analysis tools which deals with risks quantitatively are Workplace Risk Assessment and Control (WRAC), Preliminary Hazard Analysis, Failure Modes, Effects and Analysis (FMEA), Fault / Logic Tree Analysis (FTA/LTA) and Event / Decision Tree Analysis (ETA/DTA), Hazard and Operability Studies (HAZOP) and Bow Tie Analysis (Iannacchione et al., 2008).

This study combines both qualitative and quantitative risk analysis techniques. While analyzing the risks in a qualitative approach Fine-Kinney Risk Nomogram is used and the results obtained by this approach are presented in Chapter 4. This method provided an awareness about the most risky situations and a prioritization is conducted for each situation. Previous researches that handling the risks in a prioritization approach by ordering the magnitude of risks from large to small are mentioned in Section 2.5.1. Treatment of risks in a quantitative standpoint is performed by practicing two statistical forecasting techniques which are regression and time series analysis. The findings of these techniques are discussed in Chapter 5. Previous researches about accident prediction utilizing statistical measures are addressed in Section 2.5.2.

2.5.1 Previous Risk Prioritization Studies in Underground Coal Mines

According to Mahdevari et al. (2014), struck by materials (rock, wood, etc.) falling off from roof or rib and catastrophic failures are the major high risk hazards in underground coal mines and need the most attention. It is also stated that roof failure is almost always the main cause of accidents in the Kerman coal mines in Iran resulting in death, disability, injury, equipment damage, and financial losses. Mahdevari et al. (2014) specify the high and low risk hazards by using a methodology based on fuzzy TOPSIS. Instability of coalface, instability of immediate roof, firedamp explosion, emission of gases such as H_2S, CO, CO_2, NO, etc., stopping of ventilation system, wagons separation in inclines, asphyxiation due to inspiration of coal dust and toxic gases are high risk hazards where electricity problems of water pumps, water pressure from pump stations and reticulation, hazards during maintenance and repairs, drowning, radiation, reflection and excessive glare have relatively low risk.

According to Hull et al. (1996) injuries to the back, knee and multiple locations in the body are more severe than head and neck injuries. For the age factor in determing the severity of injury, they concluded that the older a mine worker is the more severe is his injury. Injuries resulting from overexertion, fall of a person, and falling object/substance are significantly more severe than injuries resulting from stepping on/striking against/struck by an object (Hull et al., 1996). The agency of accident is another factor used for that study to determine severity of injury. It is inferred that injuries involving means of transportation and the working environment are significantly more severe than injuries involving chemicals/materials/substances. When the severity is evaluated according to mine worker activity, they deduced that injuries to those engaged in transport related activities were significantly more severe than injuries to those engaged in equipment repair/maintenance/service, and metal/mechanical trades. For the mining region factor, it is concluded that injuries occurring in the Western mining region are significantly more severe than injurious incidents occurring in the Eastern mining region in NSW. They also utilized the previous hours worked to find the severity of injury and it is concluded that the more hours worked in the seven days prior to injury the less severe was a mine worker’s injury. When they look to severity of injury from the location viewpoint, they inferred that injurious incidents occurring in other underground locations such as workshops and drift areas were significantly more severe than injuries occurring at the coal face. Finally, they found that injuries experienced by mechanical unit men were significantly more severe than injuries experienced by other tradepersons (Hull et al., 1996).

In 2009, Margolis studied on Mine Safety and Health Administration's (MSHA) database on accidents, injury, and illness from the years 2003 through 2007 to examine how age, experience at the current mine, total experience as a coal miner, and experience in the current job affects injury severity. A multiple regression analysis was performed with age, and the three experience variables as independent variables and days lost as the dependent variable. According to Margolis, although getting older brings about decreases in health and safety, there are also benefits of increasing age due to experience and familiarity with the work environment. She found that as total mining experience increases, miners miss more days of work after suffering an injury. Futhermore, as age increases, miners miss more days of work after an accident (Margolis, 2009).

Leigh et al. (1990) states that incident rates record the highest values in underground mine face workers followed by underground mine non-face workers, underground mine surface workers and open cut mine workers. By using the data covering a period between 1 July 1986 and 31 December 1988 in the N.S.W. coal mining industry, the relationship between lost time injuries and factors like age, experience, occupation, part of the body injured, and shift were examined and the relative importance of these factors are discussed by looking distributions. It is indicated that workers under age 40 had a higher risk than older workers. Underground miners getting an injury had more experience than open cut miners getting an injury. The most insecure occupation is marked as underground miners. No distinction is made within underground miners because they often rotate jobs. For both surface and underground mining the trunk especially the back is the most affected body part. Lastly, most of the injuries were sustained during the day and afternoon shifts (Leigh et al., 1990).

Sarı (2002) compares the two underground coal mines by utilizing risk matrix technique in his doctorate thesis study. In ELI Soma Eynez mine, which applies both conventional and fully-mechanized longwall mining, most risky accident types are falls of ground and manual handling for mechanized panels and manual handling for conventional panels. In conventional panels, hands and main body are subjected to more injury while in mechanized panels, main body and feet are more prone to injury. It is also concluded that production workers in conventional panels suffer more from injuries compared to mechanized panels (Sarı, 2002).

2.5.2 Previous Accident Forecasting Studies Utilizing Statistical Measures

During the literature survey it is seen that the linear relationship between number of accidents and predictor variables is commonly used by researchers. In 2016, Tsoukalas and Fragiadakis, have studied the effect of working conditions on occupational injury by Multivariable Linear Regression (MVLR) method, using data of occupational accidents at ship repair sector and by comparing the predicted values with the reported data. It was demonstrated that the proposed model is a useful and efficient method for predicting the risk of occupational injury (Tsoukalas and Fragiadakis, 2016). Linear regression model explaining the occupational accidents has also been used by the researchers of the mining sector. Buzkan and Buzkan (1990), tried to explain changes in the rate of mortal accidents depending on the number of workers, total coal production, coal progression, timber consumption, and actual wage by creating a linear regression model. They have revealed that all of these variables are significant when estimating the number of mortal accidents. Furthermore, Smith (1984) studied about coal mine roof falls by using multiple linear regression techniques with variables such as, presence of cracks and water before the occurrence of fall, sloughing of coal ribs, floor heave condition and type of roof support. A much closer study to the content of this study which is conducted by Hull et al. (1996) examines the relationship between characteristics of some underground coal mines and injury severity by using multiple regression techniques. They utilized the bodypart, age, accident type, accident agency, region, hours, activity, location, and occupation as factors to determine the injury severity. The study conducted by Hull et al. (1996), examines lost-time injurious incidents that occurred in the N.S.W. underground coal mining industry during the 4-year period from 1 July 1986 to 30 June 1990 by using multiple regression techniques. They utilized the bodypart, age, accident type, accident agency, region, hours, activity, location, and occupation as factors to determine the injury severity.

Direk (2015) evaluated the roof and rib fall accidents in an underground coal mine by using Fault Tree Analysis (FTA) and found the mean time of the system as 3.73 days which means that in TTK Amasra district, a worker expectedly had an accident from roof and rib falls approximately every four days. In an another accident forecasting study, Mevsim (2016) conducted FTA on methane explosions in TTK and revealed that mean time of the system is 11 months meaning that in every 11 months a methane explosion is expected.

During the literature search it is seen that time series analysis concept is frequently utilized in order to forecast future values of accident numbers, especially in traffic accident data. It is also a very useful tool to observe the trend of occupational accidents and to make estimates. Freivalds and Johnson (1990) built a time series model for a set of injury data in a glass manufacturing facility and they showed that Box Jenkins time series approach closely suits for the data not only for fitting a seasonal cycle, but also for accommodating monthly trends. Pedregal and Carnero (2010) forecast occupational accidents for different levels of severity using Multivariate Unobserved Components models developed in a State Space framework. Through quantitative time series analysis methods Kim et al. (2011) determined the industrial accident rate and the zero accident time systematically to begin a zero accident campaign for industry. Windsor and Monforton (1999) evaluated the effect of a safety training regulation, implemented by the US Department of Labor's Mine Safety and Health Administration (MSHA) in 1999, on injury rates at stone, sand, and gravel mining operations by an interrupted time series analysis. Sarı (2002) predicted the future occurences of accidents in two underground coal mines by the aid of time series analysis. For both mines, first order linear trend equation multiplied by a monthly seasonal index was found to be appropriate.

CHAPTER 3

DATA AND STUDY AREA

3.1 Research Area

Although the most common type of coal is lignite in Turkey, the Turkish coal sector produces both hard coal and lignite in an amount of 2 million tonnes and 63 million tonnes, respectively (Turkish Hard Coal Enterprise General Directorate Industry Report, 2015). Turkey's first hard coal mining production began in 1829 in Black Sea Eregli, with the discovery of coal by Uzun Mehmet (TTK, 2016). The first actual production of hard coal was in 1848 by Galata moneychangers who rented the basin from Hazine- i Hassa, with very primitive working conditions around 40-50 thousand tonnes of coal (TTK, 2016).

In Turkey, major amount of hard coal deposits appears in Zonguldak Hard Coal Basin in northwestern Turkey along the Black Sea (Figure 3.1). Zonguldak Coal Basin is dominantly run by Turkish Hard Coal Enterprises. In 2013, 70% of total hard coal was produced by Turkish Hard Coal Enterprises while the rest was produced by private sector (Turkish Hard Coal Enterprise General Directorate Industry Report, 2015). Turkish Hard Coal Enterprises' production activities are carried out by Armutçuk, Amasra, Kozlu, Karadon, and Üzülmez districts.

Complicated geological structure of Zonguldak Hard Coal Basin is an obstacle to production with full mechanization; therefore, coal is produced with primitive techniques based on manpower. However, in recent years, implementation of mechanized digging equipment compatible with basin requirements is accomplished on pilot scale and successful results were obtained. Studies oriented at extansification of these type of equipment still proceeds (Turkish Hard Coal Enterprise General Directorate Industry Report, 2015).

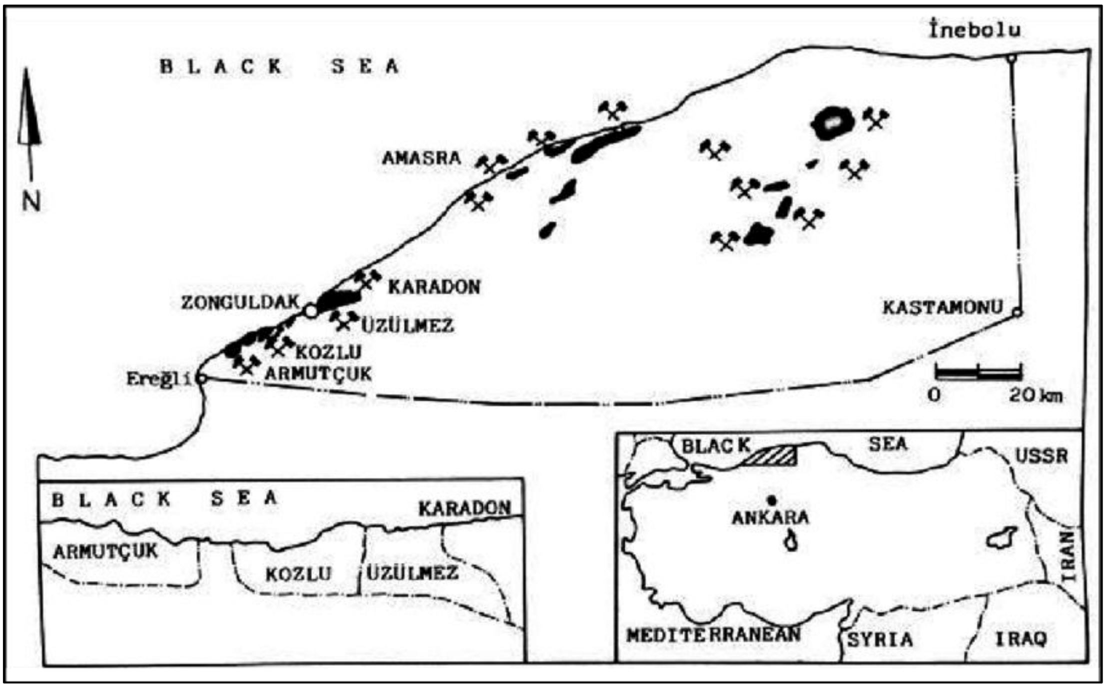


Figure 3.1 Zonguldak hard coal basin (Barış et al., 2016)

This study is conducted in Turkish Hard Coal Enterprise Üzülmez district and the data constitutes the accident records occurred during the period covering January 2003 to December 2013.

Üzülmez district gained legal entity status on 28.11.1985, a sub institution of Turkish Hard Coal Enterprise. It is an underground hard coal mine having a reserve of 303,668,492 tonnes and located in Zonguldak. Knowing that underground mines and especially coal mines are the most dangerous mining activities, this mine is chosen to be pilot region. Another reason in choosing this mine is that accident records are more detailed and trustworthy.

Üzülmez district resumes its production activities in 7 km east of Zonguldak in a 20 km^2 area. The area is surrounded by İncivez in the West; Gökgöl Tunnel in the South; Karabey Hill in the East; Kırat Hill, Güntepe Worker Lodgements, İnağzı, and Black

Sea in the North. The total reserve of the TTK Üzülmez district in 2016 is stated to be 303,269,237 tonnes. Proved, probable, and possible reserve proportions is shown in Figure 3.2 (TTK, 2016).

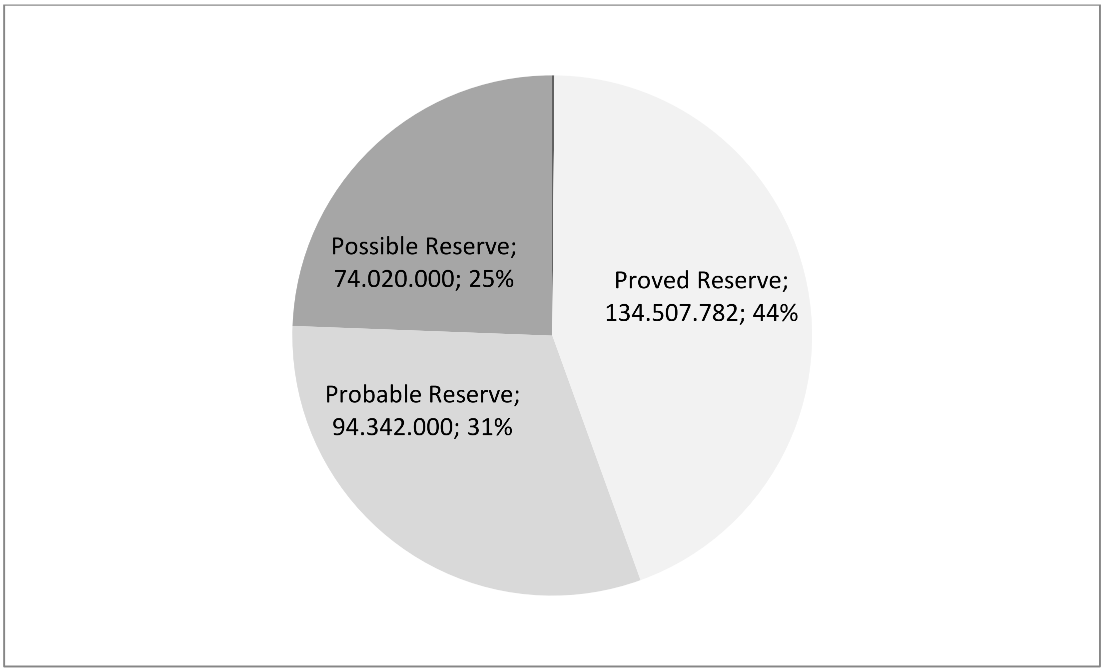


Figure 3.2 Reserve of TTK Üzülmez district (TTK, 2016)

In TTK Üzülmez district, coal production method changes panel to panel. Coal is extracted by longwall caving and retreat mining method at 33407 Nasifoğlu Batı Face, 33405 Tv Acılık Doğu Face, and 33405 Piriç Doğu Face whereas it is extracted by longwall caving and advance coal mining method at 33505 Sulu Doğu Face. Although studies about application of mechanized mining methods are still carried on, nowadays conventional extraction, transportation, and support methods are used predominantly. Chain conveyors are used for transportation of coal both throughout and end of the faces. Support units also vary by faces. Timber supports are utilized at 33407 Nasifoğlu Batı Face and 33505 Sulu Doğu Face whereas steel supports are used at 33405 Tv Acılık Doğu Face and 33405 Piriç Doğu Face.

3.2 Data Collection and Descriptive Statistics

Main features of the data collected from Turkish Hard Coal Enterprise Üzülmez district are evaluated quantitatively. The data involves the accident records of Turkish Hard Coal Enterprise Üzülmez Distinct and cover a period of January 2003 to December 2013. The accident data consists of 4802 accidents totally which covers both surface and underground accidents. A total of 4731 accidents which occurred underground is used in this study. The data includes several accident types, name, birth date, work beginning date, job, experience and education of workers suffering from accidents, affected body parts, accident date, time and location, and rest days.

The data collected under the title "accident type" divided into subtitles as roof fall, methane and other gases, electric, machine, material, transportation, explosive, and miscellaneous. Figure 3.3 shows how many accidents occurred in terms of subtitles. It can be clearly seen that accidents due to roof fall has the highest scores. The number of accidents related to roof fall is 1998 out of 4731, which corresponds to 42% of total accidents.

The second highest score is accidents related to the title "miscellaneous". Accidents arising from compressed air, crashing, rupture, insertion, sting, falling materials, bouncing materials, sliding materials, slip, fall, trip, twist, material handling and usage, fall from high, crashing into rock coming from chutes and others are united under the title "miscellaneous". These subtitles should not be recorded under a title, they must be reorganized separately. In consequence of combining these subtitles, the number of accidents under the title "miscellaneous" is quite high which corresponds to 39% of total accidents. Figure 3.4 demonstrates that 624 accidents occurred related to crashing, rupture, insertion, and sting which correspond to 34% of total "miscellaneous" accidents.

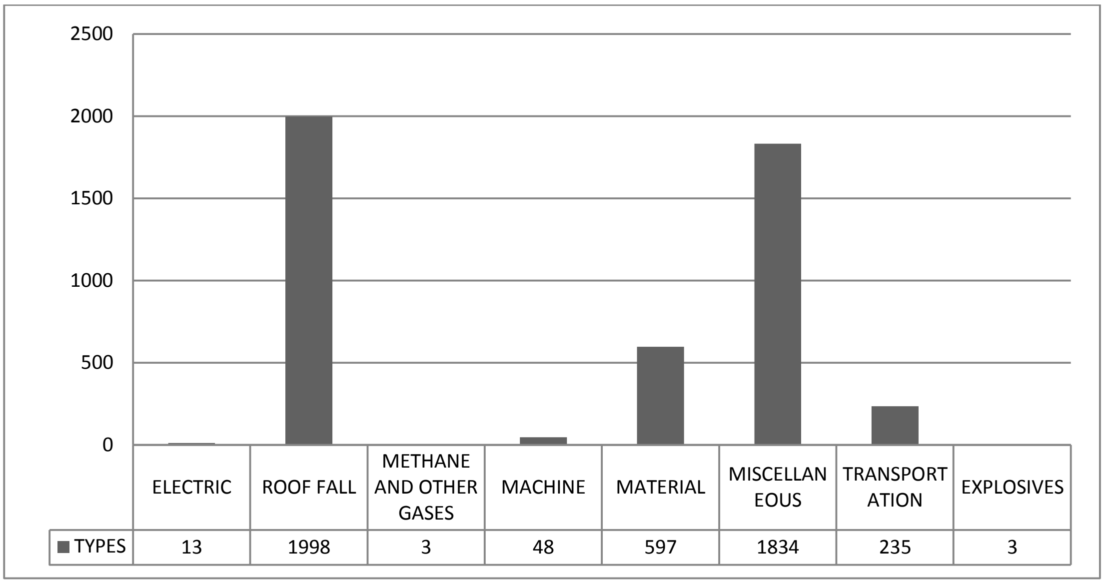


Figure 3.3 Accident numbers according to types

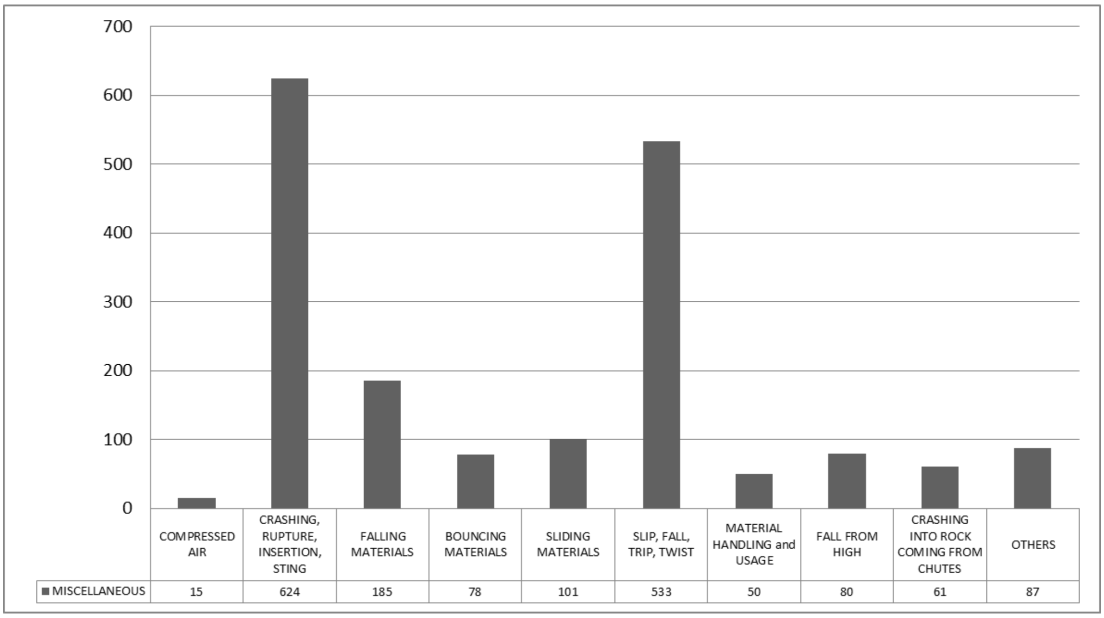


Figure 3.4 Accident numbers under the title “Miscellaneous”

The number of accidents according to the locations that they take place can be seen in Figure 3.5. Accident locations include longwall face, development headings, main transportation/haulage road, support maintenance/repair, electro mechanics shop, and miscellaneous. Longwall face seems to be most risky location by taking the number of accidents into consideration.

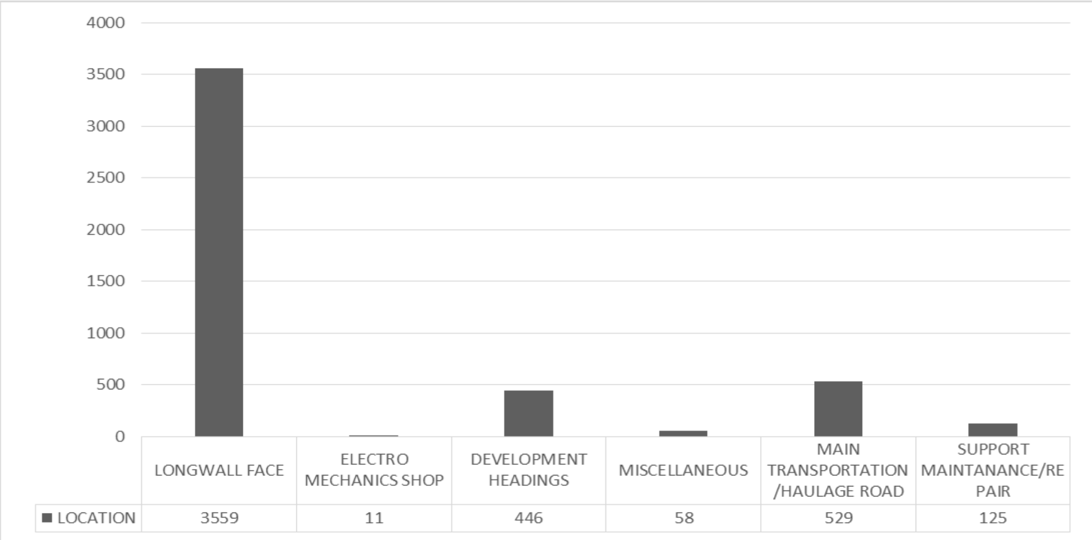


Figure 3.5 Accident numbers according to location

Evaluating the number of accidents according to working period shows that most of the accidents occur at the time interval 08:00-16:00. Shift 1 covers the working time between 08:00-16:00 while Shift 2 and Shift 3 covers the hours between 16:00-24:00 and 24:00-08.00 respectively. It can be seen from the Figure 3.6 that 2640 of total accidents occurs at Shift 1 and it corresponds to 56%. 24% occur at Shift 2 and 20% occur at Shift 3. Probably, due to all support and maintanance work together with the usual production work is carried out in first shift, half of the accidents occurred at Shift 1.

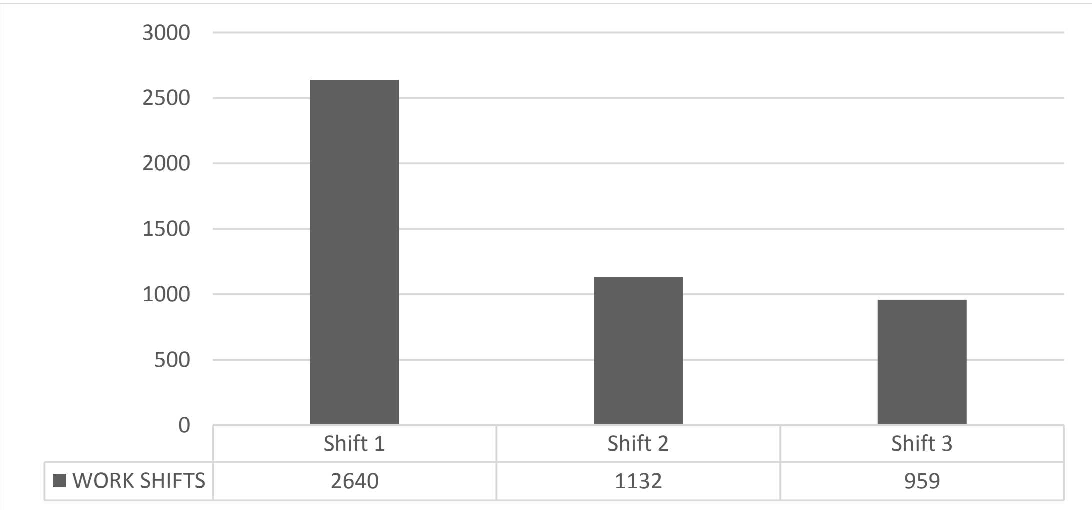


Figure 3.6 Accident numbers according to work shifts

According to data collected under the heading “job” there exists two categories; namely, primary job of the employee and the job of the employee at the time of the accident. This information is very useful in order to see whether the worker experienced an accident while he is carrying out a duty which is not related to his own primary job. Figure 3.7 shows that 4% of total accidents occurred while the worker is tasked with a job different from his usual job. Actually, it is expected that the number of accidents occurred while doing a different job are much higher than the number of accidents occurred while doing the same job. Underlying cause of this fact should be that the assignment in different jobs is an evaded thing by the managers of the mine because it leads to increasing number of accidents. Moreover, if the number of accidents according to jobs is evaluated, it can be seen from Figure 3.8 that longwall production workers have the highest share in encountering an accident. 75% of the total accidents experienced by the longwall production workers. In order to do an extensive evaluation, job distribution according to number of workers should be examined with job distribution according to number of accidents. Figure 3.9 and 3.10 display that although longwall production workers constitute the 42% of total workers, they contribute the accidents with a percentage of 75%. It can be concluded that longwall production workers have more share in accident numbers and they are the major contributors of the accidents because of the hazardous nature of the job.

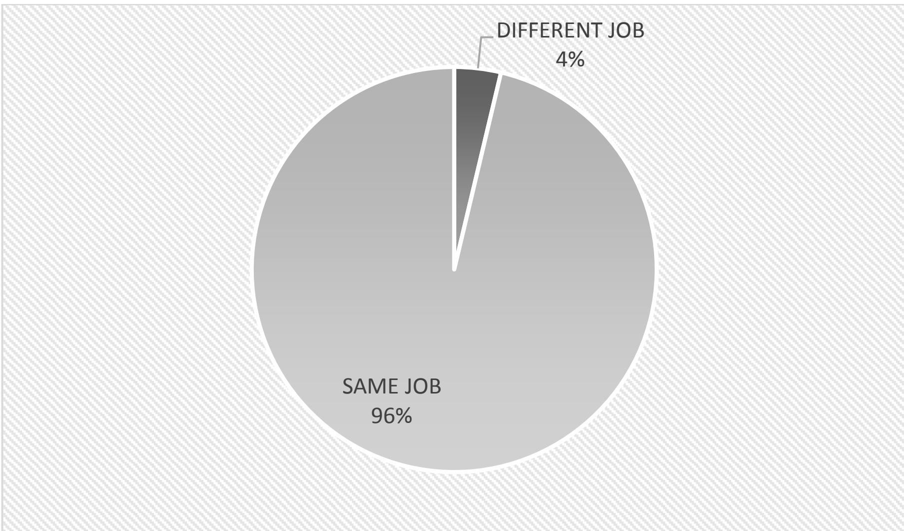


Figure 3.7 Accident distributions according to job at the instant of accident

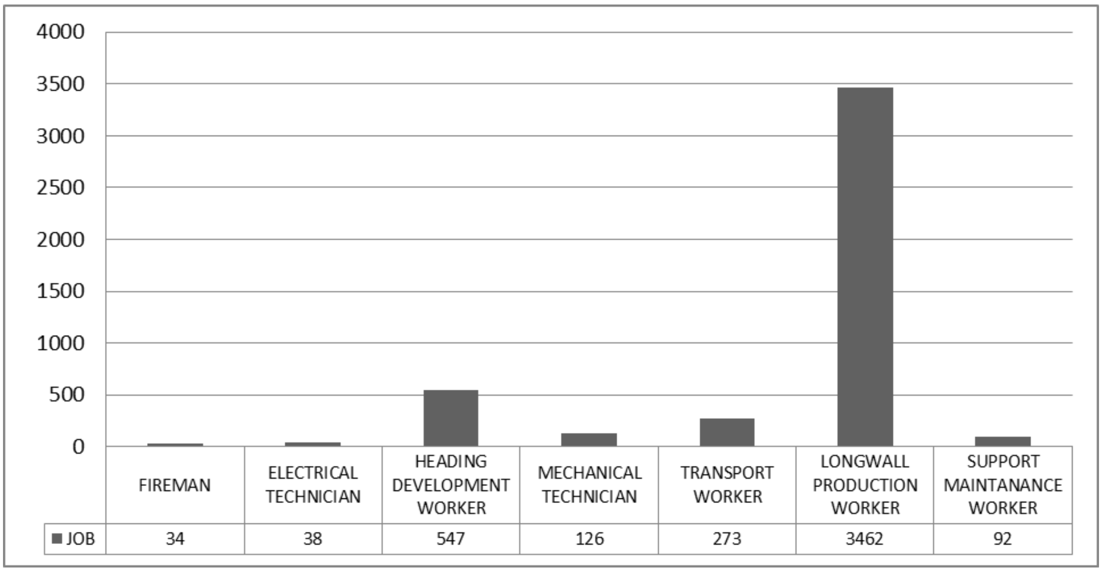


Figure 3.8 Accident numbers according to job

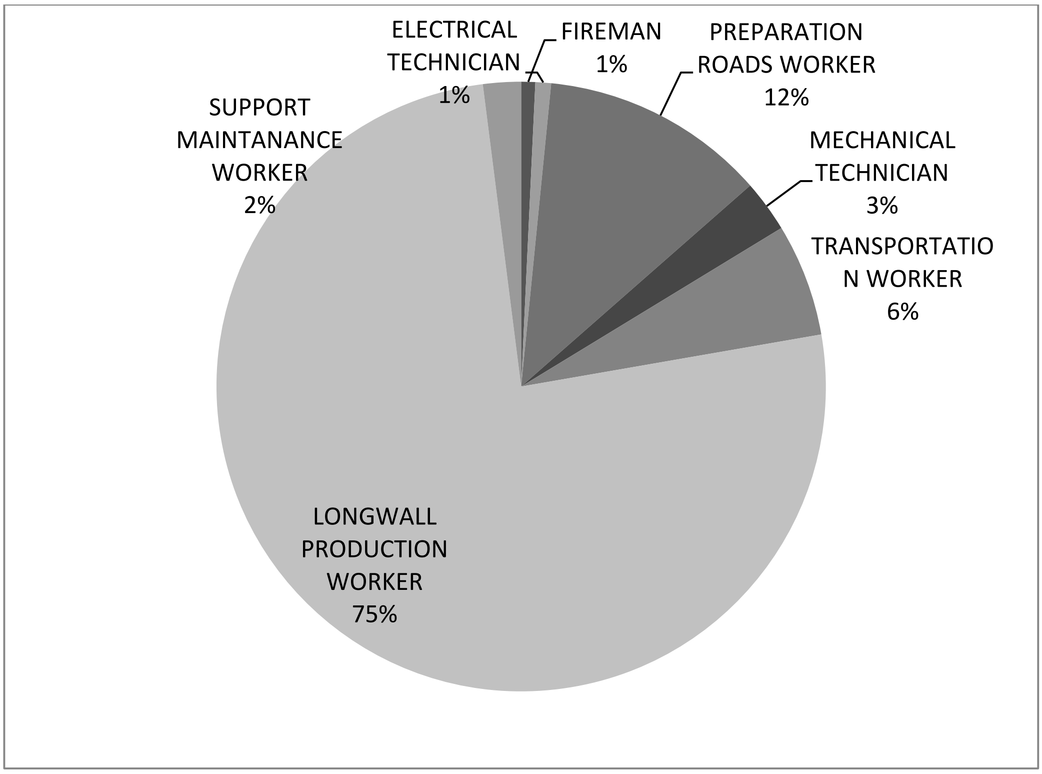


Figure 3.9 Job distributions according to number of accidents

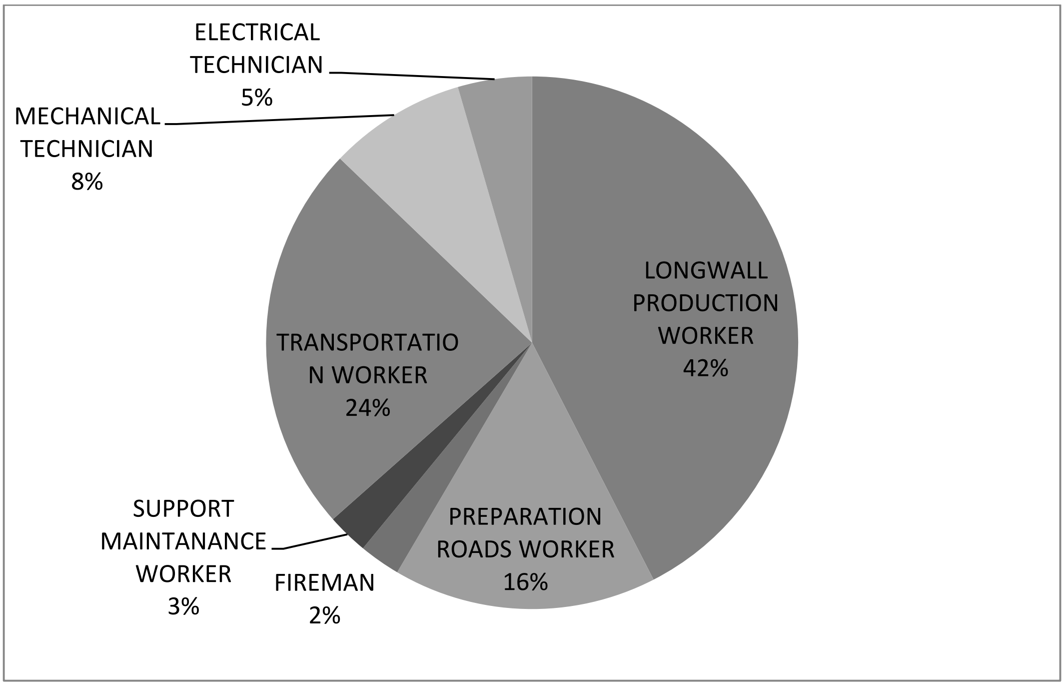


Figure 3.10 Job distributions according to number of workers

Education is another topic which should be examined when evaluating the occupational accidents. According to data collected, most of the workers suffering from accidents are primary school graduates (Figure 3.11).

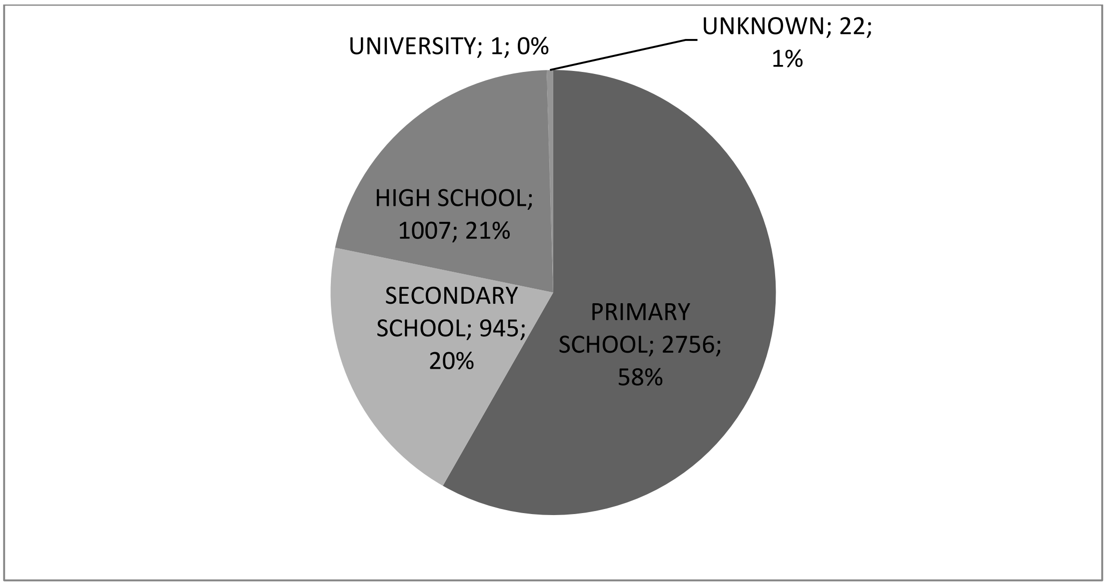


Figure 3.11 Education distributions of the workers experiencing accidents

When the accidents are handled for the case of injured body parts, 1486 of the total accidents end up with injured hand and fingers. Foot and toe has the second highest score after the hand and fingers (Figure 3.12).

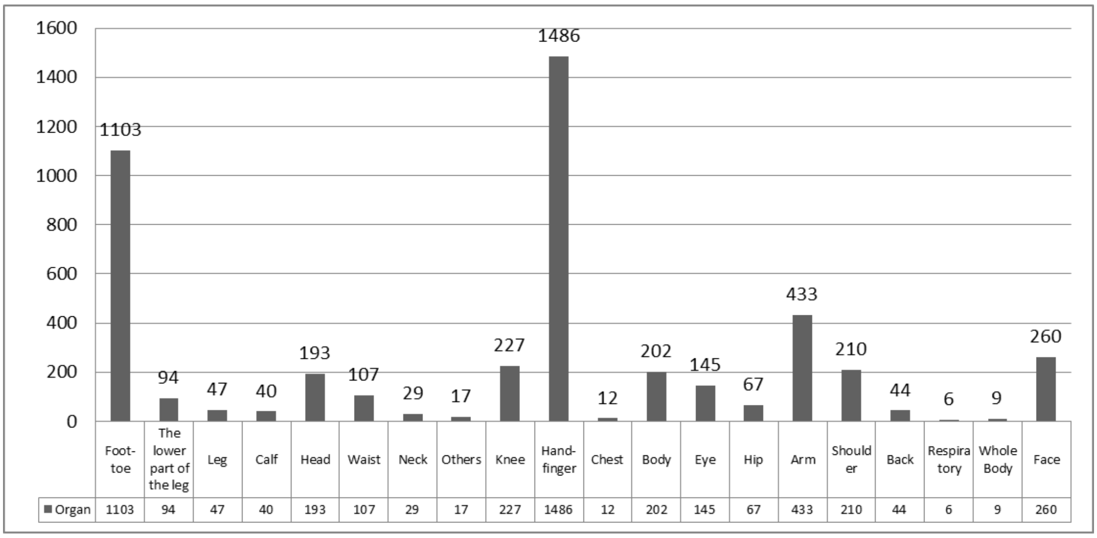


Figure 3.12 Accident numbers according to affected body part

The available data is also analyzed in terms of the ages of the workers experiencing accidents. According to data, ages of workers experiencing accidents range from 20 to 55. The distribution of ages is presented in Figure 3.13 in seven ranges which are 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, and 50-55. The ages between 30 and 34 are the most hazardous ages with 38%. The ages between 25 and 29 rank number two with 32%. It can be concluded that the workers suffering from accidents are quite young.

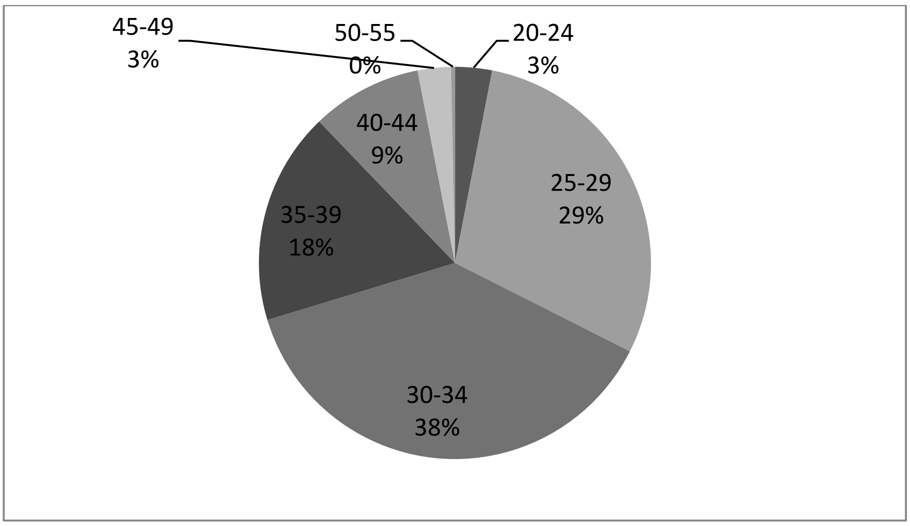


Figure 3.13 Age distribution of workers experiencing accidents

Experience is another subject that should be assessed as far as the occupational accidents are concerned. Whether the experience helps the workers in avoiding accidents or not is a very controversial issue. As it is shown in Figure 3.14, when the available data is taken into account, experience is of great value to keep away from the occupational accidents. Workers having little experience like 0-4 years and 5-8 years are more prone to accidents.

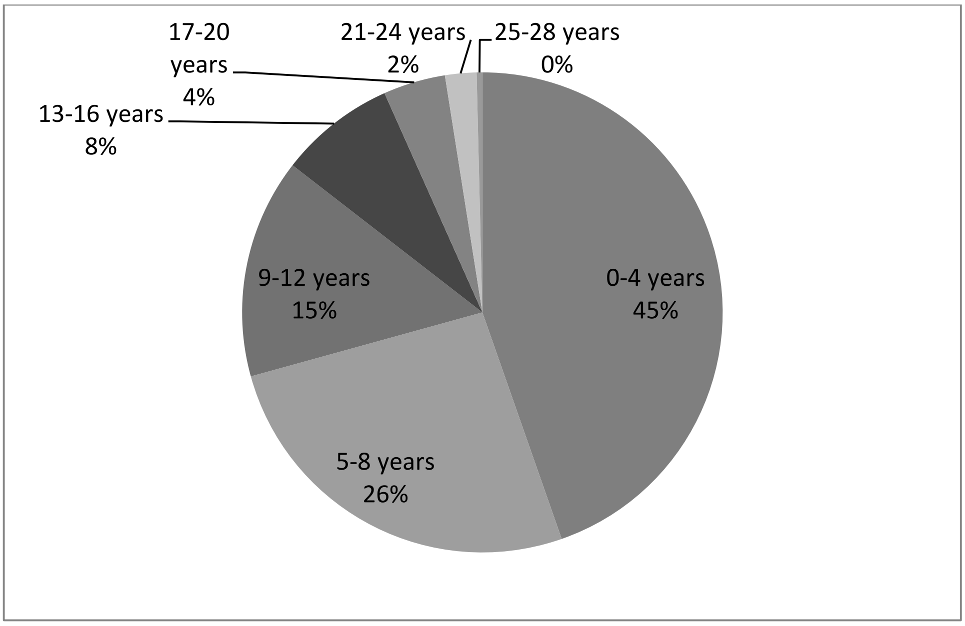


Figure 3.14 Experience distribution of workers suffering from accidents

In summary, for the study area, descriptive statistics show that;

- 4731 of the total 4802 accidents occurred in underground operations.
- Roof falls have the biggest share among all the accident types such that the number of accidents related to roof fall is 1998 out of 4731, which corresponds to 42% of total accidents. After the roof falls, miscellaneous, material, transportation, machine, electric, methane and other gases, and explosives come respectively.
- 3559 of the 4731 accidents took place in longwall face. Main transportation/haulage road, development headings, support maintanance/repair, miscellaneous, and electromechanics shop are the most accident encountered places respectively.
- 2640 of the 4731 accidents occured at Shift 1 (08:00-16:00) corresponding to 56% of the total accidents which is followed by Shift 2 and then Shift 3.

