

**T.C.
ISTANBUL GEDİK UNIVERSITY
INSTITUTE OF GRADUATE STUDIES**



**RISK MANAGEMENT OF STEEL MATERIAL IN CONSTRUCTION
PROJECTS USING ARTIFICIAL INTELLIGENCE TECHNIQUES**

MASTER'S THESIS

Zina Talib FADHIL

Engineering Management Department

Engineering Management Master in English Program

JULY 2022

**T.C.
ISTANBUL GEDİK UNIVERSITY
INSTITUTE OF GRADUATE STUDIES**



**RISK MANAGEMENT OF STEEL MATERIAL IN CONSTRUCTION
PROJECTS USING ARTIFICIAL INTELLIGENCE TECHNIQUES**

MASTER'S THESIS

**Zina Talib FADHIL
(201281007)**

Engineering Management Department

Engineering Management Master in English Program

Thesis Advisor: Prof. Dr. Güzde ULUTAGAY

JULY 2022



T.C
İSTANBUL GEDİK ÜNİVERSİTESİ
LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ MÜDÜRLÜĞÜ

Yüksek Lisans Tez Onay Belgesi

Enstitümüz, Engineering Management Department İngilizce Tezli Yüksek Lisans Programı (201281007) Zina Talib FADHIL"ın “Risk Management of Steel Material in Construction Projects Using Artificial Intelligence Techniques” adlı tez çalışması Enstitümüz Yönetim Kurulunun 18.07.2022 tarihinde oluşturulan jüri tarafından **Oy Birliği** ile Yüksek Lisans tezi olarak **Kabul** edilmiştir.

Öğretim Üyesi Adı Soyadı

Tez Savunma Tarihi: (18/07/2022)

- 1) Tez Danışmanı:** Prof. Dr. Gözde ULUTAGAY
- 2) Jüri Üyesi:** Dr. Öğr. Üyesi Tuğba Burçin GÜMÜŞ
- 3) Jüri Üyesi:** Dr. Öğr. Üyesi Mert TOLON

DECLARATION

I, Zina Talib FADHIL, do hereby declare that this thesis titled as “Risk Management of Steel Material in Construction Projects Using Artificial Intelligence Techniques” is original work done by me for the award of the master's degree in the faculty of Engineering Management. I also declare that this thesis or any part of it has not been submitted and presented for any other degree or research paper in any other university or institution. (18/07/2022)

Zina Talib FADHIL



DEDICATION

To those that guided me in learning how to stand solidly on the ground Dad.

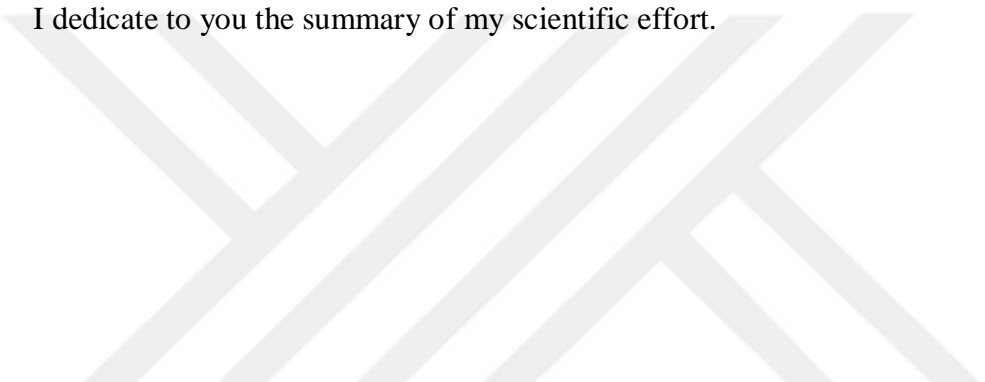
To the wellspring of kindness, compassion, and love Revered mom.

To my brother and my sisters support me and my arms and share my joys and sorrows.

To all those from whom I have received advice and support.

To all researchers, and science students,

I dedicate to you the summary of my scientific effort.



PREFACE

I am sincerely grateful and praise to God, the Lord of all that be, the Merciful.

My sincere gratitude is being extended to Prof. Dr. Gözde Ulutagay for her sound supervision, patience and guidance throughout the execution of this study.

I appreciate the people who agreed to be part of this research and gave their time and cooperation.

Special regards to all my teachers who spent even a moment trying to nourish my mind with knowledge.

Finally, I might to thank my university "Istanbul Gedik University" and especially the institution for hosting me during these wonderful years.

July 2022

Zina Talib FADHIL

TABLE OF CONTENTS

	<u>Page</u>
PREFACE	v
TABLE OF CONTENTS	vi
ABBREVIATIONS	viii
LIST OF TABLES	ix
LIST OF FIGURES	x
ABSTRACT	xii
ÖZET	xiii
1. INTRODUCTION	1
1.1 Study Topic	1
1.2 Purpose of Thesis	1
1.3 Literature Review	2
1.4 Hypothesis	4
2. LITERATURE REVIEW	5
2.1 Purpose	5
2.2 Steel Material	5
2.3 Steel Material Properties	6
2.3.1 Strength	7
2.4 A Comparison between RCC and Steel Structure	15
2.5 The Risks Management Methodology	16
2.5.1 Planning Phase	16
2.5.2 Risk Identification	17
2.5.3 Risk Analysis	17
2.5.3.1 Qualitative Analysis	17
2.5.3.2 Quantitative Analysis	17
2.5.4 Risk Response	18
2.6 Risk Management for the Steel Structure	18
2.6.1. Identification of manufacturing risks in the steel industry	18
2.7 Causes of Structural Failures with Steel Structures	22
2.8 Artificial Intelligence Techniques in Risk Management	24
3. STEEL FAILURE	27
3.1 Introduction	27
3.2 Data Collection Methods	27
3.3 Design of Questionnaire	28
3.3.1 Part I (General Information)	29
3.3.2 Part II Causes of steel Failure (Owner Perspective)	29
3.3.3 Part III Causes of Steel Failure (Contractor Perspective)	29
3.3.4 Part IV Potential Enhancements	30
3.4 Referees of the Questionnaire	30
3.5 Pilot study	31
3.6 Statistical Reliability	31
3.6.1 Statistical Reliability	31

3.6.1.1 Alpha (Cronbach) model	31
3.7 Questionnaire distribution.....	32
3.7.1 Sample size response rate.....	32
3.7.2 Questionnaire distribution administration.....	32
3.7.3 Sample description.....	33
3.8 Questionnaire Data Analysis.....	35
3.8.1 Descriptive statistics	35
3.8.1.1 Central tendency measurement	35
3.8.1.2 ANOVA test.....	35
3.9 Results of the Questionnaire	36
3.9.1 Causes of steel failure (Owner perspective).....	36
3.9.2 Causes of steel failure (Contractor perspective).....	39
3.9.3 Potential Enhancement.....	43
3.10 Steel Failure Prediction.....	45
3.10.1 Support vector machine.....	45
3.10.1.1 Building up the (SVM)	45
3.10.2 Decision tree	48
3.10.2.1 Building up Decision Tree	49
3.10.3 Neural network	50
3.10.3.1 Building up the (ANN)	51
3.11 KNIME Software	53
3.12 MATLAB Software.....	58
3.13 Summery	62
4. THE PROPOSED SYSTEM.....	63
4.1 Introduction.....	63
4.2 The Proposed System	63
4.3 Application of the Case Study	67
5. CONCLUSIONS AND RECOMMENDATIONS.....	76
5.1 Introduction.....	76
5.2 Conclusions.....	76
5.3 Recommendation.....	76
5.4 Future Work	77
REFERNCES	78
APPENDIX	85
RESUME.....	92

ABBREVIATIONS

ANN	: Artificial Neural Network
AUC	: Area under the Curve
GA	: Genetic Algorithm
GSA	: Gravitational Search Algorithm
KNIME	: Konstanz Information Miner
MATLAB	: Matrix Laboratory.
NEC	: New Engineering Contract
ROC	: Receiver Operating Characteristic curve
SfM	: Multi-image or structure-of-motion
SVM	: Support Vector Machine

LIST OF TABLES

	Page
Table 2.1: Standard Steel Grades' Minimum Yield and Tensile Strengths.....	8
Table 2.2: A List of the Hardness Classifications	9
Table 2.3: Specified Mechanical Properties of Common Stainless Steels to EN 10088-4 Used in Design.....	13
Table 2.4: Guidelines for Stainless Steel Selection	14
Table 3.1: Name of Governmental institutions and Private Companies	28
Table 3.2: Information about Arbitrators	30
Table 3.3: Reliability Cutoff Values	32
Table 3.4: Value of Alpha Cronbach for Questionnaire's Parts.....	32
Table 3.6: ANOVA Test	44
Table 3.7: Steps of SVM	46
Table 3.8: Steps for Finding SVM Parameter	47
Table 3.9: Decision Tree Building.....	49
Table 3.10: Algorithms Accuracy.....	56
Table 3.11: Algorithms Accuracy.....	59
Table 4.1: Problems Treatments with its Effects.....	70
Table 4.2: Problems Treatments with its Effects using GA in AS	73
Table 4.3: Problems Treatments with its Effects using GA in Tendering	73
Table 4.4: Problems Treatments with its Effects using GA in Contractor Selection.....	73
Table 4.5: Problems Treatments with its Effects using GA in Contract Forum.....	74

LIST OF FIGURES

	<u>Page</u>
Figure 2.1: Stress–Strain Behaviour for Steel.....	11
Figure 2.2: Typical Carbon Steel and Stainless Steel Stress-Strain Curves after Annealing	13
Figure 2.3: Construction of a Commercial Hub with a Half-Hour View	23
Figure 2.4: Same View as in Figure (2.3), After Collapse.....	23
Figure 2.5: The Structural Collapse Was Caused by a Welded I-Girder That Was 1400 mm high.....	23
Figure 3.1: Components of the Questionnaire.....	29
Figure 3.2: Work Sector Percentage of Respondents	33
Figure 3.3: Percentage of Respondents in each Ministry.....	33
Figure 3.4: The Age Percentage of Respondents	34
Figure 3.5: Educational Level of Respondents	34
Figure 3.6: The Specialization of Respondents	34
Figure 3.7: Managerial Causes of the steel Failure (Owner Perspective).....	37
Figure 3.8: Financial Causes of the steel Failure (Owner Perspective).....	37
Figure 3.9: Overexpansion/Growth Causes of the Steel Failure Owner Perspective	38
Figure 3.10: Uncontrollable Causes of the Steel Failure (Owner Perspective)	39
Figure 3.11: Managerial Causes of the steel Failure (Contractor Perspective).....	40
Figure 3.12: Financial Causes of the Steel Failure (Contractor Perspective)	40
Figure 3.13: Overexpansion/Growth Causes of the steel Failure (Contractor Perspective)	41
Figure 3.14: Uncontrollable causes of the Steel failure (Contractor Perspective) ...	41
Figure 3.15: Potential Enhancement	43
Figure 3.16: SVM Flowchart.....	48
Figure 3.17: Decision Tree Flowchart	50
Figure 3.18: Basic ANN structure	52
Figure 3.19: Excel Reader (XLS)	53
Figure 3.20: X-Partitioner	54
Figure 3.21: Learner	54
Figure 3.22: Predictor	54
Figure 3.23: Scorer	55
Figure 3.24: The Whole Model	56
Figure 3.25: ROC Curve award the contract to the lowest price using Decision Tree	57
Figure 3.26: ROC Curve using SVM.....	57
Figure 3.27: ROC Curve using Decision Tree	58
Figure 3.28: ROC Curve using Neural Network.....	58
Figure 3.29: AUC Curve using DT (MATLAB).....	59
Figure 3.30: ROC Curve Using SVM (MATLAB)	60
Figure 3.31: Regression of Trained, Validated and Tested Data Fitness for Mean FP	60
Figure 3.32: Performance of the MLP model	61

Figure 3.33: The Error Histogram of the Trained, Validated and Tested Data.....	61
Figure 4.1: Proposed System.....	63
Figure 4.2: General System.....	64
Figure 4.3: Failure System	64
Figure 4.4: Evaluation Stage.	65
Figure 4.5: Evaluation Stage	65
Figure 4.6: Project Announcement Problems	67
Figure 4.7: Problems Treatment	68
Figure 4.8: Problems Selection.....	71
Figure 4.9: Problems Number one with its Treatment.....	71
Figure 4.10: Problems Number two with its Treatment	72
Figure 4.11: Problems Number three with its Treatment.....	72
Figure 4.12: Problems with its Treatment in tendering	74
Figure 4.13: Problems with its Treatment in Contractor Selection	75
Figure 4.14: Problems with its Treatment in Contract Forum	75



RISK MANAGEMENT OF STEEL MATERIAL IN CONSTRUCTION PROJECTS USING ARTIFICIAL INTELLIGENCE TECHNIQUES

ABSTRACT

Construction risk factors and uncertainties are developing in tandem with the growth of larger, more specialized, and complicated construction projects. The thesis' major goal is to design a risk management system for managing steel deformation in buildings, and in order to accomplish this, the following goals must be met: Identify the main factors that lead to steel deformation in construction projects. Assessment of these factors and their impact on the project's cost.

A case study was taken for different ministries to determine and find the best solution for each problem in tendering stages, The Ministry of Education, Directorate of Water and Sewage, Ministry of Higher Education and Scientific Research.

A problems that gathers during the field survey were applied on these ministries to determine their impact on the on the projects performance. The selection of the algorithm to the best solution with its information.

Keywords: *Building projects, Steel structures, Risk management*

YAPI PROJELERİNDE ÇELİK MALZEMELERİN YAPAY ZEKA TEKNİKLERİYLE RİSK YÖNETİMİ

ÖZET

İnşaat risk faktörleri ve belirsizlikler, daha büyük, daha uzmanlaşmış ve karmaşık inşaat projelerinin büyümesiyle birlikte geliyor. Tezin ana amacı, binalarda çelik deformasyonu yönetmek için bir risk yönetim sistemi tasarlamaktır ve bunu gerçekleştirmek için aşağıdaki hedeflere ulaşılmalıdır: İnşaat projelerinde çelik deformasyona neden olan ana faktörleri belirleyin. Bu faktörlerin değerlendirilmesi ve proje maliyeti üzerindeki etkileri.

İhale aşamalarındaki her bir sorun için en iyi çözümü belirlemek ve bulmak amacıyla farklı bakanlıkların, Milli Eğitim Bakanlığı, Su ve Kanalizasyon Müdürlüğü, Yüksek Öğretim ve Bilimsel Araştırma Bakanlığı için bir vaka çalışması yapılmıştır.

Proje performansı üzerindeki etkilerini belirlemek için bu bakanlıklara saha araştırması sırasında toplanan bir problem uygulandı. Algoritmanın bilgisiyle en iyi çözüme seçilmesi.

Anahtar kelimeler: *Yapı projeleri, Çelik yapılar, Risk yönetimi*

1. INTRODUCTION

1.1 Study Topic

A brief at description of steel structure will be proposed and how the damage of the steel will effect both on time and cost of the projects. Further, a questionnaire will be proposed for the factors that effect on the steel deformation and their effect on the building and the develop a computer program for the steel deformation.

1.2 Purpose of Thesis

Excessive deformation demand in one or more components of a structural system causes local strength and stiffness deterioration, which can lead to a loss of structural integrity, resulting in major damage or even collapse of the structure. The precision of the analytical models used and their ability to capture the projected level of degradation inside a member are critical for reliable collapse or damagestate evaluations of existing buildings. Steel element deformation capacity and its impact on existing building collapse prediction are major topics in performance-based analysis and have been the subject of recent research projects.

The thesis' major goal is to design a risk management system for managing steel deformation in buildings, and in order to accomplish this, the following goals must be met:

1. Identify the main factors that lead to steel deformation in construction projects.
2. Assessment of these factors and their impact on the project's cost.
3. The goal also is to develop a computer program using particle swarm optimization to select the optimal method to handle deformation of the steel.

1.3 Literature Review

Businesses are encouraged by ISO 9001:2015's risk-based approach to determine if process outputs are good or unsatisfactory, and to take particular action to prevent negative effects and improve processes, one must be able to recognize and manage risks and opportunities. (Zetzsche and Dewi 2018). The definition of risk is a unknown occurrence or circumstance that, if it happens, might have a good or bad effect on influence on the goals of the project. The techniques in this knowledge area have been used to identify, analyze, and manage known hazards. As part of risk management, A contingency reserve may be allocated to recognized hazards. Unknown threats can't be properly analyzed or dealt with ahead of time. Unexpected risks are often addressed by building management reserves, which might take the shape of additional money, time, or resources. The primary phases of risk management include planning, risk identification, analysis, response to risks, assessment, monitoring, and communication of risks. are all included in risk management (Tupa, Simota, and Steiner 2017). Risk management is a complicated process that begins at the top and moves down toward the executives. Literacy studies refers to expression of a large number of ideas, perspectives, approaches, procedures at risk appraisal and risk management are valuable with managers, including risks, uncertainty, and efficiency (Ormerod 2010). The three steps that make up the whole risk assessment process hazard identification, risk analysis, and risk assessment are all included in the risk management hierarchy. A step in the risk identification process is determining the origins and sources of risk, or a risk in the case of any physical harm. A term "source of hazard" is made up meanings for many academics. Risks lead to a potential harm cause, which might be one of the following: materials, equipment, processes, or working practices. In addition to being able to fall on someone and cause harm, it is also recognized as damage when it results in human injury, health degeneration, or a combination of the two. The factors that have the intrinsic potential to create risk, either alone or in combination, are known as risk sources or hazards. A methodical strategy to identifying them is crucial to guarantee that we have a complete picture of the potential dangers and risk factors. The Hazard Identification method is one such strategy. (HAZID) (Montano et al. 2015). Identifying hazards requires taking into account hazards that are internal and external. Internal risks are those that the project team can affect or control.

External risks are those that the project team cannot influence or control. Opportunities (good outcomes) and threats (threats) are both considered while identifying risks (negative outcomes). Determining the causes and effects (what could happen and what will happen) or the causes and effects (what will occur and what will ensure) can be used to detect risks (which outcomes should be fostered or discouraged, and how each may happen) (Klöber-Koch, Braunreuther, and Reinhart 2017).

Since 1998, the American Society of Civil Engineers has undertaken an annual research that provides information on the state and performance of US infrastructure in the form of report cards to the general public (ASCE/SEI 7-10 2013). Our transportation infrastructure is in horrible shape, as seen by these report cards and previous structural collapses. Due to a lack of maintenance and repair funds, environmental degradation of structural components, and/or increased vehicular weight, one out of every nine bridges in the United States is classified structurally inadequate.

The building industry makes a substantial contribution to various countries' economic and social development around the world (Boadu, Wang, and Sunindijo 2020). According to Anaman and Osei-Amponsah (Anaman and Osei-Amponsah 2007). The development of the construction sector and the pace of macroeconomic expansion in emerging nations are closely linked. The development of production halls, office buildings, roads, infrastructure, water and electricity lines, and other economic sectors depends largely on the construction industry; for instance, the construction of these structures may boost productivity while simultaneously providing employment. This is why this sector is so important.

The following notion, which is very similar to JCSS (Joint Committee on Structural Safety) researches, will be understood within the definitions of "risk" for the purpose of this research: The risk is a quantitative probabilistic characteristic of potential harms caused by unforeseeable events that can result in the complete or partial destruction of a structure, and it is calculated by multiplying the probability (relative frequency) of a negative event with a defined intensity by the value of possible loss. Since earthquake-induced damage renders the structure more susceptible to fire effects than an undamaged building, the behavior of earthquake-damaged structures in fire is an important study subject. This is due to the fact that the principal effect of

fire on a structural system is a gradual loss of mechanical qualities as temperature rises. It is obvious that the more structural behavior is impaired following an earthquake, the shorter the time until the building collapses due to fire (Faggiano and Mazzolani 2011).

Construction risk factors and uncertainties are developing in tandem with the growth of larger, more specialized, and complicated construction projects. A scheduling risk in the structural steel construction, in particular, had a detrimental impact on the project, generating a schedule extension and cost rise. However, if such risks are addressed at the pre-construction phase, the project is expected to be completed on time. The goal of the study was to determine the structural steel work process and the potential schedule risk elements arising from activities at each stage. Site engineers of varying levels of experience and expertise will benefit from the proposed schedule risk management tool's guidance in identifying and mitigating potential hazards early on in the process, thereby lowering the project's overall risk profile (Klöber-Koch, Braunreuther, and Reinhart 2017).

1.4 Hypothesis

The hypothesis of the thesis include the following :

H0 : there is weakness in the management of the steel in the construction projects.

H1: the absence of risk management plan for the steel structure.

2. LITERATURE REVIEW

2.1 Purpose

This chapter will include a description on the steel material, definition, compositions, problems, and how to manage this material in the construction projects.

2.2 Steel Material

There are dozens of different steel compositions on the market right now. The variety and vocabulary can be intimidating to a new metallographer. Even the most experienced metallographer and metallurgist may find the classification of steels to be perplexing. Steels, on the other hand, frequently fit into a small number of well-defined categories. This chapter makes an attempt to summarize these courses. The ASM Handbook contains more thorough information (Structural behavior of simple steel structures with non-uniform longitudinal temperature distributions under fire conditions - ScienceDirect n.d.).

Steel is referred to as alloy steel when the maximum in the range indicated for the quantity of alloying elements exceeds one or more of the following criteria: A precise range or a precise minimum amount of any of the components listed below is defined or necessary within the accepted area of constructional alloy steels: 1.65 percent manganese; 0.60 percent silicon; 0.60 percent copper; or when a specific range or minimum amount of any of the following components is needed or specified: To produce the required alloying effect, any alloying element may be added, including aluminum, boron, up to 3.99 percent chromium, cobalt, columbium, molybdenum, nickel, titanium, tungsten, vanadium, and zirconium (Cramer et al. 2003).

The term steel refers to a class of iron-carbon alloys with consistently predictable elemental proportions. The carbon (C) content of iron-carbon alloys is used to identify them, as follows:

- Wrought iron that has a carbon content of more than 1.7% (some literature references claim a value of 2 percent).
- Steel production begins when the carbon percentage drops below the aforementioned threshold. Components of steel are further classified as either extra mild (C 0.15%), moderate (C = 0.15 -0.25%), semi hard (C = 0.25 - 0.50%), hard (C = 0.50-0.75%), or extra hard (C > 0.75%). Carbon content of between 0.1 and 0.25 percent distinguishes structural steel, often known as constructional steel or carpenter steel. Carbon boosts the material's strength but decreases its ductility and weldability; structural steel has a low carbon percentage for this reason. Structure steel typically contains tiny amounts of additional elements in addition to iron and carbon. Some are found in the ore naturally and cannot be removed during processing, while still others are added to the alloy to achieve the desired mechanical or physical properties.

Sulfur (S) and phosphorous (P), both of them should be avoided since they make the material less ductile and weldable. They are among the components that cannot be totally eliminated throughout the manufacturing process (just around 0.06 percent of their total material should be allowed). Nitrogen (N), oxygen (O), and hydrogen (H) are other undesirable components that might impair ductility (H). The first two also alter the material's strain ageing qualities, making it more fragile in areas where permanent deformations have occurred. Manganese (Mn) and silica (Si) are the most frequent alloying components that are applied to materials, and they both greatly increase the material's strength while also dramatically enhancing its weldability. Chromium (Cr) and nickel (Ni) may sometimes be added to the alloy; The former increases a material's strength and, if present in sufficient amounts (as in stainless steel), its resistance to corrosion, while the latter increases strength while lowering the material's deformability (Structural Steel Design to Eurocode 3 and AISC Specifications - Claudio Bernuzzi, Benedetto Cordova - كتاب Google n.d.).

2.3 Steel Material Properties

Structural steel's qualities are depend on the materials used in its construction and the chemicals used in its composition, include all steps of processing during manufacturing. Structural designers use or rely on the composition, quality, and performance characteristics established by product standards. This article examines

the most important qualities for designers to consider, as well as the appropriate criteria for specific items (An experimental study on strength and serviceability of reinforced and steel fibre reinforced concrete (SFRC) continuous composite slabs - ScienceDirect n.d.).

The influence of alloying elements on steel mechanical characteristics is a current trend in new teaching methods in technical universities. 1st This unique method enables students to have a better comprehension of subjects in less time and to link mechanical qualities to material chemical composition. This strategy gives them a broad viewpoint that allows them to comprehend, remember, and relate new concepts to old ones with less effort (Meseguer-Valdenebro et al. 2015).

2.3.1 Strength

a Yield strength

Yield strength refers to the characteristic that designers need the most often since it serves as the basis for the bulk of design code rules. Use of Steels Made for Structures (including weathering steel), the yield strength is the principal classification in European Standards. For instance, S355 steel is a structural steel having a minimum yield strength of 355 N/mm². The permissible range of values for ultimate tensile strength is also specified

in the product standards (UTS). Some aspects of design are affected by the minimal UTS.

The number in the material with a yield strength of up to 16 mm thick is referred to as hot rolled carbon steels. Designers should be aware that when plate or section thickness increases, Decreases in yield strength (When thinner material is worked more than thicker material, strength is increased). These minimum yield and tensile strengths are required by law for steels to be used in the UK are indicated the two most popular steel grades used in the UK are shown in the table below (An experimental study on strength and serviceability of reinforced and steel fibre reinforced concrete (SFRC) continuous composite slabs - ScienceDirect n.d.).

Table 0.1: Standard Steel Grades' Minimum Yield and Tensile Strengths

Grade	For nominal thickness t, yield strength (N/mm ²) (mm)				Strength of tensile material (N/mm ²) for nominal thickness (mm)	
	t ≤ 16	16 < t ≤ 40	40 < t ≤ 63	63 < t ≤ 80.3	3.03 < t ≤ 100.1	100.1 < t ≤ 149.99
S275	275	265	255	245.1	410.01	399.99
S355	355	345	335	324.99	469.99	450.1

The least possible tensile strength f_y According to the BS EN 1993-1-1: United Kingdom National Annex, if a reported thickness is at least the minimum yield value, the nominal (characteristic) ultimate strength f_y and nominal (characteristic) yield strength f_y may be utilized.

Similar values are supplied in other areas of BS EN 10025 for a variety of categories, including hollow sections to BS EN 10210-1.

Strip steels suitable for cold forming come in a variety of steel grades. The relevant product standard BS EN 10346 specifies the minimum yield and tensile strength values.

According to BS EN 1993-1-3, the values for ultimate tensile strength f_y and basic yield strength f_{yb} to be employed as design parameters are specified.

Instead of using the letter "S" as is customary with carbon steels, stainless steels are identified by their "steel number," a number (e.g., 1.4401 for an exemplary austenitic steel). The yield point in the stress-strain relationship is not well defined, As a result, A proof strength that was obtained for a certain offset permanent strain is often used to define the "yield" strengths of stainless steel (conventionally the 0.2 percent strain).

Common stainless steels used in construction have strengths between 170 and 450 N/mm². Compared to austenitic steels, The yield strength of duplex steels is higher, which as compared to frequently applied carbon steels, that have a lower yield strength. Greater ultimate strength-to-yield strength ratios are seen in austenitic and duplex stainless steels as compared to carbon steels.

For use in design, on steels Both the ultimate minimum tensile strength and the yield strength are listed in BS EN 1993-1-4 and BS EN 10088-1 with their nominal (characteristic) values.

b Toughness

All materials, by their very nature, will have some flaws. Small fissure-like imperfections like this may be seen in steel. The "crack" may quickly spread without plastic deformation if the steel isn't strong enough, resulting in a "cracked brittleness". The likelihood of cracked brittleness is increased by cooler temperatures, thickness, stress raisers, and tensile stress. Several factors that need to be taken into account throughout the specification process affect how robust and resistant to brittle fracture steel is. Effects of the Charpy V-notch test is a useful technique for determining toughness (seen on the right). This experiment a pendulum test that determines how much force is needed to break a small specimen with a notch when struck at a certain temperature.

