AI-BASED PREDICTIVE MODELING FOR SAFETY ASSESSMENT IN CONSTRUCTION INDUSTRY

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ABSTRACT

AI-BASED PREDICTIVE MODELING FOR SAFETY ASSESSMENT IN CONSTRUCTION INDUSTRY

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The predictive modeling is a popular research area among the researchers. Most of the proposed models cannot provide a solution for the needs of every contractor as the existing ones served for only a specific task. Therefore, using these systems become inevitably burden on contractors due to its difficulty of use. The thesis aims to provide an AI-based safety assessment strategy for every project. The assessment strategy encapsulated the detection of trends in safety failures and corrective actions to prevent them. The study covered two parts. The first part explained a hybrid model of ANN and Fuzzy Set Theory, based on over 17,000 incident cases. The ANN model achieved to forecast 84% incident within 90% confidence, and integrating the fuzzy inference system increased the prediction performance slightly. The second part introduced the use of LCCA as a Big Data analytics to address the heterogeneity problem. Although the model employed around 5,000 cases for training, the prediction performance was quite similar to the first part. Besides, this part included a comparison of CBR and ANN to reveal which approach demonstrated better compliance with the incident data. Results exhibited the inclusion of big data analytic improved the prediction performance despite a significant decrease in sample size. The study advanced with the fatal accident analysis to promote prevention measures. Measures offered attribute-based corrections by examining the relationships between the attributes.

Ultimately, the proposed methodology can aid construction industry professionals in analyzing prospective safety problems using the large-scale collected data during the construction.

Keywords: Predictive Modeling, Case-Base Reasoning, Artificial Neural Networks, Accident Prevention

ÖZ

İNŞAAT ENDÜSTRİSİNDE GÜVENLİK DEĞERLENDİRMESİ İÇİN YAPAY ZEKA TABANLI TAHMİN MODELİ

Ayhan, Bilal Umut
Yüksek Lisans, İnşaat Mühendisliği
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Tahmine dayalı modelleme, araştırmacılar arasında popüler bir tekniktir. Günümüze kadar olan çalışmalarda, kurulan modellerin çoğu, sadece belirli bir amaca hizmet ettiğinden dolayı, bazı durumlarda ihtiyaca cevap verememektedir. Dolayısıyla, ilgili modellerin kullanımı müteahhitler üzerinden kaçınılmaz bir yük haline gelmektedir. Sunulan bu tez ile, her projede uygulanabilecek Yapay Zeka tabanlı güvenlik değerlendirme planı geliştirilmesi amaçlanmıştır. Önerilen plan güvenlik ihlali eğilimlerini ve bunların önlenmesi için düzeltici faaliyetlerin ne olduğunu tespit edilmesini kapsamıştır. Çalışma iki bölümden oluşmaktadır. İlk kısım, 17.000'den fazla olaya dayanan, Yapay Sinir Ağları (YSA) ve Bulanık Küme Teorisi hibrit modelinden oluşmaktadır. YSA modeli, kazaların %84'ünü %90 güven ile tahmin edebilmektedir. Bulanık mantığa dayalı yorumlama sistemi ise tahmin performansını az da olsa arttırmaktadır. İkinci kısımda, veri içerisindeki heterojenlik problemi, Örtük Sınıf Analizi'nin (ÖSA) büyük veri analitiği yöntemi olarak kullanılması ile çözülmeye çalışılmıştır. Model eğitimi için birinci kısımdaki uygulamanın aksine, 5.000 civarında kaza verisi kullanılsa da, elde edilen performans ilk kısma oldukça yakın olmuştur. Ayrıca bu kısım Veri Tabanlı Çıkarımsama (VTÇ) ve YSA tahmin modellerinin karşılaştırmasını da içermektedir. Bu sayede iş kazası verilerine hangi modelin daha iyi uyum sağlayacağı gözlemlenecektir. Sonuçlar, büyük veri analitiklerinin dahil edilmesinin veri sayısında önemli bir düşüş olmasına rağmen tahmin performansını iyileştirdiğini göstermiştir. Çalışma kaza önlemlerini teşvik etmek için ölümcül kaza analizi ile ilerlemiştir. İlgili çalışma, değişkenler arasındaki ilişkileri inceleyerek, değişkenlere dayalı kaza önleyici unsurlar sunmaktadır. Sonuç olarak, önerilen çalışma ile inşaat endüstrisi profesyonellerine inşaat sırasında toplanan büyük ölçekli verileri kullanarak olası güvenlik problemlerini analiz etmede yardımcı olması amaçlanmaktadır.

Anahtar Kelimeler: Tahmine Dayalı Modelleme, Veri Tabanlı Çıkarımsama, Yapay Sinir Ağları, Kaza önleme

Dedicated to my beloved family…

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LIST OF ABBREVIATIONS

ABBREVIATIONS	
AHP	Analytical Hierarchical Process
AI	Artificial Intelligence
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
ARM	Association Rule Mining
BIC	Bayesian Information Criterion
CAIC	Consistent Akaike Information Criterion
CBR	Case-based Reasoning
CI	Consistency Index
CR	Consistency Ratio
GA	Genetic Algorithm
IOSH	Institution of Occupational Health and Safety
LCCA	Latent Class Clustering Analysis
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
NEBOSH	National Examination Board in Occupational Health and Safety
OHS	Occupational Health and Safety
RI	Random Consistency Index
ROF	Rate of Fatality

Rsq	R square
SMS	Safety Management Systems
SOR	Safety Reporting System

CHAPTER 1

INTRODUCTION

The success of the project activities in the construction projects depends on the crafting force more than automation, unlike the other industries because of its nature. The existence of crafting leads construction projects to be prone to workplace failures. For this reason, OHS is becoming one of the main pillars of construction projects for successful completion.

The construction projects have a significant number of uncertainties inherently, and the increase in complexity of the project may bring along the crucial problems in every step of the construction process. The megaprojects referring to long-lasting projects that create an enduring value can be an excellent example of the complexity. Healthcare systems and public transportation solutions are one of the megaprojects examples regarding their cost as well as scope (Lehtinen et al., 2019; Sergeeva & Zanello, 2018). The cost of the megaprojects is generally more than a million dollars, and they provide the needs and interests of the people for an extended period as well (Flyvbjerg, 2014).

However, these projects comprise a wide range of work items (Chong & Low, 2014) that make OHS management critical. The origin of the safety problems relies on the lack of communication between the workers and managers, and the complexity comes with many managerial conflicts between the stakeholders (Jia et al., 2011). Therefore, the high level of uncertainty exists among the project participants, and it creates particular problems like safety issues over time.

Moreover, the pursuit of completing the projects without delay stimulates the failures in the physical-mental conditions of the workers. Employers demand extra effort for an increase in productivity, so workers are working in a stressful environment that also triggers the accidents. Thus, construction projects are considered as one of the most dangerous working places in many countries due to having still frequent non-fatal and fatal events (Kang et al., 2017; Rubio-Romero et al., 2013).

The other cause of safety failures is coming from the problems in adaptation to safety policies. The adaptation level of countries to safety policies affects the rate of fatality, especially for companies working in several different regions. There is no viable system to predict the safety risk before the start of the project, depending on the country, project type, specific project manager, and subcontractors. Taking lessons from previous accidents remains weak due to having no accident analysis systems in a particular project.

Some statistics in literature will be given to touch upon the overall position of the construction industry in safety. The construction industry has the highest potential since the fatality and disabling rate is three times greater than the others (International Labor Organization, 2016). When delving into a deeper in the database of the International Labor Organization (2017), the observation rate of the "Day-lost" cases is more than 1.3 million annually, and the rate of the fatality (ROF) was equal to 6 for 100,000 workers. According to Zhang et al. (2013), over 26,000 workers died throughout the last 20 years. For example, Dong et al. (2013) stated that the fatality rate still escalated between the years of 2011 and 2012 in the United States, and more than 900 fatal cases occurred there (Bureau of Labor Statistics, 2016). Besides, almost 30% of the fatalities associated with the construction industry, even though the workforce in construction referred to only 5% of the total in the United Kingdom (Health and Safety Executive, 2014). Likewise, work incidents were over one-third of all industries throughout the last years in China (Tam et al., 2006; Li & Wang 2004; Liao & Perng 2008).

While considering the countries which are on a different level of adaptation to safety policies, there is a massive gap between them. Turkey is one of the countries that has been trying to adopt safety requirements. ROF values were calculated for the years between 2007 and 2016, and the results were considerably high as 22.35, whereas this ratio was just equal to 6.2 for the manufacturing industry (International Labor Organization 2017). Turkkan and Pala (2016) also indicated the seriousness of the increase in a fatality. They underlined that ROF in Turkey sloped to the over 25 from 8.6 between the years of 1998 and 2011. Similar to Turkey, the Russian Federation suffers from construction failures. ROF was equal to 18.0 for the construction industry in Russia (International Labor Organization, 2017).

On the contrary, ROF of Sweden and the United Kingdom were considerably below from the countries indicated above, but the construction industry led the others for fatal events (International Labor Organization 2017).

The information indicated above shows that the construction industry still requires a comprehensive mechanism to prevent construction accidents (Wu et al., 2010; Hallowell & Gambatese 2009; Hinze et al., 1998; Abdelhamid & Everett, 2000). At this point, data collection becomes fundamental elements as most of the problems such as cost overrun, safety, and quality issues are mainly associated with the inadequate tracking and record-keeping mechanism (Flyvbjerg et al., 2003; Ayhan & Tokdemir, 2019a; 2019b). One of the main reasons why accidents cannot be prevented is that accidents are not kept under records in every aspect. Most of the OHS professionals do not give attention to recording "At-risk behavior" and "Near misses" along with the construction sites. Instead, they should be promoted to record every detail to develop massive databases, i.e., big data. This data enables professionals to overcome existing and future problems, but the massiveness of it makes the process overwhelmingly complicated. Therefore, big data bring along its complexity, which makes the understanding process of data difficult (Vidal et al., 2015). Big data analytics have been applied to the data structure to address the heterogeneity of the data. Some examples of it can be listed as data mining, data statistics, and machine learning techniques (Bilal et al., 2016).

Construction projects, especially for the megaprojects, contain a high number of a complex process which creates an environment for safety failures. Safety problems may incline additional expenses, including healthcare, delays, and penalties (Ayhan & Tokdemir, 2019b). Solutions for safety problems require systematic investigations of incident characteristics to develop a proactive prevention system that can signify the sign of risk before. Existing studies are still limited, although researchers introduced enormous useful models for maintaining safety throughout the workplaces. Most of them fail to exhibit the dynamic nature of the projects appropriately. Moreover, some of the models already developed are not based on factual data. That means existing models are suffering from utilizing a limited source of cases and attributes.

The ultimate goal of this thesis is to prevent construction incidents by developing a systematic safety assessment mechanism that includes the data preparation, prediction, and prevention stages. In this concept, over 18,000 incidents were collected anonymously from the construction companies. The thesis examined this incident data into two different stages.

The first part comprises the first data preparation stages and the prediction stages. In this part, the complete dataset was taken into account, and the list of the attributes was determined. The Delphi technique was applied by the participation of the experts to do so. Later, a hybrid model based on Artificial Neural Network (ANN) and Fuzzy Set theory was constituted to predict the outcome of the incidents. Naive preventative actions were introduced in advance. As mentioned before, the big data has its complexity inside. That means there exists much more bulk data, which leads to heterogeneity along with the dataset. In the first part, any of the big data analytics was implemented; thus, vagueness may result in the prediction outcomes, even the use of the Fuzzy Set Theory.

In the second stage, the dataset was reduced by taking only incident cases that occurred in the megaprojects. Latent Class Clustering Analysis (LCCA) as big data analytics was applied to reach up the same achievement in prediction performance. The new list of attributes was obtained with the help of the previous studies and the experts. Besides, more information is getting into considered accordingly. As well as ANN, Case-based Reasoning (CBR) was getting into the trial for comparison. Lastly, the fatal accident analysis was handled from the fatal accidents that existed in the database, and preventative actions were measured.

Ultimately, the present thesis is seeking out how the prediction performance of the AI-based predictive model as well as preventing construction accidents. Besides, the proposed method helps the construction industry professionals to forecast the severity of the incidents by utilizing the data collected and aims to stress the importance of record-keeping by anticipating problems and taking precautions.

This thesis was structured as follows. Chapter 2 described the literature review on safety studies. The content of the literature review fragmented regarding the type of the study, and it focused on studies that utilized a predictive model. Chapter 3 presented the literature review on the techniques used in this thesis, primarily ANN and CBR, as a predictive model. Besides, the methodology of the research was introduced in detail. The construction of a predictive model, data preparation, including data process, were represented. Chapter 4 captured the analysis part and constituted models were tested regarding their properties. The study advanced with Chapter 5, where discussion of results took place. Chapter 6 explained the preventative measures determined within the respect of this thesis. Finally, Chapter 7 provided a conclusion of the study and underlined significant findings and discussion as well as the limitations and future works.

CHAPTER 2

LITERATURE REVIEW

The seriousness of accidents' outcomes has interested researchers' attention for decades. They have put a great deal of effort into learning the characteristics of accidents by identifying the attributes. Understanding the underlying correlations among the trigger attributes of an accident will accommodate a tremendous opportunity to counter work-related safety failures common to construction sites (Winge et al., 2019).

Researchers have studied the safety concern in the construction industry under several popular topics. Although their focus is to prevent accidents, the methodology of them tends to alternate in each research.

The studies have developed many analytical or expert models regarding safety problems, but the success of the proposed model depends on perceiving the correlations between the attributes.

A safety assessment is a comprehensive and well-organized examination of all features of risks to health and safety linked with significant incidents. The literature involves substantial researches that tabulate safety assessment and management. The following sections involve the studies that concentrate on popular topics among the researchers.

2.1. Safety risk

One of the most common topics on safety concerns is safety risks based on construction projects. Gürcanlı and Müngen (2009) assessed the risks that construction workers could confront at the site. They manipulated a hybrid model of safety analysis and fuzzy sets to cope with insufficient data. The proposed model may reveal the significant safety factors and items which play an essential role in enhancing the safety level of the workplace and workers.

Nguyen et al. (2016) presented an analytical model, and they validated their model with a case study. The model was integrated with Bayesian networks to capture the risks of working height. Besides, the study provided preventative measures against fall accidents throughout the sensitivity analysis. Camino Lopez et al. (2008) examined accidents in Spain. They examined the associations between the affecting attributes and discovered how these attributes affect the degree of the severity.

Mohaghegh and Mosleh (2009) exercised a Bayesian approach in safety measures to recognize the relationship between organizational factors and safety performance. Therefore, a probabilistic risk assessment was conducted with the inclusion of the regulatory elements that were accepted as principal agencies of incidents.

Mohaghegh and Mosleh (2009) tried to recognize the impact of the organizational factors on safety performance. They implemented a probabilistic risk assessment based on a Bayesian approach, so regulatory elements were considered as principal agencies for incidents. Aminbaskhs et al. (2013) exercised an Analytical Hierarchy Process (AHP) to prioritize the safety risk elements with the help of OHS experts. The stated system can be practiced as a decision tool that could allow executing the required safety prevention investment in the budgeting stage. In another study, the relationships between the type of work were associated with the accident types, and correlations between them were investigated in detail (Kim et al., 2012).

Another safety risk assessment model was proposed to analyze different construction site layouts with various safety risk levels (Ning et al., 2018). Studies were conducted to investigate the similarities between the safety and risk perceptions of the stakeholders of construction projects and those of OHS professionals (Zhang et al. 2015; Zhao et al. 2016; Liao & Chiang, 2016).

Moreover, Esmaeili et al. (2015) proposed a model depending on attribute-based risk assessment to estimate the outcome of safety concerning the fundamental attributes. Hallowell and Gambatese (2009) delivered an essential contribution to discovering the relative effectiveness of safety program elements. They did a proper safety risk classification and quantified the risk classes using the Delphi Method.

2.2. Safety management and safety performance

Performing safety management systems (SMS) is a critical element for satisfying the safety environment at construction sites. Adequate SMS requires a comprehensive investigation of the attributes that contribute to accidents.

The researchers have also made extraordinary contributions to safety management issues. Hinze (2002) analyzed the effect of incentives on keeping injuries under control. Oswald et al. (2018) aimed to develop an incident reporting technique. They carried out a case study, and the results of the case study structured the design safety observation and reporting system (SOR) for construction projects.

Van Nunen et al. (2018) practiced a bibliometric analysis of safety culture. The bibliometric analysis is capable of surveying a wide range of literature within a short time, so it provides a tremendous opportunity to hold on a view on the subjected topics. They surveyed a wide range of researches published between the years 1900 and 2015. The survey concluded that interest in OHS had grown exponentially over the last decades, and human factors became significant while addressing the safety problems and culture. In another study, a hybrid model based on the Human Factor Analysis-Classification system and Bayesian Network was established to forecast the safety performance of construction. The present model can capture the most significant risk factors and predict the probabilities of safety states proactively at the project level (Xia et al., 2018).

Choi et al. (2019) proposed an approach to determine the efficacy of the wearable sensor, which measures the physiological responses of workers. The study showed that there is a remarkable difference between workers' responses during low and high-risk activities.

Lessons learned from the results of accident investigations promote extraordinary advancement in safety performance. In this respect, safety training starts to play an essential role in accident prevention. The effectiveness of safety training was questioned in several studies (e.g., Başağa et al. 2018; Loosemore & Malouf, 2019). Providing safety training is the most efficient way to transfer theoretical knowledge about safety to the employees and create awareness of OHS. Evanoff et al. (2016) designed a training program for inexperienced construction workers to improve their knowledge about fall prevention.

2.3. Studies about big data and data mining in safety

Comberti et al. (2018) examined the vast accident datasets. They applied two different clustering techniques as the K-means method and a self-organizing map (SOM) so that the study aimed to receive useful information from the big data. Huang et al. (2018) also tried to develop a conceptual framework for decision making in safety problems using big data. The favorable influence of combining big data analytics with the safety decision-making process was presented. The results of the research stated that using big data analytics may eliminate the difficulties of the traditional approach, so it may result in obtaining more accurate insights into safety.

Association Rule Mining (ARM) is another useful technique for indicating the relationships between the attributes. Cheng et al. (2015) used ARM with genetic algorithm (GA) to discover the defect patterns. Besides, the correlation between the defect types and inspection types was investigated by considering inspection grades of 990 public construction projects (Lin & Fan, 2018).

2.4. Artificial Intelligence (AI)-based Predictive Models for Construction Safety

The literature encapsulated an extensive example of the studies about the ANN-based predictive model related to construction safety. Ung et al. (2006) developed a combined model based on ANN and Fuzzy Set Theory to identify the correlations between the OHS elements and the safety performance. This study was a remarkable example of being a pioneer to this type of study since the model developed can assess the multiple parameters leading to failures in the port areas. However, it may remain limited in some points where the authors utilized simulated data generated by experts instead of factual knowledge to construct the model.

Moreover, Goh and Chua (2013) carried out an analysis to examine the relevance between safety performance and OHS elements. Within this study, incident reports which had been prepared by companies' officers were utilized directly. The reliability of incident reports may depend on the officer's interpretation, so it is possible to report incidents subjectively in real construction.

Patel and Jha (2014) studied forecasting the prospective safety climate using a three-layer backpropagation method. The study provided an opportunity to manage the safety conditions of the Indian construction industry before the start of the project. Self-reported measures were implemented in the research so that these measures may reflect the safety climate with biases. Patel and Jha (2015) proposed another model for estimating safe work behavior. Ten patterns of safety climate, which were identified by an extensive review, were taken into account while creating the model.

Tokdemir and Ayhan (2019) investigated foreign body damage and developed a hybrid model of ANN-AHP to predict the severity level of accidents. As well as the prediction process, the most frequently observed attributes in this accident type were examined to help professionals take the necessary precautions to prevent accidents. Moayed and Shell (2010) compared the prediction performance of ANN with the logistic regression analysis. They strived to estimate the consequences of occupational diseases and disorders. The study revealed that the prediction performance of ANN was better than the logistic regression.

CBR is another AI technique, which is commonly applied to solve construction management problems. CBR can compute the similarity scores regarding the historical examples or cases stored in the case base to resolve the encountered problems (Arditi & Tokdemir, 1999a, 1999b; Doğan et al., 2008). Researchers have used CBR as a predictive tool for safety outcomes for decades, too. Besides, the CBR approach is finding exponentially more use in safety research, and most of the companies adopted this technique to increase the quality of safety and correction actions against safety problems (Virkki-Hatakka & Reniers, 2009).

Liu et al. (2013) studied on developing an early warning system for maintaining safety along with the highway construction. Goh and Chua (2009) applied the CBR with variable Fuzzy Sets and concentrated on identifying the hazards in the construction industry. They introduced a feedback mechanism to detect dangerous conditions. The proposed CBR model collected historical cases to capture the outcome of the most related cases. They also advanced their study by concerning the adaptation capability of the CBR approach (Goh & Chua, 2010).

Pereira et al. (2018a) introduced a CBR model to estimate the safety performance of construction projects. Measures regarding safety were integrated into the evaluation process. The study intended to uncover the gap in the actions, so the proposed model allowed them to use safety-related measures more useful in determining safety performance. Besides, Pereira et al. (2018b) utilized CBR and simulation modeling to tabulate the safety performance of construction sites over time. The effects of safety policies and resource allocation on safety performance were determined within this study.

The existing studies have gaps in some points in general. Most of them concentrated on only severe incidents to propose an assessment strategy. Records of unsafe conditions and near misses were generally neglected while developing models or frameworks for safety failures. However, low-severe incidents should also be prioritized as the severe ones since revealing the correlations between the triggers may aid in capturing the trend of safety failures as well.

The other problem of existing studies is about the subjective recording issue (Tixier et al., 2017). There is no transparency in record keeping of incident, especially for the companies of the construction industry. Besides, recorders can interpret the cases with a different point of view so that conflicts may arise along with the records. Tixier et al. (2017) proposed an automated record-keeping process based on Natural Language Processing. In this study, the author stated that the increase in sample cases and integrating Big Data Analytics could eliminate the problems of subjective reporting issues.

Further, existing strategies have failed to reflect the dynamic nature of the construction industry. There are hundreds of attributes leading to safety failures, but researchers dealt with only a few of them usually. The thesis developed a list of attributes, elaborated with the experts' opinion. Hence, predictive models constituted depend on factual knowledge and exhibit the dynamic nature of the construction industry as well.

The increase in the number of attributes brings an instability problem along with the dataset. The problem was overcome by applying the LCCA, which generated homogenous subsets from the origin of data.

CHAPTER 3

METHODOLOGY

3.1. Methodology of the first part

The first part of the study includes three main stages as data preparation, constructing the predictive models and the selection of the most appropriate model regarding the prediction performance, and expert module where preventative measures with Fuzzy Set Theory participated.