- 75% of the total accidents are experienced by the longwall production workers although they constitute the 42% of total workers. Then development headings worker, transportation worker, mechanical technician, support maintanance worker, electrical technician, and fireman comes respectively.
- Most of the workers suffering from accidents are primary school graduates with a share of 58%.
- 1486 of the total accidents end up with injured hand and fingers which constitutes the highest share. Foot-toe and arm come after the hand and fingers.
- The ages between 30 and 34 are the most accident prone ages corresponding to 38% of all accidents. Other age groups experiencing more accidents are 25-29, 35-39, 40-44, 45-49, 20-24, and 50-55 sequentially.
- Workers having 0-4 years experience are more prone to accidents occupying the 45% of accidents.

3.3 Occupational Accidents and Fatalities in TTK Üzülmez District

Between the years of 2003 and 2013, totally 4731 accidents occurred in underground operations such that 14 of them resulted in fatality, 1976 of them resulted in minor injury (slightly wounded), 2049 of them resulted in medium injury (wounded) and 692 of them resulted in major injury (seriously wounded). Among the results of accidents medium injuries has the highest share (Figure 3.15).

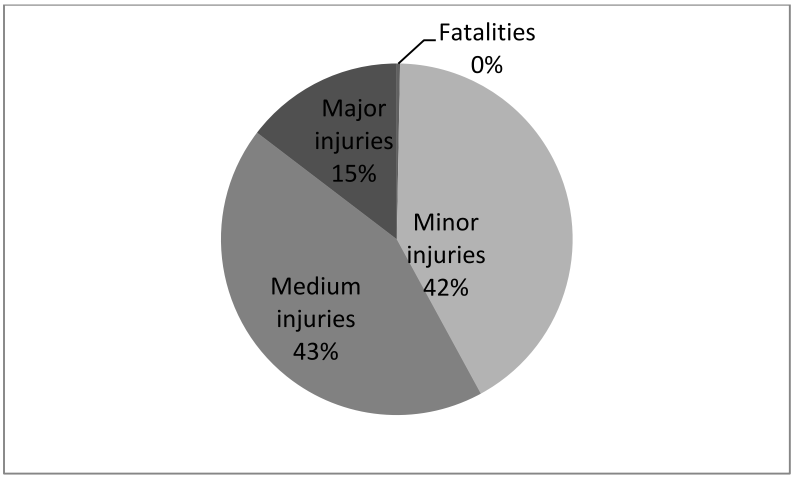


Figure 3.15 Classification of injuries according to accident severity

Another way of interpreting the interdependence of the number of occurrences of more and less serious consequence accidents is accident triangle model (Bellamy, 2014). The concept resembles an iceberg such that the visible and noticeable part (accidents) is very small compared to underwater part (incidents) (Saldaña et al., 2002). Herbert William Heinrich, an American industrial safety pioneer from the 1930s, made a contribution to the literature by bringing safety triangle concept for the first time. He deduced that for 1 serious accident or death occurs 29 accidents with lost days and 300 accidents without injuries (Figure 3.16). In 1969, Bird made a new aproach to the Heinrich's pyramid and edit the proportions after his study for the International Safety Academy, on 1,753,498 accidents in 297 companies (Saldaña et al, 2002). He stated that for 1 serious injury with disability occurs 10 Light injury (without disability), 29 accident with losses (property/equipment) and 600 incidents (Figure 3.17).

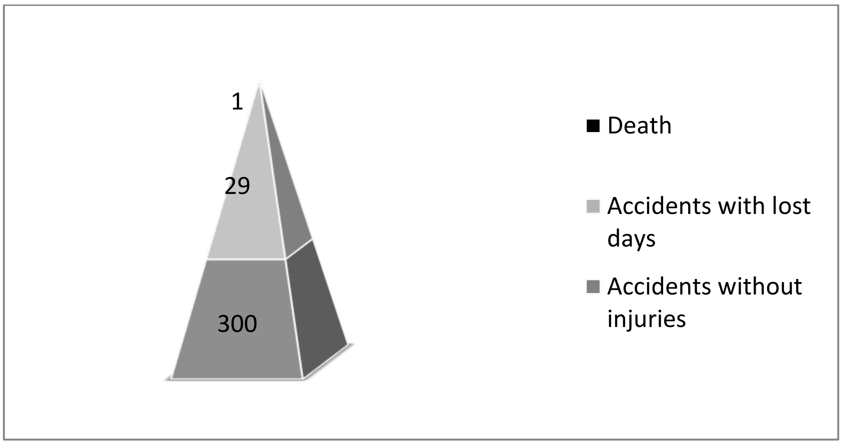


Figure 3.16 Pyramid of Heinrich (Heinrich, 1931)

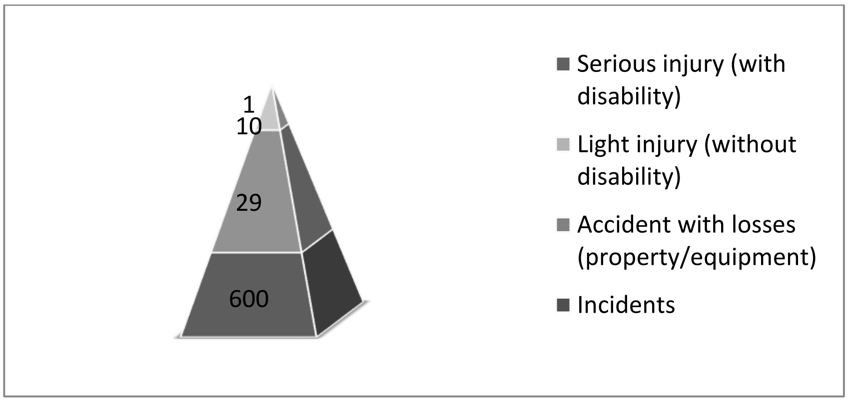


Figure 3.17 Pyramid of Bird (Bird, 1969)

If the available data has the knowledge of accidents without injuries, accident with losses (property/equipment) and incidents, proportions of Heinrich and Bird could be adapted for TTK Üzülmez district. However, if a triangle is formed with available data, it is seen that 14 fatality occurs for 692 major injury, 2049 medium injury and 1976 minor injury (Figure 3.18).

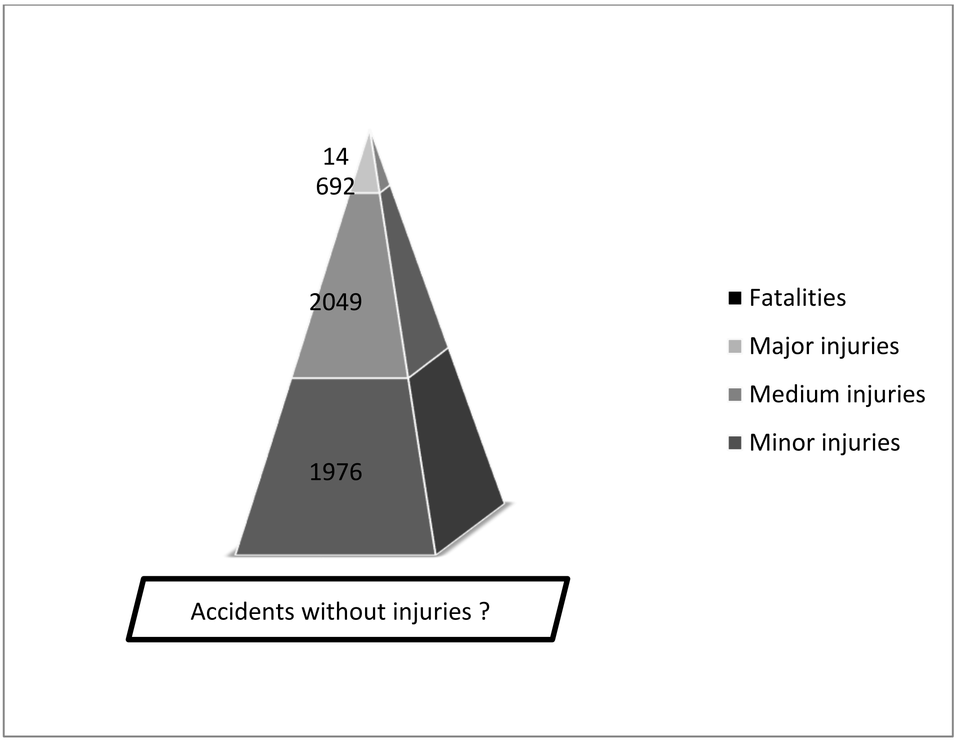


Figure 3.18 Pyramid for accidents at TTK Üzülmez District

Fatalities occured under various conditions such that 11 of these fatalities were caused by rock fall, 1 by heart attack, 1 by transportation, 1 by methane and other gases. When the locations of the accidents leading to fatality assessed, it is seen that most of them happened at longwall face (Table 3.1).

Table 3.1 Accidents leading to fatality in TTK Üzülmez District from 2003 to 2013

Fatality	**Location**	**Date**	**Time**	**Type**	**Job**	**Age**	**Experience**
1	Longwall face	26.03.2003	12:40	Roof Fall	Longwall prod. worker	31	3
2	Development headings	08.12.2003	12:00	Miscellaneous (Heart Attack)	Development headings worker	34	17
3	Longwall face	27.04.2006	20:15	Roof Fall	Fireman	42	18
4	Longwall face	14.06.2006	02:30	Roof Fall	Longwall prod. worker	44	13
5	Longwall face	08.09.2007	03:00	Roof Fall	Longwall prod. worker	29	1
6	Longwall face	04.01.2008	02:55	Roof Fall	Longwall prod. worker	38	8
7	Longwall face	04.01.2008	02:55	Roof Fall	Longwall prod. worker	35	8
8	Development headings	15.11.2008	03:15	Roof Fall	Development headings worker	44	18
9	Longwall face	11.06.2010	10:05	Transportation	Longwall prod. worker	27	2
10	Longwall face	04.09.2010	12:30	Methane and other gases	Development headings worker	32	10
11	Longwall face	10.03.2011	12:00	Roof Fall	Longwall prod. worker	30	3
12	Longwall face	13.08.2011	19:40	Roof Fall	Longwall prod. worker	30	5
13	Longwall face	28.11.2011	12:00	Roof Fall	Longwall prod. worker	38	12
14	Development headings	19.03.2012	12:00	Roof Fall	Development headings worker	37	12

CHAPTER 4

RISK SCORE MODELLING

4.1 General Information

In this chapter a risk score model is developed in order to rank the risk scores of each identified unit which are accident type, location, work shift, job, affected body part, age, and experience. A risk score model provides grading each accident type, location, work shift, job, affected body part, age, and experience and prioritizing and managing the risks accordingly. Fine (1971) defined the risk score (R) as interconnectedness between the consequences of an accident (C), the level of exposure (E) and the probability (P). Because risk does not arise without exposure, level of exposure (E) should be added to the risk formula.
Fine's formula for the risk score is given in Equation 1 (Fine, 1971).

$$\mathrm{R} = \mathrm{CxExP} \qquad \text{(Eq. 1)}$$

According to Kinney and Wiruth (1976),"risk" means the chance that some particular hazard may actually cause injury or damage. Consequence defines the magnitude of potential loss as a result of an occupational accident and is generally evaluated in two aspects namely, cost and lost workdays. Consequence of an occupational accident may be evaluated in two aspects namely, cost and lost workdays. According to Lebeau and Duguay (2013), the costs of occupational injuries can be classified into three groups: direct costs, indirect costs, and human costs. Direct costs comprised of constituents associated with the treatment and repair of the injury, such as medical costs. Direct cost data are usually found easily. Indirect costs are regarded as costs related to the lost opportunities for the injured employee, the employer, the co-workers, and the community. They involve mainly salary costs, administrative costs, and productivity losses. Different from the direct costs, indirect costs are usually more difficult to measure. Lastly, human costs are associated with the change in the quality of life of the employee and the people around him (Lebeau and Duguay, 2013). Exposure factor is the magnitude of workers' exposure to hazards and the greater the exposure to a potentially dangerous situation the greater is the associated risk. Finally, probability factor is the likelihood of occurrence of a hazardous event, in other saying the mathematical probability that it might actually occur.

In order to calculate a risk score, numerical values are assigned to these three factors. These values are arbitrarily chosen; however, they are self-consistent and together they provide a realistic but relative score for the overall risk (Kinney and Wiruth, 1976). It is also mentioned that because of the values assigned with the help of experience, some of the criteria may be adjusted over time. Since the results are intended to evaluate comparatively, the method will be acceptable in any organization as long as standards of judgement are consistent (Fine, 1971). The assigned values for the three factors forming the risk equation are given in Table 4.1, 4.2, and 4.3, respectively. The values shown with an asterisk are taken as reference. Others are interpolated according to reference points. After determining the values of these three elements of the risk formula for each special case, the risk score is calculated by substituting them into the Eq. 1. According to calculated risk score values, risk situation can be assessed based on Table 4.4. It is also referred that Table 4.4 is formed by experience; therefore, it can be adjusted when experience indicates otherwise (Kinney and Wiruth, 1976).
One of the most important point while conducting a risk analysis by Fine-Kinney method is that the risk score of one case alone is meaningless cause this method has the purpose of comparison (Fine, 1971). Therefore, in this chapter data is categorized under definite titles and risk scores of cases within a definite title are compared (Table 4.5). After this procedure is applied, the most risky accident type, location, work shift, job, affected body part, age, and experience is determined.

Table 4.1 Assigned probability values for Fine-Kinney method (Kinney and Wiruth, 1976)

Probabability	**Value**
*Might well be expected	10
Quite possible	6
Unusual but possible	3
*Only remotely possible	1
Conceivable but very unlikely	0.5
Practically impossible	0.2
*Virtually impossible	0.1

Table 4.2 Assigned exposure values for Fine-Kinney method (Kinney and Wiruth, 1976)

Exposure	**Value**
*Continuous	10
Frequent (daily)	6
Occasional (weekly)	3
Unusual (monthly)	2
*Rare (a few per year)	1
Very rare (yearly)	0.5

Table 4.3 Assigned consequence values for Fine-Kinney method (Kinney and Wiruth, 1976)

Consequence	**Value**
*Catastrophe (many fatalities, or >$107 damage)	100
Disaster (few fatalities, or >$106 damage)	40
Very serious (fatality, or >$105 damage)	15
Serious (serious injury, or >$104 damage)	7
Important (disability, or >$103 damage)	3
*Noticeable (minor first aid accident, or >$100 damage)	1

Table 4.4 Numerical risk scores (Kinney and Wiruth, 1976)

Risk score	**Risk situation**
>400	Very high risk; consider discontinuing operation
200 to 400	High risk; immediate correction required
70 to 200	Substantial risk; correction needed
20 to 70	Possible risk; attention indicated
<20	Risk; perhaps acceptable

Risk scores can also be calculated by using the nomograph given in Figure 4.1 as an alternative to Eq. 1 (Kinney and Wiruth, 1976). The scale of the nomograph is logarithmic in nature. In order to calculate a risk score by using this nomograph, as a first step values for all the factors (probability, exposure, and consequence) are determined and assigned on the nomograph. Afterwards, a line is drawn from the point for the likelihood factor through that for the exposure factor and extended to the tie line. The corresponding point on that tie line is actually the product of probability and exposure factors, although the numbers are not shown. Then, a second line is drawn from this point on the tie line through that for the consequence factor and extended to the scale for the risk score. As a result, numerical value of the risk score and its descriptive equivalent are obtained directly (Kinney and Wiruth, 1976).

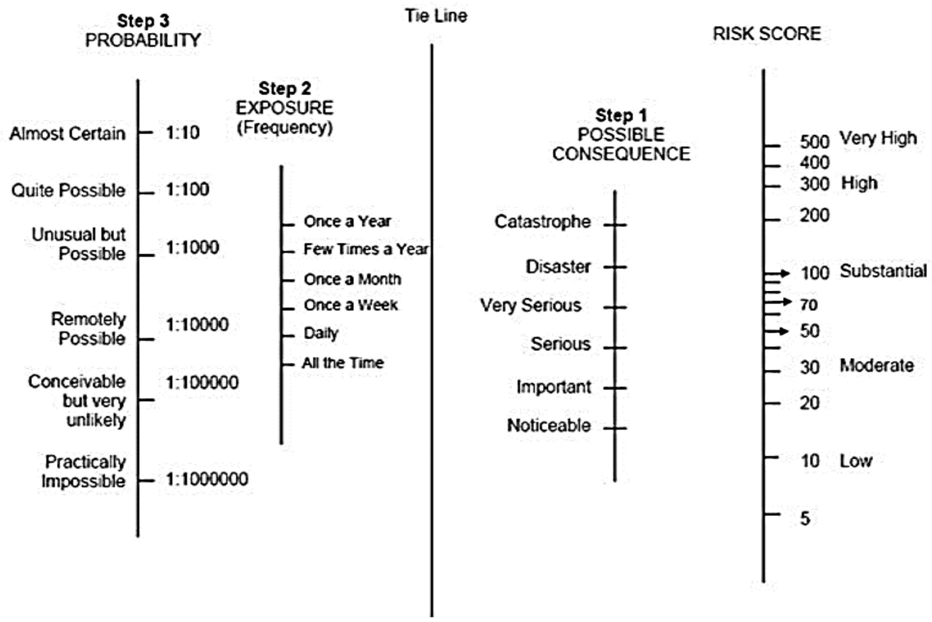


Figure 4.1 Risk score nomograph (Kinney and Wiruth, 1976)

In this study, consequence of an accident is assessed according to lost workdays. In order to find the magnitude of consequence, lost workday related to each accident is averaged by dividing total lost workday for each category to total number of accidents occurred for the same category. Exposure is taken to be the mean time between failures (MTBF). MTBF is the predicted elapsed time between inherent failures of a system. The definition of MTBF depends on the definition of what is considered a system failure. In this study, an accident is thought to be a system failure. Calculated

MTBFs show how much a worker is exposed to an accident under related category. Finally, the probability factors are calculated by dividing the number of accidents for a category to the total number of accidents.

Basic steps of risk score modeling developed for this work are:

- Categorizing the records of past accident cases according to accident type, location, work shift, job, affected body part, age, and experience which is shown at Table 4.5,
- Evaluating the probability of each case by dividing number of accidents counted for each category to the total number of accidents,
- Evaluating the exposure factors by calculating the mean times (particular time period in which the probability of failure becomes 100%) for each case by the aid of Minitab software,
- Evaluating the severity factors by finding the average number of days lost for each case,
- Computing the risk scores for each case by compiling probabability, exposure, and consequence factors by the aid of the nomograph called as Riskex Risk Score Calculator which is derived from the principle of Fine-Kinney risk score methodology.

Table 4.5 Input categorization

ACCIDENT TYPE	ACCIDENT LOCATION	WORK SHIFT	JOB	AFFECTED BODY PART	AGE	EXPERIENCE
1.Roof fall 2.Methane and other gases 3.Electric 4.Machine 5.Material 6.Transportation 7.Explosive 8.Miscellaneous	1.Longwall face 2.Development headings 3.Main transportation/haulage road 4.Support maintenance/ repair 5.Electro mechanics shop 6.Miscellaneous	1.Shift 1 2.Shift 2 3.Shift 3	1.Fireman 2.Electrical technician 3.Development headings worker 4.Mechanical technician 5.Transportation worker 6.Longwall production worker 7.Support maintenance worker	1.Foot-Toe 2.The Lower Part Of The Leg 3.Leg 4.Calf 5.Head 6.Waist 7.Neck 8.Others 9.Knee 10.Hand-Fınger 11.Chest 12.Body 13.Eye 14.Hip 15.Arm 16.Shoulder 17.Back 18.Respiratory 19.Whole Body 20.Face	1.20-25 2.25-30 3.30-35 4.35-40 5.40-45 6.45-50 7.50-55	1.0-4 2.4-8 3.8-12 4.12-16 5.16-20 6.20-24 7.24-28

4.2 Evaluation of Probabability Factors

To estimate the probability of event A, written P(A), the number of times A occurs is divided by the number of repetitions, which is called the relative frequency of event A (Biostatistics Open Learning Textbook, 2017).

$$P(A) = \frac{Number\ of\ times\ A\ occured}{Total\ number\ of\ repetitions}$$

In this study, a total of 4731 accident occurences during a period of January 2003 to December 2013 is analysed. The data provided from TTK Üzülmez district is handled at seven titles, namely, type of accidents, locations, work shifts, jobs, affected body parts, age, and experience of workers in the mine. The probability factors are calculated by dividing the total number of accidents for each title to the total number of accidents occurred during eleven years. The probabilities related to accident type, location, work shift, job, affected body part, age, and experience are given in Table 4.6, 4.7, 4.8, 4.9, 4.10, 4.11 and 4.12, respectively.

Table 4.6 Probability evaluation for accident types

Accident Type	Frequency	Probability
Electric	13	0.003
Roof Fall	1998	0.422
Methane and Other Gases	3	0.001
Machine	48	0.010
Material	597	0.126
Miscellaneous	1834	0.388
Transportation	235	0.050
Explosives	3	0.001
TOTAL	4731	1.000

Table 4.7 Probability evaluation for accident locations

Location	Frequency	Probability
Longwall face	3559	0.752
Electro Mechanics Shop	11	0.002
Development headings	446	0.094
Miscellaneous	58	0.012
Main transportation/ haulage road	529	0.112
Support Maintenance/Repair	125	0.026
Surface Facilities	3	0.001
TOTAL	4731	1.000

Table 4.8 Probability evaluation for work shifts

Work Shift	Frequency	Probability
Shift 1	2640	0.558
Shift 2	1132	0.239
Shift 3	959	0.203
TOTAL	4731	1.000

Table 4.9 Probability evaluation for jobs (This table omits the jobs that having an accident number of less than 30, cause the calculated probabilities are close to zero)

Job	Frequency	Probability
Fireman	34	0.007
Electrical technician	38	0.008
Development headings worker	547	0.120
Mechanical technician	126	0.028
Transportation worker	273	0.060
Longwall production worker	3462	0.757
Support maintenance worker	92	0.020
TOTAL	4572	1.000

Table 4.10 Probability evaluation for affected body parts

Affected Body Part	Frequency	Probability
Foot-Toe	1103	0.233
The Lower Part of the Leg	94	0.020
Leg	47	0.010
Calf	40	0.008
Head	193	0.041
Waist	107	0.023
Neck	29	0.006
Others	17	0.004
Knee	227	0.048
Hand-Finger	1486	0.314
Chest	12	0.003
Body	202	0.043
Eye	145	0.031
Hip	67	0.014
Arm	433	0.092
Shoulder	210	0.044
Back	44	0.009
Respiratory	6	0.001
Whole Body	9	0.002
Face	260	0.055
TOTAL	4731	1.000

Table 4.11 Probability evaluation for age of workers

Age	**Frequency**	**Probability**
20-24	144	0.030
25-29	1391	0.294
30-34	1791	0.379
35-39	829	0.175
40-44	431	0.091
45-49	130	0.027
50-55	15	0.003
TOTAL	4731	1.000

Table 4.12 Probability evaluation for experience of worker

Experience	**Frequency**	**Probability**
0-4 years	2112	0.446
5-8 years	1233	0.261
9-12 years	700	0.148
13-16 years	370	0.078
17-20 years	198	0.042
21-24 years	100	0.021
25-28 years	18	0.004
TOTAL	4731	1.000

4.3 Evaluation of Exposure Factors

In order to evaluate the exposure factors, for seven titles, namely, type of accidents, locations, work shifts, jobs, affected body parts, age, and experience of workers in the mine, the dates of each accident data is filtered and the time between each subsequent accident is determined. Time between each subsequent accident is entered to the Minitab 17 software, then according to the fitted distributions (smallest extreme value, Weibull, 3-parameter Weibull, exponential, 2-parameter exponential, normal, lognormal, 3-parameter lognormal, logistic, loglogistic, or 3 parameter loglogistic) mean times are calculated and when will the system fail (when will the accident occur) is determined. The fitted distributions are exponential, Weibull, lognormal, loglogistic. The key equations for the fitted distributions is reviewed briefly as following: (Rodriguez, 2010)

Exponential: T has an exponential distribution with parameter λ, denoted $T \sim E(\lambda)$, iff

$Y = \log T = \alpha + W$

where

$\alpha = -\log \lambda$ and W has a standard extreme value (min) distribution, with density $f_W(w) = e^{w-e^w}$

Weibull: T has a Weibull distribution iff

$T \sim W(\lambda, p)$ iff $Y = \log T = \alpha + \sigma W$, where W has the extreme value distribution, $\alpha = -\log \lambda$ and $p = 1/\sigma$

Lognormal: T has a lognormal distribution iff

$Y = \log T = \alpha + \sigma W$, where W has a standard normal distribution

Loglogistic: T has a log-logistic distribution iff
$Y = \log T = \alpha + \sigma W$, where W has a standard logistic distribution

Exponential distrubition is most often used to model the behavior of units that have a constant failure rate. It is utilized in analyzing the reliability and availability of electronic systems, queuing theory, and Markov chains. For example, the time to failure of electronic components, the time between customers' arrivals at a terminal, time for radioactive nucleus decay. Weibull distribution is usually used to model time-to-failure data. As an example, to calculate the probability that a part fails after one, two, or more years weibull distrubution is very useful. It has an extensive application in engineering, medical research, finance, and climatology. Lognormal distribution is used commonly for reliability analysis and in financial applications, such as modeling stock behavior. It is also known as the Cobb-Douglas distribution. Loglogistic distribution is commonly used in the biostatistics and economics fields. It is also known as the Fisk distribution.

While finding the best fitted distribution the smallest Anderson Darling value is selected and the responsible MTBF value is computed. For example, the probability of an accident due to electricity is found as 100% at 498.17 days meaning that in 498 days it is certain that a worker has an electrical accident. In another words, each worker is exposed to an electrical accident every 498 days.

The mean times for each accident type, location, work shift, job, affected body part, age, and experience are given in Table 4.13, 4.14, 4.15, 4.16, 4.17, 4.18, and 4.19, respectively.

Table 4.13 MTBF evaluation for accident types

Accident Type	Anderson-Darling	Fitted Distribution	MTBF (days)
Electric	2.171	Exponential	498.17
Roof Fall	57,015	Weibull	2.89
Methane and Other Gases			483.5
Machine	0.803	Exponential	80.87
Material	5.147	Lognormal	8.01
Miscellaneous	51.774	Loglogistic	2.98
Transportation	0.988	Exponential	18.18
Explosives			475.5

Table 4.14 MTBF evaluation for accident locations

Location	Anderson-Darling	Fitted Distribution	MTBF (days)
Longwall face	175.7	Weibull	1.97
Electromechanics	1.420	Weibull	46.27
Development headings	1.714	Weibull	10.07
Miscellaneous	0.766	Weibull	73.59
Main transportation/haulage road	3.420	Weibull	8.84
Support maintanance/repair	0.583	Weibull	34.20
Surface facilities			551

Table 4.15 MTBF evaluation for work shifts

Work Shift	Anderson-Darling	Fitted Distribution	MTBF (days)
Shift 1	108.689	Weibull	2.32
Shift 2	14.977	Lognormal	4.46
Shift 3	12.936	Weibull	5.19

Table 4.16 MTBF evaluation for jobs

Job	**Anderson-Darling**	**Fitted Distribution**	**MTBF (days)**
Fireman	0.718	Loglogistic	195.35
Electrical technician	0.700	Weibull	107.50
Development headings worker	3.506	Weibull	8.32
Mechanical technician	0.696	Lognormal	36.08
Transportation worker	0.886	Weibull	15.98
Longwall production worker	164.373	Weibull	2.01
Support maintenance worker	0.383	Weibull	43.85

Table 4.17 MTBF evaluation for affected body parts

Affected Body Part	**Anderson-Darling**	**Fitted Distribution**	**MTBF (days)**
Foot-Toe	18.194	Lognormal	4.45
The Lower Part of the Leg	0.625	Weibull	45.01
Leg	0.513	Weibull	84.88
Calf	0.574	Weibull	106.47
Head	1.333	Lognormal	22.99
Waist	0.588	Weibull	36.26
Neck	0.716	Weibull	66.10
Others	1.069	Normal	243.06
Knee	0.653	Weibull	21.15
Hand-Finger	35.138	Lognormal	3.43
Chest	1.315	Lognormal	352.98
Body	0.518	Lognormal	21.70
Eye	0.419	Weibull	29.13
Hip	0.451	Weibull	56.24
Arm	2.311	Lognormal	10.67
Shoulder	0.616	Exponential	20.61
Back	0.749	Lognormal	62.89
Respiratory			1132
Whole Body	2.176	Lognormal	382.37
Face	1.291	Weibull	16.10

Table 4.18 MTBF evaluation for age of workers

Age	Anderson-Darling	Fitted Distribution	MTBF (days)
20-24	0.690	Lognormal	23.45
25-29	28.217	Lognormal	3.75
30-34	50.143	Weibull	2.99
35-39	9.873	Lognormal	5.73
40-44	1.992	Lognormal	10.28
45-49	0.356	Weibull	31.13
50-55	1.137	Weibull	239.42

Table 4.19 MTBF evaluation for experience of worker

Experience	Anderson-Darling	Fitted Distribution	MTBF(days)
0-4 years	80.614	Lognormal	2.53
5-8 years	33.294	Lognormal	3.37
9-12 years	14.477	Lognormal	4.92
13-16 years	3.95	Lognormal	9.05
17-20 years	0.964	Lognormal	20.75
21-24 years	0.449	Weibull	39.67
25-28 years	0.994	Lognormal	226.72

4.4 Evaluation of Consequence Factors

In this study, consequence of an accident is assessed in “lost workday” aspect. Lost workday as a result of an occupational injury is a very tangible data while evaluating the consequence of an accident. The related data for the area of investigation includes a column titled as “rest day”. It shows the number of days determined by doctor during which the worker having an accident is away from the work in order to recruit. It gives the amount of rest day for all 4731 accident. In order to find the risk score of the variable consequence components of them is calculated by averaging the total rest day related to it. As an illustration for electric accident type, all the lost workdays for that type of accidents are summed and divided to total number of electrical accidents. For example, if a worker experiences an electrical accident, it is expected that he will need an average of 58 day rest (Table 4.20). If a worker experiences an accident at longwall face, he will need an average of 35 day rest (Table 4.21). If a worker has an accident during the 1st shift, he will need an average of 24 day rest (Table 4.22). The other rest day average values for job variable, affected body part variable, age variable, and experience variable are given in Table 4.23, 4.24, 4.25, and 4.26.

Table 4.20 Consequence evaluations for accident types

Accident Type	**Rest day average**
Electric	57.92
Roof Fall	23.85
Methane and Other Gases	21.33
Machine	41.94
Material	25.15
Miscellaneous	44.32
Transportation	39.36
Explosives	160

Table 4.21 Consequence evaluations for locations

Location	**Rest day average**
Longwall face	34.84
Electro Mechanics Shop	17.19
Development headings	26.96
Miscellaneous	27.78
Main transportation/haulage road	29.73
Support maintanance/repair	23.27
Surface Facilities	15.67

Table 4.22 Consequence evaluations for work shifts

Work Shift	**Rest day average**
Shift 1	24.35
Shift 2	57.24
Shift 3	28.59

Table 4.23 Consequence evaluations for jobs

Job	Rest day average
Fireman	43.21
Electrical technician	29.92
Development headings worker	22.81
Mechanical technician	27.11
Transportation worker	34.34
Longwall production worker	35.10
Support maintenance worker	25.51

Table 4.24 Consequence evaluations for affected body parts

Affected Body Part	Rest day average
Foot-Toe	30.09
The Lower Part of the Leg	41.68
Leg	28.15
Calf	16.03
Head	16.36
Waist	31.04
Neck	8.72
Others	15.71
Knee	34.04
Hand-Finger	27.02
Chest	17.92
Body	17.16
Eye	6.92
Hip	42.31
Arm	21.31
Shoulder	25.99
Back	19.02
Respiratory	0.67
Whole Body	20.55
Face	12.18

Table 4.25 Consequence evaluations for ages

Age	Rest day average
20-24	22.98
25-29	47.97
30-34	48.67
35-39	27.29
40-44	28.84
45-49	28.48
50-55	43.80

Table 4.26 Consequence evaluations for experiences

Experience	Rest day average
0-4 years	39.77
5-8 years	27.98
9-12 years	25.16
13-16 years	26.99
17-20 years	28.91
21-24 years	40.88
25-28 years	33.28

4.5 Determining the Risk Scores by Compiling the Probabability, Exposure, and Consequence Factors

In this part, the risk scores are computed and ordered for each case by compiling probabability, exposure, and consequence factors with the aid of the nomograph called as Riskex Risk Score Calculator which is derived from the principle of Fine-Kinney risk score methodology (SafetyRisk, 2016). Risk score ordering and prioritizing the risks is important for further treatment and control. If the relative seriousness of all hazards are determined, then the preventive action will be organized with right timing and with a good resource utilization. According to Kinney and Wiruth if the calculated risk score value corresponds to very high risk situation, stopping the operation should be considered until at least interim measures to correct the deficiency can be implemented, or perhaps permanent shutdown becomes necessary if the operation cannot be made safe (1976). It is also stated that for the substantial risk situation correction is needed while for the high risk situaiton correction is urgently needed.

Low risk may perhaps be acceptable whereas an attention should be indicated for moderate risk.

All the probability, exposure, and consequence of each variable given in Table 4.5 are calculated. The calculated values are entered to Riskex Risk Score Calculator for eight different accident types, seven different accident locations, three different shifts, seven different jobs, twenty different body part affected after having an accident, seven different age groups, and seven different experience duration. Riskex Risk Score Calculator is an electronic tool which works the same way as the nomograph. This calculator is both time saving and user friendly. The values determined at parts 4.3, 4.4, and 4.5 (for the probability, exposure, and consequence factors) are entered and associated risk scores are determined. Typical examples for the risk score of electrical accidents and the longwall production workers are given in Figures 4.2 and 4.3 respectively. For the electrical accidents risk score is calculated as 8.6 and which corresponds to moderate risk situation whereas for accidents experienced by longwall production workers risk score is calculated as 2358 corresponding to very high risk. The other risk scores for all cases are presented in Appendix A in Figures A1-A59.

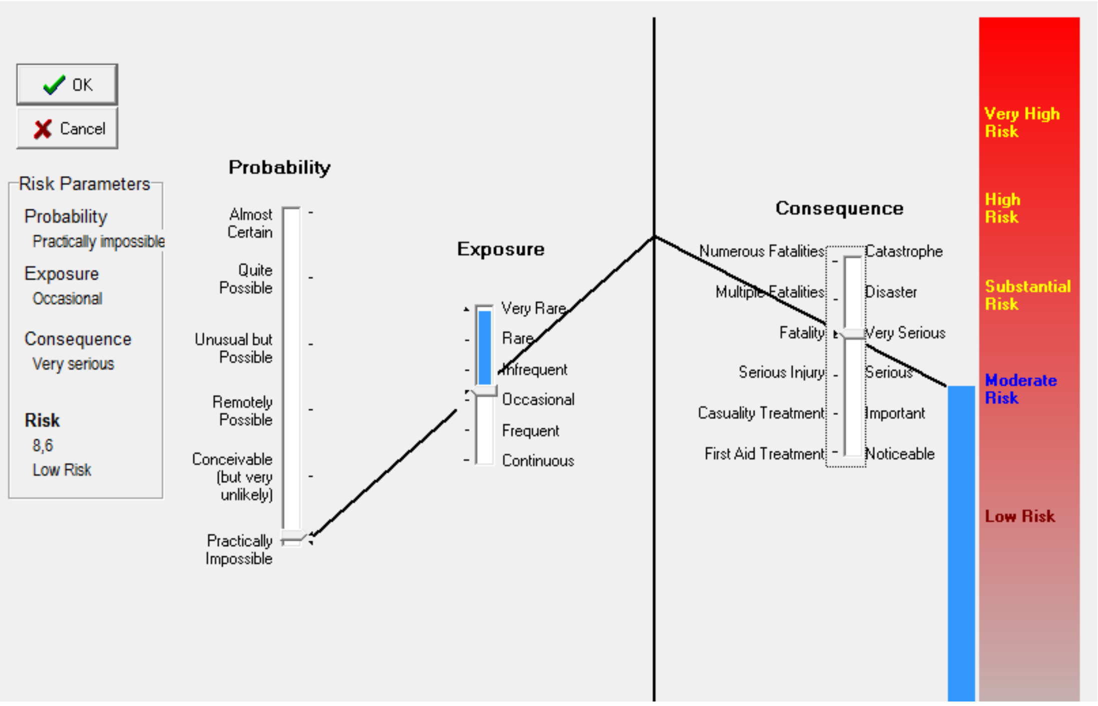


Figure 4.2 Risk score of electrical accidents

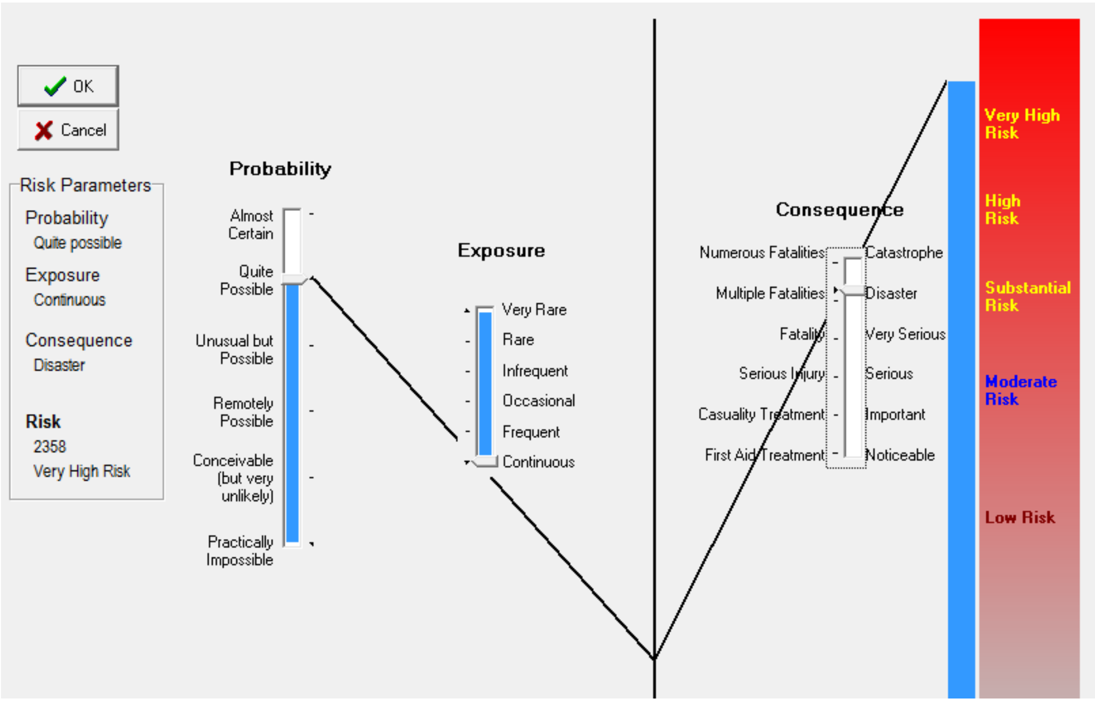


Figure 4.3 Risk score of longwall production workers

4.6 Results and Discussion

All the risk score values for each accident type, accident location, shift, job, body part affected after having an accident, age group, and experience duration calculated by Riskex Risk Score Calculator are sorted by magnitude. In this way, prioritization of risk is performed which is crucial for an effective risk analysis. Table 4.27 4.28, 4.29, 4.30, 4.31, 4.32, and 4.33 shows the risk order of each accident type, accident location, shift, job, body part affected after having an accident, age group, and experience duration, respectively. These tables depicts the risk situations as well as risk scores. According to Kinney and Wiruth if the calculated risk score value corresponds to very high risk situation, stopping the operation should be considered until at least interim measures to correct the deficiency can be implemented or perhaps permanent shutdown becomes necessary if the operation cannot be made safe (1976). It is also stated that for the substantial risk situation correction is needed while for the high risk situaiton correction is urgently needed. Low risk may perhaps be acceptable whereas an attention should be indicated for moderate risk.

The main results from the Fine-Kinney risk analysis conducted by Riskex Risk Score Calculator for TTK Üzülmez district is as following:

1. Accident type: Accidents resulting from roof falls accidents are the most attention demanding accidents while accidents due to electricity are most insignificant accidents. The second highest risk score belongs to accidents named as miscellaneous. Accidents arising from compressed air, crashing, rupture, insertion, sting, falling materials, bouncing materials, sliding materials, slip, fall, trip, twist, material handling and usage, fall from high, crashing into rock coming from chutes, and others are united under the title “miscellaneous”. This information is not useful. In order to get useful results, these subtitles should not be recorded under one title, they must be reorganized separately and risk prioritization should be conducted for each.
2. Accident location: Longwall face in which the coal is extracted and the main production take place is found to be most risky location. With a risk score of 3556.8, longwall face carry very high risk compared to other locations.
3. Shift: Although there is not a big difference between the risk scores of three shifts; shift 1 is of first priority. Working at this time period covering 08:00-16:00 is more insecure.
4. Job: Longwall production worker with a risk score of 2358 is of top priority job which outscores the risk scores of other jobs. Because of the conventional panels in the study area, it is not surprising that longwall production job is the most risky job.
5. Body part affected: Risk scores for body parts affected after having an accident are quite similar to each other. There is no prominent body part demanding a hurry attention. However, foot-toe, the lower part of the leg, knee, hand-finger, waist, hip, arm, shoulder, head, leg, and face have moderate risks and they sould be dealt formerly.
6. Age group: The findings does not show that risk increases with age or risk decreases with age. The workers having an age between 30-34 and 25-29 carry a high risk and are more prone to accidents.
7. Experience duration: The results of the risk scores according to experience can be interpreted as lower the experience higher the accident risk, except the 13-

16 years experience duration as can be seen in Table 4.33. This shows that the new employers are a safety risk until at least they have 13-16 years of experience in Üzülmez district.

8. When the descriptive statistics and the risk scores are evaluated together, it is seen that after the risk score is computed accidents related to transportation, methane and other gases and explosives come to the fore, due to high exposure and consequence factors. For the accident location, development headings get ahead due to same reason. The probability and risk score sortings of shifts does not change so, it can be concluded that exposure and consequence factors for the shifts do not have an effect as much as changing the sorting. For the job category, fireman get ahead remarkably which can be attributed to severe injuries that they have experienced leading high consequence factors. In terms of body part effected foot-toe and lower part of the leg come to the fore because of the accidents affecting these body parts end up with great number of rest days. The probability and risk score sortings of age variable does not change; therefore, exposure and consequence factors for the age variable do not have a considerable effect. Lastly, for the experience duration 17-20 come to the forefront due to high exposure and consequence factors.

Table 4.27 Ranking the risk scores of accident types

Accident Type	**Risk Score**	**Risk situation**
Roof Fall	524.0	Very high risk
Miscellaneous	358.1	High risk
Transportation	34.6	Moderate risk
Material	27.2	Moderate risk
Methane and Other Gases	18.8	Moderate risk
Explosives	14.3	Moderate risk
Machine	14.2	Moderate risk
Electric	8.6	Low risk

Table 4.28 Ranking the risk scores of locations

Location	Risk Score	Risk situation
Longwall face	3556.8	Very high risk
Development headings	79.5	Substantial risk
Main transportation/haulage road	39.2	Moderate risk
Electro Mechanics Shop	28.8	Moderate risk
Support maintanance/repair	16.6	Moderate risk
Miscellaneous	10.1	Moderate risk
Surface Facilities	1.2	Low risk

Table 4.29 Ranking the risk scores of work shifts

Shift	Risk Score	Risk situation
Shift 1	190	Substantial risk
Shift 2	95	Substantial risk
Shift 3	52.3	Substantial risk

Table 4. 30 Ranking the risk scores of jobs

Job	Risk Score	Risk situation
Longwall production worker	2358	Very high risk
Development headings worker	130.8	Substantial risk
Transportation worker	31.6	Moderate risk
Fireman	26.1	Moderate risk
Support maintenance worker	21.8	Moderate risk
Mechanical technician	18.1	Moderate risk
Electrical technician	10.8	Moderate risk

Table 4.31 Ranking the risk scores of affected body parts

Body Part	Risk Score	Risk situation
Foot-Toe	43.6	Moderate risk
The Lower Part of the Leg	31.6	Moderate risk
Knee	21.1	Moderate risk
Hand-Finger	20	Moderate risk
Waist	19.9	Moderate risk
Hip	17	Moderate risk
Arm	15.6	Moderate risk
Shoulder	14.8	Moderate risk
Head	11.8	Moderate risk
Leg	10.4	Moderate risk

Table 4.31 Ranking the risk scores of affected body parts (continued)

Body Part	Risk Score	Risk situation
Face	10	Moderate risk
Body	9.3	Low risk
Back	6.4	Low risk
Calf	5	Low risk
Eye	4.9	Low risk
Neck	3.7	Low risk
Whole Body	3.5	Low risk
Others	3.2	Low risk
Chest	3.1	Low risk
Respiratory	0.8	Low risk

Table 4.32 Ranking the risk scores of ages

Age	Risk Score	Risk situation
30-34	358.1	High risk
25-29	238.7	High risk
35-39	159.1	Substantial risk
40-44	74.8	Substantial risk
45-49	54.9	Substantial risk
20-24	11.1	Moderate risk
50-55	8.9	Low risk

Table 4.33 Ranking the risk scores of experiences

Experience	Risk Score	Risk situation
0-4 years	479.6	Very high risk
5-8 years	218	High risk
9-12 years	130.8	Substantial risk
17-20 years	58.9	Substantial risk
21-24 years	19.2	Moderate risk
13-16 years	17.6	Moderate risk
25-28 years	8	Low risk

CHAPTER 5

FORECASTING THE NUMBER OF ACCIDENTS

As well as risk scoring, in order to rank the risk scores which has performed in previous chapter, predicting the future trends of accidents is vitally important for an efficient risk analysis. In this section, in order to foresee future trend of accidents multiple linear regression and time series analysis method will be used.