Impact energy minimums are specified in the various product standards for different strength grades and sub-grades. In a nutshell, we have JR, J0, J2, and K2.

subgrade designations of non-alloy structural steel. Different designations are used when it comes to quenched and tempered steels and fine grain steels (which are generally harder and have a higher impact energy). The table below provides a list of the hardness classifications.

Table 2.2: A List of the Hardness Classifications

Criterion	Subgrade	Strength of impact	Temp.
BS EN 10025-2 BS EN 10210-1	JR	27	20
	J0	27	0
	J2	27	-20
	K2	40	-20
BS EN 10025-3 BS EN 10025-4	N	40	-20
	NL	27	-50
	M	40	-20
	ML	27	-50
BS EN 10025-5	J0	27	0
	J2	27	-20
	K2	40	-20
	J4	27	-40
BS EN 10025-6	J5	27	-50
	Q	30	-20
	QL	30	-40
	QL1	30	-60
BS EN 10025-2 BS EN 10210-1	JR	27	20
	J0	27	0
	J2	27	-20
	K2	40	-20

There are no impact energy specifications for materials with a thickness of less than 6 mm and for cold-formed steels with a thin gauge.

(BS EN 1993-1-10) and its related standards offer guidance on the choice of a suitable sub-grade to provide sufficient toughness in design conditions (UK NA). The regulations establish a "limiting thickness" of a steel to its exposure temperature, stress level, etc. (PD 6695-1-10) has helpful look-up tables, while ED007 provides advice on choosing a suitable sub-grade. It is recognised that applying these design guidelines to buildings when fatigue plays a little role is exceedingly safe-sided since they were created for bridges and crane supporting structures are examples of structures that are subject to fatigue.

Modified steel thickness restrictions are presented in SCI document P419 and can be employed in buildings when fatigue isn't a factor. These new restrictions were developed using the same methodology as the Eurocode design guidelines, but with the added benefit of reducing fatigue crack growth. The phrase "decrease" is chosen since assuming no increase at all would be equivalent to completely eliminating the effect of weariness. Based on suggested guidelines from a DIN Standard, some fatigue (20,000 cycles) is permissible.

Such structures might be described as "quasi-static," meaning that designers tend to handle all loads as if they were static, even if there may be some limited load cycling that isn't taken into account. The formula for expressing fracture growth under 20,000 cycles is the key to the new technique. This crucial statement was contributed by experts from the University of Aachen (Their involvement in the creation of the Eurocode).

NSC magazine's September 2017 issue contains a technical article provides more background. When compared to carbon steels, stainless steels are frequently more durable; minimum values are stated in (BS EN 10088-4). Austenitic and duplex steels may withstand brittle fracture at temperatures as low as -40°C , according to BS EN 1993-1-4. Ductility.

As seen in the diagram below, ductility is a measure of a material's ability to stretch or elongate between the commencement of yield and eventual fracture when subjected to tensile pressure. The designer uses ductility to redistribute stress at the

ultimate limit state, design bolt groups reduce the possibility of fatigue fracture propagation during fabrication processes like welding, bending, and straightening.

The various standards for the grades of steel in the above table require a minimum ductility value, ensuring that the design assumptions are legitimate and that, if specified correctly, the designer can be confident of their adequate performance.

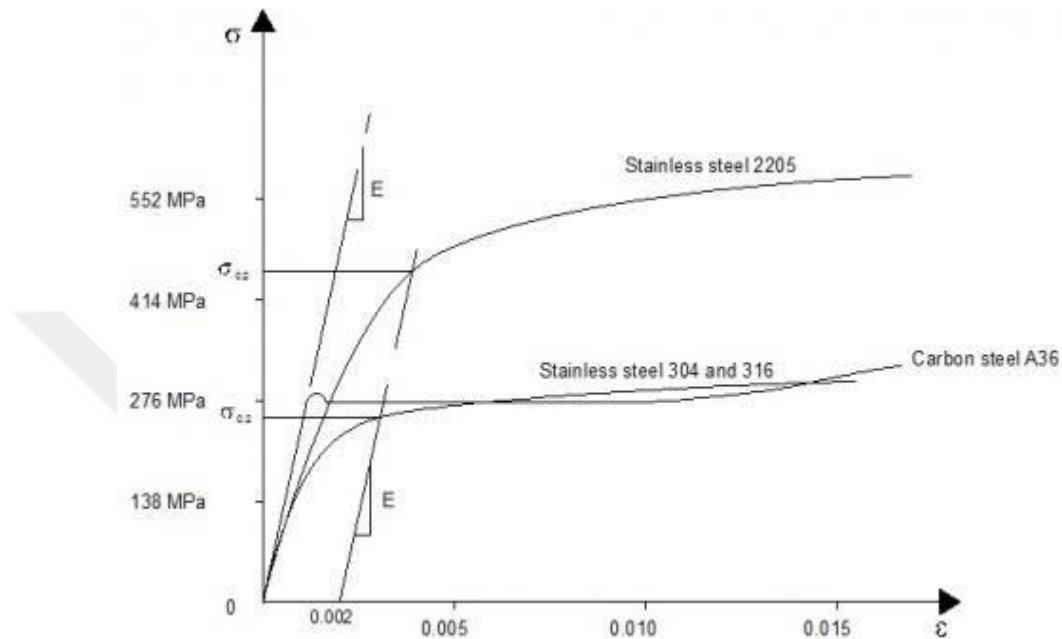


Figure 2.1: Stress–Strain Behaviour for Steel

c Weldability

All structural steels are quite similar in terms of weldability. On the other hand, Localized steel melting and cooling are required for welding. Cooling may occur quick as a result of the surrounding material, such as the beam, acts as It's a big "heat sink," and the weld (and the heat introduced) is often minimal. The "heat affected zone" (HAZ) may become harder and lose its toughness as a consequence. According to the material's thickness, toughness decreases. The alloying components, particularly, contrast however not only, the carbon content, affect embrittlement susceptibility. The 'Carbon Equivalent Value' (CEV) can be used to express this susceptibility, As a result, this value can be calculated using an expression that is included in a number of product standards for carbon steels. All structural steel products must adhere to the CEV limits set forth in BS EN 10025, and ensuring that welding method parameters are approved for the proper steel grade and CEV is a straightforward responsibility for individuals in charge of welding.

Additional steel mechanical properties:

d Another structural steel mechanical qualities that essential to a designer include:

e $E = 210,000 \text{ N/mm}^2$ Modulus of Elasticity

f $G = E/[2(1 + \nu)] \text{ N/mm}^2$, commonly expressed as $81,000 \text{ N/mm}^2$.

g 0.3 is the Poisson's ratio.

h $= 12 \times 10^{-6}/^\circ\text{C}$ Coefficient of thermal expansion (in the ambient temperature range).

i Durability

j Another important characteristic is the capacity to stop rusting. Despite the existence of specialized corrosion-resistant steels, they are seldom employed in the construction of buildings. Steel that has been exposed to the elements is an exception to this rule. Building steel is often protected against corrosion by painting or galvanizing. Factors including exposure, location, design life, and others affect the kind and level of coating protection needed. In many cases, other than sufficient fire protection, no corrosion protective coatings are required in internal dry environments. There is a wealth of information available on the corrosion resistance of structural steel.

k Weathering steel

High-strength low-alloy steel, known as weathering steel, can withstand the elements by forming a patina of rust that protects it from further deterioration over time. There is no requirement for a protective coat. It's commonly used for bridges in the UK, and it's also been utilized on the outside of some structures. The Angel of the North, for example, is an architectural element and sculptural structure made of it.

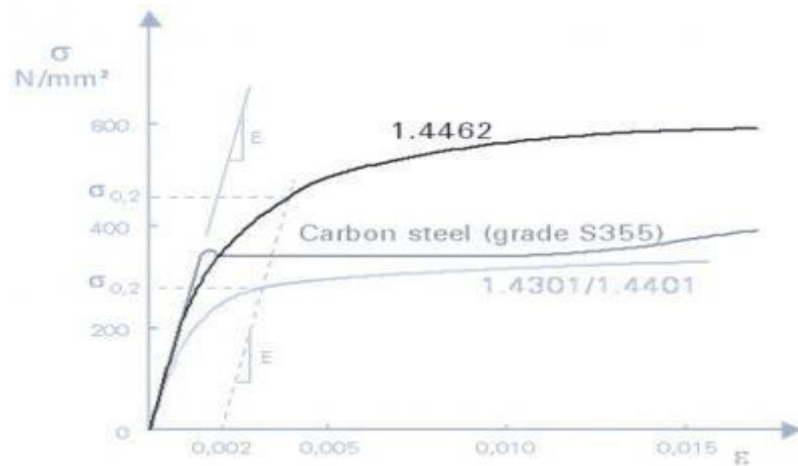


Figure 02: Typical Carbon Steel and Stainless Steel Stress-Strain Curves after Annealing

Stainless steel's high corrosion resistance makes it a useful structural material, especially in environments where a polished appearance is essential. The following are the categories for which exposure ratings are applicable.

In several ways, the stress-strain behavior of stainless steels differs from that of carbon steels. The form of the stress-strain curve is the most significant difference. Stainless steel has a more rounded reaction with no well-defined yield stress, whereas carbon steel has a linear elastic response up to the yield stress and a plateau before strain hardening. As a result, the 'yield' strengths of stainless steel are normally described for a specific offset permanent strain (conventionally the 0.2 percent strain).

Table 0.3: Specified Mechanical Properties of Common Stainless Steels to EN 10088-4 Used in Design

Description	Grade	Proof strength (N/mm ²) of no less than 0.2%	(N/mm ²) Maximum tensile strength	Fracture elongation (percent)
Basic chromiumnickel austenitic Steels	1.4301	210	520 – 720	45
	1.4307	200	500 – 700	45
Molybdenum chromiumnickel austenitic steels	1.4401	220	520 – 670	45
	1.4404	220	520 – 670	45
Duplex steels	1.4162	450	650 – 850	30
	1.4462	460	640 – 840	25

Hot rolled plate is suitable for use with the mechanical properties described. The specified strengths are 10-17% higher for cold rolled and hot rolled strip.

When thinner material is worked more than thicker material, strength is increased.

Table 0.4: Guidelines for Stainless Steel Selection

BS EN ISO 9223 Atmospheric Corrosion Class	typical outdoor setting	Suitable stainless steel
C1 (Very low)	Arctic regions and deserts (very low humidity)	1.4301/1.4307, 1.4162
C2 (Low)	minimal pollution or arid (rural)	1.4301/1.4307, 1.4162
C3 (Medium)	coastal regions with less salt ice locations that are industrialized or urban and have mild pollution	1.4401/1.4404, 1.4162 (1.4301/1.4307)
C4 (High)	Industrialized and polluted metropolitan environment Salt deposits on the coast that are not too heavy Using de-icing salts on roads	1.4462, (1.4401/1.4404), other more highly alloyed duplexes or austenitics
C5 (Very high)	industrial environments with high humidity and severe pollution marine environments with heavy salt deposits and splashes	1.4462, other more highly alloyed duplexes or Austenitics
BS EN ISO 9223 Atmospheric Corrosion Class	typical outdoor setting	Suitable stainless steel
C1 (Very low)	Arctic regions and deserts (very low humidity)	1.4301/1.4307, 1.4162
C2 (Low)	minimal pollution or arid (rural)	1.4301/1.4307, 1.4162
C3 (Medium)	coastal regions with less salt ice locations that are industrialized or urban and have mild pollution	1.4401/1.4404, 1.4162 (1.4301/1.4307)
C4 (High)	Industrialized and polluted metropolitan environment Salt deposits on the coast that are not too heavy Using de-icing salts on roads	1.4462, (1.4401/1.4404), other more highly alloyed duplexes or austenitics
C5 (Very high)	industrial environments with high humidity and severe pollution marine environments with heavy salt deposits and splashes	1.4462, other more highly alloyed duplexes or Austenitics

It is possible to employ materials designed for a higher class in a lower class, however this may not be cost effective. If some minor corrosion is acceptable, materials within brackets may be considered. In sheltered sites, Because of the increased buildup of corrosive contaminants and chlorides, a proposed grade from the subsequent corrosion class could be necessary.

2.4 A Comparison between RCC and Steel Structure

1) RCC Structures: The term "RCC" refers to reinforced cement concrete, which is cement that has been strengthened with steel bars, steel plates, steel mesh, and other elements to increase the structure's ability to withstand stress. Steel can endure both tension and compression, Cement concrete, on the other hand, is weak in tension but can withstand significant compression (A study of stable crack growth in thin SEC specimens of 304 stainless steel by computer vision - ScienceDirect n.d.).

(A) Advantages:

- RCC construction materials are readily available.
- It is long-lasting and durable.
- It is fire resistant and termite resistant.

(B) Negative aspects:

- Reinforced members have essentially no scrap value.
- It's necessary to keep an eye on everything at all times.
- The work is done by skilled labor. (2006, faulty cement notice).

2) Steel Structures: Steel structures are comprised of structural steel elements that are coupled to carry loads and provide total rigidity. Because of the high strength steel grade that was employed, this construction is trustworthy and uses less raw material than other kinds of structures, such those made of concrete and wood. In order to suit the needs of a project, structural steel is a kind of steel construction material that is produced with a certain form and chemical makeup. I-beams, HSS, channels, angles, and plates are examples of typical forms.

(A) Advantages:

1. High Strength - This indicates that the weight of a steel building will be minimal.
2. Uniformity - Unlike concrete, the properties of steel do not alter.
3. Elasticity - Steel adheres to Hooke's law to a tee.

(B) Negative aspects

1. Cost of maintenance - steel constructions are prone to corrosion when exposed to moisture and air. They must be repainted on a regular basis.
2. Steel has very small resistance against fire as compared to concrete.
3. Fireproofing cost- Steel is incombustible material however its strength is reduced tremendously at high temperatures due to common fires. (IS:456-2007).

2.5 The Risks Management Methodology

The risk management methodology consists of several steps and its explanation as follows:

2.5.1 Planning Phase

This phase refers to the planning and arranging for the events of risk management in the project. This includes several stages like meetings with all project members, work in risk management teams and the cosponsors of the project to establish a risk management plan for the project set (Pierre 2003). At this stage, the project team makes planning meeting that helps to prepare a risk management plan and the project team also should revise the project documents like the contract, work base structure (WBC), define roles and responsibilities, Preorganized documents like the company policies on managing and conduct risks when she prepares a risk management plan (Early Warning Signs of it Project Failure: The Dominant Dozen: Information Systems Management: Vol 23, No 4 n.d.).

2.5.2 Risk Identification

The risks that have an impact on the project are recorded at this stage, along with those that have an adverse impact on the objectives of the project that must be implemented. The risks are then grouped into lists, with a group of potential hazards under each class that has been discovered (Cagno, Caron, and Mancini 2001). Classify the Identification into five parts which are (CiteSeerX — Management of Project Risks in Logistics Development n.d.) :

- 1-Identifying the sources of risk (i.e. Identifications the element causes a threat within or outside the project).
- 2- Identification of project risks (i.e. The identification of restless events that could cause deviation in accomplishing the project goals) and relating to the sources of the risk.
- 3- Classification of project risk.
- 4- Identification of Risks associated with each activity.
- 5-Identification responses.

2.5.3 Risk Analysis

The identified risk is subjected to evaluation to measure its amount either as a qualitative or quantitative analysis.

2.5.3.1 Qualitative Analysis

Qualitative analysis depends on the expert's opinions to evaluate the probabilities of the risk and its impact on the project and defined its priorities The results of qualitative analysis are a list of risks, arrange according to its priorities that used as a guide to select the critical risk response and to arrange the total risk in the project (CiteSeerX — Management of Project Risks in Logistics Development n.d.).

2.5.3.2 Quantitative Analysis

This stage includes digital analysis or quantitative for known risks that effect on the goal of the project and that mean that the quantitative analysis is an attempt to reach a quantitative estimation of the impact of the risk, according to the probabilities of occurrence and consequences of the risks and there are a lot of techniques used in

this stage like simulation, Monte-Carlo, PERT and others (Use and benefits of tools for project risk management - ScienceDirect n.d.).

2.5.4 Risk Response

The risk response in projects is to rate the parts of the risk by taking action that is appropriate for the level of risk. It's critical that risk response be able to handle all types of risk events, such as planned risk responses, probable risk responses, and cost calculation for responding, all of which are regarded vital (An Integrated Methodology for Assessment and Selection of the Project Risk Response Actions - Seyedhoseini - 2009 - Risk Analysis - Wiley Online Library n.d.). Risk response uses the gathered data in the analysis step to make decisions about how to increase the project's ability to be completed on time, on budget, and on schedule. The preparation of answers to the principal dangers and the designating of individuals to be in charge of each response are the main objectives of this stage. If required, risk response may be started during quantitative analysis, and it is possible to repeat the procedure between the analysis and risk response phases (Opportunities for learning from crises in projects | Emerald Insight n.d.). Risk response includes the following:

- Establishing methods to control crucial regions and receive early warnings when concerns arise.
- Identify risk-avoidance or risk-reduction strategies.
- Begin with the most thorough research to eliminate doubt from accurate data.

2.6 Risk Management for the Steel Structure

2.6.1. Identification of manufacturing risks in the steel industry

The nuclear power plant (NPP) building project's supply chain includes enterprises that produce steel. Steel may be produced by Indonesian National Steel Industries, especially steel buildings. At the NPP project, In civil construction, steel framework can be used. There are several businesses in Indonesia, including, PT. Gunung Garuda, PT. Jagat Baja Prima Utama, PT.

Gunawan Dian Jaya Steel, PT. Krakatau Wajatama, PT. Krakatau Steel and PT, and others are all involved in the steel industry. Standard American Society for Testing and Materials (ASTM) A 572 and A 36 are used by several of these major

national steel producers, which are suitable for steel constructions used to the building of nuclear energy plants in Indonesia, such as the Light Water Reactor (L.W.R.) (Dewi et al. 2020). Specifically, we're interested in the size variable and required specifications, rules, and standards, national steel industries must produce product innovation. Risk detection is critical in the steel industrialization industry since it can affect the industry's performance as well as the performance of NPP projects. Risk identification entails identifying potential threats to the production process and outcomes. The aim of risk identification is to create a comprehensive list of hazards based on events that might result in, improve, prevent, degrade, accelerate, or delay the fulfillment of goals. It's critical to understand the dangers of passing up a good chance. For example, in the industrial sector, operational risk may be traced back to:

- i. Management of the production procedure.
- ii. Maintenance.
- iii. A procedures and Equipment used.
- iv. Materiality.
- v. Human sources.
- vi. Manufacturing technology while machines.
- vii. Machine-based settings (Tupa, Simota, and Steiner 2017).

In the steel manufacturing industries, control over quality is required to reduce operational hazards. A number of authors have suggested several statistical techniques for control over quality in the steel sector. A topic of establishing which elements influence the proper fabrication of parts that approached of many angles and statistical approaches (Debón and Carlos Garcia-Díaz 2012).

Larson and Kursiak devise a system for assessing risk. The methodology, for the most The risk estimate materials from Larson and Kusiak's risk assessment technique are combined with risk identification and evaluation procedures as a decision-making tool for process risk assessment (Dewi et al. 2020). In any organization, the number of safety-related jobs is immense, as are the obligations that come with the judgments and choices that must be taken. The well-known (technical) parts of company safety, is a small portion of the larger field of risk management, This

involves tasks like risk analysis, hazard identification, and risk assessment using management rules, procedures, and practices methodically to identify, assess, treat,

and monitor risks (Reniers 2017). The purpose of risk management is to aid practitioners in classifying risks and selecting appropriate countermeasures.

It is a tool for identifying the source of risk, predicting the consequences, and implementing risk mitigation strategies. Uncertainty is a state that can be found in one's day-to-day actions. This unpredictability creates a number of hazards that could affect industrial performance (Firdaus, Saggaff, and Tahir 2017). For every organization, risk management is a difficult task. Top management requires decision-making tools to aid in the identification, analysis, and evaluation of potential hazards. Manufacturing risks that may develop in corporate production are factored into the potential risks. Because of the nature of the job, workers in the steel manufacturing business confront numerous safety hazards. Steel making is a high-risk business, with workers exposed to several hazards due to the nature of their employment. The work environment is frequently hot and noisy, and labor duties are frequently dense and physically demanding, with the potential of crushing injuries while burns always present.

Steel industry workers realized that communication is necessary for safety measures to be practical through experience, training, accepting responsibility for teamwork, and making careful to convey occurrences that occur (Evaluation of lead release potential of new premise plumbing materials | SpringerLink n.d.). The dangers are critical for steel manufacturing safety. Risk potential can be decreased by implementing appropriate steps if concerns are discovered early on, making proactive risk management possible (Klöber-Koch, Braunreuther, and Reinhart 2018). All sources of risk must be identified, allowing for the classification of project activities in steel manufacturing as high, moderate, or low risk.

The dangers are critical for steel manufacturing safety. Risk potential can be decreased by implementing appropriate steps if concerns are discovered early on, making proactive risk management possible (Klöber-Koch, Braunreuther, and Reinhart 2018). All sources of risk must be identified, allowing for the classification of project activities in steel manufacturing as high, moderate, or low risk (Giannetti and Ransing 2016). Hazard is described as an unforeseeable event or situation that, if it occurs, can have a positive or negative impact on the project's goals. The techniques in this knowledge area have been used to identify, analyze, and manage

known hazards. As part of risk management. A contingency reserve could be applied to known hazards. Dangers

that are unknown cannot be adequately identified or managed in advance. Allocating management reserves in the form of extra money, time or resources is a frequent strategy for dealing with unforeseen risks. The primary steps in risk management are Planning for risk includes risk identification, assessment, analysis, reaction, monitoring, and communication (Modelling global risk factors affecting construction cost performance - ScienceDirect n.d.). Risk management is a complex activity that starts at the top and works its way down to the executives. The literature mentions a vast list of ideas, perspectives, approaches, and procedures for risk appraisal and risk management that are valuable for managers, including risks, uncertainty, and efficiency (Negulescu and Doval 2014). The total process of risk assessment can be characterized as hazard identification, risk analysis, and risk assessment, all of which are part of the risk management hierarchy. Identifying the causes and sources of risk, or the hazard in the context of physical damage, is part of the risk identification process. The term "source of risk" is made up of meanings from many academics. The source of risk (S.R.) is a hazard that leads to a potential cause of damage, which could be materials, equipment, methods, or work practices. It is also regarded as damage: human damage or degeneration of health, or a combination thereof, in addition to being able to fall on someone (Exposure assessment to engineered nanoparticles handled in industrial workplaces: The case of alloying nano-TiO₂ in new steel formulations - ScienceDirect n.d.). Risk sources or hazards are elements that, alone or in combination, have the inherent ability to cause risk. To ensure that all relevant sources of risk and hazards are recognized, a systematic approach to identifying them is essential. The Hazard Identification method is one such strategy (HAZID) (Proskovics et al. 2016).

Internal and external risks should be considered while identifying risks. Internal risks are those that the project team can affect or manage. External risks are those that are beyond the project team's control or influence. Identification of risks includes both possibilities (good outcomes) and dangers (negative outcomes). Identifying risks can be done by identifying causes and effects (what could happen and what will ensure) or consequences and causes (what outcomes are to be avoided or encouraged and how each might occur).

2.7 Causes of Structural Failures with Steel Structures

The majority of steel structure failures evaluated involve (quasi-) static (nonfatigue) loading. This is because the vast majority of civil engineering structures are in service where the loads are not subject to drastic variations that would cause fatigue.

Three topics will be covered in terms of the causes of structural failures in steel structures: fatigue damage, erection phase problems and similar failures occurring later in the service life of (quasi-) statically loaded steel constructions.

A- Static loading, construction phase

1- A high fraction of failures in conventional steel structures with static stress happen throughout the building period. Faulty erections are the most common cause processes that fail to account for numerous instability issues during all stages of erection and installation.

2- Floor deck in commercial building in 2008, a well-publicized collapse happened during the construction of a threestory commercial center building in Stockholm (Alpsten 2017). This instance is relevant since a clear Human grotesqueness as an mistake. This failure is not typical of the majority of cases reviewed because the problem structurally designed rather than the workmanship and execution.

Figures (2.3) and (2.4) depict the floor deck prior to and after the failure. The welded 1400 mm high I-girder visible in the center of Figure (2.4) was introduced in the structural frame during building planning because the column to the right of the I-girder had to be relocated from the normal system grid, with the I-girder providing intermediate supports for deck girders in the perpendicular direction.

A computer program was used to create the I-girder. When converting the specifications from the computer to the drawings, the throat thickness of the fillet welds was mistaken for the web thickness. Thus, the web thickness mentioned on the designs of the 1400 mm high I-girder was 7 mm, rather than the at least 12 mm required by a proper design. However, a second egregious human error was added when no web stiffeners were put over the rightend column support.



Figure 2.3: Construction of a Commercial Hub with a Half-Hour View



Figure 2.4: Same View as in Figure (2.3), After Collapse



Figure 2.5: The Structural Collapse Was Caused by a Welded I-Girder That Was 1400 mm high.

On the job site, it's also critical to hire and train a team of workers. This will take place with the client at a mutually agreed-upon venue. The initial planning,

preparation of shop drawings, material procurement, and subcontractor agreements will all be handled by the main office. Because no two construction projects are alike, several construction contracts are required to meet the needs of all parties involved. When contractors, clients, and project managers have the correct arrangement for the job, they can better manage risk and guarantee that everything runs well (Padilla-Illano 2015). It's also vital to hire and train a team of workers on the working site. This will take place at a mutually agreed-upon location with the client. The main office will be in charge of initial planning, shop drawing preparation, material procurement, and subcontractor agreements. Because no two building projects are the same, many contracts are needed to suit the demands of all parties involved. Contractors, clients, and project managers may better manage risk and ensure that everything runs well when they have the right arrangement for the job (Nagar 2021). The Northridge and Kobe earthquakes exposed the flaws in traditional empirical approaches, igniting interest in fracture research in civil (and especially seismic) engineering. As a result, current procedures have been adapted to civil engineering (Barsom and Rolfe 1999), and new models and methods have been developed (Cyclic Void Growth Model to Assess Ductile Fracture Initiation in Structural Steels due to Ultra Low Cycle Fatigue | Journal of Engineering Mechanics | Vol 133, No 6 n.d.), to address problems unique to civil (structural) engineering, such as earthquake-induced ultralow-cycle fatigue (ULCF).

2.8 Artificial Intelligence Techniques in Risk Management

The artificial neural network has better learning ability and can also perform some complex programs at the same time. This contribution to our computing is large, so increasing scholars are interested in investing in this related project. Artificial neural networks are used in various fields. In this regard, there are many researches on investment projects of artificial neural networks, and the risks of these projects also have research directions. A human neural network is an essential research subject for modern science and technology. It is also a major direction for the subsequent scientific and technological progress of mankind. It plays an indispensable role in human life, medical care, and related work and has a certain guiding role in investment projects in this area. This paper makes a comparison between the common traditional network convergence rate and the generalized network

convergence rate combined with an artificial neural network. The artificial neural network is covered by the traditional BP network convergence rate. It not only retains its original characteristics but also adds the characteristics of artificial neural networks. This problem can be idealized between enterprises, such as corporate finance, asset management, power risk management, corporate environment, production technology, and other issues, and it can also balance enterprise income and expenditure (Deng and Chang 2022).

Alanis presents an extension to the basic usage results of the recurrent neural network training algorithm of the Kalman filter and presents a predictive application for electrical energy. And it describes the one-step ahead prediction and n-step idea on European power system data and whether the proposed method is practical and applicable (Electricity Prices Forecasting using Artificial Neural Networks | IEEE Journals & Magazine | IEEE Xplore n.d.). Isik and Inalli obtained data from the Meteorological Directorate General (MGM) and modeled it with an artificial neural network and an adaptive network-based fuzzy inference system. MATLAB software is used in thermal systems for modeling and prediction of forward-looking data with high sensitivity. It can also be used to verify whether the results of the proposed method are satisfactory (Artificial neural networks and adaptive neuro-fuzzy inference systems approaches to forecast the meteorological data for HVAC: The case of cities for Turkey - ScienceDirect n.d.).

