Prediction of Bridge Fires Characteristics Using Machine Learning

by

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Abstract

Bridges are an essential component of transportation systems for traffic passage across natural or man-made obstacles. Modern urban trends and growing travel patterns have resulted in a rise in the number of bridges on motorways to avoid road conflict. A major fire might cause irreversible structural deterioration or perhaps the bridge's failure. This research studies the critical factors of bridge fire incidents using a comprehensive database containing 171 bridges. Using an Artificial Neural Network (ANN) model, the vulnerability of bridges in fire is estimated, and the extent of damage is determined based on several key factors including bridge proximity to urban, suburban, or rural areas, structural system, construction materials, annual average daily traffic (AADT), ignition source, combustible types, position of the fires, and the fire-caused damage level. The influence of each parameter on the bridge fires damage levels is investigated. Suggesting measures to reduce the risk of damage, damage levels of fire incidents in different bridges for different scenarios is predicted and a comprehensive and accurate model for definition of vulnerability of bridges under fires is proposed. The outcome of this research will help predict the risk of fire in bridges with various characteristics and the level of damage.

Keywords: Fire Incidents; Critical Factors; Bridges; Machine Learning; Vulnerability; Artificial Neural Network; Comprehensive model; Damage levels; Influential parameters.

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Chapter 1: Introduction

Bridges are an integral part of the public transportation system, and the failure of them may have serious economic and social implications. They are an essential component of transportation infrastructures for promoting traffic passage across natural barriers or man-made obstacles. Current patterns of urban development and increased traffic density have resulted in a rise in the number of bridges on freeways to reduce conflict along roads [1-3]. Bridges enable railroads and freeways to pass freely, reducing commute times, traffic congestion, and carbon emissions. A serious fire may cause irreversible structural damage or even the demolition of the bridge. Thus, a bridge will be exposed to one of the most serious risks in its lifespan. Although much attention was paid by engineers in identifying and forecasting the consequences of unintended severe load conditions like as earthquakes, winds, and ship crashes, less focus has been dedicated to the risk of fire, as shown in recent literature reviews [2, 4]. A collision in fuel transmission trucks and combustion of gasoline near the bridge is the most probable cause of many bridge fire accidents. These gasoline fires are distinct from those that occur in the buildings and represent hydrocarbon fires. Hydrocarbon fires have a higher intensity than structure fires, with a faster heating rate and a higher maximum temperature. In such fires, the bridge reaches temperatures of around 1000 °C within a few moments. These severe fires often can cause severe damage to the structural components of bridges which could lead to bridge collapses. Repairs and distractions are not economically justifiable even though the bridge does not collapse. It may be a challenge to diagnose fire losses. The general assumption and consensus are that in the case of a fire, a bridge would not collapse. However, a recent survey shows that bridge fires are a critical challenge. Between 1960 and 2008, the bridges collapse due to fire was three times the collapse because of earthquakes [1, 2]. According to a survey conducted in 18 states in the USA, 1746 bridges have collapsed for a range of reasons. Bridge type, material types, and the reasons of bridge failures were all investigated. Most of the bridges, 1006 bridges, collapsed because of hydraulic causes (e.g., scour, flood), and 515 bridges fell because of accidents, overloading, or corrosion. Just 19 bridges failed due to earthquakes, compared to 52 bridges that collapsed because of fire [1, 3, 4]. Bridge structural members are currently configured for seismic loads not for fire hazards in usual approaches of design and construction. Furthermore, Wardhaua and Hadipriono [6], and Scheer [7], showed that fire caused 3.2% and 4.9% of the overall bridge population to collapse, respectively [8]. However, there are no provisions in existing codes and guidelines for structural fire construction for bridges [4, 9]. This paper will identify bridge fire incidents, evaluate the effects on the structural integrity of bridges and provide for such compromises on our transportation infrastructure to be factored into the structural construction of bridges. Developing the dataset containing the influential parameters in bridge fire incidents, the research will perform a comprehensive literature review on bridge fires to generate a database of the fire incidents. Introducing the input data from the database, an Artificial Neural Network (ANN) model will be created. In addition, the influence of each parameter on the bridge fires damage levels is investigated to predict damage levels of fire incidents in different bridges for different scenarios, then measures to reduce the risk of damage will be addressed. Moreover, a comprehensive and accurate model for definition of vulnerability of bridges under fires will be proposed.

Chapter 2: Literature Review

2.1 Bridge fire incidents

In latest years multiple bridge fires have occurred with some resulting in major destruction or bridge failure [3]. Since most bridge fires are triggered by vehicle collisions with other vehicles or with bridge structural elements, bridge fires can be destructive [5-7]. This has been because of high-speed crashes resulting in the combustion of highly flammable hydrocarbon-based fuels. Fires can cause severe strength deterioration in structural elements due to the lack of load-carrying capacity of components, which can lead to partial or complete bridge failure [6, 7]. Except in small fire cases where the bridge does not collapse, proper review, inspection, and repairs are expected before reopening. When a bridge is closed for repairs, traffic must be diverted to roadsides, causing major disruptions in the affected area [7]. The bridge fires are reviewed below and the key parameters in the cause, type, and consequence of such fires are investigated. Twenty bridge fires that had significant impacts are described. The cause of the fire, fuel type, fire load, structure type, damage description, fire exposure time, traffic impact, financial impact, environmental impact, fire protection, and post-fire assessments have been studied. However, all this information for each bridge fire case may not be reported because of the unavailability of the data. Among these bridge fire incidents, the most important one that has been paid special attention to is the MacArthur Maze Bridge, which cost $9 million for renovation.

2.1.1 Hazel Park, Michigan, 2009

The fire incident occurred at the expressway adjacent to Hazel Park in MI. when a tanker truck carrying about 49,000 liters of gasoline and about 15,000 liters of diesel crashed under the bridge (Figure 2-1). This bridge comprised 10 steel girders with a span of 24 meters supporting a reinforced concrete deck. The collapse of the bridge occurred at temperatures over 1000 °C and resulted in a high loss of strength capacity of the exposed girders within 20 minutes of the fire incident. However, it took 105 minutes for firefighters to extinguish the fire entirely. The collision of the bridge influenced traffic flow in the area and led to expensive rehabilitation and repair expenses, as these costs were estimated at $2 million. It required many weeks of expressway diversions and several months for the bridge to be repaired [2, 7-10].

Figure 2-1 Collapse of bridge girder due to fire in Hazel Park overpass in Michigan (Photo from [8])

2.1.2 MacArthur Maze, California, 2007

The MacArthur Maze is a multi-level highway interchange bridge near Oakland. It comprised six steel girders that supported a reinforced concrete deck. The bridge collapsed in a fire accident because of a tractor-trailer collision transporting 32,555 liters of gasoline. This event resulted in large deflections in the unprotected girders and consequently the connections overstressing during the fire (Figure 2-2). The reported fire temperature was 1100 °C and two spans of the bridge collapsed in 22 minutes. Since the failure of the bridge occurred in less than half an hour, 14 minutes of firefighting response was not enough for extinguishing the fire. The approximate costs for repairs and rebuilding operations were estimated to be more than US $9 million, of which $4.3 million was dedicated to the destruction and removal of one part of the bridge and $2 million was devoted to controlling the traffic flow. Completing all construction processes and reopening the bridge to traffic took 26 days. This caused major traffic congestion and delays on one of the busiest roads in the city. The bridge shutdown was predicted to cost a daily $6 million in overall financial damage [2, 4, 8, 11, 12].

Figure 2-2 Fire-induced bridge collapse on MacArthur Maze highway in Oakland, California (Photo form [2])

2.1.3 Howard Avenue Overpass in Bridgeport, Connecticut, 2003

Because of the collision of a car with a tanker transferring 50,000 liters of heating oil on the Howard Avenue highway, a fire incident occurred. Large steel girders with a span of

22 meters supported the bridge. The fire exposure time was two hours, with a temperature of about 1100 °C. The steel girders with no fireproofing suffered from significant buckling, resulting in the bridge's collapse. Renovation of the bridge and detouring the traffic in both lanes cost about $11.2 million [11].

2.1.4 Bill Williams River Bridge, Arizona, 2006

Because of spillage fuel from a tanker truck containing 29,000 liters of diesel on the Bill Williams River Bridge in Arizona, a fire accident occurred. The bridge was composed of prestressed concrete girders that supported a concrete slab and had 14 simple spans of 23.2 meters in length. The fire blazed over 2 ½ hours, causing damage to three spans, including the concrete deck and barriers. It also extended to other entire ecosystems. The east overhang of three spans collapsed. Also, some local spalling of the prestressed concrete girders occurred. The bridge was closed for immediate rehabilitation [2, 13].

2.1.5 Montebello Freeway 60 Overpass, California, 2011

The accident of a tanker truck carrying 33,800 liters of gasoline resulted in an intense fire (Figure 2-3). The fire lasted several hours destroying the reinforced concrete overpass. The concrete slab burst because of the high intensity of the fire temperature, hence resulting in a dangerous situation for firefighters and observers [14].

Figure 2-3 Truck fire under Montebello freeway, California (Photo from [15])

2.1.6 Wiehltalbrücke (Wiehl Viaduct), Germany, 2004

A passenger car collided with a tanker truck carrying 33,000 liters of gasoline and diesel. The steel bridge spans 705 m with a width of 30.25 m. This event resulted in a gasoline tank explosion and the death of the driver. Although the bridge experienced temperatures of 1200 °C leading to the steel deck deformation about 60 m long, it did not result in the full collapse of the bridge structure. However, the bridge was severely damaged by the fire, as one section had to be replaced for €32 million. Also, it led to temporary repairs within weeks of the crash, with the addition of 27 new steel supports and 10,000 tons of polluted earth being excavated. A total renovation of the bridge began nearly two years later, with a full replacement of the weakened portion [7, 8, 14].

2.1.7 Charilaos Trikoupis (Rio-Antirrio) Bridge, Greece, 2005

One of the pylon cables of a multi-span cable-stayed bridge known as Rio Antirrio caught fire, crashed onto the deck, damaged the neighboring cable, and failed after 40 minutes into the fire. Some believe that it was caused by a lightning strike. Others speculate about the likelihood of the fire being caused by wires grinding against one another in heavy winds, or by a fault current in the electrical lines that run alongside the cables. Despite the failure of one of the 368 cables of the suspension system, it did not collapse or cause severe damage to the bridge. However, the fire incident affected the bridge's durability. The bridge closure lasted four days without being completely operational for about 40 days. Also, for nearly a month, the traffic flow was restricted to one deck. The bridge rehabilitation lasted 40 days [14].

2.1.8 Mathilde Bridge, France, 2012

Mathilde Bridge experienced a fire incident because of the overturning of a tanker truck transferring over 20,000 liters of oil and gasoline in the access curve of the bridge (Figure 2-4). The bridge contains two 115-meter-long steel spans which comprise a concrete deck supported on two girders and are braced every 4 meters. Before the fire, the traffic flow capacity of the bridge was over 80,000 vehicles per business day, approximately 20% of the transit traffic. It also accommodated a sewer line supplying the city's north end, as well as an optical fiber network. Despite the fire intensity and extent, the quick response by firefighters resulted in the prevention of the full collapse of the deck. However, damage to the bridge was too extensive. Although, they used water during the first stage of firefighting, which prevented the bridge from experiencing high elevated temperatures; it took two hours to extinguish the fire. The approximate fire temperatures were estimated to be 650–800 °C. The traffic flow was closed immediately, and navigating across the river under the bridge was also prevented [16, 17].

Figure 2-4 Fire incident on and under the Mathilde bridge, France (Photo from [16])

2.1.9 Ed Koch Queensboro Bridge, 2013

Ed Koch Queensboro Bridge caught fire because of the collision of a 12-meter tractor-trailer commuting on the bridge. The bridge has a five-span cantilever truss 1135 meters long with two levels. Steel girders were believed to be fully composite with the cross beams and to be laterally reinforced at both ends by transverse floor beams. To provide lateral support, vertical and horizontal bracing were installed between the steel girders. The four lanes upper level served automobile traffic and the five lanes lower level served other vehicular types. Because of the high intensity of the fire, two steel girders of the upper deck experienced severe deformation and damage [18].

2.1.10 Birmingham, Alabama, 2002

In Birmingham, a fire occurred where a tanker carrying 37,000 liters of gasoline crashed into the bridge. The bridge was constructed with a 37.32 meters central span and two 25.91 meters and 25.3 meters lateral spans, totaling 88.53 meters. The spans were simply supported by steel I girders which carried a reinforced concrete slab deck. Resistance against horizontal loads was provided by several cross braces and installed every 6.2 meters and two expansion joints were considered between spans of 38 mm in width along the bridge. The fire temperature was reported to be around 1100 °C resulting in the bridge's collapse. The bridge deck had to be rebuilt by a new prefabricated prestressed concrete deck, which led to detouring traffic flow of the bridge through nearby routes. Because of the severe bridge damage and because of its strategic location, the renovation and reconstruction of the modern structure lasted 54 days with an operational capacity of 240,000 cars a day. The daily cost of the bridge closure was $100,000 ($5,400,000 in total), while the cost of rebuilding the new bridge deck was $3,396,421. As a result, the expenses of this fire incident were approximately $8.8 million [7, 19].

2.1.11 Seohae Bridge, Korea, 2006

In 2006, because of heavy fog, a fuel tanker crashed with vehicles on the Seohae Bridge in Korea caused catching fire to 11 vehicles. This accident resulted in seven hours and 40 minutes of the closure of a section of the bridge and an economic loss of KRW 4 billion. In 2015, lightning caused a fire incident that broke a cable connecting to the bridge pylon. The replacement of the cable caused the bridge to be closed for twenty days. As a result, the Korea Expressway Corporation installed fire detectors and spray sprinkler systems to avoid the high expenses of future fire incidents [20].

2.1.12 I-85 Bridge near Atlanta, Georgia, 2017

During a vandalism incident underneath the I-85 bridge near Atlanta, a fire occurred due to the storage ignition of massive polyvinyl chloride (PVC) pipes and/or high-density polyethylene (HDPE) pipes beneath the bridge. I-85 bridge comprised three reinforced concrete piers carrying ten prestressed concrete girders, serving 243,000 vehicles per day. Based on the Georgia Department of Transportation (GDOT) report, the burning of these plastic pipes caused a rapid increase in temperature to 900 –1100 °C. The fire continued for around 2 hours, but the bridge's 30.3-meter span fell within the first hour. Referring to the firefighter's report, concrete spalling occurred with explosive sounds resulting in an evacuation advisory of the fire scene. Post-fire investigation revealed complete spalling of the concrete cover, causing direct fire exposure of the prestressed steel. Repair and retrofitting of the bridge cost $10 million. In addition, the reconstruction of the bridge imposed extra expenses (approximately $6.6 million) for the detouring of commuters to alternative routes. Because of the reduced traffic flow in the area, business owners around the job site experienced a decrease in customer flow and thus lower earnings. Addressing such problems, the State of Georgia, also several other counties, revised its storing rules [21, 22].

2.1.13 Route 7 Bridge near Ridgefield, USA, 2005

Because of the overturning and explosion of a tanker truck transporting 30,300 liters of gasoline, a fire started at Route 7 bridge. It was a one-span bridge made from 15 prestressed concrete box girders. A water-resistant layer and a cover of 160 mm thick bituminous concrete insulated the girders. Because the vehicle was parked on the eastern edge of the bridge's northern curb, burning fuel spilled along the bridge and then into the river beneath. The melting and evaporation of the aluminum that was initially part of the tanker truck indicate that the temperature around the vehicle might have been higher than 2,467 °C. Two lanes of traffic travel across the bridge, a passing lane on either side and a low clearance over the water. The outer portions of the bridge beams and the bottom flanges of all 15 columns were found to have spalled soon after the fire. However, the layer near the tanker truck was in good shape despite the bituminous concrete cover. Since non-destructive tests were unavailable to assess the prestressing strands' integrity, all the superstructure's beams were replaced [23].

2.1.14 Puyallup River, USA, 2002

Because of the collision of a railroad tanker transporting 113,000 liters of methanol, a fire incident under a 44.5-meter-long prestressed girder bridge occurred at the Puyallup River (Figure 2-5). The bridge deck and columns were constructed from concrete and mild steel. Confinement and reinforcement of the columns were provided by tightly wound spiral cages. Releasing and burning on-board hydrocarbons resulted in a fire of high quick temperatures lasting over an hour. The fire led to the immediate closure of the interstate freeway during the structural inspection overnight. No abnormal deflections or misalignments were observed on the bridge, hence reopening the traffic flow, and commuting of legal weight trucks was approved the next day. However, heavy trucks were prohibited from commuting on the bridge and were detoured to other nearby routes. The post-fire assessment was done based on similar procedures described in Technical Release-TR68. Some small stress relaxation was remarked in the prestressing steel while severe spalling occurred, resulting in temperatures as high as 500 °C in the steel. Even though the assessors concluded that the steel would maintain its basic material characteristics, they replaced the steel girders [22, 24].

Figure 2-5 Puyallup river bridge railroad tanker fire (Photo from [22])

2.1.15 Don Valley Parkway, Canada, 2008

A fire accident happened on the Don Valley Parkway in Toronto, Canada. A truck crashed into a pier, resulting in an almost three-hour-long fire. The existence of lengthwise cracks, spalling causing exposure of steel and a reddish concrete color was reported by the engineers. However, based on the detailed reports, bridge repair was done using reinforcement of those parts of the deck which experience intensive damage, by a new concrete slab with 200 mm thickness. A serious assessment shortly after the fire showed that the elasticity response of the structure and full restoration of cyclic loading were appropriate. Prestressing tendons were not influenced by heat, no deflection after the fire was indicated, and the concrete temperature was reported to be over 600 °C based on color changes. For the next repair, some concrete was patched, and six girders were insulated with carbon fiber reinforced polymer (CFRP) in 2009. Two load tests were conducted to analyze the bridge behavior within six years. Compared to the first load assessment, the second was similar, which may be because of the interim fixes [22, 25].

2.1.16 Deans Brook Viaduct, United Kingdom, 2011

A fire occurred on the Deans Brook Viaduct, set by arsonists in a scrap yard in a flammable material store, underneath the bridge. The superstructure comprised a reinforced concrete (RC) slab with prestressed concrete girders. The temperature of the fire under the bridge reached 800 °C. There was concrete spalling within three hours of the fire starting. Spalling exposed the prestressing steel of the beam's bottom layer. Initially, there was no remaining strength in the bottom layer and only 75% left in the top layer. The assessors concluded that at spots where the concrete cover was not damaged, no significant tension losses occurred, however, where the prestressing steel was observed, less than 15% losses occurred. Hence, overall, this resulted in a greater than 60% loss in tensile strength, and significant losses in the exposed steel at places in which the concrete layer was fully destroyed [22, 26].

2.1.17 Mezcala Bridge, Mexico, 2007

On the Mezcala cable-stayed bridge, a fire broke out after a vehicle and two buses collided with a heavy goods vehicle (HGV) transferring coconuts. This led to the failure of a high-density polyethylene (HDPE) cable-stay encased and limited damage to the adjacent cable. The use of HDPE as a corrosion protective sheath itself exacerbated the fire as contributed to the fuel load and causes the fire to be extended, which resulted in bridge damage. The replacement of two cables took two months with disruption of traffic flow on the bridge [22, 27].

2.1.18 New Little Belt Bridge, Denmark, 2013

After an HGV collided with the New Little Belt suspension bridge in Denmark, a 30- to 45-minute fire broke out at the lowest part of the cable system. A post-fire assessment was completed, the main cable was found to be only 8% weaker and its yield strength remained the same although melted galvanized coatings were seen on a near cable band. The suspension cable next to the fire needed to be replaced. The exposure fire temperature reported by firefighters was approximately 500 °C. Fully reopening the bridge to traffic flow took four months, as cable-supported structures are prone to fire [22, 28].

2.1.19 Lazienkowski Bridge, Poland, 2015

During the renovation of wooden elements of service decks stored under the Lazienkowski bridge, a fire occurred. The bridge comprised a steel deck supported by four steel girders. More than an average of 100,000 vehicles, including public transport buses, were commuting on the bridge daily. By the following morning, the fire had been extinguished. The existence of utility pipelines and cables influenced the fire's intensity and development. Initiation of fire was sped up by various kinds of insulation used in the superstructure, hence resulting in enhancing the elevated temperature for several hours. Two of the fast lanes of the traffic flow were damaged by the fire. Steel girders, piers, and equipment were also severely damaged in the fire [29].

2.1.20 San Francisco Bay Bridge highway, USA, 2007

Because of a collision of an oil tanker carrying approximately 32,000 liters of oil with another car, a fire occurred on this bridge. The fire lasted 3 hours, with temperatures reaching over 1500 °C, resulting in the collapse of the connecting ramp to the bridge. According to the California Department of Transportation, daily traffic flow on the bridge was greater than 75,000 vehicles and 280,000 people all commuting to San Francisco. Thus, this fire caused massive traffic congestion [20].

2.2 Fire Loads and locations

Bridge fires occur due to spillage in fuel tankers including on-board hydrocarbon fuels and more recently hybrid batteries, which crash into other vehicles or structural elements such as piers, girders, and walls in the abutment of bridges or by construction events (like as sparks from scaffolding or wood forms (Figure 2-6) [3, 8, 30].

Figure 2-6 Railroad tanker fire on a bridge (Photo from [16])

Usually, due to high speeds and fuel tanker trucks derailments, their collision into bridges results in explosive, intensive, and quick combustion of flammable gasoline fuels. They are commonly attributed to petrol fires known as hydrocarbon fires with low flash temperature, high fire intensity, and a fast-heating rate within the first few minutes of the fire incident, hence causing severe damage and collapse of the bridge in most cases [3, 8]. Garlock et al. [4] developed a list of recent severe bridge fire events in the context of a study on bridge fire hazards as part of the National Cooperative Highway Research Program (NCHRP) [30, 31]. This list emphasizes the hazard presented by tanker fires, by dividing different vehicles into three categories including buses, heavy goods vehicles, and tankers. It was concluded that tankers carrying gasoline-based fuels caused the most severe fire intensity and intensive damage to bridges in fire incidents [31, 32].