5.1 Multiple Linear Regression

5.1.1 General Information

Linear regression is a type of statistical analysis in which a response or outcome variable is predicted by using the relationship between two or more quantitative variables (Pardoe, 2017). One variable, denoted x, is regarded as the predictor while the other variable, denoted y, is regarded as the response. According to number of predictor variables linear regression is called as single or multiple linear regression. In a single linear regression there is only one predictor variable whereas in a multiple linear regression there is two or more predictor variables. A single linear regression and a multiple linear regression formula can be written as:

$$E(Y\,|X) = \alpha + \beta X \qquad \text{(Eq 5.1)}$$

$$E(Y\,|X) = \alpha + \beta 1X1 + \cdots + \beta pXp \qquad \text{(Eq 5.2)}$$

where α is called the intercept and the βj are called slopes or coefficients (Shedden, 2004).

In a single linear regression the estimated model yields a line while in the case of a multiple linear regression with two predictors the estimated regression equation yields a plane. If the multiple linear equation has more than two predictors, the estimated regression model yields a hyperplane.

In multiple linear regression, the direction and strength of the linear relationship between variables can be examined by correlation analysis. The correlation coefficient, always ranges between -1 and +1 and shows the direction and strength of the linear relationship between the two variables. The sign of the correlation coefficient implies the direction of the relationship whereas the magnitude of the correlation coefficient implies the strength of the relationship. For instance, a correlation coefficient of 0.9 indicates a strong, positive relationship between two variables, whereas a correlation coefficient of -0.2 indicates a weak, negative relationship. To sum up, the closer the correlation coefficient to zero, it is harder to talk about linear association between two continuous variables (Boston University School of Public Health Online Lecture Notes, 2013). In order to look how well the regression model fits the data, the R^2 value is observed. R^2 changes between 0% and 100% . The higher the R^2 value, the better the model fits the data (Minitab Express Support, 2016).

Another control parameter for the fitness of the model is to look at p value. The p value is a probability determining the evidence against the null hypothesis. Low p value means there is a strong evidence against the null hypothesis. The null hypothesis for the overall regression is that the model does not explain any of the variation in the response. A p value less than or equal to the significance level means that the model explains variation in the response. A p value greater than the significance level means that the model explains variation in the response. Therefore, a new model should be built. Significance level is usually chosen as 0.05. A significance level of 0.05 indicates a 5% risk of concluding that the model explains variation in the response when the model does not (Minitab Express Support, 2016).

5.1.2 Application of MLR to Accidents Data

The data comprises of five predictor variables which are raw coal production (tonnes) (X1), total gallery advance/daily wage (cm) (X2), total number of workers (X3), explosive consumption/raw coal production (g/tonnes) (X4) and timber consumption/raw coal production (dm^3/tonnes) (X5). Five predictor variables are examined in the sense of how they relate the response which is total accident numbers in our case. In order to perform a regression analysis, a statistical software package called as Minitab 17 is used. The calculated correlation coefficients related to correlation analysis between the variables can be seen in Table 5.1. As can be seen from the table, the correlation coeffient is 1 between the same variables meaning that moving in the same direction with the same magnitude. None of the computed correlation coefficients is zero implying that there exist a meaningful relationship between all of the variables. The calculated p-values is also compared with our significance level of 0.05. If the p values are less than the significance level, then it can be inferred that the correlation coefficients are different from 0 and they are meaningful. For the handled data, the correlation coefficients that are specified as bold are meaningful.

Table 5.1 Correlation coefficient matrix

	X1	***X2***	***X3***	***X4***	***X5***
X1	1.000				
X2	**0.226**	1.000			
X3	**0.808**	**0.308**	1.000		
X4	0.136	**0.505**	**0.422**	1.000	
X5	**0.617**	0.149	**0.732**	**0.502**	1.000

where

X1: Raw coal production (tonnes)

X2: Total gallery advance/daily wage (cm)

X3: Total number of workers

X4: Explosive consumption/raw coal production (g/tonnes)

X5: Timber consumption/raw coal production (dm^3/tonnes)

Just by examining the correlation coefficient matrix it is not possible to form the most accurate multiple linear regression equation. It has to be decided that which one of these variables must be included in the multiple linear regression equation for the most accurate results.

Due to the strong association between some of the independent variables in the matrix of correlation coefficients, (for example X1-X3, X1-X5, and X3-X5) it is more convenient to use a stepwise regression method to reduce the multicollinearity that will occur. Firstly, all of the five predictors are entered as input data to build the MLR model. It is presented in Eq. 5.3.

$$Y = 87{,}3 + 0{,}000371\ X1 - 0{,}0404\ X2 - 0{,}0344\ X3 - 0{,}0646\ X4 + 0{,}343\ X5 \qquad \text{(Eq. 5.3)}$$

The R^2 for the model containing all the variables is calculated as 17.92%. This value can be expressed in the following way. While 18% of the total changes in response value (number of accidents) can be explained by the changes caused by the independent variables included in the model (raw coal production, total gallery advance/daily wage, total number of workers, explosive consumption/raw coal production, and timber consumption/raw coal production), the remaining 82% is due to other factors which are not available and which are not included in the model. The study conducted by Hull et al. (1996), examines lost-time injurious incidents that occurred in the N.S.W. underground coal mining industry during the 4 year period from 1 July 1986 to 30 June 1990 by using multiple regression techniques. They utilized the bodypart, age, accident type, accident agency, region, hours, activity, location, and occupation as factors to determine the injury severity. The R-square value for this model was found to be 8% which is quite low when it is compared to R-square found for our model. Another study conducted by Margolis (2009), including Mine Safety and Health Administration’s (MSHA) injury data reported from all underground coal mines between the years 2003 and 2007 seeks for the relationship between age, experience, and injury severity. A multiple regression analysis was conducted with age and the three experience variables as independent variables and days lost as the dependent variable and an adjusted R-square value of 1% is found. This value is pretty low compared to R-square found for our model. Therefore, it can be concluded that the predictors (raw coal production, total gallery advance/daily wage, total number of workers, explosive consumption/raw coal production, and timber consumption/raw coal production) and response (number of accidents) chosen for this study are quite compatible.

Another control parameter for the fitness of the model is to look at p value. Results of analysis of variance test shows a p value of less than 0.0001 at a significance level of 0.05 which means that there is a statistically significant association between the response and the independent variables.

Validity of the model can also be tested by looking normal probability plot of residuals which is the difference between the predicted and observed value of y (Figure 5.1). Normal probability plot of residuals is used to confirm the assumption that the residuals are normally distributed. The normal probability plot of the residuals must more or less follow a straight line. The pattern should also be checked whether there exists a nonnormality, an outlier or an unidentified variable. When Figure 5.1 is viewed the points more or less follow a straight line. The slope doesn't change anywhere meaning that there is no evidence of an unidentified variable. However, there exists some points far away from the line which indicates that there are some outliers. Therefore there is some evidence of nonnormality. Another key output that can be used to analyze the model is residuals versus fits plot (Figure 5.2). Residuals should be randomly distributed on both sides of zero and there should not be any recognizable pattern in the points. It can be seen from Figure 5.2 that there exists some points far away from zero and far away from the other points in the x-direction; therefore, residuals are not normally distributed. The histogram of the residuals also certifies that residuals of model do not have a mean close to 0; therefore, they do not have a normal distribution as can be seen from Figure 5.3. Although the residuals seem to be nonnormally distributed, normality is not an issue for our data since there are more than 15 data points. If the number of data points is small and the residuals are not normally distributed, the p-values used to determine whether there is a significant relationship between the Xs and Y may not be accurate.

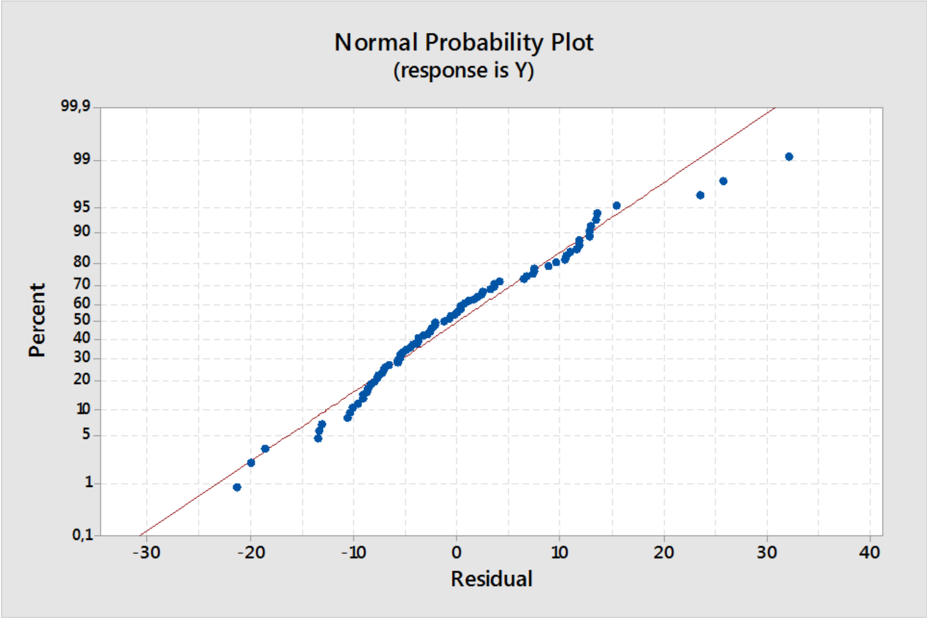


Figure 5.1 Normal probability plot of residuals

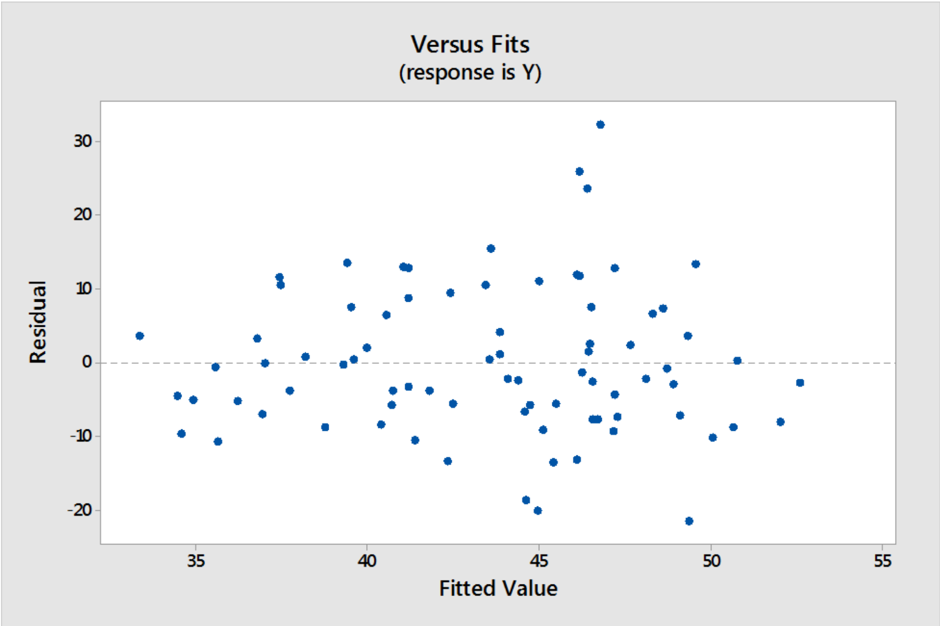


Figure 5.2 Residuals versus fits plot

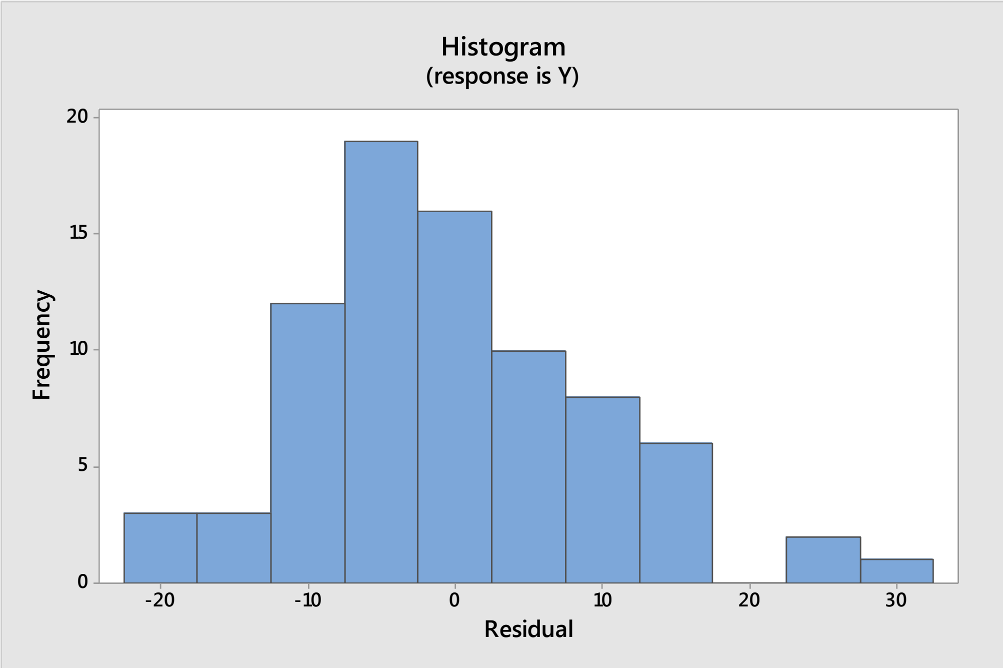


Figure 5.3 Histogram of residuals

Although the model containing all the variables seems to be statistically significant, other equations combining different independent variables must also be checked and analyzed to reach the best fitting model. In order to do this easily, Minitab has a tool named as ‘Best Subsets Regression’. It defines the best subset models that gives the highest R^2 value. It scrutinizes all possible subsets of the independent variables, starting with all models containing one independent variable, and then all models containing two independent variables, and so on. It shows the best two models for each models of the same size. The model summary of best subsets regression is interpreted at Table 5.2. R-sq, R-sq (adj) and R-sq (pred) have different interpretations and therefore they have to be examined separately. It was mentioned that the higher the R^2 value, the better the model fits the data. R-sq is most useful when comparing models of the same size while adjusted R-sq should be evaluated when comparing models that have different numbers of variables. R- sq (pred) is another form of R-sq and it has to be examined whether the model is overfit or not. If the R-sq (pred) is substantially less than R-sq, it means that the model is overfit. When the R-sq and R-sq (pred) columns of Table 5.2 are viewed, it can be seen that there is not a huge difference between them. If Mallows' Cp is small and close to the number of predictors in the model plus the constant (p), then the model is relatively unbiased in estimating the true regression coefficients and predicting future responses. S column shows the standard deviation of how far the data values fall from the fitted values; therefore the lower the value of S, the better the model (Minitab Express Support, 2016).

Table 5.2 Model summary of best subsets regression

Vars	R-sq	R-sq (adj)	R-sq (pred)	Mallows Cp	S	X1	X2	X3	X4	X5
1	11.6	10.5	7.2	4.0	10.319				x	
1	7.8	6.6	3.6	7.7	10.542			x		
2	14.0	11.9	8.5	3.7	10.239	x		x		
2	13.8	11.7	8.0	3.9	10.253			x	x	
3	16.7	13.5	9.2	3.2	10.144	x		x	x	
3	15.8	12.7	8.9	4.0	10.196	x	x	x		
4	17.6	13.4	8.0	4.3	10.154	x		x	x	x
4	17.4	13.2	8.3	4.5	10.164	x	x	x	x	
5	17.9	12.7	6.8	6.0	10.196	x	x	x	x	x

When comparing models that have different numbers of variables, adjusted R-sq should be used to decide the best equation. Higher adjusted R-sq means better fitted model. In light of this information, the highlighted rows in Table 5.2 shows the best two equation for the model. First model includes X1, X3, and X4 (Raw coal production, total number of workers and explosive consumption/raw coal production) while second model includes X1, X3, X4, and X5 (Raw coal production, total number of workers, explosive consumption/raw coal production, and timber consumption/raw coal production) in order to estimate the number of accidents. It can be concluded that total gallery advance/daily wage may not be a good predictor. Actually it is highly related to the raw coal production and it can be excluded from the model. The equations related to first and second model are given in Eq. 5.4 and 5.5, respectively. Normal probability plot of residuals, residuals versus fits plot, histogram of residuals and versus order graphs are also shown in Figure 5.4 and 5.5, respectively for two models.

$$Y = 93.4 + 0.000406\ X1 - 0.0324\ X3 - 0.0616\ X4 \quad \text{(Eq. 5.4)}$$

$$Y = 88.5 + 0.000358\ X1 - 0.0367\ X3 - 0.0756\ X4 + 0.426\ X5 \quad \text{(Eq. 5.5)}$$

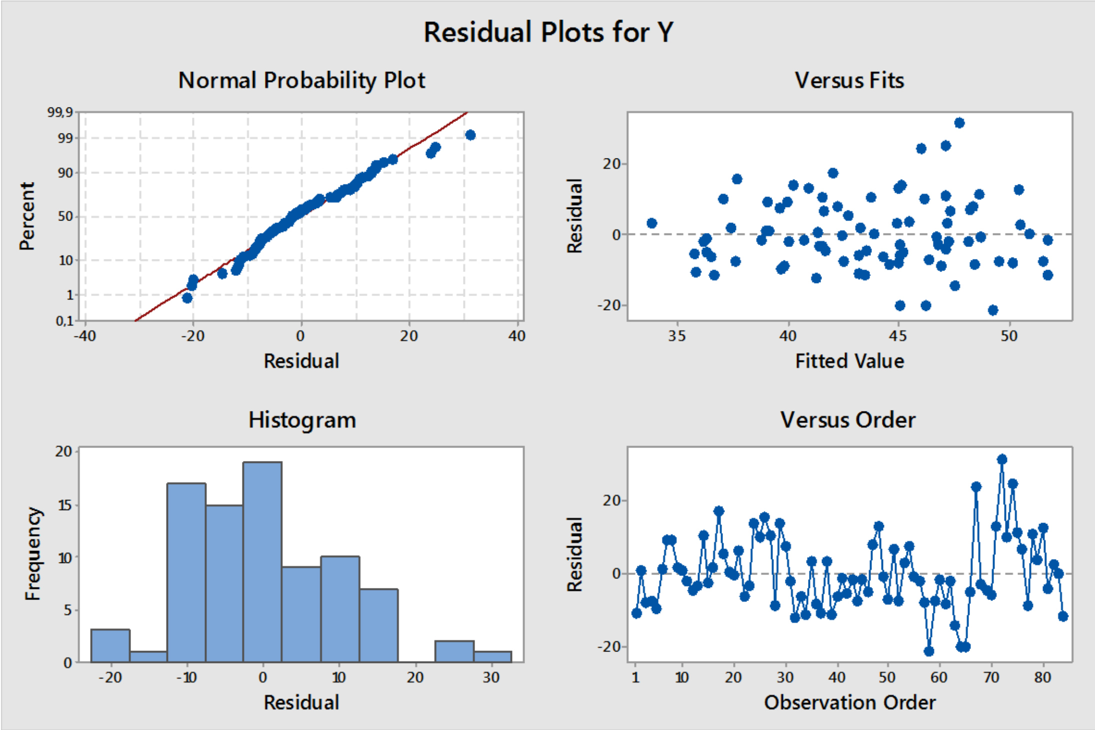


Figure 5.4 Residual plots for Y for the model containing X1, X3, and X4

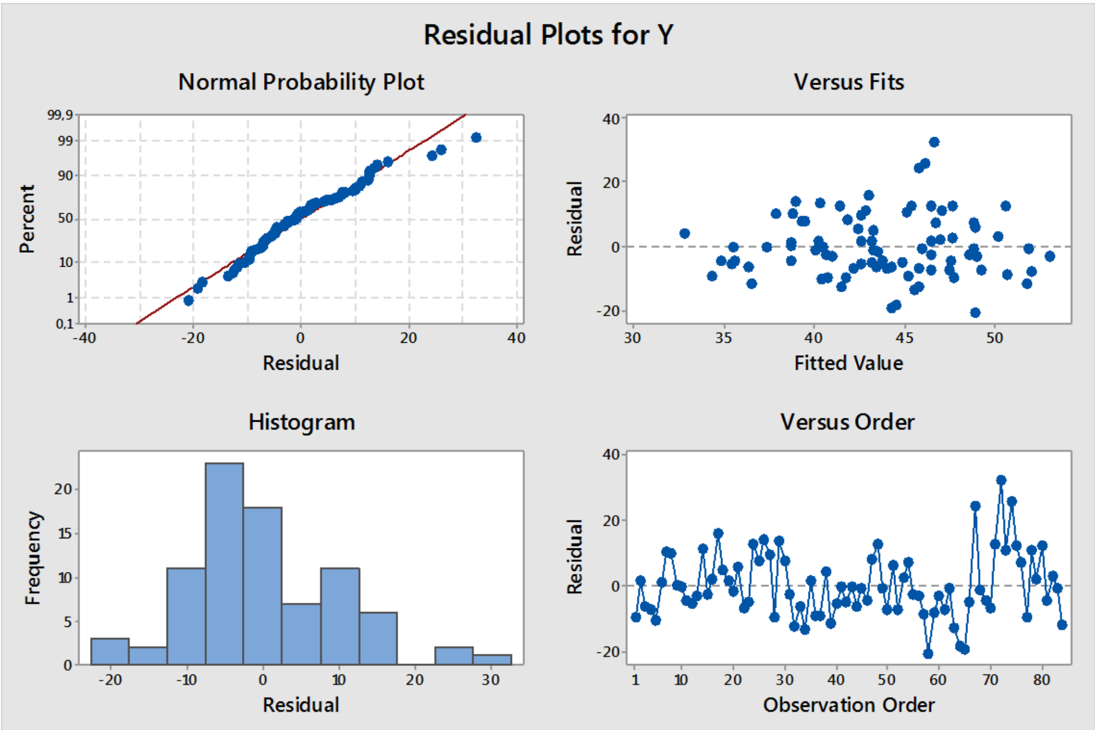


Figure 5.5 Residual plots for Y for the model containing X1, X3, X4, and X5

5.2 Time Series Analysis

5.2.1 General Information

In this part of the chapter, time series analysis, a quite different approach from multiple linear regression, is chosen for the prediction of accident numbers. Most of the statistical methods like regression do not interest about the order in which the data is collected. However, 'A time series is a sequence of values or readings ordered by a time parameter.' (Granger and Newbold, 1986). This method is utilized in many research areas such as economics (e.g. monthly employment figures), sociology (crime figures), meteorology (rainfall, temperature), medicine, seismology, and astronomy etc. The model obtained by time series analysis can be used to test some hypothesis or theory about the generating mechanism of the process, it can be used to forecast future values and it may be used to decide on a system to control future values (Granger and Newbold, 1986).

Two basic types of "time domain" can be summarized as follows: models that associate the present value of a series to past values and past prediction errors, called as Autoregressive Integrated Moving Average models (ARIMA models) and ordinary regression models utilizing time indices as x-variables which can be helpful for an initial description of the data and form the basis of several simple forecasting methods (Applied Time Series Analysis, 2017).

One of the most basic type of time series models is ARIMA. One of the easiest ARIMA type model is a model in which a linear model is used to forecast the value at the present time using the value at the previous time. This is named as AR(1) model, representing autoregressive model of order 1. The order of the model shows how many previous times is used to forecast the present time (Applied Time Series Analysis, 2017). A first order autoregressive model equation is written as:

$$y_t=\beta_0+\beta_1 y_{t-1}+\epsilon_t \qquad \text{Eq. 5.6}$$

where;

y_t: y measured in time period t

y_{t-1}: y measured in time period t-1 (if y_t is the value for this year, then, y_{t-1} becomes value for the previous year)

β_0: equation constant

β_1 : trend coefficient

ϵ_t: error term

In the first order model, only one previous time value is used. However, if it is wanted to forecast y this year (y_t) by using the values of previous two years (y_{t-1}, y_{t-2}), then the autoregressive model becomes a second-order autoregression as given in Eq. 5.7.

$$y_t=\beta_0+\beta_1 y_{t-1}+\beta_2 y_{t-2}+\epsilon_t \qquad \text{Eq. 5.7}$$

This model is an AR(2) model, in other words second-order autoregression, as the value at time t is predicted from the values at times t−1 and t−2. To sum up, a kth-order autoregression, written as AR(k), is a multiple linear regression in which the value of the series at any time t is a (linear) function of the values at times t−1,t−2,…,t−k (Regression Methods, 2017).

In order to determine the order of the auto regression model, autocorrelation function (ACF), the coefficient of correlation between two values in a time series, is calculated. The ACF for a time series y_t is shown as:

$$\mathrm{Corr}(y_t, y_{t-k})$$

where k is the time gap being considered and is called the lag. For example, a lag 1 autocorrelation is the correlation between values that are one time period apart. The ACF determines the linear relationship between an observation at time *t* and the observations at previous times. However, in an AR(*k*) model, the relationship between y_t and y_{t-k} is measured and the random variables that lie in between (i.e., $y_{t-1}, y_{t-2}, \ldots, y_{t-(k-1)}$) are skipped over. Therefore, partial autocorrelation function

(PACF**)** which calculates the correlation of the transformed time series gives more accurate results while finding the order of the auto regression model.

There exists two general aspects of time series patterns which are trend and seasonality. Trend component represents a general systematic linear or nonlinear component that changes over time and does not repeat or at least does not repeat within the time range captured by the data. Seasonality, on the other hand, in a time series is a regular pattern of changes that repeats over S time periods, where S defines the number of time periods until the pattern repeats again. If there is seasonality in monthly data, high values tend always to occur in some particular months and low values tend always to occur in other particular months. In this case, S = 12 (months per year) is the span of the periodic seasonal behavior (Applied Time Series Analysis, 2017).

Figure 5.6 clearly represents these two components at the same time (Box and Jenkins, 1976). It shows the total number of monthly international airline passenger (measured in thousands) in twelve consecutive years from 1949 to 1960. For the successive observations for each month, a line can be drawn showing that the airline industry had a steady growth over the years. Therefore a linear trend exists in this time series plot. In addition, the monthly number international airline passengers follow an almost identical pattern each year such that more people travel during holidays than during any other time of the year (How To Identify Patterns in Time Series Data: Time Series Analysis, 2013). As an another example, retail sales may peak for the Christmas season and then decline after the holidays. Therefore, time series of retail sales will typically show increasing sales from September through December and declining sales in January and February (Engineering Statistics Handbook, 2013). Seasonality is quite common in economic time series while it is less common in engineering and scientific data (Engineering Statistics Handbook, 2013).

If the data do not show a seasonal pattern while there is trend component, one of the time series trend models or double exponential smoothing model may give good results. If the data do not have a trend or seasonal component, moving average model can be a good choice.

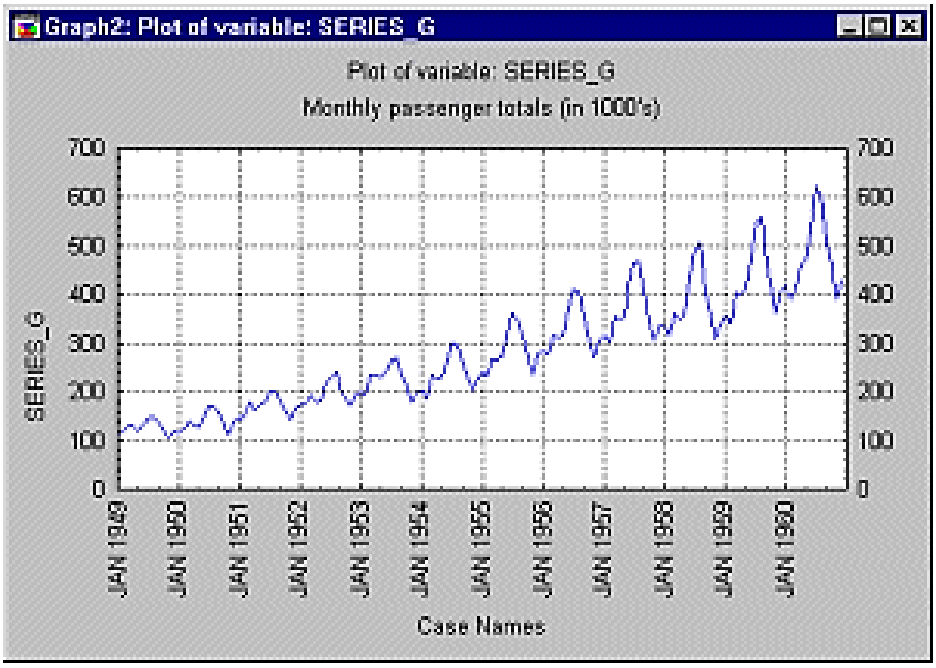


Figure 5.6 Time series plot of monthly international airline passenger

There are four different time series trend models which are linear, quadratic, exponential growth curve and S-curve (Pearl-Reed logistic). The equations for each model are:

Linear: $Y_t = \beta_0 + (\beta_1 \text{ x } t) + e_t$ Eq. 5.8

Quadratic: $Y_t = \beta_0 + \beta_1 \text{ x } t + (\beta_2 \text{ x } t^2) + e_t$ Eq. 5.9

Exponential Growth: $Y_t = \beta_0 \text{ x } \beta_1^t \text{ x } e_t$ Eq. 5.10

S-curve (Pearl-Reed logistic): $Y_t = (10^a) / (\beta_0 + \beta_1 \beta_2^t)$ Eq. 5.11

where; y_t is the variable, b_0 is the constant, b_1 and b_2 are the coefficients and t is the value of the time unit

One of the drawbacks of trend model is whether the data collected is enough so that trends or patterns in the data is fully assessed. Enough data is required to be sure that any pattern observed is a long-term pattern and not just a short-term anomaly. Trends observed over a short span of data could be part of a larger cycle and may not proceed into the future.

In order to look the accuracy of the fitted model, there are three measures which are MAPE, MAD, and MSD. For all three measures, the smaller the value, the better the fit of the model. Equations for the measures of accuracy are:

MAPE $$\frac{\sum \left|(y_t - \hat{y}_t) \ / \ y_t\right|}{n} \times 100, (y_t \neq 0)$$ Eq. 5.12

MAD $$\frac{\sum_{t=1}^{n} \left|y_t - \hat{y}_t\right|}{n}$$ Eq. 5.13

MSD $$\frac{\sum_{t=1}^{n} \left|y_t - \hat{y}_t\right|^2}{n}$$ Eq. 5.14

where; y_t equals the actual value, $y\hat{}_t$ equals the forecast value, and n equals the number of forecasts

When the data have a trend and do not have a seasonal component, as an alternative to the trend model double exponential smoothing method can be used as a general smoothing method which calculates dynamic estimates for two components namely, level (α) and trend (γ). The equations for double exponential smoothing method are as follows: (Minitab Express Support, 2016).

$$L_t = \alpha Y_t + (1 - \alpha) [L_{t-1} + T_{t-1}]$$ Eq. 5.15

$$T_t = \gamma [L_t - L_{t-1}] + (1 - \gamma) T_{t-1}$$ Eq. 5.16

$$\hat{Y}_t = L_{t-1} + T_{t-1}$$ Eq. 5.17

$$Forecast = L_t + mT_t$$ Eq. 5.18

where; L_t: level at time t, α:weight for the level, T_t:trend at time t, γ:weight for the trend, Y_t: data value at time t , $\hat{Y}_t$:fitted value, or one-step-ahead forecast, at time t and m: periods ahead from a point at time t

While performing double exponential smoothing method, the initial smoothing weights are selected as optimal ARIMA in which Minitab fits with an ARIMA (0,2,2) model to the data, in order to minimize the sum of squared errors.

If there is not a trend or seasonal component in the data, moving average procedure can be a likely choice. The fitted value at time t is the uncentered moving average at time t – 1. The forecasts are the fitted values at the forecast origin. Upper and lower limits are determined by the below equations (Minitab Express Support, 2016).

$$\text{Upper limit} = \text{Forecast} + 1.96 \times \sqrt{\boldsymbol{MSD}} \qquad \text{Eq. 5.19}$$

$$\text{Lower limit} = \text{Forecast} - 1.96 \text{ x } \sqrt{\boldsymbol{MSD}} \qquad \text{Eq. 5.20}$$

The data consists only of the monthly accident numbers from January 2003 to December 2013. Therefore, number of accidents data collected at a regular time interval (each month) is the only variable and this method is called as univariate time series. ‘The term "univariate time series" refers to a time series that consists of single (scalar) observations recorded sequentially over equal time increments.’ (Engineering Statistics Handbook, 2013)

5.2.2 Application of Time Series to Accident Data

5.2.2.1 AR(1) Model

The ACF and PACF for the data is plotted which can be seen in Figure 5.7. It can be distinguished that there is an upsurge at lag 1 in PACF. Therefore, the most suitable model for this data set appear to be an AR(1) model.

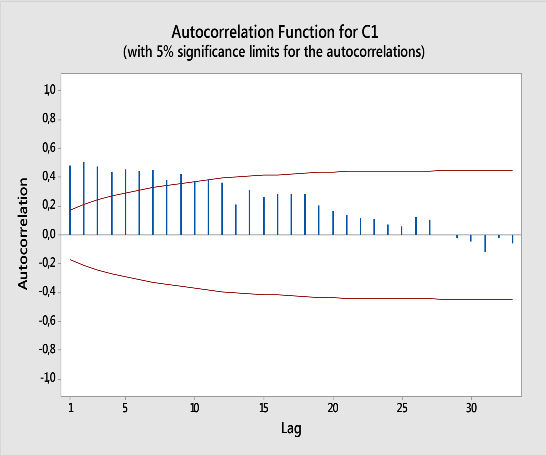


Figure 5.7.a. Autocorrelation function for all accident numbers

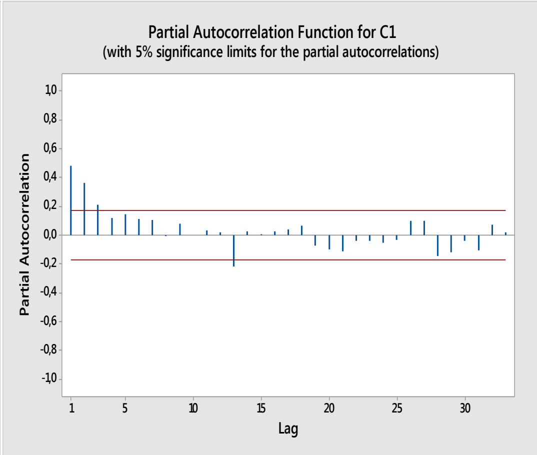


Figure 5.7.b. Partial autocorrelation function for all accident numbers

Minitab output for the AR(1) regression for the data is as follows:

$$Y_t = 18.82 + 0.4804\ Y_{t-1} \qquad \text{Eq. 5.21}$$

where,

Y_t : Forecasted number of accidents at time t

Y_{t-1} : Observed number of accidents at time t-1

The model suggests that the number of accidents will be 0.48 times the number of accidents occurred last month plus the constant. As an illustrative example, to calculate accident numbers occurred for time period 120 (December 2012), the accident numbers occurred on time period 119 (November 2012) can be used. The number of accidents is 48 for time period 119; therefore, for time period 120 it is calculated as 41. This value is quite close to actual value which is 37. The R^2 for the model is calculated as 23.34% which is not too high, but may give good predictions. However, the time series plot of data does not show a linear pattern, so further models should be looked for.

5.2.2.2 Trend Model

The first step in conducting a forecasting approach through time series analysis is to scrutinize the time series plot of data. As mentioned before, the data consists of monthly accident numbers covering 132 months. Figure 5.8 shows the time series plot of the monthly accident numbers against time. Over the entire time span, it can be seen that this data set is non-stationary. The non-stationarity of the data can also be confirmed by the plot of the sample autocorrelation function (ACF) which clearly indicates serial correlation in the data as the autocorrelation coefficients at various lags fall outside the confidence limits (Fig. 5.8).There may be a trend whereas there is no seasonality, in other saying there is no periodic fluctuations. In time series plot of accident data shown in Figure 5.8, it is clearly visible that there is no similar y values at a particular month for each year. It is also inferred from Figure 5.8 that there is no obvious outlier.

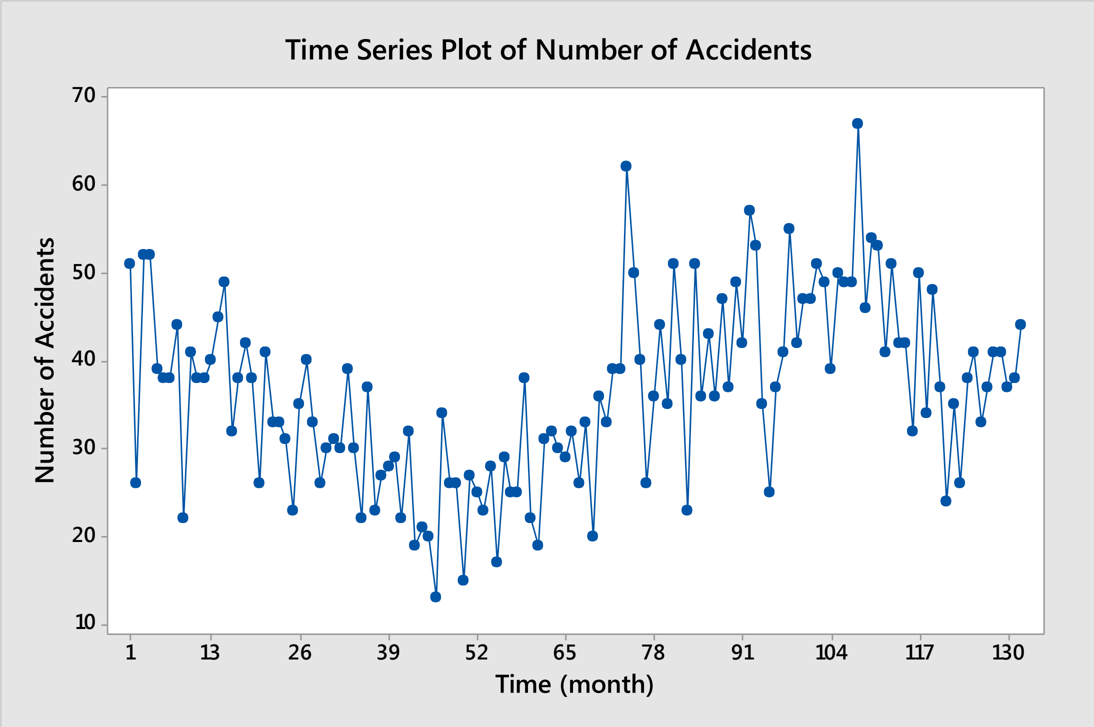


Figure 5.8 Time series plot of total number of accidents

Minitab presents a good option to fit a general trend model to time series data when there is no seasonality. By modeling patterns in the data that are usually visible and then extrapolating those patterns to the future, it provides forecasts. The smallest values for all three measures are observed in the quadratic trend model. Therefore, the final trend model for the research area is formulated as:

$Y_t = 37.33 - 0.2078 \times t + 0.002190 \times t^2$ Eq. 5.22

where,

Y_t is the forecasted number of accidents at time t

Fitted model for quadratic trend can be seen in Figure 5.10. The other trend models are presented in Appendix B in Figures B1-B2. For this model MAPE value is calculated as 23.597. It means that this model predicts the number of accidents in the research area with 23.597% error. In other saying, the model predicts the number of accidents with 76.403% effectiveness. MAD is calculated as 7.5868 which is the average of the absolute deviations. An absolute deviation is the absolute value of the actual data minus the fitted value. While MAPE expresses accuracy as a percentage, MAD denotes accuracy in the same units as the data, which helps conceptualize the amount of error. MSD is calculated as 89.1033 which is very similar to MAD, but instead of summing the absolute deviations, it sums up the squared deviations. MSD is always computed using the same denominator, n, regardless of the model, so MSD values can be compared across the models. MSD is a more sensitive measure of an unusually large forecast error than MAD.

In order to see how this model works, a demonstration could be given. For time period 112, the value for t is 112 and calculated value of Y_t is 41.53. Figure 5.9 presents the quadratic trend analysis of input data including the accident numbers for 132 months and forecasted accident number values for the next 12 months obtained from Minitab. The quadratic trend model forecasted 48, 49, 50, 50, 50, 51, 51, 52, 52, 52, and 53 accidents for the next twelve months, respectively.