The study started with determining the factors leading to construction incidents. At first, almost 18,000 construction work events were collected from the companies which have construction sites in the Euro-Asia regions. Every characteristic of the accidents, including human factors, risky behaviors, activities in the course of accidents, time, victim’s occupation, age and experience, hazardous conditions, and workplace factors.

In the first part, the victim’s properties were neglected because of the intent of the get more accurate results as the data includes a high number of missing values under these groups. Besides, the total number of attributes according to the dataset was 341 under these categories, even neglecting some groups. Eliminating the dataset from the missing information is crucial since it overwhelmingly makes the prediction worse. However, the total number of attributes was still high for the prediction process because it may cause instability. Thus, the Delphi method was applied to reduce them.

3.1.1. Data preparation step with Delphi Method

Delphi method was implemented to reduce the number of attributes, and eliminate the complexity of the dataset. The following figure stands for visualizing the process of the data preparation with the Delphi method. The process commenced with defining the criteria which are required for satisfying that the participants had sufficient knowledge on the construction industry and Occupational Health and Safety (Hallowell & Gambatese, 2010). The number of panelists should vary from 10 to 20 in the literature (Hallowell & Gambatese, 2010), and in this study, eleven experts were chosen to cooperate in the process.

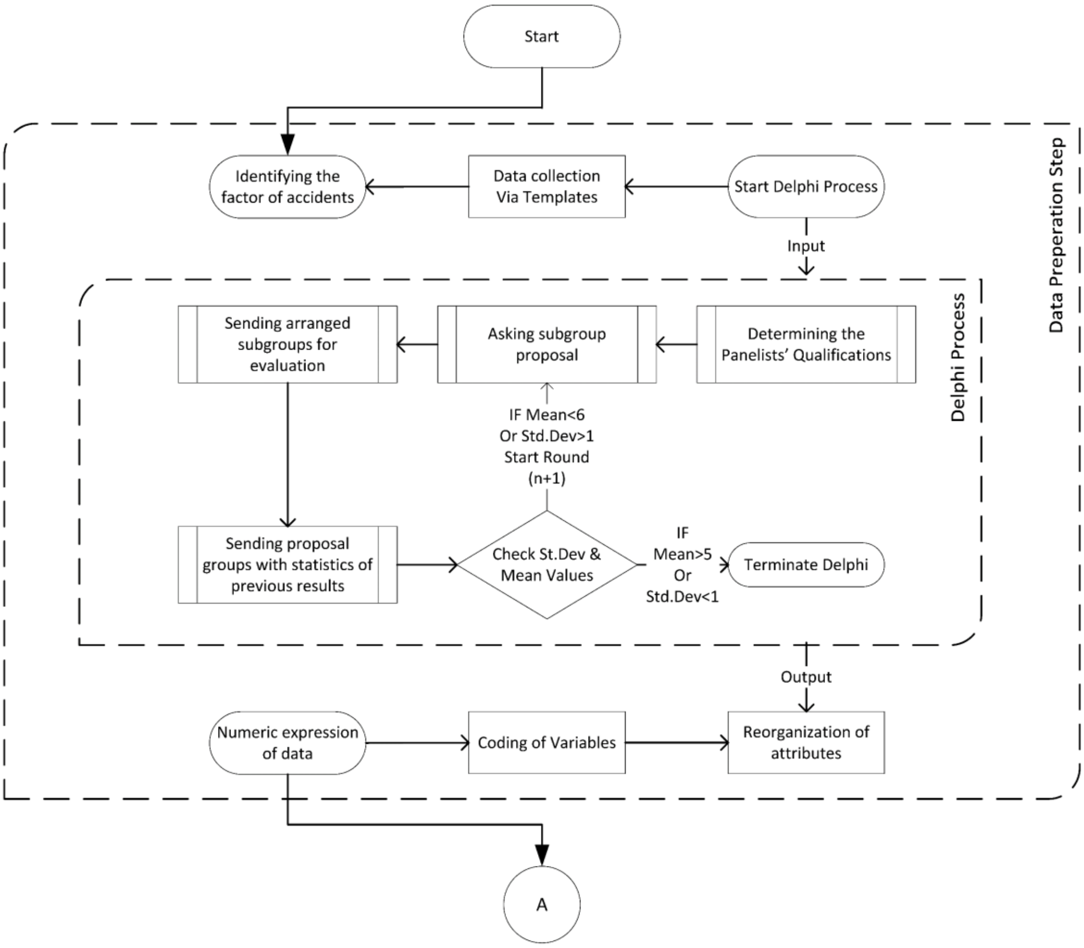


Figure 3.1: Flowchart of the data preparation step (Ayhan & Tokdemir, 2019a)

The participant number was determined regarding the criteria presented in Table 3.1. Two parameters were prominent in the selection of participants as experience and educational degrees. Therefore, the participants composed of seven civil engineers and four architects, as shown in Table 3.2. Three of the civil engineers are currently proceeding their career as academic staff, whereas the rest are working in the private sectors. On the other hand, two of the architects were academicians, and all participants have more than ten years' experience in the construction industry as well.

TABLE 3.1: Qualifications required for experts (Ayhan & Tokdemir, 2019a)

Education Degree	Experience Level
*Education Degree (at least B.S.) from the departments related to Architecture, engineering and construction industry	*At least 10 years' experience in architecture, engineering and construction industry
*At least having one of certificate indicated below; -A class Occupational Health and Safety (OHS) *Specialist Certificate -NEBOSH Certificate -IOSH Certificate	*At least 5 years' experience in OHS issue
*Having a background in training of OHS courses (at University, or any educational institution)	

To illustrate, six participants possess OHS Specialist certificates such as IOSH, NEBOSH given by the British Safety Council, and A-class OHS specialist Certificates granted by the Turkish government. The remaining ones did not have any certificate, but they had the expertise as a peer trainer or experience in giving a lecture on OHS. Further information about the participants can be found in Table 3.2.

TABLE 3.2: Experts' qualifications participated in the Delphi Process (Ayhan & Tokdemir, 2019a)

		Experience			
Title	Academic Title	in Constructi	in OHS	OHS Specialist Certificate	Experience as peer
Civil Eng. / Academic Staff	Prof.	20-25	5-10	-	YES
Civil Eng. / Academic Staff	Prof.	15-20	5-10	-	YES
Civil Eng. / Academic Staff	Assoc. Prof.	10-15	5-10	IOSH	YES
Civil Eng. / Project Man.	M. Sc.	20-25	5-10	A class	NO
Civil Eng. / Project Man.	Ph. D.	20-25	5-10	-	YES
Civil Eng. / Const. Safety Man.	M. Sc.	10-15	5-10	NEBOSH	NO
Civil Eng. / Const. Safety Man.	B. Sc.	15-20	5-10	A class	NO
Architect / Academic Staff	Prof.	25-30	>10	-	YES
Architect / Academic Staff	Asst. Prof.	25-30	>10	-	YES
Architect / Construction Safety	Ph. D.	15-20	>10	IOSH, NEBOSH	YES
Architect / Const. Safety Man.	Ph. D.	10-15	5-10	IOSH	NO

Delphi method was performed by multiple rounds by the participation of these experts to deliver a high degree of consensus among the experts (Curtis, 2004; Hallowell & Gambatese, 2010; Seyis & Ergen, 2017).

As a start, the author prepared a questionnaire that presented the attributes planned to be used. These questionnaires were sent to the participants for their comments, which shaped the content of the second questionnaire. The participants were asked to groups some of the attributes to represent them with only one expression for the intent of reducing the complexity. The participants ranked the groups defined in the forms prepared regarding their comments. They scored the groups of activities from 1 to 7, where seven stands for "strongly agree", whereas one represents the "strongly disagree".

In the end, the second questionnaire results were collected. Mean values and standard deviations of each question were calculated with regards to Equation 3.1 and Equation 3.2, respectively. In the formulation, n expresses the number of questionnaires ranking results, while Xi accounts for the ranking results answer of each participant.

$$\mu = \frac{1}{n} \sum_{i=1}^{n} X_i \tag{3.1}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \mu)^2} \tag{3.2}$$

3.1.2. Development of the prediction model with ANN

ANN can understand the unclear information and achieve a meaningful conclusion from complicated problems. The logic behind the working principle of the ANN is related to pattern recognition and classification. It works as a black box where the structure of data is recognized (Waziri et al., 2017). The ANN involves three zones: input, hidden, and output. The nodes represented the attributes of cases in the input layer, and then they associated with the nodes underlying in the hidden layer by synaptic weights, which are updated in every trial or iteration.

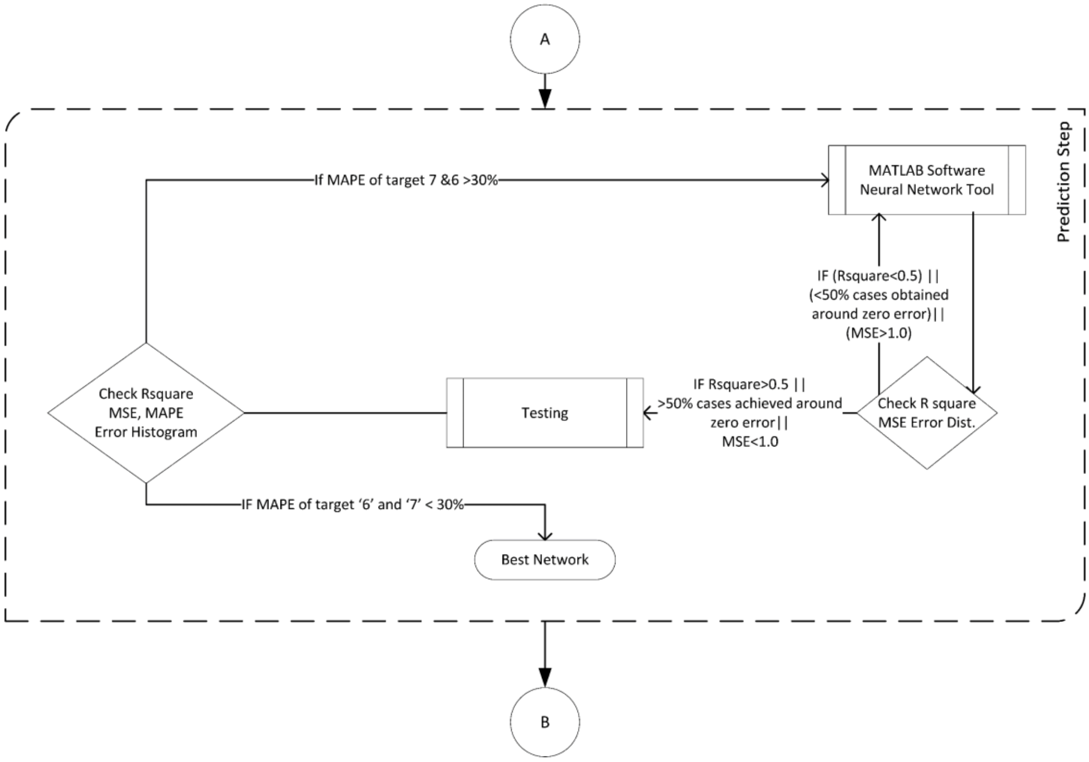


Figure 3.2: Flowchart of the prediction step (Ayhan & Tokdemir, 2019a)

The ANN has many factors that have an impact on prediction performance. The search of the best-fitted model entails implementing different combinations of the network properties. However, the existing literature has no strict rule for establishing the networks. Instead, features of the models can change regarding the data type. For this reason, previous studies can provide great instructions related to the selection of the network properties.

The literature suggested that feed-forward backpropagation is sufficient for civil engineering practice (Kulkarni et al., 2017; Arditi & Tokdemir, 1999b). Besides, sigmoid can be accepted as the most common transfer function which addresses the non-linearity inside the dataset (Waziri et al., 2017; Arditi et al., 1998). Matlab Neural Network Tool was employed to establish the networks. The network retrieved the dataset from the Excel spreadsheet and executed the training and prediction processes. Also, several training functions were tried to discover, which is better for the prediction rate. Some of the training functions available in MATLAB software environment can be given as "trainlm", "trainscg", and "traingdx" functions.

The prediction process was demonstrated in Figure 3.2 in detail. The prediction process has a two-layer control mechanism for the training and testing process, as well. At first, R square, error histograms (obtained from residuals, Equation 3.3), and the mean square error (MSE) (Equation 3.4) were checked. Later, the networks whose criteria succeeded in satisfying these conditions defined in Figure 3.2 passed to the next step, which is testing. Next, the Mean Absolute Percentage Error (MAPE) (Equation 3.5) and overall MAPE (Equation 3.6) of each incident outcome were computed.

$$Residuals = t - t' \qquad (3.3)$$

$$Mean\ Square\ Error\ (MSE) = \frac{1}{n}\sum_{i=1}^{n}(t'_i - t_i)^2 \qquad (3.4)$$

$$Mean\ Average\ Percentage\ Error\ (M_a) = \frac{1}{n}\sum_{i=1}^{n}\frac{|t'_i - t_i|}{t_i} \qquad (3.5)$$

$$Overall\ MAPE = \frac{1}{n}\sum_{i=1}^{a}(M_a \times N_a) \qquad (3.6)$$

Where t represents the actual target, whereas t^t stands for the predicted one, while a symbolizes the incident target. M_a and N_a show the individual MAPE of cases and many cases where the individual target was observed respectively.

The dataset was randomly separated into two different groups for training and testing procedures. The first group with 16,214 incidents was used in training, whereas 1,071 cases were employed in testing the models.

3.1.3. Expert module, based on Fuzzy Set Theory

The expert module was integrated into the study using the Fuzzy set theory. The module utilized the Conoco Philips Marine pyramid (2003) to reduce the vagueness of the results obtained from prediction steps, as shown in Figure 3.3. OHS experts are currently employing the Conoco Philips Marine pyramid in their construction sites to forecast the possible safety failures.

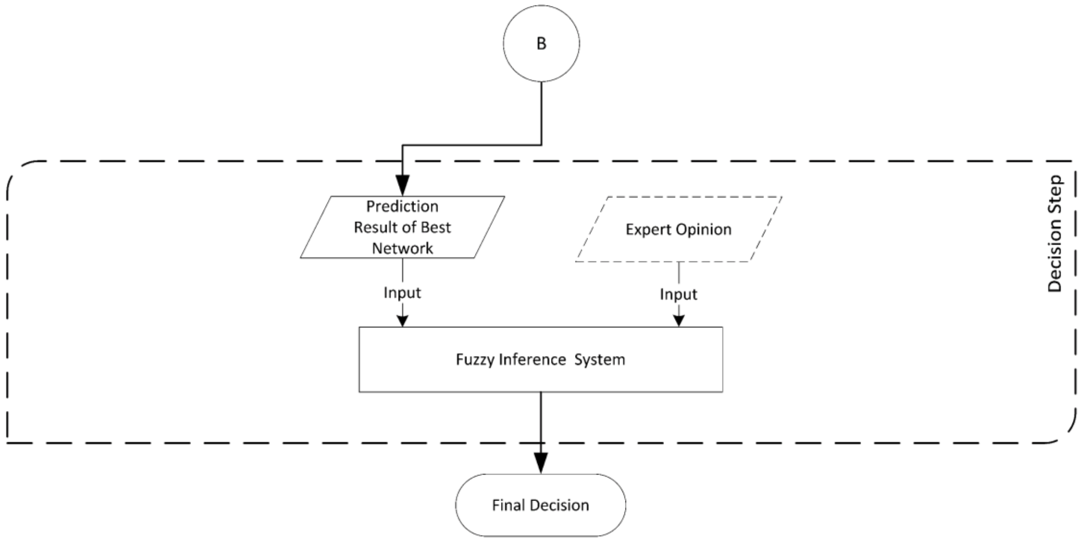


Figure 3.3: Flowchart of Decision Step (Ayhan & Tokdemir, 2019a)

The pyramid involves five different categories of incidents regarding their severity levels. These terms can be listed from the lowest severe to the highest one as; "At-risk behavior," Near Miss," "Recordable Injuries," "Lost Workday Cases," and "Fatalities". The working principles of the pyramid depend on a hierarchical process. That means a significant number of observations in one case are the preview of occurring more severe ones. In other words, it would be inevitable to confront more severe safety failures during the construction process.

Experts are extensively practicing the pyramid in accident prevention. However, its capabilities remain overwhelmingly limited in the prediction process because safety prevention cannot be handled by just observing the number of incidents. The pyramid probably collapses when the high severe incidents occur in the early stage of construction. For this reason, qualified expert judgment is required to evaluate the safety performance of construction sites as well as the Conoco-Philips Pyramid outcomes.

Therefore, the author decided to combine the Fuzzy Sets based expert module with the predictive tool of ANN. Membership functions quantified the relationships between ANN results and Expert module regarding their prediction performances. The steps of establishing the fuzzy sets initiated with developing memberships functions. In other words, linguistic variables were now expressed with the quantified expressions. Later, logical operations based on if-then rules were determined for each occasion step by step (Mamdani & Assilian, 1975). In this study, the author built the Mamdani type Fuzzy inference mechanism, which is one of the fuzzy controls and commonly used system in the literature (Ilbahar et al., 2018).

Ultimately, the vagueness of the ANN results was eliminated, and the preventative measures were determined from the fuzzy inference systems, which is based on a Conoco Philips Pyramid.

3.2. Methodology of the second part

This study consists of five steps (Figure 3.4) as well as the preventative actions part. The high-resolution format of Figure 3.4 can be found in Appendix chapter as, Appendix-A Similar to the first part, the research initiated with data preparation. However, incident cases belong to the megaproject were put aside for the intent of three significant outcomes. First, the prediction accuracy was compared with the first part regarding the decrease in the case number. Second, the megaprojects were specifically investigated, and lastly, the prediction performance of CBR and ANN was compared.

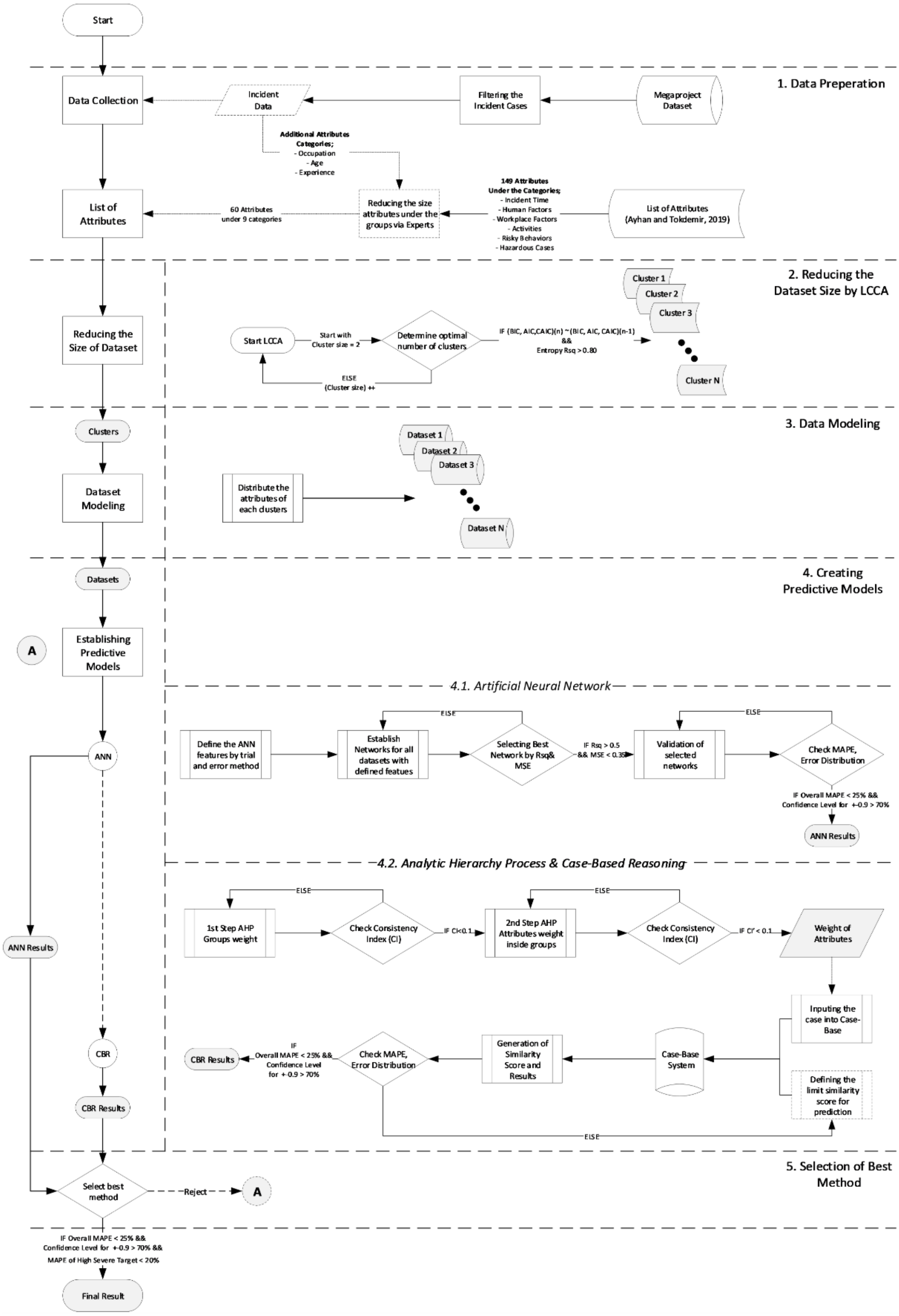


Figure 3.4: Flowchart of the predictive model (Ayhan & Tokdemir, 2019b)

Besides, the incident cases were investigated an additional three categories as the victim's occupation, experience level, and age. After elimination the cases, including missing information, 5,224 incident cases remained from different megaprojects located in the Euro-Asia region. The study started with the data preparation step. The author benefits from the list of attributes presented in the first part of the research and obtained the list demonstrated in Figure 3.5. As a result, 60 items under nine categories were determined to be used for model development.

The vast datasets bring along with the severe level of complexity as a wide range of viewpoints should be kept under record in the incident recording. The size of the data increases, and it leads to a high level of heterogeneity, which may result in incorrect conclusions during the prediction phase (Depaire et al., 2008). LCCA, which is one of the clustering techniques, was applied to address the heterogeneity problem inside the data structure. LCCA disclosed the hidden correlations and generated homogenous subsets that advanced to the prediction process.

The optimum cluster number may vary regarding the data type and size, so the LCCA proceeded until the optimum number was obtained. In Figure 3.4, the criteria for optimum clusters were represented, and details about the requirements and determination process of the optimum cluster number where indicated.

LCCA computed the probabilities of the attributes for each cluster. The probabilities denoted the rate of presence inside the groups. The attributes were aggregated regarding the probabilities, and data modeling started. Next, the predictive modeling step initiated by developing predictive models using ANN and CBR. 4,446 of 5,224 cases were separated from the dataset for the training of the models. Remaining cases were utilized for the validation process.