However, seven reasons for initiating fire were given based on previous experiences containing cars, trucks, tanker trucks, electrical problems, stored materials, forest fires, or arson [12]. In addition to gasoline and diesel, other hydrocarbons, alcohol-based liquids, tires, plastics, and solid materials were studied. The fire load position is of high importance as it defines which portions of the bridge will be most impacted by the fire (Figure 2-7). Based on the position of the tanker trucks and fuel spillage, four groups of fire load positions were investigated: (1) There was no fuel spilled into lower portions of the bridge due to the tanker being on the bridge, (2) Tanker beneath the bridge, (3) Tanker on the bridge spilled a significant amount of fuel, creating a fire in the lower parts, and (4) Tanker close to but not touching the bridge [33].

Figure 2-7 9-Mile overpass, Detroit, USA (Photo from [34])

NCHRP investigated the effects of vehicle types and various locations of the fire. The fire locations considered under the bridge were categorized into three locations; (A) The position was in the middle of the span both lengthwise and laterally; (B) The location was longitudinally aligned in the middle, however crosswise shifted outside of an exterior girder; and (C) Under the bridge, the position was laterally equal, but lengthwise displaced towards the pier at the span's end [31]. Vehicles were also divided into four categories in order of increasing fire size; that is (1) buses, (2) half -heavy- goods vehicles (1/2HGV) in both cases, no persistent bridge displacement was seen at any of the fire spots, (3) full-heavy-goods vehicles (HGV) which resulted in a substantial deflection of roughly 4 in. with the fire at point A, and (4) tanker trucks in which large permanent deflections at all fire locations evaluated in the study occurred and led to complete collapse when the tanker truck was at location A. In the case of a typical girder-type structure, the results showed that the probability of significant deflection in bridge fire incidents caused by tankers at many fire positions is considerable [31].

2.3 Structural System

Steel bridges had the highest number of collapses in fires due to the fast and severe degradation of the mechanical properties of steel at high temperatures. Wooden bridges are also vulnerable to fires, and most of the wooden bridges exposed to fire collapsed due to the combustibility of wood as the main structural material as well as the age of these wooden bridges. Concrete bridges also suffered from fires, especially in terms of spalling and the reinforcement being exposed to flames. The real case in such bridges is the one in Atlanta in 2017 which resulted in the collapse of a concrete bridge [35].

2.3.1 Cable-stayed Bridges or Suspension Bridges

Suspension bridges are usually one of the region's key routes for business, safety, and public health. Long spans allow for travel over enormous quantities of deep water, valleys, and other natural barriers. Only the existence and operation of the main cable allow for such large distances. These major cables are (usually) non-redundant structural parts that support the bridge deck's dead and live loads, as well as traffic flow. The breakdown of a main cable would undoubtedly result in the collapse of the whole bridge structure, leading to enormous economic consequences as well as the lives lost [36]. Cables and the vertical supports of the cable-stayed bridges are the key elements that would be severely affected by fires. The extreme strength of steel is the reason for its usage in the cables on bridges, however, steel is very flexible. In certain bridges, these steel cables are insulated with fire-resistant materials such as mineral fiber blankets and/or encased with corrosion-resistant stainless-steel sheets. The main vertical supports might be made of reinforced concrete, composite material, or steel. Potential fire scenarios which result in severe influences on the structural components are (1) “a heavy truck fire near the key supports or cables”, and (2) “a gas jet fire because of the pipe breakage and fuel combustion of a liquefied petroleum gas (LPG) tanker because of a crash” [37]. The integrity of cables and pylons can be impressed by the height of the unrestricted fires which are commonly attributed to long-span cable-supported bridges. Common height-unrestricted fires are those that occur near steel pylons or cables. In the height unrestricted environment, it is of importance that the flame temperature variation on the vertical side should not be disregarded, hence the flame height based on the fire temperatures rather than the vertical elevation beneath the bridge should be considered. Although cable fracture in those fire incidents has been widely studied recently, the risk of pylon damage was hardly considered. While most pylons in long-wired bridges are made of concrete, steel pylons have been increasingly used in many main bridge designs, such as the Nanjing Yangtze Bridge Fourth and Yangtze Bridge Taizhou. Usually, the stability of the entire structure will be provided by these steel pylons [38].

2.3.2 Steel Girder Bridges

With fire under the bridge, steel girders will be exposed to high temperatures. Because of the concrete slab acting as an insulation layer, the top flanges of the steel girders, compared to the bottom flanges, will experience a lower temperature rise as this layer transfers top flange heat to the deck. Lower thickness and the web's slenderness in comparison to the flanges cause a quick rise in the web temperatures. In addition, an increase in temperatures and stresses in steel enhances creep deformations, which result in a rapid rise in girder deflections. If the web has ample shear strength, the girder fails because of the yielding of the bottom flange and the creation of a plastic hinge in the middle of the span (flexural limit states). Failure may also arise because of the web buckling (shear limit state) or because of the presence of both flexural and shear limit states [1].

2.3.3 Concrete Bridges

Because of the benefits that concrete and prestressed strands have over other building materials, prestressed concrete (PC) girders are commonly utilized in bridge construction. These benefits can be divided into three categories: (1) concrete has a low cost and high resistance, can be cast quickly and easily shaped; (2) it has extended durability due to the controlled cracks by prestressing effects; (3) dimension of PC bridge girders can be reduced by prestressing. However, prestressing strands have a low fire resistance because prestressing strands with high tension stress are susceptible to fracture at high temperatures [39-41]. A PC bridge fire happened in the United States in 2006 at the Bill Williams River Bridge in Arizona. The superstructure was built of PC girders beneath a cast-in-place concrete slab, and the bridge had fourteen spans with a total length of 23.2 m [42]. In 2017, another terrible fire broke out on I-85 highway in Iowa, causing a PC bridge to fall after 40 minutes [39]. As the previous cases demonstrate, fires can represent a severe hazard to PC bridges. This is because high temperature exposure can severely degrade the strength and stiffness properties of concrete and prestressing strands. The modulus and tensile strength of prestressing strands are particularly susceptible to high temperatures. Furthermore, because of their low mass (thin web and flanges), thin-walled box girders are widely utilized as flexural components in long-span PC bridges . As a result, PC bridges are extremely prone to destruction in the event of a significant fire [43, 44].

2.4 Damage Description

Bridge collapses occur when all or considerable portions of a bridge fail, necessitating complete or partial replacement. A complete collapse occurs when many of the span's key structural elements fail, making transportation impossible (Figure 2-8). A partial collapse is defined as an occurrence in which some of the principal structural components of a bridge fail, posing the risk of accidents or loss of life to people moving on or under the structure. The unserviceable state of a structure or its parts that may or may not lead to collapse is referred to as distress (**Error! Reference source not found.**). Distress is a s tructural situation in which some deformations are performed without impacting structural integration [1, 45].

Figure 2-8 Complete collapse of a bridge (Photo from [46])

An assessment of bridge fire occurrences in the United States and Europe revealed that flames on bridges did not harm their structural integrity, with just the decks being damaged (e.g., the fire on Big Four bridges, Kentucky). For example, fires spread beneath the bridges on the SR-528 and SR-3 bridges in Merritt Island, Florida, and the Bill Williams River bridge in west-central Arizona. These two bridges were destroyed and required the replacement of the damaged sections [47].

Figure 2-9 Metropolitan expressway, Tokyo, Japan (Photo from [32])

2.5 Time of Fire Exposure

The NCHRP 12-85 project argues that the duration of a fire can be determined by its intensity. Owing to the greater bridge-ambient temperature differential in hydrocarbon fires, the bridge components heat up more quickly, stay at an elevated temperature for a longer period, and cool down quickly. The rate of gasoline leaking determines the length of fuel tanker fires. Slower leakage may result in longer-burning, lower-intensity flames. Likewise, the duration and intensity of various types of vehicle fires might vary. The garbage fire under the I-78 Bridge in Newark, NJ, lasted around 24 hours and caused a 9-inch permanent displacement of the bridge. This deflection is due to creep, and a shorter-duration fire of equal strength would not have resulted in any lasting deflection. To replicate the circumstances faced at I-65 Birmingham Bridge Fire, Alabama (Figure 2-10), a 45-minute fire occurrence is recommended for hydrocarbon tanker truck fires [31].

Figure 2-10 Permanent deflections of steel girders of the I-65 bridge (Photo from [48])

2.6 Fire Fighting Response

In the Mathilde Bridge fire, firefighters could intervene rapidly with water, reducing the temperature in the steel frame before it attained the maximum temperature of roughly 725 °C. The impact of metallurgical cooling on steel that had reached its critical temperature may have resulted in steel embrittlement if this procedure, which most certainly saved the bridge, had not been done quickly enough (Figure 2-11).

Figure 2-11 Around 40 minutes after the incident began, firefighters try to put out the fire (Photo from [48])

2.7 Traffic Impact

The position and traffic volume of the bridge have an impact on its vitality. If the bridge is on a road that crosses natural barriers (such as valleys or rivers) and there are no alternate roads for traffic diversions, any bridge closure due to fire damage can delay or shut down the traffic flow in the area [7, 11, 49]. If a bridge is located on a heavily used roadway, or on the outskirts of a city which services a substantial number of cars regularly, its failure can cause major traffic delays in the surrounding area, resulting in social and economic losses. In the case of severe destruction of a bridge by fire, the expense of maintenance is of significant consideration [20, 49]. As an example, a bridge fire incident due to a dump truck in Robbinsville, NJ, prompted the closure of Interstate 95 as well as 79 kilometers of a major highway. Traffic disruptions impacted communities hundreds of kilometers distant in Delaware and Connecticut. For the next six weeks after the crash, traffic was severely disrupted [19]. The other example is the Montebello freeway 60 overpass, 2011, in which the removal took place over two days; the eastbound overpass was destroyed the day after the collision, and the westbound intersection was then removed as well. Removal was compounded by the discovery of telephone lines nestled in asbestos inside a bridge, which required meticulous dismantling to avoid cutting telephone lines or releasing radioactive asbestos into the air. As a result, the 60 Freeway was shut down for far longer than anticipated, producing major traffic congestion in the vicinity [14].

2.8 Financial Impact

There are two types of economic losses caused by fires: direct and indirect losses. Direct losses are defined as the costs of restoration and/or reconstruction, whereas indirect losses are defined as the missed work opportunities caused by downtime (Figure 2-12) [50]. Hydrocarbon fires, or high-intensity fires, may cause major economic and public losses. In 2002, the cost of the bridge fires was estimated to reach $1.28 billion [7]. Although it is difficult to quantify the indirect cost of delayed commercial goods, this case study illustrates the critical economic services that bridges provide as well as the vulnerability of such transportation links to severe events. As an example, indirect traffic costs related to the MacArthur Maze fire were estimated to be about USD 6 million [51, 52].

Figure 2-12 One section of the collapsed bridge (Photo from [46])

2.9 Environmental Impacts

Transporters and first responders must record specific facts on any hazardous materials leak, such as the site, time of day, spilled items, volume, operator, and individuals impacted. Since 1993, the US Office of Hazardous Materials Transportation (OHMT), has made these records, known as the Hazardous Materials Information System (HMIRS), accessible to all those other states. When a leak causes an accident or fatality, transport or loss of property of $50,000 or more, a local population evacuation, or the shutdown of a major transportation facility, companies are required to notify the National Response Center (NRC) [53]. The presence of hazardous chemicals at the scene of the I-35 bridge fire was another worry that had to be assessed and dealt with, as numerous dangers existed. Fuel-filled cars and trucks were found in the river. The decomposing human remains posed a threat of illness. A large portion of the bridge's surface and structure, as well as associated pollutants, were submerged (Figure 2-13). Debris clearance efforts would generate dust, which might irritate surrounding residents (Figure 2-14). From identifying substances to monitoring the water, soil, and air, several agencies at all levels of government were actively involved in dealing with known and potential hazardous compounds [46].

Figure 2-13 Submerging the bridge and vehicles with their fuels in the river (Photo from [40])

Figure 2-14 Existence of dust and smoke in the air because of fire incident (Photo from [46])

2.10 Fire protection

Despite buildings being secured from active and/or passive fire, bridges are not normally protected from fire [54]. However, the National Fire Protection Association (NFPA) code specifies that: Essential structural elements must be safeguarded from accident and high-temperature exposure, which can result in hazardous deterioration or catastrophic collapse of the bridge or elevated roadway (NFPA 502, 2011). Although this declaration specifies that bridges must be secured against fires, there are hardly any clear guidelines on how bridges should be protected from fires [1, 55]. Passive or active are traditional fire prevention techniques. Sprinklers and suppression systems with a sensor network for identifying a fire situation are examples of active devices. The long-term repair and maintenance of these devices, along with their poor efficiency, excludes the use of sprinklers and suppression systems in bridges. Passive systems are thus more suited for bridges and can have reduced long-term operational expenses. Using fireproofing materials to cover members including cemented layers, intumescent paints, and fire-resistant materials added by spraying (SFRM) is one popular approach. Intumescent coating paints expand and char as the temperature rises, creating an insulating layer that slows the rate at which the internal steel member heats. SFRMs are usually made up of gypsum or cement, as well as other materials. Its thermal properties are more resistant to fire than bare steel. When sprayed, detailed features such as bolts, and connections can be quickly secured. However, when implementing the bridge, the impact of outside environmental conditions should be weighted [56]. Spray-on fire-resistive coatings, intumescent pads, fibrous insulation, and high-temperature board materials are all included in the UL directory. Since most of these products are for construction applications, not all items will be suitable for use on buildings exposed to the elements, such as bridges. The UL directory has materials that are long-lasting and avoid temperature increases in bridge structural components exposed to tanker fires [31, 55]. It is worth noting here that despite its strengthened properties, high-performance concrete (HPC) is still more susceptible to fire than standard strength concrete because of its significant temperature-induced strength degradations. Because of its compact mix and poor permeability, HPC is prone to fire-induced spalling. Spalling from fire reduces the cross-sectional area of concrete components, enabling more heat to flow through the reinforcement bars and thereby exacerbating the premature collapse of bridges. The inclusion of polypropylene fibers in the concrete mix allows it to melt at a low temperature of 170 °C, creating channels for vapor to evacuate, avoiding pressure building inside concrete elements, and thus, reducing spalling in them. Also, the addition of steel fibers to concrete improves concrete's tensile strength, overcoming tensile stresses caused by increased pore pressure and reducing spalling [21].

2.11 Post-Fire Inspection

A bridge or tunnel might sustain considerable structural destruction or failure in a catastrophic fire yet exposure to smaller flames may not lead to visible damage. However, localized damage, such as spalling in concrete linings (and girders) or local buckling in the web of steel girders, can still occur. Nonetheless, even when the fire has been completely extinguished, a fire-damaged transportation building cannot be reopened to passengers unless its residual capacity has been properly assessed [63]. It is critical to create methods for properly evaluating the post-fire residual capacity of structural elements in order to promote fast service restoration and to design upgrading alternatives for bridges and tunnels [21]. There are currently no regulations in place for determining the residual capacity of fire-exposed bridge members. Nevertheless, the British code, Part 8 in appendix C, stipulates that steel structural elements should be utilized ever since a fire provided their physical properties have not been severely modified or the parts have not been impacted over geometrical and size standards. Furthermore, structural elements that were deformed or deteriorated must be extensively analyzed to guarantee their stability and performance (BS: Part 8, 1990, BS: Part 2, 1992) [1]. As an example, the Bill Williams River Bridge exhibits considerable spalling at the top and bottom flanges of certain girders, according to a post-fire assessment. Traffic flow had to be diverted to alternate roads. The bridge was restored to traffic after an assessment and required repairs. The bridge needed to be retrofitted at a cost of around $700,000. The Wiehltalbrücke Bridge is another example, where a post-fire assessment revealed that a girder portion required to be changed. The bridge had to be closed for weeks after the fire tragedy for a thorough investigation and restoration. This fire cost $9.8 million (€7.2 million), making it Germany's most expensive traffic accident.

2.12 Types of Methodology

Various types of methods have been studied by many researchers in the field of bridge fire all around the world. Some of them have worked on bridges using experiments to reach the real-world science about bridges in fire, some have investigated the issue using numerical analysis to accomplish their research based on computational simulations, and others have conducted machine learning for achieving good results. A brief report of some research is explained below.

2.12.1 Experimental methods

Using experimental and computational investigations, **Aziz et al.** [57] evaluated the fire performance of common steel girders used throughout bridge construction. In their experiments, three composite girders were analyzed while being loaded and exposed to fire at the same time. Load intensity, web slenderness, and stiffeners distance were all tested factors. According to the outcomes of fire testing, conventional steel girders can fail in 30–35 minutes during normal fire circumstances. The duration to collapse and manner of failing in steel girders subjected to fire are heavily impacted by web slenderness, stiffeners distance, and fire exposure style. When the web slenderness of steel girders is approximately 50, the failure mechanism switches to web flexural bending; however, when the web slenderness of steel girders exceeds 100, the failure pattern shifts to web shear buckling. Using data from fire tests, the performance of the fire-exposed steel bridge girders was studied with a computational finite element model. According to the conclusions of numerical methods, the suggested finite element model is able to track the reaction of steel girders in combined loads and fire situations.

Alos-Moya et al. [58] analyzed open-air fire tests performed at the Valencia University in Spain, beneath an experimental bridge. The bridge that contained a 6 m span with two steel I-girders supporting a reinforced concrete slab deck, was subjected to four different fire scenarios. The results indicated that 1- the maximum gas temperatures were attained by I-girders. 2- Because gas and steel temperatures varied significantly throughout the bridge's longitudinal axis, assuming a longitudinally uniform gas or girder temperature was impractical. 3- The temperatures at the bottom flange and web of the I-girders were quite similar and substantially greater than the temperatures at the top web, and 4- The amount and position of the fire load were important factors in the bridge's response. The study allowed for the validation of the computational methods being used in bridge fire engineering, and it was a vital part of developing a performance-based strategy for the designing of fire-resistant bridges.

Beneberu et al. [59, 60] evaluated a prestressed concrete composite bridge in an open-air hydrocarbon pool fire in combination with the simulated AASHTO live load (Figure 2-15, Figure 2-16). The purpose was to explore the resilience of a concrete bridge superstructure, as well as the stiffening and the in-fire performance of carbon fiber-reinforced polymer (CFRP) in the event of a fire. Unlike standard fire testing in confined spaces, the 60-minute incident led to severe fire temperatures on the girders because of the wind effects. According to the findings, standard fire experiments must not be utilized to assess the fire resistance of concrete elements of the structure. The CFRP girder without fireproofing suffered the most damage of the three tested girders, demonstrating that the concrete bridges with these support beams are very vulnerable to fires. The fireproofing helped to keep the temperature at the CFRP-concrete contact low, protecting the bond, concrete layer, and prestressing steel.

Figure 2-15 Test setup on a full-scale prestressed concrete bridge before the fire test (Photo from [59])

Figure 2-16 Full-scale prestressed concrete bridge during the fire test (Photo from [59])

Nicoletta et al. [61] investigated the fire performance of glass fiber–reinforced polymer (GFRP) stay-in-place structural precast used in the rapid construction of reinforced concrete (RC) bridge decks. A concrete deck strengthened with a GFRP stay-in-place form is evaluated in seven beam sections. The beams were exposed to fire as well as simulated fire damage during the bending tests in four different locations. A 14.5-minute heptane pool fire was used to cause fire damage on one beam. When compared to the control beam, the fire did not cause notable degradation in the beam.

2.12.2 Numerical Modeling

Quiel et al. [30] provided a simplified design framework for assessing the reaction of a steel-supported bridge to an open-air hydrocarbon pool fire caused by a tanker truck collision and consequent gasoline leakage. The approach, which simulates a pool fire with a simplified discretized solid flame model, combines calculation methodologies depending on both fundamental concepts and real facts (to determine the fire-damaged severity). The heat transfer to structural components from the specified fire hazard was calculated with computational fluid dynamics (CFD) software programs, including the Fire Dynamics Simulator (FDS) developed by the National Institute of Standards and Technology (NIST). The concept was used for case analysis of a 2007 fire at the MacArthur Maze freeway intersection nearby Oakland, California, that resulted in the bridge collapse. The framework was then used as a device to figure out how vulnerable the overpass was in a similar fire.

Paya-Zaforteza and Garlock [3] investigated the reaction of steel girder bridges in fire by analyzing a 3D numerical model. Performing a parametric study they considered options for axial restraint of the bridge deck, different types of structural steel for the girders (carbon steel and different grades of stainless steel), different constitutive models for carbon steel, and various live and fire loads. They concluded that the numerical model should account for the constraints against thermal expansion caused by a nearby bridge or abutment. Furthermore, when bridge girders are made of carbon steel, the time to collapse is quite short (between 8.5 and 18 minutes), but when stainless steel is used, the time to collapse might practically double. As a result, stainless steel is a material worth considering for high-risk steel girder bridges, especially if the bridge is in a chemical attack and appearances are crucial.

Kodur and Naser [7, 11, 62] proposed a weighted factor technique to identify essential bridges from the view of fire danger. It considers the susceptibility level of various bridge elements, the vital character of a bridge in terms of traffic flow, and the fire preventative measures implemented in each bridge. The weighted factor for fire design, which is comparable to the one used in analyzing wind and snow loading, has been tested for several bridges that have seen fire incidents in the past.