Trend Analysis for Y(Number of Accidents)

```
Data       Y(Number of Accidents)
Length     132
NMissing   0

Fitted Trend Equation

Yt = 37,33 - 0,2078×t + 0,002190×t^2

Accuracy Measures

MAPE  23,5970
MAD    7,5868
MSD   89,1033
```

Time	Y(Number of Accidents)	Trend	Detrend
1	51	37,1287	13,8713
2	26	36,9275	-10,9275
3	52	36,7307	15,2693
4	52	36,5382	15,4618
5	39	36,3501	2,6499
6	38	36,1664	1,8336
7	38	35,9871	2,0129
8	44	35,8121	8,1879
9	22	35,6416	-13,6416
10	41	35,4754	5,5246
11	38	35,3136	2,6864
12	38	35,1561	2,8439
13	40	35,0031	4,9969
14	45	34,8544	10,1456
15	49	34,7101	14,2899
16	32	34,5702	-2,5702
17	38	34,4347	3,5653
18	42	34,3035	7,6965
19	38	34,1768	3,8232
20	26	34,0544	-8,0544
21	41	33,9364	7,0636
22	33	33,8227	-0,8227
23	33	33,7135	-0,7135
24	31	33,6086	-2,6086
25	23	33,5081	-10,5081
26	35	33,4120	1,5880
27	40	33,3202	6,6798
28	33	33,2329	-0,2329
29	26	33,1499	-7,1499
30	30	33,0713	-3,0713
31	31	32,9971	-1,9971
32	30	32,9272	-2,9272
33	39	32,8618	6,1382
34	30	32,8007	-2,8007
35	22	32,7440	-10,7440
36	37	32,6917	4,3083
37	23	32,6437	-9,6437
38	27	32,6002	-5,6002
39	28	32,5610	-4,5610
40	29	32,5262	-3,5262
41	22	32,4957	-10,4957
42	32	32,4697	-0,4697
43	19	32,4480	-13,4480
44	21	32,4307	-11,4307
45	20	32,4178	-12,4178
46	13	32,4093	-19,4093
47	34	32,4051	1,5949

48	26	32,4054	-6,4054
49	26	32,4100	-6,4100
50	15	32,4190	-17,4190
51	27	32,4323	-5,4323
52	25	32,4501	-7,4501
53	23	32,4722	-9,4722
54	28	32,4987	-4,4987
55	17	32,5296	-15,5296
56	29	32,5649	-3,5649
57	25	32,6045	-7,6045
58	25	32,6485	-7,6485
59	38	32,6969	5,3031
60	22	32,7497	-10,7497
61	19	32,8069	-13,8069
62	31	32,8684	-1,8684
63	32	32,9343	-0,9343
64	30	33,0046	-3,0046
65	29	33,0793	-4,0793
66	32	33,1584	-1,1584
67	26	33,2418	-7,2418
68	33	33,3296	-0,3296
69	20	33,4218	-13,4218
70	36	33,5184	2,4816
71	33	33,6193	-0,6193
72	39	33,7247	5,2753
73	39	33,8344	5,1656
74	62	33,9485	28,0515
75	50	34,0670	15,9330
76	40	34,1898	5,8102
77	26	34,3170	-8,3170
78	36	34,4487	1,5513
79	44	34,5846	9,4154
80	35	34,7250	0,2750
81	51	34,8698	16,1302
82	40	35,0189	4,9811
83	23	35,1724	-12,1724
84	51	35,3303	15,6697
85	36	35,4925	0,5075
86	43	35,6592	7,3408
87	36	35,8302	0,1698
88	47	36,0056	10,9944
89	37	36,1854	0,8146
90	49	36,3696	12,6304
91	42	36,5581	5,4419
92	57	36,7510	20,2490
93	53	36,9483	16,0517
94	35	37,1500	-2,1500
95	25	37,3561	-12,3561
96	37	37,5665	-0,5665
97	41	37,7813	3,2187
98	55	38,0005	16,9995
99	42	38,2241	3,7759
100	47	38,4521	8,5479
101	47	38,6844	8,3156
102	51	38,9211	12,0789
103	49	39,1622	9,8378
104	39	39,4077	-0,4077
105	50	39,6575	10,3425
106	49	39,9118	9,0882
107	49	40,1704	8,8296
108	67	40,4334	26,5666
109	46	40,7008	5,2992
110	54	40,9725	13,0275
111	53	41,2486	11,7514
112	41	41,5291	-0,5291

113	51	41,8140	9,1860
114	42	42,1033	-0,1033
115	42	42,3969	-0,3969
116	32	42,6950	-10,6950
117	50	42,9974	7,0026
118	34	43,3042	-9,3042
119	48	43,6153	4,3847
120	37	43,9309	-6,9309
121	24	44,2508	-20,2508
122	35	44,5751	-9,5751
123	26	44,9038	-18,9038
124	38	45,2369	-7,2369
125	41	45,5743	-4,5743
126	33	45,9161	-12,9161
127	37	46,2623	-9,2623
128	41	46,6129	-5,6129
129	41	46,9679	-5,9679
130	37	47,3272	-10,3272
131	38	47,6909	-9,6909
132	44	48,0590	-4,0590

Forecasts

Period	Forecast
133	48,4315
134	48,8083
135	49,1896
136	49,5752
137	49,9652
138	50,3596
139	50,7583
140	51,1614
141	51,5690
142	51,9808
143	52,3971
144	52,8178

Figure 5.9 Quadratic trend analysis results

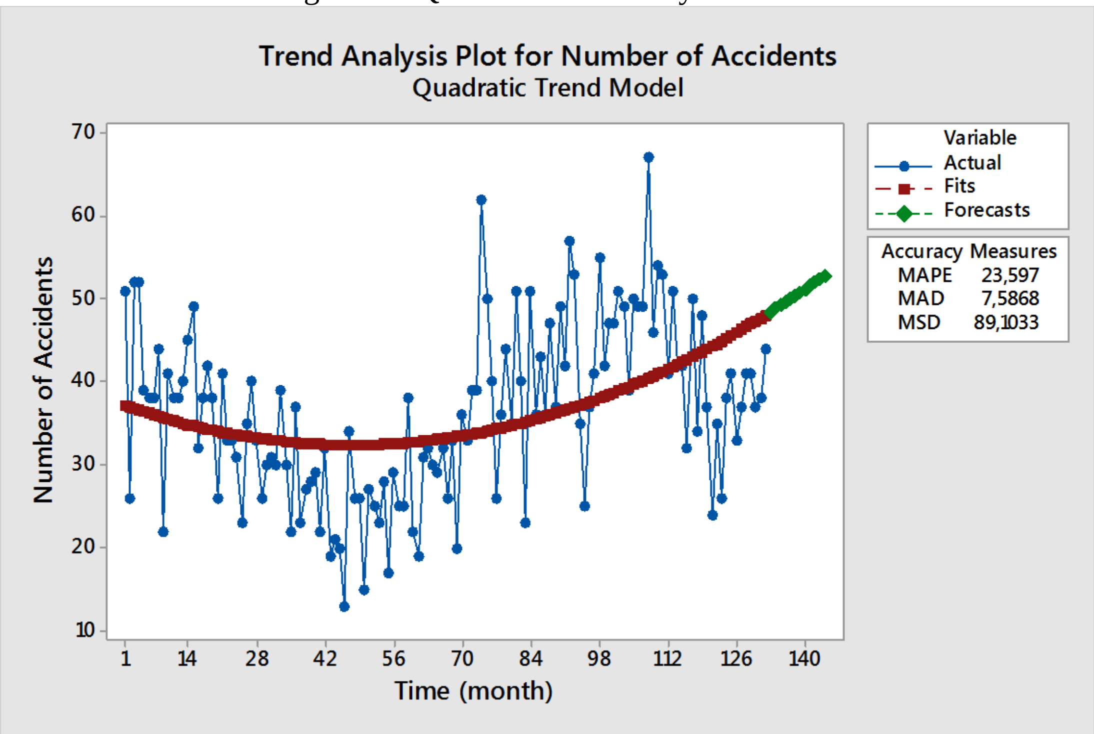


Figure 5.10 Fitted model for quadratic trend

5.2.2.3 Double Exponential Model

Since the data seems to have a trend and do not show seasonality, double exponential smoothing method can be performed and compared with trend analysis model. The fitted model for double exponential smoothing method is presented in Figure 5.11 and the results are demonstrated in Figure 5.12. In this method, Minitab warns the users in projecting forecasts too far into the future. It is recommended to forecast only six periods into the future which corresponds to six months.

For each forecast there are lower and upper prediction limits. A 95% prediction interval means with a 95% confidence the prediction interval contains the forecast at the specified time (Minitab Express Support, 2016). The calculated forecasts with upper and lower limits can be seen in Table 5.8. As can be seen from Table 5.8, double exponential smoothing model forecasted 42.80, 42.81, 42.82, 42.82, 42.83, and 42.84 accidents for the next six months, respectively. MAPE, MAD, and MSD values are calculated as 22.893, 7.827, and 104.462 which are smaller than the MAPE, MAD, and MSD values calculated for quadratic trend model. For all three measures, the smaller the value, the better the fit of the model.

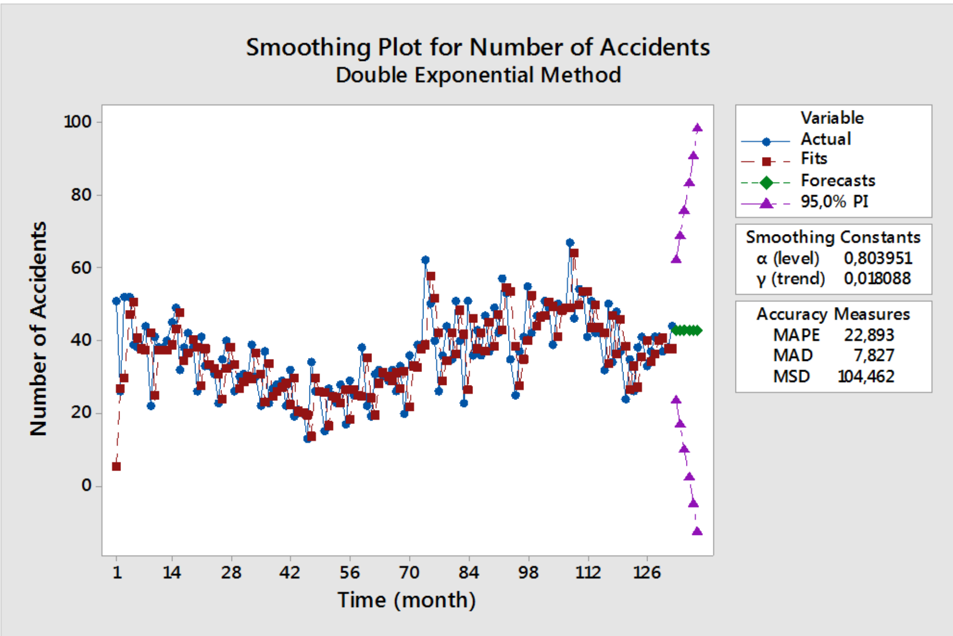


Figure 5.11 Fitted model for double exponential smoothing

Double Exponential Smoothing for Y(Number of Accidents)

```
Data    Y(Number of Accidents)
Length  132

Smoothing Constants
α (level)  0,803951
γ (trend)  0,018088

Accuracy Measures
MAPE   22,893
MAD     7,827
MSD   104,462


Forecasts
Period  Forecast     Lower    Upper
133      42,8013   23,6243  61,9782
134      42,8083   17,0161  68,6005
135      42,8153    9,9170  75,7137
136      42,8224    2,5862  83,0586
137      42,8294   -4,8694  90,5283
138      42,8365  -12,3993  98,0722
```

Figure 5.12 Results for double exponential smoothing

5.2.2.4 Moving Average Model

The former two time series models are built grounded on that data does not show a seasonal pattern although it seems to have trend. Actually a trend exists when there is a long-term increase or decrease in the data. Time series plot of data seems to bear an increasing trend at the time interval that is studied on (Figure 5.8). Furthermore the plot of the sample autocorrelation function (ACF) indicates the nonstationarity of the data (Fig. 5.7). However, if there existed more data points for future accident records, the trend would have changed. Moreover, trend would have disappeared and the data would become stationary. Therefore, it is helpful in determining the best model to look on a third time series model which is called as moving average such that there is not a trend or seasonal component in the data.

The fitted model for moving average method is presented in Figure 5.13 and the results are demonstrated in Figure 5.14. Figure 5.13 displays that the fits closely follow the data which indicates that the model fits the data. In this method Minitab forecasts the same values whatever the forecast horizon is chosen. It is possible to forecast farther into the future but the forecast line will be flat. However, a flat forecast is not necessarily a bad forecast either.

For this model MAPE value is calculated as 16.537. It means that this model predicts the number of accidents in the research area with 16.537% error. In other saying, the model predicts the number of accidents with 83.463% effectiveness. MAD is calculated as 5.3043 which is the average of the absolute deviations. An absolute deviation is the absolute value of the actual data minus the fitted value. While MAPE expresses accuracy as a percentage, MAD denotes accuracy in the same units as the data, which helps conceptualize the amount of error. MSD is calculated as 49.1193 which is very similar to MAD, but instead of summing the absolute deviations, it sums up the squared deviations. MSD is always computed using the same denominator, n, regardless of the model, so MSD values can be compared across the models. MSD is a more sensitive measure of an unusually large forecast error than MAD. As can be seen moving average model gave the best accuracy values. When the MAPE, MAD, and MSD values are compared with the former two model the smallest ones are seen at the moving average model. This model forecasted the number of accidents as 36 for the next month and subsequent five months.

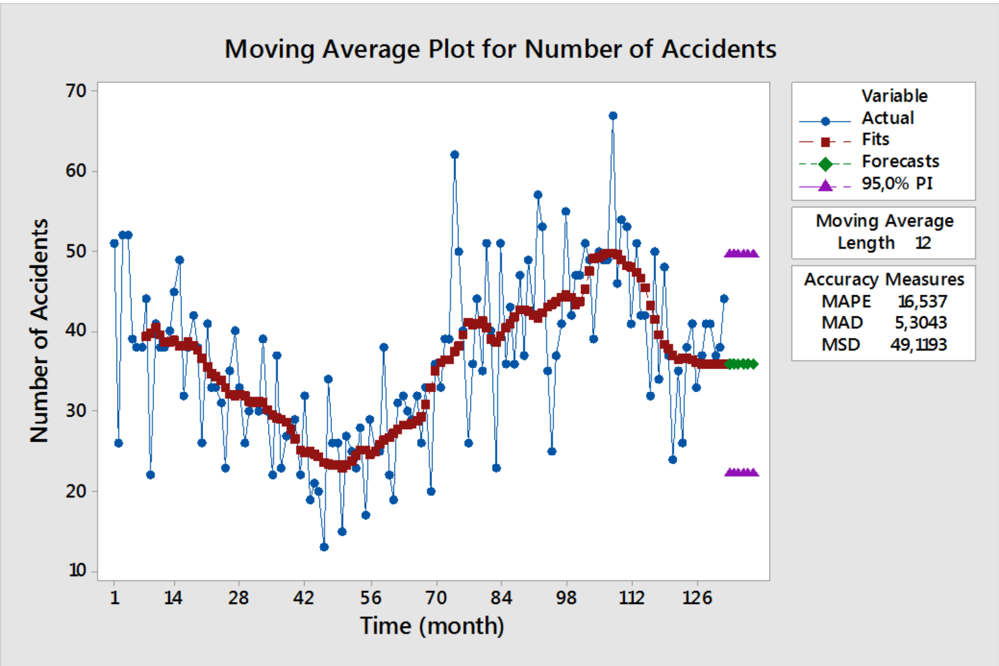


Figure 5.13 Fitted model for moving average method

Moving Average for Number of Accidents

```
Data      Number of Accidents
Length    132
NMissing  0
Moving Average
Length  12

Accuracy Measures

MAPE  16,5375
MAD    5,3043
MSD   49,1193

Forecasts

Period  Forecast    Lower    Upper
133      35,9583  22,2219  49,6948
134      35,9583  22,2219  49,6948
135      35,9583  22,2219  49,6948
136      35,9583  22,2219  49,6948
137      35,9583  22,2219  49,6948
138      35,9583  22,2219  49,6948
```

Figure 5.14 Results for moving average method

In order to predict the future number of accidents for the high risk groups determined by Riskex Risk Score Calculator in Chapter 4, time series models for each of them are built. Results of time series analysis shows that for the high risk groups of Üzülmez district data determined in Chapter 4, due to lack of both seasonality and trend, moving average models fit better again. Consequencely, the number of accidents expected to occur in the future is calculated for the roof fall type of accidents, accident location of longwall face, accidents at shift 1, accidents experienced by longwall production workers, accidents affecting foot-toe, age group of 30-34, and 0-4 years experience.

i. Roof fall type of accidents

The data consists of the number of roof fall accidents occurred at Üzülmez district for each month covering 132 months from January 2003 to December 2013. Figure 5.15 shows the time series plot of the monthly roof fall accident numbers against time. Over the entire time span, it can be seen that this data set is non-stationary. There is no seasonality, in other saying there is no periodic fluctuations. There is no trend at first glance and it is also proved by practising trend analysis. If the data do not have a trend or seasonal component moving average procedure can be a likely choice.

When the moving average procedure is performed it is seen that yield results (MAPE: 26.7, MAD:3.3, and MSD:17.5) are reliable. Moving Average results for roof fall accidents can be seen on Figure 5.17 and fitted model is represented in Figure 5.16. The expected number of roof fall accidents for the next month is 14, with the lower and upper 95% prediction intervals of 5.3 and 21.6, respectively. In 2015, a quite similar result in another district of TTK is found by using Fault Tree Analysis (FTA). It is deduced that in TTK Amasra district, a worker expectedly had an accident from roof and rib falls approximately every 3.73 days (Direk, 2015). In another saying, in a month, 8 roof fall accidents are expected in TTK Amasra district by FTA method whereas 14 roof fall accidents are expected in TTK Üzülmez district by time series analysis method.

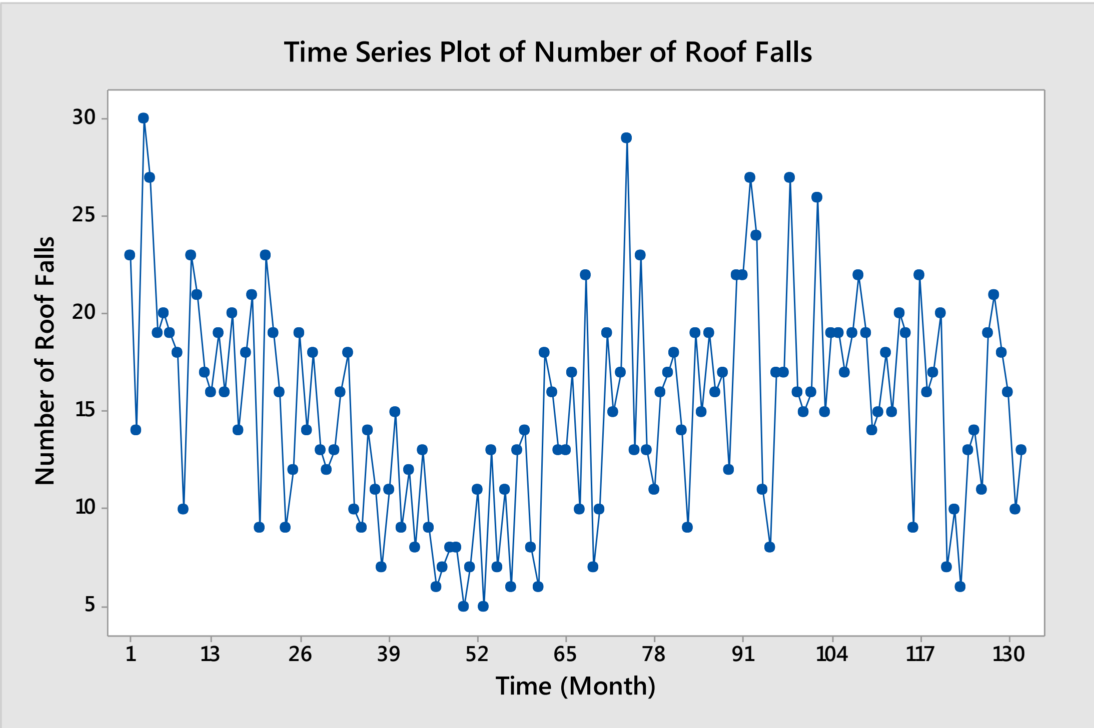


Figure 5.15 Time series plot for roof fall accidents

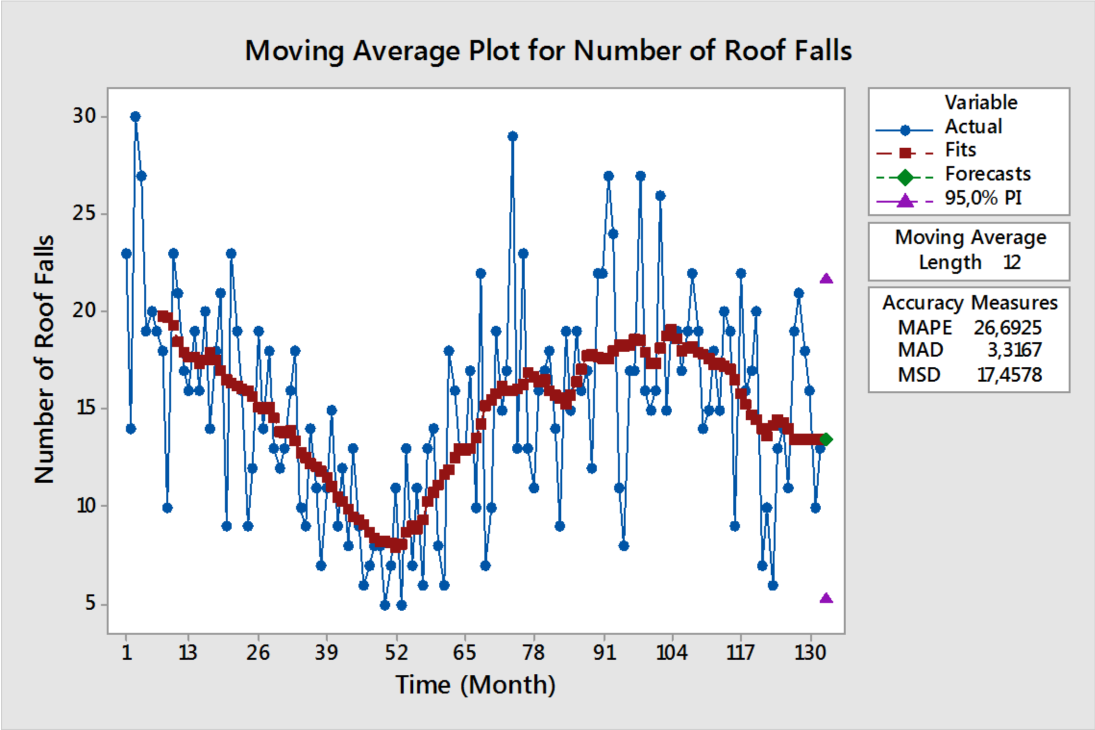


Figure 5.16 Fitted model for roof fall accidents

Moving Average for Y(Number of Accidents)

```
Data      Y(Number of Accidents)
Length    132
NMissing  0


Moving Average

Length  12


Accuracy Measures

MAPE  26,6925
MAD    3,3167
MSD   17,4578


Forecasts

Period  Forecast    Lower    Upper
133      13,4583  5,26910  21,6476
```

Figure 5.17 Moving average results for roof fall accidents

ii. Accident location of longwall face

The fitted model for longwall face accidents is found to be moving average method as in the case of roof fall accidents. The data consists of the number of longwall face accidents occurred at Üzülmez district for each month covering 132 months from January 2003 to December 2013. Figure 5.18 shows the time series plot of the monthly longwall face accident numbers against time. It is seen that data set is non-stationary, there is neither seasonality nor trend. Cause the data do not have a trend or seasonal component moving average procedure is significant.

Moving Average results for longwall face accidents can be seen on Figure 5.20 and fitted model is represented in Figure 5.19. Calculated accuracy values (MAPE: 19.8, MAD:4.4, and MSD:34.4) are reliable. The expected number of roof fall accidents for the next month is 26.

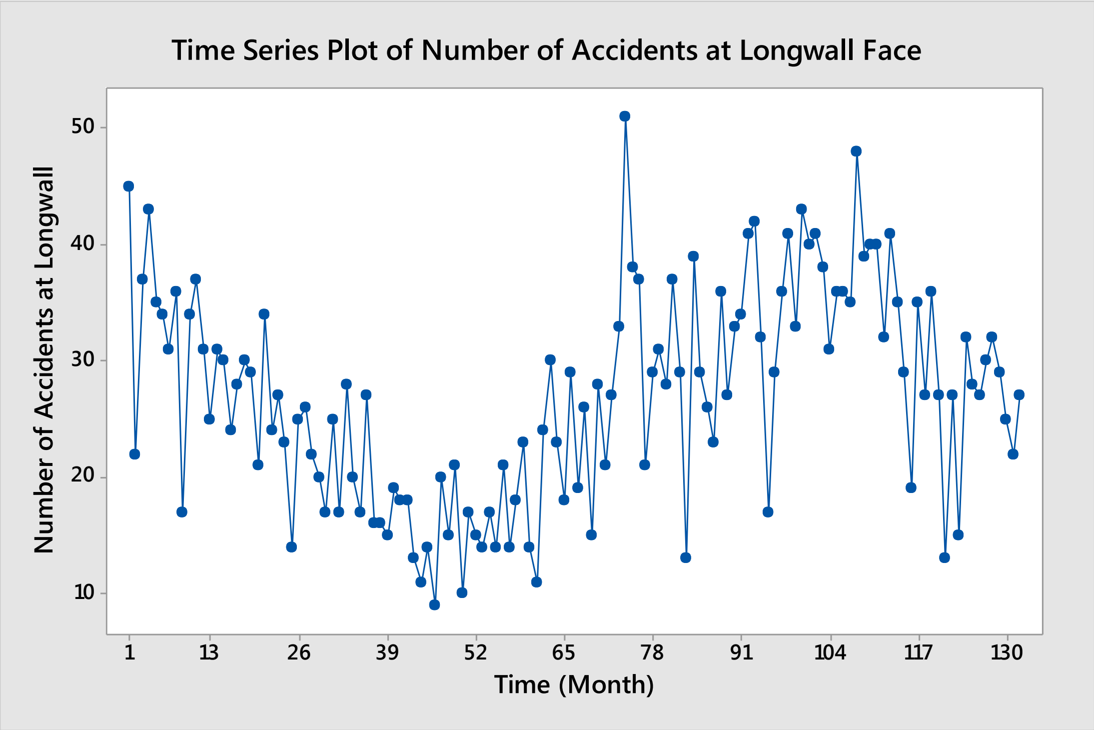


Figure 5.18 Time series plot for longwall face accidents

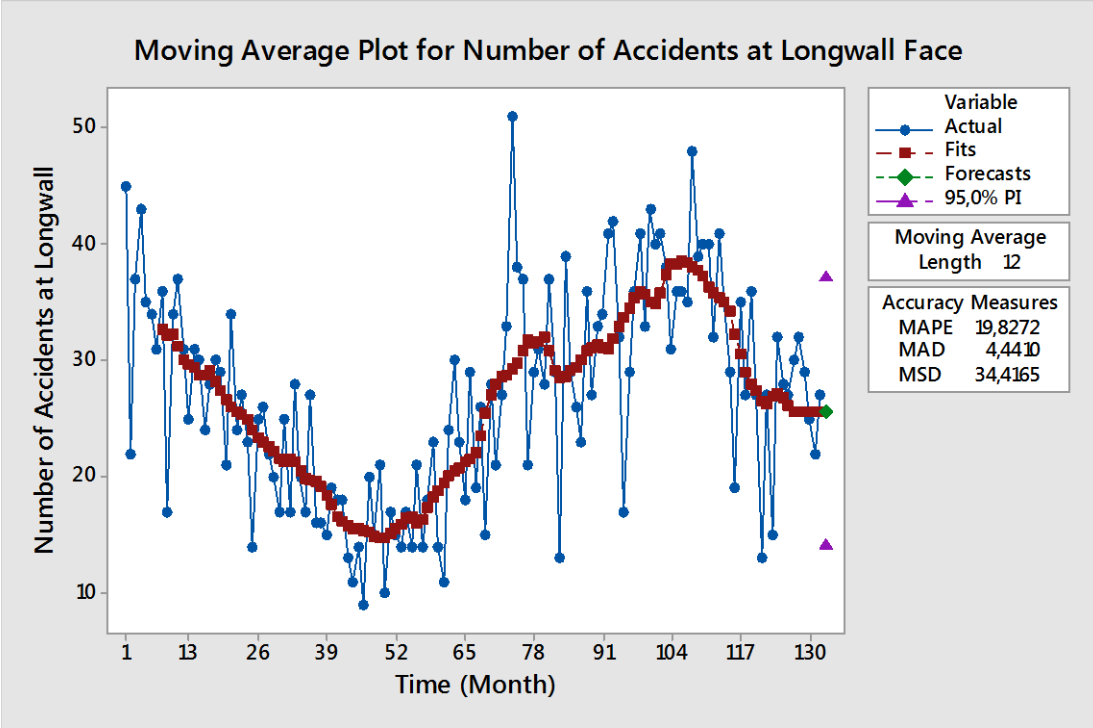


Figure 5.19 Fitted model for longwall face accidents

Moving Average for Y(Number of Accidents)

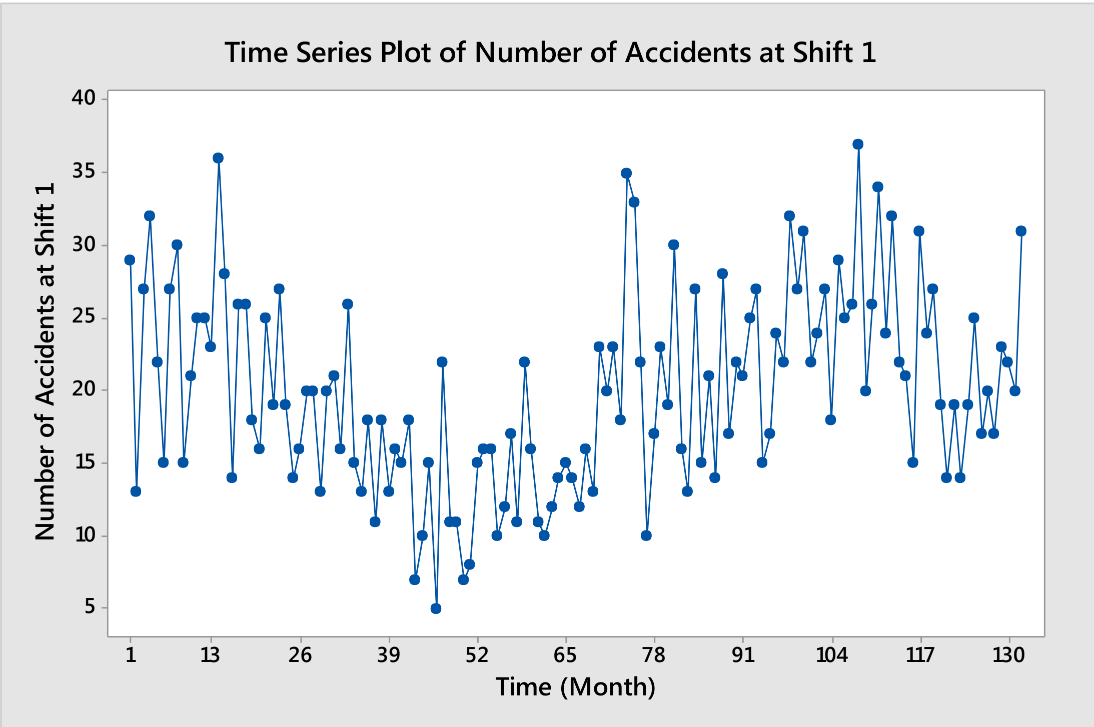
```
Data        Y(Number of Accidents)
Length      132
NMissing    0


Moving Average

Length  12


Accuracy Measures

MAPE  19,8272
MAD    4,4410
MSD   34,4165


Forecasts

Period  Forecast     Lower     Upper
133      25,5833   14,0851   37,0816
```

Figure 5.20 Moving average results for longwall face accidents

iii. Accidents at shift 1

The fitted model for the accidents occurred at shift 1 is found to be moving average method. The data consists of the number of accidents occurred at shift 1 for each month covering 132 months from January 2003 to December 2013. Figure 5.21 shows the time series plot of the monthly accident numbers against time. It is seen that data set is non-stationary, there is neither seasonality nor trend. Therefore moving average method becomes prominent.

Moving Average results for accidents at Shift 1 can be seen on Figure 5.23 and fitted model is represented in Figure 5.22. The expected number of accidents at shift 1 for the next month is 20.



5.21 Time series plot for accidents occurred at shift 1

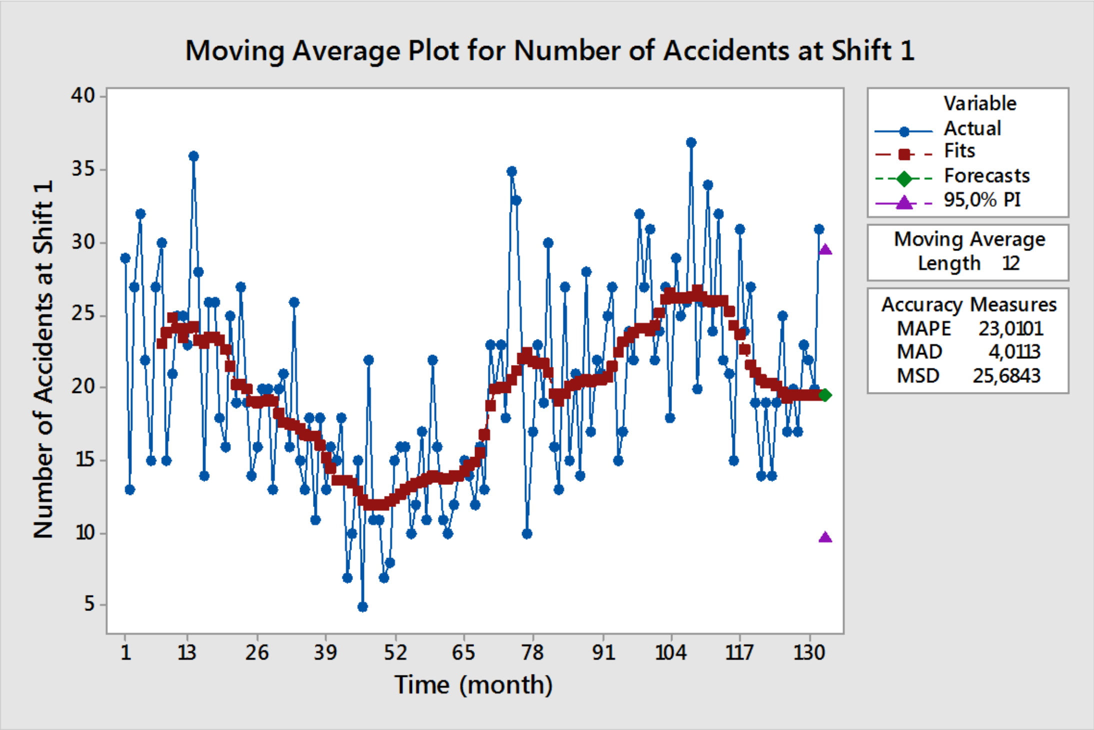


Figure 5.22 Fitted model for accidents occurred at shift 1

Moving Average for Y(Number of Accidents)

```
Data       Y(Number of Accidents)
Length     132
NMissing   0


Moving Average

Length  12


Accuracy Measures

MAPE   23,0101
MAD     4,0113
MSD    25,6843


Forecasts

Period  Forecast     Lower     Upper
133      19,5833  9,65029   29,5164
```

Figure 5.23 Moving average results for accidents occurred at shift 1

iv. Accidents experienced by longwall production workers

The fitted model for the accidents experienced by longwall production workers is found by moving average method. The data consists of the number of accidents experienced by longwall production workers for each month covering 132 months from January 2003 to December 2013. Figure 5.24 shows the time series plot of the monthly accident numbers against time. It is seen that data set is non-stationary, there is neither seasonality nor trend. Therefore moving average method becomes prominent.

Moving Average results for accidents experienced by longwall production workers can be seen on Figure 5.26 and fitted model is represented in Figure 5.25. MAPE, MAD, and MSD values are calculated as 21, 4.6, and 37.5, respectively. The expected number of accidents experienced by longwall production workers for the next month is 24.

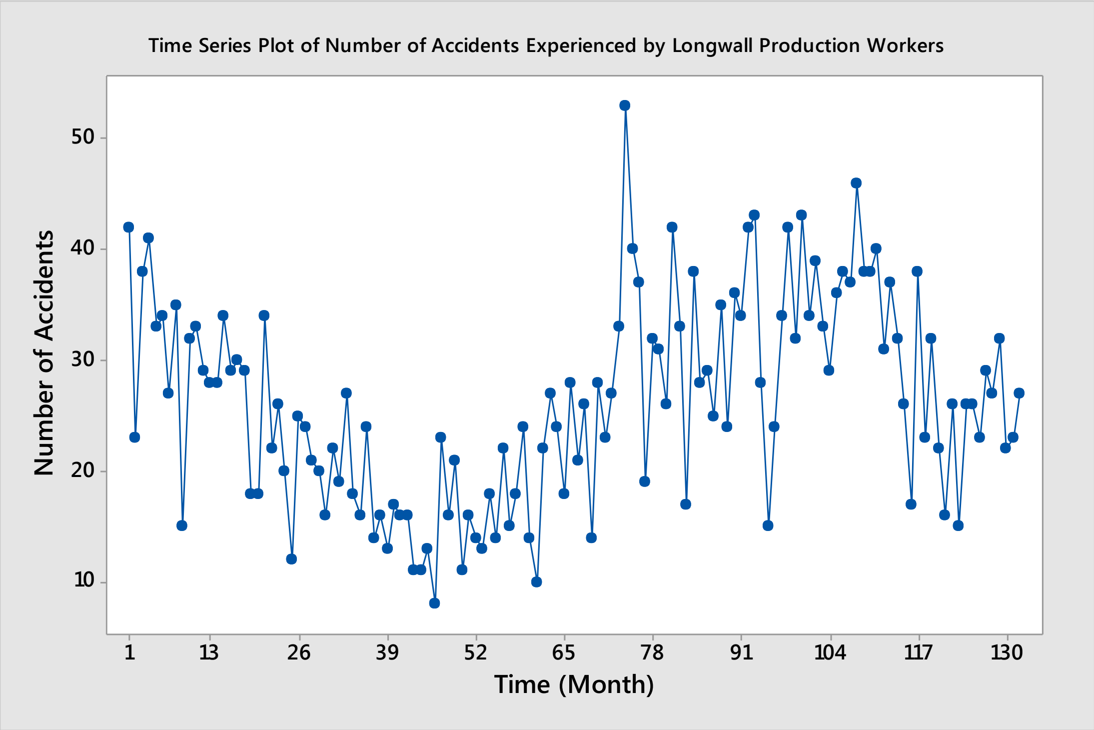


Figure 5.24 Time series plot for the accidents experienced by longwall production workers

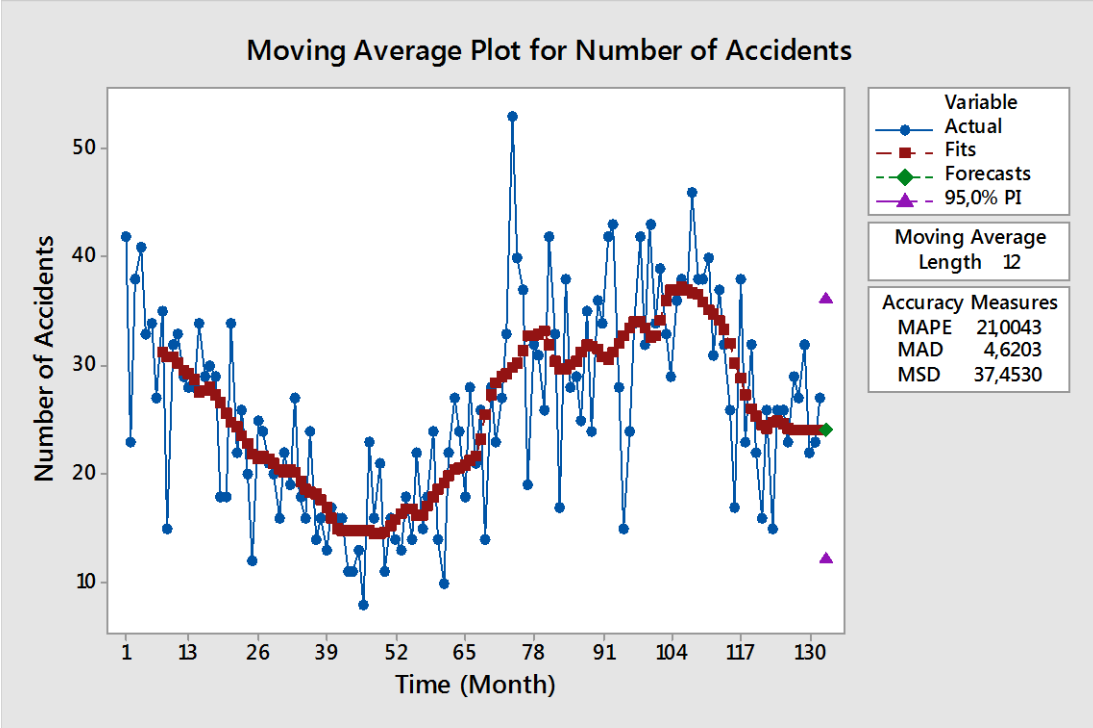


Figure 5.25 Fitted model for accidents experienced by longwall production workers

Moving Average for Y(Number of Accidents)

```
Data       Y(Number of Accidents)
Length     132
NMissing   0


Moving Average

Length  12


Accuracy Measures

MAPE  21,0043
MAD    4,6203
MSD   37,4530


Forecasts

Period  Forecast    Lower    Upper
133       24,125  12,1303  36,1197
```

Figure 5.26 Moving average results for accidents experienced by longwall production workers

v. Accidents affecting foot-toe

The fitted model for the accidents affecting foot-toe is found by moving average method. The data consists of the number of accidents affecting foot-toe for each month covering 132 months from January 2003 to December 2013. Figure 5.27 shows the time series plot of the monthly accident numbers against time. It is seen that data set is non-stationary, there is neither seasonality nor trend.

Moving Average results for accidents affecting foot-toe can be seen on Figure 5.29 and fitted model is represented in Figure 5.28. The expected number of accidents affecting foot-toe for the next month is 7. However, the accuracy measures for this model is quite high, lowering the reliability of the model.

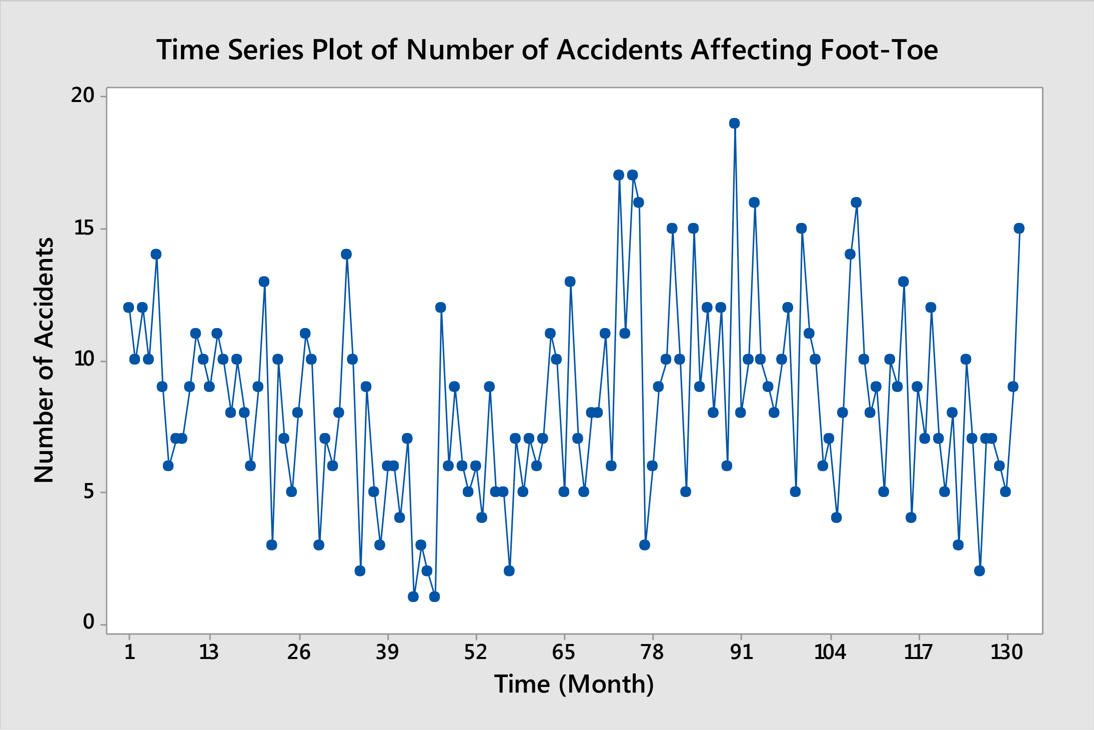


Figure 5.27 Time series plot for the accidents affecting foot-toe

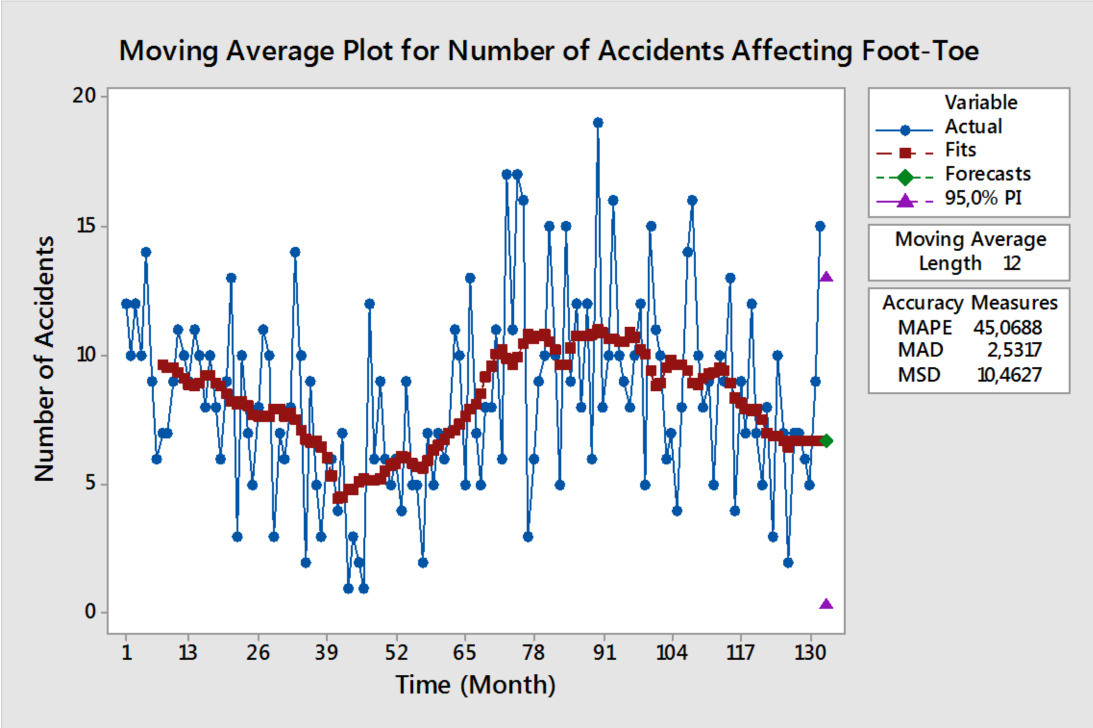


Figure 5.28 Fitted model for accidents affecting foot-toe

Moving Average for Y(Number of Accidents)

```
Data        Y(Number of Accidents)
Length      132
NMissing    0


Moving Average

Length  12


Accuracy Measures

MAPE   45,0688
MAD     2,5317
MSD    10,4627


Forecasts

Period  Forecast     Lower     Upper
133      6,66667  0,326937  13,0064
```

Figure 5.29 Moving average results for accidents affecting foot-toe

vi. Accidents experienced by age group of 30-34

For the accidents experienced by age group of 30-34 the fitted model is moving average. The data consists of the number of accidents experienced by age group of 30-34 for each month covering 132 months from January 2003 to December 2013. Figure 5.30 shows the time series plot of the monthly accident numbers against time. It is seen that data set is non-stationary, there is neither seasonality nor trend. Therefore moving average method becomes prominent.