SVM is based on the principle of Structure Risk Minimization as opposed to the principle of Empirical Risk Minimization supported by conventional regression techniques. Through introduced the theory of the SVM-Regression, considered and extracted substances components of construction project as parameters, this research seted up the Model of the Construction Project Cost Forecasting based on the SVM. The research results show that the prediction accuracy of SVM-Regression is better than that of neural network (A Novel Approach Based on Support Vector Machine to Forecasting the Construction Project Cost | IEEE Conference Publication | IEEE Xplore n.d.).

Proposes an integrated analytical framework for effective management of project risks using combined multiple criteria decision-making technique and decision tree analysis. First, a conceptual risk management model was developed through thorough literature review. The model was then applied through action research on a

petroleum oil refinery construction project in the Central part of India in order to demonstrate its effectiveness. Oil refinery construction projects are risky because of technical complexity, resource unavailability, involvement of many stakeholders and strict environmental requirements. Although project risk management has been researched extensively, practical and easily adoptable framework is missing. In the proposed framework, risks are identified using cause and effect diagram, analysed using the analytic hierarchy process and responses are developed using the risk map. Additionally, decision tree analysis allows modelling various options for risk response development and optimises selection of risk mitigating strategy (Project risk management using multiple criteria decision-making technique and decision tree analysis: a case study of Indian oil refinery: Production Planning & Control: Vol 23, No 12 n.d.).

3. STEEL FAILURE

3.1 Introduction

This chapter will include the factors that relate to the steel failure and building a predictive model to predict the the failure using artificial intelligence techniques (Artificial neural network, support vector machine and decision tree) and using two program, MATLAB and KINME, first a questionnaire is formed in order to display the most reasons that lead to the failure and then the predictive model will be used.

The main approach is questionnaire to collect data (Kallet 2004). Clarify this style part must define that done to response the question of research, define how that done, reason of experimental purpose with clarify how the outcomes were analysis with computation were complete as well as tests of statistical were completed to analyze the information.

3.2 Data Collection Methods

To achieve the aim of the thesis, the necessary must be collected in different methods. The research relied on covering the required data to implement the theoretical aspect on many sources which represented the scientific references of books, magazines, studies and relevant papers, whether available inside or outside the country, the Internet or paper. This study is directed to specialists working in the construction sector from different disciplines and covered both the public and private sectors. Table (3.1) illustrates the names of governmental institutions and private companies that have been conducting the questionnaire with their specialists.

Table 0.1: Name of Governmental institutions and Private Companies

Name of Ministry	Name of Governmental Institution or Private Company
Ministry of Higher Education and Scientific Research	University of Diyala – Collage of Engineering University of Baghdad - Collage of Engineering University of Diyala - Department of Construction and Housing
Ministry of Construction, Housing and Municipalities And Public Works	<ul style="list-style-type: none"> ✓ Directorate of Diyala Buildings ✓ Diyala Housing Department ✓ Roads and Bridges Directorate ✓ Directorate of Works and General Maintenance ✓ Directorate of Diyala Municipalities
Ministry of Health	Department of Engineering and Maintenance
Ministry of Education	School Buildings Directorate
Ministry of Water Resources	Directorate of Water Resources in Diyala
Ministry of Communications	Directorate of Communications and Postal – Diyala
The Ministry of Electricity	Diyala Electricity Directorate
	<ul style="list-style-type: none"> ✓ Diyala Privet Companies ✓ AL –Nashmai Land ✓ AL-Shariefy Land

3.3 Design of Questionnaire

After conducting the review of previous studies, all the information that helps of the study were collected, organized, studied and analyzed to be suitable for conducting the study and after several stages of meetings, discussions and amendments conducted the questionnaire of this was developed.

The questionnaire was consisted of four parts as shown in figure (3-1) was designed in Arabic (Appendix A). The English version was also attached to (Appendix B) and the questionnaire was attached with reference to the secrecy of answers received from the respondents for the purpose of encouraging a higher response rate. Each part of the questionnaire will be clarified.

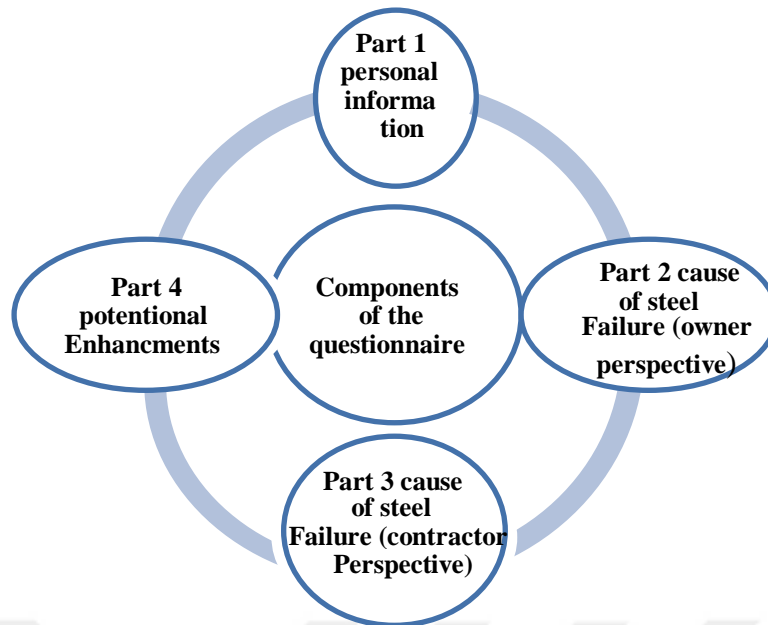


Figure 0.1: Components of the Questionnaire

3.3.1 Part I (General Information)

This part provides the respondent's name, gender, age, ministry or company, and sector of job, also categories for their education background, areas of expertise, jobs held, and work experience.

3.3.2 Part II Causes of steel Failure (Owner Perspective)

This part was used to describe the causes that lead to the failure during the project life cycle from point of view of the owner in order to specify the most reasons that result to the failure of the steel performance.

3.3.3 Part III Causes of Steel Failure (Contractor Perspective)

This part is as the same as section (3.3.2) but from point of view of the contractor in order to define the most reasons that lead to the failure.

The five-likert scale was used to design the first two sections. The measurement Scale is (1: No , 2: rarely 3: some time ,4: mostly , 5: always). Each respondent was asked to rate each question on a scale of one to ten based on his perceptions of the Iraqi construction sector's climate (A technique for the measurement of attitudes. - PsycNET n.d.).

3.3.4 Part IV Potential Enhancements

This part included a list of the potential method to enhance the process for the steel. This section includes (5) closed questions using a fivepoint Likert scale. The weighing scale is (1: No , 2: rarely 3: some time ,4: mostly , 5: always). Each respondent was asked to rate each question on a scale of one to ten based on his perceptions of the Iraqi construction sector's climate (A technique for the measurement of attitudes. - PsycNET n.d.).

3.4 Referees of the Questionnaire

Arbitration of the questionnaire is an effective way for professionals to assess whether the questionnaire measures what believe it measures (McKee and Privitera 2017). According to the arbitration, the questionnaire was presented to three groups of experts and were invited to share their views and recommendations on the questionnaire in order to validate its authenticity. In the first category, questions of the questionnaire and their suitability for the nature of the study were evaluated and whether the questionnaire questions reflected the research principle.

The second party involved statistical experts to evaluate whether the questionnaire was fairly accurate in terms of architecture for statistical analyses.

Finally, the third party was called for feedback on the Arabic and English questionnaire languages, and Table (3-2) lists all of the experts' credentials as well as their countries of origin.

Table 0.2: Information about Arbitrators

Group	Expert	Educational Qualification	Place of Work	Country of Expert
Engineers	C1	Ph.D. in construction management	University of Diyala	Iraq
	C2	Ph.D. in Road and airport engineering	University of Diyala	Iraq
	C3	Ph.D. in architectural engineering	University of Baghdad	Iraq
	C4	M.Sc. in construction management	Southampton University	UK
	C5	M.Sc. in construction management	University of Technology	Iraq
	C6	M.Sc. in construction management	University of Technology	Iraq
	C7	M.Sc. in construction management	University of Baghdad	Iraq
	C8	Bachelor of Civil Engineering and Revit Trainer	AL –Nashmai Land	Iraq

Table 0.2: (Cont.) Information about Arbitrators

Group	Expert	Educational Qualification	Place of Work	Country of Expert
Statistic	S1	Ph.D. in statistics	University of Diyala	Iraq
	S2	Ph.D. in statistics	University of Diyala	Iraq
Language	L1	Ph.D. Arabic Language	University of Diyala	Iraq
	L2	M.Sc. English Language	University of Diyala	Iraq

3.5 Pilot study

An initial or limited test analysis for respondents whose features are like the original respondents' characteristics can be described as a small study (McKee and Privitera 2017).

The main objective of the study is identify difficulties while identify problems that more confusing than others, which enables corrective It is necessary to take action and enhance the testing procedure.

The pilot study will use a sample size of 30–50 participants. A total of 40 samples were needed for statistical testing (McKee and Privitera 2017).

3.6 Statistical Reliability

In any investigation, the use of an appropriate measuring instrument as one of the fundamental criteria includes access to satisfactory data. listed that one of the research main goals is to design and distinguish research method three important characteristics (be meaningful, be accurate, be efficient) (McKee and Privitera 2017). As a result, reliability tests were done on the data from the pilot research. Section (3.6.1) show the tests included in the pilot study using (IBM SPSS V.25).

3.6.1 Statistical Reliability

Alpha (Cronbach) model will be used to check the reliability of the questionnaire.

3.6.1.1 Alpha (Cronbach) model

One of the most common ways to gauge dependability and value is demonstrated by the alpha cronbach's high reliable value, which ranges from 0 to 1 and is closest to 1 (Yockey 2016).

Table (3-3) provides a classification for the alpha-Cronbach coefficient's value for the level of reliability.

Table 3.3: Reliability Cutoff Values

Cronbach's alpha	Degree of Reliability
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

Source: (Yockey 2016).

The findings were found in the good limits of the Alpha Cronbach system for the questionnaire, which supports the reliability of the questionnaire. Table (3-4) shows the values for those portions of Alpha Cronbach.

Table 0.4: Value of Alpha Cronbach for Questionnaire's Parts

Items	Value of α	Degree of reliability
Causes of steel Failure (Contractor Perspective)	0.9	Excellent
Causes of steel Failure (owner Perspective)	0.93	Excellent
Potential Enhancement	0.8	Good

3.7 Questionnaire distribution

The distribution of the questionnaire is the first steps and it consist of the following:

3.7.1 Sample size response rate

The sample of the questionnaire was 250 and (220) forms were collected from original (250) distributed forms, so the response rate was $(220 \div 250 = 88\%)$ it is relatively high response rate due to personal delivery of forms. After checking forms an (20) forms incomplete are excluded so the final number of forms that used in the analysis is (200) forms.

3.7.2 Questionnaire distribution administration

The questionnaire is distributed using the interview process. It noted that interview approach has a reasonably high response rate and decreases in contrast to other

methods like online questionnaires the likelihood of wrong or insufficient responses. The interview process was twofold. Some governmental organizations provided with facilities to conduct one or more seminars to talk about contractors and answered the questionnaire after these seminars. The seminars were held in two forms. Small numbers of other companies did not have facilities or use the second Form, namely the direct interview with the interview (Basic Conceptual Model | SpringerLink n.d.).

3.7.3 Sample description

The following figures illustrate the characteristics of the target sample in the survey:

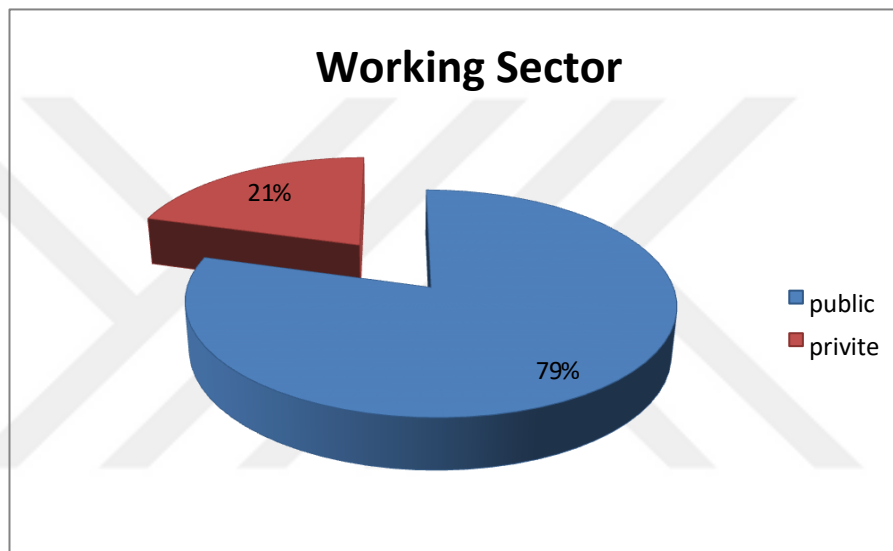


Figure 0.2: Work Sector Percentage of Respondents

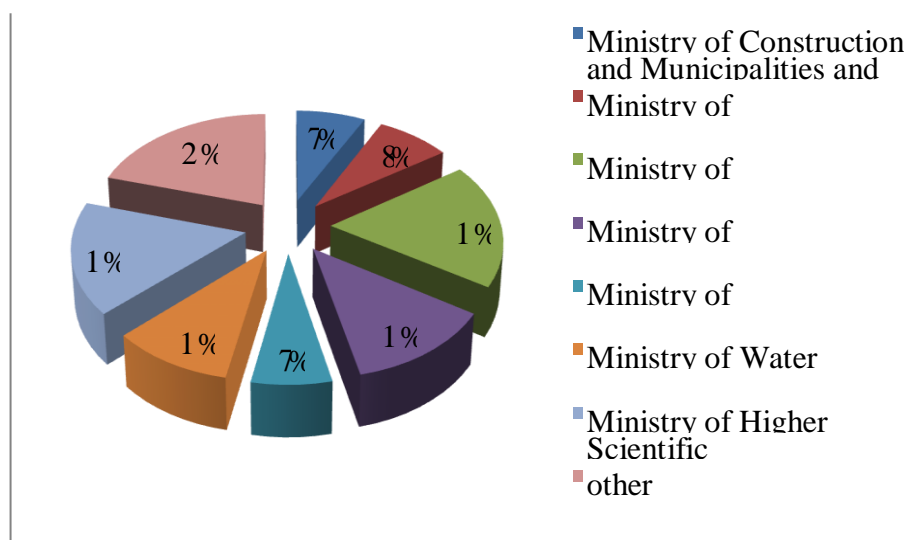


Figure 3.3: Percentage of Respondents in each Ministry

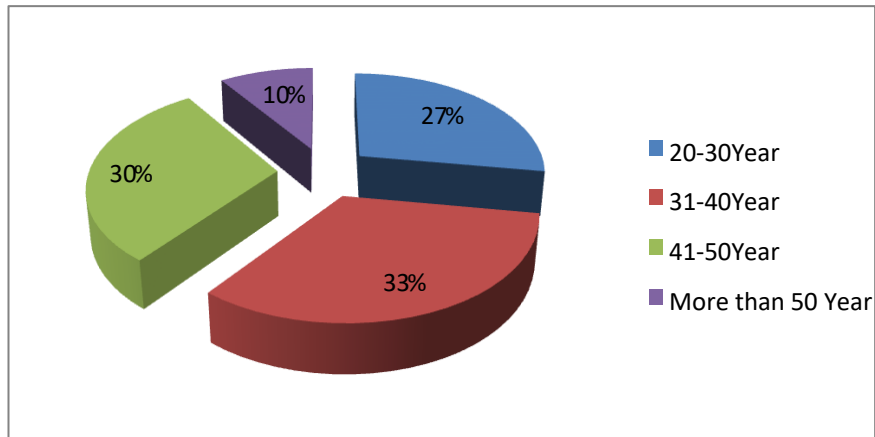


Figure 3.4: The Age Percentage of Respondents

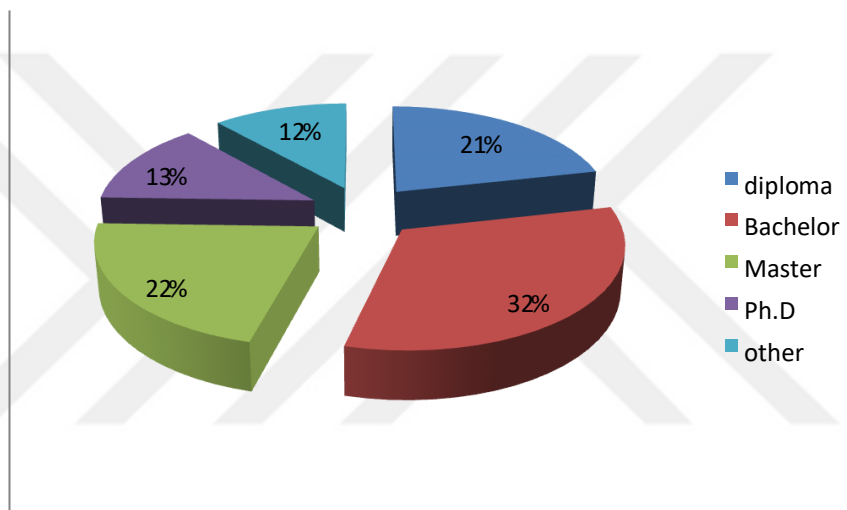


Figure 0.5: Educational Level of Respondents

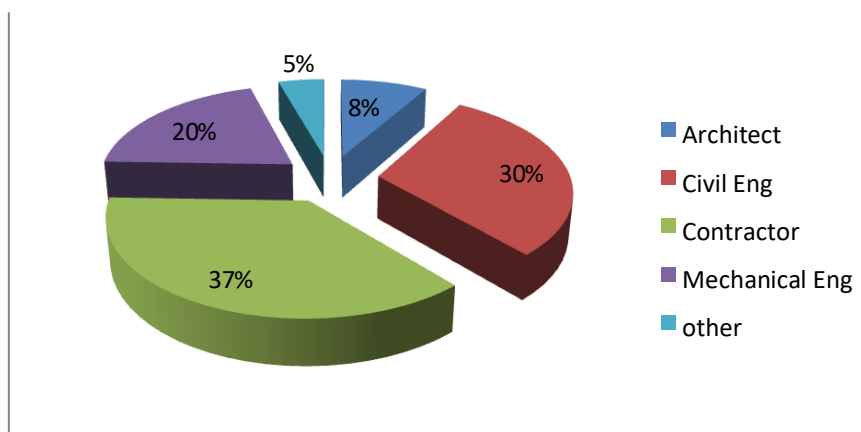


Figure 0.6: The Specialization of Respondents

3.8 Questionnaire Data Analysis

In order to gain a full view of the views of the expert in Iraqi architecture, engineering and construction (AEC) about the aspect that leads to the steel collapse, a quantitative methodological approach has been employed to interpret the data from questionnaires. The following is explained with this methodological technique.

3.8.1 Descriptive statistics

Descriptive statistics are definable as statistical tools for data summarization, data organization and data simplification (Measuring teacher practices and student academic engagement: A convergent validity study. - PsycNET n.d.). Descriptive statistics that have been used are.

3.8.1.1 Central tendency measurement

The core trend of the statistics relates to the notion of representative (average) value that seeks to characterize the distribution of values that is of the best single value (Measuring teacher practices and student academic engagement: A convergent validity study. - PsycNET n.d.).

3.8.1.2 ANOVA test

Variance analysis (ANOVA) is a method to diagnose differing experimental community means by using a statistical tool. ANOVA is guaranteed in experimental designs with a dependent variable which represents an incessant parameter number results measurement and many experimental classes within one or more (categorical) independent variables. Individual variables are called factors in the vocabulary of ANOVA and classes are referred to as levels within each factor. The spectrum of ANOVA parts can be intimidating to those who are not initiated, such as: variance partitioning, key effects, interactions, variables, sum of squares, medium squares, F values, alpha familiar, various comparative methods (or post-hoc tests), impact scale, statistical strength, etc. (Analysis of Variance: The Fundamental Concepts: Journal of Manual & Manipulative Therapy: Vol 17, No 2 n.d.). The ANOVA Oneway process generates a one-way analysis of variance by a single (independent) component for a quantitative dependent variable. Variance analysis is used to assess the hypothesis of multiple means being identical. The 2 sample t test is being

expanded. Perhaps you're curious about how different ways, so that the differences between the means are identified. There are two kind of quantitative means assessments: a prior comparison and a further test, or post hoc analysis. Contrasts are experiments developed up to then and after the test is conducted. Trends may also be checked across divisions.

3.9 Results of the Questionnaire

SPSS version 25 was used to do quantitative statistical analysis on the questionnaire data. Factors that contributed to the steel default on the construction project were evaluated through the data analysis.

3.9.1 Causes of steel failure (Owner perspective)

In this study multiple questions were posed about the government agency or private sector in which the participants were working, as well as other questions aimed at understanding the reasons of steel damage (owner perspective) in order to gain an overview of the history and position of employment of the respondents.

The management reasons of the contractor's loss as seen in Figure (3.7) in the following percentages: The lack of contractor experience is 11.76 %, change to the owner or key personnel is 8.08 %, the lack of contract experience is 12.55 %, the lack of work experience is 12,9 %. The use of project management techniques is 13.1 %, damage to sprayed fire resistive management 8.4%, poor project management 13.1%, claims 11.76%, award contracts to the lowest price 14.95%, increase number of projects 13.04%.

The highest cause is award the contract to the lowest cost bid as it's the most frequent reasons that lead to the steel failure, the most projects have been behind the schedule and over cost due to the award the contract to the lowest bid, which result in delay in just in time material and in their required quality. While (poor project management the unused of project management techniques and increased the number of projects that managed by the contractor) almost contain the same percentage, as these three causes interrelated together and each of them depend on the other, as when the number of the projects increase the contractor staff will be distributed on many sites of different nature that lead to poor management and poor quality of the projects. The causes (lack of contractor experience in business, lack of experience in

contracts, lack of experience in the line of work and claim) also almost the same percentage as the lack in experience will lead to many mistakes and the contractor will apply for change order and if his request decline it will lead to claims.

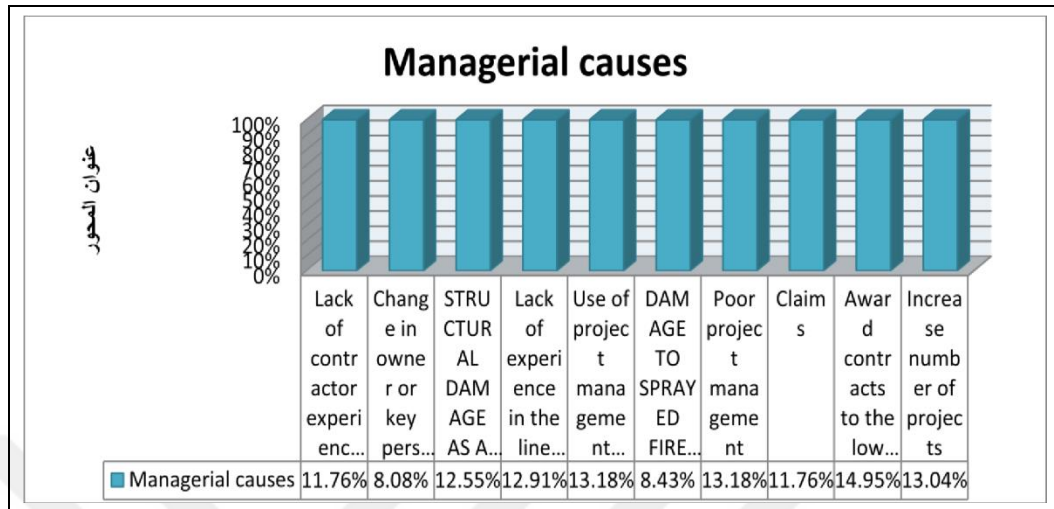


Figure 3.7: Managerial Causes of the steel Failure (Owner Perspective)

Figure (3-8) shows the financial causes of the steel failure where the percentages as follow: due to market forces, profit margins are low is 15.62%, lack of resources is 15.62 %, cash flow mismanagement is 16.93 %, delay in collecting payments from clients is 18.38%, fluctuation in construction material cost is 16.93 %, poor cost estimation is 16.52 %.

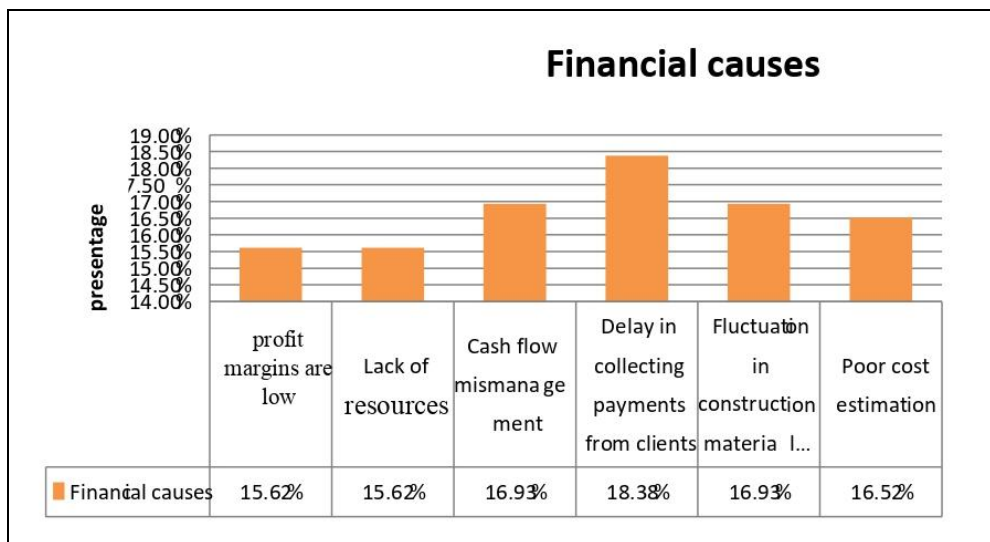


Figure 0.8: Financial Causes of the steel Failure (Owner Perspective)

The highest cause that lead to the steel failure is delay in payment from clients, The problem of late payments in the construction business is a worldwide issue. The payout for the awarded project will generally be dependent on project success.

Within 14 days after submit finished material and paperwork with the architect, the general guidance must be paid. Most of the delay is caused by contractors failing to accurately omit those records that are appropriate, and payment officials must make sure the paperwork is complete in order to prevent delay in paying contractors. In the case of such an issue, the records will be returned for review and amendment to the appropriate contractors. It takes two more days for the treasury to process the payments and three days in the financial department. Overall, reimbursement will take an additional week. There is also a provision under which contractors may be charged three months after the date of signature prior to the certification of the invoice. The second highest level is the fluctuation cost And the relationship between cost of fluctuation and cost of linear building. 97 percent of the costs of construction projects are affected by the fluctuation in the prices of construction material and labor.

Figure (3.9) shows the overexpansion/growth causes of the steel failure where the percentages as follow: Increased number and size projects and a lack of management growth as the business grows is 36.16% and Controlling equipment cost and usage is 27.9%.