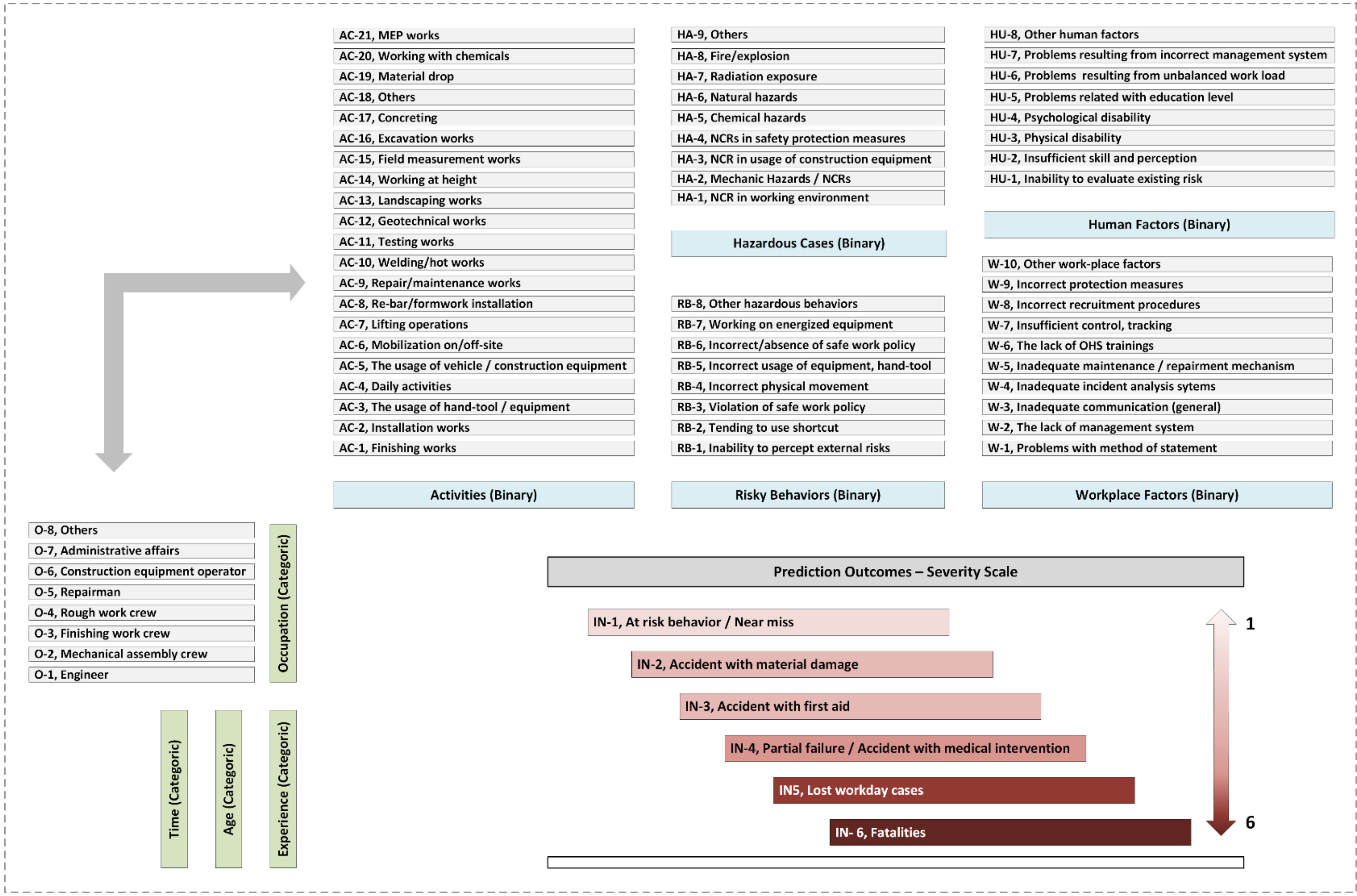


Figure 3.5: List of the attributes (Ayhan & Tokdemir, 2019b)

CBR requires computing the weight of the attributes before calculating the similarity scores since the impact of attributes on incident cases may be fragmented. The author preferred to compute the weight of attributes using AHP because of having a large incident domain. Ultimately, the outcome of incidents was investigated with a severity scale from 1 to 6, as shown in Figure 3.5. The two prediction strategies (ANN and CBR) governed prediction progress with different datasets obtained by LCCA. After receiving the final results, the preventative actions were discussed.

3.2.1. Latent Class Clustering Analysis (LCCA)

The clustering technique can generate a finite number of subsets the complex data. The clustering approaches do not require the feedback or results of the training cases to learn the structure of the data; instead, the working principle depends on learning the underlying structure of the dataset. For this reason, it is called an unsupervised learning mechanism. Similar cases tend to converge and generate latent clusters. In this study, the author decided to use Latent Class Clustering, which is one of the popular clustering methods to address the civil engineering problems (e.g., Depaire et al., 2008; De Oña et al., 2013; Sasidharan et al., 2015).

LCCA provides some striking advantages compared with the traditional methods (De Oña et al., 2013; Vermunt & Magidson, 2002; Sasidharan et al., 2015). For example, LCCA calculates statistical criteria, which signify the optimal number of clusters inside the dataset. These criteria can be listed as the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), and Consistent Akaike Information Criterion (CAIC). Further, LCCA can cope with a larger dataset since it does not need memory, unlike the traditional clustering techniques (Depaire et al., 2008). The most notable advantage of LCCA is that this technique enables researchers to work with a mixture of variables into the same dataset, such as categorical, ordinal, or continuous (Moustaki & Papageorgiou, 2005). For further information about the LCCA, and analysis with different variables, researchers can see (Vermunt & Magidson, 2002; Moustaki & Papageorgius, 2005).

The structure of the incident data involves a significant level of heterogeneity. LCCA overcame this problem as it is capable of obtaining mutually exclusive homogenous subsets from complex datasets (Sasidharan et al., 2015). LCCA was performed with aiming different cluster sizes to select the most suitable model. The analysis initiated with two clusters and proceeded to the ten clusters.

Then, BIC, AIC, CAIC, and Entropy Rsq (3.7) criteria for each analysis were examined to determine the cluster number. After, attributes were distributed to the clusters according to their presence probabilities for each cluster.

$$Entropy\ R_{sq} = 1 - \frac{-\sum_{i=1}^{n}\sum_{c=1}^{C} P_{ic}\log(P_{ic})}{n(\log C)} \quad (3.7)$$

where "P_{ic}" stands for the following probability that crash "i" belongs to cluster "c," "n" expresses the number of crashes, and "C" stands for the total number of clusters.

The correctness of predictive models defined the most noticeable datasets in megaproject incidents. Hence, it may provide an opportunity to capture the principal attributes of construction incidents as well.

3.2.2. Analytical hierarchical process (AHP)

AHP is one of the multi-criteria decision-making tools used in the literature (Alonso & Lamata, 2006; Saaty, 2008; Badri et al., 2012). AHP makes a pairwise comparison of alternatives by experts' judgments or frequency of data. The striking advantage is its capability to overcome the inconsistency of expert's opinions, which may lead to bias in the decision-making process (Aminbakhsh et al., 2013). The steps of AHP can be explained as follow (Saaty, 2008; Ayhan & Tokdemir, 2019b);

- Define the problems, and structure the decision hierarchy from the top to the goal.
- Build a comparison matrix for alternatives, considering Table 3.3.

  $$C = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix},\ where\ a_{ij} > 0,\ a_{ij} \times a_{ji} = 1; \forall\, i,\ a_{ij} \times a_{jk} = a_{ik};\ \forall i, j, k \quad i, j, k = 1,2,\ldots n \quad (3.8)$$

where, C is a comparison matrix, and a_{ij} represents the individual preference of pairwise comparison. The element of matrix C should satisfy the conditions indicated above (3.8).

- Calculate the s_i by totaling the pairwise comparison values of each column in the C matrix. Then, comparison results are divided into the s_i to obtain matrix B (3.9). The weight of alternatives w_i is calculated using the equation in (3.11).

$$B = \begin{bmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{n1} & \cdots & b_{nn} \end{bmatrix} \tag{3.9}$$

$$b_{ij} = \frac{a_{ij}}{s_i} \qquad \forall\ i\ ,j \quad i,j = 1,2,..n \tag{3.10}$$

$$w_i = \frac{\sum_{j=1}^{n} b_{ij}}{n} \qquad \forall\ i\ ,j \quad i,j = 1,2,..n \tag{3.11}$$

- To check the consistency of AHP, the "Consistency Ratio" CR should be calculated, and it should be equal to or less than 10%. First, the A and W matrixes will be multiplied, and the maximum value taken as λ_{max}. According to Saaty (1990), the consistency of the model can be calculated using the equations in (3.12) and (3.13). The Random Consistency Index (RC) value can be determined from Table 3.4.

$$CI = \frac{\lambda_{max} - n}{n-1} \qquad CI, Consistency\ Index \tag{3.12}$$

$$CR = \frac{CI}{RI} \qquad RI, Random\ Consistency\ Index \quad CR, Consistency\ Ratio \tag{3.13}$$

In this study, AHP was used to compute the weight of attributes for the CBR step. The two-step pairwise comparison was performed to designate the weights. AHP put a significant contribution by providing an appropriate solution for the weight calculation.

TABLE 3.3: AHP Scale (Ayhan & Tokdemir, 2019b)

Numeric Scale	Definition	Reciprocals
1	The equal importance of two elements	1
3	Low importance of one element over another	1/3
5	Strong importance of one element over another	1/5
7	Very strong importance of one element over another	1/7
9	The absolute importance of one element over another	1/9
2,4,6,8	Intermediate values	1/2, 1/4, 1/6, 1/8

TABLE 3.4: Alonso-Lamata RI Values (Ayhan & Tokdemir, 2019b)

Size	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
RI	0	0	0.52	0.88	1.11	1.25	1.34	1.41	1.45	1.49	1.51	1.54	1.55	1.57	1.58	1.6	1.61	1.62	1.63	1.63	1.64

3.2.3. Case-based reasoning (CBR)

Unlike the ANN, CBR does not work as a black box. Instead, CBR solves the problems by controlling the similarity rate of historical cases (Aha, 1998; Mount & Liao, 2001). CBR resembles human thinking, which means CBR tries to retrieve the most similar cases from the stored cases while solving a problem. For this reason, similar cases are essential in concluding the present problems. The prediction rate of the CBR is high and gives consistent solutions against the problem because of its capability to evaluate resembles between the cases (Chiu, 2001). The fundamental advantage of the CBR is its ability to generate a quick response to the queries since CBR needs only to find the relevant cases from its database instantly (Arditi & Tokdemir, 1999b).

The CBR has four steps as retrieve, reuse, revise, and retain (Yang & Yau, 2000). In summary, the CBR process begins with the new case entry to the case base. Then, the CBR algorithm matches the current problem with the cases in case-base to calculate the similarity scores. If the retrieved cases are suitable, which implies consistency, a new entry case will be affiliated to the case base for the reuse process. Otherwise, the present case will be revised to obtain a more suitable outcome while forecasting the problems. Lastly, each output will be evaluated and retained in the case base for future work (Chen et al., 2010).

As mentioned, the CBR takes the cases stored in case-base to calculate the similarity scores of test cases. Several matching strategies are utilized to match the cases regarding the structure of the dataset and the intended level of preciseness. These strategies can be listed as an exact match, partial match, etc. In this study, the dataset formed from the binary variables, so the author preferred to use the exact match strategy for calculating the similarity scores.

The weight of the attributes is also playing a significant role in determining the similarity scores as each attribute has a different contribution to the severity level of the incident. As an adaptation strategy of the model, the manual adaptation method was employed since the author calculated the weight of the attributes using AHP.

The CBR algorithm obtained the similarity scores between zero and one. The increase in similarity scores indicates a high level of matches. Due to the size of the case base, CBR inevitably generates more than one case with high similarity scores. For that reason, a threshold was set to achieve more accurate results.

Within the scope of this study, the script was written in MATLAB 2017 software. The CBR-based script committed to calculating the similarity scores and producing the prediction outcome of incidents. The process began with a weight assignment. Later, test and input cases with the attribute weights were shifted to the MATLAB environment to anticipate the severity score of the incidents for each dataset.

CHAPTER 4

COMPUTATIONAL PROCESS

4.1. First Part

4.1.1. Data preparation

Data preparation started with the Delphi process. Eleven participants, given in Table 3.2, were selected as a decision-maker to determine the list of the attributes.

At first, the existing data was investigated in detail by the author to achieve the immature form of the attribute list. While doing that, triggering factors and accident history signified the list, but correction should be necessary since more than one expression was employed to explain similar cases. For this reason, the author aimed to accumulate similar expressions together and proposed them into a questionnaire format to eleven participants confidentially. Thus, the exact list of the attribute was predicated on expert opinions.

In the beginning, the participants were asked for their opinion on grouping the items given in handout, so their comments shaped the first questionnaire of the Delphi process. They ranked the proposal groups of attributes between 1 to 7, where one expressed the strongly disagree, and the seven stands for describing the strongly agree opinion. The scoring process completed by collecting the results from participants, and the calculation of mean value (3.1) and standard deviation (3.2) resolved whether the second round was necessary to satisfy consensus among participants.

Mean value implied the central tendency of the feedback, whereas standard deviation showed the fluctuation on the answer, i.e., consensus (Curtis, 2004; Hallowell & Gambatese, 2010; Seyis & Ergen, 2017). In the present study, the scoring score should be closer to the seven since the aim was to create only one expression to remove similar ones. In other words, bulk information was intended to get rid of along with the data to increase the prediction performance. Besides, the standard deviation should be smaller than one, as shown in Figure 3.1, to not advance the further round in Delphi, but these conditions could not be succeeded in the first round. Then, the second round started accordingly. The Delphi process concluded with the second round.

TABLE 4.1: Comparison of Questionnaire Statistics between first and second round in Delphi Process (Ayhan & Tokdemir,2019a)

Subgroup Proposal	Mean value of the questionnaire results		Std. Dev.		Std. Dev./Mean	
	1st Round	Final Round	1st Round	Final Round	1st Round	Final Round
Level of Skills	5.82	6.55	1.40	0.52	0.24	0.08
Low Learning Ability	4.91	6.09	1.14	0.70	0.23	0.12
Physical Condition	4.45	6.27	1.29	0.90	0.29	0.14
Physical Fatigue	5.55	6.36	0.82	0.67	0.15	0.11
Emotional Problems	5.45	6.36	0.69	0.50	0.13	0.08
Non-participating OHS Trainings	5.64	6.36	1.21	0.92	0.21	0.15
Educational Problems / Knowledge Level	5.73	6.18	1.10	1.08	0.19	0.17
Problems related with Manager	5.00	6.36	1.10	0.67	0.22	0.11

Variation in the results regarding the rounds was demonstrated in Table 4.1 to have a better understanding of the importance of performing more than one round. Table 4.1 presented eight subgroup proposals with their statistics to see how to ensure the consensus between the experts. Ultimately, the Delphi process made a significant drop in attribute size, which decreased from 341 to 149 under the six groups. The list of the attribute was given in Table 4.2, and they were coded in binary format to express the occasions. The high-resolution format of Table 4.2 was demonstrated in Appendix chapter, as Appendix-B. The outcome of the construction accidents in the dataset was classified regarding the target list in Table 4.3. Therefore, the author established the predictive models to estimate the severity level information concerning information in this table, as well.

TABLE 5. Attributes (ATR) and their expressions

Workplace Factors		Human Factors		Activities in the course of the incident		Risky Behaviors		Hazardous Cases	
ATR	Expression	ATR	Expression	ATR	Expression	ATR	Expression	ART	Expression
WF-1	Tool & Equipment	HF-1	Work overload	AA-1	Maintenance / Repair	RB-1	Individual violation	HC-1	Tool & Equipment
WF-2	Improper way to wipe out wastes	HF-2	Usage of alcohol or drugs	AA-2	The usage of equipment	RB-2	Unsafe usage of tool/equipment	HC-2	Temperature of Environment
WF-3	Inadequate maintenance / repair	HF-3	Excessive concentration	AA-3	Concrete / Screed Works	RB-3	Inability to realize external factors	HC-3	Working Area and Layout
WF-4	Inadequate review in start-up op.	HF-4	Feeling extremely embarrassed	AA-4	Finishing (General)	RB-4	Lack of attention	HC-4	Natural Events
WF-5	Uncertain reporting responsibilities	HF-5	Negative effects of Whether	AA-5	Installation of Str. Steel	RB-5	Impetuous activities	HC-5	Insufficient Equipment
WF-6	Inadequate information handling	HF-6	Level of Skills	AA-6	Installation of Re-bars	RB-6	Working above limits	HC-6	Electrified systems
WF-7	Inability to remember information	HF-7	Learning ability	AA-7	Other activities	RB-7	Group violation	HC-7	Being exposed to excess noise
WF-8	Inability to perceive information	HF-8	Being absent-minded	AA-8	Break	RB-8	The violation in the safe working procedure	HC-8	Other hazardous cases
WF-9	Inadequate Communication b/w stakeholders	HF-9	Using shortcut	AA-9	Electrical Assembly	RB-9	Other risky behaviors	HC-9	Improper instigation systems
WF-10	Having trouble in lessoning pre-cases	HF-10	Behavior	AA-10	Hand-powered lifting	RB-10	The usage of damaged safety systems	HC-10	Improper application of PPE
WF-11	Inadequate change management	HF-11	Physical condition	AA-11	Assembling scaffold	RB-11	Incorrect loading / lifting	HC-11	Using of improper vehicle
WF-12	Lack of expression in remedial measures	HF-12	Physical fatigue	AA-12	Assembling frameworks	RB-12	Incorrect Usage of PPE	HC-12	Being exposed to chemicals
WF-13	Unsatisfied training facilities	HF-13	Emotional Problems	AA-13	Hot works	RB-13	The usage of protection measures	HC-13	Mechanical dangers
WF-14	Other workplace factors	HF-14	Other human factors	AA-14	Excavation Works	RB-14	Being unfamiliar with existing risks	HC-14	Being exposed to radiation
WF-15	Missing maintaining reports	HF-15	Education Level	AA-15	Using chemical materials	RB-15	Deactivation of safety systems	HC-15	Dangerous Chemicals
WF-16	Problems in control of equipment	HF-16	Non-participating OHS training	AA-16	Carpenter's Works	RB-16	Procedures / Orders	HC-16	Lack of organization
WF-17	Inadequate plan of action	HF-17	Negative consolidation of Behaviors	AA-17	Lifting Operations	RB-17	Non-fixed equipment or material	HC-17	Inadequate equipment
WF-18	Taking precautions inadequately	HF-18	Claim / Instruction Confliction	AA-18	Mechanical Assembly	RB-18	Levity	HC-18	Fire or explosion
WF-19	Insufficient administration	HF-19	Claim / Instruction Confusion	AA-19	Going up / down a ladder	RB-19	Engagement in violence		
WF-20	Failure in ergonomic design	HF-20	Working below the capacity	AA-20	Driving of vehicle	RB-20	Inability to percept risk		
WF-21	Lack of meetings about OHS	HF-21	inability to make a decision	AA-21	Smoking	RB-21	Using equipment beyond one's authority		
WF-22	Lack of communication about OHS	HF-22	Limited body movement	AA-22	Cleaning				
WF-23	Insufficient methods for work competence	HF-23	Deficiency in concentration	AA-23	Tests				
WF-24	Not following processes of work	HF-24	Vulnerability to material	AA-24	Topography Works				
WF-25	Unavailable work-hazard analysis	HF-25	Existing wound / Disease	AA-25	Cafeteria Works				
WF-26	Problems in MoS / standards / specifications	HF-26	Lack of practical experience	AA-26	Working at height				
WF-27	Inability in recruitment and placement	HF-27	inability to percept risk	AA-27	Walking				
WF-28	Inadequate usage / storage / transportation of equipment	HF-28	Hypercapnic respiratory failure						
WF-29	Failure in Engineering Design	HF-29	Stress & Lack of concentration						
WF-30	Inability to evaluate probable system failures	HF-30	Problems related to Manager						
WF-31	Incoherent performance standards	HF-31	Inability to maintain existing position						
WF-32	Problems arising from subcontractors	HF-32	Inadequate mechanical skills						
WF-33	Not able to assess operational preparation	HF-33	Administration problems						
WF-34	Problems on Policy / Standards / Procedure	HF-34	Memory loss						
WF-35	Inadequate usage of PSP								
WF-36	Having trouble in procurement agency								
WF-37	Having trouble in the identification of danger								
WF-38	Problems in identifying dangerous products								
WF-39	Intense work pressure for continuity of work								
WF-40	Applying new methods without giving any instruction about it								
WF-41	Insufficient Health and Safety award								
WF-42	Insufficient Health and Safety manifestation								
WF-43	Insufficient employment orientation								
WF-44	Insufficient Risk Assessment								
WF-45	Insufficient or complicated instructions								
WF-46	Having trouble delivering the necessary method of statements / standards / instructions to related units								
WF-47	Change of materials beyond one's authority								
WF-48	Not performing acceptance of confirmation								

The coding progress was completed in MS Excel. First, attributes were appointed to the incidents, and linguistic terms explained the accidents. The ANN-based predictive model required mathematical expressions to accommodate and solve accident cases. As mentioned before, the attributes accumulated under five different categories except for time. On the same occasion, more than one attribute can inevitably be observed under the same type, so categorical expression for the coding process was not the solution for model development. Therefore, the dataset was converted to the binary format, which can also render the ANN process more effectively.

TABLE 4.3: Target list (Ayhan & Tokdemir, 2019a)

Attributes	Expression
T-1	At Risk Behavior
T-2	Near Miss
T-3	The Incident with Partial Failure
T-4	The Incident requiring First Aid
T-5	The Incident requiring Medical Intervention
T-6	Lost Workday Cases
T-7	Fatalities

4.1.2. Development of the ANN model and analysis

The author used the MATLAB Neural Network tool for developing a predictive model. Several criteria controlled the prediction performance of the ANN models. Prediction performance was adjusted by changing the features of the network, such as learning rate, transfer function, neuron-input ratio, and learning function.

A trial and error process handled the model development, so different parameters supervised the development process. Three learning functions were employed as trainscg, trainlm, and traingdx. The working behaviors of them differed from each other, so they all required a different combination of the features.

At first, the author established numerous networks to capture the best combination of the ANN parameters. While doing that, the R square, error histograms from residuals (3.3), and MSE (3.4) values were calculated and measured to eliminate the unsuccessful models. Besides, the working time of the ANN model in training and prediction was crucial for the model in proceeding the next step.

The successful models should satisfy the conditions given below:

- R square should be greater than 0.5
- MSE should be less than 1.0
- Minimum 50% of the cases should be predicted with almost zero error (Check the residual histogram)

If the criteria indicated above were satisfied, the models stepped forward to the validation process. The ANN models tried to predict the outcome of 1,071 incident cases, and MAPE (3.4)-MAPE overall (3.5) tested the performance. Fourteen networks with different features were developed. Table 4.4 indicated the values of the conditions defined for controlling the performance. The first assessment only captured the training performance, so the results did not include the MAPE of the test cases.