Aziz and Kodur [62] suggested a technique for assessing the residual strength of steel girders that have been subjected to fire. They analyzed the load-bearing capacity, thermal and structural reaction, and residual capacity of the fire exposed bridge girder in three stages: before the fire, during the fire, and after the fire. The proposed method was evaluated by numerical modeling on a typical steel girder using the finite element computer program ANSYS. The most important element impacting the residual strength of a fire-exposed bridge girder was the maximum fire temperature. As a result, during the heating phase of a hydrocarbon fire with a temperature increase of roughly 1100 °C, a steel bridge girder loses most of its resistance and collapses.

Alos-Moya et al. [63] used a numerical study of the I-65 overpass fire in Birmingham, Alabama, USA in 2002 to study the bridge fire behavior and offer modeling instructions. A fire model based on Computational Fluid Dynamics (CFD) and a Finite Element (FE) software getting the thermo-mechanical bridge response were presented. Parametric studies that addressed the heat release rate of spilled fuel, discretization of the fire temperature in the transition from CFD to FE modeling, and boundary conditions were used to verify the models. In research, the validated model was utilized to assess the impact of fire scenarios (CFD compared to standard fires) and live load. Results showed the significant role of the numerical models in replicating the bridge's response, also as a foundation for a performance-based design method of the bridges in fire, and little effect of the live loads on the bridge's performance. Furthermore, applying the Eurocode standard and hydrocarbon fires across the whole length of the bridge did not appropriately depict an actual bridge fire reaction for intermediate span bridges like the one in their study.

Peris-Sayol et al. [64] analyzed the behavior of a typical girder to tanker fires considering the effects of fire location, bridge geometry (vertical elevation, span numbers), and wind velocity on the bridge behavior. Significant numerical challenges, including the simulation of bridge deck bearings and the bridge deck components that are considered in the calculations, were also addressed in their research. The fire models were created using a Computational Fluid Dynamics (CFD) approach, and the thermo-mechanical reaction of the bridge was quantified using finite elements. The findings revealed that tanker fires cause severe damage to the abutments of single-span bridges with limited vertical elevation and in low wind circumstances. They demonstrated that forecasting bridge response with FE models is feasible, as well as saving substantial modeling and processing time.

Peris-Sayol et al. [65] analyzed information from 154 bridge fire incidents regarding the damage levels of bridges in fire. They evaluated the key factors of bridge fire damage including the vehicle type and its fire position, bridge vertical clearance, and constitutive material of the deck. In a regression model, the study of variation (ANOVA) statistical technique was utilized to analyze the influence of various factors (like as bridge structure or deck composition) on the dependent parameter by measuring the means of three or more classes concerning one or more factors (bridge damage level). The effect was represented by the p-value, which is a coefficient and a low p-value indicated a substantial impact. The analysis indicated that timber bridges are the most susceptible and that the majority of fires resulting in the bridge collapsing or being demolished are caused by a tanker hauling gasoline under the bridge, or on the bridge causing a large spillage under the bridge.

Garlock et al. [66] advocated a thorough examination of real fire accidents, real events on fire dangers, and post-fire evaluation and restoration procedures in bridges. As a result, their study highlighted the significance of fire hazards in bridges, provided working engineers with practical tools to devise methods for bridge fire damage repair, and indicated topics for further research.

Moon Ok Kim et al. [20] presented an approach for assessing fire hazards while installing sprinklers and standpipe systems on cable bridges. The fire risk for these bridges was graded based on the likelihood of fire events, firefighting circumstances, bridge fire susceptibility, and the impact of fire on social and economic life. The extent of fire hazard was estimated by allocating weightage factors towards each group, and the risk of fire was analyzed for 70 existing and under-construction cable bridges in Korea. These data might be utilized to guarantee that appropriate fire suppression devices are installed on every bridge based on its fire hazard.

Gong and Agrawal [67] used a nonlinear finite-element model to investigate the structure–fire relationship of long-span cable-supported bridges, especially anchored suspension bridges, self-anchored suspension bridges, and cable-stayed bridges. A typical steel box girder was subjected to several fire simulations resembling fire boat and vehicle incidents to explore the safety of such bridges. Through two fire scenarios, the durability of the three bridges was assessed based on fire severity and duration, as well as axial compressive force in the deck. According to the numerical simulations, the inherent axial force in the deck had a detrimental impact on structural behavior by inducing buckling failure under fire loads. Due to the almost negligible axial force in the deck, anchored suspension bridges had the highest safety factor among those three bridges. In both the truck and ship fire scenarios, self-anchored suspension bridges had significantly greater axial compressive force in the deck and were the most susceptible. A longitudinal change in axial forces in cable-stayed bridge decks was observed. As a result, their fire susceptibility is determined by the fire location, the existing axial force value, and the deck's load capacity.

Cui et al. [38] proposed a method for assessing the stability of a three-pylon suspension bridge in the presence of a tanker fire near the middle steel pylon. Thermal performance assessment and structural performance evaluation were the two phases of the suggested method. The initial phase was defining and simulating fire situations as well as the heat transfer mechanism from fire to the middle pylon. The second phase involved a numerical simulation of the burning period, fire region, and fire position, as well as testing durability under various fire situations. The findings revealed that existing fire temperature curves, which do not account for height effects, vastly overstate the impact of fires caused by tankers. The durability factor drops considerably after 30 minutes and is strongly proportional to the size and location of the fire. The technique and results were useful in assessing, managing, and maintaining the safety of cable-supported bridges with steel pylons.

Kodur et al. [68] offered a method for establishing fire-prevention plans for major bridges in two phases, specifically, evaluating the fire risk in a bridge and designing solutions for reducing the danger of fire on a crucial bridge. In the first phase, an analytical approach was used to calculate a fire-based significance criterion to evaluate a bridge's fire susceptibility, and in the second stage, an incremental finite element analysis was used to create various solutions for limiting the effects of fire danger upon the bridge if it was likely to be damaged by fire. The utility of this method was demonstrated in studies on three large steel bridges that failed because of fire incidents in recent years. The proposed strategy was shown to be a practical way for identifying key bridges in danger of fire and thereafter developing ways to resolve fire threats in these kinds of essential bridges.

Alnahhal et al. [69] using a finite-element method (FEM) studied the structural performance of the fiber-reinforced polymer (FRP) bridge deck. Comparing the simulation solutions with the New York State Department of Transportation's field performance, they performed a fully coupled thermal-stress analysis by FEM under high thermal load conditions to forecast degradation processes and the fire resistance limit of the structure. Damage models of the FRP deck caused by the snow and ice plow procedure were also carried out to rule out the risk of bridge failure if damage occurred. According to thermal models, they concluded that the effect of increased temperatures on the FRP bridge deck is particularly sensitive. Under all fire conditions, the FRP deck achieved the fire resistance limit early in the fire occurrence. Eliminating the top 5 mm of the FRP deck layer from the damage simulations due to the snowplows revealed the improbability of bridge failure in the worst-case damage scenario. Considering the specified damage scenarios, the results of both stages of modeling revealed the safety and reliability of the FRP systems. Furthermore, their study discussed the required immediate procedures for repairing the damaged region of FRP deck panels, as well as the bridge's potential usage following the damage event.

To validate the fire simulations that are the initial stage in analyzing any bridge fire incident, **Alos-Moya et al.** [70] used temperature data of the Valencia bridge fire experiments performed at the Valencia University, in Valencia (Spain) to validate the fire algorithms. Both a basic technique (Heskestad and Hamada's correlation) and complicated computational methods (Computational Fluid Dynamics simulations constructed with the Fire Dynamics Simulator–FDS- software) were used for validation. The Valencia bridge fire experiments included four fire events under a composite bridge with Heat Release Rate (HRR) values ranging from 361 to 1352 KW. The results revealed that using Heskestad and Hamada's relationship produced a great performance in its implementation limitations (HRR < 0.764 MW) but did not perform well above them, suggesting that it would be useful for designing lower size bridge fire experiments but not for analyzing actual bridge fires. FDS, on the other hand, gives accurate temperature forecasts and may be used to investigate bridge fire reactions. This research was rather a critical element along in the investigation of bridge fires and in improving the robustness of infrastructure systems in the presence of fire dangers. It also focused on the issues that might develop during open-air fire experiments, with the wind playing a significant role.

Using the FEM computer software ANSYS, **Kodur et al.** [9] examined the fire behavior of a steel bridge girder under various situations. The research took into consideration the essential aspects that impacted fire resistance, such as the fire situation, fire insulation, and composite performance resulting from an interaction between steel and concrete. According to numerical analyses, the composite action resulting from steel girder–concrete slab interaction considerably improved the structural behavior (and fire resistance) of a steel bridge girder under fire scenarios. Other important aspects influencing steel bridge girder fire resistance were fire insulation and the type of fire situation.

Dotreppe et al. [71] used the computer software SAFIR to do a numerical study to model the failure of the Vivegnis Bridge in Belgium due to a fire. A gasoline explosion caused a catastrophic regional fire at one of the bridge's piers. 3D beam components were used to represent principal girders, lateral girders, concrete slabs, and arches, while truss elements were utilized to simulate bracings and fasteners. Large displacements and high-temperature material characteristics were regarded in the model. The hydrocarbon temperature-time curve specified in Eurocode was used to perform a transient structural study. Both the timing of collapse and the manner of failure agreed well with the site surveys.

Nigro et al. [72] investigated the thermo-mechanical behavior of 0.15 or 0.20 m thick concrete slabs reinforced with fiber-reinforced polymers (FRP) installed on the outside, factoring two potential heating phases: (a) the bridge's asphalt paving with a 180°C temperature in the asphalt layer, and (b) a fire incident on the deck caused by a vehicle crash. In this example, the external ambient fire curve of EC-1 part 1–2 were examined, although the requirements of this code apply to structures rather than bridges. They found that (a) for slab thicknesses less than 20 cm, it is strongly suggested to use heat-resistant epoxy cement, and (b) if the FRP reinforcement is situated on the slab top, an insulation layer (concrete with expanded-clay) of at least 4 cm thick is required to prevent hurting the FRP reinforcement.

Eisel et al. [73] reported the research and steps done to rehabilitate the Wiehltal bridge following a fire due to an accident involving a tanker transporting 33000 liters of petroleum. Using computational fluid dynamics, material tests were performed as well as a numerical model of the fire. The fire's flames attained temperatures of 1200 °C, although bridge damage was minimized since, thanks to ventilation, the maximum thermal resistance of the steel plates was around 500 °C.

Using the computer software SAFIR, **Kodur et al.** [2] conducted a test case to demonstrate the fire resistance of a composite girder. By considering the girder as a collection of beam components, an unprotected steel girder and a steel girder shielded with fire protection (12 mm) were both examined. The research considered standard operating seen in common bridges, including stress loads, fire situations, and high-temperature material characteristics. The case study assumed that a petrol truck collided with a highway bridge, generating a large fire heating midspan of the bridge's bottom. According to uncoupled thermal-structural simulations, the exposed steel girder formed a plastic hinge, causing deformation acceleration and collapse in less than 30 minutes. The shielded bridge, on the other hand, functioned admirably in the face of fire, with no breakdown occurring because the isolated girder lost little stiffness.

Payá-Zaforteza and Garlock [3] investigated a 12.20 m simply supported bridge developed by the United States Department of Transportation. The bridge's cross-section consisted of five steel girders supporting a reinforced concrete slab that has not been physically attached to the girders. A 3D model of the bridge was created using the software package Lucas and solid components were exposed to a hydrocarbon design fire, which may be triggered, for instance, by a gasoline tanker collision or spilling. By changing the amount of combination of dead and live and the axial constraint (fixed or free), the structural reaction to fire was investigated. The periods of the bridge collapse were found to be relatively short (less than 10 minutes in all situations studied) and were mostly unaffected by the magnitude of the live load. The bridge's lateral displacements were also large enough that the connection between the deck and the nearby span or abutment had to be considered.

Gong and Agrawal [18] presented comprehensive research on the numerical model of a fire incident on the Ed Koch Queensboro Bridge, a major long-span truss bridge connecting Manhattan to Queens in New York City, due to a truck collision, resulting in the shutdown of one lane for many weeks. They conducted in-depth research on numerical simulation of the complete fire mechanism and prognosis of the structural reaction of the deck exposed to the fire load. The approach of sequentially coupled thermal-stress analysis was utilized to analyze the incident and anticipate the thermomechanical reaction of structural elements subjected to actual fires. They created the fire with FDS and then used ABAQUS to perform the thermal analysis to define the fire intensity on the Queensboro Bridge. The simulation findings revealed a strong agreement between predicted and measured damages, with the modeled out-of-plane displacement of the girders subjected to fire matching much with observed deflections. The technique described was a successful strategy for modeling and simulation of fire-structure interactions and has wide applicability to other civil structures.

2.12.3 Machine Learning Techniques

Machine-learning techniques can be used to solve specific problems such as data analysis, language translation, automatic control, and optimization techniques, as well as more classical issues including speech processing, facial detection, handwriting recognition, medical data science, and games [74]. Machine learning has been effectively designed to address issues in a wide range of applicable disciplines, with the following examples demonstrating the variety of applications:

2.12.3.1 Machine Learning in Structural Engineering

Using an artificial neural network, **Moradi et al.** [75] analyzed the efficiency of the most critical factors on fire-resistance rating (FRR) and residual strength index (RSI). The developed ANN model for predicting the FRR and RSI of CFST columns yielded correlations. The ANN models were trained, validated, and tested using almost 300 experimental datasets gathered from the literature. For FRR and RSI, the network's correlation coefficient (R) is 0.967 and 0.97, respectively. The R coefficients for the FRR and RSI-generated correlations from the ANN model are 0.61 and 0.74, respectively. In addition, the obtained correlations were compared to the restrictions of known empirical relationships. The ANN model was shown to be more precise and reliable than the current relationships based on the comparison results. A graphical user interface was also designed for estimating the FRR and RSI of CFST columns.

Krishna et al. [76] investigated an image-based approach for analyzing the condition of RC bridge components. They separated their studies into two categories: RC rectangular beams and scaled (1:12) T-shaped beams as well as simulation model validation for T-shaped beams, and artificial neural network training (ANNs). In their investigation, they used Digital Image Correlation (DIC) as a simulated sensor to collect data. On a piece of 100-ton dynamic testing equipment, rectangular RC beams with dimensions of 1800 mm×150 mm×200 mm and scaled (1:12) RC T-beams were evaluated in bending loads at four different locations. Using a finite element model (FEM) software, SAP2000, they experimented with a 28-day compression test on prism specimens to provide the stress-strain curves to have utilized them as input data for material simulation. A local damage index (LDI) was applied to evaluate the state of structural elements. Verification of FEM results through practical testing can provide a moment-curvature spine curve, allowing for more evaluation of deterioration and excess moment strength of full-scale bridges designed by the Ministry of Road Transport and Highways (MoRTH). A feed-forward backpropagation approach was utilized to train the ANNs using experimental and numerical data in their research. Both rectangular and T-beam ANNs were created separately. The residual capacity of the beam component and the accompanying DI were directly determined by the output parameter of ANNs. ANNs were discovered to be capable of appropriately identifying the extent of the damage. The results of the tests, simulations and ANN forecasts were found to be quite good.

Kandel et al. [77] used fiber Bragg grating sensors to analyze the behavior of prestressed concrete bridge girders and proposed a statistical damage identification and recognition technique. Artificial Neural Networks are used in the proposed approach to connect the strain patterns collected at different sensor positions all over the evaluated girder. The approach can detect and locate damage at the sensor position without the requirement for detailed loading information, making it suitable for long-term inspections in ordinary traffic situations. Experimental data from structural analysis of a large-scale prestressed concrete bridge girder is used to demonstrate the technique.

Nguyen and Dinh [78] proposed utilizing Artificial Neural Networks (ANN) to better forecast deck conditions of bridge structures in Alabama, USA. The National Bridge Inventory (NBI) dataset was used to generate a library of 2572 bridges for the ANN model's training, verification, and evaluation, which included eight input variables, one output parameter, and the deck rating. The eight input variables are the existing bridge age, average daily traffic, design load, main structure layout, approach span configuration, number of main spans, percent of daily truck traffic, and average daily traffic growth rate. The findings revealed that the proposed ANN model can effectively estimate the bridge deck's condition rating with a 73.6% accuracy. The precision of the suggested model increased to 98.5% when a margin error of ±1 was applied. Furthermore, a sensitivity analysis of different input factors indicated that the existing bridge age was the most significant predictive variable of bridge deck rating. The design load and main structure layout were the next. The impact of the other input variables on the performance of the ANN was found to be negligible. Finally, the ANN was shown to be capable of producing a bridge deck deterioration curve, which assists in visualizing a deck's condition rating as well as safety margins during its residual life span.

Cattan and Mohammadi [79] explained how neural network systems were used to create relationships between subjective views and bridge characteristics, as well as intuitive and statistical assessments. It was demonstrated that neural networks may be successfully trained and utilized to estimate a rating according to bridge characteristics. The special application challenge for railway bridges in the passenger train network of the Chicago metropolitan region was issued. The study demonstrated that successful network training is possible, particularly when the input data set comprises parameters with a varied collection of intercorrelation coefficients. The network got a prediction value of roughly 73% when the link between the subjective evaluation of the bridge and bridge parameters was explored. The relationship between subjective and analytical assessment was also studied in the study. The prediction rate in this example was around 43%. The neural network system showed a substantially superior performance ratio in developing the link between the bridge rating and bridge specifications when compared to traditional statistical approaches and the fuzzy-logic technique.

Artificial intelligence technologies, including Artificial Neural Networks (ANNs) and Case-Based Reasoning (CBR), have been suggested since the late 1990s to construct degradation models that overcome the limits of existing models by learning from data and modeling complicated connections. **Morcous** [80] compared the use of ANNs and CBR in simulating bridge degradation using data from the Quebec Ministry of Transportation's bridge deck. The goal of this comparison was to evaluate the benefits and drawbacks of the two systems so that transportation authorities could choose the one that best suited their needs.

Gasser et al. [81] created an ANN degradation evaluation method in Missouri. For this purpose, data from long-span bridges were utilized, with 80% of the data points being used for training and 20% being used for testing. In addition, a linear regression model was developed to serve as a foundation for assessing the efficiency of the suggested ANN. The created methodology worked successfully in predicting the state of bridges in the future. Using the established model, the Missouri Department of Transportation will be able to more effectively allocate funding and time for bridge preservation, repair, and restoration. Since this model was developed for bridges in Missouri, it may be adapted for use in other bridge inspections around the country.

Huang [82] conducted statistical research to discover important features affecting degradation and created an applied model for predicting bridge conditions in the future. Based on data acquired from past control and monitoring of concrete decks in Wisconsin, 11 critical parameters and constructed an artificial neural network (ANN) model were selected to forecast related degradation. An examination of the use of ANN revealed that it functioned well in terms of pattern categorization while simulating deck degradation. The created model can effectively estimate the quality of bridge decks, providing useful information for service planning and management at a project as well as network levels.

To simulate time-series element-level data, **Lee et al.** [83] employed restricted historical bridge inspection records. They proposed the Backward Prediction Model (BPM), an Artificial Neural Network (ANN)-based prediction model for producing previous bridge condition evaluations based on limited bridge surveys. The BPM builds correlations with existing bridge evaluations based on a limited number of bridge inspection records by using non-bridge variables from the past, such as traffic density, population, and weather. The resulting algorithm may anticipate the lacking previous performance evaluations for specific bridge components. The study's findings may aid in reducing the unpredictability of forecasting future bridge condition ratings, thereby ensuring the accuracy of different BMS analyzed data.

Using the National Bridge Inventory (NBI) database, **Li and Burgueo** [84] employed soft computing approaches to construct deterioration predictive techniques for bridge abutment walls. Multilayer Perceptron Networks (MLPN), Radial Basis Function Networks (RBFN), Support Vector Machines (SVM), Supervised Self-Organizing Maps (SSOM), Fuzzy Neural Networks (FNN), and Ensembles of Neural Networks (ENN) were among the techniques used. The most effective model was an Ensemble of Neural Networks (ENN) with a unique data organizing plan and polling method, which identified damage with an accuracy of 86%. The prediction models were used to create bridge degradation curves, which were then compared to surveys. The findings demonstrated that well-developed damage forecasting models may be beneficial for both existing bridge repair and future bridge design.

2.12.3.2 Machine Learning in Fire Safety Engineering

To estimate the susceptibility of bridges to fire hazards, **Abedi and Naser** [85] used two machine learning algorithms (Deep Learning and Genetic Algorithm). Data from 135 international bridge fires were used to build these solutions. The conclusions resulted in the creation of a Rapid, Automated, and Intelligent (RAI) technique for identifying fire-prone bridges and estimating the predicted degree of damage a current, projected, or historical bridge would suffer in the case of a bridge fire. The RAI approach was built with a better framework and lower processing complexity, making it easily scalable and transportable for analyzing fire-vulnerable bridges in real-world scenarios.

Kodur and Naser [74] used a machine learning (ML) technique to assess numerous steel and concrete bridges to determine their fire hazard susceptibility. To obtain the greatest accuracy, three algorithms were employed to construct this ML approach: Random Forest (RF), Support Vector Machine (SVM), and Generalize Additive Model (GAM). They discovered that the suggested machine learning-based technique is a useful tool for identifying risk-based bridges and determining their susceptibility in fire hazard situations. Furthermore, their study demonstrated the feasibility of incorporating Machine Learning (ML) into structural engineering applications as an analysis assistance technique (i.e., instead of experimental tests, advanced simulations, and analytical approaches).