Moving Average results for accidents experienced by age group of 30-34 can be seen on Figure 5.32 and fitted model is represented in Figure 5.31. MAPE, MAD, and MSD values are calculated as 22.1, 2.5, and 10, respectively. The expected number of accidents experienced by age group of 30-34 for the next month is 15.

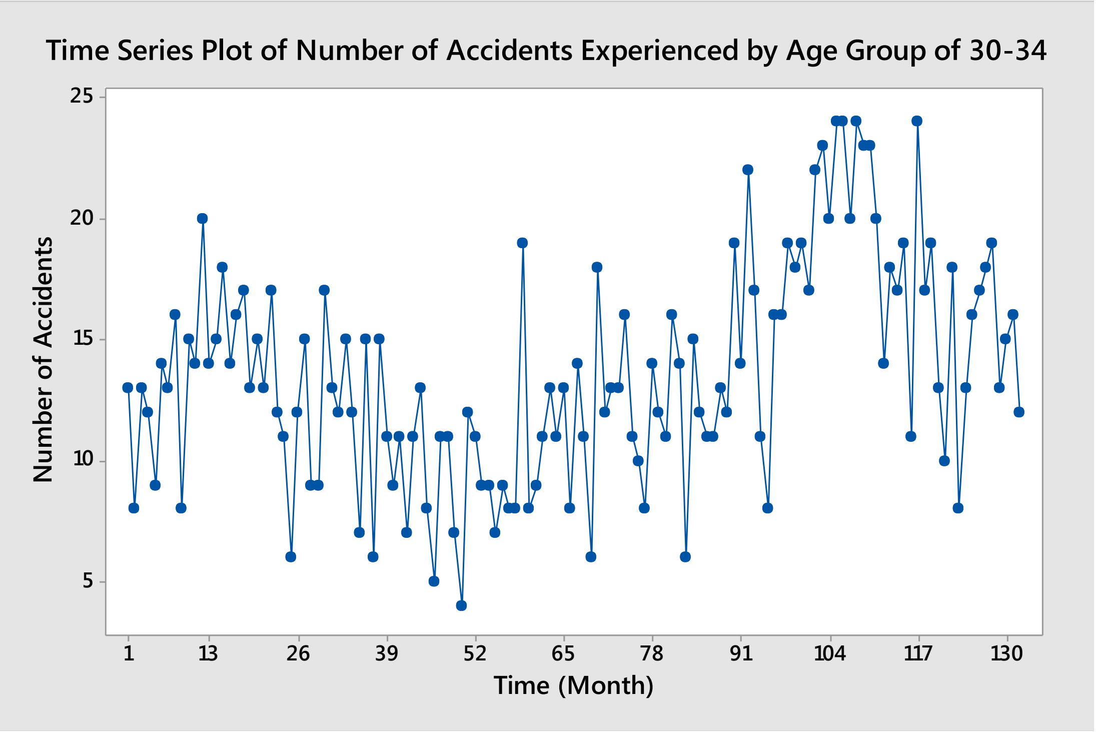


Figure 5.30 Time series plot for the accidents experienced by age group of 30-34

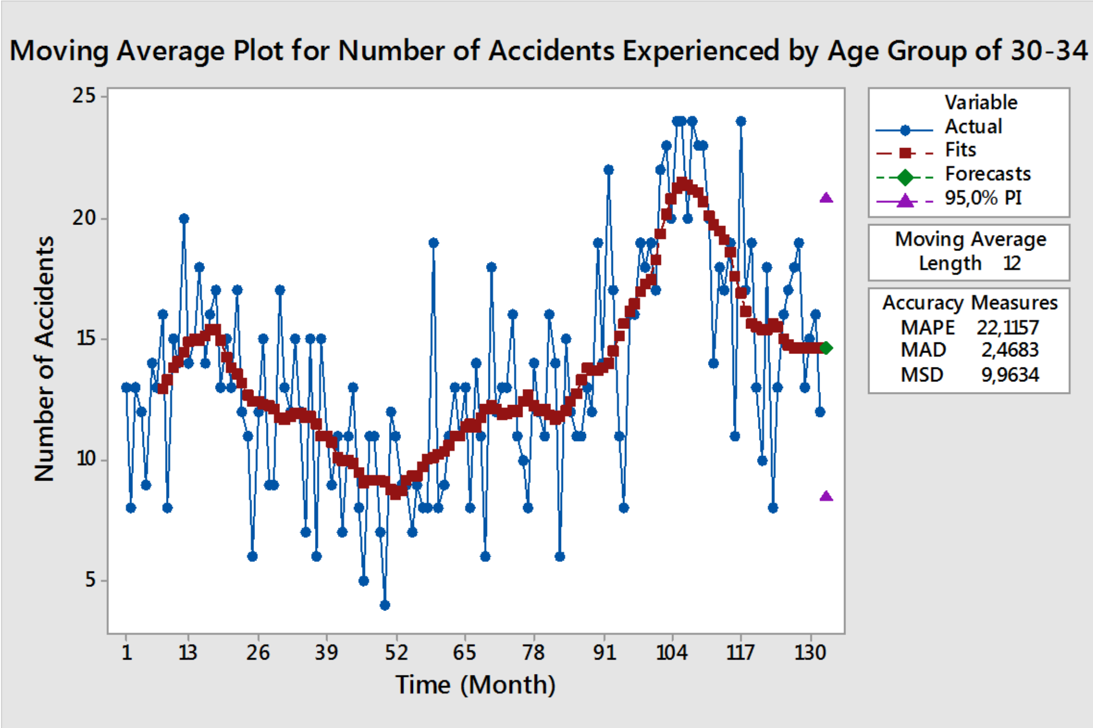


Figure 5.31 Fitted model for the accidents experienced by age group of 30-34

Moving Average for Y(Number of Accidents)

```
Data      Y(Number of Accidents)
Length    132
NMissing  0


Moving Average

Length  12


Accuracy Measures

MAPE  22,1157
MAD    2,4683
MSD    9,9634


Forecasts

Period  Forecast    Lower    Upper
133       14,625  8,43839  20,8116
```

Figure 5.32 Moving average results for the accidents experienced by age group of 30-34

vii. Accidents experienced by workers having 0-4 year experience

For the accidents experienced by workers having 0-4 year experience the fitted model is moving average. The data consists of the number of accidents experienced by workers having 0-4 year experience for each month covering 132 months from January 2003 to December 2013. Time Series plot for the accidents experienced by workers having 0-4 year experience is shown in Figure 5.33.

Moving Average results for accidents experienced by workers having 0-4 year experience can be seen on Figure 5.35 and fitted model is represented in Figure 5.34. The expected number of accidents experienced by workers having 0-4 year experience for the next month is 11.

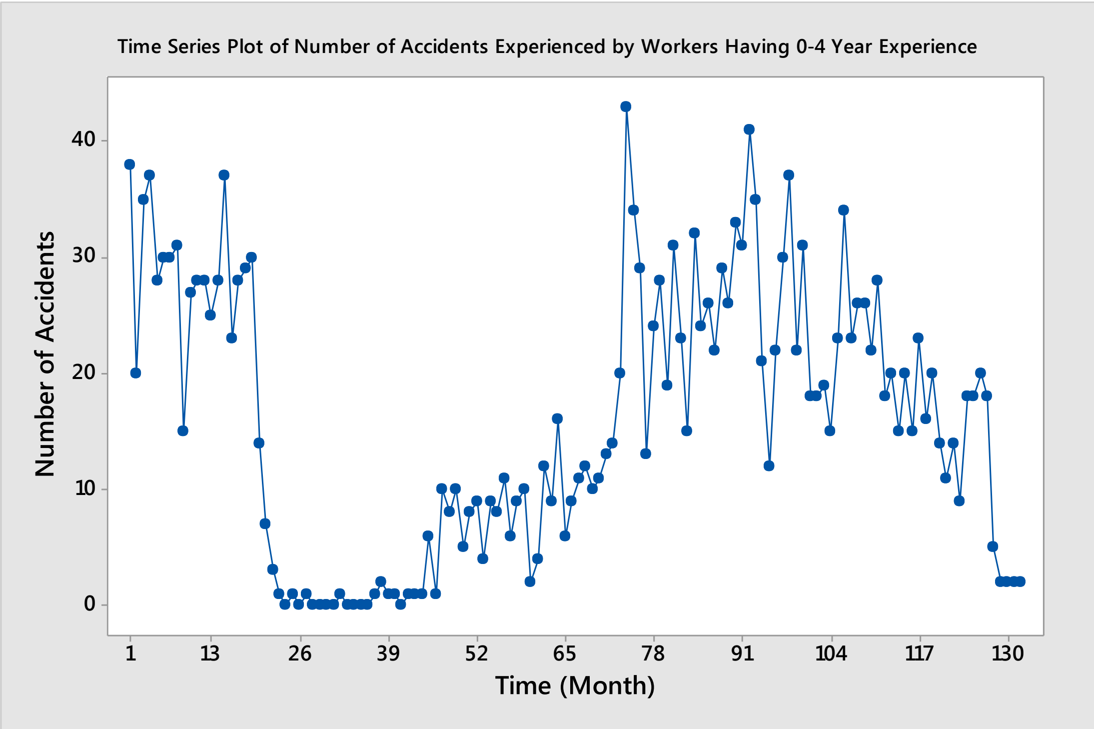


Figure 5.33 Time series plot for the accidents experienced by workers having 0-4 year experience

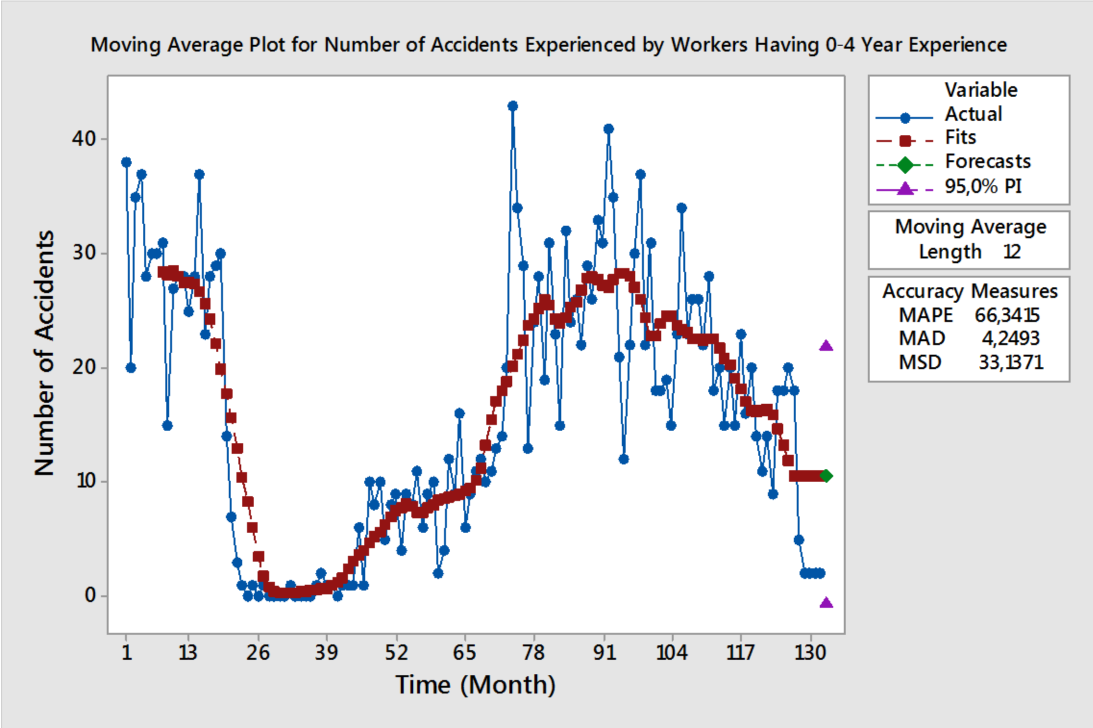


Figure 5.34 Fitted model for the accidents experienced by workers having 0-4 year experience

```
Data        Y(Number of Accidents)
Length      132
NMissing    0


Moving Average

Length   12


Accuracy Measures

MAPE    66,3415
MAD      4,2493
MSD     33,1371


Forecasts

Period   Forecast       Lower     Upper
133       10,5833   -0,699164   21,8658
```

Figure 5.35 Moving average results for the accidents experienced by workers having 0-4 year experience

5.3 Results and Discussion

In Chapter 5, forecast analysis is performed by using two frequently used quantitative techniques which are regression and time series analysis. Summary of forecasting techniques used for the study is given in Table 5.3 to make a comprehensive comparison.

In order to see the effect of variables such as raw coal production, total gallery advance, total number of workers, explosive consumption, and timber consumption on number of accidents, multiple linear regression (MLR) is practiced. It is seen that total gallery advance is not influential on determining the number of accidents cause it does not take part neither of the equations. Founded equations to predict the total number of accidents by MLR method is given in Table 5.3. Total gallery advance is highly related to the raw coal production and due to this reason it can be excluded from the model. The R^2 for these models are calculated as 17%. This value can be expressed in the following way. While 17% of the total changes in response value (number of accidents) can be explained by the changes caused by the independent variables included in the model (raw coal production, total number of workers, explosive consumption/raw coal production, and timber consumption/raw coal production), the remaining 82% is due to other factors which are not available and which are not included in the model. Forecast horizon is 1 month for MLR meaning that it is only possible to forecast the number of accidents for the next month. Forecast horizon is the length of time into the future for which the forecasts are made.

To forecast the number of accidents just by utilizing the number of accidents occurred before, time series models are built. Firstly, a first order autoregressive (AR(1)) model is set. Although the model yielded a relatively reliable R-square value which is bigger than that founded for the MLR model, it is thought that another time series model should be looked for. The main reason of this was that the time series plot of data does not show a linear pattern which is conflicting with the AR(1) model. When time series plot of the data is constituted and ACF is examined, it is seen that the data is non-stationary, there exists a trend and there is no seasonality. So, trend and double exponential models are worked on. Among the trend models the lowest MAPE, MAD, and MSD values are seen in quadratic model, so the quadratic model is better fitting from the other trend models. Due to the existence of the trend and lack of seasonality, double exponential model is practised as additional to trend model. MAPE, MAD, and MSD values calculated for the double exponential model are quite close to MAPE, MAD, and MSD values calculated for the quadratic trend model (Table 5.3). Based on the fact that if there existed more data points for future accident records, the trend would have changed and even disappear, moving average model is applied to data as a third model. When the MAPE, MAD, and MSD values are compared with the former two model the smallest ones are seen at the moving average model (Table 5.3). So, moving average model is the best fit model among all the time series forecasting techniques for determining total number of accidents in TTK Üzülmez.

Table 5.3 Summary of forecasting techniques

	Regression	**Time Series Analysis**			
	MLR	**AR(1)**	**Quadratic Trend Model**	**Double Exponential Model**	**Moving Average Model**
Variables	Raw coal production(X1), Total gallery advance(X2), Total number of workers(X3), Blasting consumption(X4), Timber consumption(X5)	Number of accidents occurred previous year	Time	Time	Time
Prediction Interval	Monthly	Monthly	Monthly	Monthly	Monthly
Equation	$Y = 93.4 + 0.000406\ X1 - 0.0324\ X3 - 0.0616\ X4$ $Y = 88.5 + 0.000358\ X1 - 0.0367\ X3 - 0.0756\ X4 + 0.426\ X5$	$Y_t = 18.82 + 0.4804\ Y_{t-1}$	$Y_t = 37.33 - 0.2078\times t + 0.002190\times t^2$	-	-
R-square	17%	23%	-	-	-
MAPE	-	-	23.597	22.893	16.537
MAD	-	-	7.5868	7.827	5.3043
MSD	-	-	89.1033	104.462	49.1193
Forecast Horizon	Short term (1 month)	Short term (1 month)	Long term (12 months)	Short-medium term(6 months)	Short term (1 month)

Moreover, results of time series analysis show that for the high risk groups of Üzülmez district data determined in Chapter 4, due to lack of both seasonality and trend, moving average models fit better again. The accuracy values and expected number of accidents for high risk groups are given in Table 5.4. Because of the better accuracy values, moving average model is the best fit model in estimating the future number of accidents both for total number of accidents and the number of accidents of high risk groups.

Table 5.4 Accuracy values and expected number of accidents for high risk groups

High Risk Groups	**MAPE**	**MAD**	**MSD**	**Forecasted Number of Accidents for 133. month**	**Average Number of Accidents**
Roof fall	26.7	3.3	17.5	14	15
Longwall face	19.8	4.4	34.4	26	27
Shift 1	23.01	4.01	25.68	20	20
Longwall production workers	21.00	4.62	37.45	24	26
Accidents affecting foot-toe	45.07	2.53	10.46	7	8
Age group of 30-34	22.12	2.47	9.96	15	14
0-4 year experience	66.34	4.25	33.14	11	16

5.4 Validation of the Time Series Models

Since there is not huge difference between the accuracy values of all the time series models, especially quadratic trend model and double exponential model, they are compared by looking how they close the actual number of accidents. When the accuracy values are evaluated moving average model should be used, but as can be seen in Table 5.3, quadratic trend model has the advantage of long time forecasting capacity and due to the small difference between the accuracy values, whether it may be used or not should be analysed. Forecast horizon is the length of time into the future for which the forecasts are made. In order to do that the number of accidents data for the first 126 months is evaluated by four time series models seperately and output values for the last 6 months is compared with the real number of accidents occurred in second half of the last year. At this point, it is vitally important to state that a time series model should be updated as soon as the new data is obtained. Because, when the newly arrived data is entered, the model changes completely.How much the forecasted values approach to the real values is tabulated in Table 5.5. Detrend values shows the difference between real value and the forecasted value. Percentage error shows the detrend over real value; therefore a percentage error value close to zero means forecasted value aproaches to real value quite well. Moving average model has the smallest percentage error values which also certifies the goodness of fit of this model. According to percentage error values, second best fit model is AR(1) model. As can be seen in Table 5.3 like moving average method AR(1) model has the disadvantage of short forecast horizon. If it is needed to forecast longer time periods quadratic trend model can be used instead of double exponential model cause it has smaller percentage error values.

Table 5.5 Real, trend, and detrend values for the last 6 months

Month	Real value	Quadratic Trend Model			Double Exponential Model			Moving Average Model			AR(1) Model		
		Forecast value	Detrend	% Error	Forecast value	Detrend	% Error	Forecast value	Detrend	% Error	Forecast value	Detrend	% Error
127	37	34.4	2,6	7	49,8	-12,8	-35%	37,04	-0,04	0%	34,6732	2,3268	6%
128	41	34.3	6,7	16	50,3	-9,3	-23%	37,04	3,96	10%	36,5948	4,4052	11%
129	41	34.2	6,8	17	50,8	-9,8	-24%	37,04	3,96	10%	38,5164	2,4836	6%
130	37	34.1	2,9	8	51,3	-14,3	-39%	37,04	-0,04	0%	38,5164	-1,5164	-4%
131	38	33.9	4,1	11	51,7	-13,7	-36%	37,04	0,96	3%	36,5948	1,4052	4%
132	44	33.7	10,3	23	52,2	-8,2	-19%	37,04	6,96	16%	37,0752	6,9248	16%

Forecasting the future accident numbers with time series analysis method has given good accuracy values in this research. The moving average model was found to be the best fit model for time series analysis due to best accuracy results and lower percentage errors. The MAPE value which gives result about the precision of the model was found to be 16.5%. It means that the model predicts the number of accidents with 16.5% error and with 83.5% accuracy. Sarı has also used time series technique in order to predict number of accidents in two different lignite mines. In his study, a MAPE value of 21.55% for ELI and 19.87% for GLI was computed which are quite greater than the MAPE value calculated in this study. However, at this point it is important to mention that this research is conducted in a lignite mine.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

In this research study, the relative seriousness of all hazards is determined and the future trend of accidents is predicted in underground coal mining operations of TTK Üzülmez district.
The main conclusions drawn from this study can be listed as:

i. At the study area, descriptive statistics show that 4731 of the total 4802 accidents occurred in underground operations. Roof falls have the biggest share among all the accident types such that the number of accidents related to roof fall is 1998 out of 4731, which corresponds to 42% of total accidents. 3559 of the 4731 accidents took place in longwall face which is the most accident encountered places. At Shift 1 (08:00-16:00) 2640 accidents occurred, corresponding to 56% of the total accidents. Although they constitute the 42% of total workers, 75% of the total accidents are experienced by the longwall production workers. Most of the workers suffering from accidents are primary school graduates with a share of 58%. Total of 1486 accidents end up with injured hand and fingers which constitutes the highest share. The ages between 30 and 34 are the most accident prone ages corresponding to 38% of all accidents. Workers having 0-4 years experience are more prone to accidents occupying the 45% of accidents.

ii. The risk scores are computed by compiling probabability, exposure, and consequence factors with the help of the nomograph called as Riskex Risk Score Calculator which is derived from the principle of Fine-Kinney risk score methodology. The sortings according to the magnitude of risk are given below from the highest risk to the lowest risk;

- Accident type: Roof fall, miscellaneous, transportation, material, methane and other gases, explosives, machine and electric
- Accident location: Longwall face, development headings, main transportation/haulage road, electro mechanics shop, support maintanance/repair, miscellaneous, electromechanics shop, and surface facilities
- Shift: Shift 1, shift 2, and shift 3
- Job: Longwall production worker, Development headings worker, Transportation worker, fireman, support maintanance worker, mechanical technician, electrical technician
- Body part affected after having an accident: Foot-toe, the lower part of the leg, knee, hand-finger, waist, hip, arm, shoulder, head, leg, face, body, back, calf, eye, neck, whole body, others, chess, and respiratory
- Age group: 30-34, 25-29, 35-39, 40-44, 45-49, 20-24, and 50-55
- Experience duration: 0-4, 5-8, 9-12, 17-20, 21-24, 13-16, and 25-28

iii. Multiple Linear Regression (MLR) yielded two best fit models for the handled data by practicing on ‘Best Subsets Regression’ tool. First model includes X1, X3, and X4 (Raw coal production (tonnes), total number of workers, and explosive consumption/raw coal production (g/tonnes)) while second model includes X1, X3, X4, and X5 (Raw coal production (tonnes), total number of workers, explosive consumption/raw coal production (g/tonnes), and Timber consumption/raw coal production (dm^3/tonnes)) in order to estimate the number of accidents. In both models an R-square value of about 17% is calculated. It means while 17% of the total changes in response value (number of accidents) can be explained by the changes caused by the independent variables included in the model, the remaining 83% is due to other factors which are not available and which are not included in the model.

iv. Four different time series analysis models are built for the data, respectively, a first order autoregressive AR(1) model, trend model, double exponential model and moving average model.

- For the AR(1) model, an R-square value of 23.34% is calculated which is greater than that founded for the MLR model.
- Among the trend models best values related to accuracy are obtained from quadratic trend model. MAPE, MAD, and MSD values are calculated as 23.597, 7.5868, and 89.1033 respectively. This model predicts the number of accidents in the research area with 23.597% error. In other saying, the model predicts the number of accidents with 76.403% effectiveness
- For the double exponential model, MAPE, MAD, and MSD values are calculated as 22.893, 7.827, and 104.462 respectively which are quite closer to trend model.
- Moving average model produced the best accuracy results. MAPE, MAD, and MSD values are calculated as 16.537, 5.3043, and 49.1193 respectively which are smaller than the double exponential and quadratic model. When the accuracy values are evaluated moving average model should be used, but quadratic trend model and double exponential have the advantage of long time forecasting capacity and due to the small difference between the accuracy values, whether it may be used or not is analysed by looking how much the forecasted values approach to the real values for the last 6 months. Moving average model has the smallest percentage error values which also certifies the goodness of fit of this model. If it is needed to forecast longer time periods quadratic trend model can be used instead of double exponential model cause it has smaller percentage error values.

Some points caught that worth of recommendation during this study are:

i. Proper and regular recording of occupational accidents with near misses in detail is of capital importance before performing an effective risk in order to obtain better results and to give right decisions.

ii. In Turkey, the most widely used risk assessment technique is 5x5 risk matrix. In 5x5 risk matrix method, risk is defined by using two variables, namely, consequence (C), and the probability (P). However, it is a well known fact that, risk does not arise without exposure. Therefore, risk assessment process should be taken to a more advanced level and definition of the risk should be revised by adding a new variable called as exposure (E). Then, the prioritization of the risks could be more reliable and give more realistic results.

iii. In time series modelling, for a better trend analysis, more data should be obtained to see the whole term of trend. Enough data is required to be sure that any pattern observed is a long-term pattern and not just a short-term anomaly. Trends observed over a short span of data could be part of a larger cycle and may not proceed into the future. Another recommendation is that established models should not be used for predictions with longer time horizons cause shorter time horizons predictions always give more reliable results. Moreover, forecasts should be updated frequently as new data become available.

iv. The methods used and the models built in this study can also be utilized for a metal mining and a detailed comparison can be made. Accident type, location, work shift, job, affected body part, age, and experience that must be most worthy of notice would probably change for a metal mine and the methods used in this study can easily and clearly show the dissimilarity between a metal and coal mine. Alternatively, this study can also be applied to different coal basins of Turkey and a risk map can be generated. Moreover, by applying accident forecasting techniques, another map involving the accident number trends of coal basins can be drawn and this information can be used by the related government institution in order to arrange the number of audits.

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APPENDIX A

RISK SCORES FOR ALL CASES

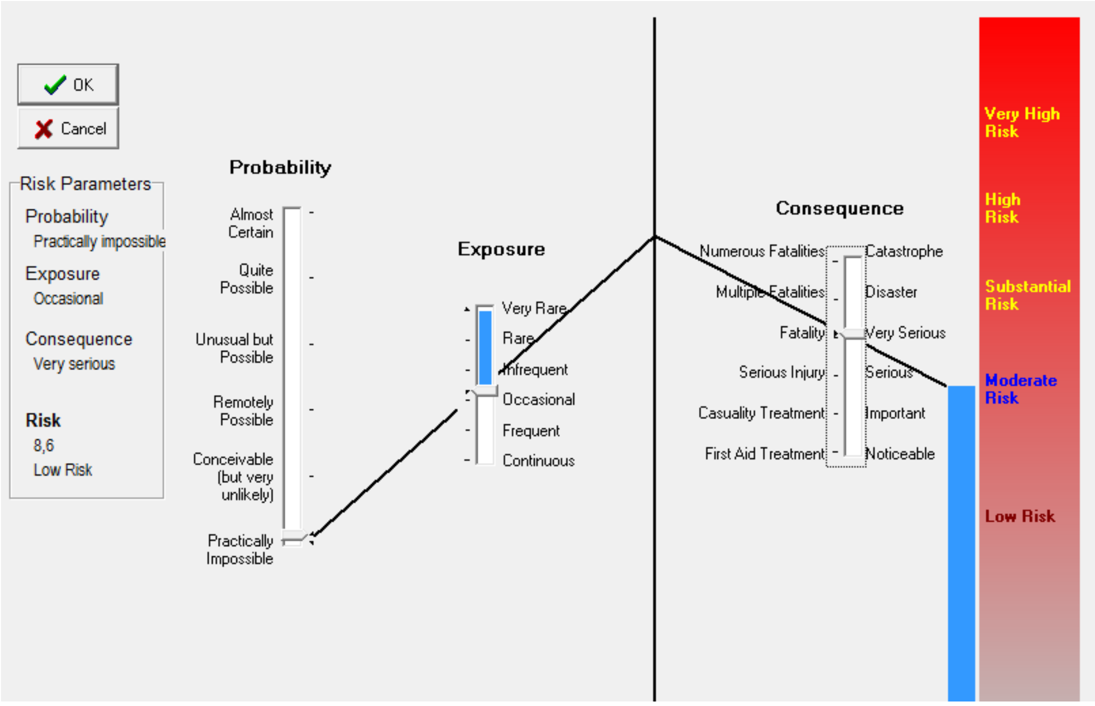

Figure A.1 Risk score of electrical accidents

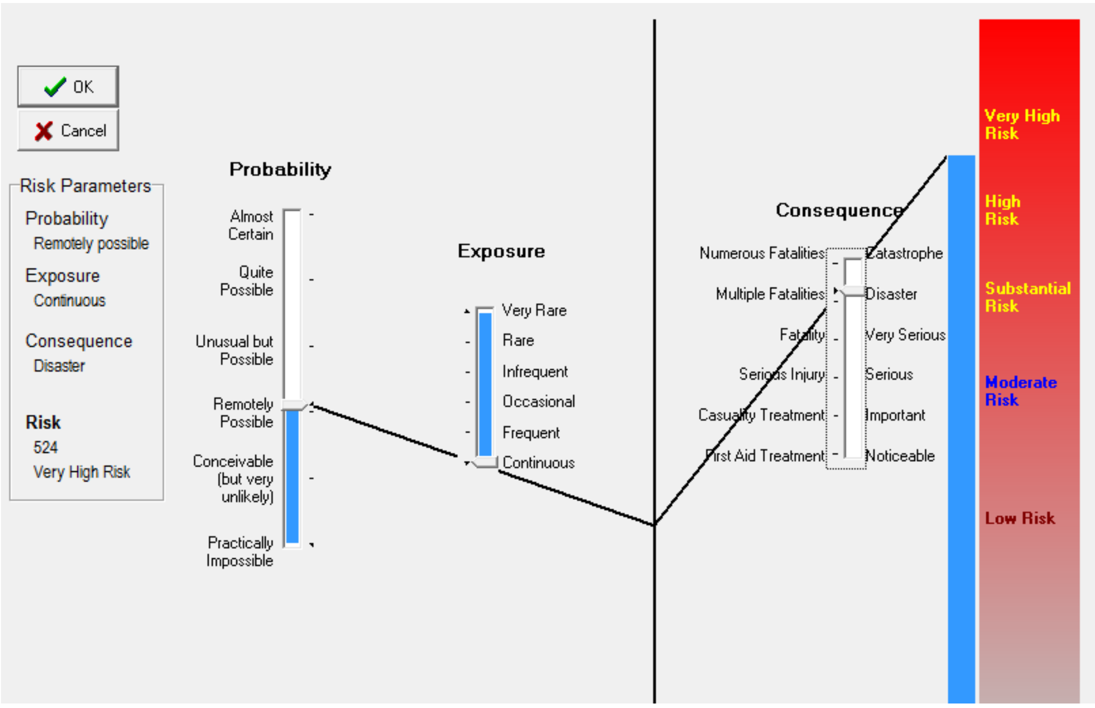

Figure A.2 Risk score of roof fall accidents

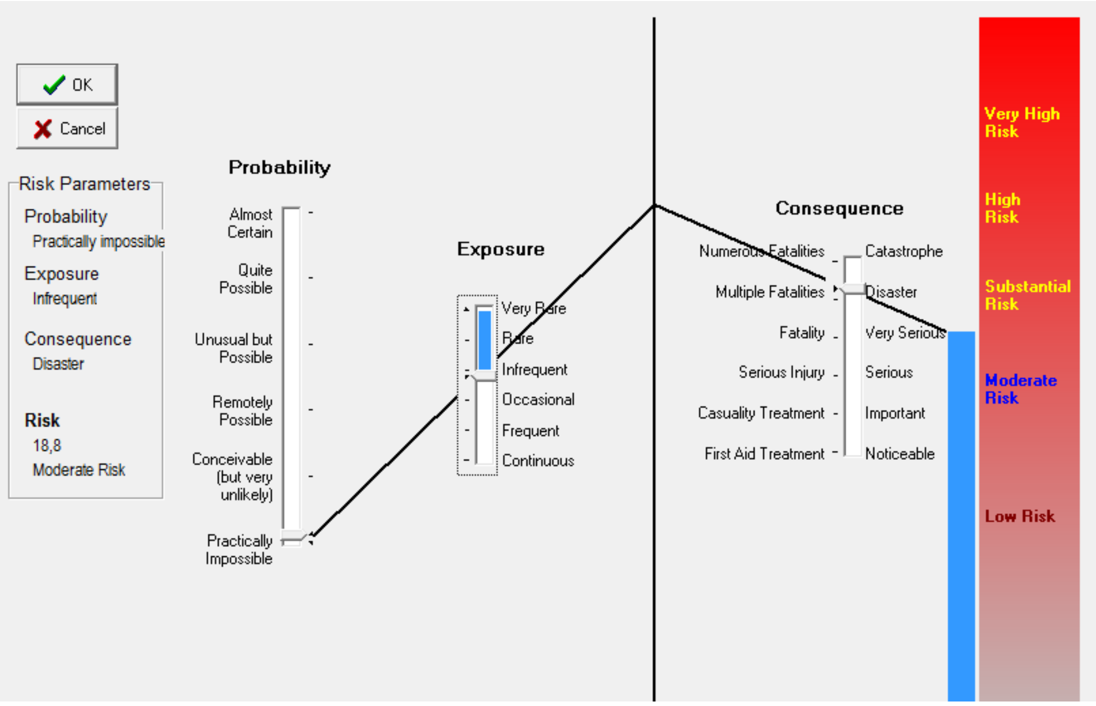

Figure A.3 Risk score of accidents related to methane and other gases

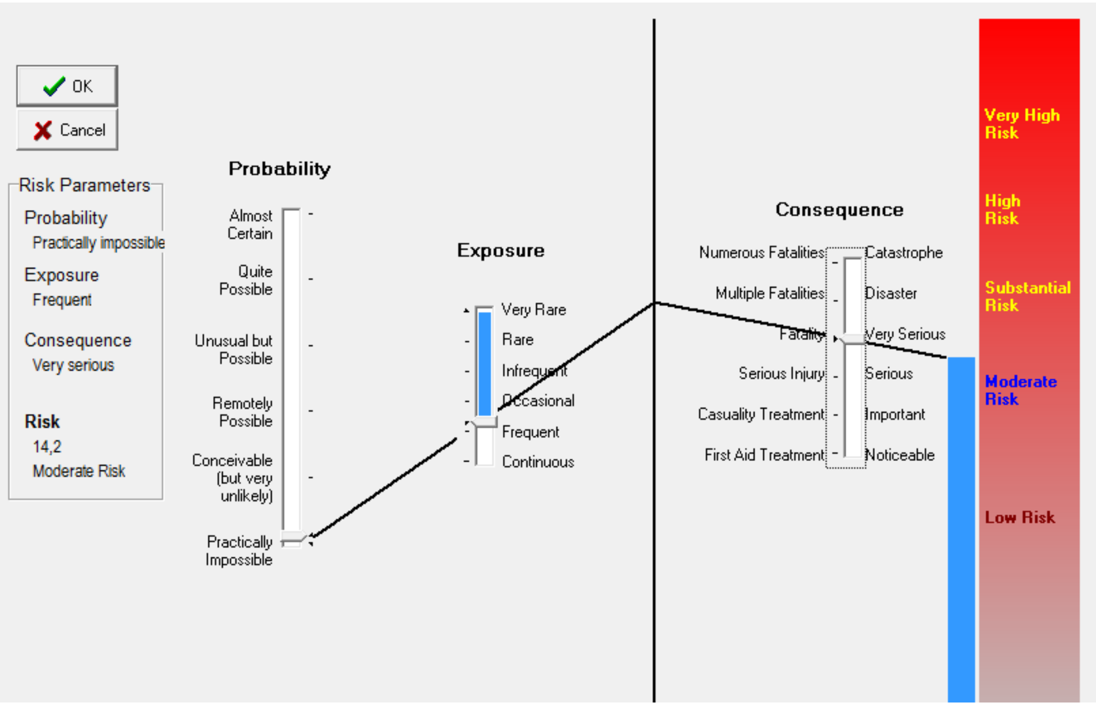

Figure A.4 Risk score of mechanical accidents

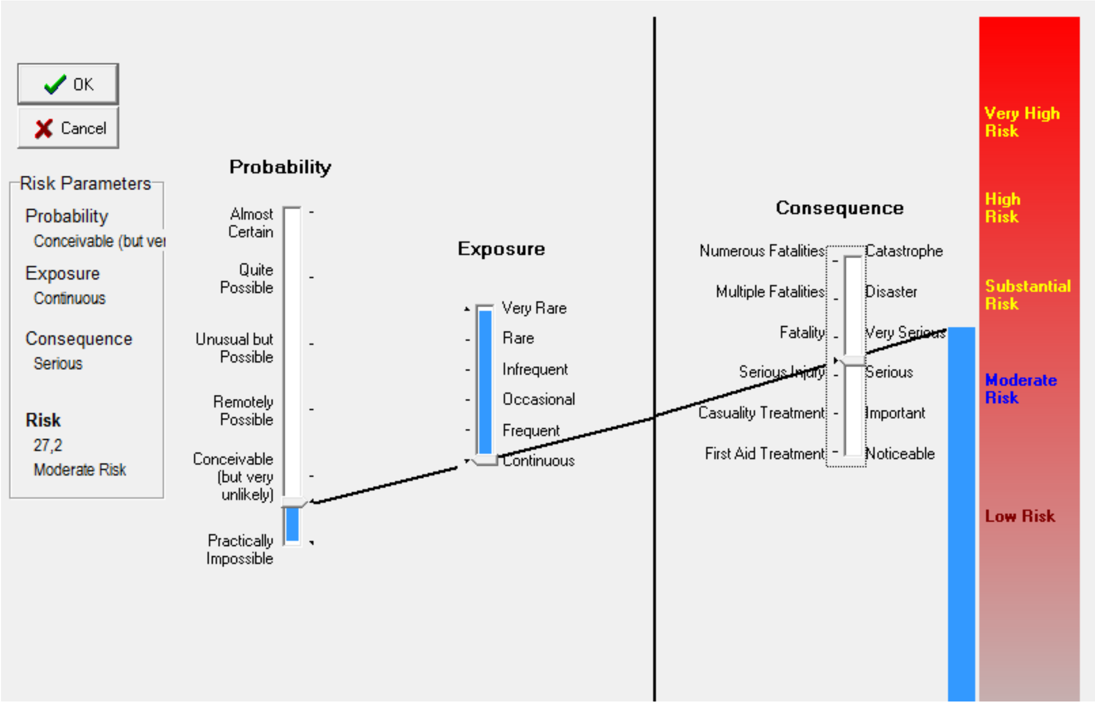

Figure A.5 Risk score of material accidents

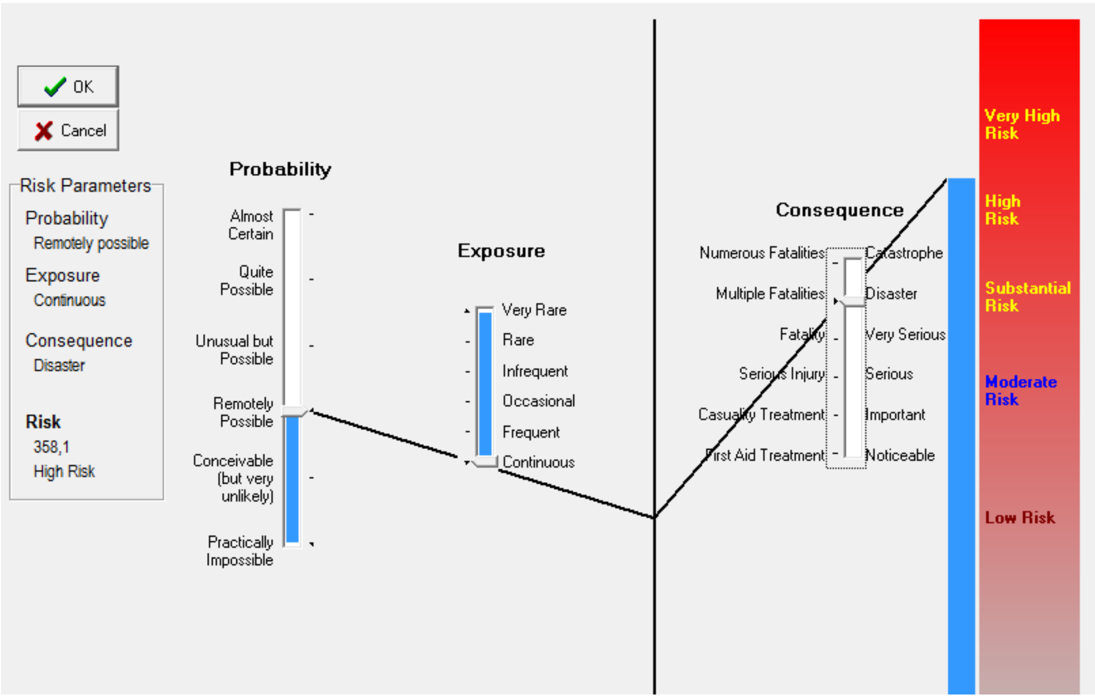

Figure A.6 Risk score of miscellaneous accidents

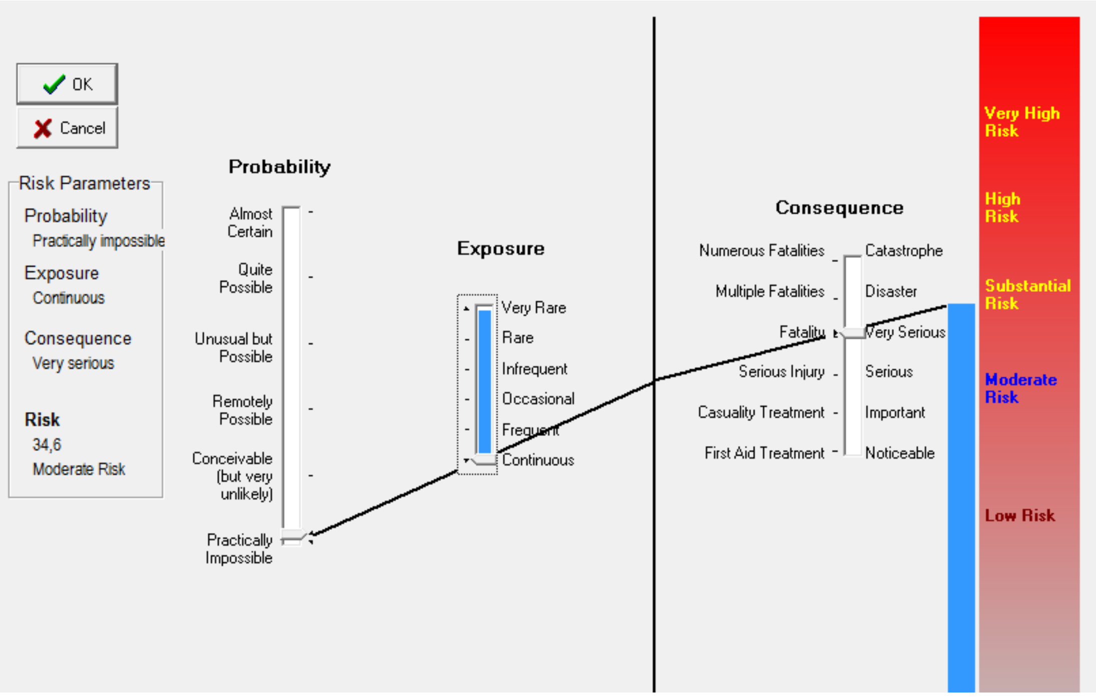

Figure A.7 Risk score of transportation accidents

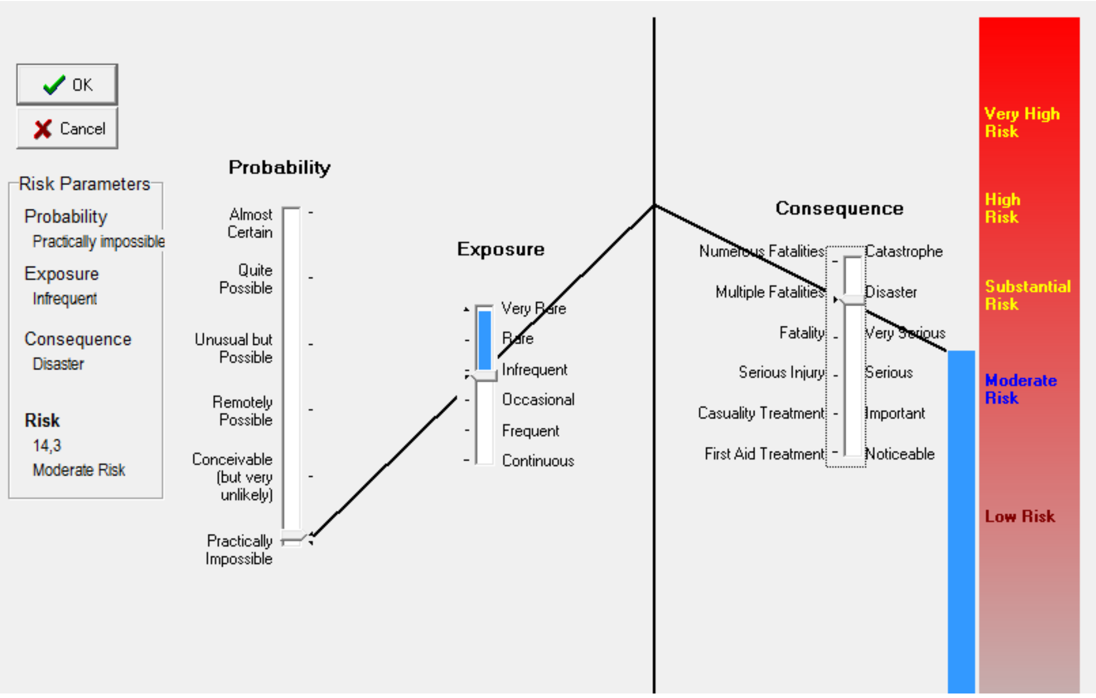

Figure A.8 Risk score of accidents related to explosives and blasting agents

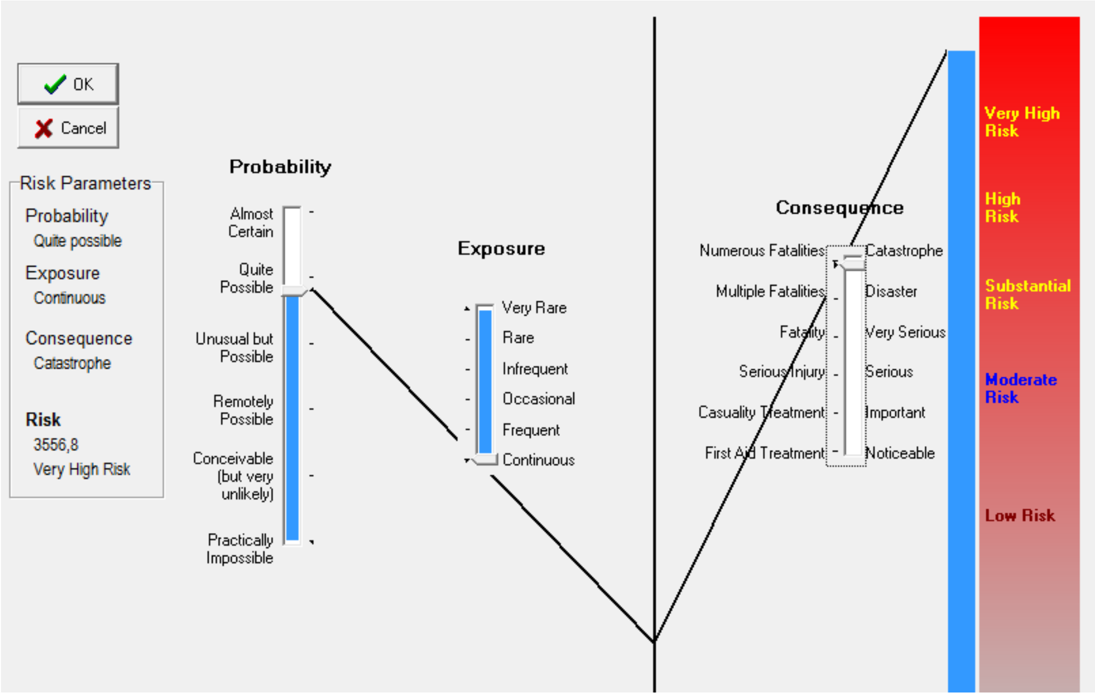

Figure A.9 Risk score of accidents which take place in longwall face and coal roadways