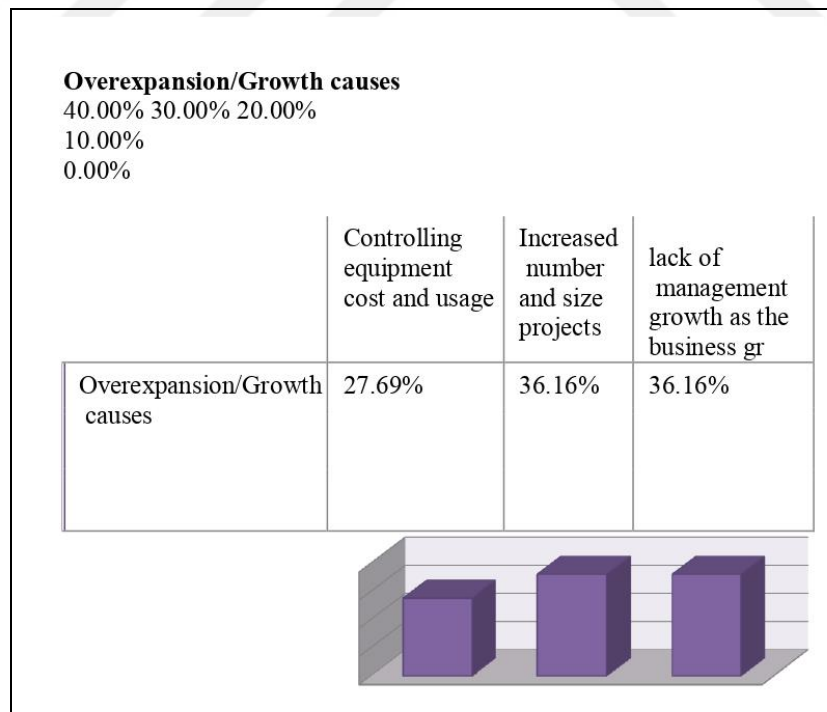


Figure 3.9: Overexpansion/Growth Causes of the Steel Failure Owner Perspective

Overexpansion causes have been cited by many authors as one of the main causes that lead to the steel failure (Assessment of factors affecting maintenance cost of

public school facilities | Emerald Insight n.d.). Surveyed the literature on the major causes of steel failure from the perspective of the surety industry was overexpansion causes.

Figure (3-10) shows the uncontrollable causes of the steel failure where the percentages as follow: bad weather is 6.44 %, unforeseen conditions, past experience, resources for plant and equipment, contractor site management/execution abilities, employee competency, and cost overruns is 9.47%, contractor familiarity with geography area is 9.19, contractor relationship with local authority is 9.19%, time overruns is 9.12 % and quality defect is 8.70%.

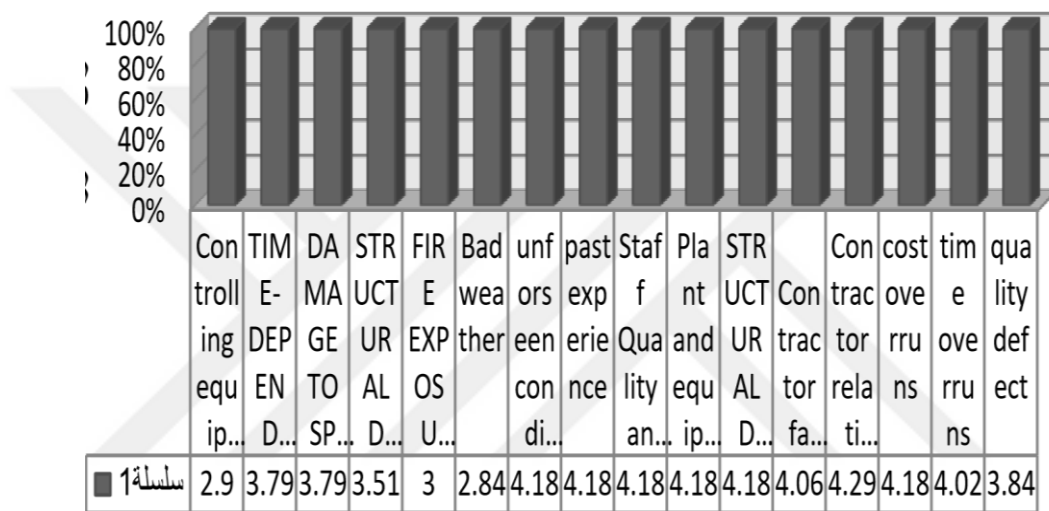


Figure 3.10: Uncontrollable Causes of the Steel Failure (Owner Perspective)

3.9.2 Causes of steel failure (Contractor perspective)

In this study multiple questions were posed about the government agency or private sector in which the participants were working, as well as other questions aimed at understanding the reasons of contractor loss (owner perspective) in order to gain an overview of the history and position of employment of the respondents.

The management cause of the contractor loss is shown in Figure (3.11) with the following percentages: lack of experience in business with the contractor is 7.47%, change of owners or key staff is 8.51%, lack of contract experience 9.77%. lack of work experience is 10.84%, use of project management techniques is 11.42%, stationed job project leader is 7.32%, poor project management is 11.42%, claims is 10% project manager and award the contract to the lowest price 12.34%, increase number of projects 10.65%.

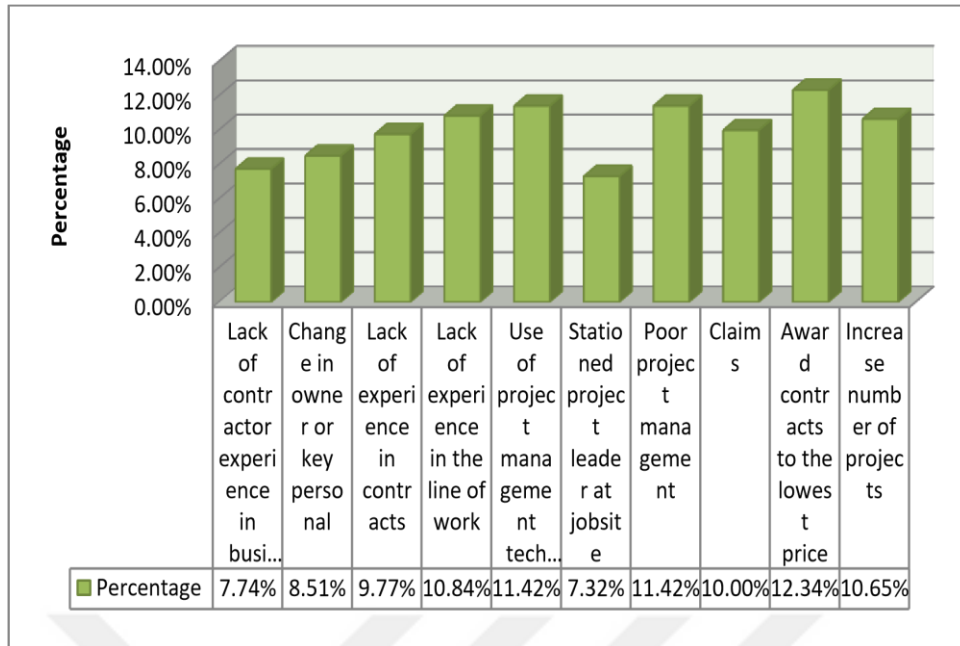


Figure 3.11: Managerial Causes of the steel Failure (Contractor Perspective)

Figure (3.12) shows the financial causes of the steel failure where the percentages as follow: Low profit margin as a result of market rivalry is 16.09%, reduction capital is 16.09 %, cash flow mismanagement is 17.09 %, delay in collecting payments from clients is 15,7%, fluctuation in construction material cost is 17.09 % poor cost estimation is 17.94 %.

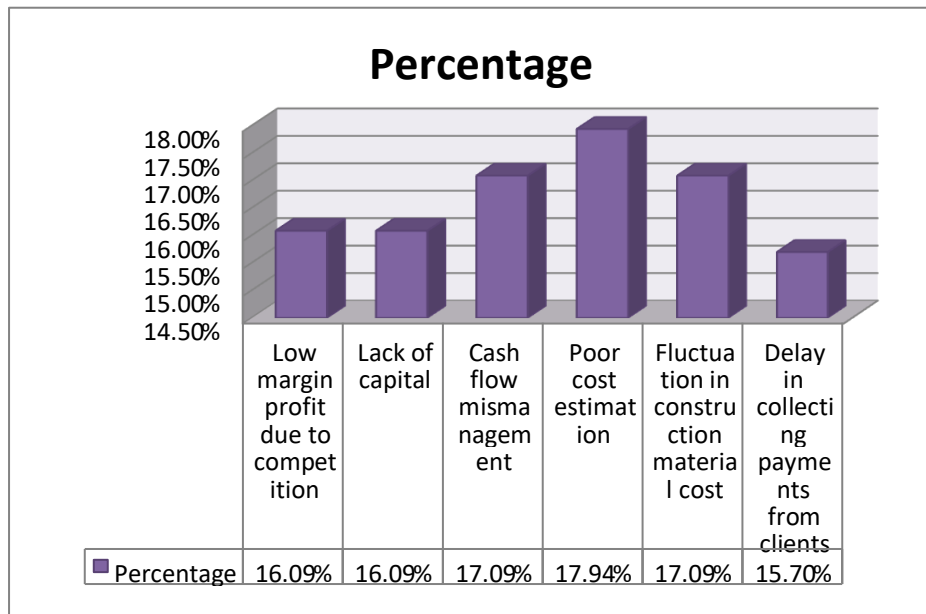


Figure 0.12: Financial Causes of the Steel Failure (Contractor Perspective)

Figure (3.13) shows the overexpansion/growth causes of the steel failure where the percentages as follow: Increased number and size projects and Inadequate training

for new managers despite the company's expansion is 36.58% and Controlling equipment cost and usage is 26.84%.

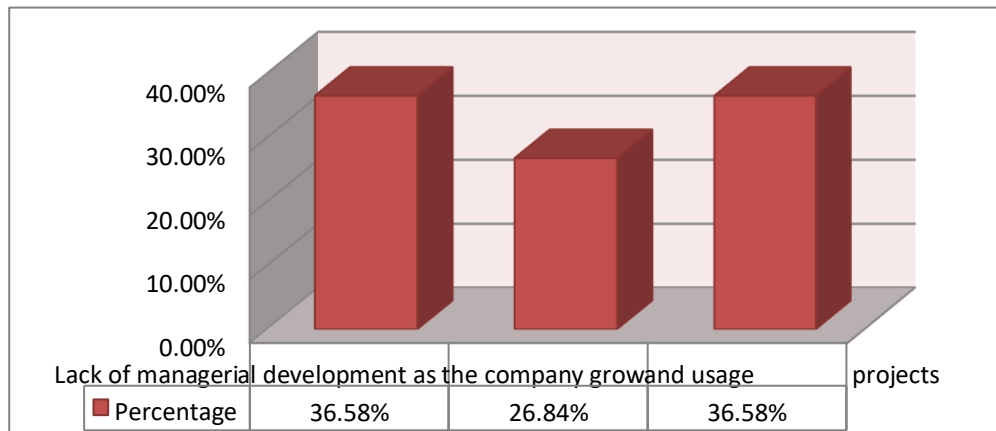


Figure 3.13: Overexpansion/Growth Causes of the steel Failure (Contractor Perspective)

Figure (3.14) shows the uncontrollable causes of the steel failure where the percentages as follow: bad weather is 5.87 %, unforeseen conditions, past experience, cost overruns at 9.53 percent, contractor familiarity with the geography region at 9.04 percent, contractor relationship with local authority at 9.93 percent, time overruns at 8.92 percent, and quality defects at 9.07 percent are all within acceptable ranges.

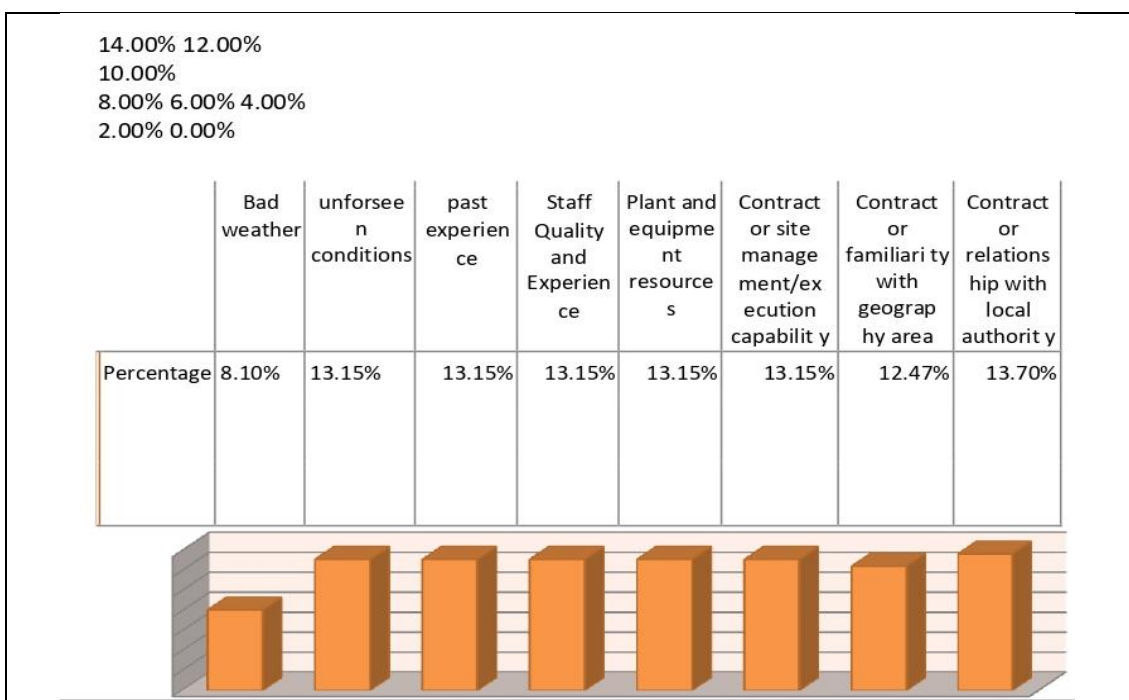


Figure 3.14: Uncontrollable causes of the Steel failure (Contractor Perspective)

The author made another statistical test which is relative important index in order to show the important of cause from both owner and contractor perspective, table (3.5) show RII for both parties. The RII was calculated to know the most important factors that effect on the steel failure and perspective to take.

RII= (3.2) (Kassem, Khoiry, and Hamzah 2020).

Table 3.5: Relative Important Index of Steel Failure

Causes	RII (owner)	Rank	Causes	RII (Contractor)	Rank
Time dependent deformation of perimeter walls due to fire and load redistribution	86.98%	1	Lack of experience in contracts	90.00%	1
damage to sprayed fire-resistive material as a result of airplane impact	85.71%	2	Bad weather	83.78%	2
Structural damage and failures as a result of collapse	82.06%	3	unforeseen conditions	83.78%	2
past experience	82.06%	3	past experience	83.78%	2
Staff Quality and Experience	82.06%	3	Staff Quality and Experience	83.78%	2
Plant and equipment resources	82.06%	3	Plant and equipment resources	83.78%	2
Contractor site management/execution capability	82.06%	3	Contractor relationship with local authority	83.78%	2
cost overruns	82.06%	3	Increase number of projects	81.08%	3
Lack of experience in contracts	81.11%	4	Use of project management techniques	80.54%	4
time overruns	80.48%	5	Stationed project leader at jobsite	80.54%	4
Quality defects	76.83%	6	Poor project management	80.54%	4
Use of project management techniques	76.67%	6	Contractor site management/execution capability	79.46%	5
Poor project management	76.67%	6	time overruns	79.46%	5
Increase number of projects	75.87%	7	cost overruns	78.38%	6
Lack of experience in the line of work	75.08%	8	Lack of experience in the line of work	76.49%	7
Contractor familiarity with geography area	73.0%	9	Increased number and size projects	75.14%	8

As presented in table (3.5) the rank for steel failure from contractor perspective differ from that of the owner, from the owner point of view award contracts to the lowest price is number one where lack of experience in contracts from contractor

perspective and the two causes represent a problem in the contract stage. Contractor relationship with local authority has the second rank for both owner and contractor as it consider from the main causes in our construction environment, cost overruns unforeseen conditions, past experience, staff quality and experience, plant and equipment resources and contractor site management/execution capability consider the third rank from the owner point of view as most projects suffer from cost overruns while from the contractor is increase number of projects as the contractor will face difficulty in the managemen.

3.9.3 Potential Enhancement

This section includes the most beneficial method that could enhance or limit the cause of the failure.

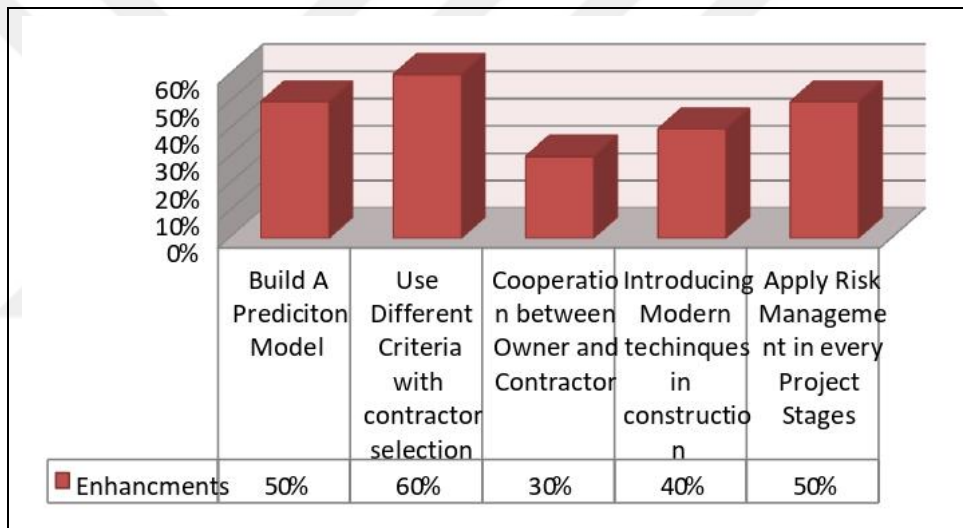


Figure 3.15: Potential Enhancement

The author applied number of these methods which are building a predictive model for the contractor failure, use a different criteria for contractor selection and introducing modern techniques in construction. In this chapter a prediction model will be built by using Neural Network, Support vector Machine and decision tree using two program MATLAB and KINME.

Before the prediction is made, ANOVA test is performed on data to get familiar with most significant causes that effective. Table (3-6) show the ANOVA test for both owner and contractor.

Table 0.5: ANOVA Test

Causes	ANOVA (owner)	Significant	ANOVA (Contractor)	Significant
Lack of contractor experience in business	0.187	Non	0.072	Non
Change in owner or key personal	0.004	Sig	0.011	Sig
Contractor familiarity with geography area	0.001	Sig	0.423	Non
Lack of experience in the line of work	0	Sig	0.062	Non
Use of project management techniques	0.001	Sig	0.315	Non
Stationed project leader at jobsite	0.431	Non	0	Sig
Poor project management	0.002	Sig	0.315	Non
Claims	0.003	Non	0.033	Sig
Award contracts to the lowest price	0.023	Sig	0.139	Non
Increase number of projects	0	Sig	0.155	Non
Low margin profit due to competition	0.001	Sig	0.016	Sig
Lack of capital	0.001	Sig	0.016	Sig
Cash flow mismanagement	0	Sig	0.115	Non
Poor cost estimation	0.005	Sig	0.006	Sig
Fluctuation in construction material cost	0	Sig	0.115	Non
Delay in collecting payments from clients	0.038	Sig	0.578	Non
Controlling equipment cost and usage	0.08	Non	0.759	Non
Increased number and size projects	0	Sig	0.155	Non
Lack of managerial development as the company grow	0	Sig	0.155	Non
Bad weather	0.039	Sig	0.046	Sig
unforeseen conditions	0.303	Non	0.149	Non
past experience	0	Sig	0.048	Sig
Staff Quality and Experience	0.002	Sig	0	Sig
Plant and equipment resources	0.002	Sig	0	Sig
Contractor site management/execution capability	0.003	Sig	0	Sig
Lack of experience in contracts	0.003	Sig	0	Sig
Contractor relationship with local authority	0.003	Sig	0	Sig
cost overruns	0.003	Sig	0	Sig
time overruns	0.002	Sig	0	Sig
Quality defects	0.002	Sig	0	Sig

In the test of ANOVA, the significant is measured based on the 0.05 scale, if its more than 0.05 there is no significant and less than 0.05 is significant, some certain causes have significant by the owner differ from that of the contractor, and some are in

common, the causes that are significant from the owner point of view were taken to make the prediction as they are the largest percentage in the populations.

3.10 Steel Failure Prediction

This section include the prediction of the steel failure using Neural Network, Support vector Machine and decision tree using two program MATLAB and KINME. Appendix C shows the distributed projects.

3.10.1 Support vector machine

Support Vector Machines (SVMs) are state-of-the-art learning mechanisms that work in recognition of actual patterns and data mining applications, such as text categorization, hand-written character recognition, image classifications and bioinformatics. Though they have very exact solutions, classification must be carried out at high speed in online applications. This is because a large number of simple tasks are normally necessary to make the SVM classifier complex and costly (Keerthi, Chapelle, and DeCoste 2006). SVM model was used in construction projects with many applications and prequalification issues were used by SVM contractors (Breast cancer diagnosis based on feature extraction using a hybrid of K-means and support vector machine algorithms - ScienceDirect n.d.). Predict the approximate SVM project parameter cost (Support vector machine cost estimation model for road projects n.d.). Comparison of the successes of various models in the expense forecast of construction project at the start of the planning phase (Meharie and Shaik 2020).

3.10.1.1 Building up the (SVM)

SVM's fundamental thinking lies in Extracting the information and patterns hidden in the data by nonlinearly changing the input space into a higher dimensional space. The connection amidst the variables input and output in high-dimensional space is nonlinear. SVR is distinguished from other approaches by achieving high accuracy by depending on a few training observations known as help vectors (Jain et al. 2014). The steps as shown in table (3.7).

Table 3.6: Steps of SVM

Step	Equation	Description
With the provision of training data, $(x_1, y_1) \dots (x_m, y_m)$ ($x_i \in X = \mathbb{R}^n$, $y_i \in Y = \mathbb{R}$, the total number of samples used for training (m) are created at random from some unknown function. SVM approximates the regression function	$F(x) = \omega \cdot \phi(x) + b$	where x is the input parameter; $\phi(x)$ shows the high-dimensional feature spaces that are nonlinearly mapped from the input space. x ; ω is the weight coefficient; b is the deviation value.
coefficients of ω and b are estimated by minimizing the regularized risk function	$\frac{1}{2} \ \omega\ ^2 + C \frac{1}{n} \sum_{i=1}^n L_c(y f(x_i))$	$\ \omega\ ^2$ is a It feasible to make a function as flat as possible by reducing a "regularized term." The regularization constant is denoted by C . ϵ where the SVM cuts off at a certain threshold
code $(1/n) \sum_{i=1}^n L_\epsilon(y_i, f(x_i))$ if the empirical error is determined by the ϵ -insensitive loss function	$L_\epsilon(y - f(x)) = \begin{cases} y - f(x) - \epsilon & \text{if } y - f(x) \geq \epsilon \\ 0 & \text{otherwise} \end{cases}$	value of zero is assigned The loss value is proportional to the distance between the expected value and the tube's radius if the expected value is within the tube (ϵ) of the tube is assigned otherwise.
To get the estimation of ω and b , Eq. (1) is transformed to the primal objective function (4) by introducing the positive slack variables ζ_i^* .	$\text{Min} \frac{1}{2} \ \omega\ ^2 + C \frac{1}{n} \sum_{i=1}^n \zeta_i^*(\epsilon)$	Optimizing problems can be solved with Lagrange multipliers such as α_i and α_i^* are presented; the method of partial derivatives applied to the fundamental variables.
An advent the kernel function can be rewritten as $K(x_i, x_j)$, Eq. (1)	$\sum_{i=1}^n (\alpha_2 - \alpha_1) \cdot K(x_1, x) + b$	
radial basis functions (RBF) are very easy to compute numerically and have desirable nonlinear properties in high-dimensional spaces, they are frequently used as kernel functions.	$\exp\{-g \ \mathbf{x}_i - \mathbf{x}_j\ ^2\}$	year input vector (x_j) and kernel parameter (g). The c and g parameters are major determinants that have a direct effect on the precision of the model prediction.

Source: (Ma et al. 2018).

Step length c and grid size g can be optimized in three major ways as shown in table (3.8):

Table 3.7: Steps for Finding SVM Parameter

Step	Description
The rough selection is the first step	There are several grids dividing the area of c and g , and their step size is 1. In particular, g is set to be 1 in a one-time search when the value of c is changed as a grid of 2-8 to 28 with a 0.05 space spacing. After that, we divide the data into three identical sets and train them, the ϵ -SVR is applied to the regression model's training. There is a suitable g for each province in terms of parameter c . If there is more than one parameter, the one with the smallest MSE should be used.
The second step is making a specific choice.	The step length of c and g is 0.5, and the space of c and g is divided into tiny grids. When the value of c is changed from 2-4 to 24, g is specifically fixed to be 0.5 in one-time search. The data is then equally trained across three times., the ϵ SVR is used to train the regression model. Similarly, there also exists an appropriate g that makes the MSE lowest
The third step is the	At first, the rough selection result of c and g is solved.
Training processing	respectively. Then the precise selection result of c and g is certainly confirmed, respectively. Therefore, the optimal values of c and g are calculated, respectively. Finally, the optimal parameters of c and g are used to be trained by the ϵ -SVR model, in order to find out the decision function of the prediction model.

Source: (Ma et al. 2018)

Table (3.7) and (3-8) shows the whole process of the SVM, and to be more accurate, figure (3.16) shows the framework for the algorithm in a simplified form.

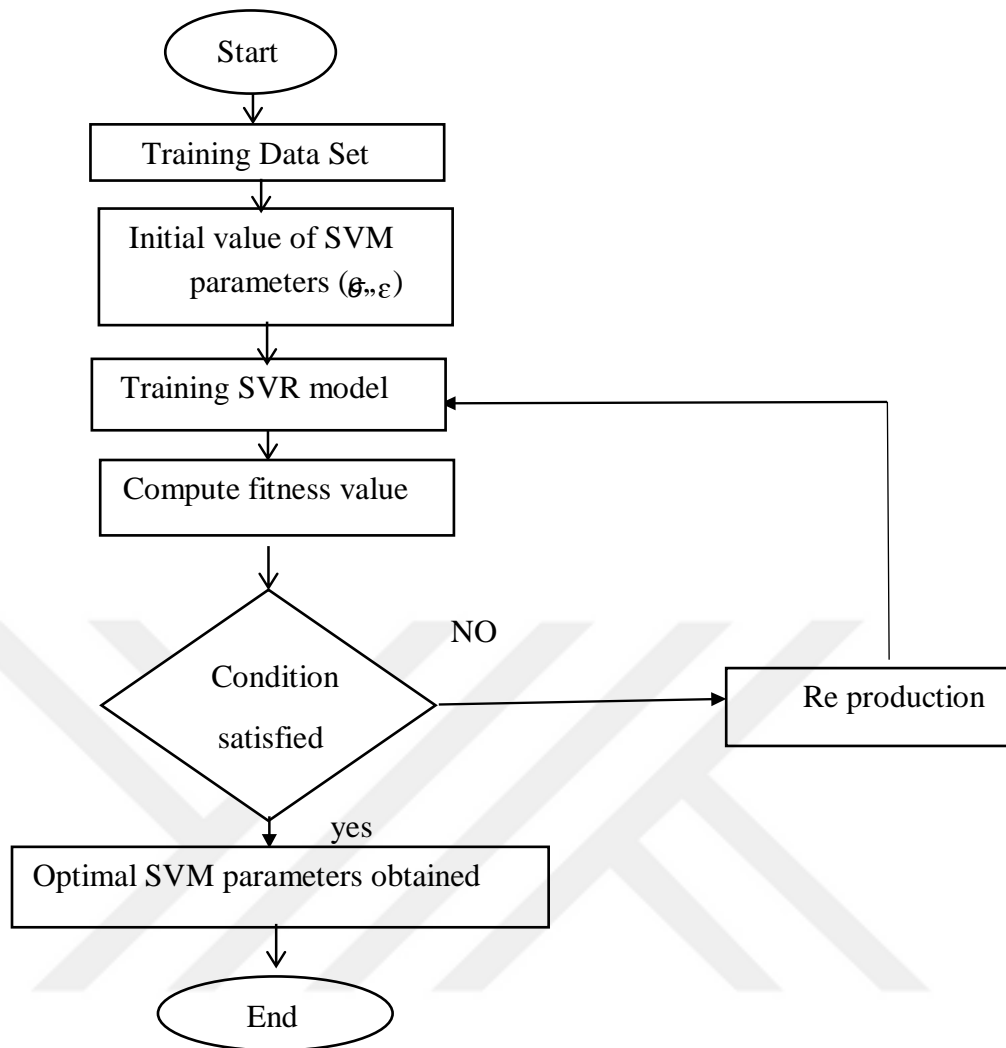


Figure 0.16: SVM Flowchart

3.10.2 Decision tree

Decision tree is a tree structure like a flux-chart, which denotes any internal node by rectangles and the leaf knots by ovals. The algorithm most widely used is simpler to execute and more comprehensible than for other algorithms of classification (Yadav and Pal 2012). The decision-making tree has shown how many students are likely for next year to disappear, to fail or to be advanced.