Chapter 3: Development of Machine Learning Model in Bridge Fires

Machine Learning (ML) is a subset of Artificial Intelligence (AI) that concentrates on algorithms and statistical models allowing computers to complete tasks without explicit instructions. It is a strong process of extracting a model from a huge database for making predictions [86]. Using input data and generating a special output, a machine learning algorithm accomplishes a goal without being explicitly written (i.e., hardcoded). These algorithms are soft programmed that automatically adjust or modify their design based on repetition (i.e., experience) doing the target objective progressively. The process of adaptation is known as training which involves providing patterns of inputs as well as expected outputs. The algorithm then optimizes its configuration not only to provide the intended result when given the training inputs but also to generalize achieving the desired result when given new, previously unknown data. This training is the learning phase of machine learning. The training is not confined to a one-time adaption over a certain period. A competent algorithm, like people, may engage in lifetime education as it analyzes new information and improves out of its failures [87]. Artificial Neural Networks (ANNs) modeling was employed in this study.

3.1 Definition of Neural Network

In summary, a functional neural network is a set of linked neurons that gradually learn from their surroundings (data) to acquire key linear and nonlinear patterns in huge datasets, allowing it to provide trustable predictions of future scenarios comprising even chaotic and incomplete data. They are the fundamental processing elements that perform regional data analysis within a net. These synapses form parallelized nets, the performance of which is governed by the topology of the network (how neurons are structured and connected), the strength of interconnected neurons, and the processing conducted at neurons [88]. Haykin states that "A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects: 1. Knowledge is acquired by the network through a learning process; 2. Interconnection strengths between neurons, known as synaptic weights are used to store knowledge." [89].

3.1.1 How the Artificial Neural Networks Work

The ANN is a type of machine learning in which the network is supposed to emulate the brain's functioning. Signals are sent from one neuron to the next in the brain. The nodes and vectors in the network indicate the transmission of data in such a way (Figure 3-1).

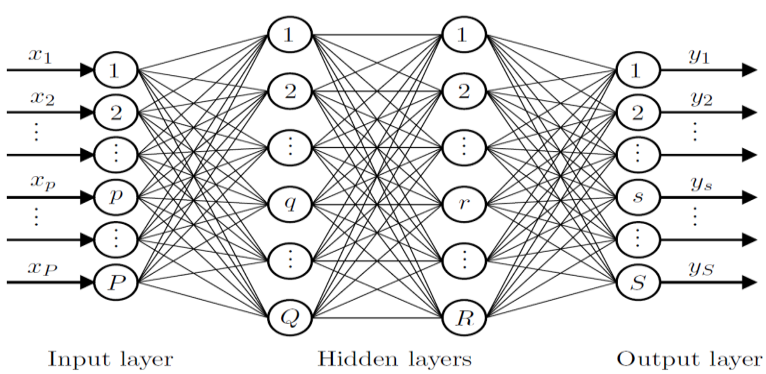


Figure 3-1 A typical multilayer neural network topology (Photo from [86])

The primary benefit of the ANN is that it can represent a complicated issue using basic arithmetic equations. Once the number of input variables is considerable, the ANN is substantially more accurate than standard regression procedures such as polynomial function fitting. This may properly manage numerous outputs at the same time. Artificial Neural Networks (ANN) can learn any nonlinear and complicated function, which is critical since many of the relations between inputs and outputs in real life are both nonlinear and complex. As a result, these networks are commonly referred to as Universal Function Approximators. ANNs can learn weights that map any input to the desired output. ANN does not place any limits on the input variables, unlike many other prediction algorithms.

A typical ANN is made up of three layers: an input layer, one or more hidden layers, and an output layer. The network layer comprises nodes, and each node in a layer is linked with every node in the layer just above. A weight and a bias term are applied to each node in a hidden layer. Typically, finding the ideal configuration based on quality and performance is a trial-and-error procedure. This would be primarily dependent on experience and may take a longer time. A linearly separable parameter may usually be estimated with one hidden layer, while more hidden layers are recommended for real-world situations [86]. A multilayer perceptron, or MLP, is a sort of neural network wherein the synapses are distributed across many layers. The perceptron is the first and most basic neural network architecture [90]. The output of the n^{th} neuron in the m^{th} layer of MLP is defined by the equation below:

$$O_n^m = f_n^m\left(\left(w^{(m-1)}\right)^T O_n^{(m-1)} + b^m\right) \qquad \text{Eq. 1}$$

where, f_n^m is the function of n^{th} neuron in the m^{th} layer, $w^{(m-1)}$ is the weight from the $(m-1)^{th}$ layer to the m^{th} layer, b^m is m^{th} layer bias (Figure 3-2).

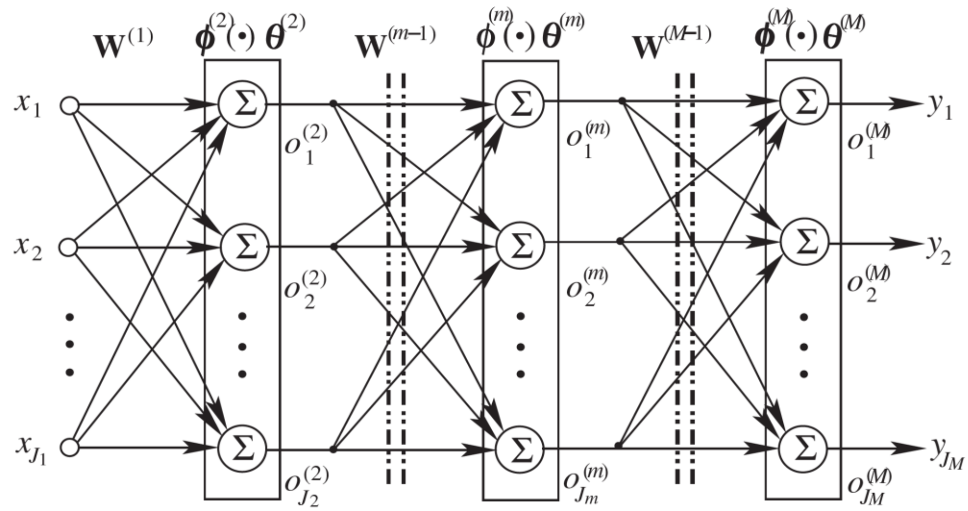


Figure 3-2 The architecture of an MLP (Photo from [91])

MLP can do identification, grouping, and function estimation. Almost every function may be approximated using a neural network with three or four layers and a reasonable number of neurons in the hidden layers. A four-layer network, in general, employs fewer weights to calculate functions but generates more local minimum [91].

3.1.1.1 Feed-forward and Back-propagation Networks

There are two phases in neural network processing consisting of feed-forward and back-propagation. During the feedforward phase, synaptic weights (which can be prescribed or random) are added to the input matrix and transmitted through hidden layers and from the hidden layer to the output layer. The model is assessed at the output layer as part of the training process, and the difference between predicted and actual values is calculated. Each iteration reduces the computation error, and a comprehensive repetition is referred to as an 'epoch.' The weight and bias of the nodes for the specified input-output database are determined using optimization algorithms throughout the training phase. If the error exceeds the targeted error, the neural network undergoes backpropagation, in which the weights are readjusted at each neuron. The process is then repeated until the stipulated goal error is attained after the weights are changed. Due to its convenience, the backpropagation of error (BPE) method is widely employed for this purpose [76, 86].

3.1.1.2 Supervised Learning and Unsupervised Learning

There are two types of training methods including supervised learning and unsupervised learning. The conjunction of supervised learning with back-propagation is used for providing the right output for the training while the combination of unsupervised learning and a counter propagation network is utilized where a proper output database is unavailable. In both classification and regression implementations, supervised learning is commonly utilized [76, 86]. Supervised learning is the most extensively used learning strategy. Attaining a certain level of stability in the weights pattern learning is believed to occur. A function is activated in the input layer in each node, as well as the weights in other layers of the node's connections. Comparing the resulting output with the intended answer, a total error is measured. The previous output is changed with the maximum level of precision at the output layer, and then the weights are modified. As a result, the error is transmitted back to the network. When a variety of input patterns are processed, meaning that the network will have been trained. However, there is no assurance in determining the network's level of learning, and the number of diverse input-output patterns or situations in the training set is qualitative. Now, this network is capable of multiple computations for a variety of tasks, including pattern recognition, linear optimization, speech recognition, and prediction [92].

3.2 Construction of the ANN Model

The ANN is initially trained with some of the available data. Training means algorithms to find proper weights so that the error is minimized. By using supervised learning algorithms, the output of the network is checked with actual answers (targets) and, if needed, weights are updated. The error rate between outputs and targets is determined using MSE.

$$E = \frac{1}{N}\sum_{p=1}^{N} \left|\left|y_p - \hat{y}_p\right|\right|^2 \qquad \text{Eq. 2}$$

Where N is the number of samples, y is the target and ŷ is network output. The mathematical advantages of mean squared error are most apparent when used to evaluate the performance of linear regression, since it allows one to separate the variance in a dataset into variation explained by the model and variation explained by chance. An estimator's quality is measured by the MSE. This function should be optimized, which means that the error function should decline toward zero, and a gradient-descent approach should be applied. One of these algorithms is the error backpropagation [93, 94]. The first value of "w" must be adjusted if the computed MSE does not fit inside a reasonable range, and this is a back-propagation process [75].

3.3 The Bridge Fire Dataset

To successfully use machine learning to detect sensitive bridges to fire dangers, a good database covering diverse bridges and fires is required. As a result, a literature study was conducted initially to investigate major bridge fires. During this process, identifying critical elements (from a fire-vulnerability standpoint) for achieving a correct database is challenging, which will contribute to the development of an optimized machine learning architecture with minimal processing complexity [7, 11, 30, 44, 65, 95-98].

Using machine learning analysis, in this research, eight of the most critical parameters of 171 international bridge fires have been collected including type of the area, structural system of the bridge, material of the bridge, Annual Average Daily Traffic (AADT) supplied by the bridge, fire ignition source, type of combustibles, position of the fire, and damage level imposed on the bridge because of a fire. Each of which will be discussed more below (Figure 3-3, Figure 3-4).

It is notable that there are some limitations in this study as follow:

1- Wooden bridges have not been considered as they are vulnerable to fires and most of them which exposed to fires collapsed due to the combustibility of wood as well as the age of these wooden bridges. Since considering them will affect the network output, they removed from the database input.

2- All steel bridges in this study are unprotected steel. They have not been insulated with fireproofing materials such as the most bridges.

3- In the case of cars, trucks and tankers which the fire incidents ocuur due to collision or crash, the position of the fires is on the bridges, under the bridges and on the bridegs with fuel spills indicating that bridegs are directly exposed to the fires, so the distance between fire ignition source and bridge has been ignored.

4- The model does not consider the strength of bridge structures; it is only based on the previous incidents.

A thorough investigation of the bridge fires was conducted on each incident to determine its suitability for machine learning. Out of the 171 bridge fires, 41 of them were not used in machine learning because the reason for the fire was not related to the traffic flow. The purpose of this study was to mainly investigate how traffic flow and volume and the types of goods transported within the transport system can impact the probability of fire occurrence as well as the intensity and the damage caused by such fires. The parameters used in the ANN model are discussed in section 3.3.1. The remaining fire incidents that were not considered in the ANN model are discussed in section 3.3.2.

Identificative Name	Area	1: rural 2: suburban 3: urban	Structural System	1: Cable supported 2: Truss/Arch 3: Box Girders 4: I Girders	Material	1: Prestressed Concrete 2: Reinforced Concrete 3: Steel	AADT
Riderwood	Suburban	2	I Girders	4	Steel	3	22000
NYS Thruway	Urban	3	I Girders	4	Steel	3	23856
Chester Creek	Urban	3	I Girders	4	Steel	3	10454
Valdese	Rural	1	I Girders	4	Steel	3	8500
Benjamin Franklin Brigde	Urban	3	Cable supported	1	Steel	3	100000
Overpass Cypress/Spring	Suburban	2	I Girders	4	Reinforced Concrete	2	58000
RI37 Expressway	urban	3	I Girders	4	Steel	3	42000
I-285 over GA400	urban	3	I Girders	4	Steel	3	250000
Denville	Suburban	2	Box Girders	3	Prestressed Concrete	1	75298
Independance Parkway	Urban	3	I Girders	4	Reinforced Concrete	2	31721
Birmingham 2002	Urban	3	I Girders	4	Steel	3	240000
Puyallup River	Suburban	2	I Girders	4	Prestressed Concrete	1	80156
Flint	Suburban	2	I Girders	4	Steel	3	15881
Elkridge	Rural	1	I Girders	4	Steel	3	73632
I-75 Big slough Canal	Suburban	2	I Girders	4	Prestressed Concrete	1	30565
Howard Avenue	Suburban	2	I Girders	4	Steel	3	120000
Mungo River bridge	Rural	1	Truss	2	Steel	3	14780
Wiehltal bridge	Rural	1	Box Girders	3	Steel	3	18700
Birmingham 2004	Urban	3	I Girders	4	Steel	3	240000
Charilaos Trikoupis Bridge	Suburban	2	Cable supported	1	Steel	3	11000
Opatovice	Rural	1	Truss	2	Steel	3	50000
Norwalk River Bridge	Rural	1	I Girders	4	Prestressed Concrete	1	19100
Bruckner Expressway	Urban	3	I Girders	4	Steel	3	55675
Queensboro Bridge Oct. 2005	Urban	3	Truss	2	Steel	3	96662
Brooklyn-Queens Expressway 06	Urban	3	I Girders	4	Steel	3	153000
Belle Isle	Suburban	2	I Girders	4	Prestressed Concrete	1	100000
Bill Williams Bridge	Rural	1	I Girders	4	Prestressed Concrete	1	25987

Figure 3-3 The bridge fire incidents dataset (Part 1)

Ignition Source	1: Car 2: Truck 3: Tanker 4: Elecrical Problem 5: Storage 6: Other	Type of Combustible (in case of tanker, truck or storage)	1: Gasoline 2: Diesel 3: Alcohol Liquids 4: Other Hydrocarbon Liquids 5:None 6: Other Solids	Position of the fire	1: On the bridge 2: Under the bridge 3: On with spill under bridge	Damage	1: Minor 2: Medium 3:Partial Damage 4: Massive Damage 5: Collapse
Tanker	3	Gasoline	1	OSU	3	Massive	4
Tanker	3	Gasoline	1	Under	2	Collapse	5
Tanker	3	Gasoline	1	OSU	3	Massive	4
Tanker	3	Gasoline	1	Under	2	Collapse	5
Cigarrete	6	None	5	on	1	Medium	2
Tanker	3	Gasoline	1	On	1	Minor	1
Tanker	3	Jet Fuel	1	Under	2	Medium	2
Tanker	3	Gasoline	1	Under	2	Massive	4
Tanker	3	Gasoline	1	OSU	3	Massive	4
Tanker	3	Gasoline	1	Under	2	Massive	4
Tanker	3	Gasoline	1	Under	2	Massive	4
Railroad Tanker	3	Methanol	3	Under	2	Partial	3
Tanker	3	Propanol	3	Under	2	Massive	4
Tanker	3	Gasoline	1	on	1	Minor	1
Tanker	3	Gasoline	1	On	1	Partial	3
Tanker	3	Fuel Oil	4	Under	2	Collapse	5
Tanker	3	Petroleum	1	On	1	Collapse	5
Tanker	3	Gasoline	1	Under	2	Massive	4
Tanker	3	Gasoline	1	Under	2	Massive	4
Thunderbolt	6	None	5	on	1	Partial	3
Carbon Fire	6	None	5	under	2	Massive	4
Tanker	3	Gasoline	1	OSU	3	Massive	4
Tanker	3	Fuel Home	4	on	1	Minor	1
Wood Scaffolding Fire	6	None	5	Under	2	Minor	1
Tanker	3	Gasoline	1	Under	2	Collapse	5
Truck	2	gasoline	1	Under	2	Minor	1
Tanker	3	Diesel	2	OSU	3	Medium	2

Figure 3-4 The bridge fire incidents dataset (Part 2)

3.3.1 The parameters considered in the database for the ANN model

3.3.1.1 Area Type

Although the exact location of bridges has been defined in the available database, the bridge fires have been grouped into three categories based on the area types the bridges are located. Rural areas include little roadways with low traffic. Suburban area includes bridges in cities and industrial zones. It refers to high-speed roadways that serve as transitions between low-speed urban streets and high-speed rural highways. The last area type is urban in which the bridges are part of the cities' highway systems. Urban roadways are characterized by low to moderate posted speeds, frequent entrances, and moderate to heavy residential or commercial development. The distribution of each case has been figured out in Figure 3-5.

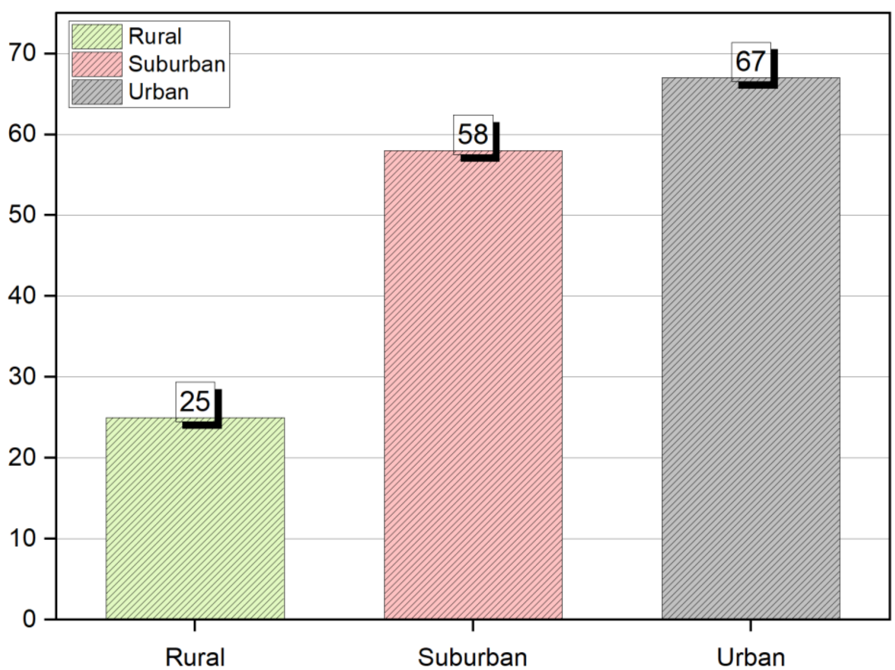


Figure 3-5 Statistics of the developed dataset (Area Type)

3.3.1.2 Structural System of the Bridge

The structural system of the bridges was initially divided into five categories: cable-stayed bridges, suspension bridges, truss or arch bridges, box girder bridges, and I girder bridges. As cables and vertical supports of the cable-stayed and suspension bridges are the key elements that would be severely affected by fires and the extreme strength of steel is the reason for their usage in the cables on bridges [37, 99], it was included both in one group as cable-supported bridges. For this reason, the structural system of bridges in this dataset has been categorized into four groups: cable-supported bridges, truss or arch bridges, box girder bridges, and I girder bridges whose distribution has been illustrated in Figure 3-6.

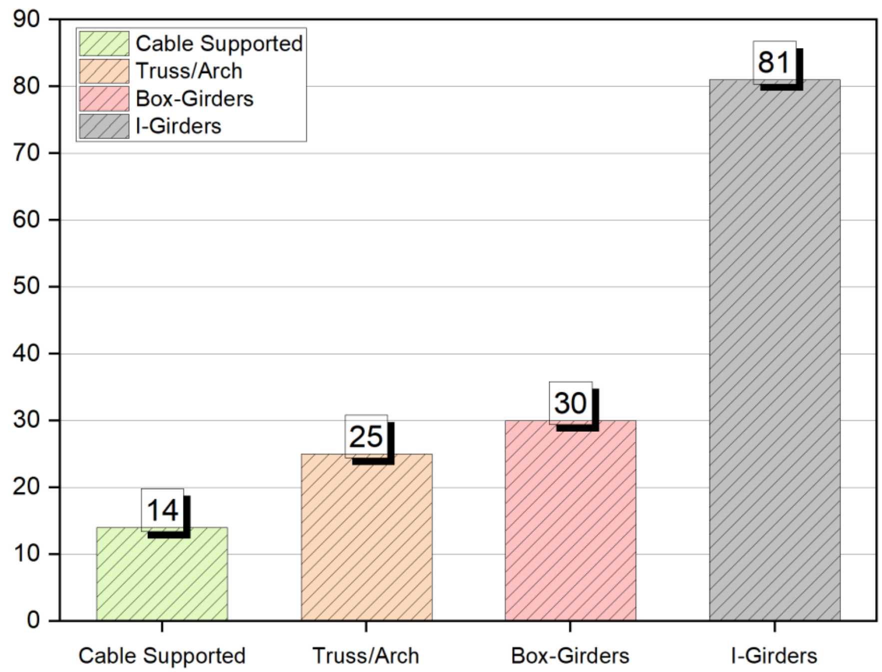


Figure 3-6 Statistics of the developed dataset (Structural System)

3.3.1.3 Material of the Bridge

Materials of the bridges in the initial database had been grouped into five classifications; prestressed concrete, reinforced concrete, steel-concrete known as a composite (which constitutive material is the combination of both steel and concrete), steel, and timber or wood. But it was reduced into three categories including prestressed concrete, reinforced concrete, and steel for two main reasons; first, the research showed that among those 171 bridge fire incidents most of the collapses occurred in timber bridges which studies show that they are more vulnerable to fire than the other materials because of the timber's combustibility. Since the selection of precise input data for the neural network training will result in getting a better and more accurate output, timber bridges were removed from the database, so that the network can predict the probability of collapse in other types of bridges and the damage severity of other types with a good correlation factor. Furthermore, based on recent research, in bridge fire incidents, as the girders are mostly responsible for supporting the bridge concrete slab deck and are more susceptible to damage, only the material of the girders is investigated in the database which is classified into three groups consisting prestressed concrete, reinforced concrete, and steel that their distribution has been shown in Figure 3-7. Therefore, composite material as a representative of slabs material was removed from the dataset. In addition, when it comes to construction materials, it is important to note that although these three materials can meet technical requirements in normal circumstances, they may have limitations in fire situations. Steel structural members, for example, are susceptible to fire hazards due to the material's poor thermal behavior. While reinforced or prestressed concrete bridges may be less vulnerable, specifically the ones that contain specific reinforcements (steel and/or polypropylene fibers) to prevent spalling phenomena due to the elevated temperatures [100].