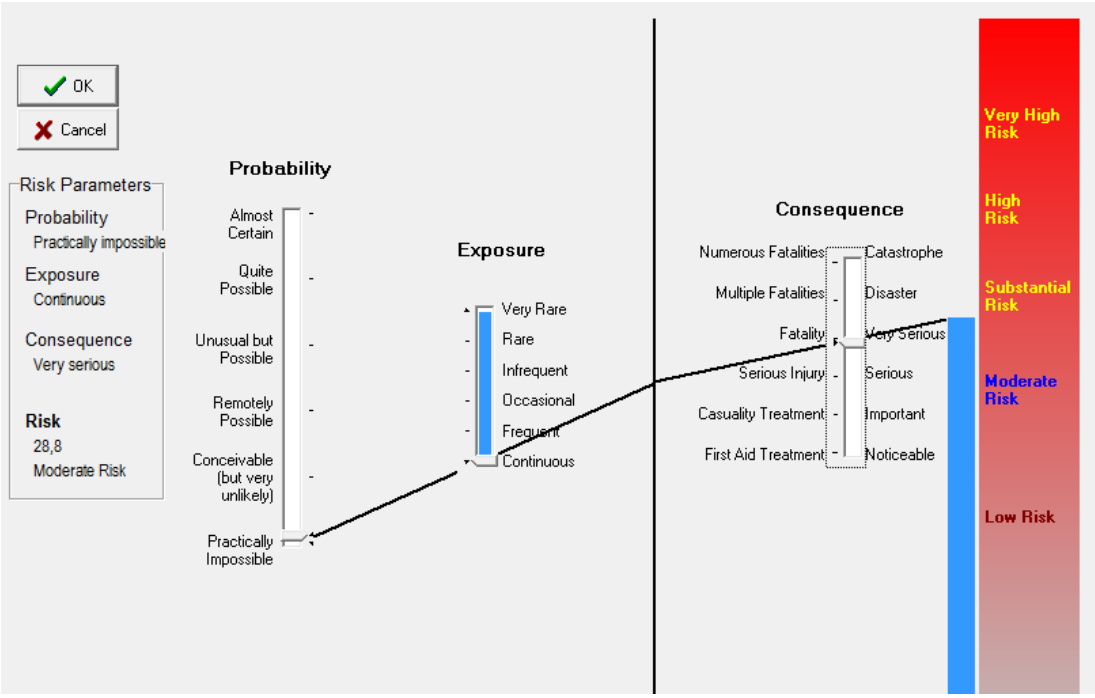

Figure A.10 Risk score of accidents which take place in electromechanics

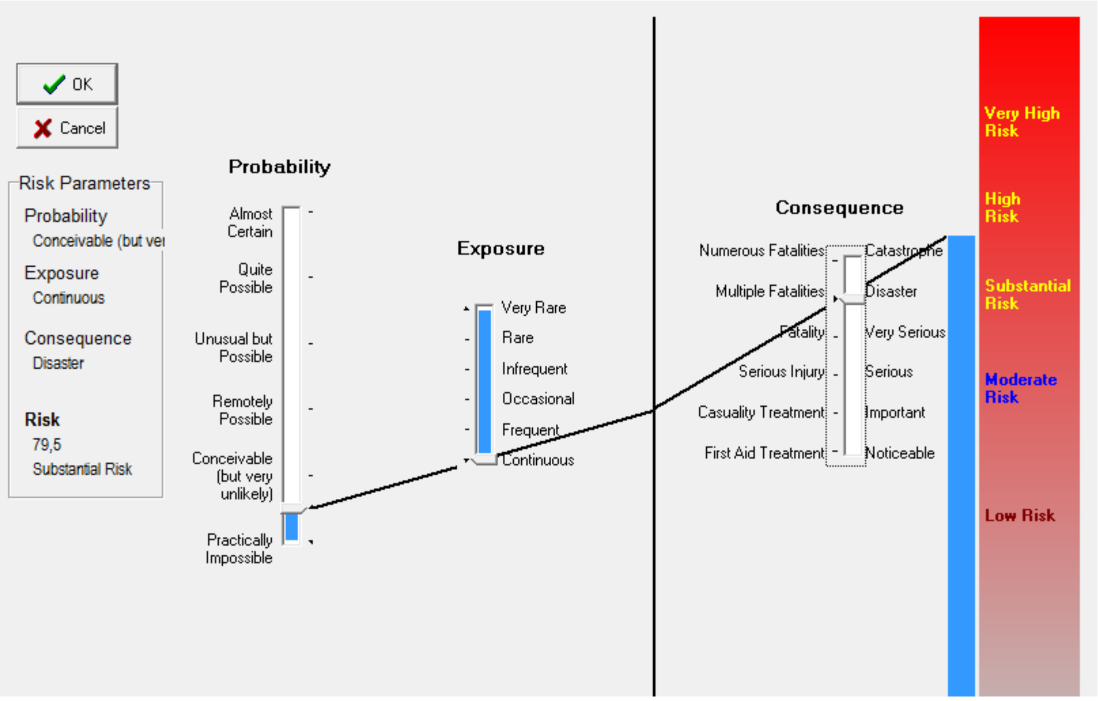

Figure A.11 Risk score of accidents which take place in preparation ways

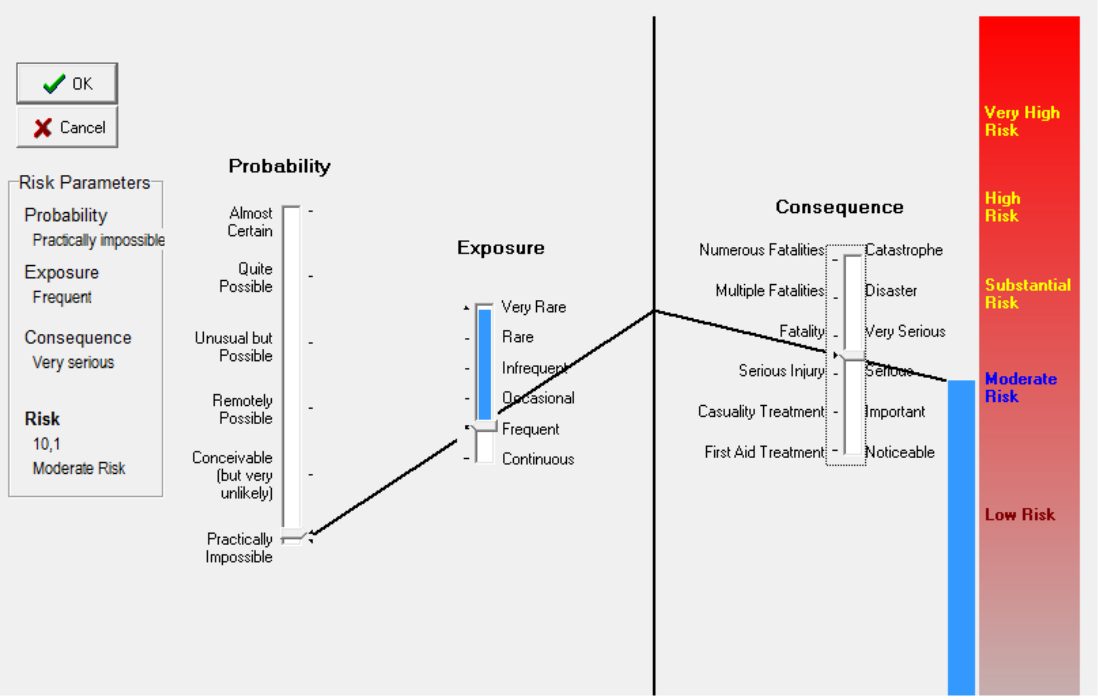

Figure A.12 Risk score of accidents which take place in miscellaneous locations

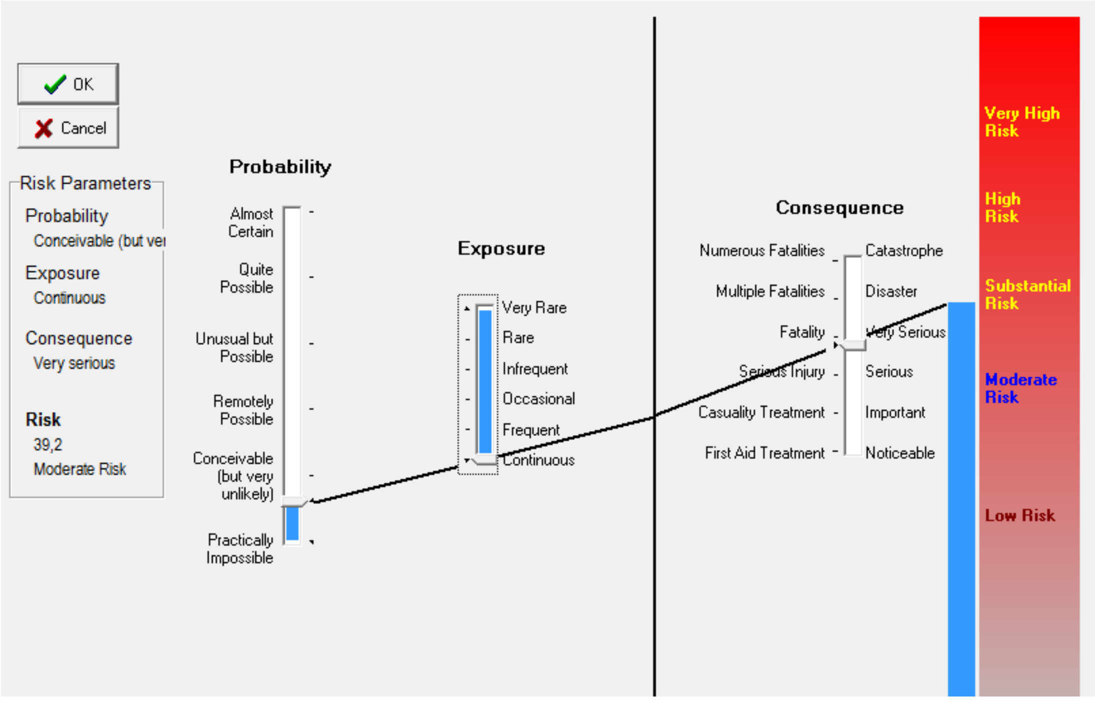

Figure A.13 Risk score of accidents which take place in haulage ways

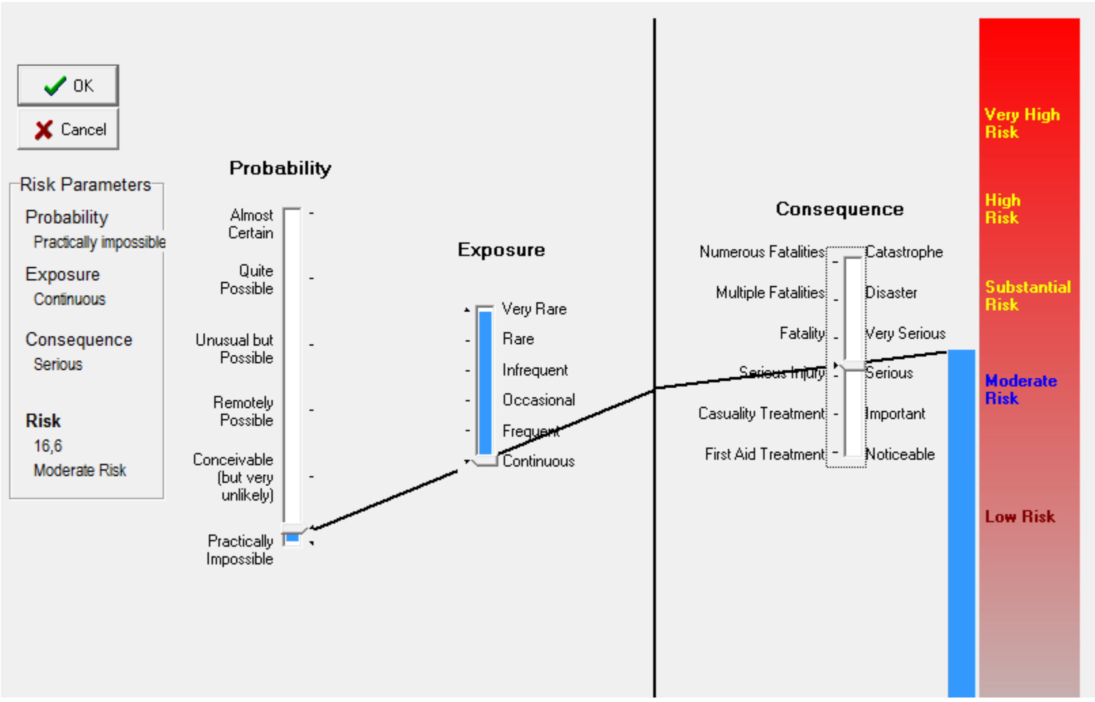

Figure A.14 Risk score of accidents which take place in support maintenance galleries