In comparison to other classification methods the decision tree can be built very quickly. Decision tree classifiers achieve equal and often better performance relative to other approaches. Algorithm for decision tree may be applied in serial or parallel mode depending on data volumes, computing resource memory and algorithm scalability. The algorithms types are C4.5, ID3 Decision Tree.

3.10.2.1 Building up Decision Tree

The main components of a decision tree model are nodes and branches and the most important steps in building a model are splitting, stopping, and pruning, as shown in table (3-9).

Table 0.8: Decision Tree Building

Terms	Description
Nodes	Decision that will divide all records into two or more mutually exclusive subsets is represented by a root node, also known as a decision node. Internal nodes, also known as chance nodes, show one of the options that could be accessible at that moment in the tree structure; the node's top edge is linked to its parent node, and its lower edge is joined to its leaf nodes or child nodes. The results of a succession of decisions or events are described by leaf nodes, often referred to as end nodes.
Branches	Branch nodes stand in for random events or occurrences that arise from internal and root nodes. A hierarchy of branches is used to create a decision tree model. A classification decision rule is represented by each route a leaf node is reached from the root node through internal nodes. These "if-then" rules may also be used to represent these decision-tree paths. "If condition 1 and condition 2 and condition... and condition k exist, then result j happens," for instance.
Splitting	When dividing up parent nodes into more refined child nodes, we employ all input variables that are pertinent to the target variable. It is possible to take in both discrete and continuous variables. It's possible to use (which are divided into two or more categories). To Be Continued
	Prior to creating the model, it is necessary to determine the most crucial input variables. Based on the values of these variables, the root node and subsequent internal nodes must then split the data into two or more categories or "bins," as appropriate. To choose amongst several possible input variables, Various measures of the "purity" of the generated offspring nodes (i.e., the proportion with the objective condition) are used as selection criteria, including the entropy, Gini index, classification error, information gain, gain ratio, and twoing criteria.
Stopping	When creating a statistical model, it is important to take into account both the competing model properties of complexity and robustness. A model's ability to accurately anticipate future data will decrease as it becomes more sophisticated. Building an extremely intricate decision tree model that is sufficiently broad to ensure that every leaf node's records are 100% pure is an extreme scenario (i.e., In every case, the desired result was recorded). A result of being too suited to the current observations and having few records in each leaf, such a decision tree would have weak generalizability and be unable to accurately forecast future instances (i.e., lack robustness). When creating a decision tree, halting rules must be used to avoid this from occurring and keep the model from being too complicated.
Pruning	Stopping rules don't always operate properly in certain circumstances. Growing a big decision tree is an alternate approach to decision tree modeling tree first, and then reduce the size of the tree by deleting nodes that don't offer much new information..

Source: (Song and Lu 2015).

Table (3.9) show the main steps that usually used in the decision tree and figure (3.17) show the flowchart of the algorithm, as it's based on the decision to check the condition verified and checked.

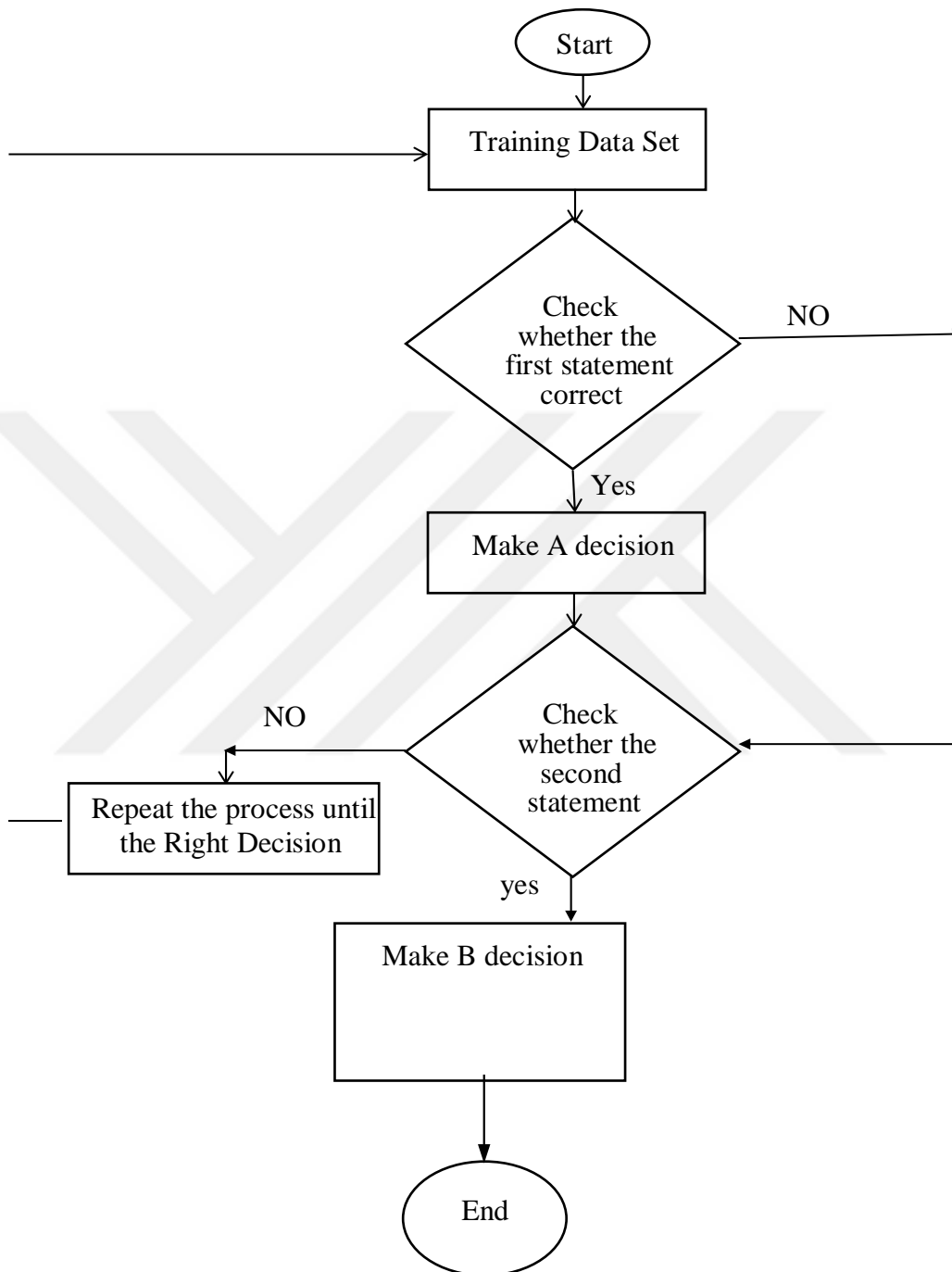


Figure 0.17: Decision Tree Flowchart

3.10.3 Neural network

The Neural Network is a processing paradigm that simulates the functioning of the biological nervous system. It is a useful tool for modelling complex systems because

it can predict contractors' responses to changes in the bidding environment. It is powerful in learning the relationships among variables to aid in understanding the influence of their change with the performance. (ANN) models were used in many prediction applications in literature in construction projects (Poh, Ubeynarayana, and Goh 2018). Predicting price winning awards (Research on QR image code recognition system based on artificial intelligence algorithm n.d.). Predicting schedule performance (Prediction of schedule performance of Indian construction projects using an artificial neural network: Construction Management and Economics: Vol 29, No 9 n.d.), contractor risks of contractor defaults and labour productivity (Al-Sobiei, Arditi, and Polat 2007). After its success in many applications in construction projects. ANN learning has been used mainly to create neural functions as an objective function in this thesis.

3.10.3.1 Building up the (ANN)

In the simplest forms of the (ANN), One input layer, one hidden layer, and one output layer are present. To reach the fitting, the neurons existing in hidden layers shall increase and/or adding more hidden layers. This process iterative and aims to reach the network that does not overfit. However, increasing these elements of the (ANN) makes the network learn too much and ends up memorizing the data without recognizing the features present in them. In literature, they call this phenomenon "overtraining" or "over-fitting (Feng and Simon 2017). The formation of the ANN structure is bounded by the number of inputs, outputs, and the amount of training data. Previous studies recommended that the neurons quantity should fall between the count of inputs and outputs. They also suggested that the size of neurons in hidden layers should form $\frac{2}{3}$ to $\frac{1}{2}$ of the sizes sum of the number of inputs and outputs (Introduction to Neural Networks with Java - Jeff Heaton - كتيب Google n.d.). However, many proposed that there is not one empirical way in order to discover best frame unless by trial-and-error or handcrafting (Kulkarni, Londhe, and Deo 2017), (How effective are neural networks at forecasting and prediction? A review and evaluation - Adya - 1998 - Journal of Forecasting - Wiley Online Library n.d.), (The use of artificial neural networks in construction management: a review: Construction Management and Economics: Vol 14, No 5 n.d.). Taking into consideration, the number of hidden nodes is better limited to $N_{HN} \leq N_{INP} + 1$

where N_{1NP} is the number of input nodes (Basheer and Hajmeer 2000). The value of mean squared error (Neural networks | Guide books n.d.), or sum square error (Basheer and Hajmeer 2000). Of validation data are commonly used to stop the training.

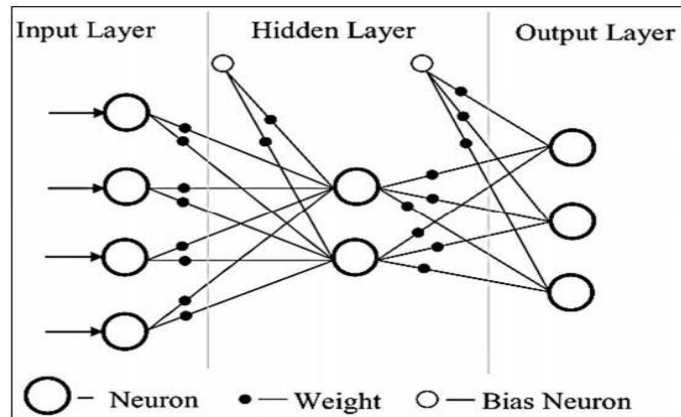


Figure 0.18: Basic ANN structure

Source: (Combined Economic and Emission Dispatch Using Improved Backpropagation Neural Network: Electric Machines & Power Systems: Vol 28, No 1 n.d.).

Furthermore, Sheela and Deepa accurately observed the impact of the number of neurons on the overtraining. For instance, in the application of complex problems in the ecosystem such as predicting the wind speed, a scholar conducted a review on the relations that determines the number of neurons (Sheela and Deepa 2014).

In neural networks training in the study relied on 70% of data, 15% for validating the networks, and 15% for testing them. The validation dataset is used to stopover the process of training when there is no more improvement observed in the learning performance. The test dataset, however, aims to additionally examine that the network by taking a broad view, though it does not affect the training result. The regression and error histogram plots represent each group for the networks to represent the accuracy of the network's prediction.

The author use multilayer instead one layer as it determines the ability of the network to learn specific patterns. With more layers the NN not only becomes more complex but also requires additional resources.

Users can graphically design data flows (or pipelines) in KNIME, execute part or all analysis processes, and then utilize interactive widgets and views to evaluate the results and models. KNIME is a Java program built on the Eclipse platform. It uses the extension system to include plugins with more capabilities.

3.11 KNIME Software

KNIME (/naɪm/), the Konstanz Information Miner (KNIME - the Konstanz information miner: version 2.0 and beyond: ACM SIGKDD Explorations Newsletter: Vol 11, No 1 n.d.). The data analysis, reporting and integration software is free and open source. With its compact data pipeline "Lego of Analytics" design, KNIME integrates multiple modules for ML/DM projects. Assembly can be done with the help of a graphical user interface and JDBC, without or with limited code, of nodes that combine data streams, including pre-processing (ETLs: extraction, transformation, loading), for simulation, data interpretation and visualization. In pharmaceutical science, KNIME is used since 2006 (Tiwari and Sekhar 2007). It also uses consumer data collection, commercial information intelligence, text mining, financial data analysis in other fields, for example CRM. The results as shown in appendix D.

The model was built by using the three algorithm as the following steps:

1. Upload the file that contain a data about 100 projects from different ministries, a questionnaire with most significant causes was made and distributed on the worker on these 100 projects to show the effects of these causes on the steel performance as show in in figure (3.19).

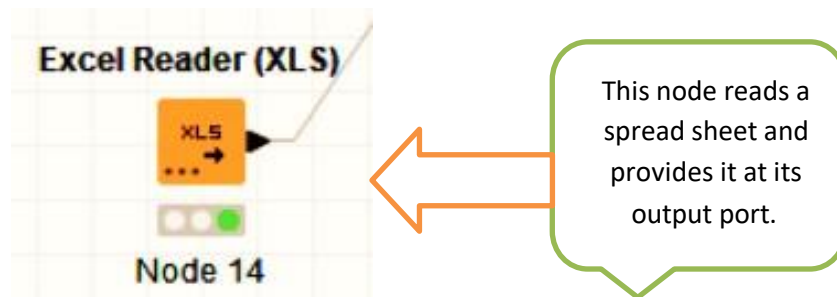


Figure 3.19: Excel Reader (XLS)

2. Ting in order to perform the prediction as shown in figure (3.20).

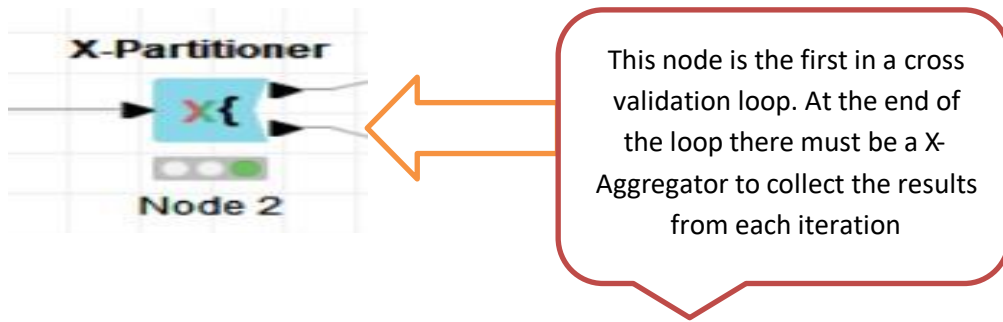


Figure 0.20: X-Partitioner

3. The third step is performing the data for testing and training as shown in figures (3.21) and (3.22).



Figure 3.21: Learner



Figure 0.22: Predictor

4. The last step compare the predicted with the actual and produce the accuracy of each algorithm used.

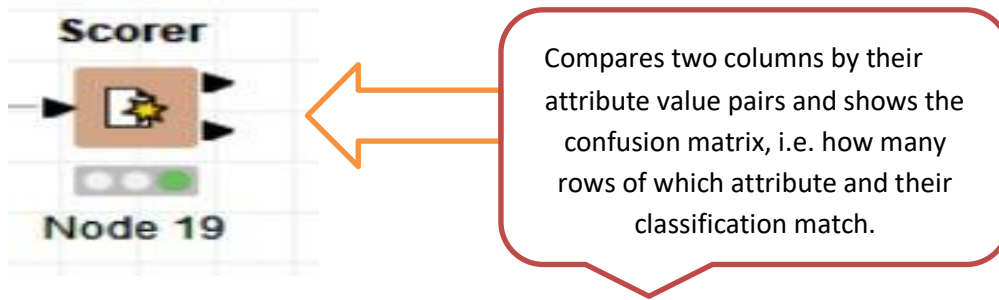


Figure 0.23: Scorer

The final sample that consist of the three algorithms is shown in figure (3.24), by gathering all nodes of the three techniques to form the final model, the neural network need a normalization in order to convert the data to (0,1) for convenience of the neural mechanism and every technique need a scorer to calculate the accuracy from the following equation.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3.1)$$

(SafetyLit: Hospital and pre-hospital triage systems in disaster and normal conditions; a review article n.d.).

True positive (TP) = the number of cases correctly identified as poor

False positive (FP) = the number of cases incorrectly identified poor

True negative (TN) = the number of cases correctly identified satisfy

False negative (FN) = the number of cases incorrectly identified satisfy

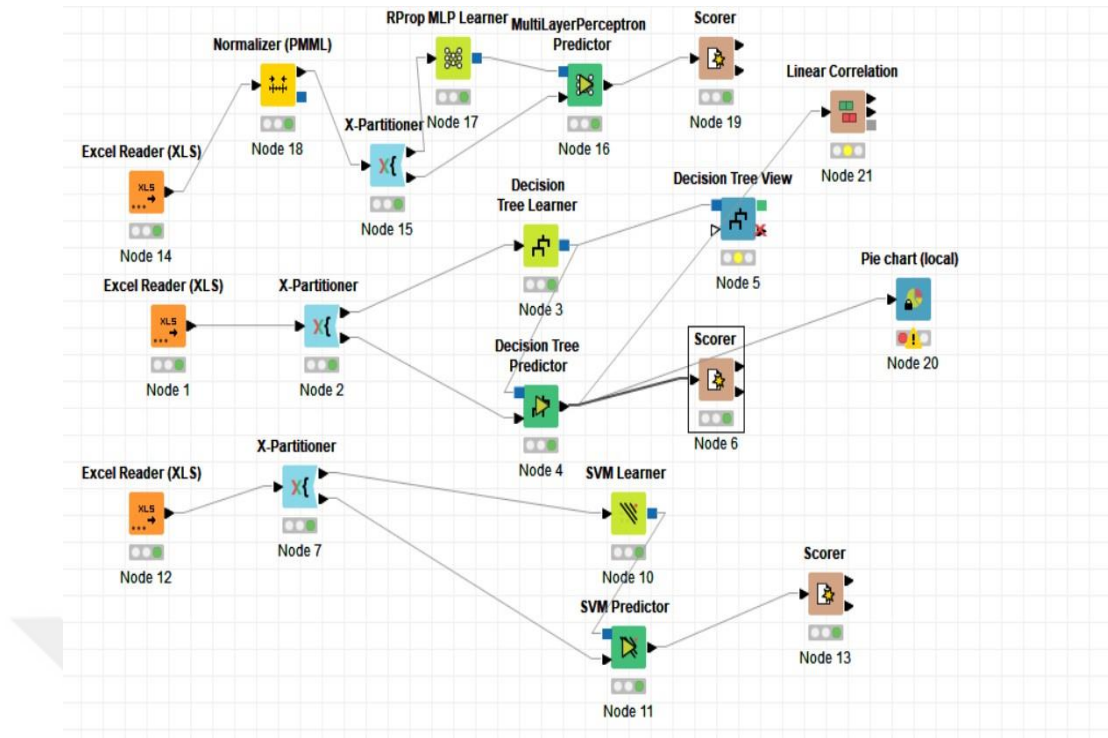


Figure 0.24: The Whole Model

The prediction accuracy for each algorithm is shown in table (3.10).

Table 0.9: Algorithms Accuracy

Algorithm	Accuracy
Neural Network	84.6
Support Vector Machine	70
Decision Tree	93.3

The ROC curve that is showing the highest accuracy in the forecast A graphical plot showing the diagnostic potential of the differential classifier method as their distinct discriminatory threshold is a receiver operating feature curve or Receiver Operating Characteristic curve. Originally, the method was designed for military radar receiver operators, which is why it was called as such as shown in figure (3.25) and (3.26).

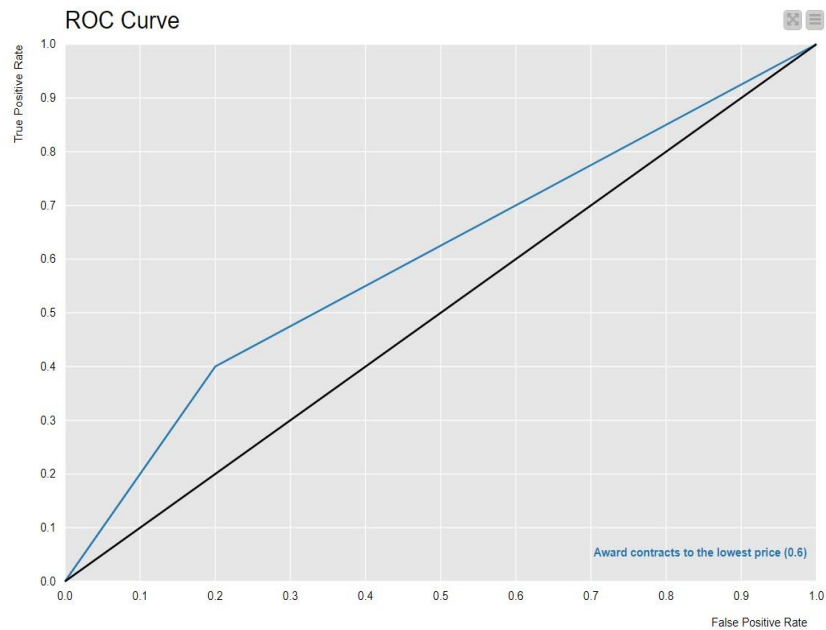


Figure 3.25: ROC Curve award the contract to the lowest price using Decision Tree
 As shown in figure (3.25), the curve show that the algorithm made an error in the prediction as it show 60% in the input award the contract to the lowest price with matching output. The same applied in figure (3.27) and (3.28) as the curve represent the internal accuracy of each factor as for figure (3.27) mean that poor management was correctly predicted by 60% true and 40% false.

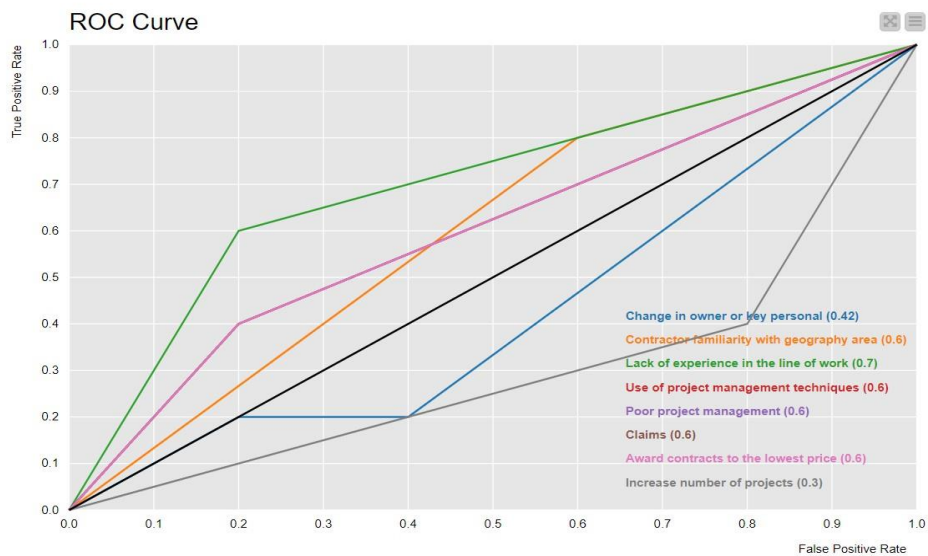


Figure 3.26: ROC Curve using SVM

Figure (3.27) show the SVM have a prediction range from 0.3 to 0.7 in most input with relation to the output.

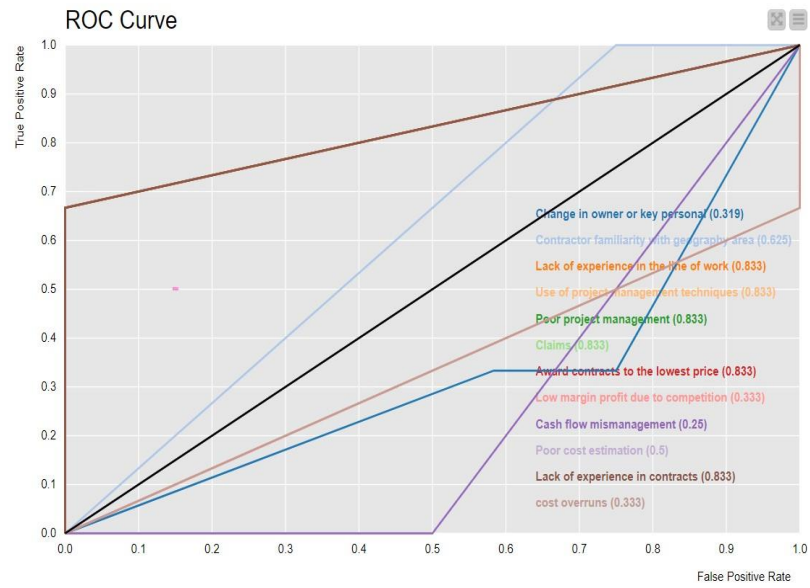


Figure 3.27: ROC Curve using Decision Tree

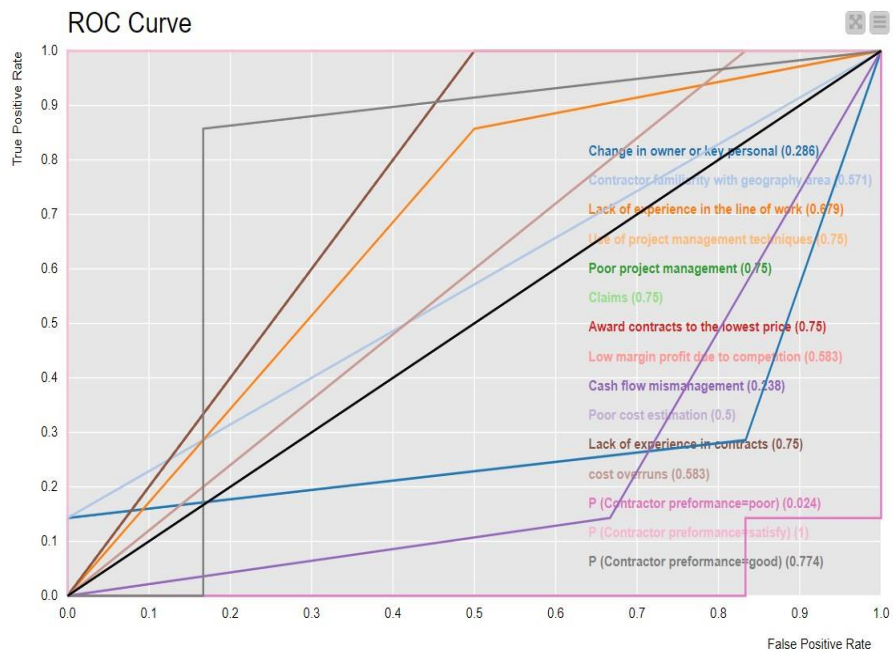


Figure 3.28: ROC Curve using Neural Network

3.12 MATLAB Software

A proprietary multilingual programming language and numerical computation environment generated by Matrix Works is the MATLAB (the abbreviation for "matrix laboratory." MATLAB enables matrix manipulation, feature and data tracking, algorithm execution, user interface creation, and program interfacing in language-specific format.