According to Table 4.4, each training function needed a different combination of the parameters. For example, an increase in neuron-input size up to 2.5 always improved the prediction performance regardless of the type of training function. However, the increase in neuron numbers enlarged the time spending on the model development process. Especially for the trainlm, which uses Levenberg-Marquardt optimization, training duration was too long since it requires more memory than the others. Traingdx is another function used for ANN models. This function strived to find the local minima and maxima, so the learning rate, which indicates the distance of the interval between the derivative points became too crucial. Therefore, change in neuron-input ration did not affect the performance of the models.

TABLE 4.4: Network results for training process (Ayhan & Tokdemir, 2019a)

ID	# of cases	# of neuron	Input Size	Transfer Function	Training Function	Learning Rate	Epoch Number	MSE	Rsq (Training)
Network 1	**16,214**	**149**	**149**	**tansig**	**trainscg**	**0.01**	**1000**	**0.70894**	**0.68966**
Network 2	16,214	75	149	tansig	trainscg	0.01	1000	0.70387	0.59598
Network 3	16,214	300	149	tansig	trainscg	0.01	1000	0.80349	0.70218
Network 4	**16,214**	**370**	**149**	**tansig**	**trainscg**	**0.01**	**1000**	**0.9045**	**0.81109**
Network 5	16,214	250	149	tansig	trainscg	0.01	1000	0.75	0.75
Network 6	16,214	250	149	logsig	trainscg	0.01	1000	0.73393	0.62268
Network 7	**16,214**	**30**	**149**	**tansig**	**trainlm**	**0.01**	**1000**	**0.94631**	**0.76**
Network 8	16,214	70	149	tansig	traingdx	0.01	1000	0.78204	0.51281
Network 9	16,214	149	149	tansig	traingdx	0.01	1000	1.504	0.35
Network 10	16,214	300	149	tansig	traingdx	0.01	1000	2.9014	0.21891
Network 11	16,214	75	149	tansig	traingdx	0.0001	1000	0.75324	0.53612
Network 12	16,214	75	149	tansig	traingdx	0.0001	2000	0.81728	0.54014
Network 13	16,214	75	149	tansig	traingdx	0.0001	3000	0.69114	0.60908
Network 14	**16,214**	**75**	**149**	**tansig**	**traingdx**	**0.0001**	**10000**	**0.76462**	**0.62656**

Table 4.4 showed that networks 1, 4, 7, and 14 have the best values for the criteria. Rsq, error histograms, and MSE values regarding the epoch number were demonstrating in the following figures, respectively.

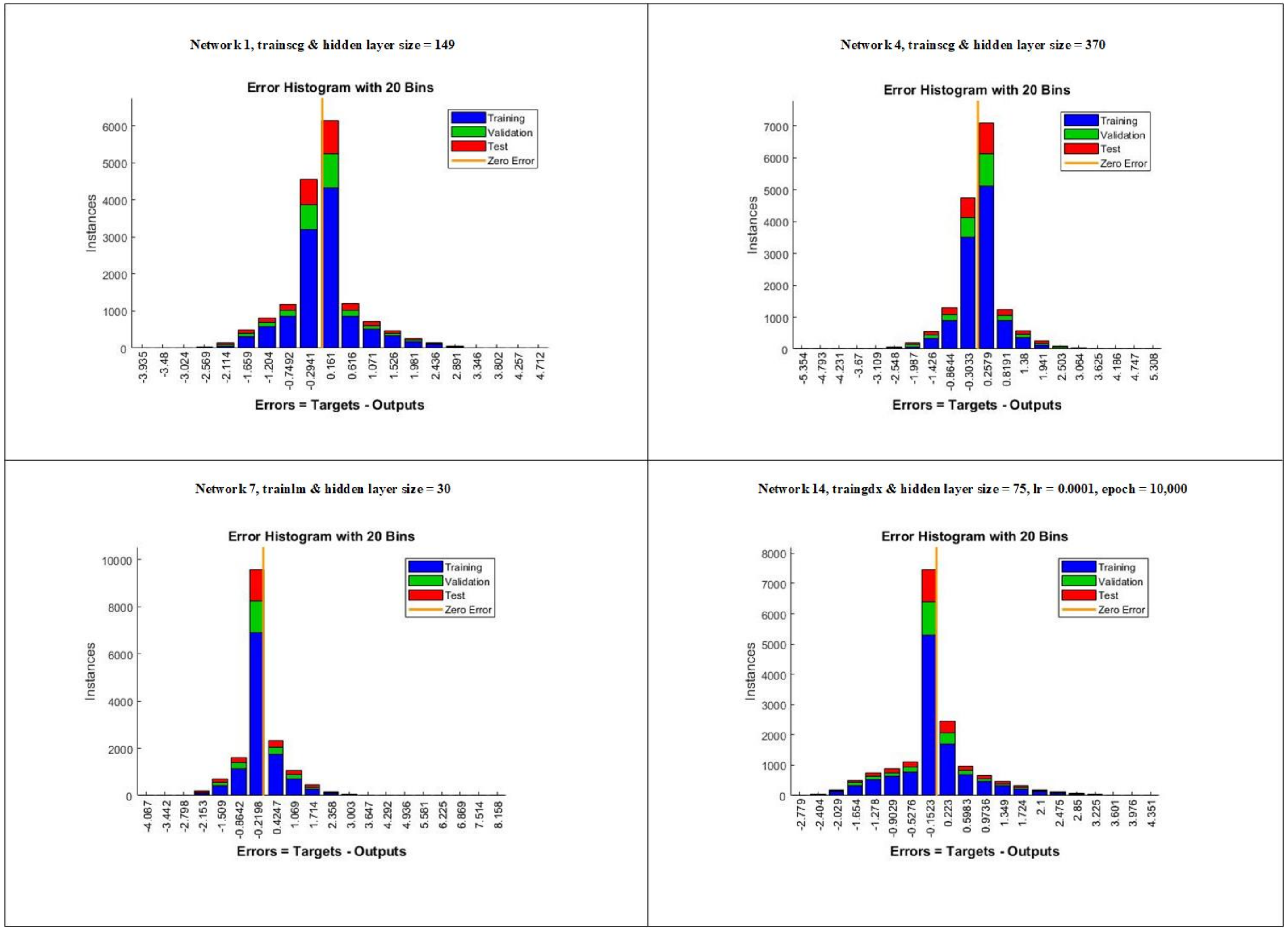


Figure 4.1: Error histograms of the best four networks (Ayhan & Tokdemir, 2019a)

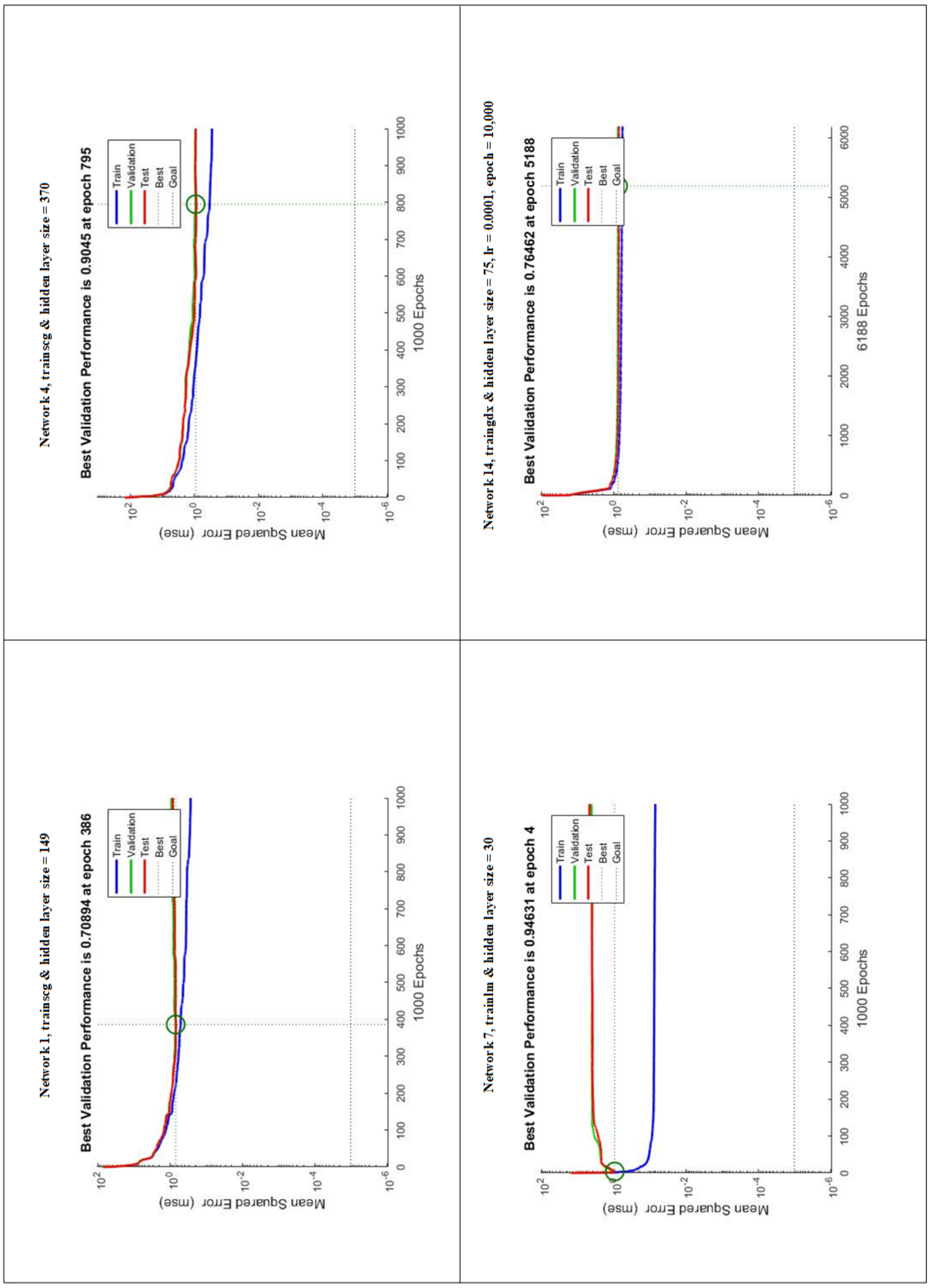


Figure 4.2: Best validation performance of the networks (Ayhan & Tokdemir, 2019a)

Figure 4.2: Best validation performance of the networks (Ayhan & Tokdemir, 2019a)

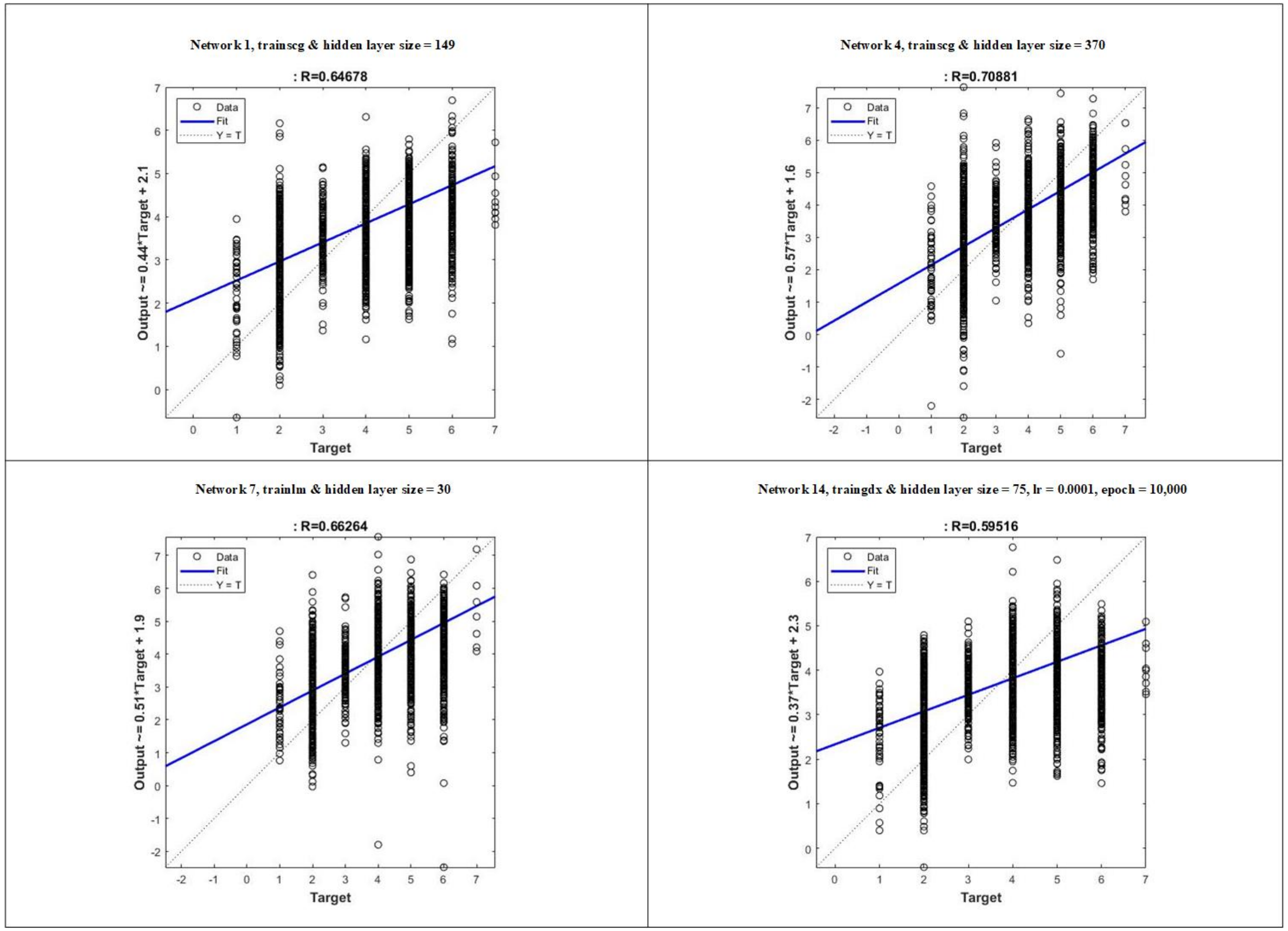


Figure 4.3: Rsq of the four networks (Ayhan & Tokdemir, 2019a)

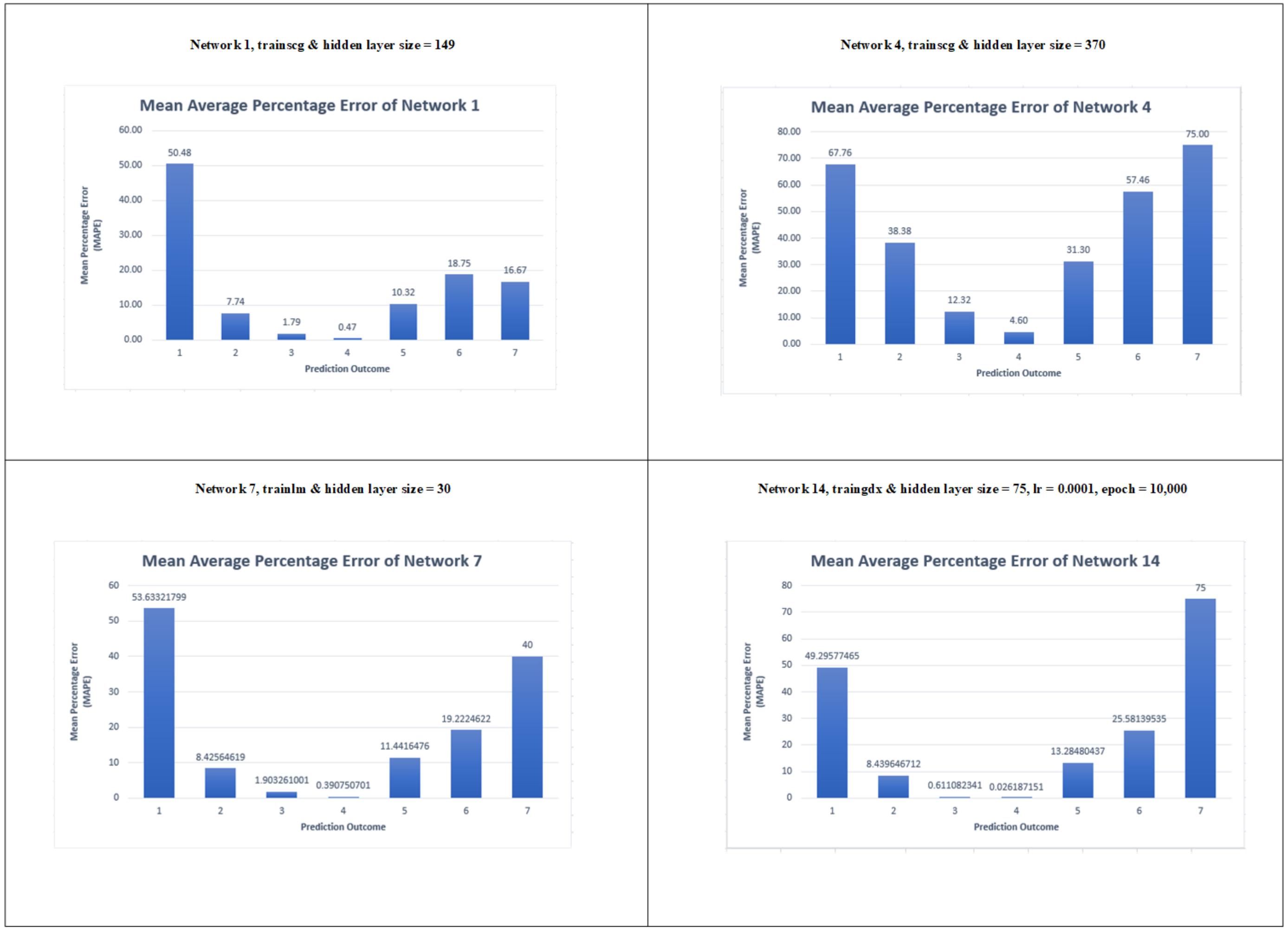
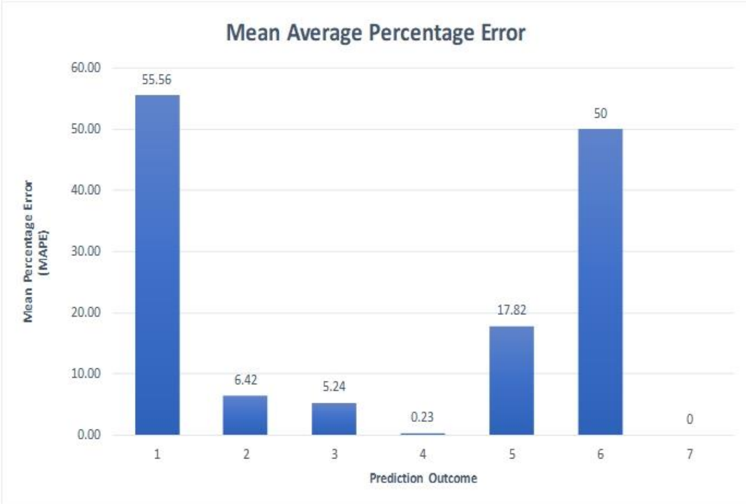


Figure 4.4: MAPE values of 4 networks for training (Ayhan & Tokdemir, 2019a)



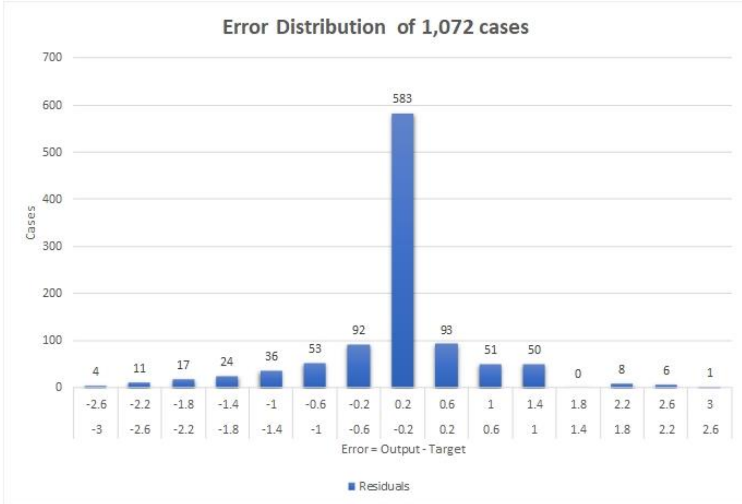


Figure 4.5: MAPE and Error distribution of test cases (Ayhan & Tokdemir, 2019a)

There was almost no difference in Rsq, MSE values, and error distributions. However, although the Rsq of network 1 was not the highest one, Figure 4.4, which presented the MAPE values, signified the best network. The training accuracy of network 1 was better for high severe construction accidents. The model can predict fatal accidents with 16.67% MAPE. Besides, T-3 and T-4 were estimated with almost zero error. This information made the network 1 step forward to the validation process.

The author randomly put aside 1,071 cases for the validation process of the model developed. The simple script was written in MATLAB software to split the dataset into the two slots for training and testing. Then, the testing datasets were put into the networks to demonstrate the prediction performance of the best model. Figure 4.5 represented that the prediction behaviors of the model resembled the training one, too. The errors in the T-3 and T-4 was negligible as similar to the performance obtained training progress. However, the fatal accident and lost workday cases prediction accuracy were 50% and 100% accordingly. Besides, more than 50% of the cases were predicted with +- 0.2 errors on a scale of 1 to 7.

4.1.3. Integrating the expert module

The expert module was integrated into the ANN model to eliminate the vagueness of the prediction results. The machine-based prediction process cannot be entirely trustworthy, especially for severe incidents. Expert opinion should be taken into account while interpreting the results of the predictive model, so the expert module applying the working principle of the Fuzzy Set Theory took place. The model utilized the manner of the Conoco Philips Marine pyramid. The first step of developing a model with the Fuzzy set is to determine the type of the memberships functions so that they converted the linguistic terms to the numerical expressions. Geometric shapes accounted for explaining the relationships along with the fuzzy data, and some examples can be S-curve, trapezoidal, and triangular forms (Arditi et al., 2001).