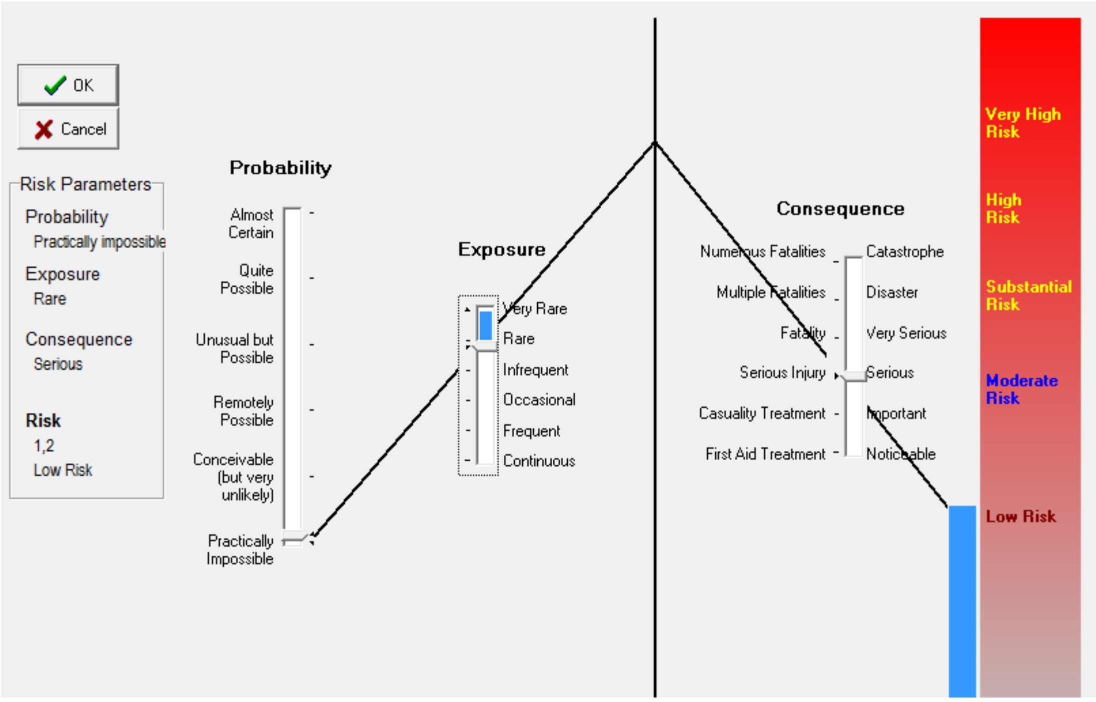

Figure A.15 Risk score of accidents which take place in surface facilities

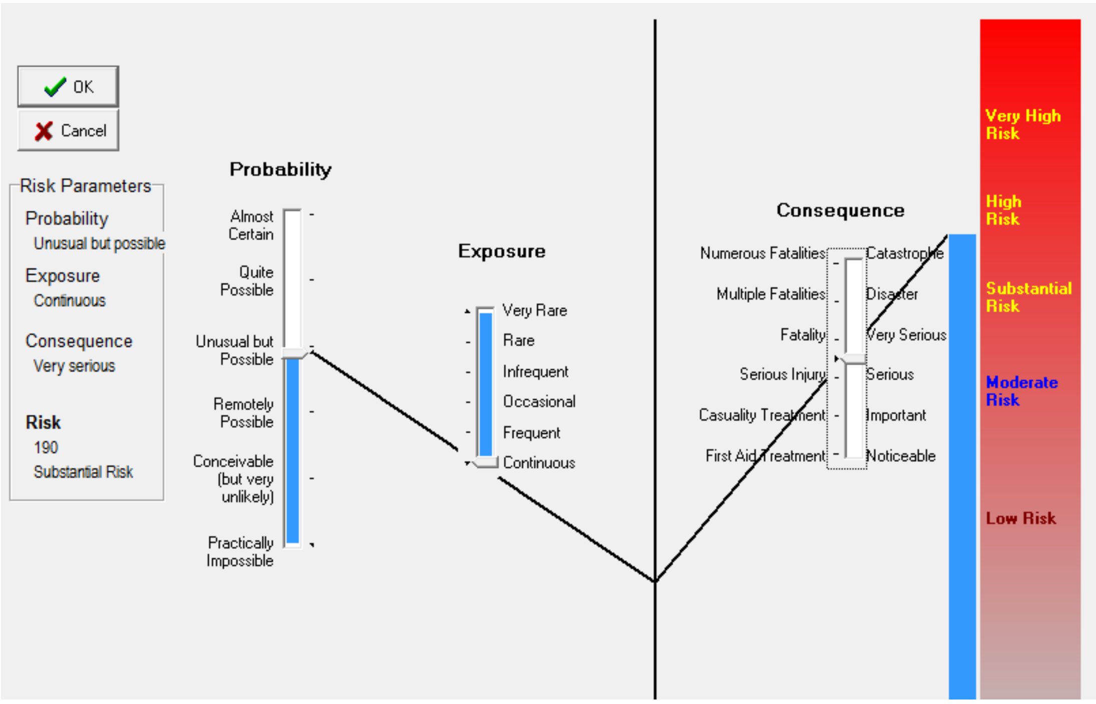

Figure A.16 Risk score of accidents which take place on shift 1

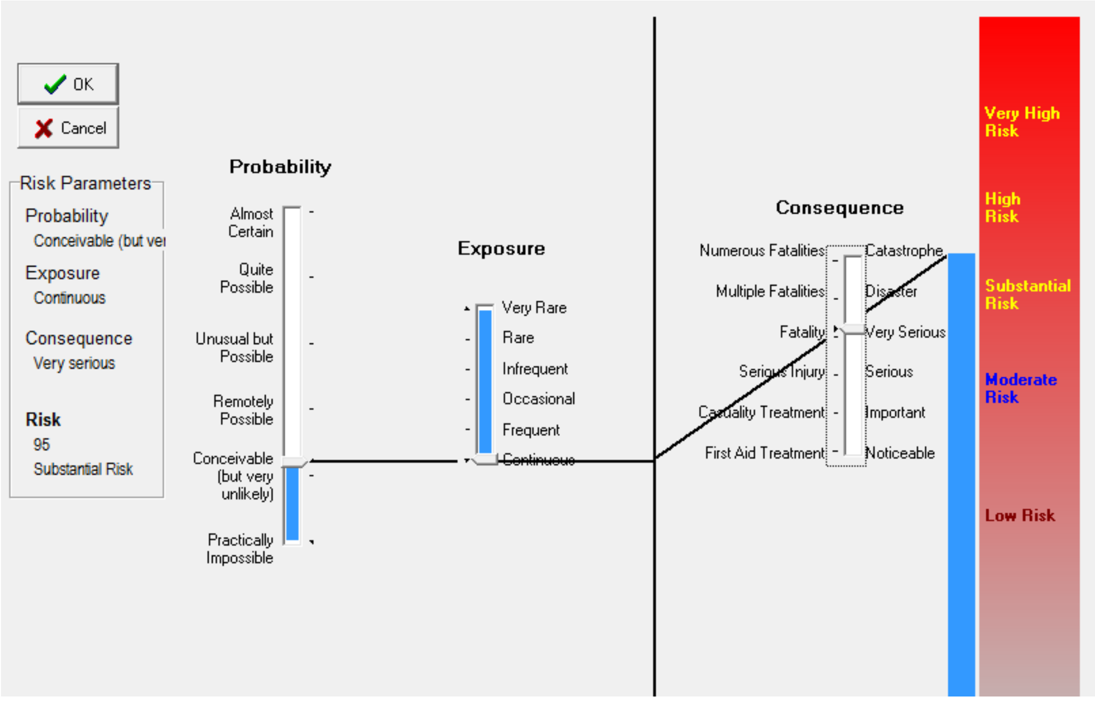

Figure A.17 Risk score of accidents which take place on shift 2

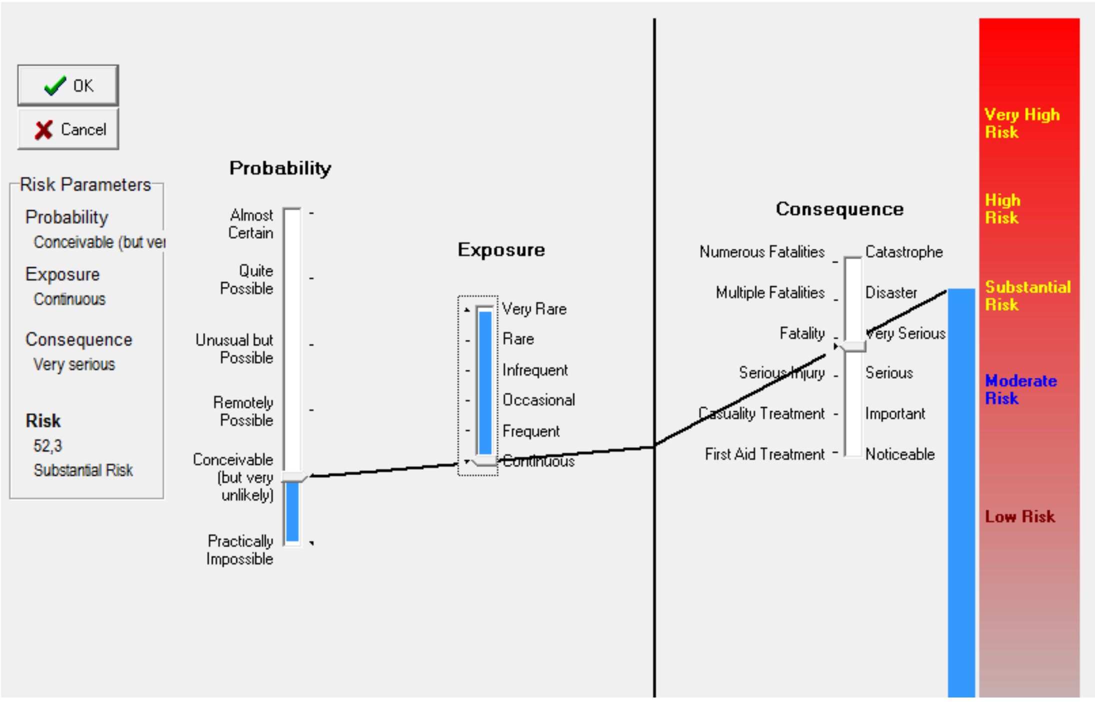

Figure A.18 Risk score of accidents which take place on shift 3

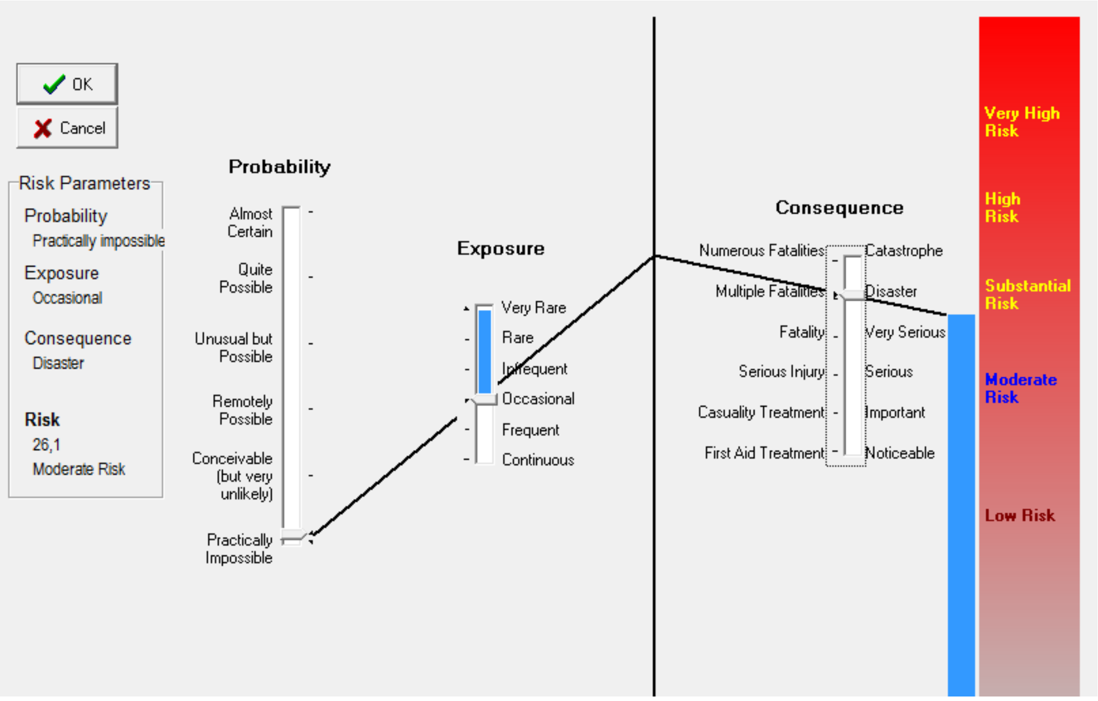

Figure A.19 Risk score of accidents experienced by blasters

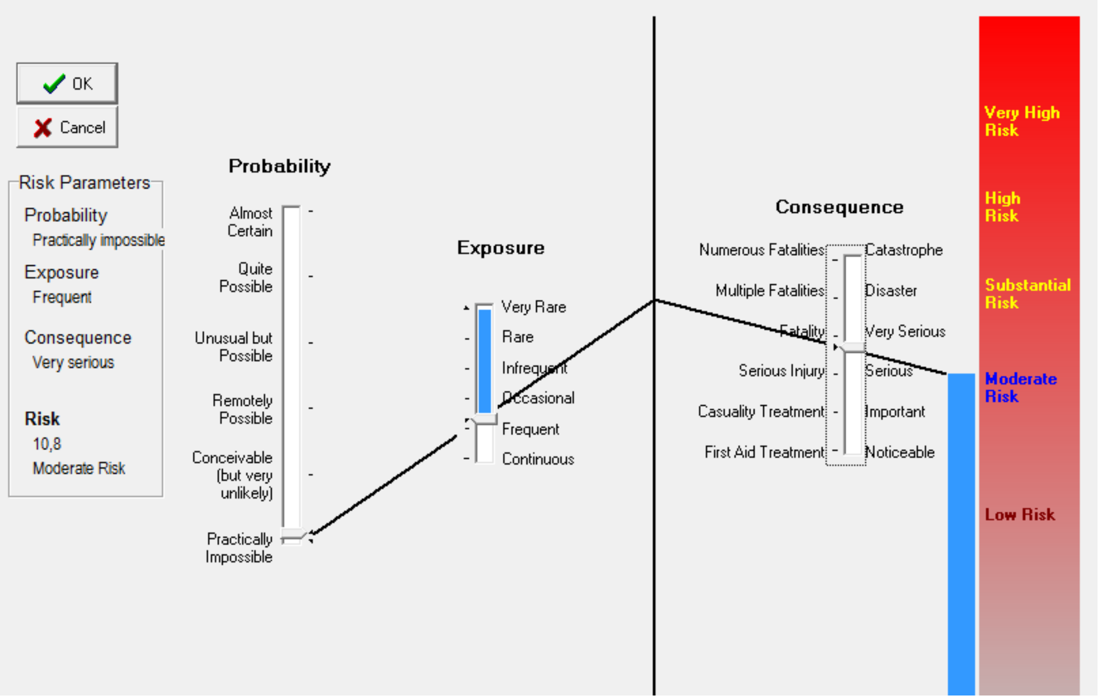

Figure A.20 Risk score of accidents experienced by electricians

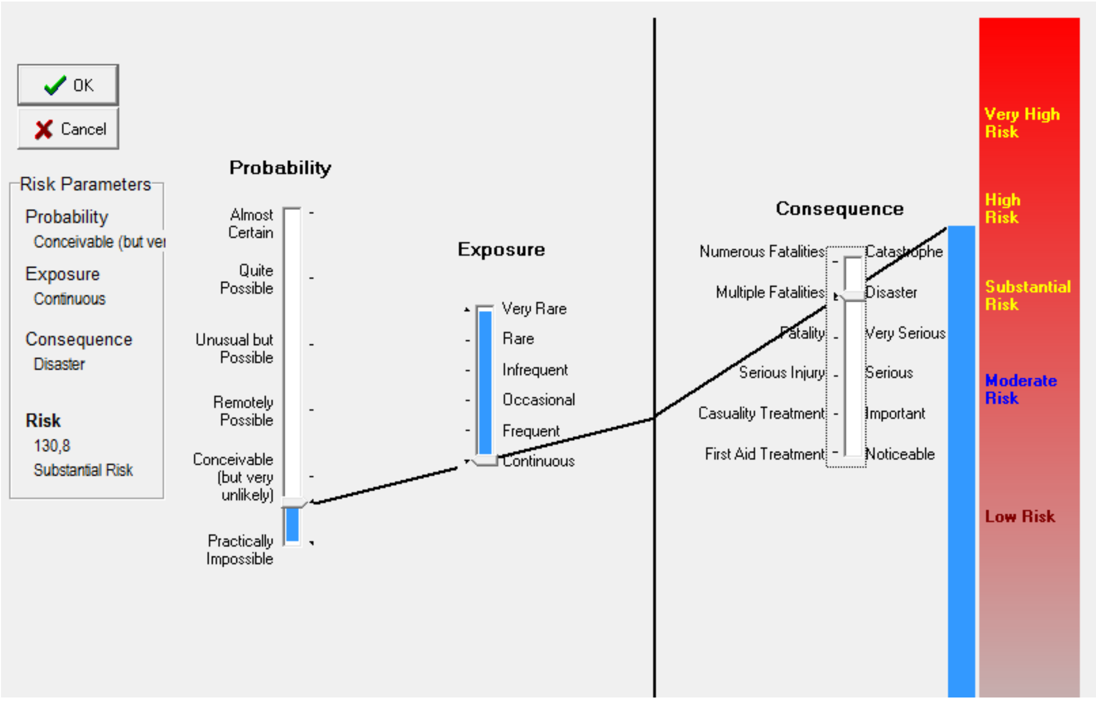

Figure A.21 Risk score of accidents experienced by preparation road workers

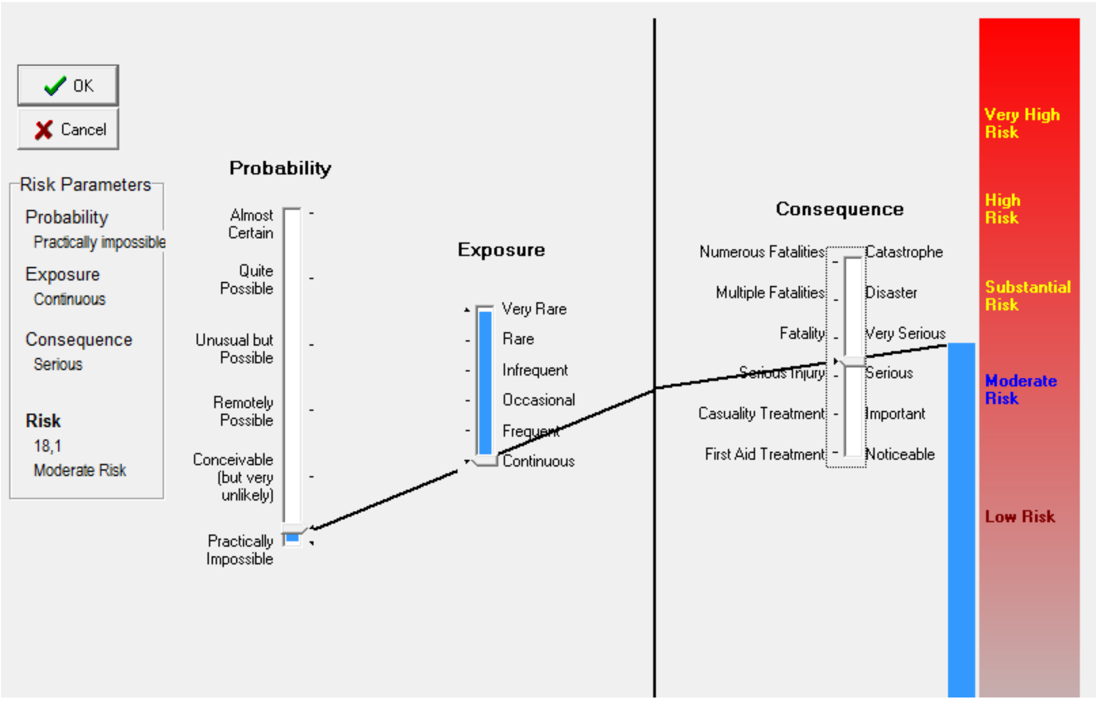

Figure A.22 Risk score of accidents experienced by mechanicians

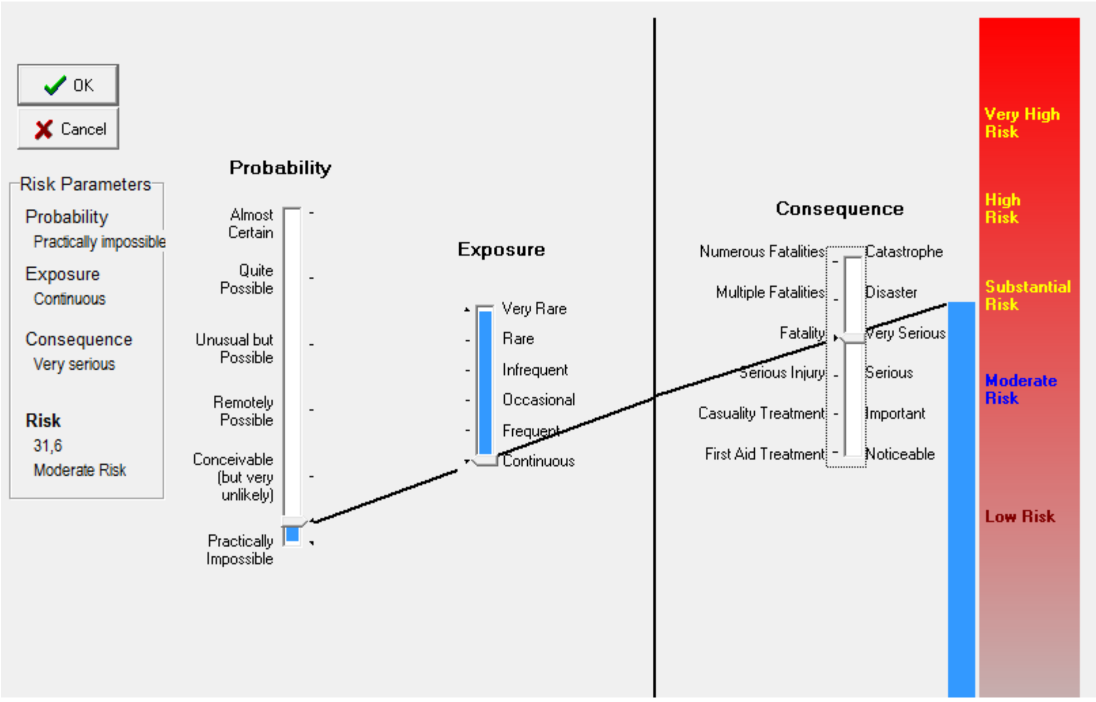

Figure A.23 Risk score of accidents experienced by transportation workers

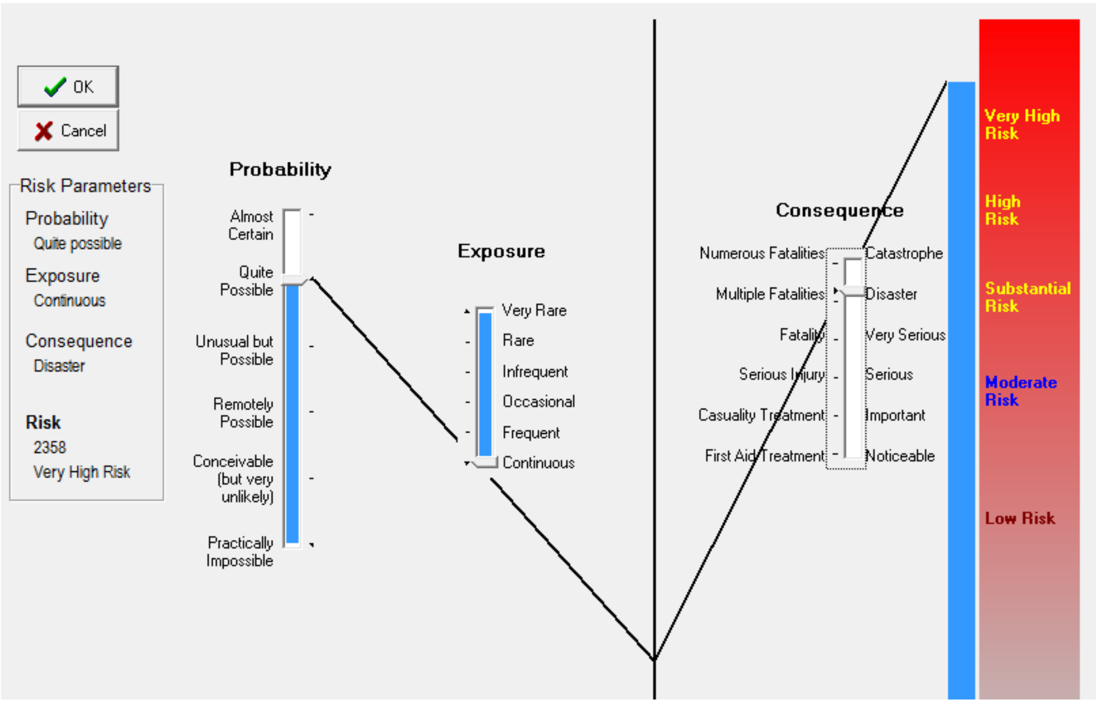

Figure A.24 Risk score of accidents experienced by longwall production workers

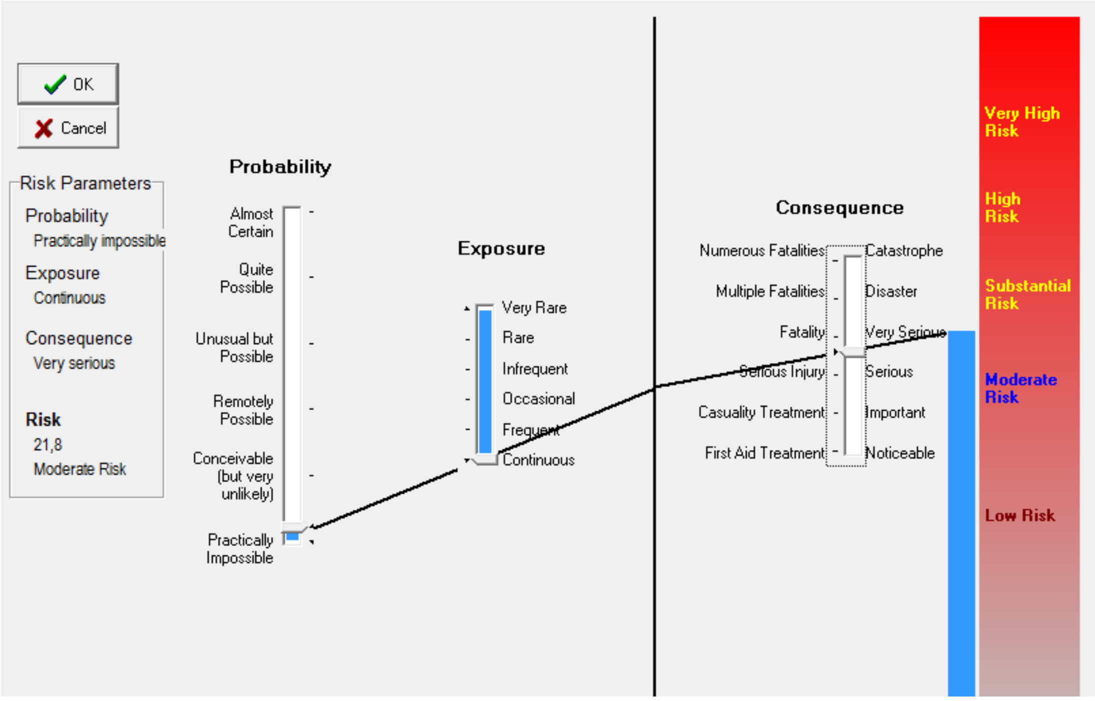

Figure A.25 Risk score of accidents experienced by support maintenance workers

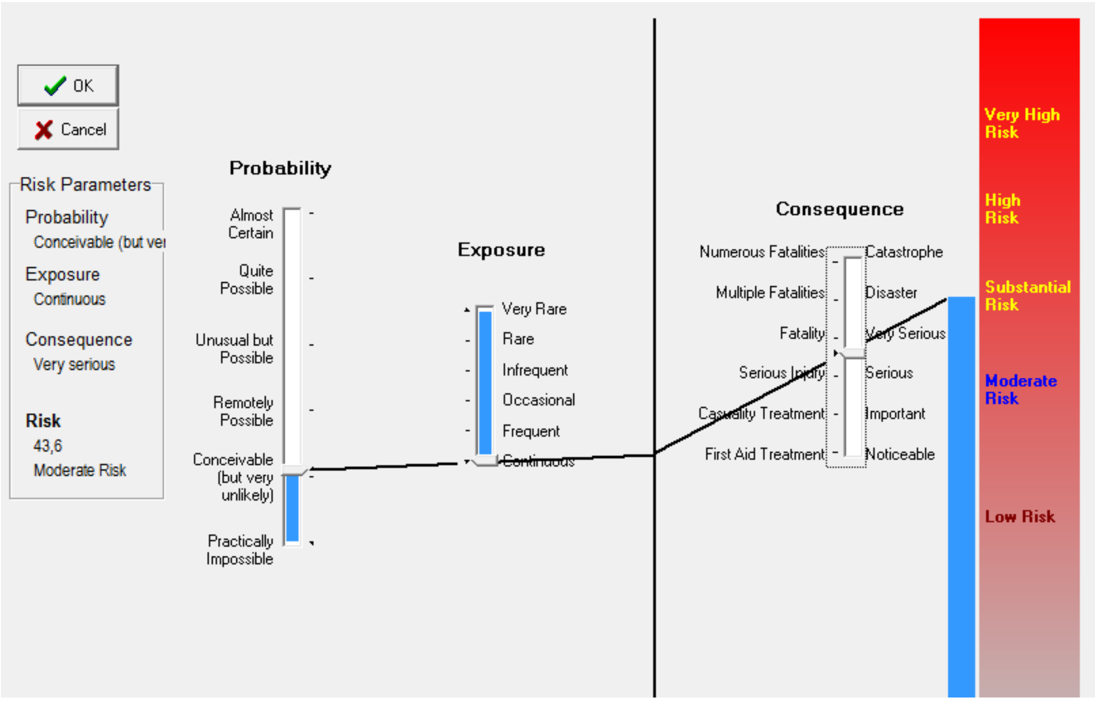

Figure A.26 Risk score of accidents affecting foot-toe

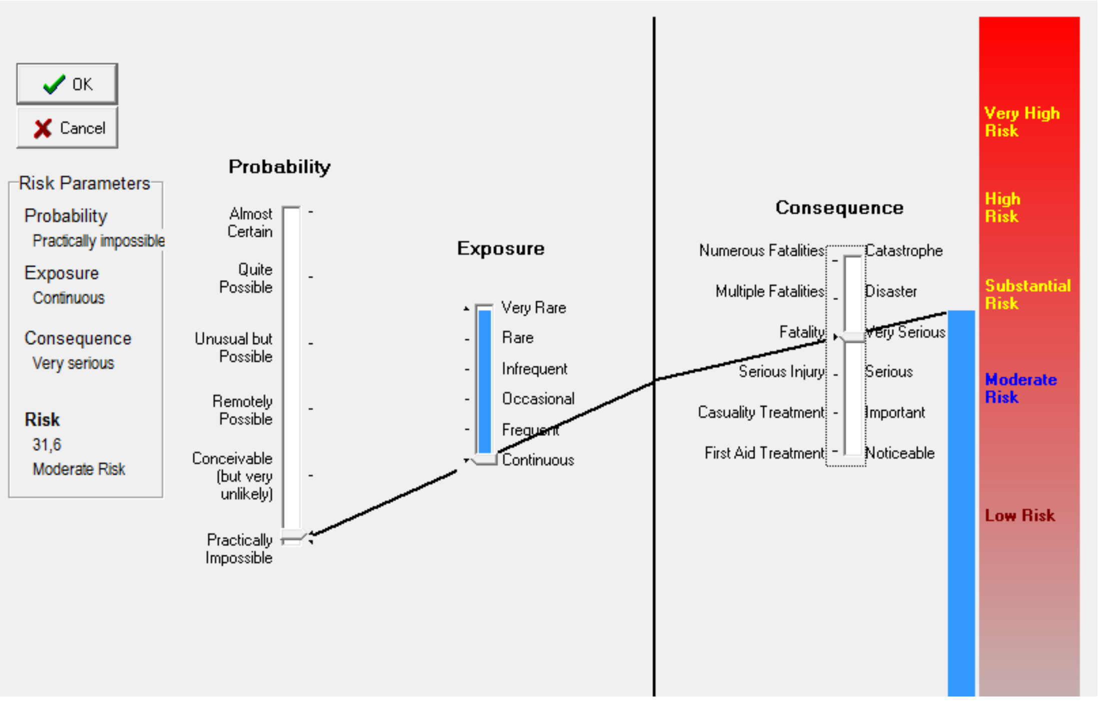

Figure A.27 Risk score of accidents affecting the lower part of the leg

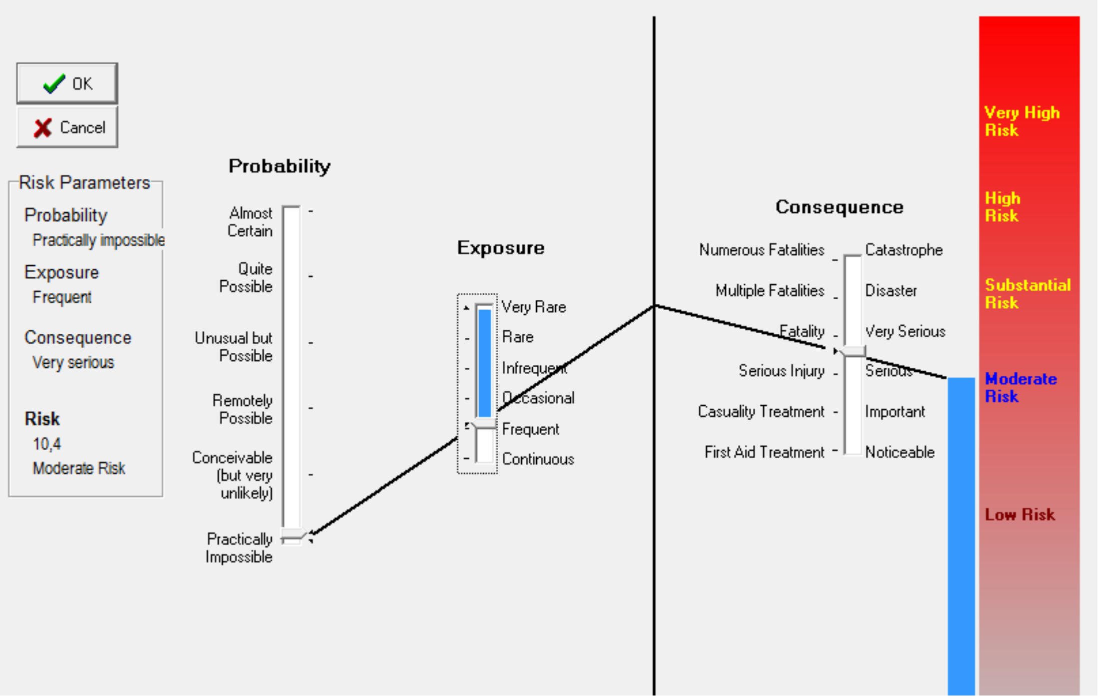

Figure A.28 Risk score of accidents affecting the leg

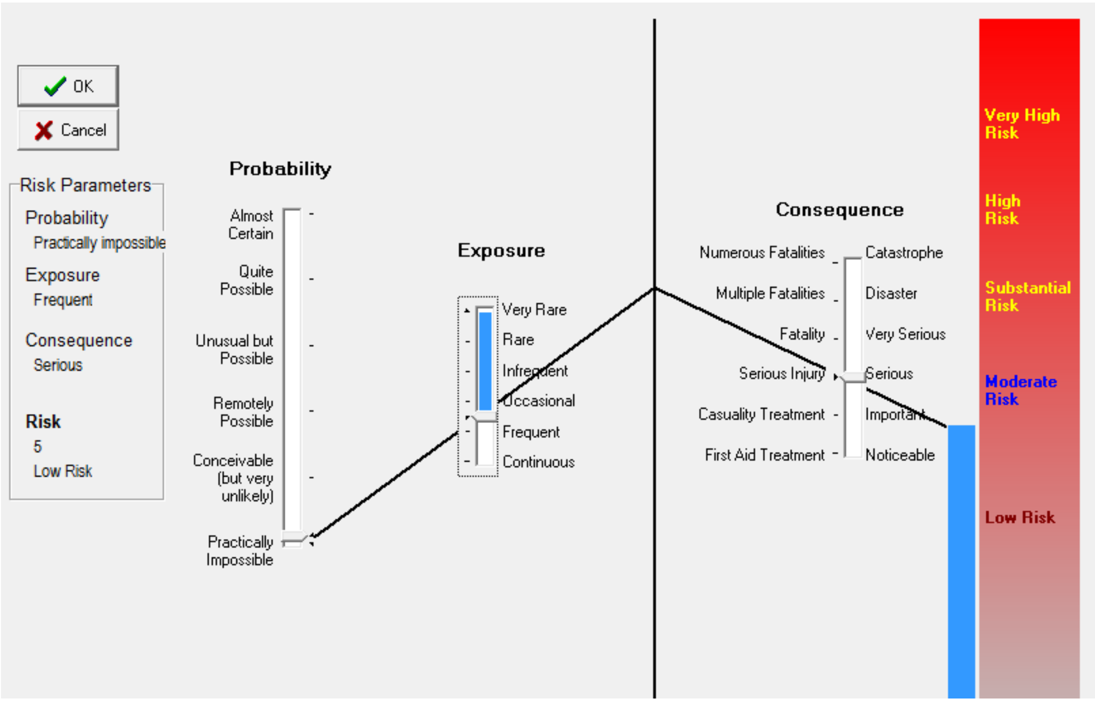

Figure A.29 Risk score of accidents affecting the calf

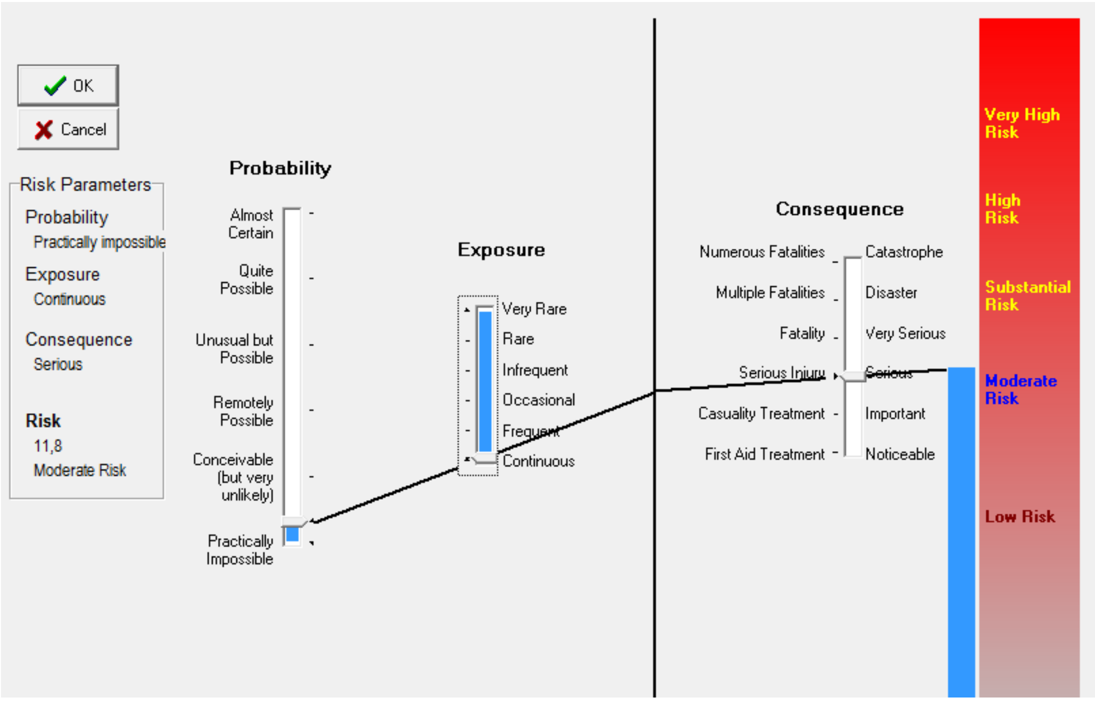

Figure A.30 Risk score of accidents affecting the head

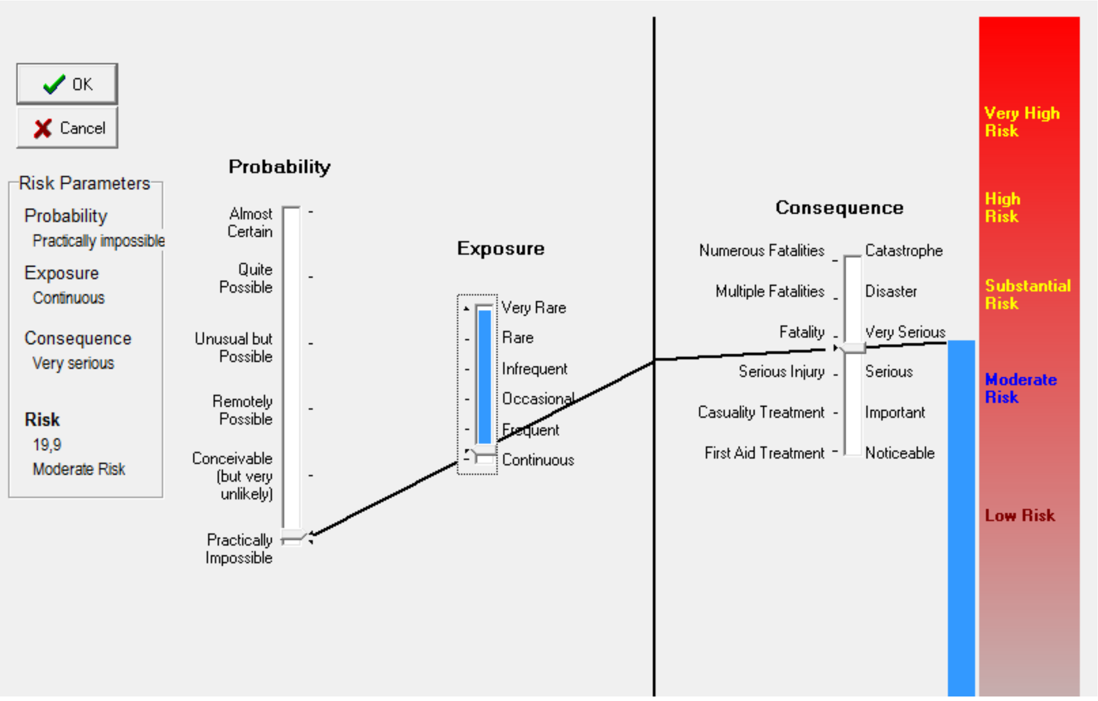

Figure A.31 Risk score of accidents affecting the waist

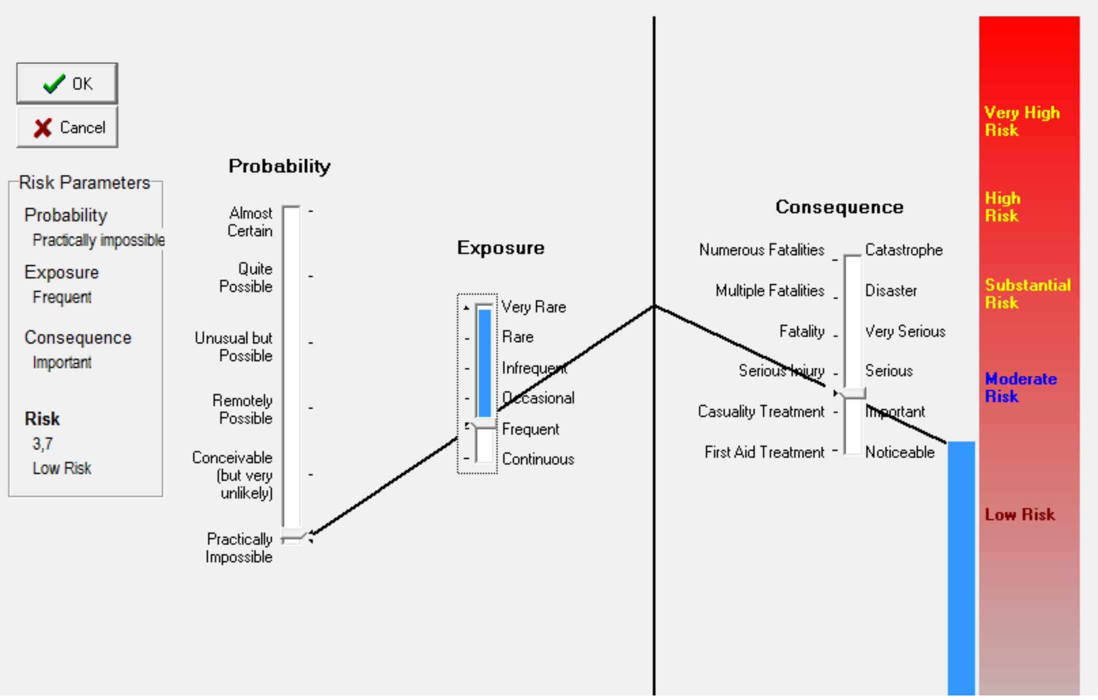

Figure A.32 Risk score of accidents affecting the neck

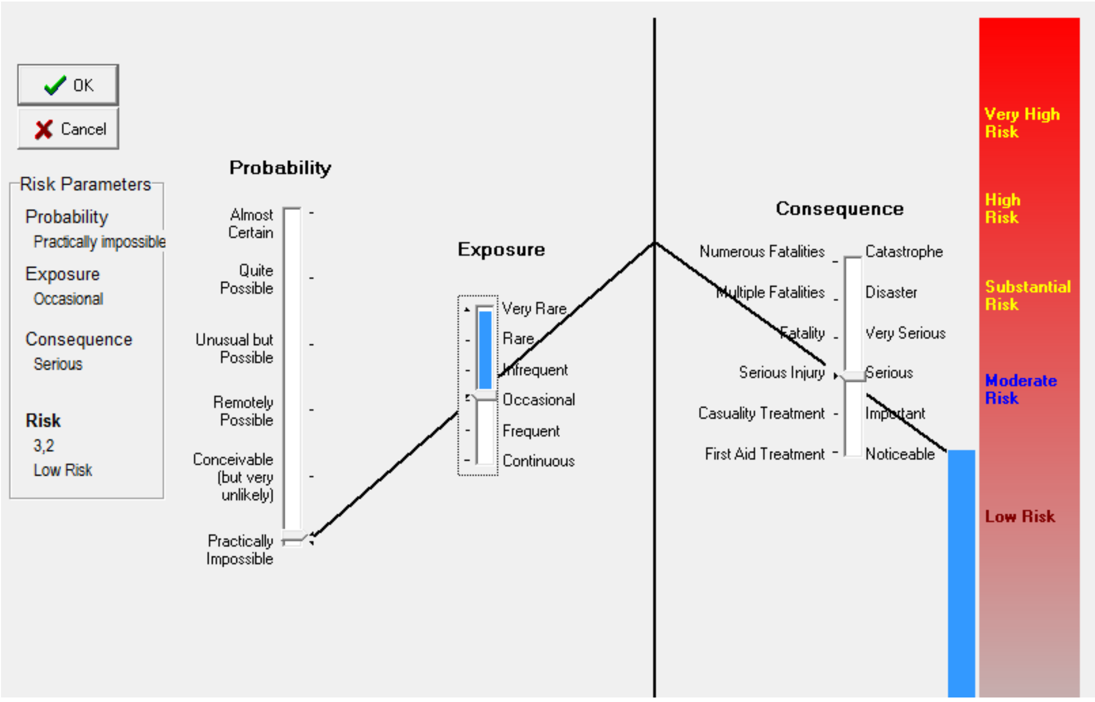

Figure A.33 Risk score of accidents affecting the other parts

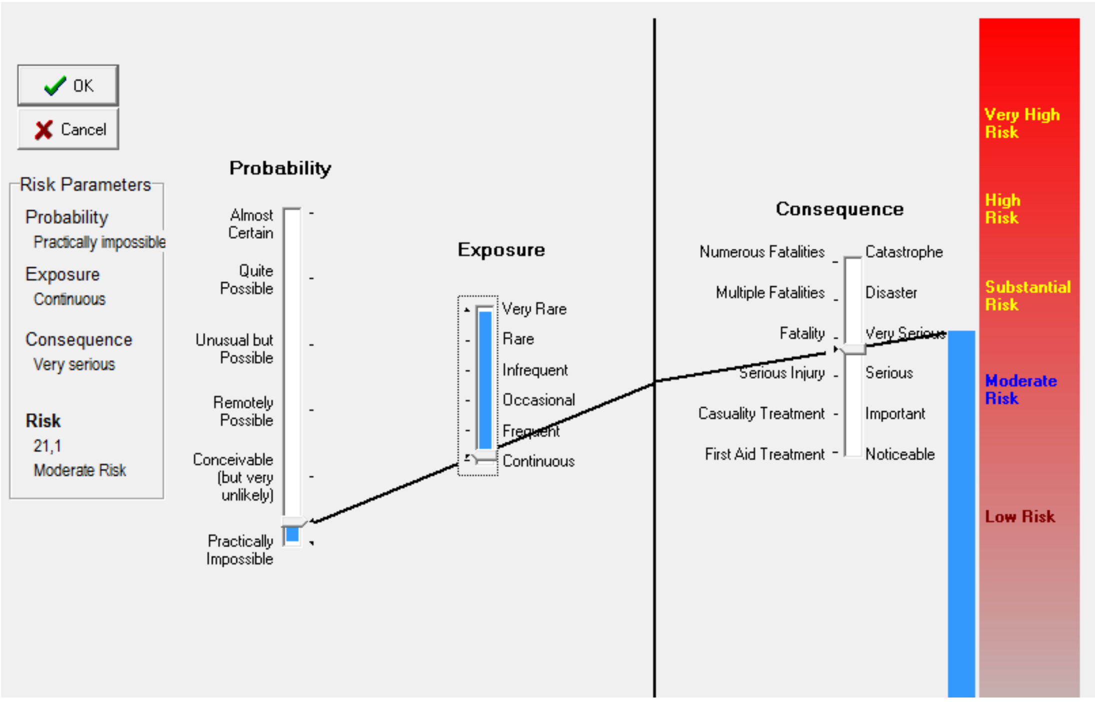

Figure A.34 Risk score of accidents affecting the knee

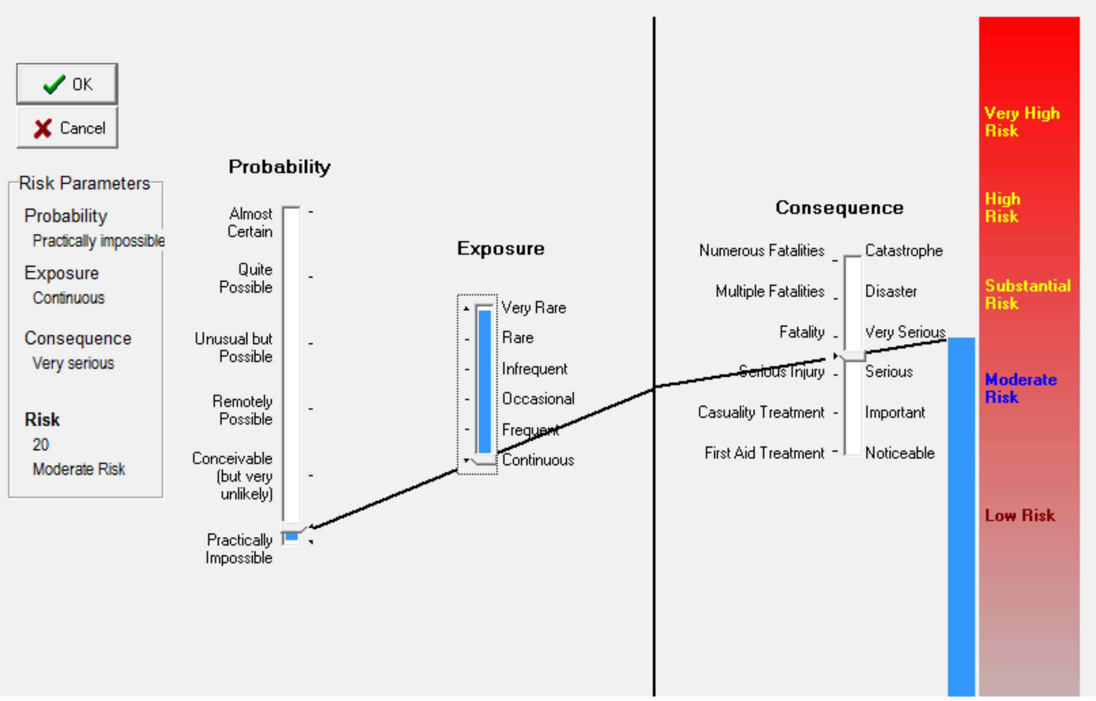

Figure A.35 Risk score of accidents affecting the hand-finger

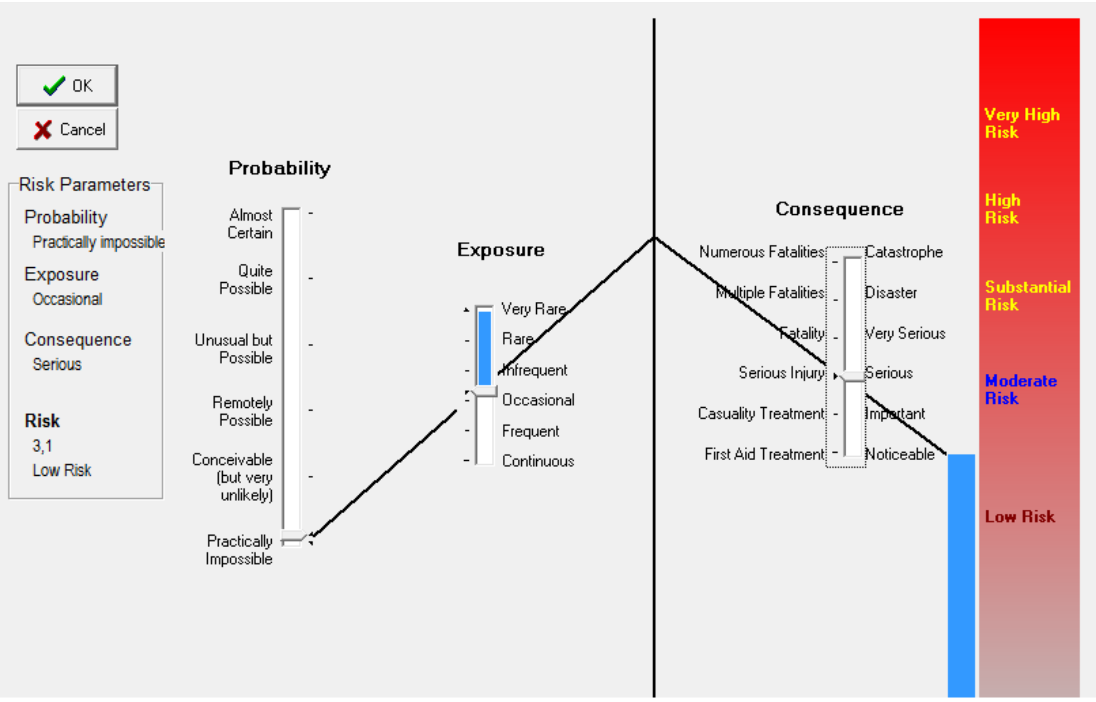

Figure A.36 Risk score of accidents affecting the chest

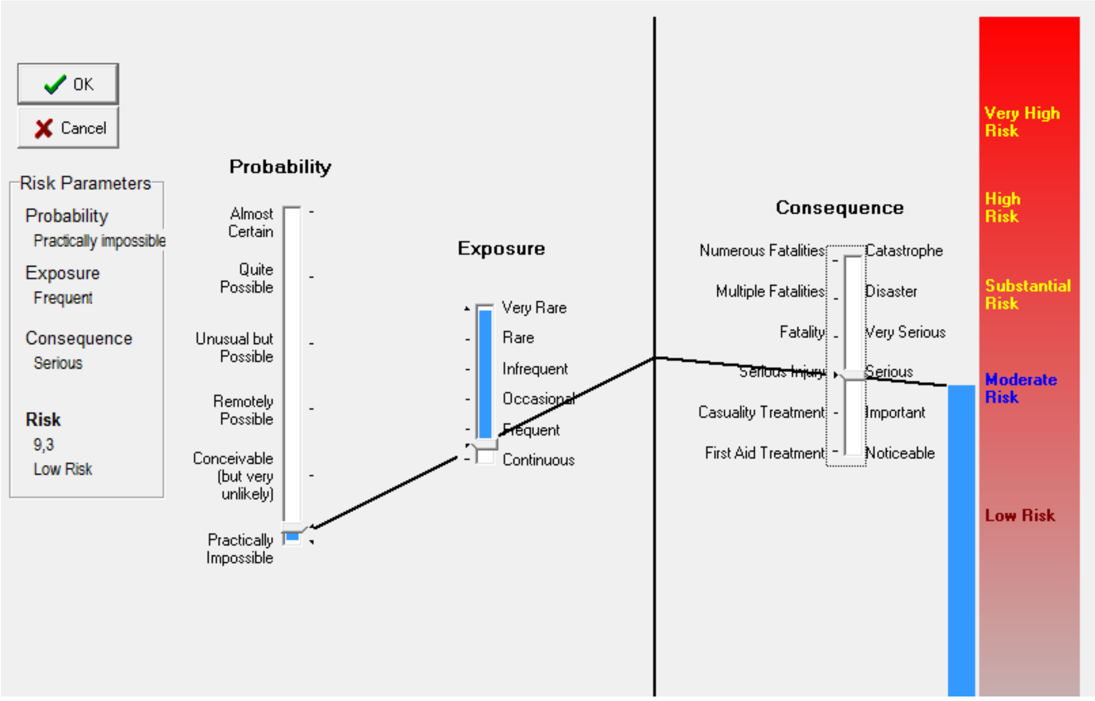

Figure A.37 Risk score of accidents affecting the body

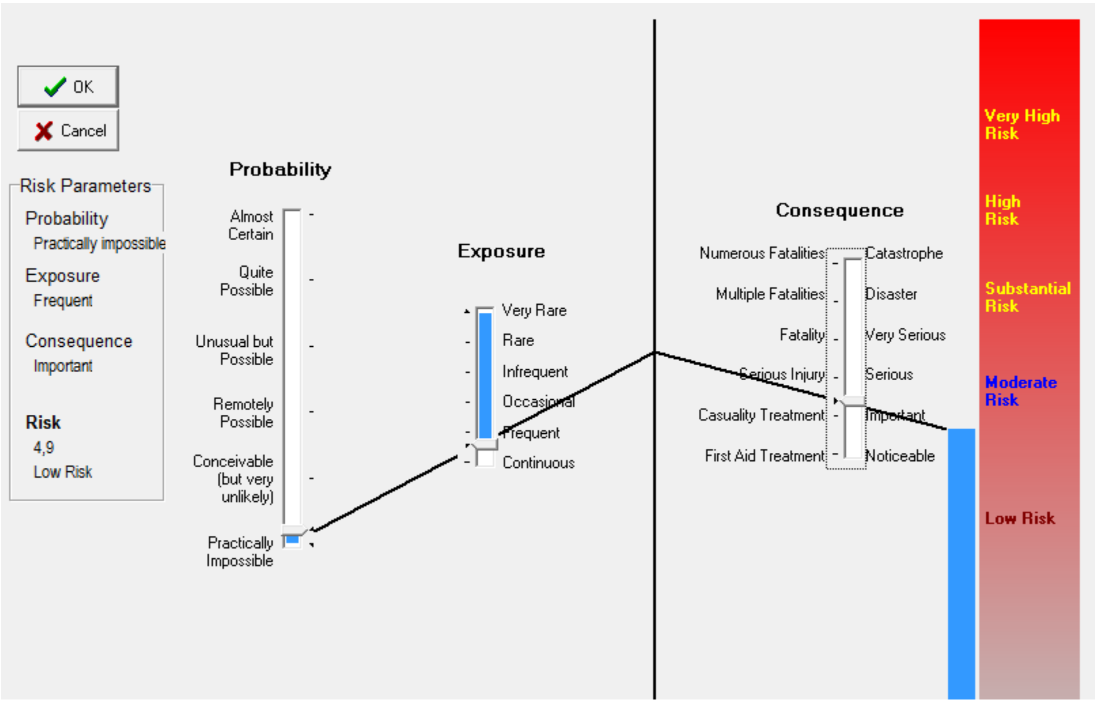

Figure A.38 Risk score of accidents affecting the eye

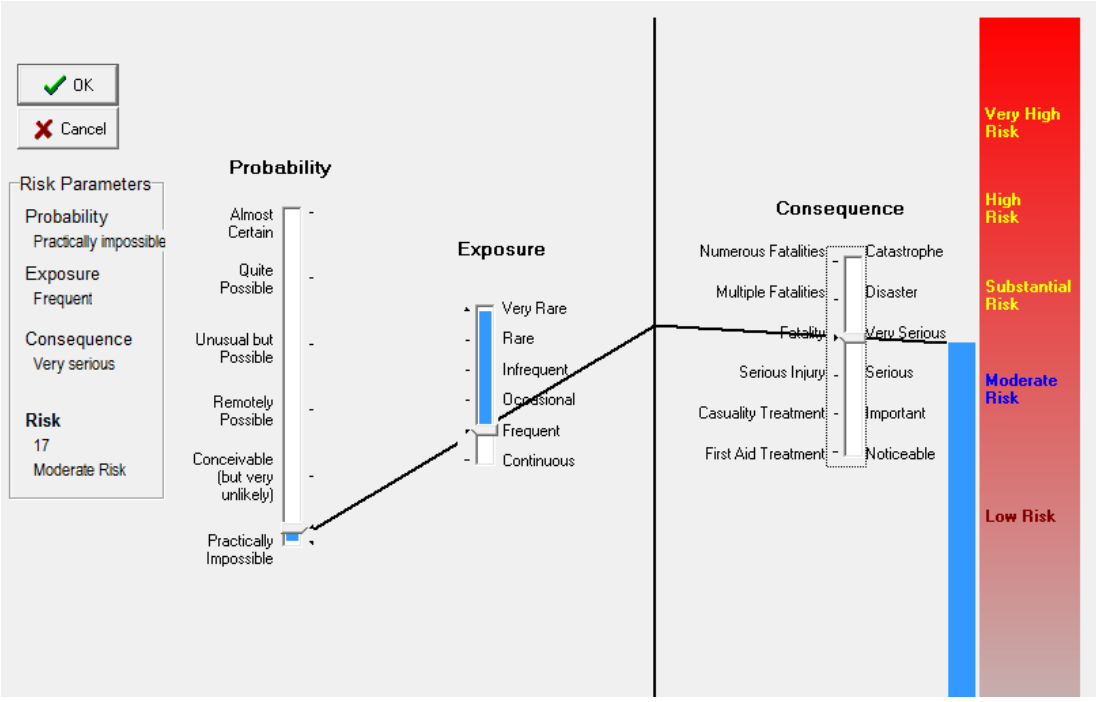

Figure A.39 Risk score of accidents affecting the hip

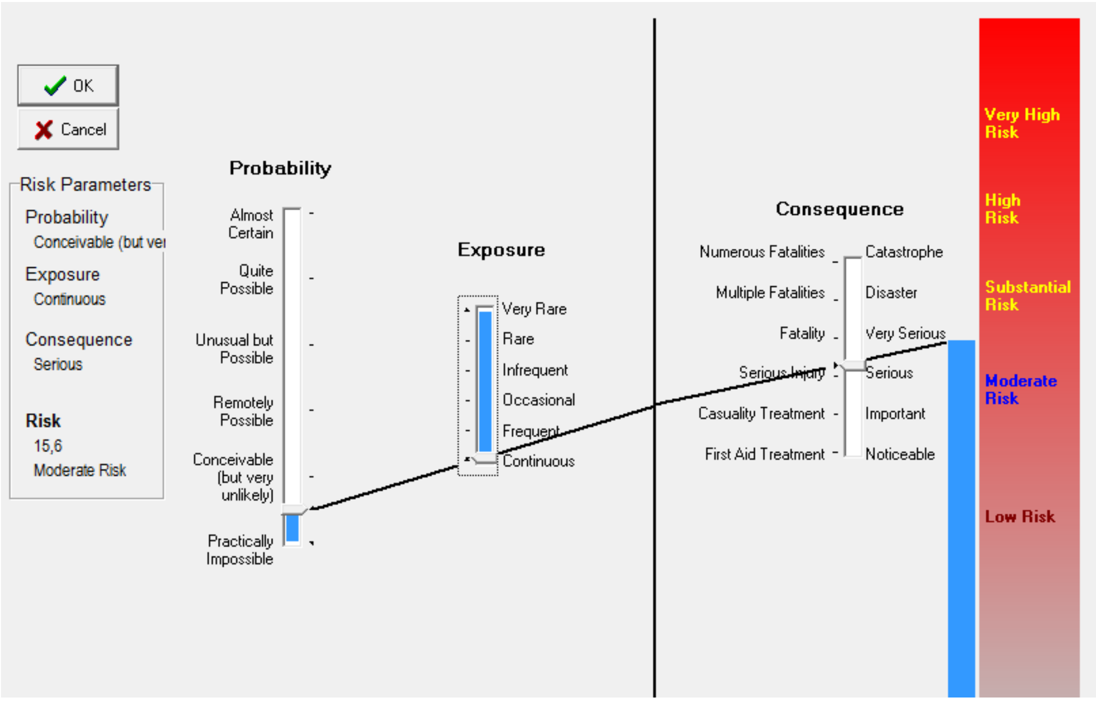