While the MATLAB is designed mainly Numerical computation with access to symbolic computing capacity is made possible via the MuPAD symbolic engine, which is utilized as a toolbox. Simulink adds a complementary kit to add interactive and embedded machine graphic multi-domain simulation and modelbased architecture.

The three algorithms were applied using MATLAB software in order to compare the accuracy of the two software (KNIME and MATLAB) so the steel performance can be predicted. Table (3.11) show the results of the three algorithms:

Table 0.10: Algorithms Accuracy

Algorithm	Accuracy
Neural Network	83.9
Support Vector Machine	69
Decision Tree	91.3

As shown in table (3.9) SVM show best results in the contrast of KNME software, however the MATLAB enhance the accuracy. Figure (3.29) show the region underneath the curve The decision tree's AUC curve, which represents the overall accuracy of the components that are connected. The same applied in figure (3.30).

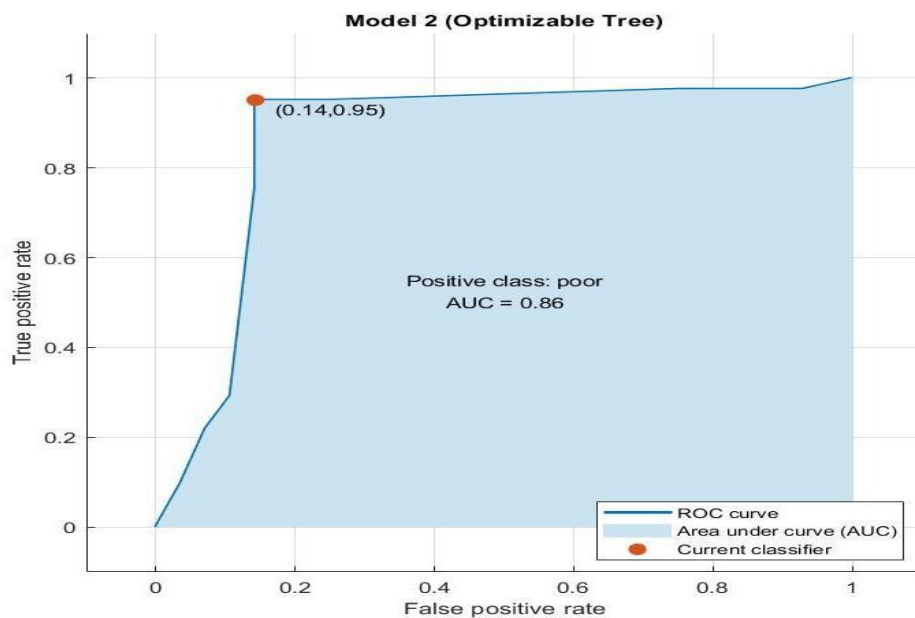


Figure 0.29: AUC Curve using DT (MATLAB)

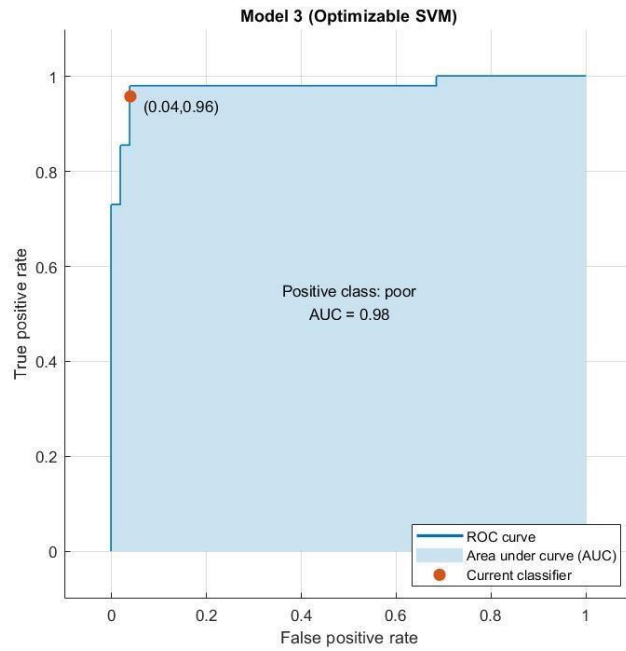


Figure 3.30: ROC Curve Using SVM (MATLAB)

The completed network is accurate because of the following:

- The plot of the network output against the target values in Figure (3-31) shows the regression values that determine the relationship between them. The regression of the blue line for the trained data is 0.89, validated in green is 0.662 and tested in red is 0.783, and all the data in black 0.839.

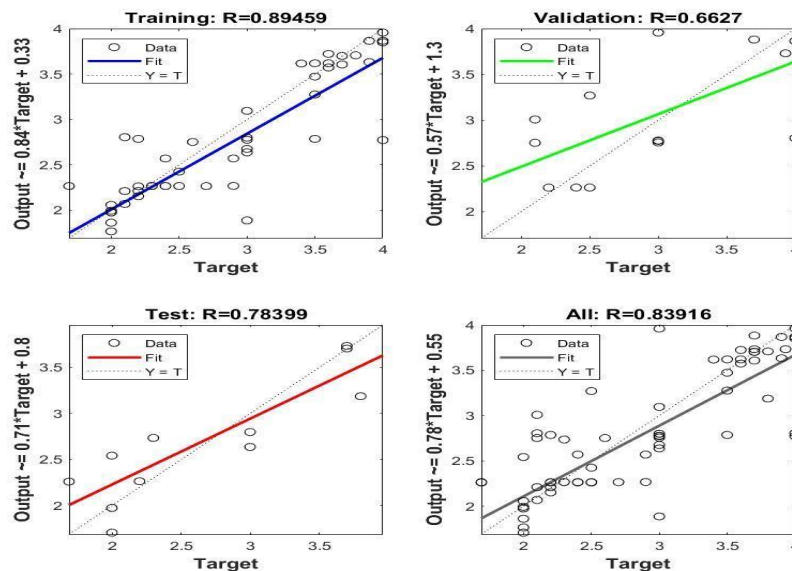


Figure 0.31: Regression of Trained, Validated and Tested Data Fitness for Mean FP

- The mean square error MSE changes with the iterations for the trained in dashed line validated in the dotted line and tested data in solid line as shown in Figure (3-32).

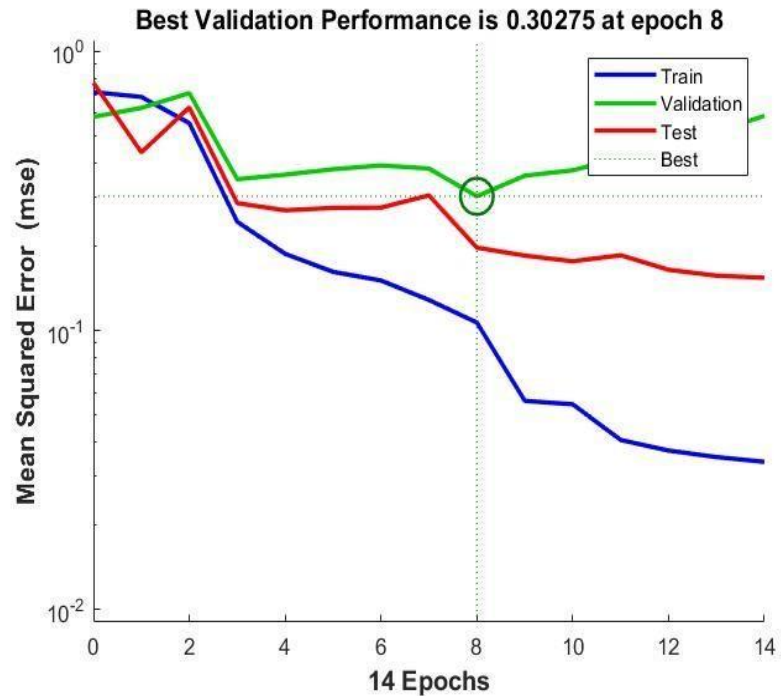


Figure 0.32: Performance of the MLP model

- After completing the iterations Figure (3-33) shows the error histogram of the trained value in blue, validated in green, and tested in red.

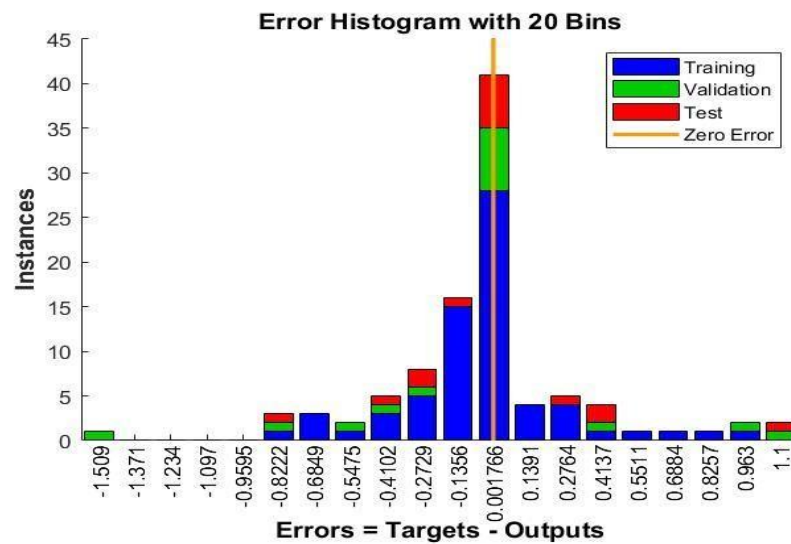


Figure 3.33: The Error Histogram of the Trained, Validated and Tested Data

3.13 Summery

The steel failure consider of major concern and the success of any project, therefore the output of this chapter which are the method to enhance the contractor performance will be divided on the later chapters as using different criteria"s.



4. THE PROPOSED SYSTEM

4.1 Introduction

As shown in the previous chapters, the steel management system and the main reasons that the cause steel to be failed or about to fail or tend to have an obstacles during the implementation in the later stages.

This chapter introduce a proposed system to manage the problems during the construction producer and in implementation methods.

4.2 The Proposed System

This consists of (2) stages starting from the project causes of the failure from owner and second from contractor perspective, as the first, the figure (4.1) show the flowchart of the proposed system.

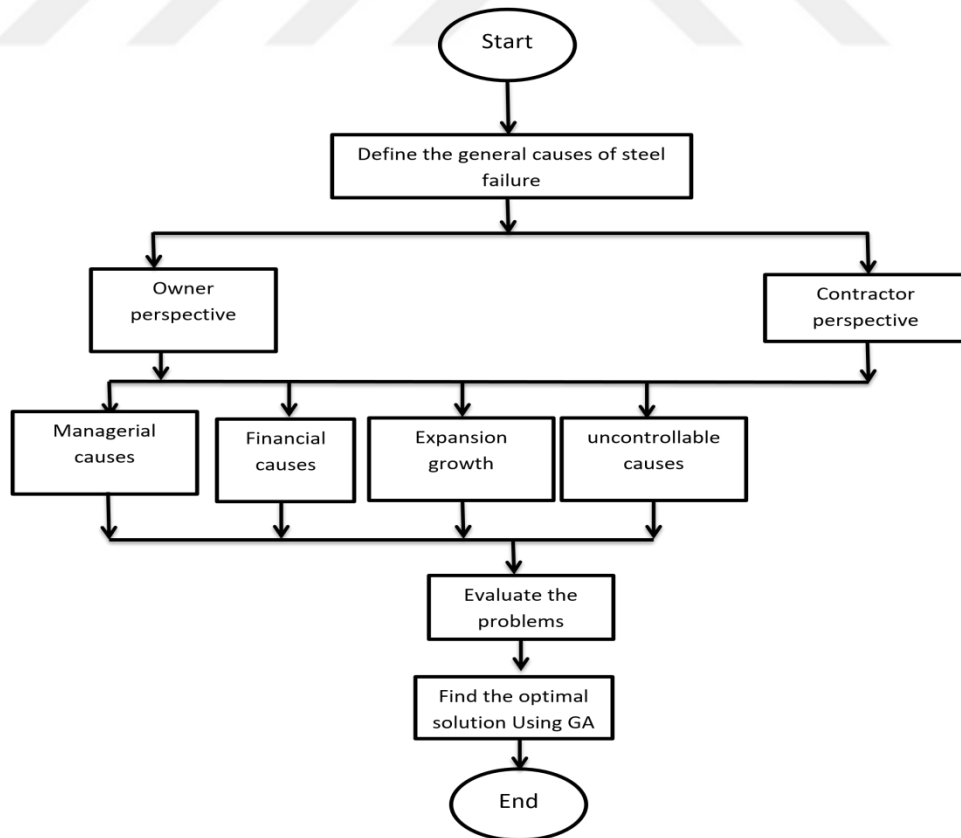


Figure 0.1: Proposed System

A- Stage 1

Give a general introduction about the system as shown in the figure (4.2):



Figure 4.2: General System

B- Enter general causes of steel failure

In this stage, the user can enter to the system and select the stage that contain the problem in order to move to the next stage for the treatment. Figure (4.3) show the contract system figure.

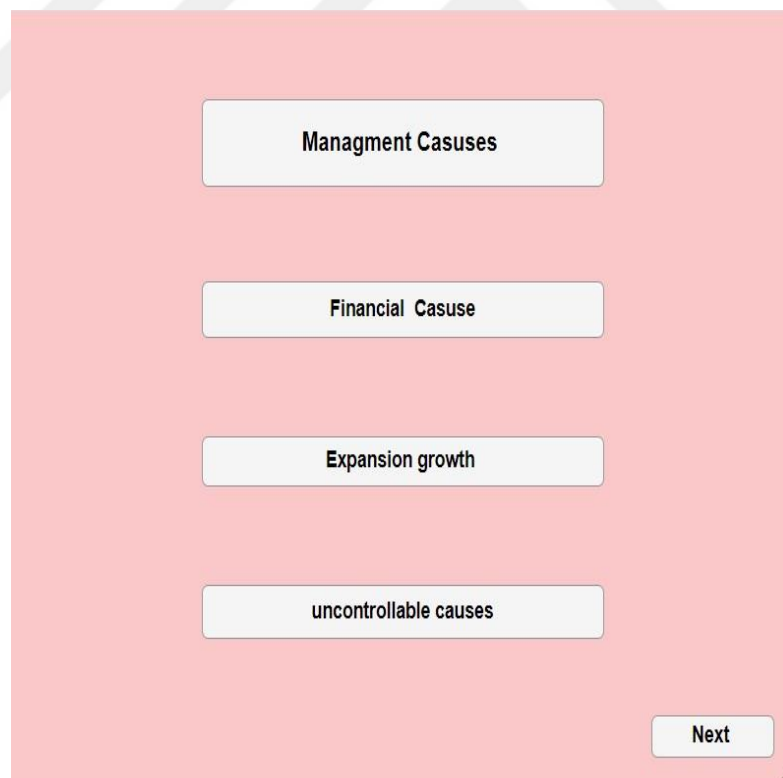


Figure 0.3: Failure System

C-Stage three In this stage, each problem is been evaluated based on the expert opinion as shown in figure (4.4).

impact	assessment
1= too low	less than 5 too low
2=low	5-10 low
3=medium	10-15 medium
4 =high	15-20 high
5-very high	more than 20 too high

Figure 0.4: Evaluation Stage.

D- Stage four

In this stage, each problem that has been identified and evaluated will be treated based on the genetic algorithm to select the optimal solution. Figure (4.5) show the treatment stage.

Column 1	Column 2	Column 3	Column 4

Figure 0.5: Evaluation Stage

The model of the genetic algorithm as follow:

Based on Darwin's theory of the survival of the fittest, GA is an adaptable global-optimization search tool that mimics how evolution works in nature. According to the "fittest principle," a population of individuals evolves naturally in such a way that

those who are fittest have a better chance of surviving. The algorithm is based on three principle, selection, crossover and mutation.

The algorithm of applying genetic as follow:

Algorithm :Find the Solutions Using GA

Input: Data set of the entire projects Output: find the optimal solution

Step (1): Input the GA parameters

Step (2): Define the file name

Step (3): Define the range of the data

Step (4): Define the mathematical model $D = T_{ij} - t_j * x_{ij}$

$D \leq 0.2 * D_t$ $C = C_{ij} * x_{ij}$ $C \leq 0.2 * C_t$

q is the quality of the problem solution

D is the time constrain

D_t is the duration for one project

T_{ij} time of the solution

t_j time of the problem

C_{ij} cost of the solution

C_t the total cost for the project

Step (5): Define upper and lower limit for X_{ij} X_{ij} from 0-1

Step (6): SelectParents Fcn (Cost,SelectionNum,SelMethod)

PopSize = size(Cost,1); switch SelMethod case 1

R = randperm(PopSize); ParIndexes = R(1:SelectionNum);

Step (7):cross over Switch Cross Method case 1

Beta1 = rand;

Beta2 = rand;

Off1 = Beta1*Par1 + (1-Beta1)*Par2;

Off2 = Beta2*Par1 + (1-Beta2)*Par2;

case 2

Step (7) : Calculate the objective function Max $y = q * x_{ij}$

Step (8) : Update the population By repeating the step 5 to 7

Step (8) : Optimize the projects optimize the projects by finding the best solution for each problem according to step 5.

END.

The application of the case study will be discussed in the next section.

4.3 Application of the Case Study

A case study was taken for different ministries to determine and find the best solution for each problem in tendering stages, The Ministry of Education, Directorate of Water and Sewage and Ministry of Higher Education and Scientific Research.

A problems that gathers during the field survey were applied on these ministries to determine their impact on the on the projects performance.

At first the problems were taking in the Announcement stage to determine their effect and find the optimal solutions.

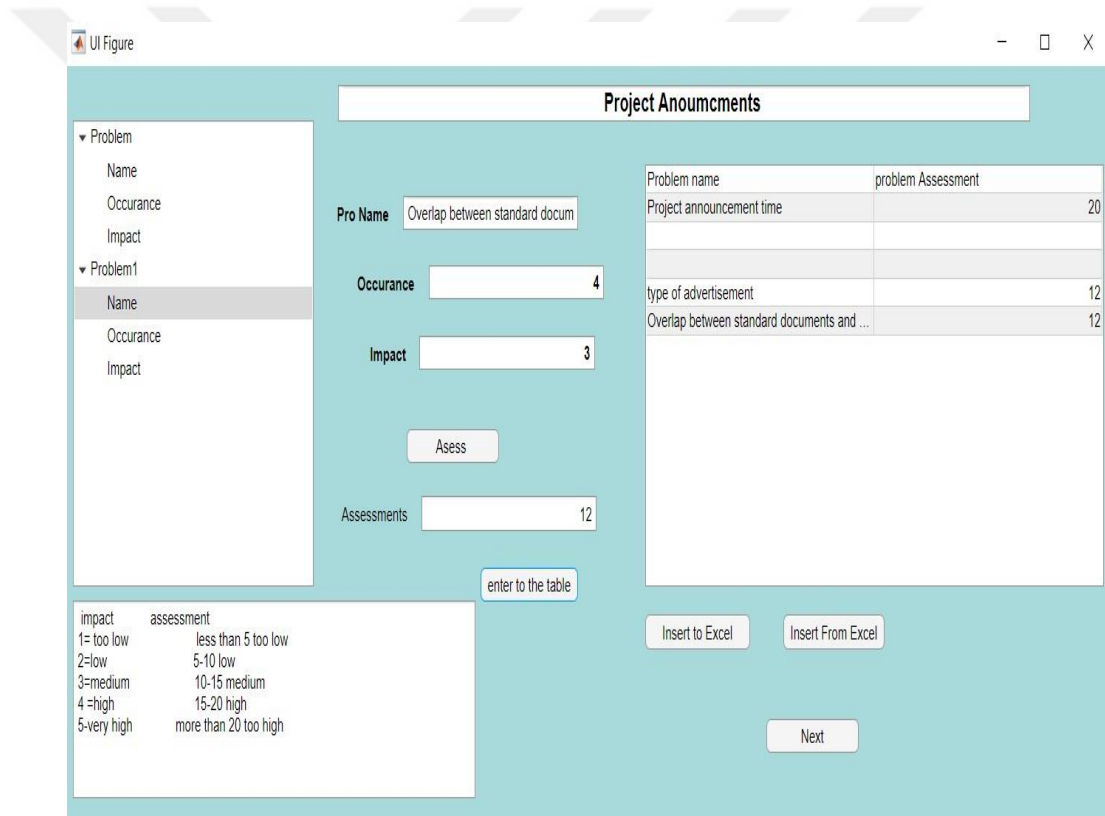


Figure 0.6: Project Announcement Problems

The definition of each part as follow :

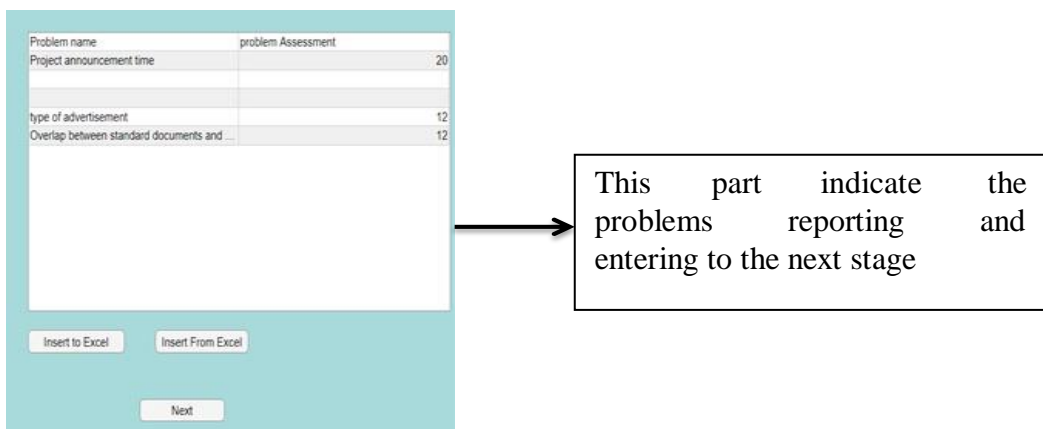
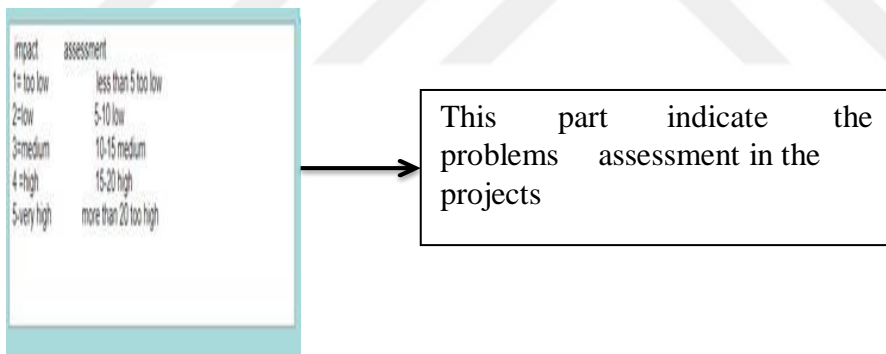
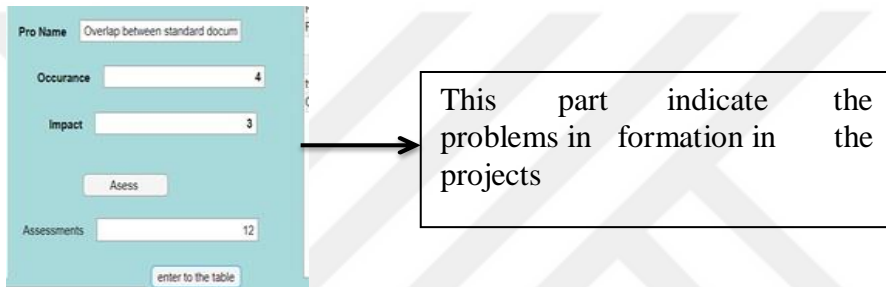
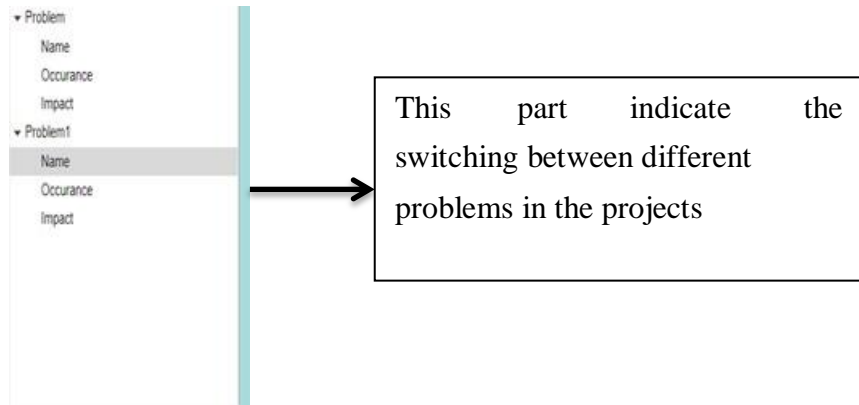


Figure 0.7: Problems Treatment

Figure (4.6) show the problems in first stage of the contracting procedure which is project announcement stage, as to move to the next window to find the optimal solution for the three problems.

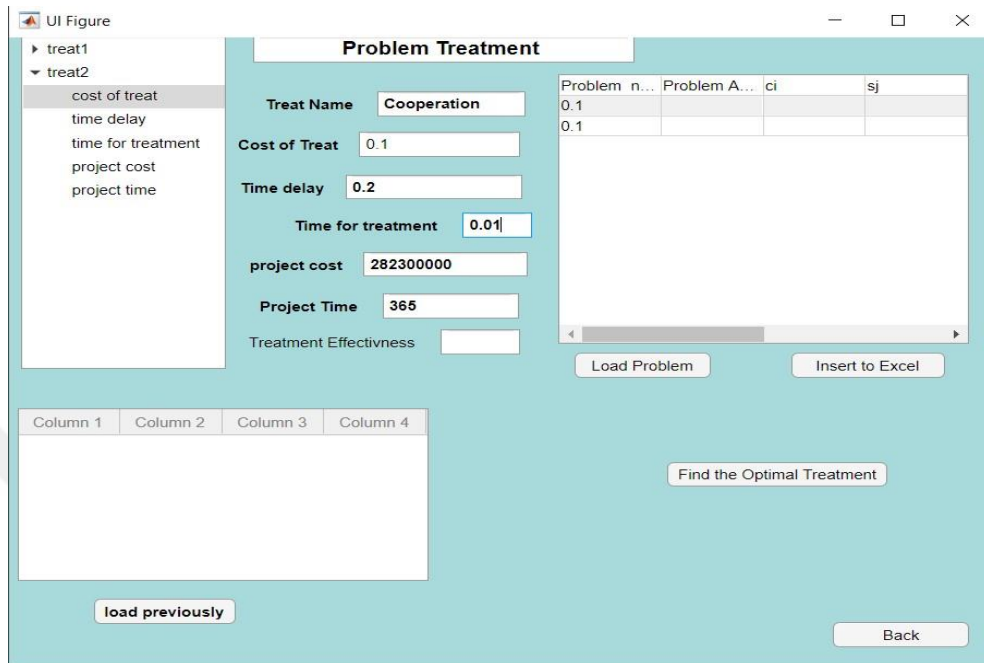


Figure 0.7: (Cont.) Problems Treatment

Figure (4.8) indicate the problem treatment of the first stage and the definition for each part as follow:

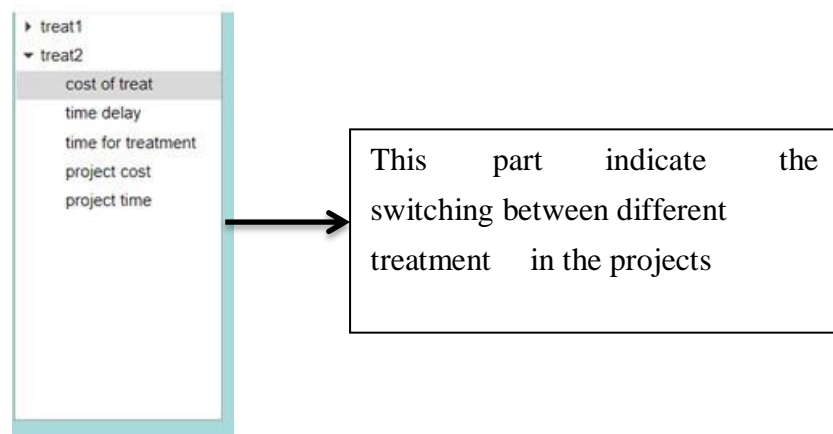


Figure 0.7: (Cont.) Problems Treatment

Treat Name

Cost of Treat

Time delay

Time for treatment

project cost

Project Time

Treatment Effectivness

This part indicate the treatment information in the projects

Problem n...	Problem A...	ci	sj
0.1			
0.1			

Load Problem Insert to Excel

Find the Optimal Treatment

This part indicate the problem treatment option

Figure 0.7: (Cont.) Problems Treatment

After each treatment was entered, the genetic algorithm will select the optimal solution for each problem depending on its effect as shown in table (4.1).