TABLE 4.5: Linguistic variables and fuzzy numbers (Ayhan & Tokdemir, 2019a)

Prediction Step Outcome		Expert Module Outcome		Final Results	
Linguistic Variables	Fuzzy Numbers	Linguistic Variables	Fuzzy Numbers	Linguistic Variables	Fuzzy Numbers
At Risk Behavior	(1,1,2)	At Risk Behavior	(1,1,2)	At Risk Behavior	(1,1,2)
Near Miss	(1,2,3)	Near Miss	(1,2,3)	Near Miss	(1,2,3)
Incident with Partial Failure	(2,3,4)	Recordable Injuries	(2,3,4)	Incident with Partial Failure	(2,3,4)
Incident requiring First-Aid	(3,4,5)	Lost Workday Cases	(3,4,5)	Incident requiring First-Aid	(3,4,5)
Incident requires medical intervention	(4,5,6)	Fatalities	(4,5,5)	Incident requires medical	(4,5,6)
Lost Workday Cases	(5,6,7)			Lost Workday Cases	(5,6,7)
Fatalities	(6,7,7)			Fatalities	(6,7,7)

TABLE 4.6: The comparison of prediction results after training and testing

Target	ATR	Prediction Results	
		Testing	Training
At Risk Behavior	T-1	44.44%	49.52%
Near Miss	T-2	93.58%	92.26%
Incident with Partial Failure	T-3	94.76%	98.21%
Incident requiring First aid	T-4	99.77%	99.53%
Incident requiring Medical Intervention	T-5	82.18%	89.58%
Lost Work Day Cases	T-6	50.00%	81.25%
Fatalities	T-7	100.00%	83.33%

In civil engineering applications, the triangular membership function is commonly used, so the author decided to employ the same. For each input, three different memberships functions were determined. Hence, Table 4.5 demonstrated the memberships functions of linguistic variables and their membership values in detail.

The next step is to establish if-then rules regarding prediction accuracy. The basis of the if-then rules depended on the accuracy performance of the system. The following table exhibited the training and testing performance of the best network. As mentioned before, the pyramid does not deal with accidents like our study because it involved the T-3, T-4, and T-5 under the recordable injury category where ANN can forecast the results with almost zero errors. Therefore, a set of rules was developed regarding the factual knowledge of the pyramid and information in Table 4.6. Thirty-five set of rules were developed to increase the prediction performance of ANN by implementing Fuzzy sets. Some examples of the if-then rules were drafted below to have a better understanding of the logic behind it.

- If the prediction step outcome indicates the result of the incident as "Fatalities," even expert module results can be concluded as a "Near Miss," the outcome is "Fatalities."
- If the prediction step intimates the results as "Incident requiring first-aid," and the expert module as "At risk behavior," the outcome could be found as "Incident requiring first-aid" since the accuracy of prediction step at that target is too high.

- If the prediction step states that the results are "At-Risk Behavior," but the expert module indicates that the results are "Fatality." Then, the final result was accepted as "Fatality" as opposed to encountering 30 high-severe incidents, according to the Conoco Philips Pyramid.

Ultimately, the first part of the model concluded, and the study advanced to set the corrections measures to prevent accidents. Details about this are given in Chapter 6 after the discussion of the findings part.

4.2. Second part

4.2.1. Reducing the size of the dataset by LCCA

The aim of performing the LCCA is to create homogenous subgroups from the dataset, which has a high level of heterogeneity. Heterogeneity causes severe problems in the prediction process since the model cannot understand the underlying structure of the dataset and achieve meaningful results. LCCA enhanced the quality of the data, which may improve prediction performance.

During the analysis, all megaproject data was participated in the analysis without considering the target of the incidents. The reason was that the clustering techniques are the unsupervised learning mechanism that does not require any information about the target values. The attributes except for the victim's properties indicated in Figure 3.5 described the incident cases, and analysis initiated. The LCCA analysis was performed on XLSTAT 2018 software. The optimum number of clusters should be determined, so more than one analysis was carried out regarding the various cluster numbers from two to ten.

Several criteria control the optimum cluster number as BIC, AIC, and CAIC. Lower values of the first these values indicated the success of the clustering process. That means the subsets obtained via the analysis are becoming more homogenous. The increase in cluster number is appearance entailing to achieve more homogenous subgroups because each case has its characteristics, so the data structure tends to move apart more step by step. However, the value of these criteria is always going down with an increase in clusters. After a certain point, the rate of decrease in these values is becoming smaller, and the model reached the balance. Besides, Entropy Rsq (3.7) was calculated to support the indicated criteria in determining the optimum cluster number. The Entropy Rsq is varying between the zero and one, and the closest value to one indicates better results.

Figure 4.6 visualized the analysis results to capture the optimum number of the cluster along with the dataset in return. When the cluster number was equal to the five, BIC and CAIC values became coherent and did not show a dramatic drop until that point. Also, Entropy Rsq was equal to 0.85 and did not incline to the one in further steps. These values showed that the classification of the model was almost wholly acquired when the cluster number was equal to five.

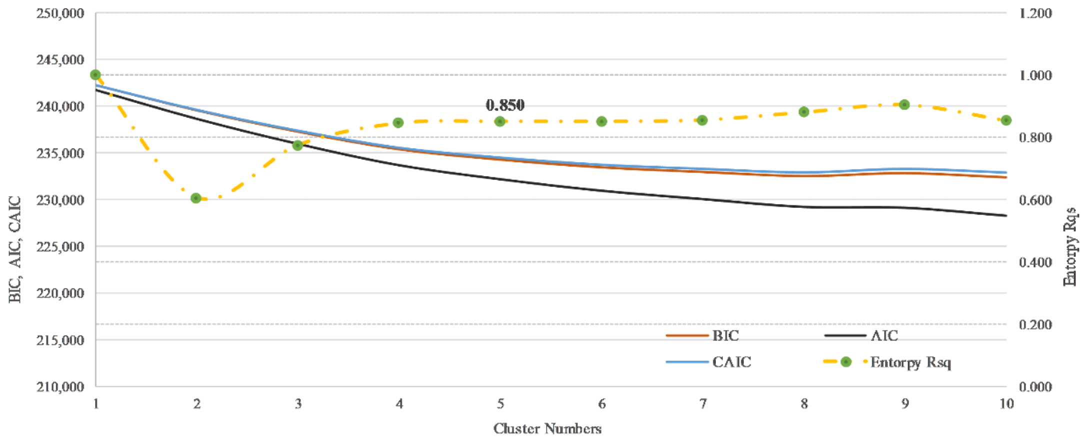


Figure 4.6: Demonstration of BIC, AIC, CAIC and Entropy Rsq (Ayhan & Tokdemir, 2019b)

After determining the cluster number, the analysis stepped forward to distributing the attributes regarding the presence probability regarding the clusters. The results of the analysis were exported to Tableau 2018 software to visualize the presence probability of the attributes for each cluster. Figure 4.7 stands for the attributes which have been represented in binary characters only if the categoric ones participated in the analysis. The probability distribution of binary-expressed attributes was estimated for the absence (0) and presence (1) states of all the incidents. However, only the present state of the attributes for each cluster was delivered in Figure 4.7 to prevent confusion. The figure classified the clusters concerning their size as well.

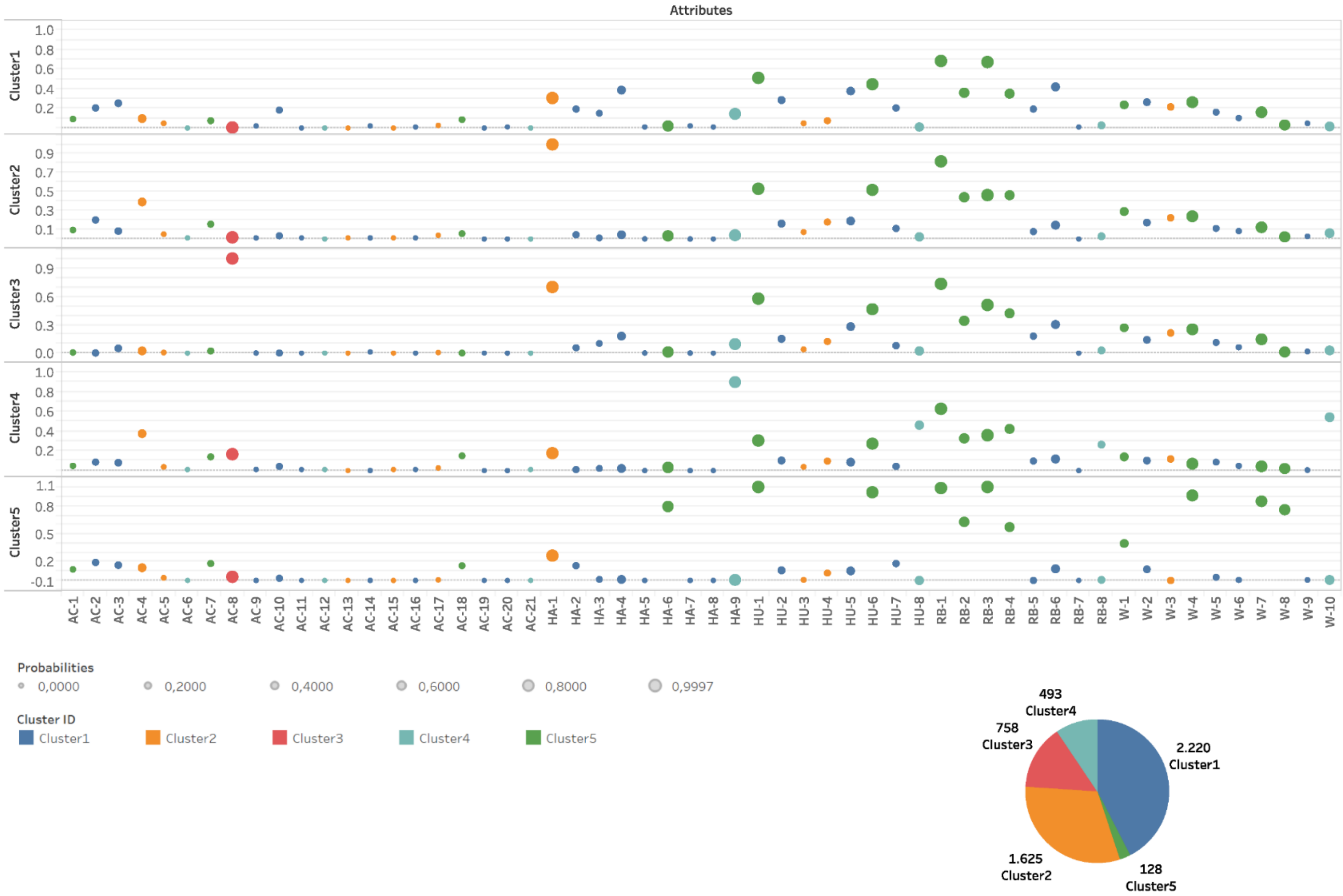


Figure 4.7: LCCA Results (Ayhan & Tokdemir, 2019b)

As mentioned, the present probabilities controlled the classification process. For example, AC-8, "Mobilization on/off-site" was remarked in red to imply the Cluster 3. That means the highest probability of AC-8 was observed in Cluster 3. Therefore, it was assigned to the third dataset. In some cases, presence probabilities were too low for various reasons. Firstly, a high number of attributes were managed in analyzing the incidents. Secondly, the presence probability may unsurprisingly become smaller while the cluster size was huge, as in Cluster 1 and Cluster 2.

Eventually, the remaining attributes were controlled correspondingly and distributed to the related groups to create the datasets.

4.2.2. Data modeling

LCCA developed five datasets, which had different attributes. The attributes were classified according to the clusters, and incident cases were rearranged for five additional datasets accordingly. Linguistic variables described the work-related failures, but they should be converted to the mathematical expression for the computational process. The predictive models need to understand the underlying structure of the data and provide inferential statistics for interpreting the results in return. Hence, six separate datasets, including the original one, were established. The data process was handled by integrating the binary coding system along with all datasets. The author performed the modeling on the MS Excel environment because of its ability to adapt most of the available software in the market. Datasets were ready to proceed with the predictive model development.

4.2.3. Development of the ANN model regarding clusters

The model development procedures followed the tracks of the first part as the ANN-based predictive models were developed with the same manner of understanding. The first part of the study gave tremendous instruction on selecting the best combination of the network parameters. Although the best network reached the best network status because of its prediction performance, the trainlm was also showing an acceptable performance. The reason why it was not chosen for the further step was also related to the time spending on the training process. In the first part, the attribute size was too large, so an increase in neuron-input ratio considerably increased the model development time. The author reduced the attribute number at first and obtained homogenous subsets from them, so significant drops in attribute numbers were observed. Hence, the trainlm learning function was decided to be used for the training process of the ANN models. Besides, the transfer function is another essential parameter for model development as the transfer function identifies relationships between the nodes by synaptic weights. The sigmoid functions are one of the most common functions that introduce the nonlinear correlation among the nodes and highly recommended by the researchers (e.g., Waziri et al., 2017; Arditi et al., 1998). As a result, tansig was utilized as a transfer function.

The ANN models utilized 4,466 incident cases for training, and remaining data was taken into consideration to validate the models constituted. Parallel to the knowledge explained in the previous paragraph, thirteen networks from five clusters were obtained to select the best network. The first criteria were the Rsq and MSE (3.4) values of the models. Networks, which satisfied its competence on these criteria, advanced to the next step where test cases were implemented to validate the models. Similar to the first part, MAPE (3.5) of singular target and overall MAPE (3.6) were computed.

Table 4.7 demonstrated the predictive model performance regarding the first criteria. LCCA aggregated the attributes according to the presence of probabilities, so differentiates in the input size concerning the clusters were observed from Table 4.7. The hidden layer size cannot be strained with consistent values because of the variations in input sizes. Hence, the author decided to investigate them in terms of neuron-input size ratio accordingly. As well as the ratio, the learning rate was also adaptive to the models, so iterations also included different learning-rate values.

TABLE 4.7: ANN networks (Ayhan & Tokdemir,2019b)

Dataset	Network ID	Train Function	Input Size (a)	Hidden Layer Size (n)	n/a Ratio	Learning Rate	Maximum Iteration	R Square	MSE
Cluster 1	C1-1	trainlm	29	29	1	0.01	2000	0.65715	0.32
	C1-2	trainlm	29	29	1	0.05	2000	0.65918	0.33
	C1-3	**trainlm**	**29**	**29**	**1**	**0.1**	**2000**	**0.6402**	**0.34**
	C1-4	**trainlm**	**29**	**58**	**2**	**0.05**	**2000**	**0.68427**	**0.27**
Cluster 2	C2-1	trainlm	13	13	1	0.05	2000	0.4461	0.54
	C2-2	trainlm	13	26	2	0.05	2000	0.5009	0.49
Cluster 3	C3-1	trainlm	5	5	1	0.05	2000	0.2955	0.6277
	C3-2	trainlm	5	10	2	0.05	2000	0.33159	0.6113
	C3-3	trainlm	5	10	2	0.2	2000	0.32588	0.6159
Cluster 4	C4-1	trainlm	11	11	1	0.05	2000	0.21911	0.56909
	C4-2	trainlm	11	22	2	0.05	2000	0.43547	0.54137
Cluster 5	C5-1	trainlm	18	18	1	0.05	2000	0.53736	0.44912
	C5-2	**trainlm**	**18**	**36**	**2**	**0.05**	**2000**	**0.67615**	**0.30536**

The results indicated that C1-3, C1-4, and C5-2 were one of the best networks, among others. These models advanced through the validation process, MAPE of the singular target and overall MAPE were calculated to decide the best network performance for test cases. Figure 4.8 presented the MAPE and overall MAPE of the targets with a bar chart, and Figure 4.9 supported these statistics by visualizing the fluctuation in residuals (3.3).

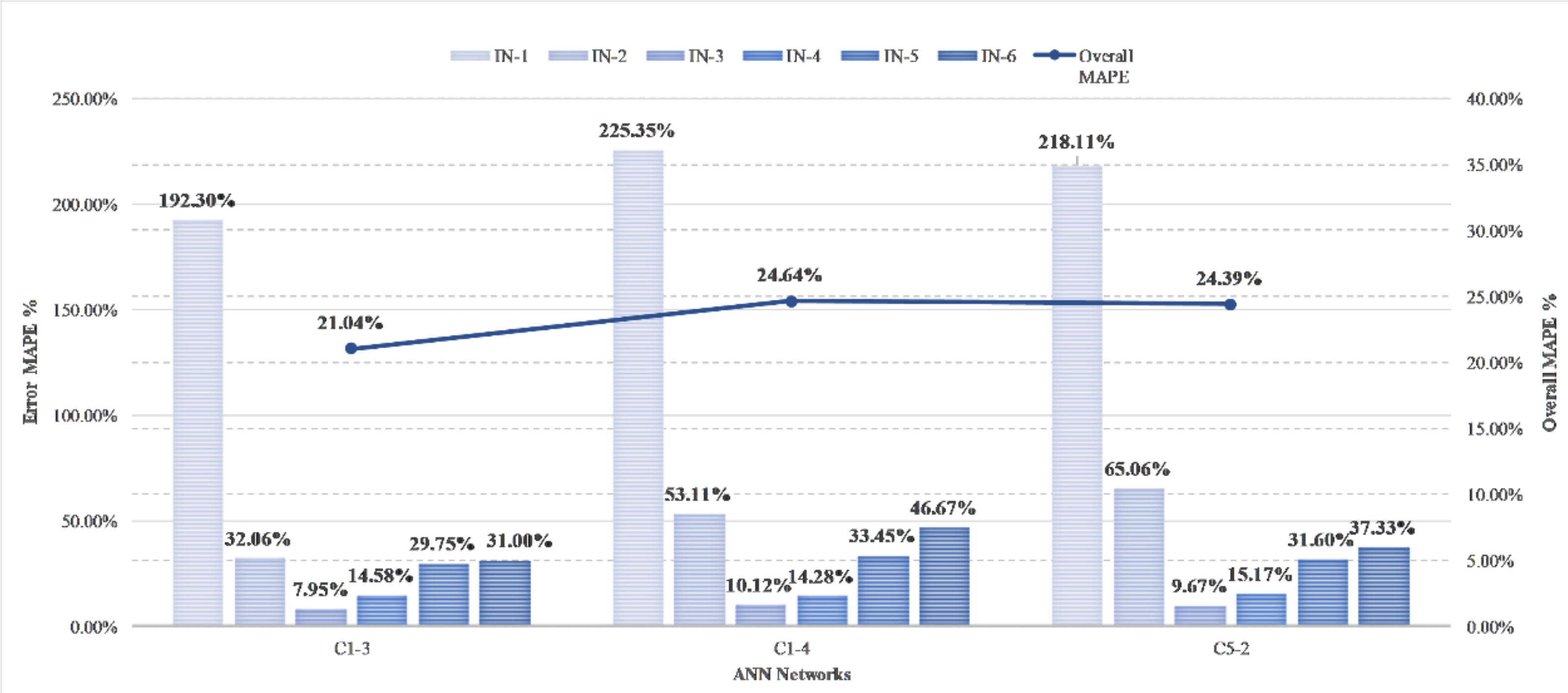


Figure 4.8: MAPE values of ANN Network for 758 test cases (Ayhan & Tokdemir, 2019b)

The common things between the networks were that the prediction accuracy was too low in "At-risk behavior" and "Near-misses". However, the overall MAPE was the smallest for C1-3, whose datasets belonged to cluster 1. Besides, the Box and Whisker chart presented the deviation in the results of the model more comprehensively. The variation in C1-3 was smaller than in the others. The upper and lower quartiles of the boxes were closer to zero. Thus, the best model was selected as C1-3.

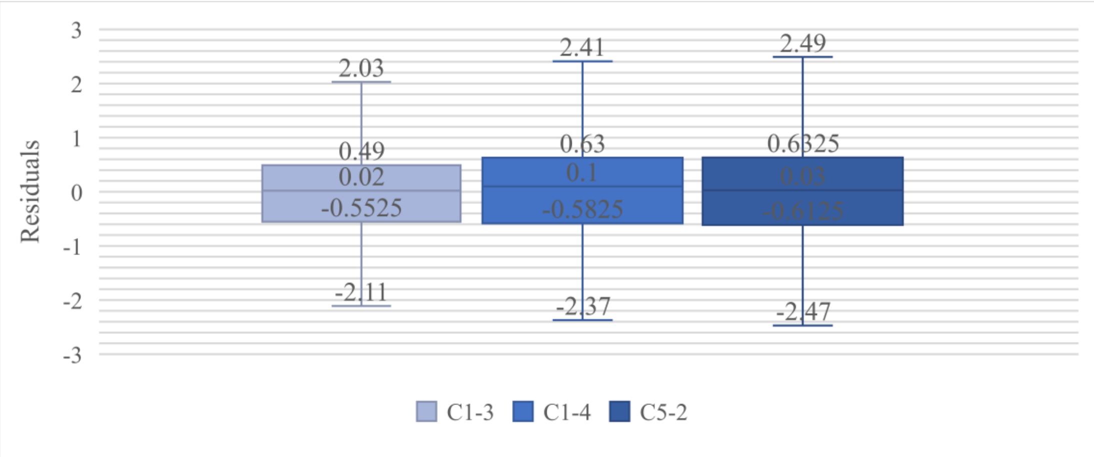


Figure 4.9: Box and Whisker Plot of Residuals (ANN-758 Test Cases) (Ayhan & Tokdemir, 2019b)

4.2.4. Development of the CBR model regarding clusters

4.2.4.1. Weight calculation by AHP

The logic behind the CBR depends on the similarity scores. The attributes, which formed the incident cases, established the frame of the data structure, and the data structure scaled the rate of resembles between the stored cases and test cases. However, each attribute has a different contribution to the results regarding its observation rate, and this results in having different weights. The similarity score of the test cases was also affected because resemblance in highly weighted attributes put more significance on the results. The author decided to calculate the weight of the attributes manually, so AHP began. AHP started with determining the problems, which were the incident cases in this study. Then, the decision-making process proceeded where attributes formed the structure of it.

TABLE 4.8: The weight of Attributes after AHP (Ayhan & Tokdemir, 2019b)

1st Stage AHP			2nd Stage AHP																					
			The weight of attributes inside groups																					
CR	Attributes Groups	Group Weight	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	CR'
0.06	Occup.	0.11	0.03	0.26	0.15	0.36	0.09	0.04	0.02	0.05	-	-	-	-	-	-	-	-	-	-	-	-	-	0.04
	Exp.	0.1837	0.19	0.36	0.26	0.14	0.04	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.04
	Age	0.2335	0.28	0.45	0.18	0.09	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.02
	Time	0.163	0.03	0.02	0.10	0.32	0.17	0.24	0.08	0.05	-	-	-	-	-	-	-	-	-	-	-	-	-	0.03
	AC	0.0671	0.07	0.11	0.10	0.13	0.05	0.01	0.09	0.11	0.03	0.08	0.01	0.01	0.01	0.03	0.02	0.02	0.03	0.06	0.01	0.01	0.01	0.08
	RB	0.0913	0.27	0.15	0.21	0.15	0.07	0.10	0.02	0.03	-	-	-	-	-	-	-	-	-	-	-	-	-	0.07
	HA	0.0439	0.31	0.11	0.10	0.20	0.02	0.07	0.03	0.02	0.15	-	-	-	-	-	-	-	-	-	-	-	-	0.07
	HU	0.0516	0.30	0.11	0.02	0.06	0.15	0.23	0.08	0.04	-	-	-	-	-	-	-	-	-	-	-	-	-	0.02
	WF	0.0554	0.21	0.13	0.15	0.18	0.08	0.05	0.10	0.03	0.02	0.06	-	-	-	-	-	-	-	-	-	-	-	0.04

The two-level pairwise comparison took place while computing progress. First, the comparison was handled among the nine attributes categories, and then comparison delved into deeper between the attributes under the individual categories as well. AHP concluded which one was more superior to trigger the incidents.