Figure A.40 Risk score of accidents affecting the arm

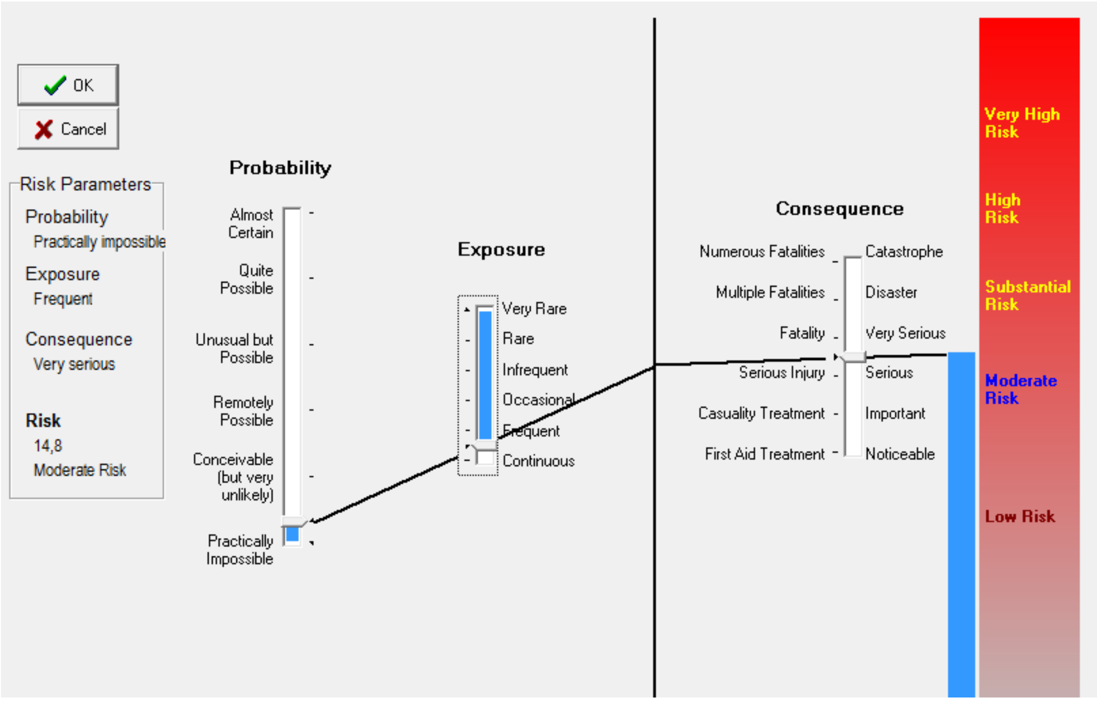

Figure A.41 Risk score of accidents affecting the shoulder

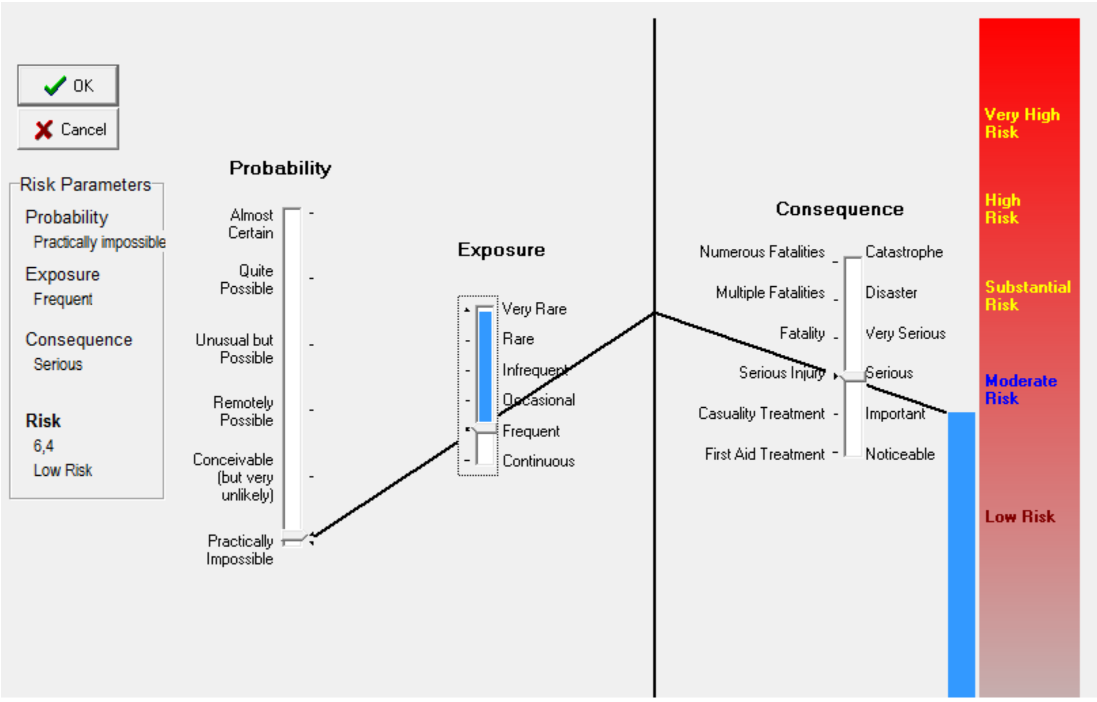

Figure A.42 Risk score of accidents affecting the back

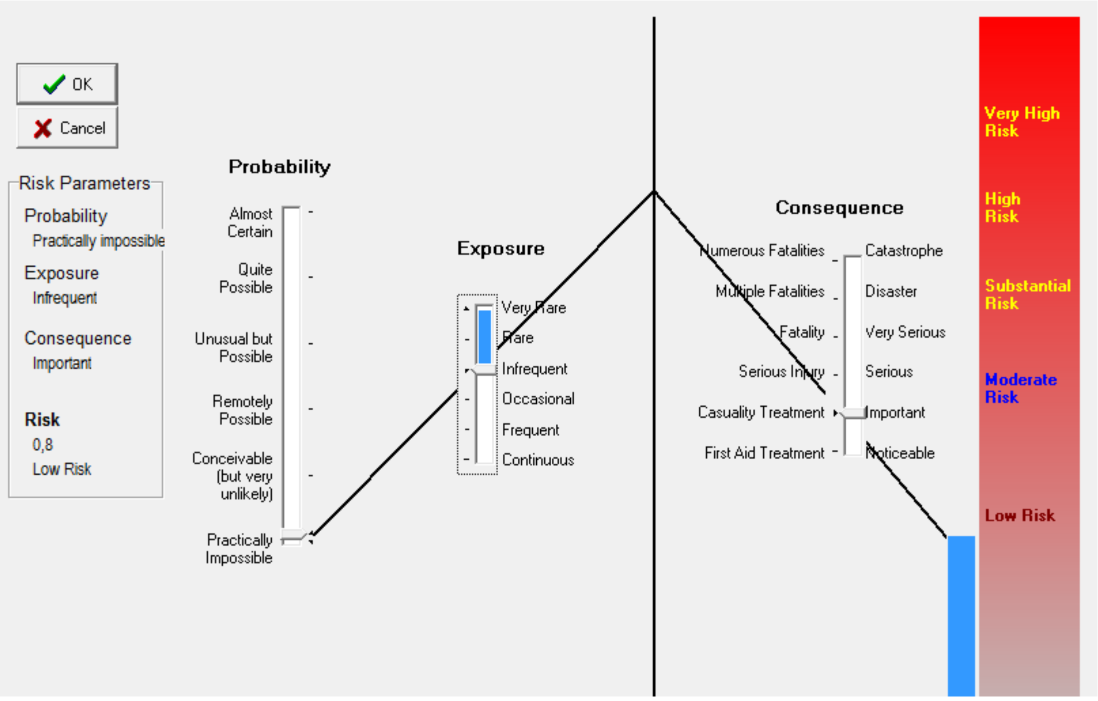

Figure A.43 Risk score of accidents affecting the respiratory

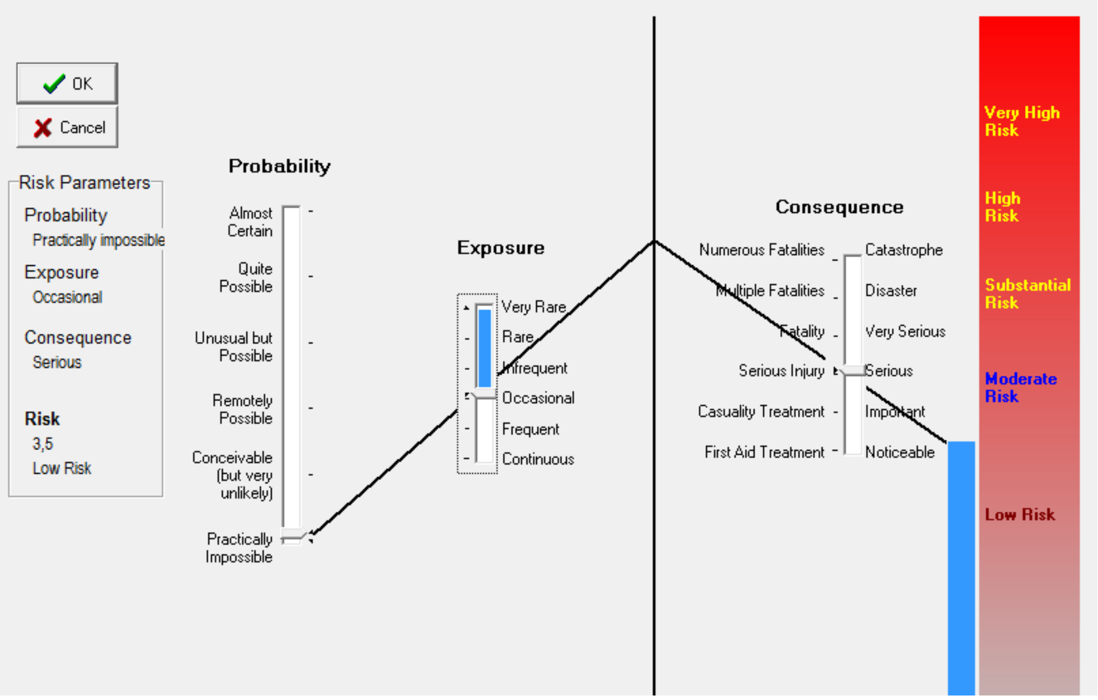

Figure A.44 Risk score of accidents affecting the whole body

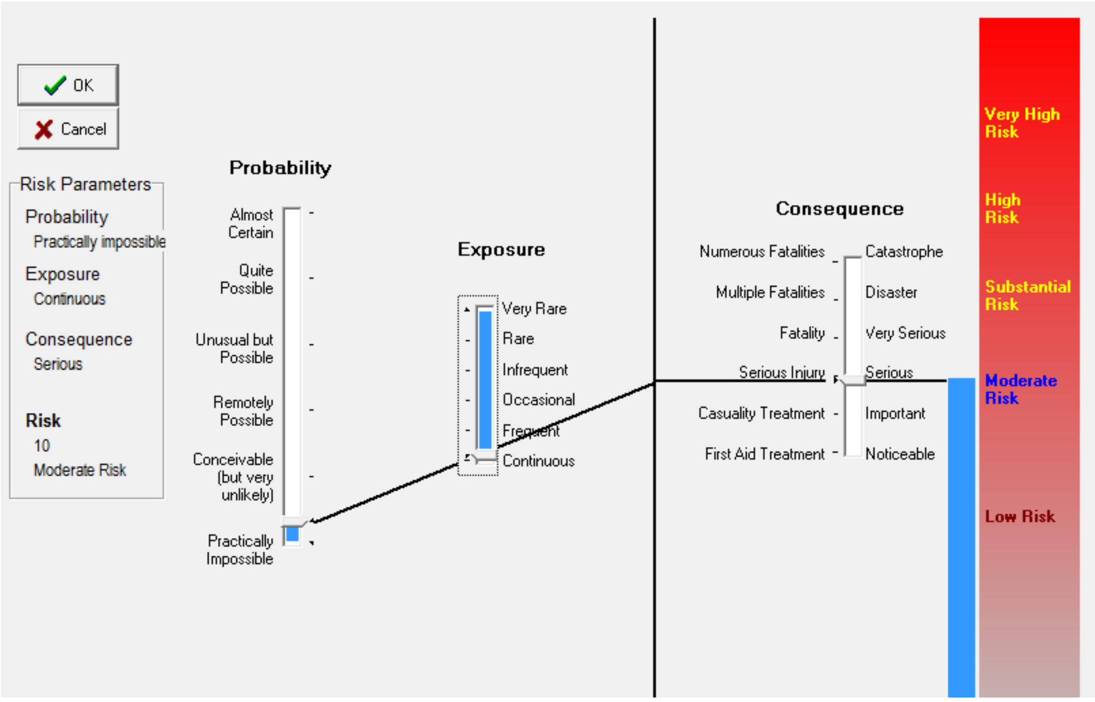

Figure A.45 Risk score of accidents affecting the face

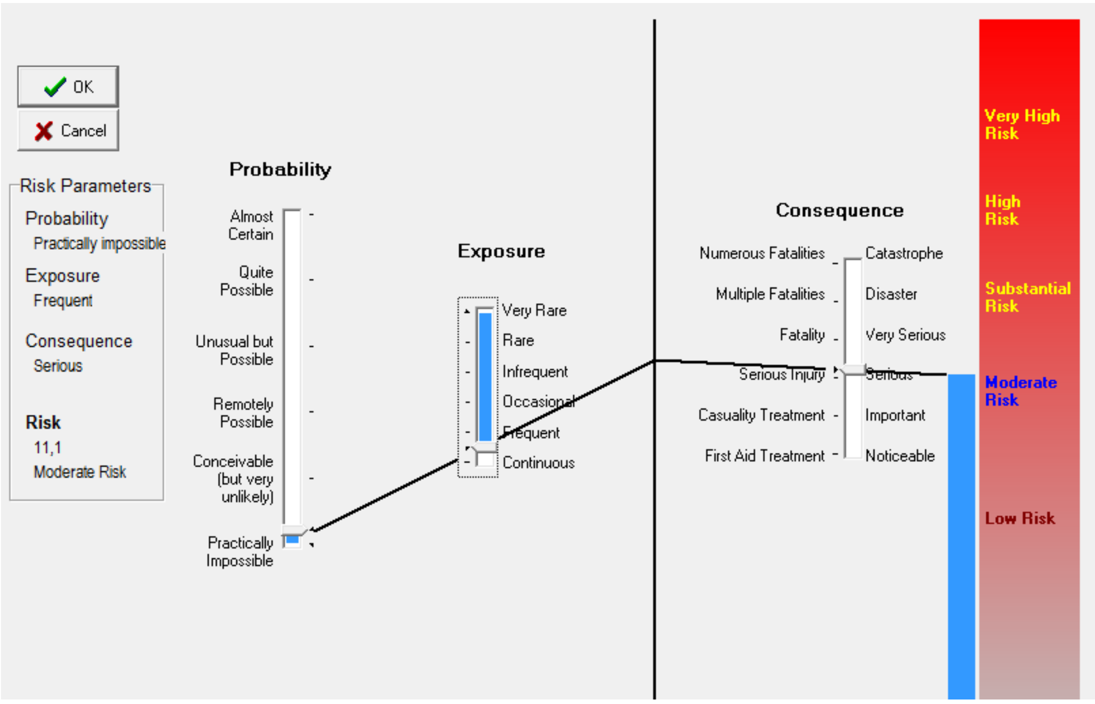

Figure A.46 Risk score of accidents experienced by the workers at the age interval of 20-24

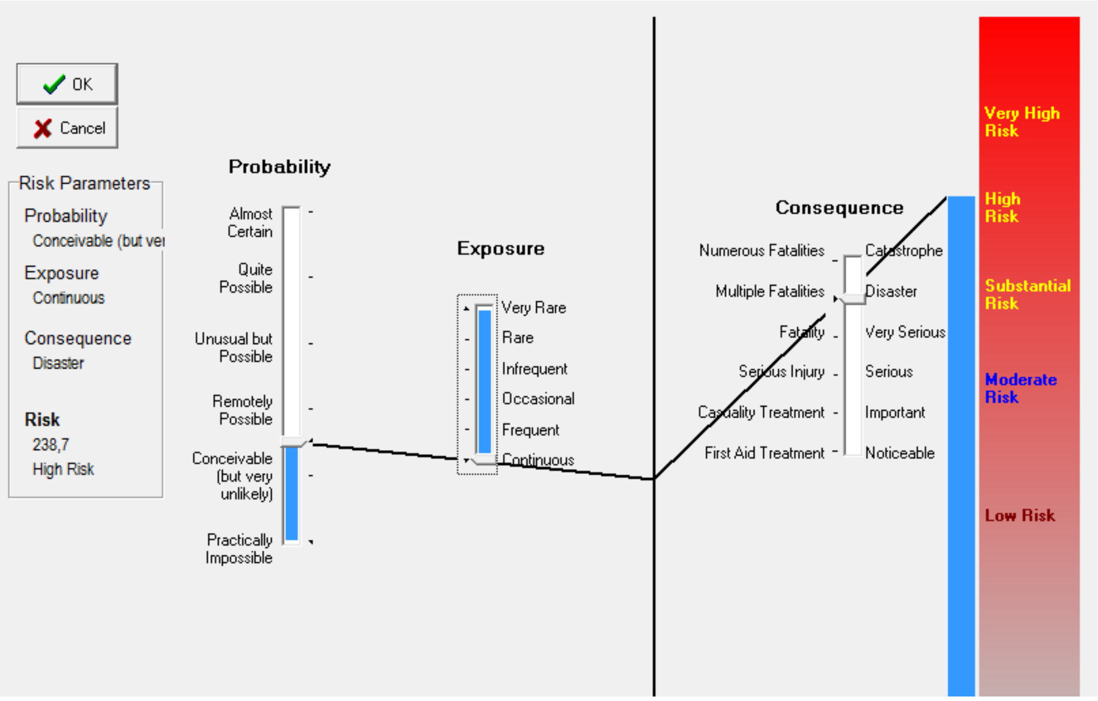

Figure A.47 Risk score of accidents experienced by the workers at the age interval of 25-29

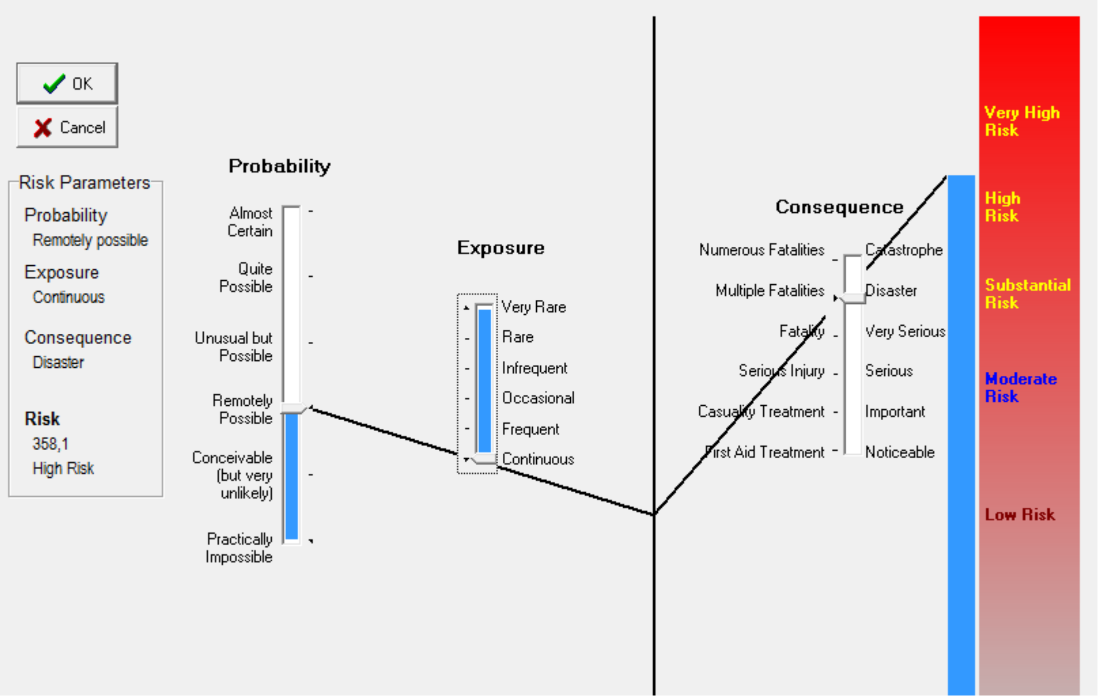

Figure A.48 Risk score of accidents experienced by the workers at the age interval of 30-34

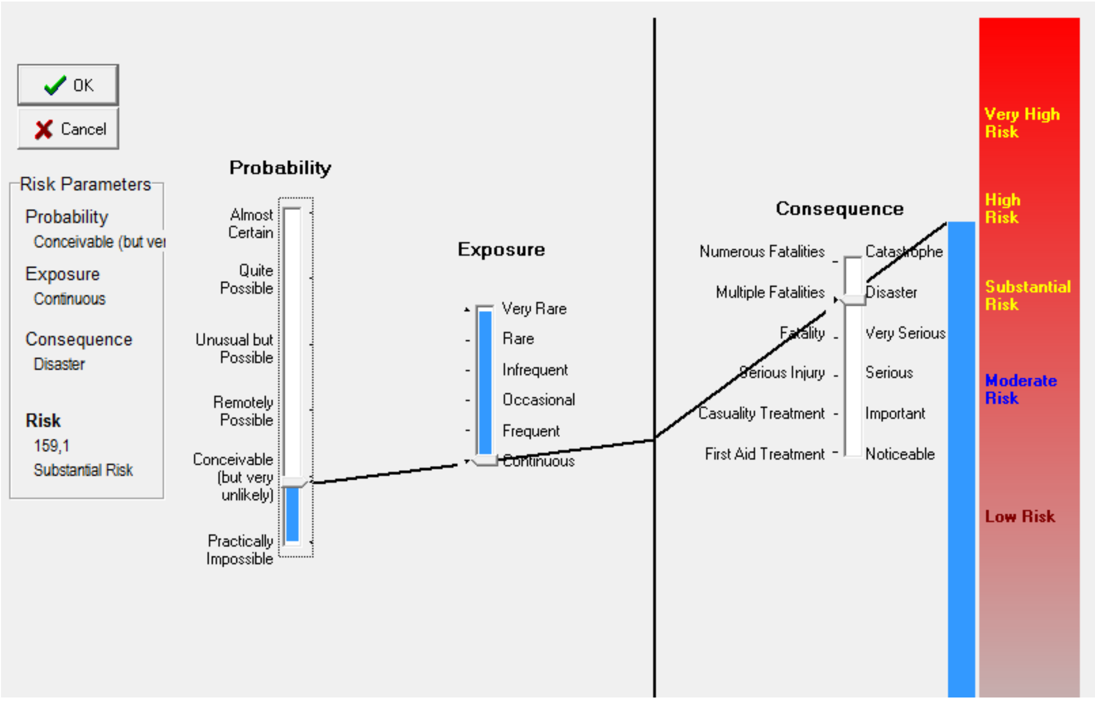

Figure A.49 Risk score of accidents experienced by the workers at the age interval of 35-39

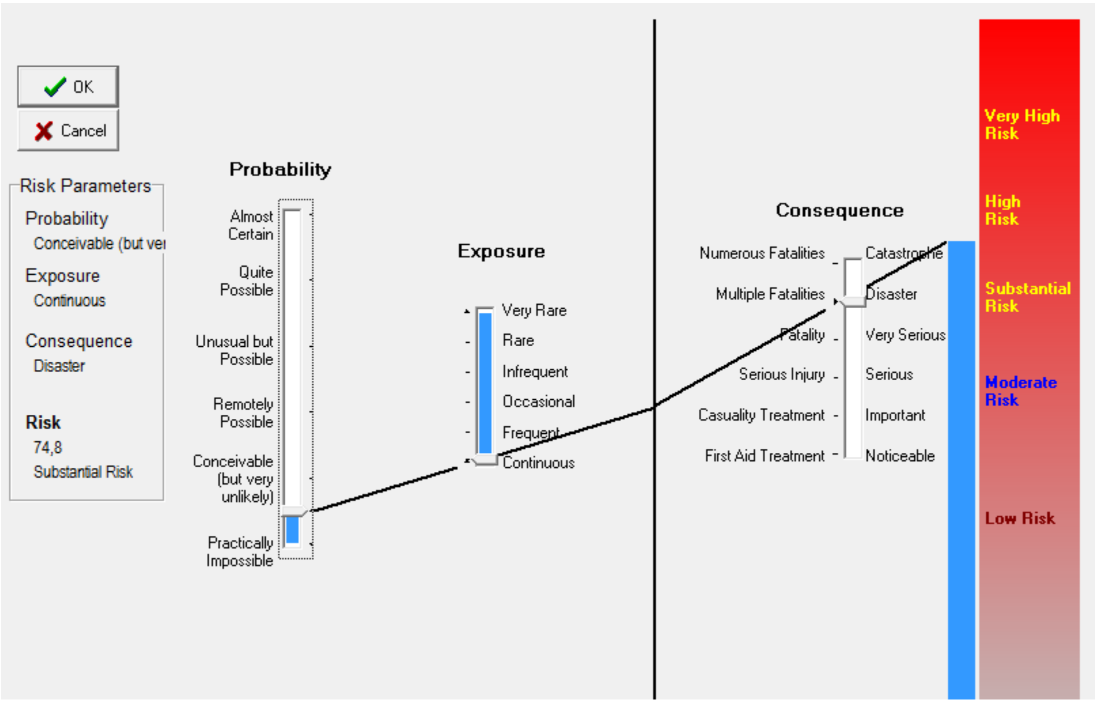

Figure A.50 Risk score of accidents experienced by the workers at the age interval of 40-44

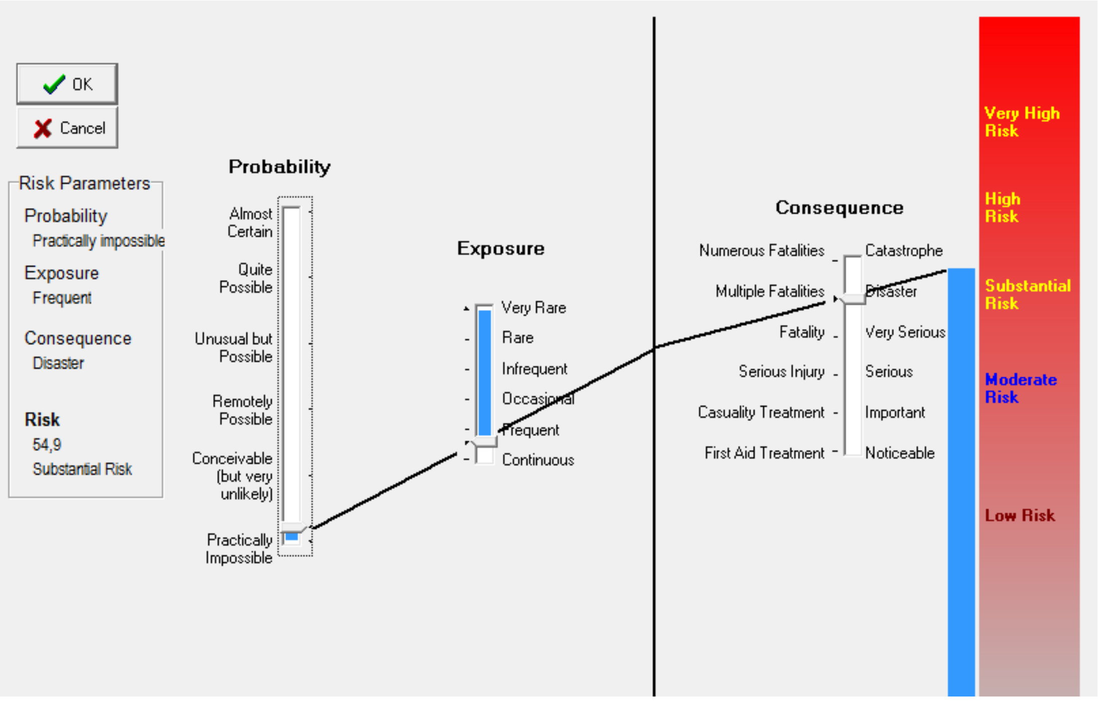

Figure A.51 Risk score of accidents experienced by the workers at the age interval of 45-49

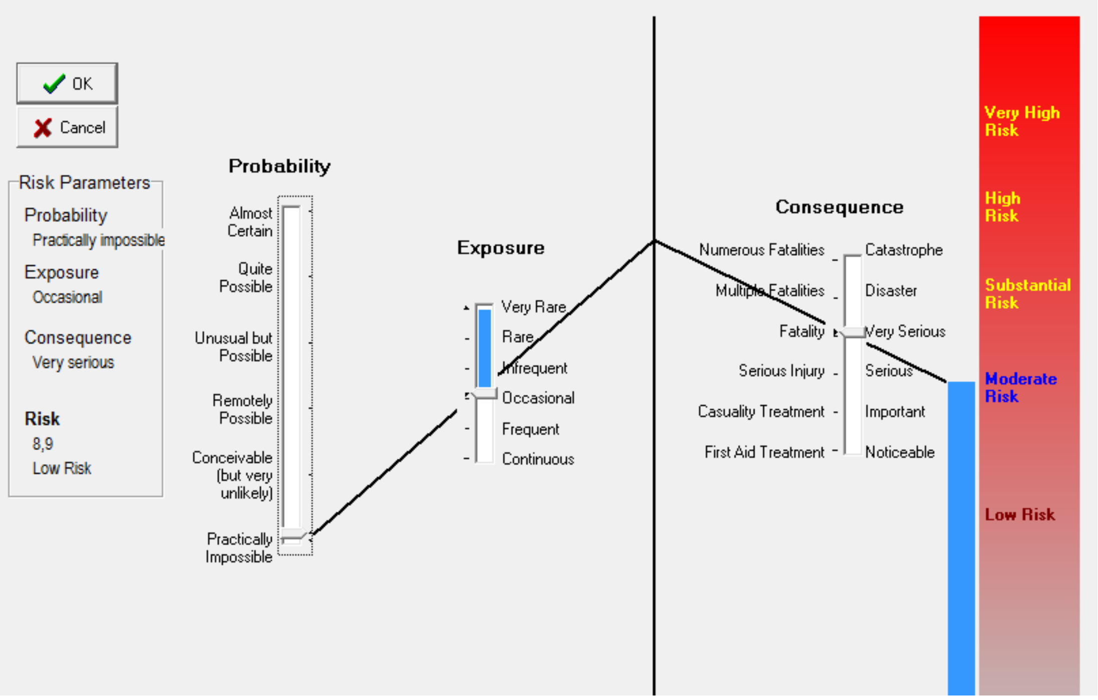

Figure A.52 Risk score of accidents experienced by the workers at the age interval of 50-55

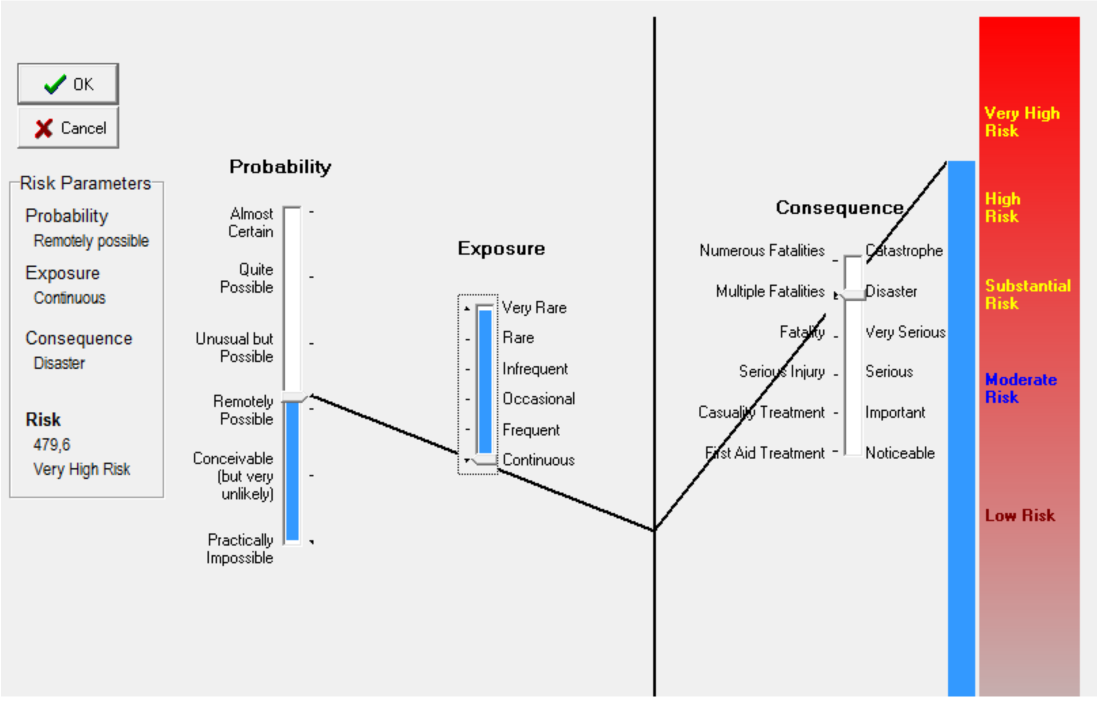

Figure A.53 Risk score of accidents experienced by the workers having an experience of 0-4 years

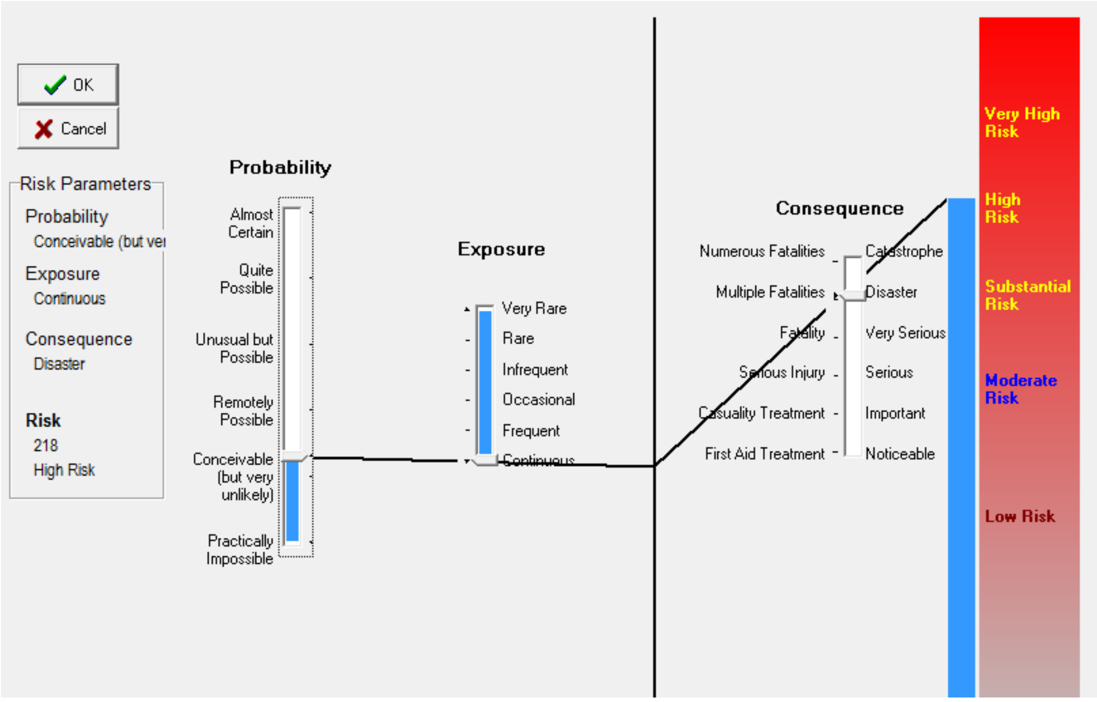

Figure A.54 Risk score of accidents experienced by the workers having an experience of 5-8 years

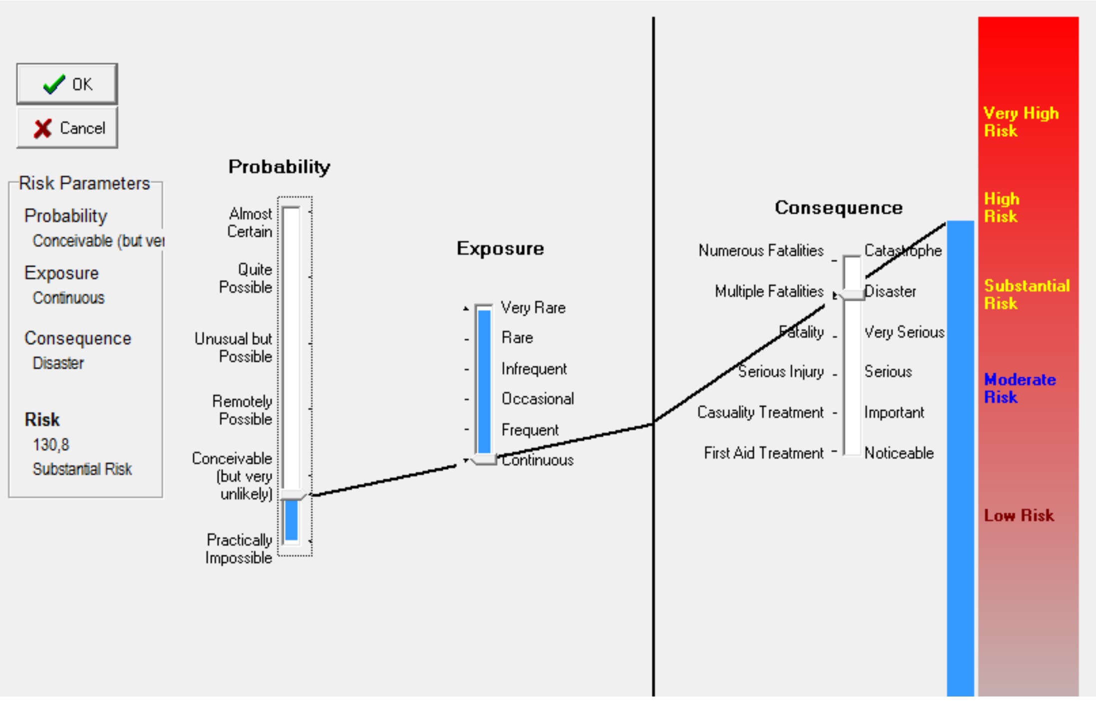

Figure A.55 Risk score of accidents experienced by the workers having an experience of 9-12 years

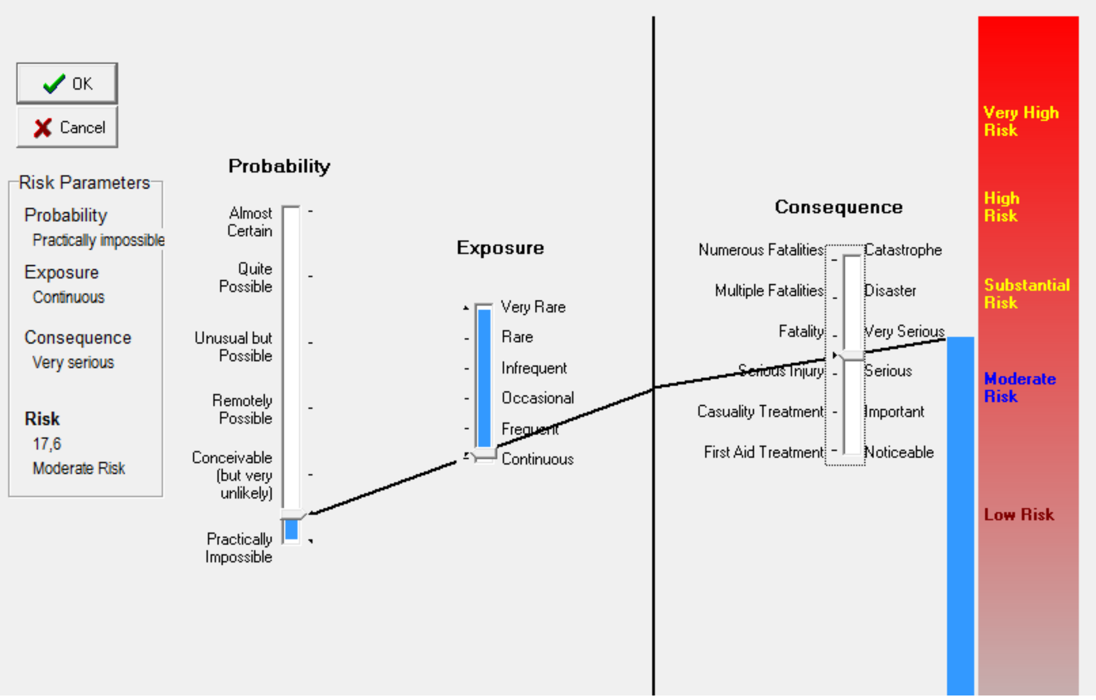

Figure A.56 Risk score of accidents experienced by the workers having an experience of 13-16 years

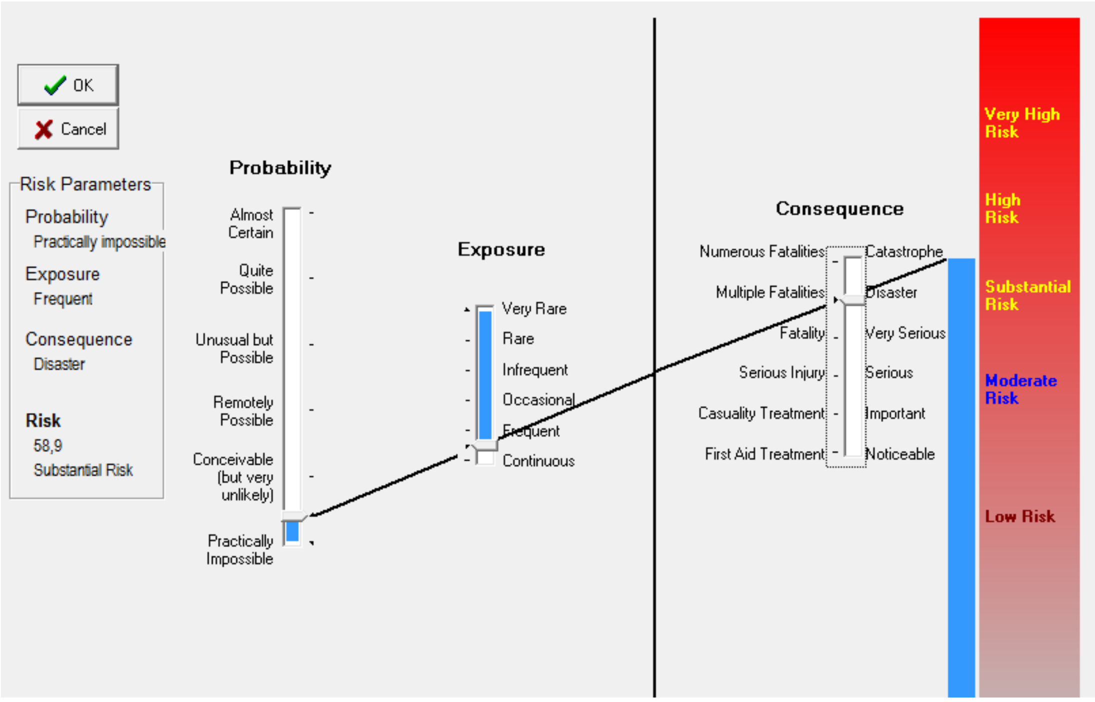

Figure A.57 Risk score of accidents experienced by the workers having an experience of 17-20 years

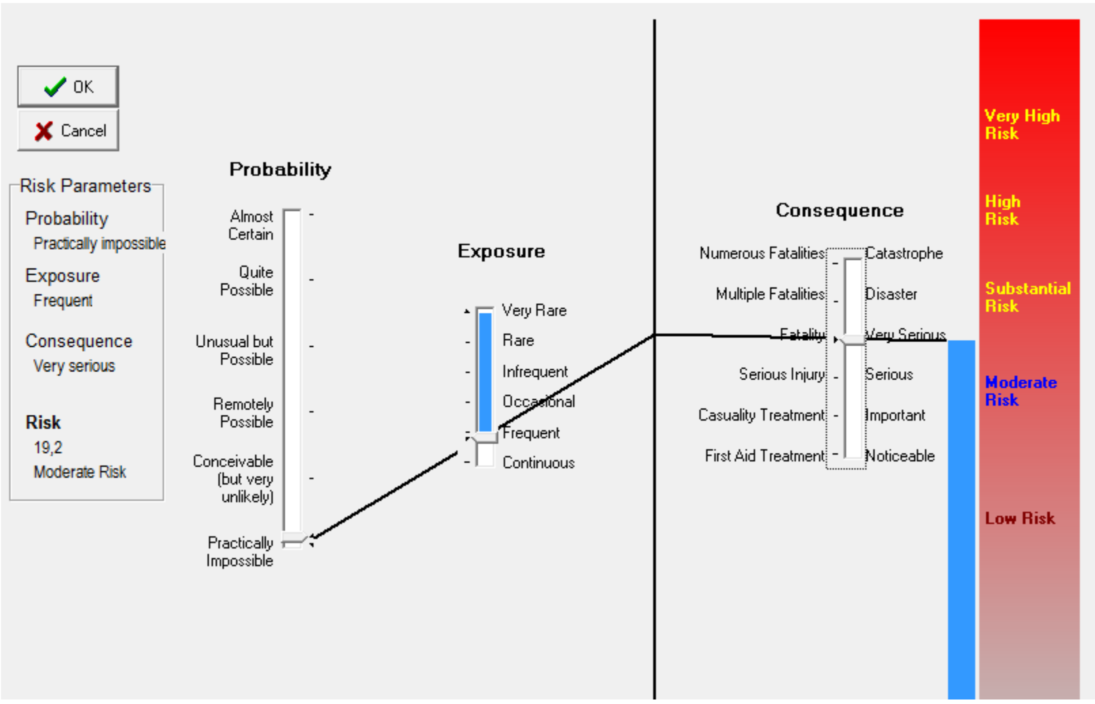

Figure A.58 Risk score of accidents experienced by the workers having an experience of 21-24 years

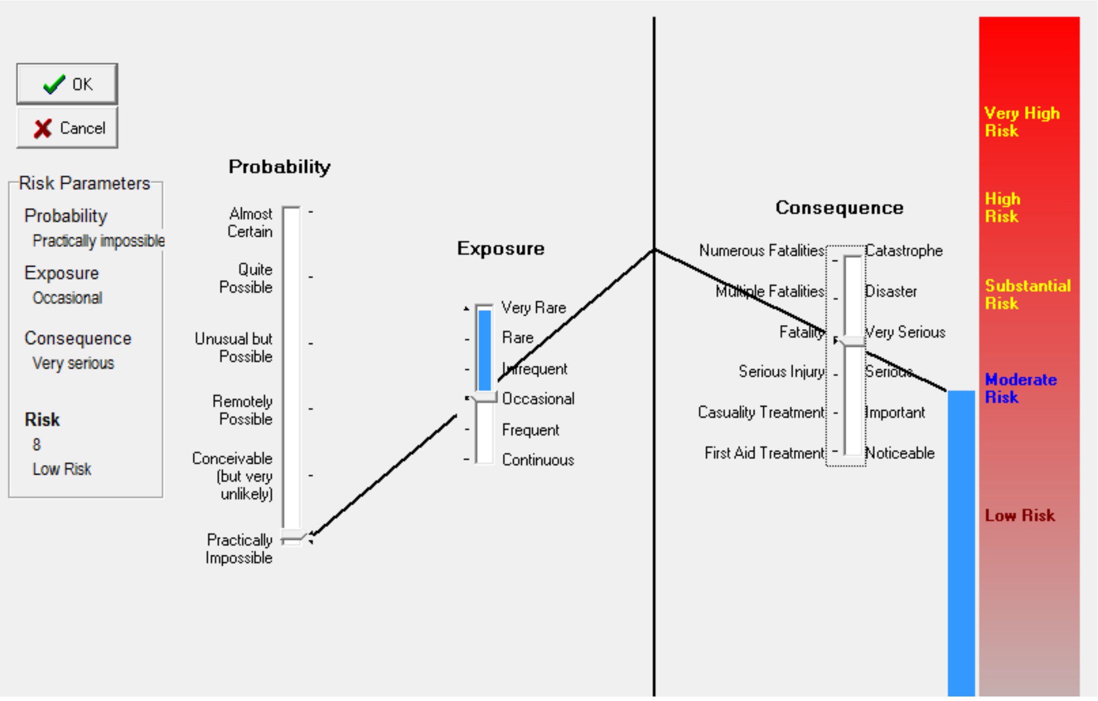

Figure A.59 Risk score of accidents experienced by the workers having an experience of 25-28 years

APPENDIX B

OTHER TIME SERIES TREND MODELS

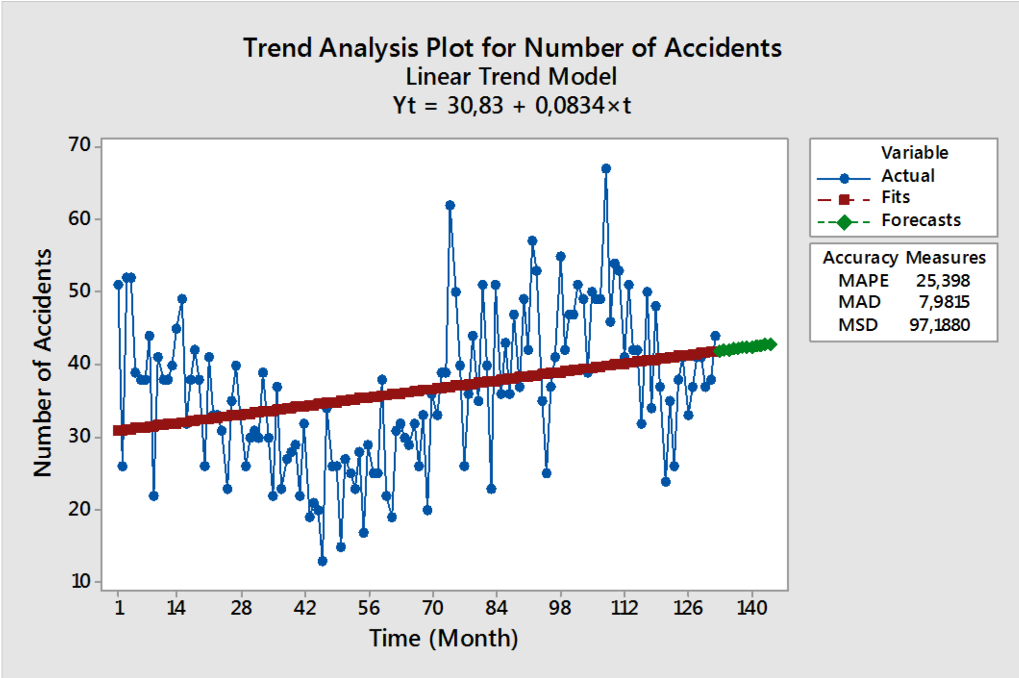

Figure B.1 Fitted model for linear trend

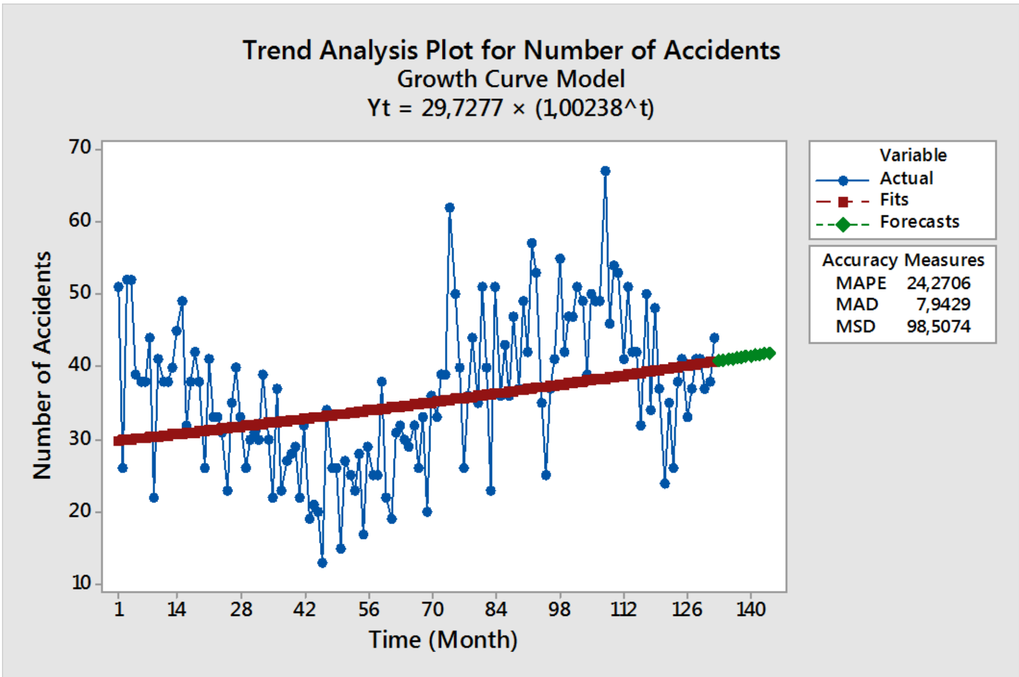

Figure B.2 Fitted model for growth curve trend