Table 0.1: Problems Treatments with its Effects

Items	Responsive	Effectiveness
Time-Dependent Perimeter Wall Deformation Due To Fire	Implementation method	0.77
	Use new techniques	0.84
	Controlling for Outside Influences	0.9
Impact From An Airplane Causes Harm To Spray-On Fire-Resistant Material.	Continues checking	0.77
	Disciplined Use of maintenance and Subtle Use of Influence	0.94
	Controlling for Outside Influences	0.8
Structural Damage And Failures As A Result Of Collapse	Modifying the existing instructions	0.77
	Modifying the existing method of implantation	0.84
	Cooperation	0.8
Staff Quality and Experience	The controlled application of force and deceptive use of influence	
	Acknowledge automated reporting systems	0.98
	Create a Flow of Communication	0.79

These Problem with treatment were enter to the project to find the optimal solution as shown in figure (4-9), after deciding the problem number and project the algorithm will start to find the optimal solution.

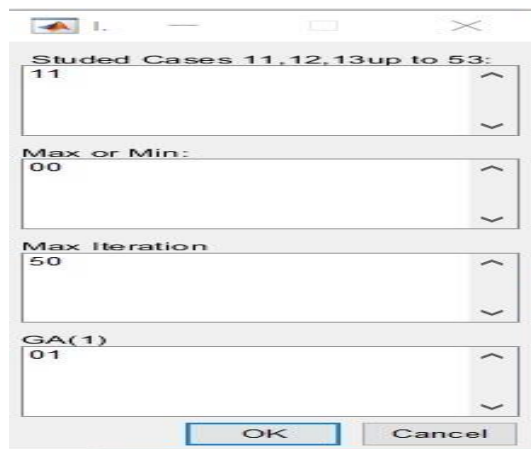


Figure 0.8: Problems Selection

After the problem selection and decide the maximum iteration, the algorithm will start to find the best solution for each problem, the effectiveness were collected based on the expert opinion that range from (0-1).

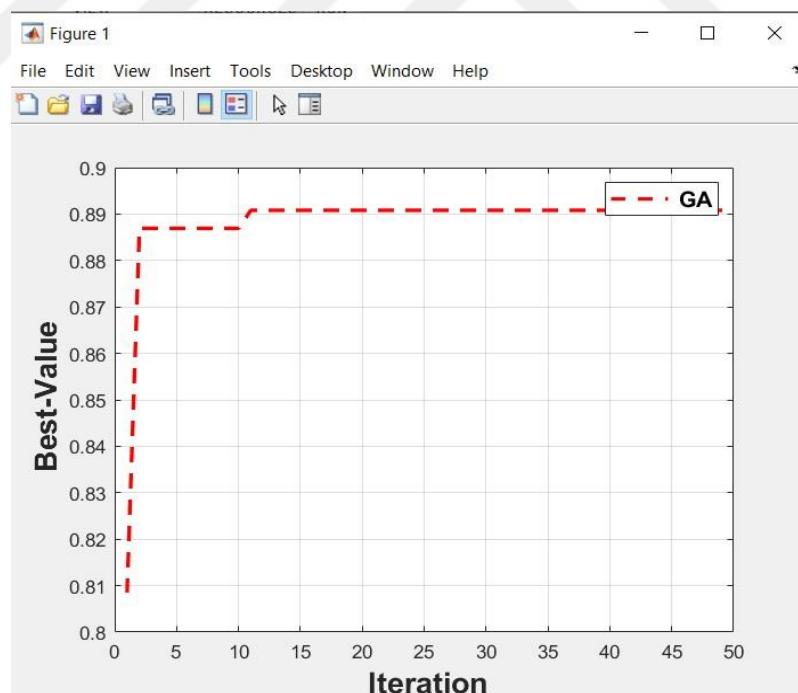


Figure 0.9: Problems Number one with its Treatment

Figure (4.10) show the treatment for the first problem which that the controlling for outside influences is the best solution with effectiveness almost 0.9.

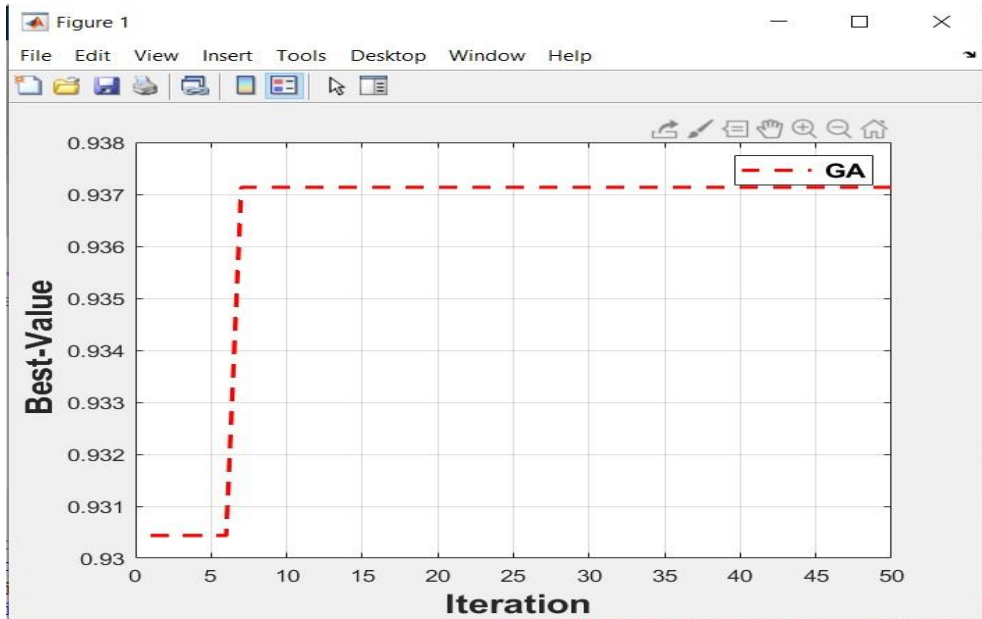


Figure 4.10: Problems Number two with its Treatment

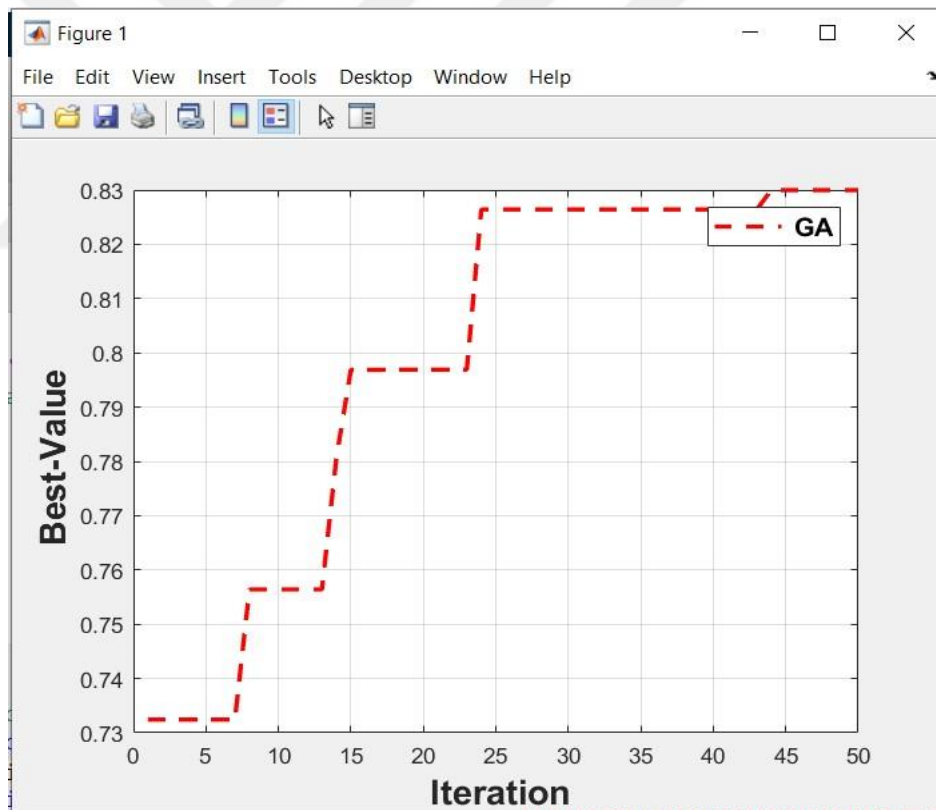


Figure 4.11: Problems Number three with its Treatment

After the selection, the procedure will continue to the other stages as the same manner.

Table 0.2: Problems Treatments with its Effects using GA in AS

Trouble	Xij	z	ci	Si	Sij	Period	cost	e	v
1	0.9	0.77	0.01	0.03	0.02	365	1.1E+09	0.9	0
2	0.9	0.79	0.01	0.03	0.02	365	1.1E+09	0.9	0
3	0.9	0.87	0.01	0.1	0.04	365	1.1E+09	0.8	0
4	0.9	0.87	0.01	0.2	0.1	365	1.1E+09	0.88	0

Table 0.3: Problems Treatments with its Effects using GA in Tendering

Trouble	Xij	z	ci	Si	Sij	Period	cost	E	V
1	0.9	0.77	0.01	0.03	0.02	365	1.1E+09	0.78	1.60E-08
2	0.9	0.79	0.01	0.03	0.02	365	1.1E+09	0.8	2.07E-07
3	0.9	0.87	0.01	0.1	0.04	365	1.1E+09	0.88	4.47E-08
4	0.9	0.87	0.01	0.2	0.1	365	1.1E+09	0.88	6.41E-08
5	0.99	0.89	0.2	0.1	0.015	365	1.1E+09	0.9	0.000381
6	0.99	0.79	0.1	0.34	0.2	365	1.1E+09	0.8	0.000131
7	0.99	0.79	0.001	0.05	0.02	365	1.1E+09	0.8	1.28E-08
8	0.99	0.88	0.019	0.04	0.025	365	1.1E+09	0.89	4.04E-07
9	0.99	0.77	0.01	0.03	0.02	365	1.1E+09	0.78	7.31E-06
10	0.99	0.87	0.01	0.1	0.02	365	1.1E+09	0.88	6.24E-06

Table 0.4: Problems Treatments with its Effects using GA in Contractor Selection

Trouble	Xij	Z	ci	Si	Sij	Period	cost	e	v
1	0.99	0.83	0.09	0.1	0.025	365	1.1E+09	0.84	0
2	0.99	0.83	0.12	0.1	0.05	365	1.1E+09	0.84	0
3	0.99	0.83	0.02	0.05	0.05	365	1.1E+09	0.84	0
4	0.99	0.89	0.01	0.2	0.15	365	1.1E+09	0.9	0
5	0.99	0.89	0.1	0.2	0.15	365	1.1E+09	0.9	0
6	0.99	0.91	0.1	0.25	0.15	365	1.1E+09	0.92	0

Table 0.5: Problems Treatments with its Effects using GA in Contract Forum

Trouble	Xij	z	ci	Si	Sij	Period	cost	E	V
1	0.99	0.83	0.09	0.1	0.02 5	365	1.1E+0 9	0.8 4	1.19E- 08
2	0.99	0.83	0.12	0.1	0.05	365	1.1E+0 9	0.8 4	1.04E- 08
3	0.99	0.83	0.02	0.0 5	0.05	365	1.1E+0 9	0.8 4	1.08E- 08
4	0.99	0.89	0.01	0.2	0.15	365	1.1E+0 9	0.9	0.00011 4
5	0.99	0.89	0.1	0.2	0.15	365	1.1E+0 9	0.9	9.29E- 07
6	0.99	0.911	0.1	0.2 5	0.15	365	1.1E+0 9	0.9 2	2.93E- 11
7	0.99	0.82	0.01 7	0.1	0.01 3	365	1.1E+0 9	0.8 3	1.65E- 05
8	0.99	0.89	0.01	0.2	0.15	365	1.1E+0 9	0.9	2.46E- 09
9	0.99	0.89	0.01	0.2	0.15	365	1.1E+0 9	0.9	3.64E- 05
10	0.99	0.84	0.07	0.1 5	0.13	365	1.1E+0 9	0.8 5	3.28E- 10

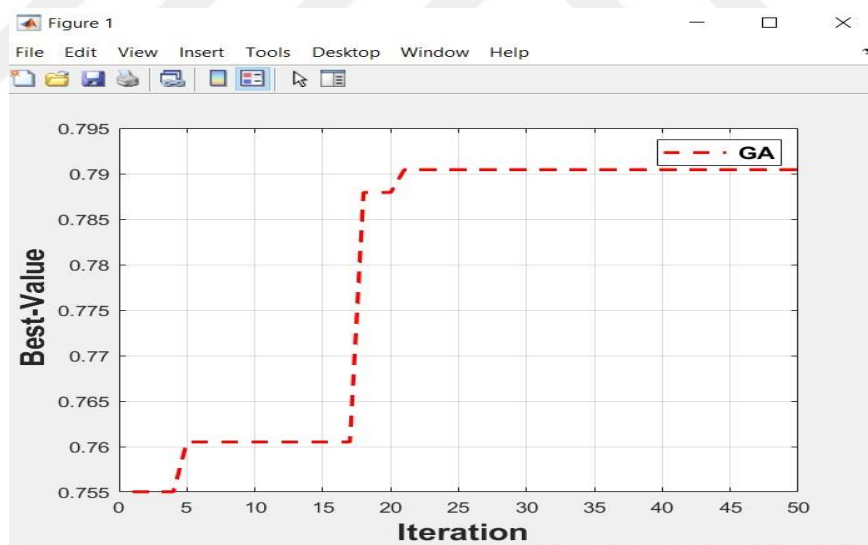


Figure 0.12: Problems with its Treatment in tendering

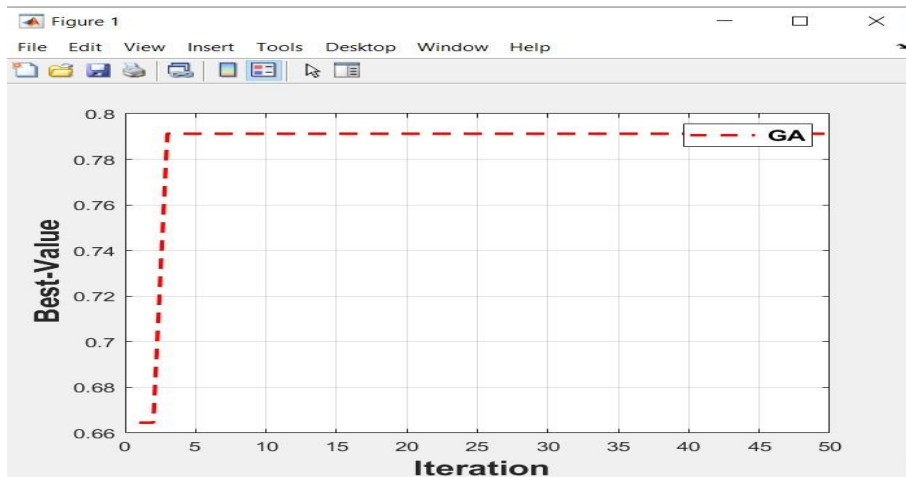


Figure 0.13: Problems with its Treatment in Contractor Selection

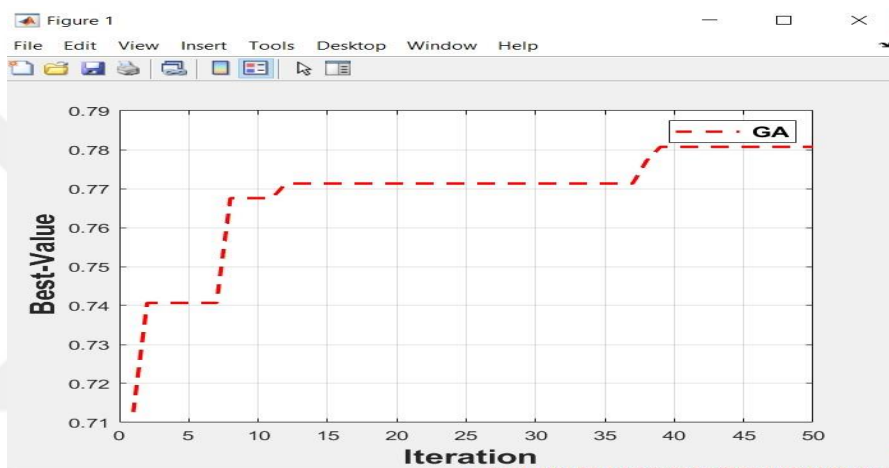


Figure 0.14: Problems with its Treatment in Contract Forum

From table (4.2) to (4.5) show the selection of the algorithm to the best solution with its information, the solutions is shown in the appendix.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

These pages include the conclusions based on work that has been done in addition to recommendation for the future work.

5.2 Conclusions

Based on the previous chapters, the conclusions can divide according the following:

1. Using several variables to pick contractors appears to be the most beneficial component.
2. Looking at it from the perspective of the contractor, lack of experience in contracts consider as the main reasons that lead to its failure, Fire and load redistribution cause time-dependent deformation of perimeter walls, consider the main reasons from the owner point of view.
3. Decision Tree show the best algorithm in prediction the steel performance in KNIME software while SVM is the best with MATLAB and both show good performance and the different return in the programming language for the both software.
4. The proposed system for merging the risk management with steel consider an efficient method to manage the risks in construction procedure.
5. GSA considers an effective tool for selecting the best response for the risks.

5.3 Recommendation

Base on the conclusions , the following can recommended:

1. Use of different criteria for steel failures based on different environment system.

2. Conduct a meeting for developing an accurate scope of work for the project and make it as the main condition.
3. The type of the implementation should be considered when designing any format of steel.
4. Integrate the risk management plan with every stage of the projects.

5.4 Future Work

The futures study as follow:

1. Study other material system such as concrete.
2. Develop smart tool that directly see the effectiveness.
3. Merge the risk management with cost management in the construction stages.

REFERENCES

- ieeexplore.ieee.org**, (August 8, 2022). "A Novel Approach Based on Support Vector Machine to Forecasting the Construction Project Cost | IEEE Conference Publication | IEEE Xplore." <https://ieeexplore.ieee.org/abstract/document/4725548>
- sciencedirect.com**, (June 23, 2022). "A Study of Stable Crack Growth in Thin SEC Specimens of 304 Stainless Steel by Computer Vision - ScienceDirect." <https://www.sciencedirect.com/science/article/abs/pii/S013794494002955>
- psycnet.apa.org**, (June 20, 2022). "A Technique for the Measurement of Attitudes. - PsycNET." <https://psycnet.apa.org/record/1933-01885-001>
- Al-Sobiei, Obaid Saad, David Ardit, and Gul Polat**. 2007. "Predicting the Risk of Contractor Default in Saudi Arabia Utilizing Artificial Neural Network (ANN) and Genetic Algorithm (GA) Techniques." <http://dx.doi.org/10.1080/01446190500041578> 23(4): 423–30. <https://www.tandfonline.com/doi/abs/10.1080/01446190500041578>.
- Alpsten, Göran**. 2017. "Causes of Structural Failures with Steel Structures." IABSE Workshop 2017: Ignorance, Uncertainty and Human Errors in Structural Engineering: 100–108.
- sciencedirect.com**, (June 23, 2022). "An Experimental Study on Strength and Serviceability of Reinforced and Steel Fibre Reinforced Concrete (SFRC) Continuous Composite Slabs - ScienceDirect." <https://www.sciencedirect.com/science/article/abs/pii/S0141029616000924>.
- onlinelibrary.wiley.com**, (June 23, 2022). "An Integrated Methodology for Assessment and Selection of the Project Risk Response Actions Seyedhoseini 2009 Risk Analysis Wiley Online Library." <https://onlinelibrary.wiley.com/doi/epdf/10.1111/j.1539-6924.2008.01187.x>.
- tandfonline.com**, (June 20, 2022). "Analysis of Variance: The Fundamental Concepts: Journal of Manual & Manipulative Therapy: Vol 17, No 2." <https://www.tandfonline.com/doi/abs/10.1179/jmt.2009.17.2.27E>
- Anaman, Kwabena Asomanin, and Charity Osei-Amponsah**. 2007. "Analysis of the Causality Links between the Growth of the Construction Industry and the Growth of the Macroeconomy in Ghana." *Construction Management and Economics* 25(9): 951–61.
- sciencedirect.com**, (August 8, 2022). "Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference Systems Approaches to Forecast the Meteorological Data for HVAC: The Case of Cities for Turkey-

ScienceDirect.” <https://www.sciencedirect.com/science/article/abs/pii/S0360544218306765>.

ASCE/SEI 7-10. 2013. American Society of Civil Engineers, Reston Minimum Design Loads and Associated Criteria for Buildings and Other Structures. Structural Engineering Institute of the American Society of Civil Engineering, Reston.

emerald.com, (June 23, 2022). “Assessment of Factors Affecting Maintenance Cost of Public School Facilities | Emerald Insight.” <https://www.emerald.com/insight/content/doi/10.1108/IJBPA-02-2019-0019/full/html>.

Barsom, J, and S Rolfe. 1999. “Fracture and Fatigue Control in Structures: Applications of Fracture Mechanics, Third Edition.” Fracture and Fatigue Control in Structures: Applications of Fracture Mechanics, Third Edition.

Basheer, I. A., and M. Hajmeer. 2000. “Artificial Neural Networks: Fundamentals, Computing, Design, and Application.” Journal of Microbiological Methods 43(1): 3–31.

link.springer.com, (June 23, 2022). “Basic Conceptual Model | SpringerLink.” https://link.springer.com/chapter/10.1007/0-387-23273-7_2?noAccess=true

Boadu, Elijah Frimpong, Cynthia Changxin Wang, and Riza Yosia Sunindijo. 2020. “Characteristics of the Construction Industry in Developing Countries and Its Implications for Health and Safety: An Exploratory Study in Ghana.” International Journal of Environmental Research and Public Health 17(11): 1–21.

sciencedirect.com, (June 23, 2022). “Breast Cancer Diagnosis Based on Feature Extraction Using a Hybrid of K-Means and Support Vector Machine Algorithms - ScienceDirect.” <https://www.sciencedirect.com/science/article/abs/pii/S0957417413006659>

Cagno, Enrico, Franco Caron, and Mauro Mancini. 2001. “Risk Analysis to Assess Completion Time of a Tram-Line.” Project Management 7 (January 2001): 26–31.

citeseerx.ist.psu.edu, (June 23, 2022). “CiteSeerX — Management of Project Risks in Logistics Development.” <http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.26.4935>

tandfonline.com, (June 23, 2022). “Combined Economic and Emission Dispatch Using Improved Backpropagation Neural Network: Electric Machines & Power Systems: Vol 28, No 1.” <https://www.tandfonline.com/doi/abs/10.1080/073135600268496>

Cramer, Christopher J., William B. Tolman, Klaus H. Theopold, and Arnold L. Rheingold. 2003. “Variable Character of O - O and M - O Bonding in Side-on (H₂) 1:1 Metal Complexes of O₂.” Proceedings of the National Academy of Sciences of the United States of America 100(7): 3635–40.

- ascelibrary.org**, (June 20, 2022). “Cyclic Void Growth Model to Assess Ductile Fracture Initiation in Structural Steels Due to Ultra Low Cycle Fatigue | Journal of Engineering Mechanics | Vol 133, No 6.”
<https://ascelibrary.org/doi/pdf/10.1061/%28ASCE%290733-9399%282007%29133%3A6%28701%29>.
- Debón, A., and J. Carlos Garcia-Díaz.** 2012. “Fault Diagnosis and Comparing Risk for the Steel Coil Manufacturing Process Using Statistical Models for Binary Data.” *Reliability Engineering & System Safety* 100: 102–14.
- Deng, Limei, and Ying Chang.** 2022. “Risk Management of Investment Projects Based on Artificial Neural Network.” *Wireless Communications and Mobile Computing*.
- Dewi, Dharu et al.** 2020. “Manufacturing Risk Identification in the Steel Industry.” *E3S Web of Conferences* 190: 1–11.
- tandfonline.com**, (June 23, 2022). “Early Warning Signs of It Project Failure: The Dominant Dozen: Information Systems Management: Vol 23, No4.”
<https://www.tandfonline.com/doi/pdf/10.1201/1078.10580530/46352.23.4.20060901/95110.4?needAccess=true>.
- ieeexplore.ieee.org**, (August 8, 2022). “Electricity Prices Forecasting Using Artificial Neural Networks | IEEE Journals & Magazine | IEEE Xplore.”
<https://ieeexplore.ieee.org/abstract/document/8291461>.
- link.springer.com**, (June 24, 2022). “Evaluation of Lead Release Potential of New Premise Plumbing Materials | SpringerLink.”
<https://link.springer.com/article/10.1007/s11356-018-2816-2>.
- sciencedirect.com**, (June 23, 2022). “Exposure Assessment to Engineered Nanoparticles Handled in Industrial Workplaces: The Case of Alloying Nano-TiO₂ in New Steel Formulations - ScienceDirect.”
<https://www.sciencedirect.com/science/article/abs/pii/S0021850216300118>.
- Faggiano, Beatrice, and Federico M. Mazzolani.** 2011. “Fire after Earthquake Robustness Evaluation and Design: Application to Steel Structures.” *Steel Construction* 4(3): 183–87.
<https://onlinelibrary.wiley.com/doi/full/10.1002/stco.201110025> (June 18, 2022).
- Feng, Jean, and Noah Simon.** 2017. “Sparse-Input Neural Networks for High-Dimensional Nonparametric Regression and Classification”: 1–37.
<http://arxiv.org/abs/1711.07592>.
- Firdaus, Muhammad, Anis Saggaff, and Mahmood Md Tahir.** 2017. “Finite Element Analysis of Composite Beam-to-Column Connection with Cold-Formed Steel Section.” *AIP Conference Proceedings* 1903 (November).
- Giannetti, Cinzia, and Rajesh S. Ransing.** 2016. “Risk Based Uncertainty Quantification to Improve Robustness of Manufacturing Operations.” *Computers and Industrial Engineering* 101: 70–80.
<http://dx.doi.org/10.1016/j.cie.2016.08.002>.