The process was followed, as stated in chapter 3.2.2, and the analysis obtained the results in Table 4.8. At the end of the calculation, consistency indexes (by following (3.12) and (3.13)) of the two pairwise comparisons were computed to satisfy the defined criteria. As a result, all conditions were solved, and the weight of the attributes was used to develop CBR models accordingly.

4.2.4.2. Calculating the weighted similarity score of test cases

The CBR process included five steps in a row. The MATLAB script was coded by the author to calculate the weighted similarity score of the test cases. The codes were custom-tailored systems that can adapt each type of the datasets no matter the size of the data differs. Each dataset took the weight values regarding their attributes, and the datasets were remodeled in the MS Excel file. Then, the script accommodated the weights and incident cases in an Excel spreadsheet to computational progress. The summary of the CBR steps can be described as follow:

Step 1: Determining the matching type

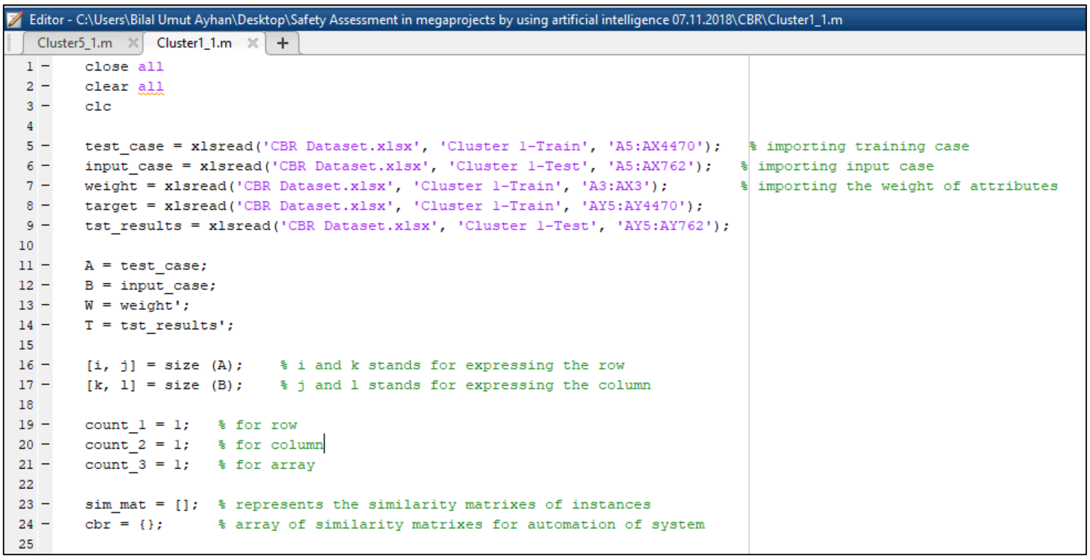
The matching strategy is essential since the similarity score computation directly linked to it. More than one strategy exists concerning the type of data, such as proportional matching and exact match. Exact matching was more convenient for this study as data composed a full of linguistic expression as an attribute. That means attributes would get only 1.0 or 0.0 for their resembles rate. Proportional similarity cannot be accepted.

Step 2: Determining thresholds for calculating weighted similarity score

The threshold values aided to reduce the vagueness of the prediction results. All cases in case-base were assigned some values over 1.0 to demonstrate how they are similar to the test cases. However, the highest case cannot always indicate the consequences of incidents correctly. The threshold for the similarity scores helped to eliminate conflicts and achieve more realistic results in return. Two-level thresholds were settled to check which one is more accurate for the type of data. These values were 0.75 and 0.90, respectively. If the constituted model cannot satisfy the criteria defined before, these values would be getting to be changed accordingly.

Step3: Retrieving the dataset from the Excel Spreadsheet to MATLAB

The script was coded in MATLAB to import the incident cases. The code retrieved the cases and started the computation process. Figure 4.10 represented the detail of the MATLAB script. The codes between lines 5 and 9 retrieve the related data from the Excel spreadsheet. Remaining codes were given with their expression. The comments remarked with green colors and expressed their purposes.



Editor - C:\Users\Bilal Umut Ayhan\Desktop\Safety Assessment in megaprojects by using artificial intelligence 07.11.2018\CBR\Cluster1_1.m

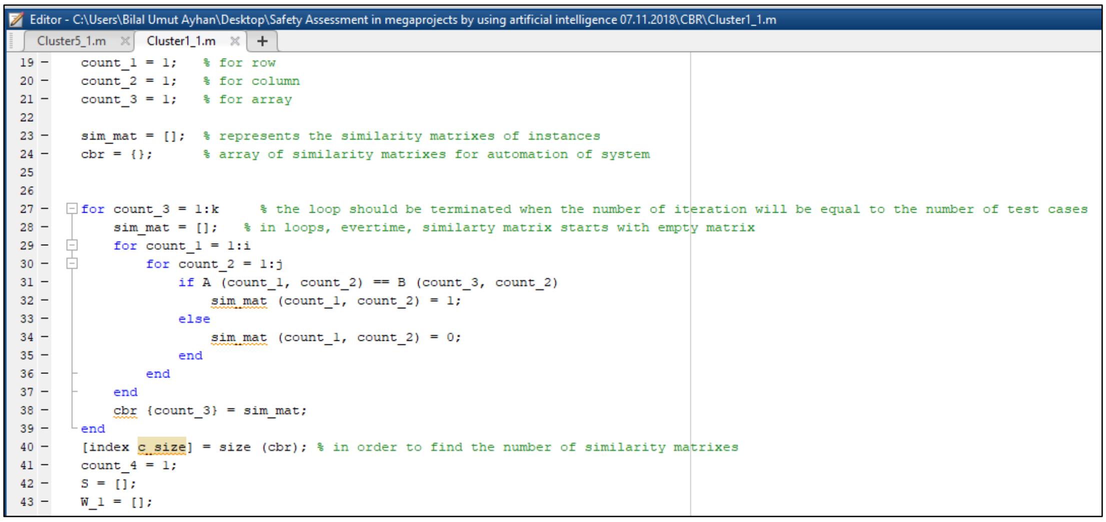
Cluster5_1.m | Cluster1_1.m

```
1   close all
2   clear all
3   clc
4
5   test_case = xlsread('CBR Dataset.xlsx', 'Cluster 1-Train', 'A5:AX4470');   % importing training case
6   input_case = xlsread('CBR Dataset.xlsx', 'Cluster 1-Test', 'A5:AX762');   % importing input case
7   weight = xlsread('CBR Dataset.xlsx', 'Cluster 1-Train', 'A3:AX3');        % importing the weight of attributes
8   target = xlsread('CBR Dataset.xlsx', 'Cluster 1-Train', 'AY5:AY4470');
9   tst_results = xlsread('CBR Dataset.xlsx', 'Cluster 1-Test', 'AY5:AY762');
10
11  A = test_case;
12  B = input_case;
13  W = weight';
14  T = tst_results';
15
16  [i, j] = size (A);    % i and k stands for expressing the row
17  [k, l] = size (B);    % j and l stands for expressing the column
18
19  count_1 = 1;   % for row
20  count_2 = 1;   % for column
21  count_3 = 1;   % for array
22
23  sim_mat = [];  % represents the similarity matrixes of instances
24  cbr = {};      % array of similarity matrixes for automation of system
25
```

Figure 4.10: MATLAB code generated by the author for retrieving data

Step 4: Calculating the weighted similarity scores:

AHP produced the weight of the attributes, but relative weight can change regarding the clusters. The reason is that AHP generated the weight of all datasets, but the weights should be normalized regarding the new dataset coming from the clusters. At every trial, weights were calculated repetitively, and MATLAB script retrieved them for model development. Figure 4.11 displayed a part of the codes written for calculating the similarity scores. The codes generated the similarity matrixes regarding the stored case in case-base. Then the matrixes were multiplied with the normalized weight scores to obtain weighted similarity scores.


Editor - C:\Users\Bilal Umut Ayhan\Desktop\Safety Assessment in megaprojects by using artificial intelligence 07.11.2018\CBR\Cluster1_1.m

Cluster5_1.m | Cluster1_1.m

```
count_1 = 1;   % for row
count_2 = 1;   % for column
count_3 = 1;   % for array

sim_mat = [];  % represents the similarity matrixes of instances
cbr = {};      % array of similarity matrixes for automation of system


for count_3 = 1:k     % the loop should be terminated when the number of iteration will be equal to the number of test cases
    sim_mat = [];   % in loops, evertime, similarty matrix starts with empty matrix
    for count_1 = 1:i
        for count_2 = 1:j
            if A (count_1, count_2) == B (count_3, count_2)
                sim_mat (count_1, count_2) = 1;
            else
                sim_mat (count_1, count_2) = 0;
            end
        end
    end
    cbr {count_3} = sim_mat;
end
[index c_size] = size (cbr); % in order to find the number of similarity matrixes
count_4 = 1;
S = [];
W_1 = [];
```

Figure 4.11: Generating the similarity matrixes

Step 5: Controlling the errors of test cases (758) by checking MAPE and overall MAPE

In this step, the MAPE of each target and overall MAPE values were calculated. Figure 4.12 plotted the errors of the models with a bar chart. The results were controlled to satisfy the criteria given in the previous chapter, and the remaining process advanced with a comparison of the model.

By following the procedures indicated above, the first cluster dataset achieved the best prediction. Besides, the threshold value of 0.90 obtained better performance in prediction. Further, the residuals were calculated to control the amplitude of the results predicted. Similar to the ANN models, Box and Whisker plot were applied to graph the residuals. Besides, the smaller fluctuation was observed in the CBR-90-1 model as shown in Figure 4.13. The upper and lower quartiles of the boxes were much closer to each other.

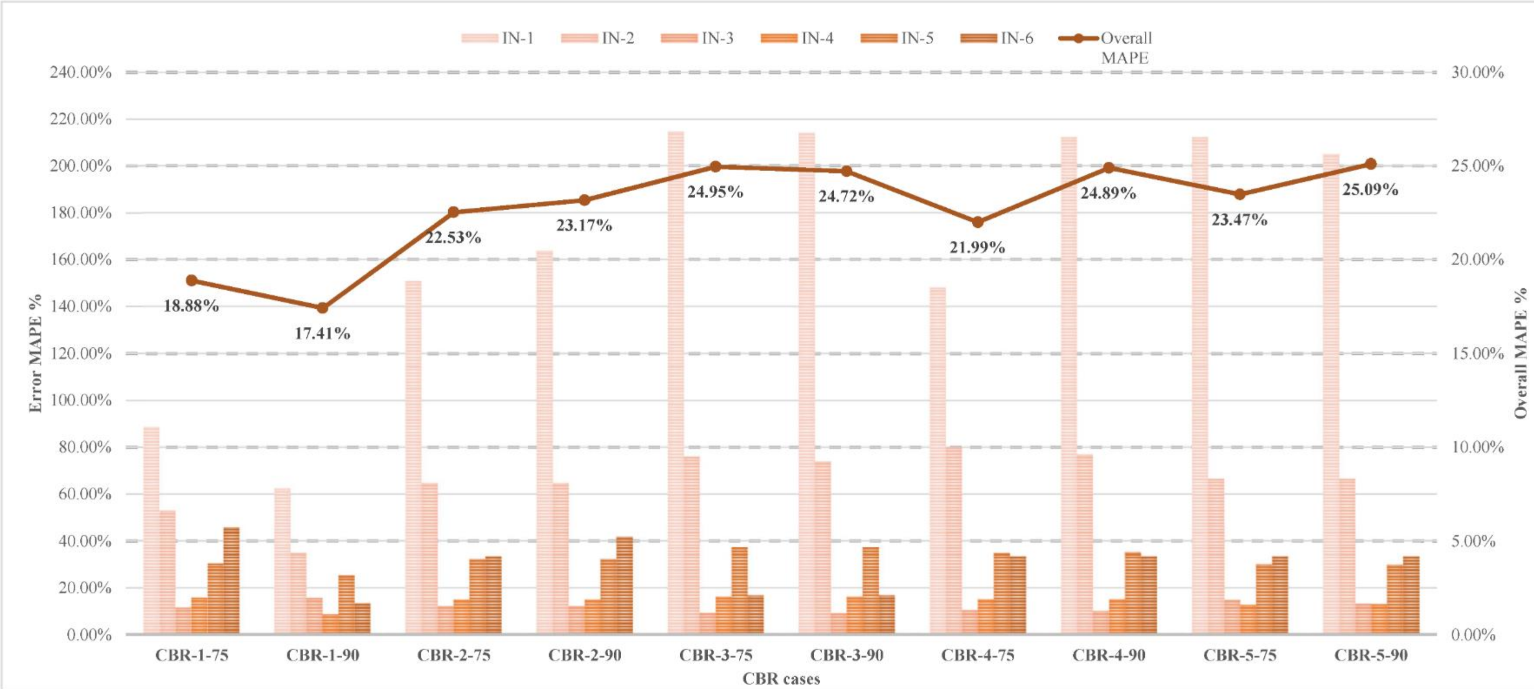


Figure 4.12: MAPE of CBR for 758 Test cases (Ayhan & Tokdemir, 2019b

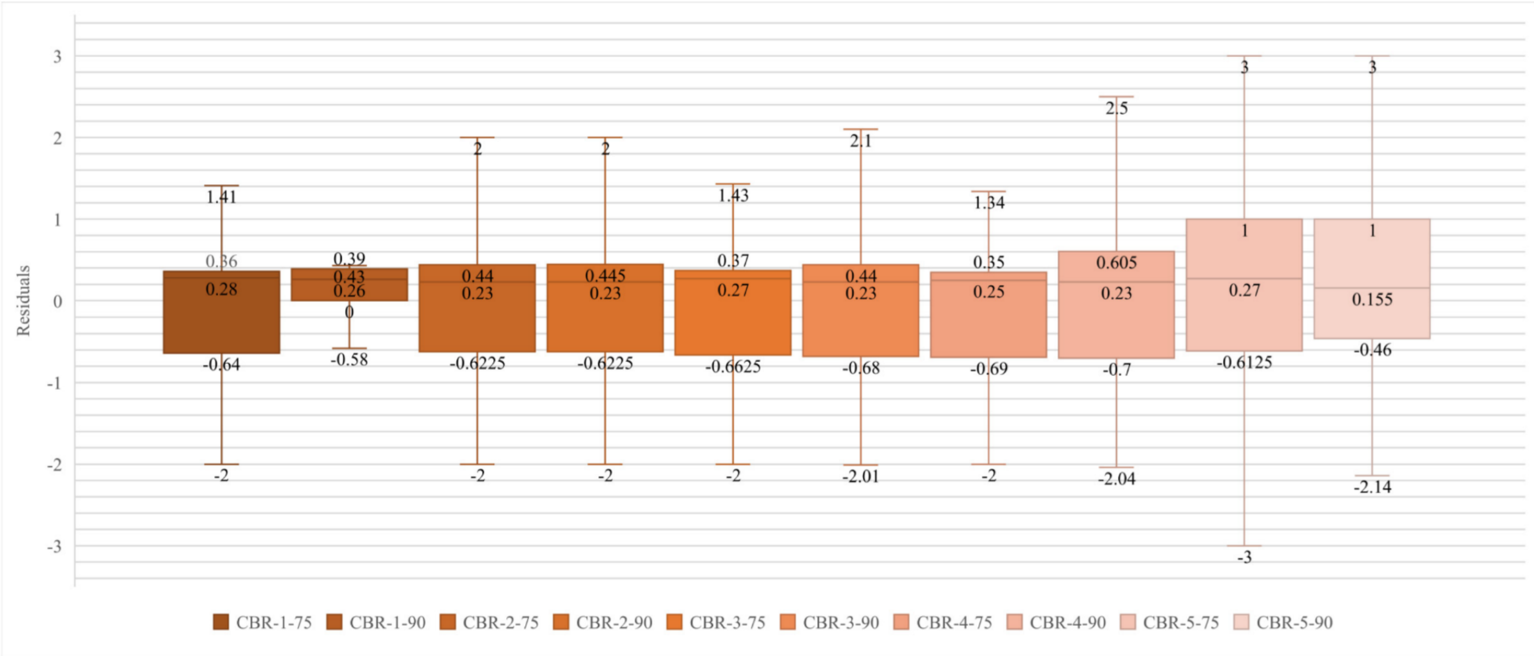


Figure 4.13: Box and Whisker Plot of Residuals (CBR-758 Test Cases) (Ayhan & Tokdemir, 2019)

CHAPTER 5

DISCUSSION OF FINDINGS

The thesis explained the pillars of three predictive model development. The models adopted ANN and CBR techniques during the prediction process. Besides, the model differed from each other by dealing with different datasets. The first datasets included over 17,000 incident cases, and ANN was only applied to establish a model. The model tried to forecast the seven different outcomes. Then, the Fuzzy Inference system was integrated to eliminate the vagueness of the prediction results. The machine-based predictive model had some shortcomings because any methods of big data analytics were applied to reduce heterogeneity. Instead, the expert model based on Fuzzy Set Theory was taken into account to do so.

Moreover, the proposed study included the frame of the attributes list. The author intended to base attributes on a piece of factual knowledge. The experts' opinions should be taken into consideration, so the Delphi method was employed to create a list of attributes. The participants in the Delphi process cannot be influenced by each other so that they can reflect their opinion on this subject under any pressure. Therefore, their judgments on questions prepared by the author formed the underlying structure of the attributes' list and enlightened future work, as shown in the development of the models in part 2.

The other outcome of the first part was the prediction accuracy of the constituted model. Table 5.1 displayed the results of the predictive models. The MAPE values were calculated regarding the individual outcome of the incidents. The present table also consisted of the results of the prediction after applying the Fuzzy logic. The integration of the expert model slightly improved the prediction performance of the target "At-Risk Behavior" and "Lost-Workday Case," respectively. Besides, the ANN model accomplished to predict the outcome of 84% incident within 90% confidence.

The second part of the analysis started from that point. The second part covered the development of the ANN and CBR models to compare for finding which one is adaptable to incident cases. Before establishing the predictive model, the second part included the Big Data Analytic implementation to reduce the heterogeneity throughout the dataset. As mentioned before, incidents that belonged to the megaprojects were moved apart from data to constrain the aim.

TABLE 5.1: Comparison of the prediction results of ANN and ANN-Fuzzy for part (Ayhan & Tokdemir, 2019a)

		Prediction Result	
Target	ID	ANN	ANN+Fuzzy
At Risk Behavior	T-1	49.52%	57.38%
Near Miss	T-2	92.26%	92.26%
Incident with Partial Failure	T-3	98.21%	98.21%
Incident requiring First Aid	T-4	99.53%	99.53%
Incident requiring Medical Intervention	T-5	89.58%	89.58%
Lost Work Day Case	T-6	81.25%	87.62%
Fatalty	T-7	83.33%	83.33%

The proposed system encompassed the solution for big data problems in megaprojects. Incident cases were expressed with the new list of attributes that were prepared regarding the expert opinion. An additional process was handled to make the attribute list more compact so that more logical expressions took place when describing the work-related events. Therefore, the number of attributes dropped significantly, even participation of new groups like the victim's age, experience, and occupation.

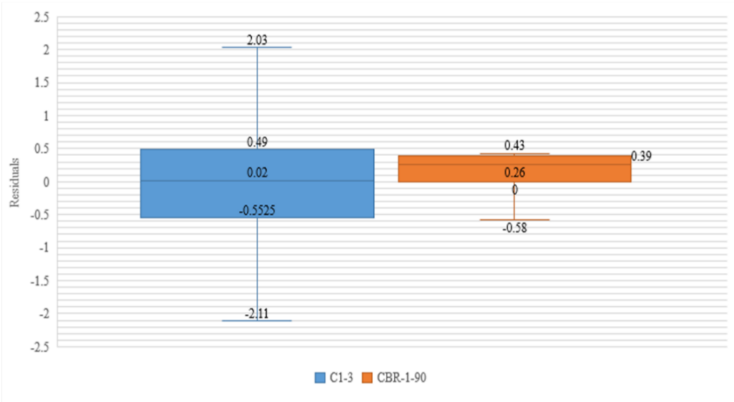
The first aim was to reduce complexity, so LCCA was applied to do so. LCCA optimized five different clusters, so the attributes were distributed to each cluster regarding their presence probabilities in each of them. As a result, the analysis obtained five different datasets that formed the basis of the predictive models in the second part. In the previous chapter, the model accuracy in the prediction process was displayed. The strategy for finding the best model was the most critical step for the success of the predictive models. Both approaches had their features and differed from each other. They should be modified regarding the characteristics of the dataset to achieve better accuracy. For ANN, learning function and the ratio between the hidden layer size and input size prioritized, so the best performance was captured when learning function was "trainlm," and ratio was equal to one accordingly.

CBR also had different characteristics that had an impact on the prediction performance of the model. The matching strategy was one of them. An exact matching strategy was decided to be used since the model included full of linguistic variables expressed in binary format. Secondly, threshold values for similarity scores were settled because the most similar case cannot always reflect the exact result. The CBR achieved the best prediction performance regarding the cases whose similarity scores were higher than 0.90.

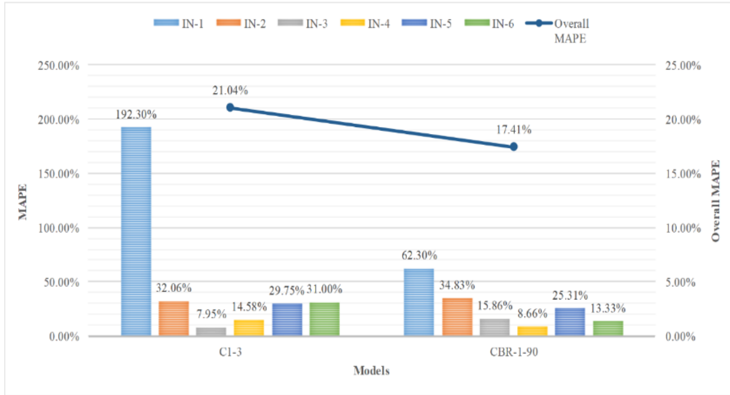
The best model of CBR and ANN was selected and compared their results for better understanding. Figure 5.1 revealed the differences between the models well. The CBR responded better to incident data. The difference between the upper and lower quartile was considerably low in CBR. Besides, the MAPE and overall MAPE values were smaller, too. In addition to these, Figure 5.1 (D) exhibited that 86% of the incident cases were predicted with 18% at most.