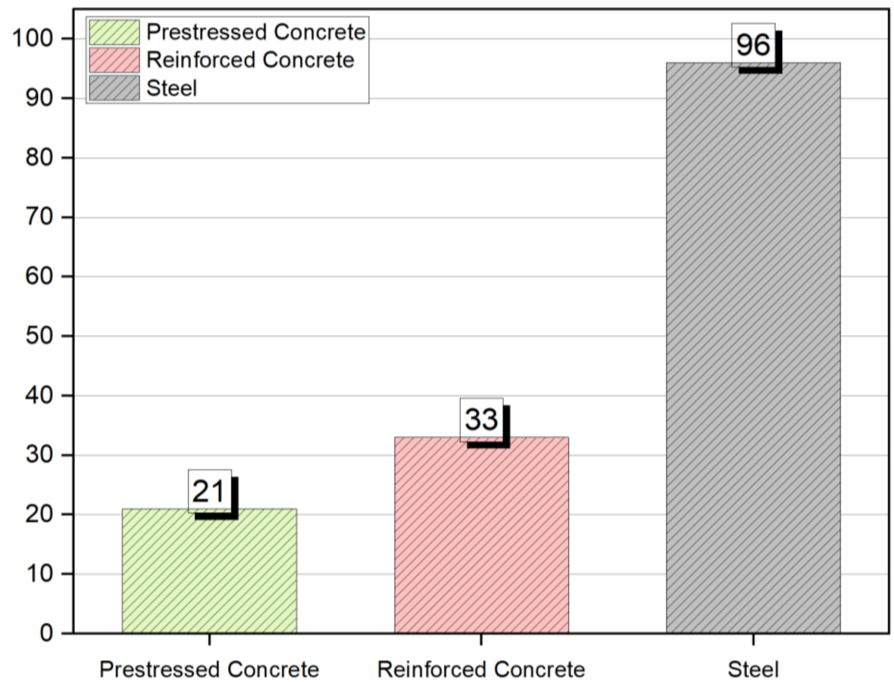


Figure 3-7 Statistics of the developed dataset (Material)

3.3.1.4 Annual Average Daily Traffic of the Bridge (AADT)

In this study, the average daily traffic of the bridges has been collected annually based on relevant sites. This critical parameter has the main role in the classification of bridges. As in the area type groups identifying the bridges in exact three categories rural, suburban, and urban is not gained easily, because of the area's varieties, regarding this factor the bridges can be divided into three classes low, medium, and high densely populated groups. So, the annual average daily traffic of bridges has been divided into five intervals with 60,000 growths as shown in Figure 3-8.

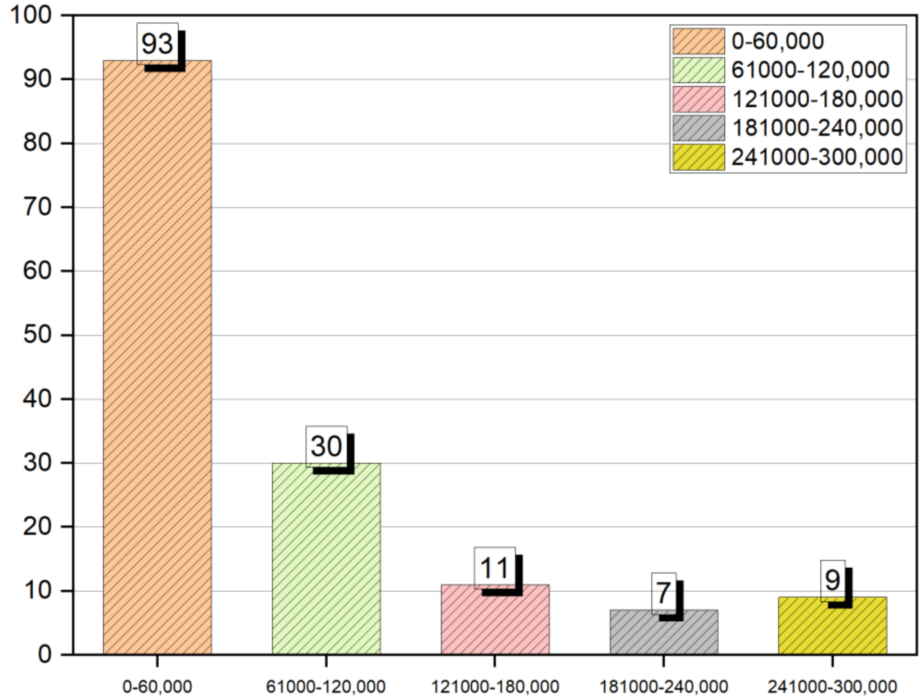


Figure 3-8 Statistics of the developed dataset (AADT)

3.3.1.5 Fire Ignition Source

Identifying whether the fire originates from which source, it has been categorized into six sources which their distribution in the database has shown in Figure 3-9.

- Cars: when a flaming car starts a fire, the fire is fueled by both the car's pieces and the fuel, which is almost often gasoline or diesel.
- Trucks: when a truck transporting non-highly flammable fuels caused a fire. Only the truck bursts into flames in some cases, whereas both the vehicle and the cargo catch fire in others.
- Tankers: this includes tanker trucks and trains transporting very hazardous liquids fuels.

- Electrical problems: electrical systems are frequently transported along bridges, increasing the danger of faulty wiring and subsequent fires in the bridge or its vicinity.
- Storage: the region beneath a bridge is frequently used as a storage area, and the objects stored there might cause a fire and destroy the bridge's structure.
- Arson/wildfires: bridges damaged in forest fires or intentionally set blazing by arsonists.
- Others: these are fires that do not fit into any of the groups, including scaffolding fires or flames with an unclear source. However for simplifying the dataset wildfires and arson also were put in this category [65].

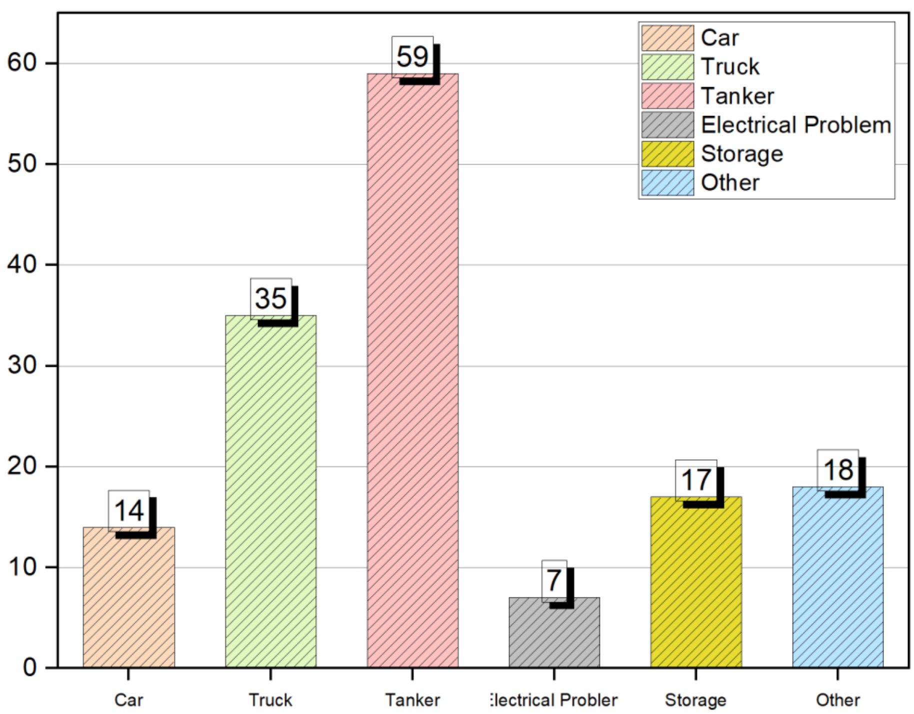


Figure 3-9 Statistics of the developed dataset (Ignition Source)

3.3.1.6 Combustible Type

In the case of fire caused by cars, trucks, and tankers the type of fuels is classified into eight groups containing gasoline, diesel, alcohol liquids, other hydrocarbon liquids, other solids, and none of them indicating unknown combustible types as illustrated in Figure 3-10. Also, in comparison with the initial dataset, two categories including tires and plastics have been added to the other solids groups.

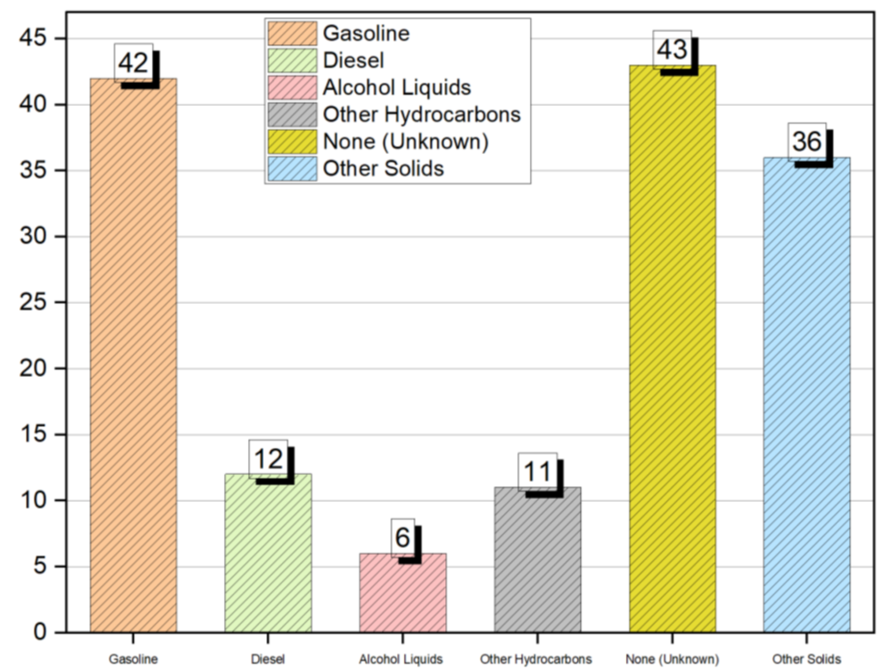


Figure 3-10 Statistics of the developed dataset (Combustible Type)

3.3.1.7 Fire Position

The position of the fire in these bridge fire incidents has been determined in three groups; on the bridge, under the bridge, and on the bridge when a spillage occurs due to fuel spill of the vehicles carrying highly flammable fuels. However, in the initial dataset, the nearness position of the bridge when a fire occurs adjacent to the piers or columns of the bridges also had been considered which was removed from the modified database, since the direct impact of fires on or under the bridges are to be investigated. Their distribution has been illustrated in Figure 3-11.

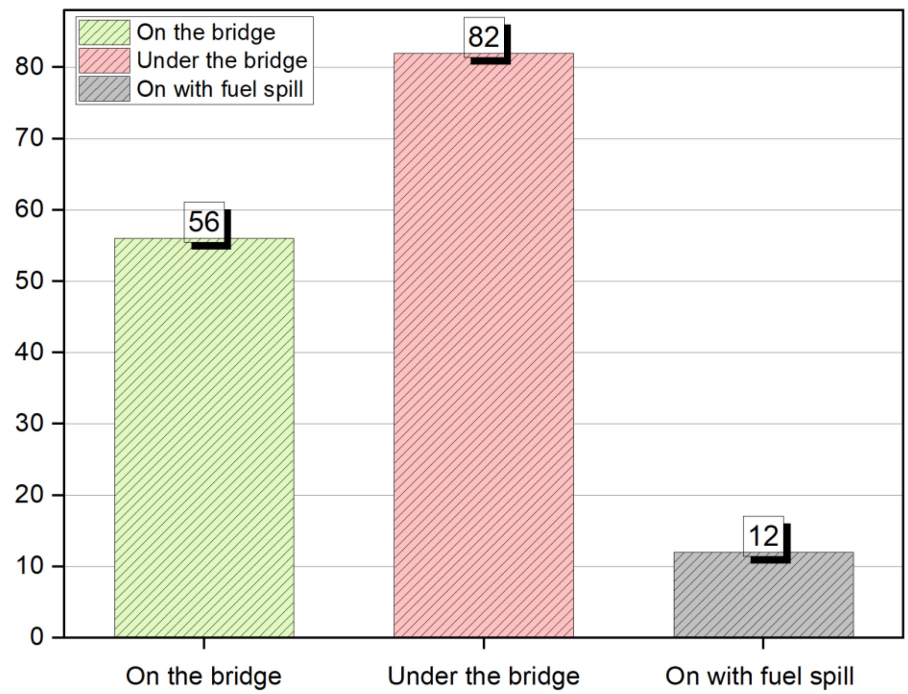


Figure 3-11 Statistics of the developed dataset (Fire Position)

3.3.1.8 Damage Level (DL)

The level of damage in the bridge fire incidents has been defined into five categories which highlight the incremental damage intensity of the fire-induced bridges respectively: minor, medium, partial damage, massive damage, and collapse from the lowest (Damage Level 1) to the highest (Damage Level 5) [101].

Damage Level 1 (Minor): Superficial Damage

Damage to the deck surface, lower deck, or equipment is minimal, with no structural damage.

Damage Level 2 (Medium): Slight Damage

Bridge structural damage that can be repaired without having to replace the main structural parts. For instance:

1. Concrete spalling without affecting reinforcement bars.
2. Concrete blackening or reddening.
3. Slight damage to major beams that do not require replacement.

Damage Level 3: Partial Damage

This category includes damage that necessitates the replacement of major structural components, such as exposed and damaged concrete reinforcement.

Damage Level 4: Massive Damage

The bridge is severely damaged, yet it does not collapse. However, due to concerns about its remaining strength and the possibility of maintenance, it is dismantled and replaced with a new construction. For instance:

1. Large portions of steel constructions that are irreversibly buckled or distorted.
2. Massive spalling with exposed and irreparable reinforcing in concrete buildings.

Damage Level 5: Structural Collapse

Total or partial bridge collapse.

Figure 3-12 shows some examples that illustrate these bridge damage levels.

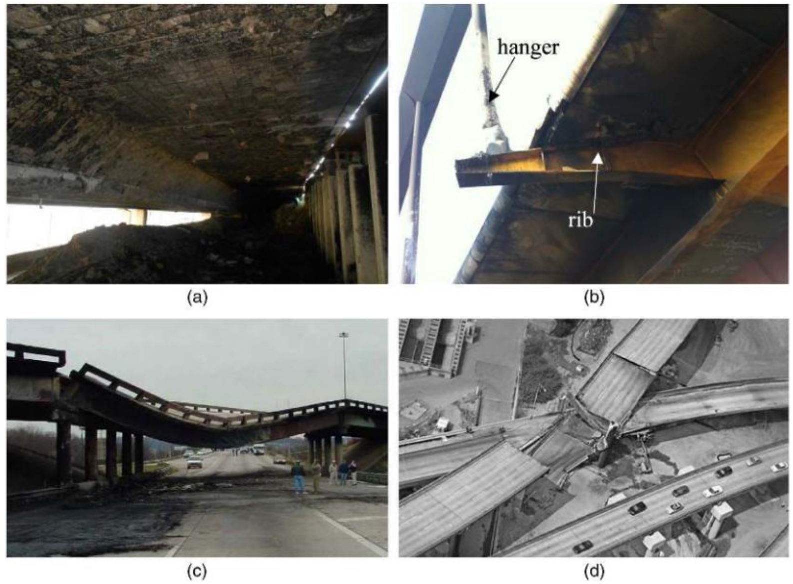


Figure 3-12 Some examples of bridge damage levels: (a) damage level 2: concrete spalling after a fire in a prestressed concrete bridge in Madrid, Spain; (b) damage level 3: damage to the hanger and rib of a bowstring bridge in Spain; (c) damage level 4: I-20/I-59/I-65 interchange in Birmingham, Alabama, U.S.; (d) damage level 5: collapse of a portion of the MacArthur Maze in Oakland, California, U.S. (Photo from [101])

In the case of minor damage, the bridge does not demand shutdown while when considerable damage or collapse occurs it needs shutdown, and detouring near routs will be inevitable as an alternative solution. The distribution of them has been shown in Figure 3-13.

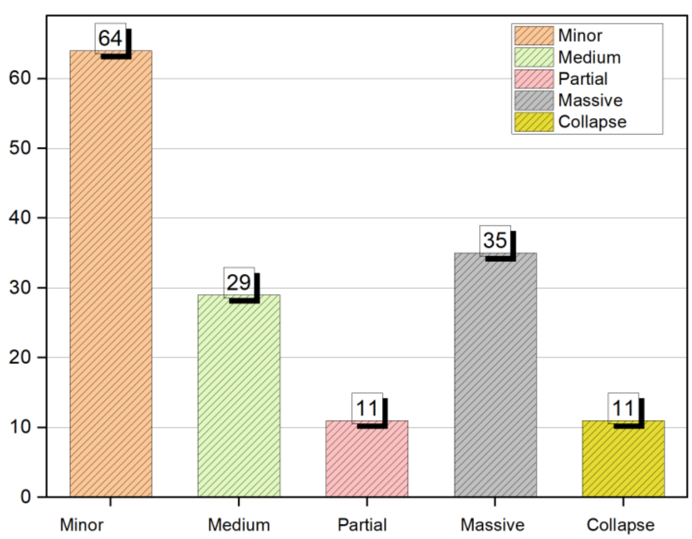


Figure 3-13 Statistics of the developed dataset (Damage Level)

3.3.2 Influencing parameters on the bridge fires (second part of the database)

Since the number of data points in the second part of the database is insufficient to operate a network, the database is presented as graphs. The graphs are used to evaluate the probability of fire incidents on various bridges caused by alternative ignition sources other than vehicle accidents. The ignition sources that are gathered in the second database are limited to electrical problems, storage under the bridges, and other sources including wildfires, arson, scaffolding fires, or fires with an unknown source. As a result, the investigated parameters, in this case, are the area types (i.e., rural, suburban, and urban regions), structural systems (i.e., cable bridges, truss/arch bridges, box girder bridges, and I girder bridges), materials (i.e., reinforced concrete (RC), prestressed concrete (PC), and steel (ST)), and fire positions which include on or under the bridges.

3.3.2.1 The possibility of bridge fire incidents in different area types

The data points may be reorganized as depicted in Figure 3-14 by considering the area types where the incidents happened. Electrical problems over the bridges are caused by short circuits in electrical equipment, storage under the bridges that are typically used by governmental offices to store some flammable or inflammable fuels or are used for storing some other materials under the bridges, and others such as wildfires, arson, scaffolding fires, and fires with unknown reasons were the ignition sources for investigated incidents. According to the collected database from various bridge fire accidents, the chance of bridge fire events in rural areas is the lowest compared to suburban and urban areas. This may be due to the rural area's nature which is attributed to small roadways with low traffic flow, generally located away from cities, having a simple configuration of bridges without any additional equipment such as electrical ones. Moreover, the other reason can be the absence of storage under the bridge in this type of area as generally, rural bridges have lower lanes and traffic. As a result, fire accidents are less likely to occur on bridges in this area. Moving toward suburban areas which included highways in cities or industrial estate entrances, the probability of fire events increases, with most of them being minor.

Figure 3-14 also demonstrates that bridges in urban areas with highways in densely populated areas have a higher risk of major damage than bridges in other areas. In other words, the number of fire incidents with various damage levels ranging from minor to medium, massive, and eventually bridge collapse is higher in urban regions than in rural and suburban areas.

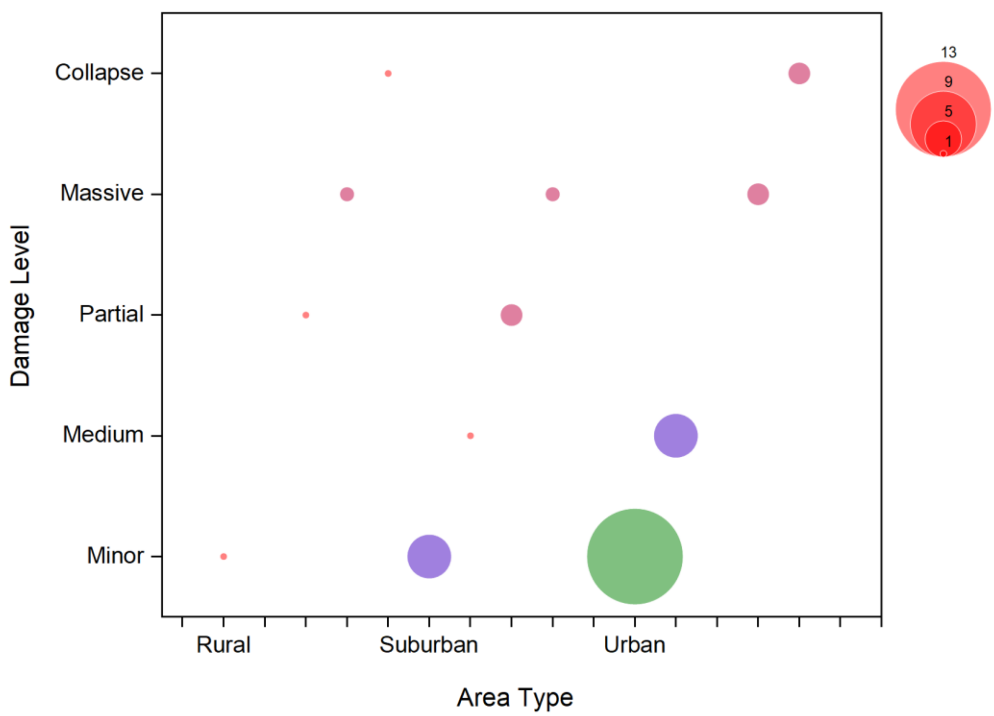


Figure 3-14 The possibility of the bridge fire incidents based on area types

3.3.2.2 The variation of bridge fire incidents based on the structural system

The number of bridge fire events involving four structural systems, particularly regarding cable-supported bridges, truss/arch bridges, box girder bridges, and I girder bridges, is shown in Figure 3-15. As may be observed, the severity of damage in cable-supported bridges is frequently minor. The probable reason is that the most susceptible parts of such bridges are the steel cables, and in most incidents owing to the prompt reaction of firefighters, the cables are not exposed to the fire due to low flame height, therefore they do not sustain significant damage. Flame height will be an issue in these bridges during fire conditions, rather than vertical clearance which is considered in other types of bridge structures. While, the structural parts of truss/arch bridges will be exposed to fire and high temperatures, even though the severity of the damage is minor. Minor and massive damages are more dominant in box girder bridges. Finally, due to their web slenderness, which causes buckling of the web, the chance of collapse in I girder bridges is higher than in other structural systems, resulting in significant damage intensity.