- jstor.org**, (June 23, 2022). “Greedy Function Approximation: A Gradient Boosting Machine on JSTOR.” <https://www.jstor.org/stable/2699986>
- onlinelibrary.wiley.com**, (June 20, 2022). “How Effective Are Neural Networks at Forecasting and Prediction? A Review and Evaluation – Adya 1998 – Journal of Forecasting – Wiley Online Library.” [https://onlinelibrary.wiley.com/doi/abs/10.1002/\(SICI\)1099-131X\(199809\)17:5/6%3C481::AID-FOR709%3E3.0.CO;2-Q](https://onlinelibrary.wiley.com/doi/abs/10.1002/(SICI)1099-131X(199809)17:5/6%3C481::AID-FOR709%3E3.0.CO;2-Q)
- books.google.com.tr**, (June 23, 2022). “Introduction to Neural Networks with Java – Jeff Heaton-كتاب Google.” [https://books.google.com.tr/books?hl=ar&lr=&id=Swlcw7M4uD8C&oi=fnd&pg=PR35&dq=Heaton,+J.+\(2008\).+Introduction+to+neural+networks+with+Java.+Heaton+Research,+Inc.&ots=TLy9SaaXu3&sig=bipljY7BIC6mdLE1V_diPfcT_Qs&redir_esc=y#v=onepage&q=Heaton%2C%20J.+\(2008\).+I](https://books.google.com.tr/books?hl=ar&lr=&id=Swlcw7M4uD8C&oi=fnd&pg=PR35&dq=Heaton,+J.+(2008).+Introduction+to+neural+networks+with+Java.+Heaton+Research,+Inc.&ots=TLy9SaaXu3&sig=bipljY7BIC6mdLE1V_diPfcT_Qs&redir_esc=y#v=onepage&q=Heaton%2C%20J.+(2008).+I)
- Jain, Rishee K., Kevin M. Smith, Patricia J. Culligan, and John E. Taylor.** 2014. “Forecasting Energy Consumption of Multi-Family Residential Buildings Using Support Vector Regression: Investigating the Impact of Temporal and Spatial Monitoring Granularity on Performance Accuracy.” *Applied Energy* 123: 168–78.
- Kallet, Richard H.** 2004. “How to Write the Methods Section of a Research Paper.” *Respiratory care* 49(10): 1229–32.
- Keerthi, S. Sathiya, Olivier Chapelle, and Dennis DeCoste.** 2006. “Building Support Vector Machines with Reduced Classifier Complexity.” *Journal of Machine Learning Research* 7: 1493–1515.
- Klöber-Koch, J., S. Braunreuther, and G. Reinhart.** 2017. “Predictive Production Planning Considering the Operative Risk in a Manufacturing System.” *Procedia CIRP* 63: 360–65. <http://dx.doi.org/10.1016/j.procir.2017.03.118>.
- Klöber-Koch, J., S. Braunreuther, and G. Reinhart** 2018. “Approach for Risk Identification and Assessment in A Manufacturing System.” *Procedia CIRP* 72: 683–88. <https://www.sciencedirect.com/science/article/pii/S2212827118303780> (June 24, 2022).
- dl.acm.org**, (June 20, 2022). “KNIME the Konstanz Information Miner: Version 2.0 and beyond: ACM SIGKDD Explorations Newsletter: Vol 11, No 1.” <https://dl.acm.org/doi/abs/10.1145/1656274.1656280>
- Kulkarni, P S, S N Londhe, and M C Deo.** 2017. “Journal of Soft Computing in Civil Engineering Artificial Neural Networks for Construction Management: A Review Article Info Abstract.” *Journal of Soft Computing in Civil Engineering* 1(2): 70. <http://creativecommons.org/licenses/by/4.0/>.
- Ma, Zhitong, Cantao Ye, Huashan Li, and Weibin Ma.** 2018. “Applying Support Vector Machines to Predict Building Energy Consumption in China.” *Energy Procedia* 152: 780–86. <https://www.sciencedirect.com/science/article/pii/S1876610218307902> (June 24, 2022).

- McKee, Heather R., and Michael D. Privitera.** 2017. "Stress as a Seizure Precipitant: Identification, Associated Factors, and Treatment Options." *Seizure* 44: 21–26. <http://dx.doi.org/10.1016/j.seizure.2016.12.009>.
- psycnet.apa.org,** (June 24, 2022). "Measuring Teacher Practices and Student Academic Engagement: A Convergent Validity Study. PsycNET." <https://psycnet.apa.org/record/2018-32193-001>
- Meharie, M. G., and Nagaraj Shaik.** 2020. "Predicting Highway Construction Costs: Comparison of the Performance of Random Forest, Neural Network and Support Vector Machine Models." *Journal of Soft Computing in Civil Engineering* 4(2): 103–12.
- Meseguer-Valdenebro, José L et al.** 2015. "Teaching Mechanical Properties of Different Steels for Engineering Students." *Journal of Materials Education* 37(May 2016): 3–4.
- sciencedirect.com,** (June 23, 2022). "Modelling Global Risk Factors Affecting Construction Cost Performance - ScienceDirect." <https://www.sciencedirect.com/science/article/abs/pii/S0263786302000170>
- Montano, Nicola et al.** 2015. "Advances in Diagnosis and Treatment of Trigeminal Neuralgia." *Therapeutics and Clinical Risk Management* 11: 289–99.
- Nagar, Dharakeshwari.** 2021. "American Welding Society Senior Certified Welding Inspector AWS-SCWI Certification Program for the Year – 2021 Online / Direct Seminar Authorized International Agency: Betz Engineering & Technology Zone Betz Engineering & Technology Zone About Us ...": 1–5.
- Negulescu, Oriana, and Elena Doval.** 2014. "Managers' Position Against Risk, Uncertainty and Efficiency within the Green Industry: Ten Questions." *Procedia - Social and Behavioral Sciences* 124: 339–43. <http://dx.doi.org/10.1016/j.sbspro.2014.02.494>.
- dl.acm.org,** (June 20, 2022 "Neural Networks | Guide Books." <https://dl.acm.org/doi/abs/10.5555/128933>). "Opportunities for Learning from Crises in Projects | Emerald Insight."
- emerald.com,** (June 23, 2022). <https://www.emerald.com/insight/content/doi/10.1108/1753837111120207/full/html>.
- Ormerod, Paul.** 2010. "Risk, Recessions and the Resilience of the Capitalist Economies." *RiskManagement* 12(1): 83–99.
- Padilla-llano, David A.** 2015. "A Framework for Cyclic Simulation of Thin-Walled Cold-Formed Steel Members in Structural Systems."
- Pierre, Sten Byström & Andreas.** 2003. "Risk Management in the Bidding Context."
- Poh, Clive Q.X., Chalani Udhyami Ubeynarayana, and Yang Miang Goh.** 2018. "Safety Leading Indicators for Construction Sites: A Machine Learning Approach." *Automation in Construction* 93: 375–86.

- tandfonline.com**, (June 20, 2022). "Prediction of Schedule Performance of Indian Construction Projects Using an Artificial Neural Network: Construction Management and Economics: Vol 29, No 9." <https://www.tandfonline.com/doi/abs/10.1080/01446193.2011.608691>
- tandfonline.com**, (August 8, 2022). "Project Risk Management Using Multiple Criteria Decision-Making Technique and Decision Tree Analysis: A Case Study of Indian Oil Refinery: Production Planning & Control: Vol 23, No 12." <https://www.tandfonline.com/doi/abs/10.1080/09537287.2011.586379>
- Proskovics, Roberts, Gail Hutton, Ralph Torr, and Matti Niclas Scheu**. 2016. "Methodology for Risk Assessment of Substructures for Floating Wind Turbines." *Energy Procedia* 94(January): 45–52. <http://dx.doi.org/10.1016/j.egypro.2016.09.189>.
- Reniers, G.** 2017. "On the Future of Safety in the Manufacturing Industry." *Procedia Manufacturing* 13: 1292–96. <https://doi.org/10.1016/j.promfg.2017.09.057>.
- degruyter.com**, (June 24, 2022). "Research on QR Image Code Recognition System Based on Artificial Intelligence Algorithm." <https://www.degruyter.com/document/doi/10.1515/jisys-2020-0143/html?lang=de>
- safetylit.org**, (June 24, 2022). "SafetyLit: Hospital and Pre-Hospital Triage Systems in Disaster and Normal Conditions; a Review Article." [https://www.safetylit.org/citations/index.php?fuseaction=citations.viewdetails&citationIds\[\]=citjournalarticle_527217_12](https://www.safetylit.org/citations/index.php?fuseaction=citations.viewdetails&citationIds[]=citjournalarticle_527217_12)
- Sheela, K. G., and S. N. Deepa**. 2014. "Selection of Number of Hidden Neurons in Neural Networks in Renewable Energy Systems." *Journal of Scientific and Industrial Research* 73(10): 686–88.
- Song, Yan Yan, and Ying Lu**. 2015. "Decision Tree Methods: Applications for Classification and Prediction." *Shanghai Archives of Psychiatry* 27(2): 130–35.
- sciencedirect.com**, (June 23, 2022). "Structural Behavior of Simple Steel Structures with Non-Uniform Longitudinal Temperature Distributions under Fire Conditions -ScienceDirect." <https://www.sciencedirect.com/science/article/abs/pii/S0379711202000097>
- books.google.com.tr**, (June 18, 2022). "Structural Steel Design to Eurocode 3 and AISC Specifications - Claudio Bernuzzi, Benedetto Cordova" [https://books.google.com.tr/books?hl=ar&lr=&id=kAcICgAAQBAJ&oi=fnd&pg=PP10&dq=Bernuzzi,+C.,+%26+Cordova,+B.+\(2016\).+Structural+steel+design+to+Eurocode+3+and+AISC+specifications.+John+Wiley+%26+Sons.+&ots=xEnfPnndD0&sig=57pW411n1TFjG0_LLgFluIhG574&redir_esc=y#v=onepage&q=Bernuzzi%2C+C.%2C+%26+Cordova%2C+B.+\(2016\).+Structural+steel+design+to+Eurocode+3+and+AISC+specifications.+John+Wiley+%26+Sons.&f=false](https://books.google.com.tr/books?hl=ar&lr=&id=kAcICgAAQBAJ&oi=fnd&pg=PP10&dq=Bernuzzi,+C.,+%26+Cordova,+B.+(2016).+Structural+steel+design+to+Eurocode+3+and+AISC+specifications.+John+Wiley+%26+Sons.+&ots=xEnfPnndD0&sig=57pW411n1TFjG0_LLgFluIhG574&redir_esc=y#v=onepage&q=Bernuzzi%2C+C.%2C+%26+Cordova%2C+B.+(2016).+Structural+steel+design+to+Eurocode+3+and+AISC+specifications.+John+Wiley+%26+Sons.&f=false)

- iugspace.iugaza.edu.ps**, (June 23, 2022). “Support Vector Machine Cost Estimation Model for Road Projects.”
<https://iugspace.iugaza.edu.ps/handle/20.500.12358/26544>
- tandfonline.com**, (June 20, 2022). “The Use of Artificial Neural Networks in Construction Management: A Review: Construction Management and Economics: Vol 14, No 5.” <https://www.tandfonline.com/doi/abs/10.1080/014461996373296>
- Tiwari, Abhishek, and Arvind K.T. Sekhar**. 2007. “Workflow Based Framework for Life Science Informatics.” *Computational Biology and Chemistry* 31(5–6): 305–19.
- Tupa, Jiri, Jan Simota, and Frantisek Steiner**. 2017. “Aspects of Risk Management Implementation for Industry 4.0.” *Procedia Manufacturing* 11(June): 1223–30. <http://dx.doi.org/10.1016/j.promfg.2017.07.248> (July 1, 2022).
- sciencedirect.com**, (June 23, 2022). “Use and Benefits of Tools for Project Risk Management - ScienceDirect.”
<https://www.sciencedirect.com/science/article/abs/pii/S0263786399000368>
- Yadav, Surjeet Kumar, and Saurabh Pal**. 2012. “Data Mining: A Prediction for Performance Improvement of Engineering Students Using Classification.” 2(2): 51–56. <http://arxiv.org/abs/1203.3832>.
- Yockey, Ronald D**. 2016. “Validation of the Short Form of the Academic Procrastination Scale.” *Psychological reports* 118(1): 171–79.
- ncbi.nlm.nih.gov**, (June 23, 2022). <http://www.ncbi.nlm.nih.gov/pubmed/29693513>
- Zetsche, Dirk Andreas, and Tsany Ratna Dewi**. 2018. “The Paradoxical Case Against Interest Rate Caps for Microfinance And: How FinTech and RegTech Resolve the Dilemma.” *SSRN Electronic Journal*.

APPENDIX

Appendix-A: Provide The MATLAB Codes

```
function [Y, XF, AF] = MY Neural Network Function(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 02-Aug-2022 22:58:26.
%
% [Y] = MY Neural Network Function(X,~,~) takes these arguments:
%
% X = 1xTS cell, 1 inputs over TS time steps
% Each X{1,ts} = 18xQ matrix, input #1 at time step TS.
%
% and returns:
% Y = 1xTS cell of 1 outputs over TS time steps.
% Each Y{1,ts} = 1xQ matrix, output #1 at time step TS.
%
% where Q is number of samples (or series) and TS is the number of time steps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.keep = [1 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17];
x1_step2.xoffset = [1;1;2.7;1;2.1;2.5;2.5;2.5;2.5;2.5;2.5;3;3;3];
x1_step2.gain =
[2;2;0.0484261501210654;2;1.05263157894737;1.17647058823529;1.17647058823
529;1.17647058823529;1.17647058823529;1.17647058823529;1.17647058823529;
1.33333333333333;2;2;2];
x1_step2.ymin = -1;

% Layer 1
b1 = [-1.6668626851514711795;-
1.253686693798228724;0.90973530682528602753;-0.60735209718344207452;-
0.12590532281255553682;-0.16154628179309635239;-
0.51883071549071124728;0.82915129741149817821;1.2124716614714827756;1.5
953540371467176406];
IW1_1 = [0.45405348806826500985 -0.47956973951846293414
0.28231507942446543158 0.27629198628384876724 -0.088949522298705230305 -
0.30917958522181532288 0.41252286129171955587 0.56219149239228183301 -
0.18308039384060192933 -0.60337815035849307055 -0.47182345069111708558 -
0.12345711563629270524 -0.47664821797120182634 -0.13608374603043152384
```

0.56539157869540435097 -0.10696609087736777544;0.36772361464349728744
0.56397423868626839205 -0.48314354544121357327 -0.6269628822361466014 -
0.12351923076791529454 0.19695728191123756945 -0.42257420332665340812 -
0.29334053896048833954 0.34154169102493409094 -0.51394247904903123114
0.30130002164088104388 -0.42670647173121745155 0.51387109954551224433
0.50325085346138132003 0.11264159226387189527 -0.44031339166776040095;-
0.33319479964541232064 0.72586309272298876749 0.57286048177317261398 -
0.39438254104530878763 0.26271114388496941139 0.11163993451995563033
0.22946223695428086264 0.38232921839464617531 0.065008903106053422816 -
0.010457360080927270707 -0.31470051796154119295 -0.22901538375696217642
-0.78665407442767176782 -0.41359871567471206966 -0.28636671789848916481
0.56233315190660004834;0.44410887766152223888 0.16576889275942155444
0.69929118246833232853 -0.5446593102479759807 0.34370965842895717657 -
0.62350188407789541856 0.028565616190460718649 -0.52924432853847946934 -
0.1186021202306650757 0.18910413109709145463 -0.14702060880337175508
0.72171793217902724393 0.38835200941195296975 -0.075875315589609554356
0.16068754398675494377 0.54091435359902928504;-0.15127549059580253088
0.81088396415105923332 0.21752942832756308467 -0.33943231304417254002 -
0.38332317622148165404 -0.54688730878306301975 0.69967156509611794224
0.56919879763787872839 0.55429094984416305003 0.57506198751162984628 -
0.37395720405264598618 -0.11084330383407253739 0.2872215295929492207 -
0.42667686490306910851 0.015105507041667479151
0.049846741316626544394;-0.8536589039665996026 -
0.0061689644903395457476 0.43408407040436169932 0.254991277231811031 -
0.15274988952988016733 -0.44591524834563511792 0.46678591860125867585 -
0.4353355113653170072 -0.52167848673511962865 -0.73157412742710248299 -
0.096129680567153180659 0.66693998547042931957 0.09599751010339191426 -
0.31725392087491316451 -0.5030799734381461441 -0.16514614329760723965;-
0.35774780258092353513 -0.32276402149026106603 0.30131052083200121627
0.16673085775644672091 -0.09313418725303014567 0.89043637177742063216
0.15191411929831385996 -0.43591087660709787466 0.47385469470523688962
0.16815188659058016851 -0.32819397631341173938 -0.20387529604606316469 -
0.3404777050736685351 0.44876577046213161903 -0.40008707167159285323 -
0.28922405213673524349;-0.13723393619650720021 0.60155306390790463933 -
0.17556036568207850079 -0.6627909160527973853 -0.1760959628721918413 -
0.025589804691915934987 -0.8737075975813453077 -0.26146209814692789042
0.50878172824251888251 0.073066988739392518815 0.35608000439726589237
0.77990118093785265607 -0.2112486273326096009 0.20200478411190228578 -
0.77041824485278953549 0.5129747691222239598;0.68908735514110686093
0.4118639934877617037 0.23300432706206189448 0.57124347669063724187
0.2398836880790728987 0.1323157541960704453 -0.46748513000607971879
0.13711816433533502435 -0.19038985730637275617 -0.70270583049467150172
0.23883218968408734262 -0.59906919640817135608 -0.4263266138139758521
0.075908137083952734181 -0.47114785635314426759 -
0.22824630382605068379;0.6775372394303483814 0.77319683011065432066 -
0.39031615471645936255 -0.43542203988416156024 0.33711753187134779752 -
0.59020904935773488287 -0.24341625227897611961 -0.032613660409400217766
0.092857577411567415737 -0.21334398582454200399 0.33220544675704688498
0.00072093595185777903378 0.32014578125212861393 -
0.49406783035760631906 -0.29396643703868574615 -0.57080673035222295741];

```

% Layer 2
b2 = -0.31293607534468226294;
LW2_1 = [0.1452981871482836862 -0.46484180536792618632 -
0.0039178819975330680947 -0.16738418679593664029 -
0.31491958898483390916 -0.67826874562101502342 0.31311459285569698263
1.1341306784493874193 0.095721164506762435042 -0.63596218744942745182];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.865800865800866;
y1_step1.xoffset = 1.69;

% ===== SIMULATION =====

% Format Input Arguments
Is Cell X = is cell(X);
If ~is Cell X
    X = {X};
End

% Dimensions
TS = size(X, 2); % time steps
If ~is empty(X)
    Q = size(X {1}, 2); % samples/series
Else
    Q = 0;
End

% Allocate Outputs
Y = cell (1, TS);

% Time loop
For TS=1: TS

% Input 1
Temp = remove constant rows - apply (X {1,ts},x1_step1);
Xp1 = map min max - apply (temp, x1_step2);

% Layer 1
a1 = tan sig-apply (rep mat (b1, 1, Q) + IW1_1*Xp1);

% Layer 2
a2 = rep mat (b2,1, Q) + LW2_1*a1;

% Output 1
Y{1,ts} = map min max-reverse(a2,y1_step1);
End

% Final Delay States

```

```

XF = cell (1, 0);
AF = cell (2, 0);

% Format Output Arguments
if ~is Cell X
Y = cell2mat(Y);
End

% ===== MODULE FUNCTIONS =====

% Map Minimum and Maximum Input Processing Function
Function y = map min max-apply(x, settings)
    y = bsx fun(@minus, x, settings. X offset);
y = bsx fun(@times, y, settings. gain);
y = bsx fun(@plus, y, settings. ymin);
End

% Remove Constants Input Processing Function
Function y = remove constant rows-apply(x, settings)
y = x (settings. keep,:);
End

% Sigmoid Symmetric Transfer Function
Function a = tan sig-apply (n,~)
a = 2 ./ (1 + exp (-2*n)) - 1;
End

% Map Minimum and Maximum Output Reverse-Processing Function
Function x = map min max-reverse(y, settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
End

Function [y1] = My Neural Network Function(x1)
%MY NEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 02-Aug-2022 22:58:41.
%
% [y1] = my Neural Network Function(x1) takes these arguments:
%   x = 18xQ matrix, input #1
% and returns:
%   y = 1xQ matrix, output #1
%   where Q is the number of samples.

%#ok<*RPMT0>

```

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1

```
x1_step1.keep = [1 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17];
x1_step2.xoffset = [1;1;2.7;1;2.1;2.5;2.5;2.5;2.5;2.5;2.5;3;3;3];
x1_step2.gain =
[2;2;0.0484261501210654;2;1.05263157894737;1.17647058823529;1.17647058823
529;1.1
7647058823529;1.17647058823529;1.17647058823529;1.17647058823529;1.33333
333333333;2;2;2;2];
x1_step2.ymin = -1;
```

% Layer 1

```
b1 = [-1.6668626851514711795;-
1.253686693798228724;0.90973530682528602753;-0.60735209718344207452;-
0.12590532281255553682;-0.16154628179309635239;-
0.51883071549071124728;0.82915129741149817821;1.2124716614714827756;1.5
953540371467176406];
IW1_1 = [0.45405348806826500985 -0.47956973951846293414
0.28231507942446543158 0.27629198628384876724 -0.088949522298705230305 -
0.30917958522181532288 0.41252286129171955587 0.56219149239228183301 -
0.18308039384060192933 -0.60337815035849307055 -0.47182345069111708558 -
0.12345711563629270524 -0.47664821797120182634 -0.13608374603043152384
0.56539157869540435097 -0.10696609087736777544;0.36772361464349728744
0.56397423868626839205 -0.48314354544121357327 -0.6269628822361466014 -
0.12351923076791529454 0.19695728191123756945 -0.42257420332665340812 -
0.29334053896048833954 0.34154169102493409094 -0.51394247904903123114
0.30130002164088104388 -0.42670647173121745155 0.51387109954551224433
0.50325085346138132003 0.11264159226387189527 -0.44031339166776040095;-
0.33319479964541232064 0.72586309272298876749 0.57286048177317261398 -
0.39438254104530878763 0.26271114388496941139 0.11163993451995563033
0.22946223695428086264 0.38232921839464617531 0.065008903106053422816 -
0.010457360080927270707 -0.31470051796154119295 -0.22901538375696217642
-0.78665407442767176782 -0.41359871567471206966 -0.28636671789848916481
0.56233315190660004834;0.44410887766152223888 0.16576889275942155444
0.69929118246833232853 -0.5446593102479759807 0.34370965842895717657 -
0.62350188407789541856 0.028565616190460718649 -0.52924432853847946934 -
0.1186021202306650757 0.18910413109709145463 -0.14702060880337175508
0.72171793217902724393 0.38835200941195296975 -0.075875315589609554356
0.16068754398675494377 0.54091435359902928504;-0.15127549059580253088
0.81088396415105923332 0.21752942832756308467 -0.33943231304417254002 -
0.38332317622148165404 -0.54688730878306301975 0.69967156509611794224
0.56919879763787872839 0.55429094984416305003 0.57506198751162984628 -
0.37395720405264598618 -0.11084330383407253739 0.2872215295929492207 -
0.42667686490306910851 0.015105507041667479151
0.049846741316626544394;-0.8536589039665996026 -
0.0061689644903395457476 0.43408407040436169932 0.254991277231811031 -
0.15274988952988016733 -0.44591524834563511792 0.46678591860125867585 -
0.4353355113653170072 -0.52167848673511962865 -0.73157412742710248299 -
0.096129680567153180659 0.66693998547042931957 0.09599751010339191426 -
```

```

0.31725392087491316451 -0.5030799734381461441 -0.16514614329760723965;-
0.35774780258092353513 -0.32276402149026106603 0.30131052083200121627
0.16673085775644672091 -0.09313418725303014567 0.89043637177742063216
0.15191411929831385996 -0.43591087660709787466 0.47385469470523688962
0.16815188659058016851 -0.32819397631341173938 -0.20387529604606316469 -
0.3404777050736685351 0.44876577046213161903 -0.40008707167159285323 -
0.28922405213673524349;-0.13723393619650720021 0.60155306390790463933 -
0.17556036568207850079 -0.6627909160527973853 -0.1760959628721918413 -
0.025589804691915934987 -0.8737075975813453077 -0.26146209814692789042
0.50878172824251888251 0.073066988739392518815 0.35608000439726589237
0.77990118093785265607 -0.2112486273326096009 0.20200478411190228578 -
0.77041824485278953549 0.5129747691222239598;0.68908735514110686093
0.4118639934877617037 0.23300432706206189448 0.57124347669063724187
0.2398836880790728987 0.1323157541960704453 -0.46748513000607971879
0.13711816433533502435 -0.19038985730637275617 -0.70270583049467150172
0.23883218968408734262 -0.59906919640817135608 -0.4263266138139758521
0.075908137083952734181 -0.47114785635314426759 -
0.22824630382605068379;0.6775372394303483814 0.77319683011065432066 -
0.39031615471645936255 -0.43542203988416156024 0.33711753187134779752 -
0.59020904935773488287 -0.24341625227897611961 -0.032613660409400217766
0.092857577411567415737 -0.21334398582454200399 0.33220544675704688498
0.00072093595185777903378 0.32014578125212861393 -
0.49406783035760631906 -0.29396643703868574615 -0.57080673035222295741];

```

```

% Layer 2

```

```

b2 = -0.31293607534468226294;
LW2_1 = [0.1452981871482836862 -0.46484180536792618632 -
0.0039178819975330680947 -0.16738418679593664029 -
0.31491958898483390916 -0.67826874562101502342 0.31311459285569698263
1.1341306784493874193 0.095721164506762435042 -0.63596218744942745182];

```

```

% Output 1

```

```

y1_step1.ymin = -1;
y1_step1.gain = 0.865800865800866;
y1_step1.xoffset = 1.69;

```

```

% ===== SIMULATION =====

```

```

% Dimensions

```

```

Q = size(x1, 2); % samples

```

```

% Input 1

```

```

xp1 = remove constant rows-apply (x1, x1_step1);
xp1 = map min max-apply (xp1, x1_step2);

```

```

% Layer 1

```

```

a1 = tan sig-apply (rep mat (b1,1,Q) + IW1_1*xp1);

```

```

% Layer 2

```

```

a2 = rep mat (b2,1, Q) + LW2_1*a1;

```

```

% Output 1
y1 = map min max-reverse (a2,y1_step1);
End

% ===== MODULE FUNCTIONS =====

% Map Minimum and Maximum Input Processing Function
Function y = map min max-apply(x, settings)
y = bsx fun (@minus, x, settings. X offset);
y = bsx fun (@times, y, settings. gain);
y = bsx fun (@plus, y, settings. Y min);
End

% Remove Constants Input Processing Function
Function y = remove constant rows-apply(x, settings)
y = x (settings. keep,:);
End

% Sigmoid Symmetric Transfer Function
Function a = tan sig-apply (n,~)
a = 2 ./ (1 + exp (-2*n)) - 1;
End

% Map Minimum and Maximum Output Reverse-Processing Function
Function x = map min max-reverse (y, settings)
x = bsxfun(@minus, y, settings. Y min);
x = bsxfun(@divide, x, settings. gain);
x = bsxfun(@plus, x, settings. X offset);
End

```

RESUME

Zina Talib FADHIL

EDUCATIONAL INFORMATION:

- 2003-2004, he graduated from Baghdad University of Technology, Department of Metallurgical Engineering, Production and Metallurgical Engineering with a bachelor's degree.
- Between the years 2020-2022, I studied Engineering Management at Istanbul Gedik University.