The study revealed several ultimate outcomes in terms of data preparation and prediction performance of the predictive models with the surveillance of the results.

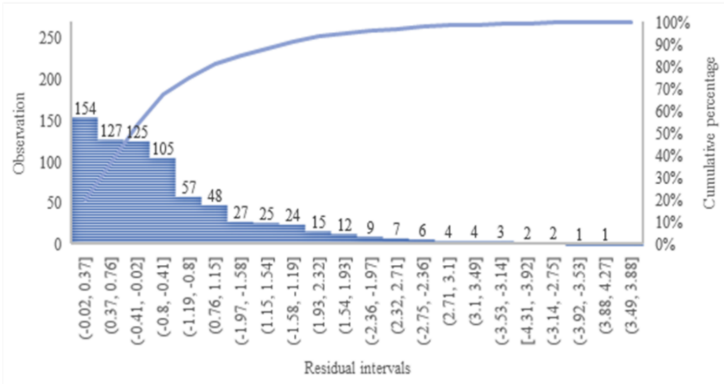
The research involved two main pillars. The first prediction model utilized almost 18,000 incident cases for the development of the model. The bulk information inside the data was eliminated with the expert opinion throughout the Delphi method, and any method for Big Data Analytics was applied in advance. The model required more cases to learn the hidden patterns between the accident outcomes and their triggers, so it required more cases in return. Besides, the author implemented a final modification to remove the vagueness of the ANN results by applying the Fuzzy Set Theory. The proposed system achieved an excellent prediction performance, especially for the events, which concluded with T-3, T-4, and T-5, as shown in Table 5.1. The inclusion of the Expert module also slightly enhanced accuracy.



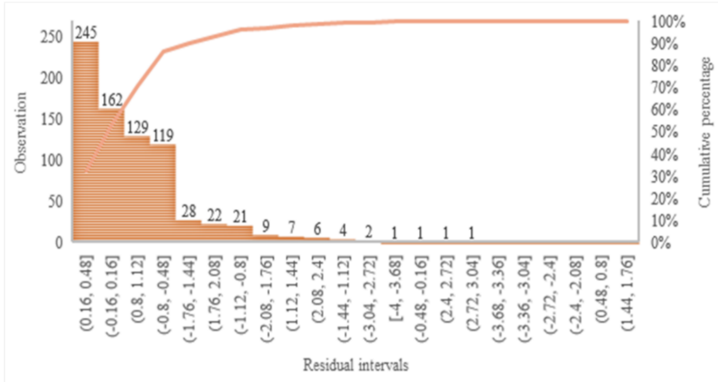
A)



B)



C) ANN



D) CBR

Figure 5.1: Comparison of CBR and ANN results (Ayhan & Tokdemir, 2019b)

The second part included the development of two different prediction models. Although there was a small variation between the outcomes, most of the targets were the same (see Figure 3.5 and Table 4.3). The size of the dataset was dramatically reduced to accumulate the megaproject information, and more characteristics about the incident were taken into consideration.

Before the initiation of the model development, the list of attributes was readjusted to create a more coherent frame. It was crucial since the attribute list quality may directly influence the capability of understanding the relationships among the hidden patterns. Despite these improvements, the model did not have quite homogenous, so LCCA was applied to satisfy this. LCCA generated homogenous subsets from a complex one, and these subsets were getting in to be used for developing a predictive model. CBR and ANN were compared to determine which one was better for adopting the incident data. CBR revealed a better performance and reached almost the same success with the model constituted in the first part.

CHAPTER 6

DEVELOPMENT OF PREVENTATIVE MEASURES

Chapter 6 introduces the correction actions settled regarding the results of the prediction process. Since the study composed of two different parts, it also provided two different solutions for preventing accidents in return.

The correction actions of the first part was derived from the results of the Fuzzy Inference System. Table 6.1 demonstrated the detail of preventative actions. The system divided the results of the prediction process into three different groups, and preventative measures were determined accordingly. The lowest severe groups involved the near misses and at-risk behavior cases. The system proposed to find out a direct cause of possible incidents. If the prediction process were executed during the construction phase, the system would generate more solutions. The solution was elaborated to raise awareness of the workers by giving a toolbox.

When the results of the prediction were in the second level severity groups, the system offered a partial stoppage during the construction and suggested a modification on Method of Statement. In the most severe groups, the system recommended the stoppage and authorizing a research team to disclose the root cause.

The proposed corrective measures show promising solutions but were cot capable of producing a solution, which addresses the cause of accidents directly. That means triggering factors of incidents were not considered in detail while measuring corrections. Therefore, it remained limited in some cases. To overcome the weakness of this system, the author introduced the second system, which was enhanced by considering fatal accident analysis where attributes were taken into account.

TABLE 6.1: Preventative actions proposed in the first part (Ayhan & Tokdemir, 2019a)

ID	Incident	Actions to be taken
A	1-2	Find the direct cause of the prospective incident. Start to give toolbox frequently to raise awareness of employees
B	3-4-5	Partial Stoppage. Check the method of the statement of work. Find the direct cause of the prospective incident. Start to give toolbox frequently to raise awareness of employees
C	6-7	Stop construction. Check method of the statement of work and find the direct cause of the prospective incident. Set up a research team to seek out the root cause

This second part proposed a predictive model to eliminate incidents. If the collected data is analyzed correctly and the predictive model established with the right parameters, preventative actions can be taken to reduce incidents. Prior research focused on forecasting the severity level of construction incidents according to the severity scale illustrated in Figure 3.5. However, predicting the results of incident scenarios is not always enough to avoid safety failures in large-scale construction projects. Preventative actions should be introduced according to the prediction outcome. The incident data, especially for fatal ones, have to be investigated comprehensively to set up preventative measures. The reason is that the attributes play a vital role in developing preventative action strategies. Therefore, three preventative actions were determined to avoid incident cases based on the significance of the attributes (Figure 6.1).

The proposed model was tested with real project data to show the implementation of preventative actions. First, five fatal incidents were chosen for the testing process. The general description of the cases presented in Table 5 was converted to the model format by showing the incidents with the list of attributes in Figure 2. The active attributes in the selected data are shown in Figure 10. The test cases were entered into the prediction model. The proposed CBR model was able to forecast the results of incidents with almost zero errors in total. Next, according to the results of the study and the observation rate of attributes in all the cases, the active attributes were classified into three main categories as A, B, and C. The attributes were given in descending order from A class to C class. Detailed information about their classification features has also been given in Figure 6.1. The outcome of 5 test cases ended up within the range of 5-6, which indicates the highest severity such as lost workday cases and fatalities. As a result, the third preventative action, which suggests detecting possible problem areas before construction and tracking these areas during the construction process, was selected to address the risk of incidents

TABLE 6.2: Characteristics of representative fatal incidents (Ayhan & Tokdemir, 2019b)

ID	Prediction Results	Direct Cost	Description
1	5.6	40,000 $	The incident occurred during piling installation work. The drilling pile operator started to maneuver to lift the second casing pile. At that moment, the concrete mason worker was caught between the drilling machinery and casing pile inserted into the ground for a 25-30 second period. The incident caused a fatal injury in the hip and abdomen area. The incident time was 19:58 which was near breaking time. The victim was 56 years old and had more than 30 years' experience.
2	5.7	600,000 $	The incident occurred during shuttering work. The victim worked until lunchtime. To continue the work, the other crew switched with the working crew at lunchtime. The formwork was attached with anchorages, but the crew forgot to attach two anchorage points. When the victim came back, he thought that console platform work was completed. As he stepped on the platform, the console collapsed, and he fell. The console platform came into the safety net before him and net closed. Therefore, the safety net could not catch him, and he continued falling to the ground.
3	6	120,000 $	The incident occurred at break time. One of re-bar workers climbed to the mezzanine floor to chat with his wife without informing his supervisor. Due to unknown reasons, he fell from a 6-meter height around 00:45 a.m.
4	5.45	400,000 $	The incident occurred while working at height. The victim had not attached himself to a lifeline or any anchorage point. Therefore, the victim lost his balance and fell from a height of 11 meters.
5	6	520,000 $	The incident occurred while the welding inspector was rising in the aerial lift to check the welding works for the elevator. When the aerial lift reached the height limit, the inspector tried to solve the problem by pushing the controllers on the aerial lift, which caused it to become unbalanced. The aerial lift collapsed, and the inspector lost his life.

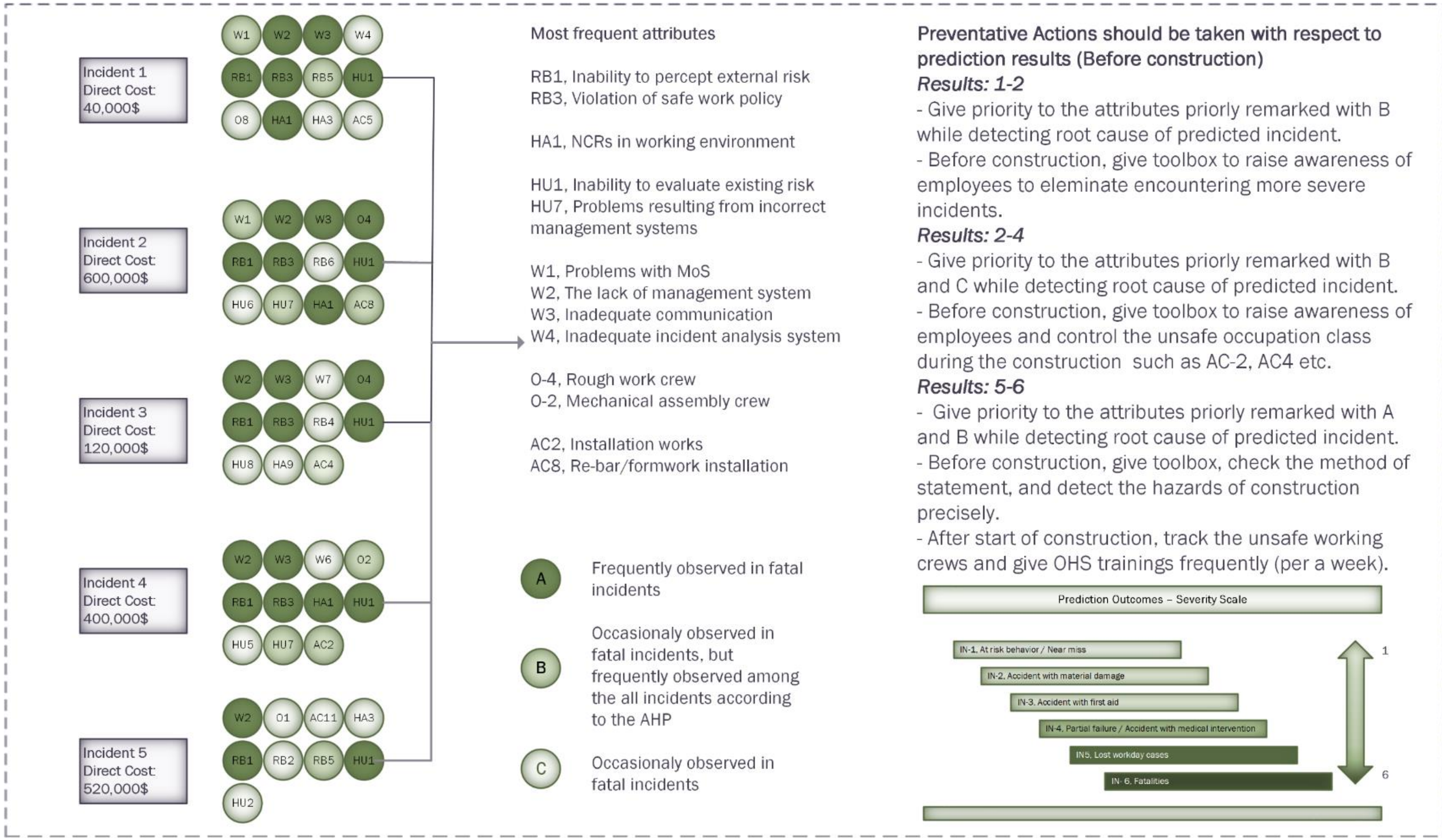


Figure 6.1: Fatal incident analysis and preventative actions (Ayhan & Tokdemir, 2019b

By controlling the classified attributes as A, B, and C, professionals have an opportunity to observe possible root causes. In other words, the study provided instructions for exploring the main triggering factors before the construction process by analyzing the attributes in detail. Ultimately, professionals can quickly detect the root causes of predicted incidents and apply the preventative actions indicated in Figure 6.1.

Megaprojects tend to suffer from the cost overrun issue (Boateng et al., 2015). Safety problems are also significant since they create additional unexpected expenditures as well as health problems. Table 6.2 shows that the direct cost of safety failures might make a significant contribution to the cost overrun. Moreover, construction companies may lose their reputation, so the indirect cost of safety failures may result in 3-10 times higher cost than the direct cost. For this reason, preventative actions have great importance in avoiding both health and cost problems.

CHAPTER 7

CONCLUSION

The present thesis introduced a novel predictive model based on different AI models. The study provided an excellent opportunity to observe different strategies about predictive modeling in safety issues. The study included two distinct parts, which can also be considered as hierarchical progress of AI-based predictive modeling. The main objective of this study was to prevent occupational incidents. Two critical problems urged to study on this objective.

The first one was to touch upon the importance of record keeping. The predictive models were introduced to contrive a possible accident before it occurs. This kind of model manipulated historical data to retrieve a meaningful relationship between the attributes and the target values. Hence, the accuracy of the model depends on the correctness of the data collected. The current state in the construction industry is, unfortunately, far from this manner as most of the incident records were not entirely correct. Companies hesitate to damage their reputation by construction incidents, so most of the high severe work events were recorded as near miss or at-risk behavior cases. The author hypothesized that the AI-based predictive system would aid in eliminating these inconsistent situations by increasing accurate records in high severe events.

The second one was to provide a consistent model for the industry to predict construction accidents without spending much more additional expenditures. The construction industry suffers from a lack of proper system or model to forecast the possible risks for construction incidents. Many researchers devoured themselves to develop a model, but most of them may remain insufficient due to not considering the dynamic nature of the construction industry. Besides, uncertainty about this subject brings a notable expense that most of the contractors do not tend to spend. Therefore, the study presented herein aimed to remediate current problems existing in the construction industry.

The study contained two different parts. In the first part, the collection procedure of incidents took place, and the application of the Delphi technique was introduced to explain how the primary form of the list of attributes was obtained. The victim's properties were not considered at this moment as there was a high number of missing information, which may lead to creating trouble in the prediction process. Therefore, items given in Table 4.2 reexplained the incident cases and model development procedures initiated. The hybrid model of ANN and Fuzzy Set Theory was constituted, and the hybrid model achieved to predict the outcome of construction incidents with high accuracy. Although the machine-based models revealed reliable results, the system required a final stage correction. The integration of the Fuzzy Inference system showed a slight improvement in some targets.

However, the pursuit of making all system automated resulted in emerging the second part of the study where a considerable smaller dataset was used. The dataset only captured the megaproject dataset, where complexity is a severe problem along with the data structure. Variation in records causes to heterogeneity problem, which makes the prediction process difficult since the AI models could have a difficulty to understand the relationships between the data items. LCCA was applied to overcome heterogeneity problem inside the data. The analysis generated homogenous subgroups, and prediction models used these subsets as a frame of the models accordingly. Thus, the ANN and CBR models cast the prediction process, and CBR appealed better performance than the other. Besides, the adaptation capability of CBR was better since it allowed to new attributes lists entry.

The present thesis has several outcomes. The study revealed expedites the incident reporting process as the importance of the record-keeping system was underlined very clearly. The data preparation process via the Delphi process and expert opinion may aid professionals on OHS since they have an excellent opportunity to benefit from the list of the attributes. That means the list of attributes obtained in this study can serve as a crucial step towards formatting the characteristics of incidents with consistent and reliable terms.

Another significant outcome was to show how to establish an AI-based predictive model. Two different data sets were utilized to compare the different approaches. The first part included a hybrid model of ANN and Fuzzy sets, whereas the second one applied the LCCA as Big data analytics to address the heterogeneity problems along with the dataset. The model in the first part used over 17,000 cases for training. It managed to predict fatal incidents with 83.33% accuracy.

On the other hand, the constituted model achieved to estimate fatal incidents with 86.67% accuracy. The total prediction rate was close to the performance obtained in the first part, although the data domain was one-third of the data used previously. The outcomes proved that the implementation of big data analytics improved the prediction rate by coping with the complexity of data. In summary, the study concluded that AI techniques give promising results in predicting issues, like incidents, which are described with textual formats. Further, CBR showed better performance in predicting the outcome of construction incidents.

Additionally, the study provided preventative measures, including before and during the construction stages, to deal with possible incident scenarios. However, the preventative actions may be premature at this stage because it might be necessary to formulate more strategic solutions by considering the dynamics of construction projects.

As well as the benefits, the study has limitations. In megaprojects, so many OHS staff have to be appointed to manage and record the OHS problems throughout the lifecycle of the construction project. The inclusion of too many OHS staff may induce inconsistency during the data reporting stage because staff interpretations may include and lead to deviations in the results of the prediction model. Hence, at the start of the construction phase, OHS professionals should be trained to solve this problem in advance. However, a simple training program cannot overcome this issue unless the training of OHS professionals and employees is sustained.

Furthermore, in each attribute category, there are still unknown or undefined attributes that were expressed as "Others". In a future study, the attributes list should be improved to obtain compatible characteristics that can describe all types of incidents. As was mentioned before, the prediction model should be updated with new entries. CBR can adapt this process more quickly because it does not require adjusting the attributes list to make predictions or retrieve cases. Furthermore, the preventative actions part needs to be improved by applying a risk evaluation system such as the Bowtie method, which can visualize the causal relationships in high-risk cases. It can also be enhanced to make this process adaptable to all types of work. Thus, it can serve as a custom-tailored model that can adapt to everything. Ultimately, the most significant contribution of this research is that it provided an innovative approach combining several different techniques for safety assessment for the construction industry, especially for megaprojects.

The study has certain limitations despite its contributions as well. First of all, the prediction process can be modified to enhance accuracy. The bulk information inside the dataset was removed by applying LCCA, but some other Big data Analytic may be taken into consideration to achieve more homogenous subsets. Secondly, finding the best prediction model in ANN depended on a trial and error process. This process can be linked to an automation system such as GA tools, which can proceed to work until capturing the best trial.

Moreover, the author utilized the AHP to calculate the weight of attributes, triggering construction accidents. The reason for using AHP was having enough number of observations that help computing the weights without requiring experts' opinion. Some other techniques as Binary-Dtree, Info D-tree, and Info Top models can be implemented to decide which one was better. These systems were used for further studies to augment the prediction performance of the CBR models.

Lastly, the present thesis introduced two different prevention measures, but they remained limited at specific points. The most prominent lack of these model was that they were unable to adopt the new cases. They cannot reflect the dynamic nature of the construction industry even though the prediction models constituted can do that. For further study, the author improved the attribute-based fatal accident analysis system by including one of the data mining systems. ARM can be utilized to determine the correlations between the attributes so that corrective measures can be easily settled regarding the relationships founded.

REFERENCES

Abdelhamid, T. S., & Everett, J. G. (2000). Identifying Root Causes of Construction Accidents. *Journal of Construction Engineering and Management*, *126*(February), 52–60.

Aha, D. W. (1998). The omnipresence of case-based reasoning in science and application." *Knowledge-based Systems*, 11, 261–273.

Alonso, J. A., & Lamata, M. T. (2006). Consistency in the analytic hierarchy process: a new approach. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, *14*(4), 445–459.

Aminbakhsh, S., Gunduz, M., & Sonmez, R. (2013). Safety risk assessment using analytic hierarchy process (AHP) during planning and budgeting of construction projects. *Journal of Safety Research*, *46*, 99–105.

Arditi, D, Oksay, F. E., & Tokdemir, O. B. (1998). Predicting the Outcome of Construction Litigation Using Neural Networks. *Computer-Aided Civil and Infrastructure Engineering*, *13*(2), 75–81.

Arditi, David, & Tokdemir, O. B. (1999a). Comparison of Case-Based Reasoning and Artificial Neural Networks. *Journal of Computing in Civil Engineering*, *13*(3), 162–169.

Arditi, David, & Tokdemir, O. B. (1999b). Using Case-Based Reasoning to Predict the Outcome of Construction Litigation. *Computer-Aided Civil and Infrastructure Engineering*, *14*(6), 385–393.

Ayhan, B. U., & Tokdemir, O. B. (2019a). Predicting the outcome of construction incidents. *Safety Science*, *113*(September 2018), 91–104.

Ayhan, B. U., & Tokdemir, O. B. (2019b). Safety assessment in megaprojects using artificial intelligence. *Safety Science*, *118*, 273–287.

Badri, A., Nadeau, S., & Gbodossou, A. (2012). Proposal of a risk-factor-based analytical approach for integrating occupational health and safety into project risk evaluation. *Accident Analysis and Prevention*, *48*, 223–234.

Başağa, H. B., Temel, B. A., Atasoy, M., & Yıldırım, İ. (2018). A study on the effectiveness of occupational health and safety trainings of construction workers in Turkey. *Safety Science*, 110, 344–354.

Bilal, M., Oyedele, L. O., Qadir, J., Munir, K., Ajayi, S. O., Akinade, O. O., … Pasha, M. (2016). Big Data in the construction industry: A review of present status, opportunities, and future trends. *Advanced Engineering Informatics*, *30*(3), 500–521.

Boateng, P., Chen, Z., & Ogunlana, S. O. (2015). An Analytical Network Process model for risks prioritisation in megaprojects. *International Journal of Project Management*, *33*(8), 1795–1811.

Camino López, M. A., Ritzel, D. O., Fontaneda, I., & González Alcantara, O. J. (2008). Construction industry accidents in Spain. *Journal of Safety Research*, 39(5), 497–507.

Chen, W. T., Chang, P., Chou, K., & Mortis, L. E. (2010). Developing a CBR-based adjudication system for fatal construction industry occupational accidents . Part I : Building the system framework. *Expert Systems With Applications*, *37*(7), 4867–4880.

Cheng, Y., Yu, W. Der, & Li, Q. (2015). GA-based multi-level association rule mining approach for defect analysis in the construction industry. *Automation in Construction*, 51, 78–91.

Chiu, T. F. (2001). An application of hierarchy-oriented case-based reasoning in the pilot production. *Chung Hua Journal of Management*, 2(1), 75–87.

Choi, B., Jebelli, H., & Lee, S. H. (2019). Feasibility analysis of electrodermal activity (EDA) acquired from wearable sensors to assess construction workers' perceived risk. *Safety Science*, 115, 110–120.

Chong, H. Y., & Low, T. S. (2014). Accidents in Malaysian construction industry: Statistical data and court cases. *International Journal of Occupational Safety and Ergonomics*, *20*(3), 503–513.