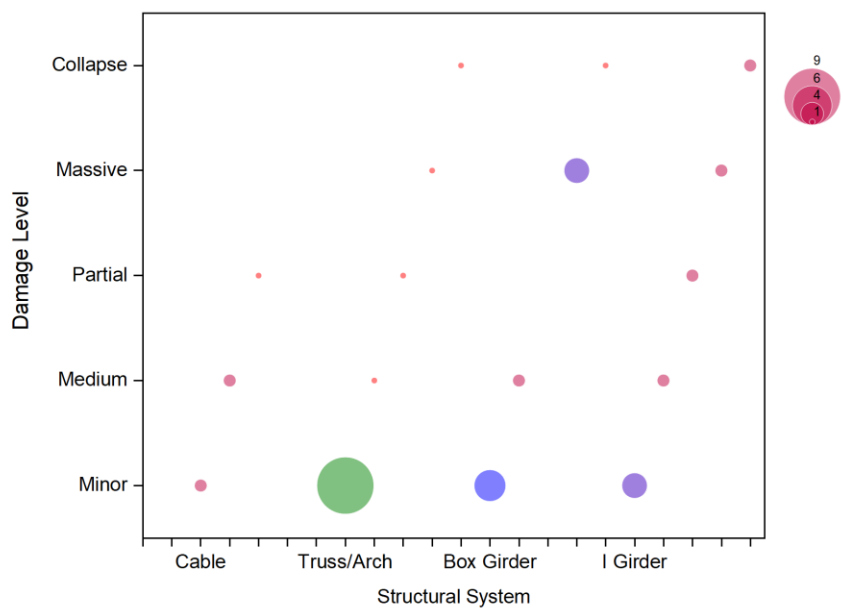


Figure 3-15 The possibility of bridge fire incidents with different structural systems

3.3.2.3 The variety of bridge fire incidents based on materials

The number of bridge fire accidents with different bridge materials including reinforced concrete (RC), prestressed concrete (PC), and steel (ST) is shown in **Figure 3-16**. As can be seen, the damage levels in reinforced concrete vary from minor to massive, which may result in spalling of the concrete at high elevated temperatures. The damage levels in prestressed concrete will be lower than in the prior one. According to the database, steel is the most vulnerable material in fires, with damage levels ranging from minor to collapse. This is due to steel's poor thermal behavior when compared to reinforced concrete and prestressed concrete.

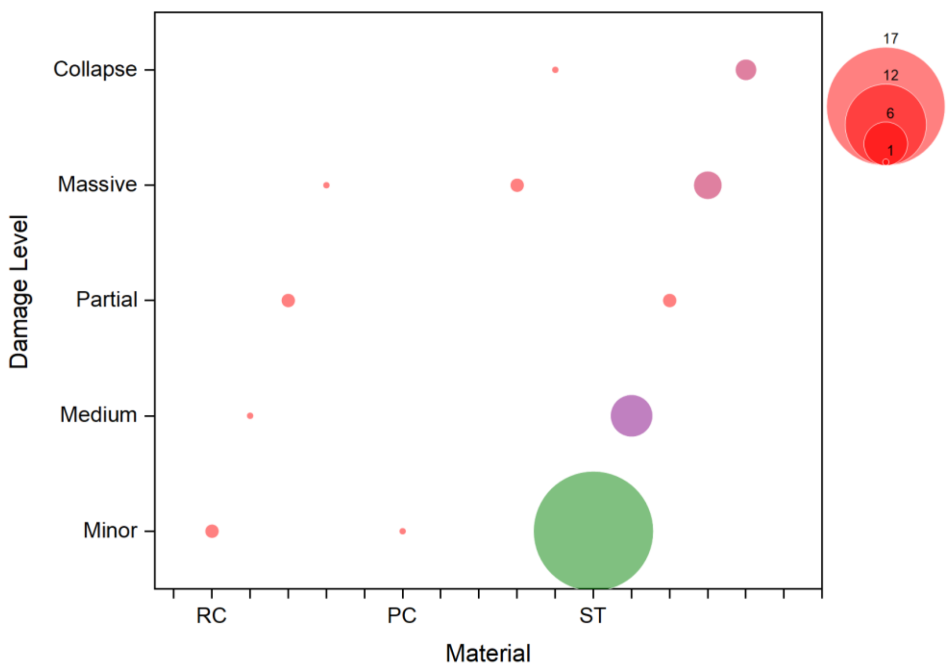


Figure 3-16 The possibility of bridge fire incidents based on the materials

3.3.2.4 The variety of bridge fire incidents based on the fire positions

Figure 3-17 shows the number of bridge fire incidents when the fire occurs on the bridges or under the bridges. In the case of a fire under a bridge, the likelihood of minor, medium, partial, massive, or collapse damages is greater than in the case of a fire on a bridge. The reason for this is that when a fire occurs on a bridge, the concrete layer of the bridge slab deck acts as an insulation layer, dissipating heat and high temperatures, whereas when a fire occurs under a bridge, the girders are directly exposed to fire and experience elevated temperatures, resulting in significant damage. Also, this might be due to the storage tank's position or other forms of fires, such as arson and/or wildfires that start from under a bridge. As a result, in fire incidents, the expected accident is fire under the bridges that the need for resolving is completely felt.

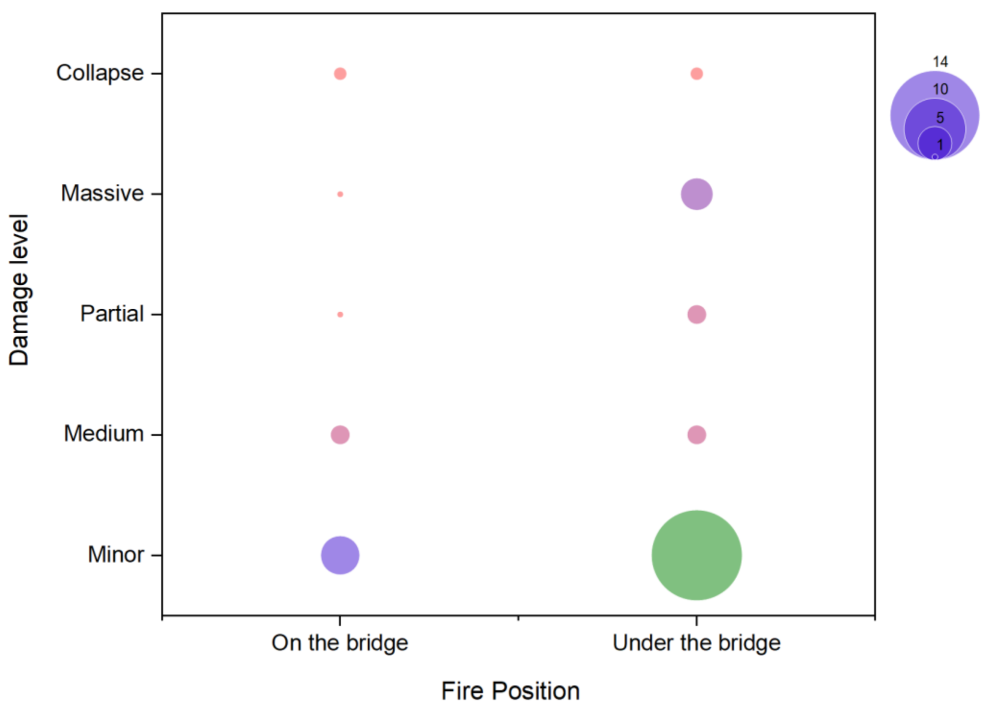


Figure 3-17 The possibility of bridge fire incidents based on the fire positions

Following the verification of the second part of the database, the first part's data will be assessed by the neural network to explore the effect of seven parameters on bridge fires based on neural network predictions.

3.4 Developed Neural Network

The data used in this research is in a wide range of variations, and the use of these data can affect the accuracy of optimized network weights. Therefore, the data were linearly normalized, i.e., min-max normalization, in the range of [0 - 1] before use. Because the min-max generalization is a linear transformation, it can accurately retain all data value relations [102]. Weights were chosen at random and centered in the range [-0.77 – +0.77]. This weight initiation strategy has been experimentally proven to improve the ANN's performance and training time [103]. A poor weight initialization can cause divergence of outputs or stuck at the local minimum points [90]. So, after identifying the input and output parameters of the neural network, it is time to change the qualitative parameters into quantitative ones to introduce an intelligible dataset to the network. Based on the numbers of data in each category, a code has been dedicated to them with zero and one. For example, when the bridge zone area which is defined by three parts, rural, suburban, and urban is to be introduced to the network, three codes have been allocated including 000 for the rural areas, 001 for the suburban, and 010 for the urban areas.

- For the bridge structural system, 000 to the cable-supported bridges, 001 to the truss/arch bridges, 010 to the box girder bridges, and 011 to the I girder bridges have been devoted.

- In the bridge material part, 000 to the prestressed concrete, 001 to the reinforced concrete, and 010 to the steel material have been dedicated.
- Ignition sources have been allocated by the following codes, 000 to the cars, 001 to the trucks, 010 to the tankers, 011 to the electrical problems, 100 to the storage, and 101 to the others.
- Combustible fuels are coded by 000 for gasoline, 001 for diesel, 010 for alcohol liquids, 011 for other hydrocarbon liquids, 100 for none, and 101 for others.
- Fire position has been coded by 000 for on the bridges, 001 for under the bridges, and 010 for on the bridges when fuel spill occurs and flows under the bridges.
- Changing the AADT into apprehensible data for the neural network, they have been divided into five groups in which an interval between 0-60000 defines as the first group by dedicating a code of 000, range between 61000-120000 as the second group with a code of 001, 121000-180000 as the third group by coding 010, 181000-240000 as the fourth group by coding 011, and 241000-300000 as the fifth group by code 100.

3.5 Modeling the network

The practice of portraying a real-world phenomenon or object as a sequence of mathematical formulas is known as modeling [104]. It is critical to find the network's optimal design, which delivers both a well-set and strong reliability simultaneously [105]. Because of its acceptable resolution, good accuracy, and short training time, the Levenberg-Marquardt (LM) method was utilized to train the network [106, 107].

3.5.1 Number of Neurons

The learning process is completed when the network achieves the target performance. The number of ideal neurons needed at each layer, on the other hand, is unknown and is normally found through trial and error [90]. This challenge was solved using a constructive approach. This approach locates the smallest net capable of providing the needed performance and is ideal for transmitting local answers (or local minima), but it is time-consuming [108]. The appropriate number of neurons has been determined through empirical investigation [109]. The proper design was selected as the suggested ANN model after evaluating multiple architectures with varied numbers of neurons in each layer [75].

3.5.2 Network Performance

After determining the optimal network, the network is able to define complex relationships between input parameters as well as the ability to generate new outputs. When there is no information available, generalization entails assuming the value on the hypersurface, which necessitates approximation. Learning is a nonlinear curve-fitting procedure in mathematics, whereas generalization is the interpolation and extrapolation of the input information [90]. The variety of variables in the issue, the difficulty of the factors, and the network topology all influence the network's capacity to produce new outputs. The number of neurons collected in the previous stage was used to build the neural network (Figure 3-18).

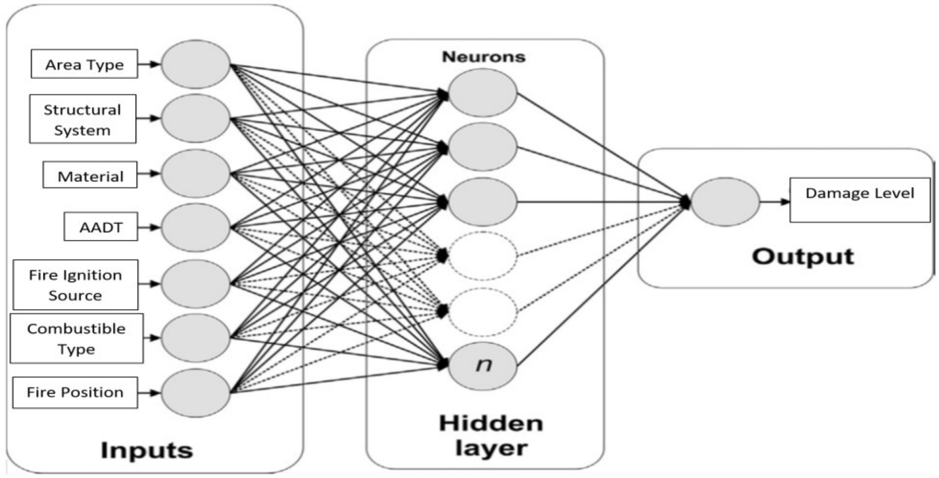


Figure 3-18 Proposed ANN model (Photo from [90])

Nonlinear least squares problems are solved using the Levenberg–Marquardt (LM) Algorithm. The gradient descent and the Gauss-Newton methods are combined in this curve-fitting method. The steepest descent method is a generic minimization technique that updates parameter values in the "downhill" direction, that is, in the opposite direction of the objective function's gradient. For problems with simple objective functions, the gradient descent approach converges efficiently. The Gauss-Newton technique is a sum-of-squares objective function minimization approach. In the parameters around the optimal solution, it is assumed that the objective function is approximately quadratic. The Gauss-Newton approach converges substantially quicker than gradient-descent methods for moderately sized problems [110].

Within the network training operation, the gradient descent strategy is an excellent way for detecting the least sets of errors more quickly. As the name indicates, gradient descent employs the error gradient to descend the error [111]. The error is correlated to the network's output and is dependent on the hidden neurons' weighted output and weights. The chain rule of differentiation can therefore be extended from error to the first layer's weight. Backpropagation as a gradient descent technique, is a method that was initially proposed by Werbos [111] and afterwards by Rumelhart [112]. The network weights move in the opposite direction to the performance function slope in backpropagation.

The Levenberg-Marquardt (LM) method divides data into three sections by default: 70 percent for training, 15 percent for validation, and 15 percent for testing. The hidden layer's activation function is TANSIG, which creates data values between [-1, +1]. The output layer's activation function is PURELIN, which is a linear transfer function that maintains the input constant. Equations (3) and (4) represent the TANSIG and PURELIN functions, respectively [75].

$$\boldsymbol{y = tansig\ (x) = \frac{2}{(1+e^{-2x})} - 1} \qquad \textbf{Eq. 3}$$

$$\boldsymbol{y = purlin\ (x) = x} \qquad \textbf{Eq. 4}$$

The network optimization is done by adjusting the weights within every layer, which would be the basic goal of the network training. The network performance is shown in Figure 3-19 with a mean squared error of 3.0375, the best validation performance was obtained at the 23rd epoch. The physical meaning of MSE is to demonstrate the difference between the outcome and target for a single observation. For example, in the current model, the MSE of 3 indicates that the average squared difference between prediction and real outcomes is 3 unit, i.e., when the real fire incident is 3, the network predict $\pm\sqrt{3}$ times of results. It is worth noting that the MSE of 3 is related to the validation data which cover 15% of the dataset. The proposed network predict the fire-induced damages for training dataset with a reasonable accuracy. The MSE value of training and test data were 0.0574 and 1.3884, respectively. "Validation dataset" is commonly utilized to describe model assessment during tuning hyperparameters and data preparation, whereas "test dataset" is commonly used to describe model evaluation when comparing it to other final tuned models. To put it another way, validation data aids model performance by fine-tuning the model's weight after each epoch through a trial and error procedure. Following the training phase, the test set indicates of the model's ultimate accuracy. In Figure 3-19, the slight increase in error can be ignored since it is in a very low order.

The R-value for the network is 0.92158 illustrated in Figure 3-20. The estimate of the network reveals the network's correct performance. As a consequence, the suggested network learns the relationship between input and output variables and offers accurate results.

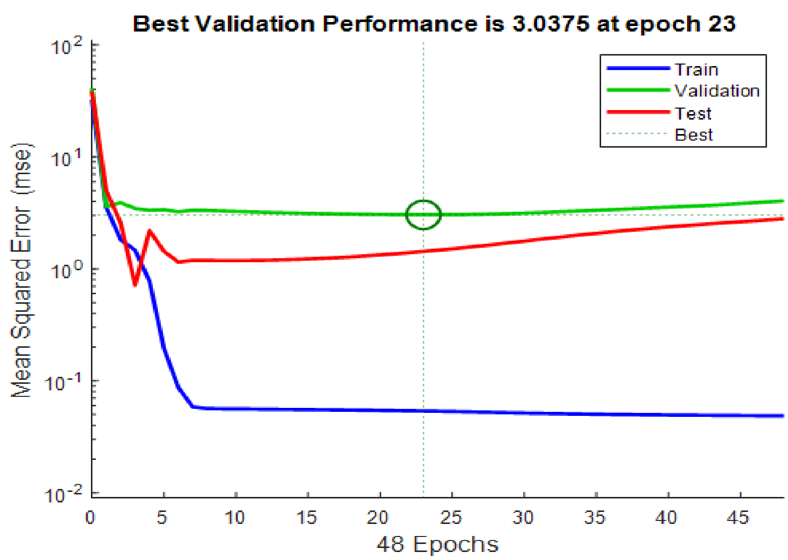


Figure 3-19 Performance function of the proposed network

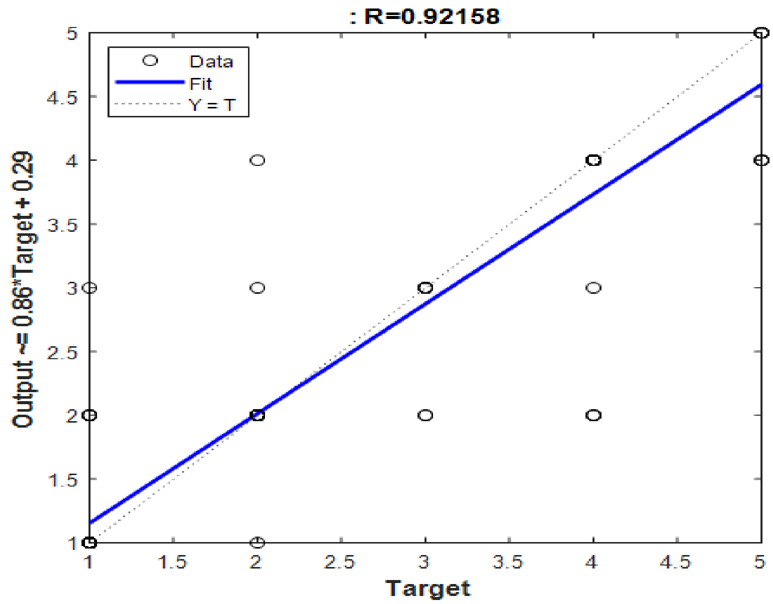


Figure 3-20 Regression values of the proposed ANN

3.5.3 Stability analysis

The comparison of the network's output and the target of the dataset is plotted in Figure 3-21. As can be seen, the proposed network can predict the severity of the accident with reasonable accuracy. Figure 3-22 depicts the predicted-to-real result ratio versus the influencing parameters, which represent the stability in predicting the network.

The numbers in the horizontal axis show the range of each parameter depending on the considered items in each one. For example, for AADT, since they are normalized between 0 and 1, datapoints placed between 0 and 1 in the horizontal axis.

Structural systems are between 1 to 4 as they consist of four kinds (i.e., cable-supported bridges, truss/arch bridges, box-girder bridges, I-girder bridges). Area type (i.e., rural, suburban, urban), material (i.e., prestressed concrete, reinforced concrete, steel), ignition source (i.e., cars, trucks, tankers), and fire position (i.e., on the bridge, under the bridge, on the bridge with fuel spill) are between 1 to 3, and combustible type (i.e., gasoline, diesel, alcohol liquids, other hydrocarbon liquids, none, others) is between 1 to 6. The affecting parameters, which were normalized in the [0, 1] domain due to their large variation were described in section 3.4. The variation of data around the horizontal line beginning with a ratio of 1 illustrates the stability of parameters. The closer the data is to this line, the more stable the parameters are. According to Figure 3-22, the values of AADT have less stability compared to other input parameters. More stable parameters among the inputs are the type of combustible since it is much closer to the horizontal line starting from 1. It should be mentioned that as the input parameters were quantified and normalized between 0 and 1, many of the data points were duplicated and had the same spot in the graph. However, the network could predict the results with acceptable accuracy. The proposed network can predict the intensity of damages based on several factors.