Comberti, L., Demichela, M., & Baldissone, G. (2018). A combined approach for the analysis of large occupational accident databases to support accident-prevention decision making. *Safety Science*, *106*(December 2016), 191–202.

Curtis, I. A. (2004). Valuing ecosystem goods and services: A new approach using a surrogate market and the combination of a multiple criteria analysis and a Delphi panel to assign weights to the attributes. *Ecological Economics*, *50*(3–4), 163–194.

De Oña, J., López, G., Mujalli, R., & Calvo, F. J. (2013). Analysis of traffic accidents on rural highways using Latent Class Clustering and Bayesian Networks. *Accident Analysis and Prevention*, *51*, 1–10.

Depaire, B., Wets, G., & Vanhoof, K. (2008). Traffic accident segmentation by means of latent class clustering. *Accident Analysis and Prevention*, *40*(4), 1257–1266.

Doğan, S. Z., Arditi, D., & Günaydin, H. M. (2008). Using decision trees for determining attribute weights in a case-based Mmodel of early cost prediction. *Journal of Construction Engineering and Management*, *134*(2), 146–152.

Dong, X. S., Choi, S. D., Borchardt, J. G., Wang, X., & Largay, J. A. (2013). Fatal falls from roofs among U.S. construction workers. *Journal of Safety Research*, *44*(1), 17–24.

Esmaeili, B., Hallowell, M. R., & Rajagopalan, B. (2015). Attribute-Based Safety Risk Assessment . II : Predicting Safety Outcomes Using Generalized Linear Models. *Journal of Construction Engineering and Management*, *141*(8), 1–11.

Evanoff, B., Dale, A. M., Zeringue, A., Fuchs, M., Gaal, J., Lipscomb, H. J., & Kaskutas, V. (2016). Results of a fall prevention educational intervention for residential construction. *Safety Science*, 89, 301–307.

Flyvbjerg, B. (2014). What You Should Know About Megaprojects and Why: An Overview. *Project Management Journal*, *45*(2), 6–19.

Flyvbjerg, B., Holm, M. K. S., & Buhl, S. L. (2003). How common and how large are cost overruns in transport infrastructure projects? *Transport Reviews*, *23*(1), 71–88.

Goh, Y. M., & Chua, D. K. H. (2009). Case-Based Reasoning for Construction Hazard Identification: Case Representation and Retrieval. *Journal of Construction Engineering and Management*, *135*(11), 1181–1189.

Goh, Y M, & Chua, D. K. H. (2010). Case-Based Reasoning Approach to Construction Safety Hazard Identification : Adaptation and Utilization. *Journal of Construction Engineering and Management*, *136*(February), 170–178.

Goh, Yang Miang, & Chua, D. (2013). Neural network analysis of construction safety management systems: a case study in Singapore. *Construction Management and Economics*, *31*(5), 460–470.

Gürcanli, G. E., & Müngen, U. (2009). An occupational safety risk analysis method at construction sites using fuzzy sets. *International Journal of Industrial Ergonomics*, *39*(2), 371–387.

Hallowell, M. R., & Gambatese, J. A. (2009). Construction Safety Risk Mitigation. *Journal of Construction Engineering & Management*, *135*(December), 1316–1323.

Hallowell, M. R., & Gambatese, J. A. (2010). Qualitative Research: Application of the Delphi Method to CEM Research. *Journal of Construction Engineering and Management*, *136*(1), 99–107.

Health and Safety Executive. (2014). Annual Report and Account 2013/2014, Her Majesty's Stationery Office, London

Hinze, J. (2002). Safety Incentives: Do They Reduce Injuries? *Practice Periodical on Structural Design and Construction*, *7*(May), 81–84.

Hinze, J., Pedersen, C., & Fredley, J. (1998). Identifying Root Causes of Construction Accidents. *Journal of Construction Engineering and Management*, *124*(1), 67–71.

Huang, L., Wu, C., Wang, B., & Ouyang, Q. (2018). Big-data-driven safety decision-making: A conceptual framework and its influencing factors. *Safety Science*, *109*(April), 46–56.

Ilbahar, E., Karaşan, A., Cebi, S., & Kahraman, C. (2018). A novel approach to risk assessment for occupational health and safety using Pythagorean fuzzy AHP & fuzzy inference system. *Safety Science*, *103*(October 2017), 124–136.

International Labor Organization. (2016). *Safety and Health at Work*. ⟨http://www.ilo.org/ilostat/faces/! ⟩ Jan

ILO (International Labor Organization). (2017) ⟨https://www.ilo.org/ilostatcp/CPDesktop/⟩ (Aug. 01, 2018).

Jia, G., Chen, Y., Xue, X., Chen, J., Cao, J., & Tang, K. (2011). Program management organization maturity integrated model for mega construction programs in China. *International Journal of Project Management*, *29*(7), 834–845.

Kang, Y., Siddiqui, S., Suk, S. J., Chi, S., & Kim, C. (2017). Trends of Fall Accidents in the U.S. Construction Industry. *Journal of Construction Engineering and Management*, *143*(8), 04017043.

Kim, Y. A., Ryoo, B. Y., Kim, Y.-S., & Huh, W. C. (2012). Major Accident Factors for Effective Safety Management of Highway Construction Projects. *Journal of Construction Engineering and Management*, 139(6), 628–640.

Kulkarni, P. S., Londhe, S. N., & Deo, M. C. (2017). Artificial Neural Networks for Construction Management: A Review ARTICLE INFO ABSTRACT. *Journal of Soft Computing in Civil Engineering*, *1*(2), 70–88.

Lehtinen, J., Peltokorpi, A., & Artto, K. (2019). Megaprojects as organizational platforms and technology platforms for value creation. *International Journal of Project Management, 37*(1), 43–58.

Leu, S., Yang, C., & Huang, J. (2000). Resource leveling in construction by genetic algorithm-based optimization and its decision support system application.

Li, L. P., & Wang, S. (2004). Trends in Injury-Related Incidence and Mortality Among Inpatients in Guangdong Province in 1997–2001. *Biomedical and Environmental Science,* 17, 333–340.

Liao, C. W., & Perng, Y. H. (2008). Data mining for occupational injuries in the Taiwan construction industry. *Safety Science*, *46*(7), 1091–1102.

Liao, C. W., & Chiang, T. L. (2016). Reducing occupational injuries attributed to inattentional blindness in the construction industry. *Safety Science*, 89, 129–137.

Lin, C.-L., & Fan, C.-L. (2018). Examining Association Between Construction

Inspection Grades and Critical Defects Using Data Mining and Fuzzy Logic. *Journal of Civil Engineering and Management*, 24(4), 301–317.

Liu, Y., Yi, T. H., & Xu, Z. J. (2013). Safety early warning research for highway construction based on case-based reasoning and variable fuzzy sets. *The Scientific World Journal*, *2013*.

Loosemore, M., & Malouf, N. (2019). Safety training and positive safety attitude formation in the Australian construction industry. *Safety Science*, 113, 233–243.

Mamdani, E.H., & Assilian, S., (1975). An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller. *International Journal of Man-Machine Studies* 7 (1), 1–13.

Moayed, F. A., & Shell, R. L. (2010). Application of Artificial Neural Network Models in Occupational Safety and Health Utilizing Ordinal Variables. *The Annals of Occupational Hygiene*, *55*(2), 132–142.

Mohaghegh, Z., & Mosleh, A. (2009). Measurement techniques for organizational safety causal models: Characterization and suggestions for enhancements. *Safety Science*, *47*(10), 1398–1409.

Mount, C., & Liao, T. W. (2001). “Prototype of an intelligent failure analysis system. *ICCBR 2001, LNAI 2080*, D. W. Aha and I. Watson, eds., Springer, Berlin Heidelberg, 716–730.

Moustaki, I., & Papageorgiou, I. (2005). Latent class models for mixed variables with applications in Archaeometry. *Computational Statistics and Data Analysis*, *48*(3), 659–675.

Ning, X., Qi, J., & Wu, C. (2018). A quantitative safety risk assessment model for construction site layout planning. *Safety Science*, 104, 246–259.

Nguyen, L. D., Tran, D. Q., & Chandrawinata, M. P. (2016). Predicting Safety Risk of Working at Heights Using Bayesian Networks. *Journal of Construction Engineering and Management*, *142*(9), 04016041.

Oswald, D., Sherratt, F., & Smith, S. (2018). Problems with safety observation reporting: A construction industry case study. *Safety Science*, *107*(March), 35–45.

Patel, D. A., & Jha, K. N. (2015). Neural Network Model for the Prediction of Safe Work Behavior in Construction Projects. *Asce*, *141*(1), 1–13.

Patel, D. a, & Jha, K. N. (2014). Neural Network Approach for Safety Climate Prediction. *Journal of Man*, *31*(3), 1–11.

Pereira, E., Han, S., & AbouRizk, S. (2018). Integrating Case-Based Reasoning and Simulation Modeling for Testing Strategies to Control Safety Performance. *Journal of Computing in Civil Engineering*, *32*(6), 04018047.

Pereira, E., Hermann, U., Han, S., & AbouRizk, S. (2018). Case-Based Reasoning Approach for Assessing Safety Performance Using Safety-Related Measures. *Journal of Construction Engineering and Management*, *144*(9), 04018088.

Rubio-Romero, J. C., Carmen Rubio Gámez, M., & Carrillo-Castrillo, J. A. (2013). Analysis of the safety conditions of scaffolding on construction sites. *Safety Science*, *55*, 160–164.

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, *1*(1), 83.

Sasidharan, L., Wu, K.-;Feng, & Menendez, M. (2015). Exploring the application of latent class cluster analysis for investigating pedestrian crash injury severities in Switzerland. *Accident Analysis and Prevention*, *85*, 219–228.

Sergeeva, N., & Zanello, C. (2018). Championing and promoting innovation in UK megaprojects. *International Journal of Project Management*, *36*(8), 1068–1081.

Seyis, S., & Ergen, E. (2017). A decision making support tool for selecting green building certification credits based on project delivery attributes. *Building and Environment*, *126*, 107–118.

Tam, C. M., Tong, T. K. L., & Chan, K. K. (2006). Rough set theory for distilling construction safety measures. *Construction Management and Economics*, *24*(11), 1199–1206.

Tixier, A. J. P., Hallowell, M. R., Rajagopalan, B., & Bowman, D. (2017). Construction Safety Clash Detection: Identifying Safety Incompatibilities among Fundamental Attributes using Data Mining. *Automation in Construction*, *74*, 39–54.

Tokdemir, O. B., & Ayhan, B. U. (2019). The Analysis of Accidents with Contact of Sharp Objects by using Analytic Hierarchy Process and Artificial Neural Networks Extended. *DÜMF Journal of Engineering*, *10*(1), 323–334. https://doi.org/10.24012/dumf.466493

Turkkan, A., & Pala, K. (2016). Trends in occupational injuries and fatality in Turkey. *International Journal of Occupational Safety and Ergonomics*, *22*(4), 457–462.

Ung, S. T., Williams, V., Bonsall, S., & Wang, J. (2006). Test case based risk predictions using artificial neural network. *Journal of Safety Research*, *37*(3), 245–260. https://doi.org/10.1016/j.jsr.2006.02.002

U.S Bureau of Labor Statistics (2017). ⟨https://www.bls.gov/iif/⟩ (Feb. 01,2019)

Van Nunen, K., Li, J., Reniers, G., & Ponnet, K. (2018). Bibliometric analysis of safety culture research. *Safety Science*, *108*(August 2017), 248–258.

Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis, 89–106.

Vidal, L., Marle, F., & Bocquet, J. (2011). Measuring project complexity using the Analytic Hierarchy Process. *International Journal of Project Management*, 29(2011) 718-727.

Virkki-Hatakka, T., & Reniers, G. L. L. (2009). A case-based reasoning safety decision-support tool: Nextcase/safety. *Expert Systems with Applications*, *36*(7), 10374–10380.

Waziri, B. S., Bala, K., & Bustani, S. A. (2017). Artificial Neural Networks in Construction Engineering and Management. *International Journal of Architecture, Engineering and Construction*, *6*(1), 50–60.

Winge, S., Albrechtsen, E., & Mostue, B. A. (2019). Causal factors and connections in construction accidents. *Safety Science,* 112, 130–141.

Wu, W., Gibb, A. G. F., & Li, Q. (2010). Accident precursors and near misses on construction sites: An investigative tool to derive information from accident databases. *Safety Science*, *48*(7), 845–858.

Xia, N., Zou, P. X. W., Liu, X., Wang, X., & Zhu, R. (2018). A hybrid BN-HFACS model for predicting safety performance in construction projects. *Safety Science*, *101*(August 2017), 332–343.

Zhang, S., Teizer, J., Lee, J. K., Eastman, C. M., & Venugopal, M. (2013). Building Information Modeling (BIM) and Safety: Automatic Safety Checking of Construction Models and Schedules. *Automation in Construction*, *29*, 183–195.

Zhang, P., Lingard, H., Blismas, N., Wakefield, R., & Kleiner, B. (2015). Work-Health and Safety-Risk Perceptions of Construction-Industry Stakeholders Using Photograph-Based Q Methodology. *Journal of Construction Engineering and Management*, 141(5).

Zhao, D., McCoy, A. P., Kleiner, B. M., Mills, T. H., & Lingard, H. (2016). Stakeholder perceptions of risk in construction. *Safety Science*, 82, 111–119.

APPENDIX-A

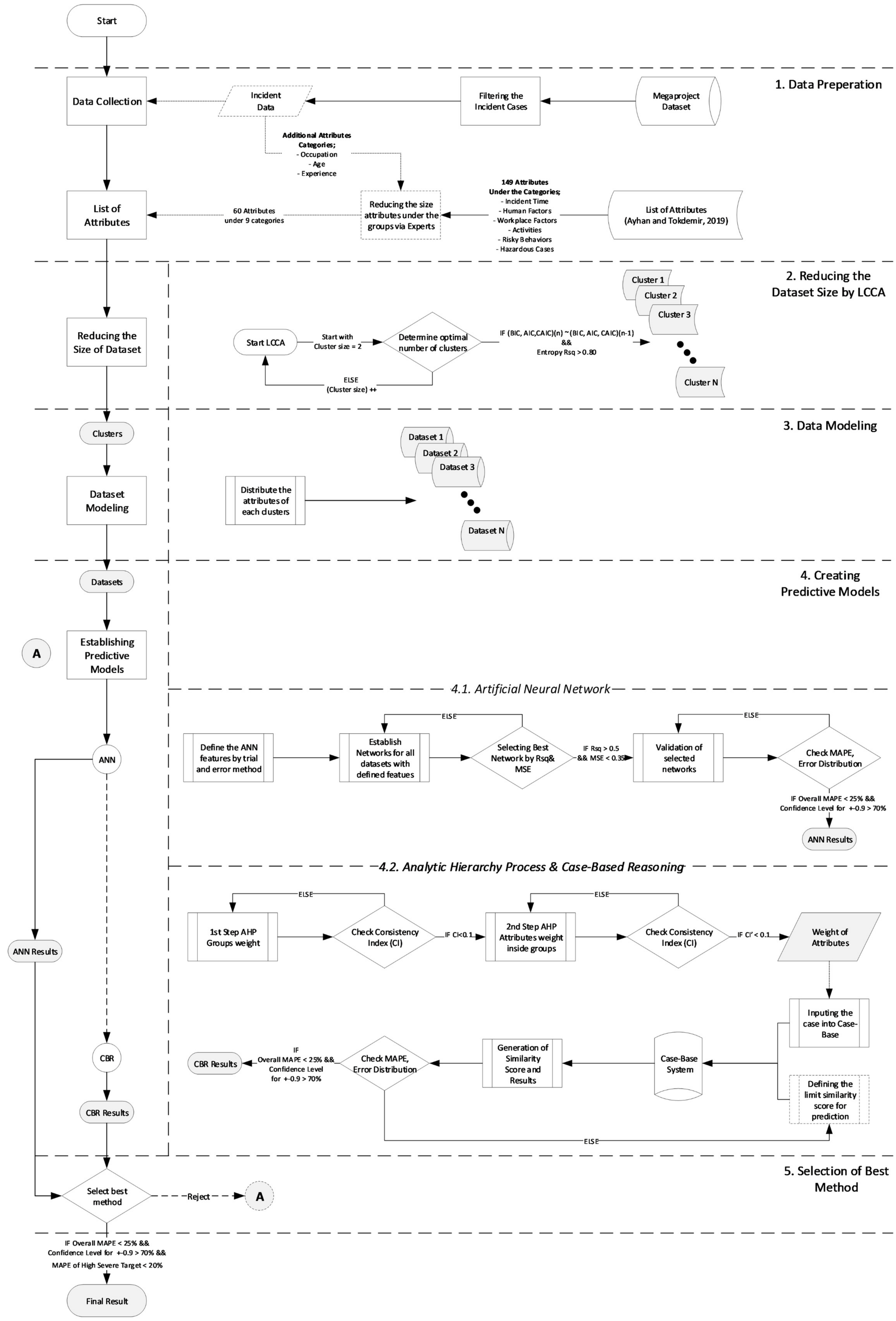


Figure A.1: Flowchart of the predictive model (Ayhan & Tokdemir, 2019b)

APPENDIX-B

TABLE B.1: The list of attributes obtained by Delphi (Ayhan & Tokdemir, 2019a)

Workplace Factors		Human Factors		Activities in the course of the incident		Risky Behaviors		Hazardous Cases	
ATR	Expression	ATR	Expression	ATR	Expression	ATR	Expression	ART	Expression
WF-1	Tool & Equipment	HF-1	Work overload	AA-1	Maintenance / Repair	RB-1	Individual violation	HC-1	Tool & Equipment
WF-2	Improper way to wipe out wastes	HF-2	Usage of alcohol or drugs	AA-2	The usage of equipment	RB-2	Unsafe usage of tool/equipment	HC-2	Temperature of Environment
WF-3	Inadequate maintenance / repair	HF-3	Excessive concentration	AA-3	Concrete / Screed Works	RB-3	Inability to realize external factors	HC-3	Working Area and Layout
WF-4	Inadequate review in start-up op.	HF-4	Feeling extremely embarrassed	AA-4	Finishing (General)	RB-4	Lack of attention	HC-4	Natural Events
WF-5	Uncertain reporting responsibilities	HF-5	Negative effects of Whether	AA-5	Installation of Str. Steel	RB-5	Impetuous activities	HC-5	Insufficient Equipment
WF-6	Inadequate information handling	HF-6	Level of Skills	AA-6	Installation of Re-bars	RB-6	Working above limits	HC-6	Electrified systems
WF-7	Inability to remember information	HF-7	Learning ability	AA-7	Other activities	RB-7	Group violation	HC-7	Being exposed to excess noise
WF-8	Inability to perceive information	HF-8	Being absent-minded	AA-8	Break	RB-8	The violation in the safe working procedure	HC-8	Other hazardous cases
WF-9	Inadequate Communication b/w stakeholders	HF-9	Using shortcut	AA-9	Electrical Assembly	RB-9	Other risky behaviors	HC-9	Improper instigation systems
WF-10	Having trouble in lessoning pre-cases	HF-10	Behavior	AA-10	Hand-powered lifting	RB-10	The usage of damaged safety systems	HC-10	Improper application of PPE
WF-11	Inadequate change management	HF-11	Physical condition	AA-11	Assembling scaffold	RB-11	Incorrect loading / lifting	HC-11	Using of improper vehicle
WF-12	Lack of expression in remedial measures	HF-12	Physical fatigue	AA-12	Assembling frameworks	RB-12	Incorrect Usage of PPE	HC-12	Being exposed to chemicals
WF-13	Unsatisfied training facilities	HF-13	Emotional Problems	AA-13	Hot works	RB-13	The usage of protection measures	HC-13	Mechanical dangers
WF-14	Other workplace factors	HF-14	Other human factors	AA-14	Excavation Works	RB-14	Being unfamiliar with existing risks	HC-14	Being exposed to radiation
WF-15	Missing maintaining reports	HF-15	Education Level	AA-15	Using chemical materials	RB-15	Deactivation of safety systems	HC-15	Dangerous Chemicals
WF-16	Problems in control of equipment	HF-16	Non-participating OHS training	AA-16	Carpenter's Works	RB-16	Procedures / Orders	HC-16	Lack of organization
WF-17	Inadequate plan of action	HF-17	Negative consolidation of Behaviors	AA-17	Lifting Operations	RB-17	Non-fixed equipment or material	HC-17	Inadequate equipment
WF-18	Taking precautions inadequately	HF-18	Claim / Instruction Confliction	AA-18	Mechanical Assembly	RB-18	Levity	HC-18	Fire or explosion
WF-19	Insufficient administration	HF-19	Claim / Instruction Confusion	AA-19	Going up / down a ladder	RB-19	Engagement in violence		
WF-20	Failure in ergonomic design	HF-20	Working below the capacity	AA-20	Driving of vehicle	RB-20	Inability to percept risk		
WF-21	Lack of meetings about OHS	HF-21	inability to make a decision	AA-21	Smoking	RB-21	Using equipment beyond one's authority		
WF-22	Lack of communication about OHS	HF-22	Limited body movement	AA-22	Cleaning				
WF-23	Insufficient methods for work competence	HF-23	Deficiency in concentration	AA-23	Tests				
WF-24	Not following processes of work	HF-24	Vulnerability to material	AA-24	Topography Works				
WF-25	Unavailable work-hazard analysis	HF-25	Existing wound / Disease	AA-25	Cafeteria Works				
WF-26	Problems in MoS / standards / specifications	HF-26	Lack of practical experience	AA-26	Working at height				
WF-27	Inability in recruitment and placement	HF-27	inability to percept risk	AA-27	Walking				
WF-28	Inadequate usage / storage / transportation of equipment	HF-28	Hypercapnic respiratory failure						
WF-29	Failure in Engineering Design	HF-29	Stress & Lack of concentration						
WF-30	Inability to evaluate probable system failures	HF-30	Problems related to Manager						
WF-31	Incoherent performance standards	HF-31	Inability to maintain existing position						
WF-32	Problems arising from subcontractors	HF-32	Inadequate mechanical skills						
WF-33	Not able to assess operational preparation	HF-33	Administration problems						
WF-34	Problems on Policy / Standards / Procedure	HF-34	Memory loss						
WF-35	Inadequate usage of PSP								
WF-36	Having trouble in procurement agency								
WF-37	Having trouble in the identification of danger								
WF-38	Problems in identifying dangerous products								
WF-39	Intense work pressure for continuity of work								
WF-40	Applying new methods without giving any instruction about it								
WF-41	Insufficient Health and Safety award								
WF-42	Insufficient Health and Safety manifestation								
WF-43	Insufficient employment orientation								
WF-44	Insufficient Risk Assessment								
WF-45	Insufficient or complicated instructions								
WF-46	Having trouble delivering the necessary method of statements/ standards / instructions to related units								
WF-47	Change of materials beyond one's authority								
WF-48	Not performing acceptance of confirmation								