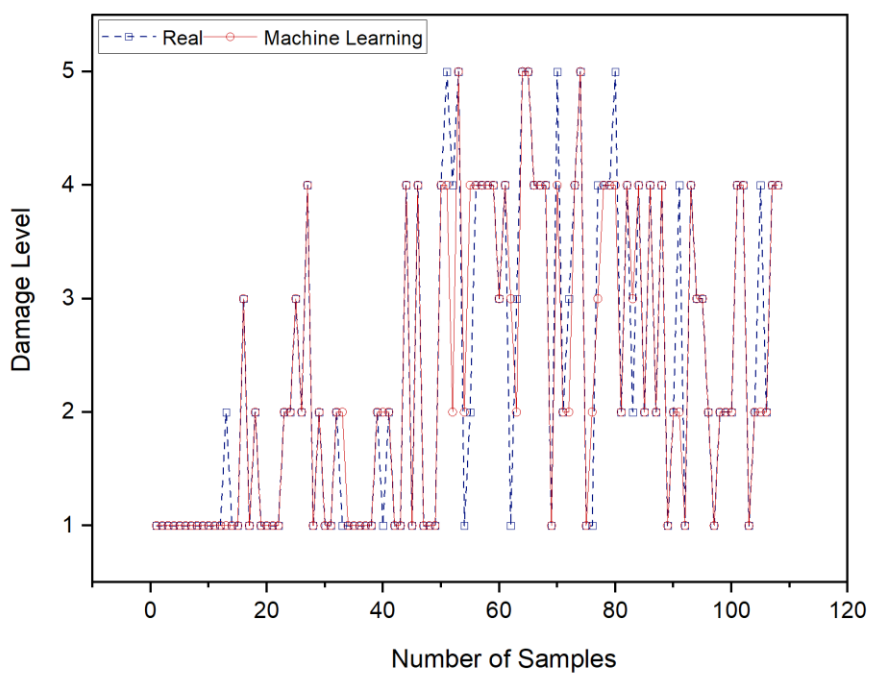


Figure 3-21 The comparison of the network output and the target of the dataset

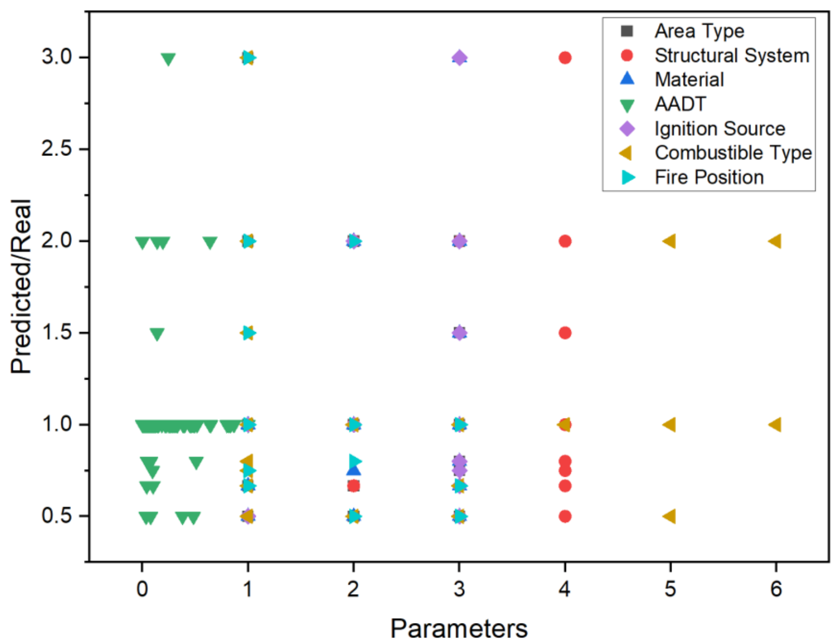


Figure 3-22 Stability of network prediction for input parameters

3.5.4 Generalization of the eight parameters based on the neural network result

The second portion of the problem may be tackled by utilizing data generalization by ensuring proper network estimates. Figure 3-23 demonstrates the correlation matrix of all data for the damage severity. The distribution of the individual parameters is depicted by the diagonal histograms. The off-diagonal scatter plots show how individual parameters relate to one another. As can be observed, the structural system, material, ignition source, and fire position are all positively correlated with damage severity. It indicates that moving toward the I girder bridges, steel, tankers, and under fires, the damage level will be increased from minor to collapse of the bridges. Furthermore, material and structural systems are also negatively correlated, while AADT and area are positively correlated. Moreover, the ignition source has a negative correlation with the combustible type as well as the fire position. In addition, damage severity is negatively correlated with combustible type. The red line are not best fit, they show the trend of the data. The limitation of the model consist the restriction in estimating specific kind of bridges. In other words, the model can not predict the damage level for any other bridges than cable-supported, truss/arch, I girder, and box girder bridges. Moreover, the proposed model is able to predict the results of fire-induced damages for bridges made with reinforced concrete, prestressed concrete, or steel.

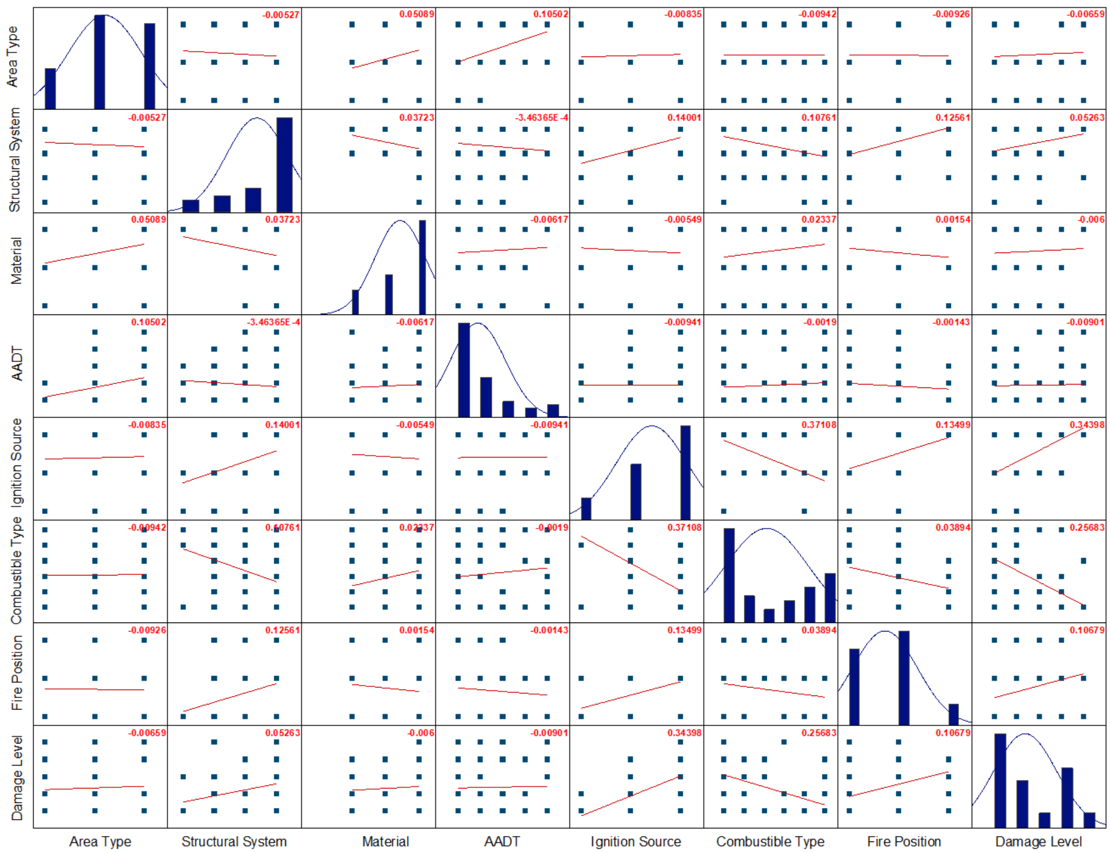


Figure 3-23 Histograms and correlation scatter plots of data

3.5.5 Sensitivity Analysis

Garson's factor is being utilized to examine the influence of parameters supplied as network input. The following equation is for a network having a hidden layer:

$$\mathbf{Q_{ik}} = \frac{\sum_{j=1}^{L}\left(\frac{w_{ij}}{\sum_{r=1}^{N} w_{rj}}\vartheta_{jk}\right)}{\sum_{i=1}^{N}\left(\sum_{j=1}^{L}\frac{w_{ij}}{\sum_{r=1}^{N} w_{rj}}\vartheta_{jk}\right)} \qquad \textbf{Eq. 5}$$

Where $\sum_{r=1}^{N} w_{rj}$ is the sum of the connection weights between the N input neurons and the hidden neuron j, and ϑ_{jk} is connection weight between the hidden neuron j and the output neuron k [112, 113]. The result of the sensitivity analysis is plotted in Figure 3-24. As can be seen, almost all the parameters had a similar influence on the resulted damage severity. Besides, as no parameter had relatively low effectiveness, it can be concluded that no irrelevant or extra parameters have been chosen. Since all the parameters have the same influence on the results, it can be said that the change in the amount of each parameter does not make any significant variation in results.

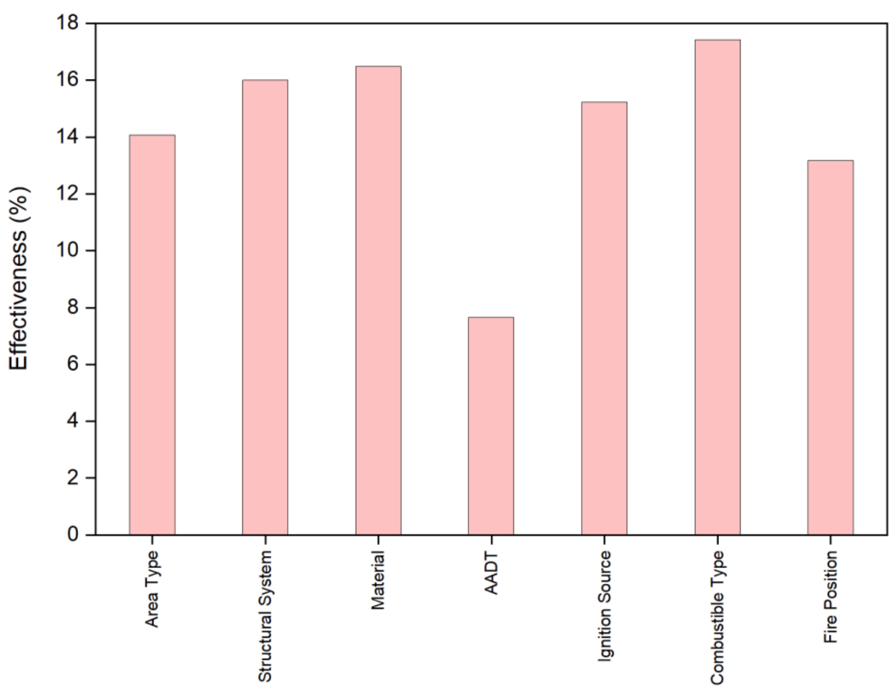


Figure 3-24 Relative importance of the input parameters in the proposed model

Chapter 4: Implementation of the ANN model in bridge fires

With the neural network model presented and verified in chapter 3, the current chapter aims to benefit from the verified model to investigate fire incidents that have not been in the database. The main objective of developing the ANN model was to look at unseen possible incidents in real-world applications. Thus, 9200 bridge fires were created and the damage level was calculated for each incident using the ANN model. The impacts of each parameter on the damage level were investigated by generating bar charts where the respective parameter was studied. There were seven parameters in the model, and in each plot, several parameters were presented altogether with a focus on one parameter.

Other than the damage levels which are the results from the ANN model, two new indices were generated using the damage levels. These indices are called Average Weighted Damage Index (AWDI) and Major Damage Index (MDI).

4.1 Average Weighted Damage Index (AWDI) and Major Damage Index (MDI)

To better study the bridge fires using the ANN model, the average weighted damage index (AWDI) and major damage index (MDI) were calculated. Five damage levels (DL) ranging from 1 to 5 have been introduced, which progressively define the damage intensity. It indicates that the factor for minor damage is 1 and the factor for bridge collapse is 5. The numbers of each case (n) with the relevant damage levels (DL) will then be defined in each group of the selected data. The Average Weighted Damage Index (AWDI) is calculated as follows:

$$\boldsymbol{AWDI = \frac{\sum_{DL=1}^{5}(DL \times n)}{\sum n}} \qquad \textbf{Eq. 6}$$

Also, a Major Damage Index (MDI) is used to predict the most severe damage levels (DL) in bridge fires. The summation of cases in damage levels 4 and 5, which reflect massive damage and bridge collapse in a fire, is specified. The major damage index (MDI) will then be obtained as follows:

$$\boldsymbol{MDI} = \frac{\sum(n4+n5)}{\sum n} \times 100 \qquad \textbf{Eq. } 7$$

4.2 The effect of area type, structural system, and material on bridge fires

The following graphs analyze the impact of seven researched parameters on bridge fires depending on the severity of the damage: area type, structural system, material, AADT, ignition source, combustible type, and fire position.

Figure 4-1 shows the average weighted damage indices (AWDI) investigating the effects of three parameters; these parameters are area types (i.e., rural, suburban, and urban areas), structural configurations (i.e., cable bridges, truss/arch bridges, box girder and I girder bridges), and the main construction material of the bridges (i.e., reinforced concrete (RC), prestressed concrete (PC), and steel (ST)) on bridge fires. Regarding the area types, the AWDI of bridge fires in rural and suburban areas is higher than in urban areas. The reason is the accessibility of the bridges to fire departments and receiving a quick response of firefighters shortly after the fire. As the urban areas are attributed to the bridges in the cities' highway systems, so the proximity of the bridge fires to fire stations is easily facilitated. Also, travel speeds within the urban areas are lower than in rural and suburban areas which results in fewer and minor accidents. It is worth noting that (AWDI) in suburban areas is higher than in rural areas. As suburban areas are represented by the bridges in the industrial accessibilities or on the outskirts of cities wherein the traffic volume is higher than in rural areas which leads to more possibility of accidents and fire incidents. Furthermore, they are closer to fire departments than rural regions, which means that fires may be extinguished quickly once they occur.

Figure 4-1 shows that the (AWDI) is the highest in I-girder bridges. The reason is that in all structural systems, top flanges will have a lower temperature rise than bottom flanges because the concrete slab acts as an insulation layer and distributes top flange heat to the deck. The temperature variations between the slab and the bottom flange cause considerable thermal gradients throughout the girder-slab cross-section. Also, the lower thickness of the web and its slenderness in contrast to the bottom flanges produces a rapid rise in web temperatures [1]. As a result, I girder bridges are more susceptible to fire than other structural configurations.

In addition, Figure 4-1 illustrates that for all structural systems, the AWDI is the highest in bridges with steel (ST) as the main structural element followed by prestressed concrete (PC) and then reinforced concrete (RC). This is owing to the lack of fireproofing on steel girders and the high thermal conductivity of steel, which results in a quick rise in steel temperature during a fire. Steel structural members experience much faster degradation in strength than concrete members [1]. Also, an increase in temperatures and stresses in steel increases creep deformations, which results in a rapid rise in girder deflections [1, 114].

In prestressed concrete, the prestressing strands have a low fire resistance because prestressing strands with high tension stress are susceptible to fracture at high temperatures [41, 115]. Concrete elements experience spalling at elevated temperatures. Spalling from fire reduces the cross-sectional area of the concrete components, enabling more heat to flow through the reinforcement bars and thereby exacerbating the premature collapse of the bridges [116, 117].

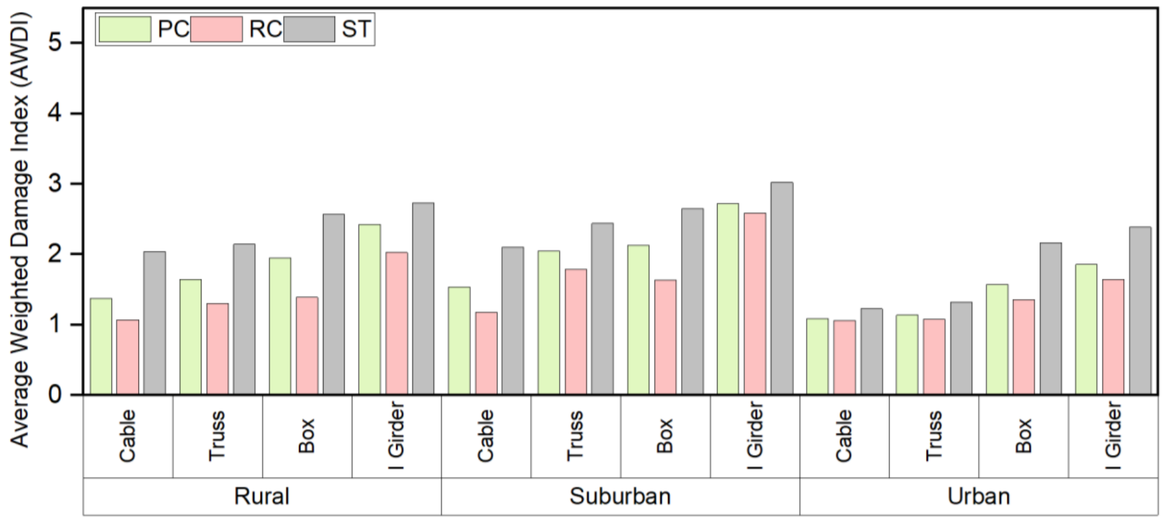


Figure 4-1 The Average Weighted Damage Index (AWDI) of area types, structural systems, and materials in bridge fire incidents

Figure 4-2 shows the major damage index (MDI) described in section 4.1. The MDI considers the significant damage levels including massive damage and bridge collapse (i.e., damage levels of 4 and 5). The graph represents the probability of bridge fires with damage levels of 4 or 5. According to the graph, the MDI of steel I girder bridges in rural, suburban, and urban areas are around 30%, 40%, and 21%, respectively. This indicates that steel I girder bridges are more vulnerable in suburban areas with the greatest damage level (DL), as also found in Figure 4-1. In addition, generally the MDI of the cable-supported bridges, regardless of the constituent material, is relatively low indicating the suitable structural system to sustain under severe thermal loading in the case of fire under bridges where the cables are not close to the fire. The integrity of cables and pylons can be impressed by the height of the unrestricted fires which are commonly attributed to long-span cable-supported bridges. Common height-unrestricted fires are those that occur near steel pylons or cables. In the height unrestricted environment, it is of importance that the flame temperature variation on the vertical side should not be disregarded, hence the flame height based on the fire temperatures rather than the vertical elevation beneath the bridge should be considered.

Furthermore, reinforced concrete (RC) bridges perform the best in all structural systems and material classes. This is not far from the expectation due to the suitable fire performance of the RC compared to other types of material. However, moving toward the I girder structural system, the MDI increases. The other interesting result is the lower anticipated MDI in urban areas. The most reasonable fact for this trend may be attributed to the higher possibility of the presence of fire-fighting stations as well as ease of access and adjacency to the accident location.

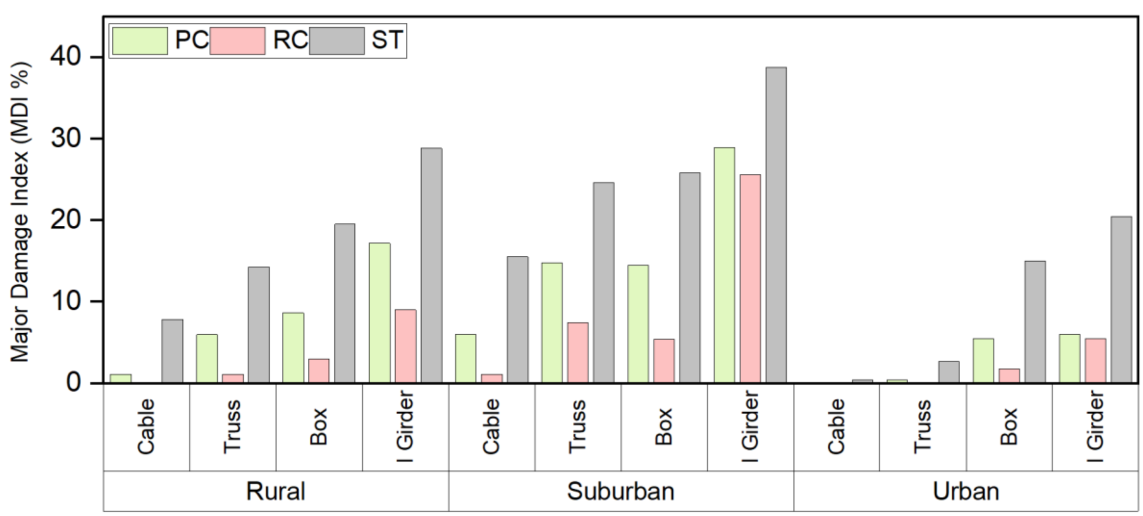


Figure 4-2 Major damage index (MDI) in different areas, structural systems, and materials

4.3 The effects of an ignition source, combustible type, and fire position on bridge fires

Figure 4-3 displays the influence of ignition sources (i.e., cars, trucks, and tankers) and combustible types (i.e., gasoline, diesel, alcohol liquids, hydrocarbon liquids, solids, and none) on bridge fires. The position of fire in Figure 4-3 is on, under, and on the bridges with fuel spills. The predictions of the ANN model show that the bridge fires caused by tankers have the highest damage levels (DL) followed by trucks and cars. Since tankers normally transport a high volume of highly flammable fuels that result in severe bridge fires. The most intense fires and damage levels in tanker fires are caused by gasoline, alcohol, and hydrocarbon fuels which are highly flammable. They are commonly attributed to petrol fires known as hydrocarbon fires with low flash temperature, high fire intensity, and a fast-heating rate within the first few minutes of the fire; hence, they can cause severe damage and collapse of the bridge in most cases [3, 8]. When the ignition source is a truck, the most severe fires are caused by solids. In terms of fire position, the most severe damage levels (DL) are predicted when a fire occurs under a bridge; this is valid for all ignition sources (i.e., cars, trucks, and tankers) and in all combustible types. Once a fire occurs under a bridge, the girders are directly exposed to flames and high temperatures. However, if a fire breaks out on a bridge, the concrete layer of the bridge deck functions as an insulation layer, dissipating the heat rather than allowing it to pass through the top of the girders; so the damage level (DL) is lower [1].

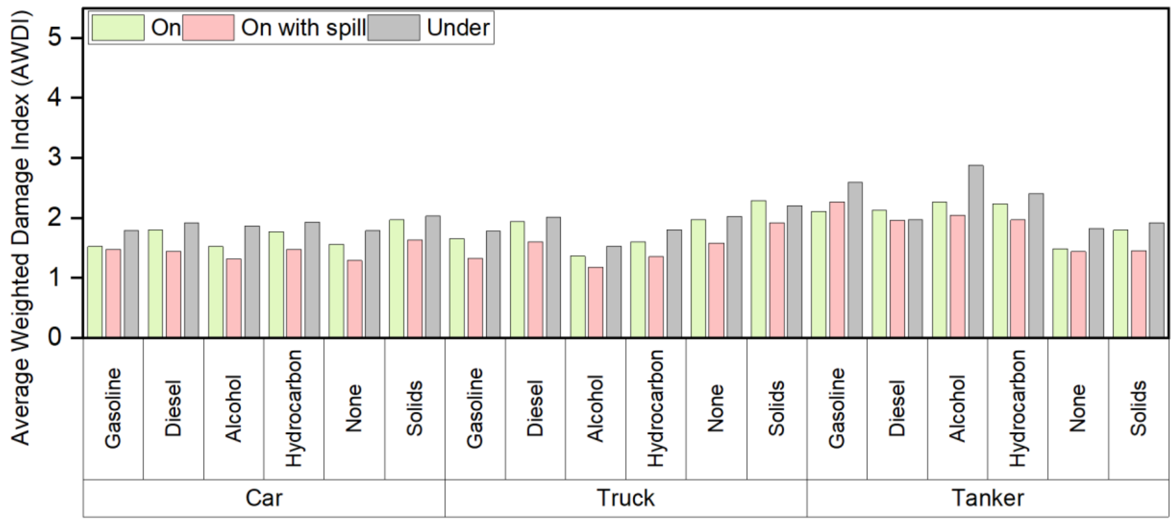


Figure 4-3 The average weighted damage level of ignition sources, combustible types, and fire positions in the bridge fire incidents

Figure 4-4 displays the MDI values in bridge fires where various ignition sources, combustible types, and fire positions are studied together. The most severe MDI results from tankers with gasoline, alcohol, and other hydrocarbons as combustibles, and when the fire is located under bridges. Figure 4-4 demonstrates that when the fire is under bridges and the combustible type is gasoline, the MDI of cars, trucks, and tankers are 7%, 12%, and 24%, respectively, defining tankers as the most vulnerable ignition source in bridge fires. Moreover, when the ignition source is a tanker and the fire position is under, the highest MDI is for other hydrocarbon liquids with an MDI of 30%. The MDI for gasoline and alcohol is 24%, and 25%, respectively. Furthermore, in the case of tankers carrying alcohol liquids, the fire position under the bridges has the highest MDI (30%), while when the fire occurs on the bridges, the MDI is 16%, and in the case of fire on the bridges with fuel spill, the MDI is 10%.

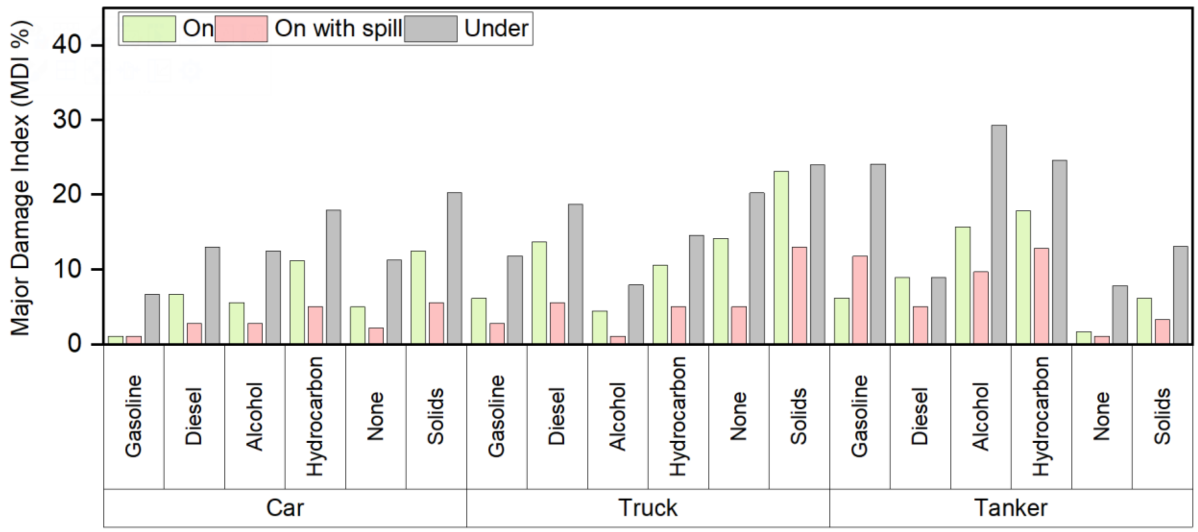


Figure 4-4 Major damage index in different ignition sources, combustible types, and fire positions

4.4 The effect of area types on bridge fire damage levels

Figure 4-5 shows the influence of area types (i.e., rural, suburban, and urban) on bridge fires. The graph was created with the assumption that some parameters would remain constant. AADT 2 is the one that is being considered among the AADTs, tankers have been chosen as one of the ignition sources, other hydrocarbon liquids are the selected combustible types for this layout, and the fire location is under bridges. According to Figure 4-5, suburban regions suffered the most severe damage, with a damage level (DL) of 5 signifying the collapse of bridges in the fire. However, rural areas experience the next high damage levels (DL) in the range of 3 identifying partial damages in bridge fires. While in urban areas, bridges usually sustain the lowest intensity of damage, with a level of 1 indicating minor damage. As previously mentioned, it is due to easy access to fire departments and the prompt reaction of firefighters in fire emergencies. As real cases, it can be pointed out Brooklyn Bridge and Queensboro Bridge fire incidents happened twice and three times in two consecutive years in June 2012 and July 2013 (Figure 4-6). The bridges have been located in the urban area in New York, USA, which shows a higher probability of fire incidents in urban areas. However, in both cases, the severity of the damages was minor which indicates the proximity of fire stations to the incidents and the possibility of the quick response of firefighters in urban areas.

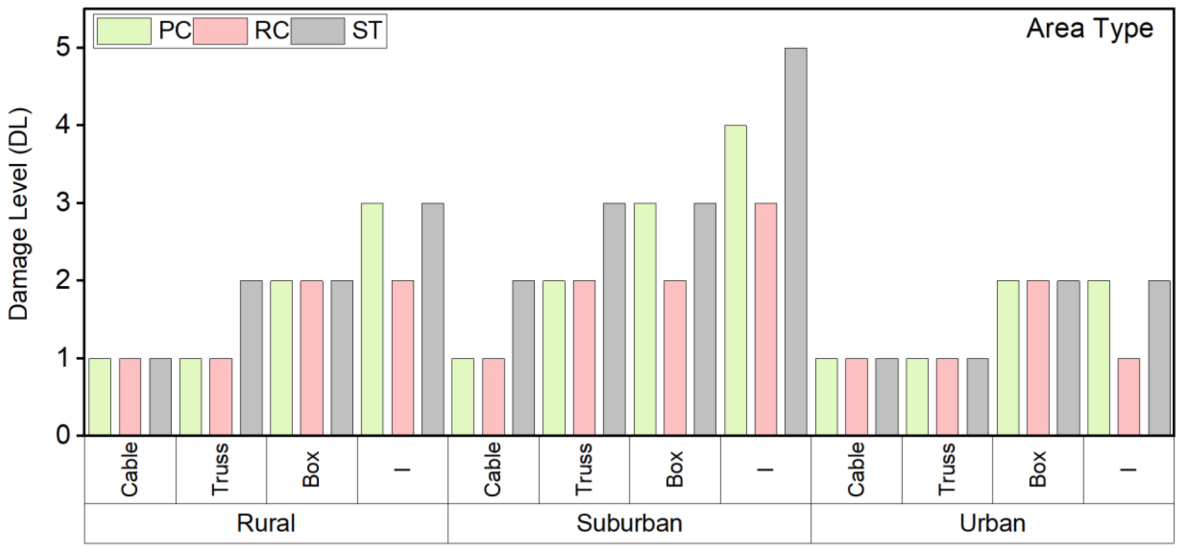
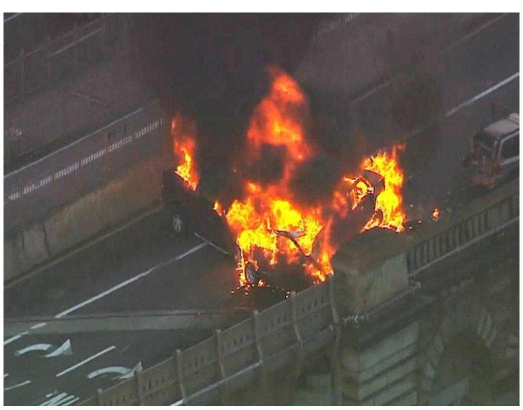


Figure 4-5 The damage level in different area types in bridge fires



(a) (b)

Figure 4-6 Bridge fires on (a) Brooklyn Bridge, NY, USA, 2012, (b) Queensboro Bridge, NY, USA, 2005 (Sky News)

4.5 The effect of structural systems on bridge fire damage levels

Figure 4-7 shows the effects of structural systems (i.e., cable-supported bridges, truss/arch bridges, box girder bridges, and I girder bridges) on fire damage levels (DL). Suburban areas in area type categories, AADT 2 among the other AADTs, tankers as ignition sources, and other hydrocarbon liquids as combustible types are the constant variables used to generate this figure. According to Figure 4-7, the I girder bridges can suffer the most with damage levels (DL) reaching 5 for steel I girders when a fire occurs under bridges. According to the parametric studies, in steel I girders the rate of deflection dramatically increases in the final phase of exposure to elevated temperatures, which leads to the prevalence of plasticity in the bottom flange and more buckling of the web caused by faster strength and stiffness degradation of steel at high temperatures, as well as the effect of high temperature creep. Finally, the steel girder fails due to a lack of load-bearing capacity caused by significant web buckling and mid-span deflection (Figure 4-8) [1].

As a real case, it can be referred to Birmingham, Alabama, USA, 2002 bridge fire incident in which the structural system was steel I girder carrying a reinforced concrete slab deck (Figure 4-8). The fire temperature was reported to be around 1100 °C resulting in the bridge's collapse. While damage levels (DL) in box girder bridges are mostly 2 or 3 indicating medium and partial damages, damage levels (DL) in truss/arch bridges can reach 3, and damage levels (DL) in cable-supported bridges are limited to 2 indicating medium damages and mostly 1 showing the minor damage. The reason for this is that the most critical components of the cable-supported bridges in the fire are the cables, which are normally not exposed to fire since as mentioned, in the case of fire under the bridges the vertical clearance is a contributing factor, while in the case of fire on the bridges the critical factor is the flame height which defines the vulnerability of cables in bridge fires. As a real case consider the bridge fire in Chari Laos Trikoupis (Rio-Antirrio) Bridge, in Greece in 2005. One of the pylon cables of a multi-span cable-stayed bridge known as Rio Antirrio caught fire, crashed onto the deck, damaged the neighboring cable, and failed after 40 minutes into the fire. Despite the failure of this cable, it did not collapse or cause severe damage to the bridge. However, the fire incident affected the bridge's durability [14].

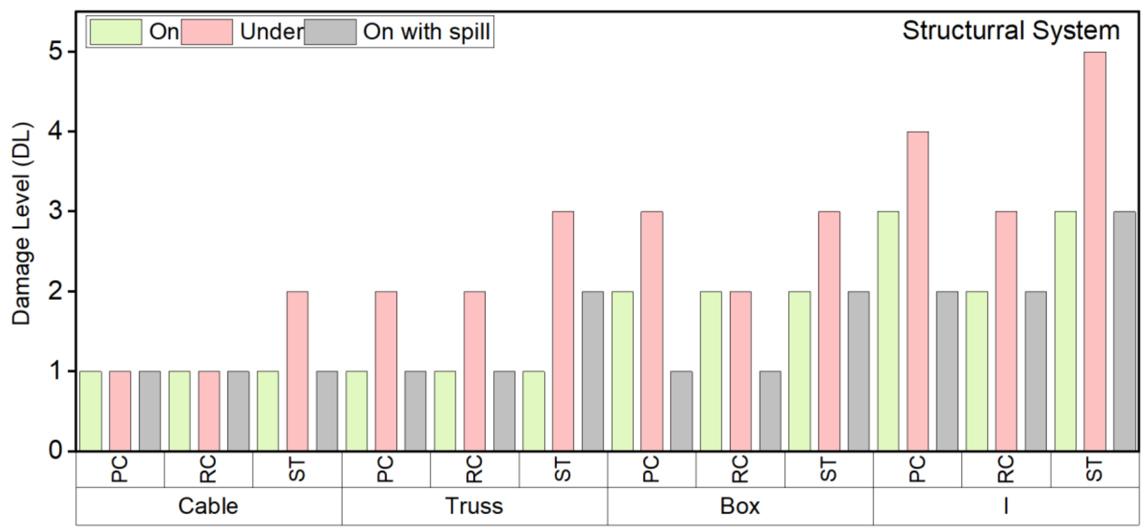


Figure 4-7 The effects of structural system on bridge fire damage levels

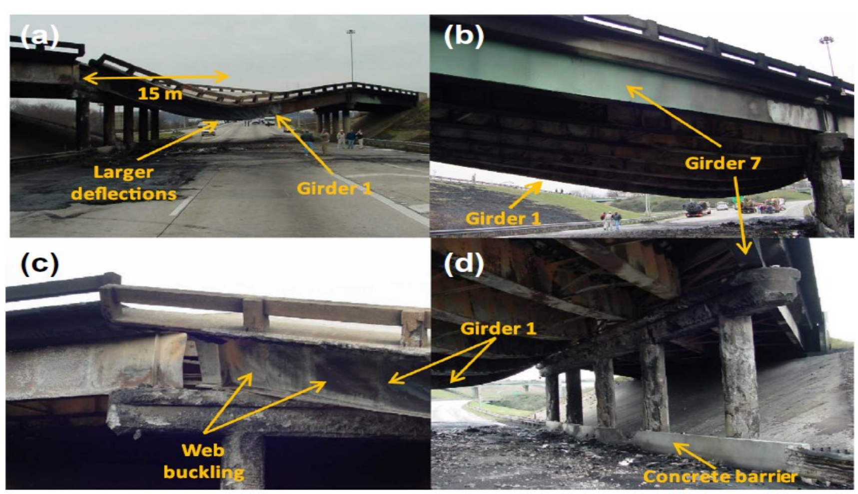


Figure 4-8 Web buckling and mid-span deflection of steel I girder bridges (Photo from [17])

4.6 The effect of material on bridge fires

Figure 4-9 illustrates the influence of materials (i.e., reinforced concrete (RC), prestressed concrete (PC), and steel (ST)) on bridge fire damage levels. To generate the results in Figure 4-9, four parameters needed to be chosen and kept constant. These parameters are suburban areas, AADT 2, tankers, and other hydrocarbon liquids. According to Figure 4-9, steel bridges have the highest damage levels (DL), with a level of 5 denoting bridge collapse in fire accidents. As previously stated, it is important to note that all steel bridges in this study are unprotected steel. It indicates that steel has not been insulated with a fireproofing material, so it is exposed to fire directly. The maximum damage level (DL) in prestressed concrete is 4, and the maximum damage level (DL) of reinforced concrete is 3 (Figure 4-9). As an example, consider the MacArthur Maze bridge fire in California in 2007 when the bridge collapsed because of a tractor-trailer collision transporting gasoline. It comprised six steel girders supporting a reinforced concrete deck. This event resulted in large deflections in the unprotected steel girders and consequently the connections overstressing during the fire. The reported fire temperature was 1100 °C and two spans of the bridge collapsed in 22 minutes [2, 4, 8, 11, 12]. The other example is the bridge fire in Deans Brook Viaduct, United Kingdom, 2011, that a fire incident occurred on the bridge, set by arsonists in a scrap yard storing flammable material under the bridge. The superstructure comprised a reinforced concrete (RC) slab with prestressed concrete girders. The temperature of the fire under the bridge reached 800 °C. There was concrete spalling within three hours of the fire starting. Spalling exposed the prestressing steel of the beam's bottom layer (Figure 4-10). The assessors concluded that at spots where the concrete cover was not damaged, no significant tension losses occurred. Hence, overall significant losses were observed in the exposed steel at places in which the concrete layer was fully destroyed [22, 26].

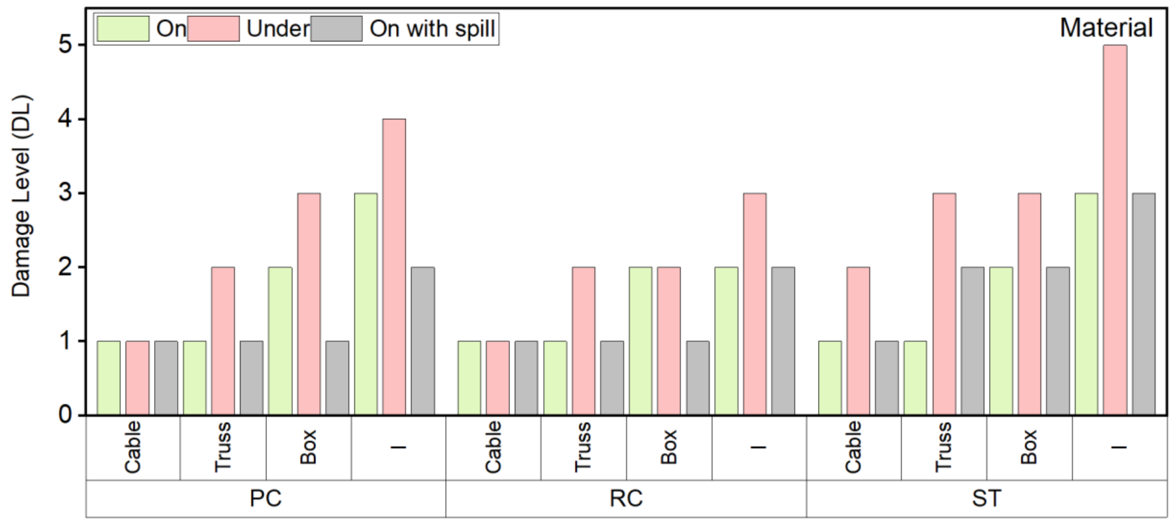


Figure 4-9 The effect of material on the bridge fire incidents

Figure 4-10 Concrete spalling of a bridge deck in spain and bridge girder in Deans Brook Viaduct (Photo from [59])

4.7 The effects of ignition source on bridge fires

The effects of ignition sources (i.e., cars, trucks, and tankers) on bridge fires are shown in Figure 4-11. Four parameters were kept constant to create the results in this graph. These parameters are I girder bridges, steel, AADT 2, and other hydrocarbon liquids. According to Figure 4-11, the highest damage levels (DL) are caused by fires involving tankers. This is in agreement with Figure 4-3 and Figure 4-4 which indicated the average weighted damage index (AWDI) and major damage index (MDI), respectively, tankers experience the highest damage intensities followed by trucks and cars. As previously stated, in these two figures all parameters have been considered simultaneously. It indicates that as none of the seven parameters including area type, structural system, material, AADT, ignition source, combustible type, and fire position were held constant, they covered comprehensive data of the neural network output. However, Figure 4-11 further demonstrates that tankers have the highest overall damage levels (DL), with 2 indicating medium damages, 3 suggesting partial damages, and 4 indicating massive damages. The reason for this is that, in comparison to trucks and cars, tankers often transport a large volume of extremely flammable fuels resulting in severe damage in bridge fires. As an example, consider Howard Avenue Overpass in Bridgeport, Connecticut in 2003, because of the collision of a car with a tanker transferring 50,000 liters of heating oil on the bridge supported by large steel girders. The fire exposure time was two hours, with a temperature of about 1100 °C. The steel girders with no fireproofing suffered from significant buckling, resulting in the bridge's collapse. Another bridge fire incident was Mathilde Bridge in France in 2012 due to the overturning of a tanker truck transferring over 20,000 liters of oil and gasoline in the access curve of the bridge. The bridge was comprised of steel spans supporting a concrete deck. The approximate fire temperatures were estimated to be 650–800 °C. Despite the fire intensity and extent, the quick response by firefighters resulted in the prevention of the full collapse of the deck. However, damages to the bridge were too extensive [16, 17]. Figure 4-12 shows a semi-truck that caught fire and dangled from a bridge, and snarled traffic on I-80, west of Reno. The truck hit a bridge wall on eastbound I-80 near Floriston and instantly caught fire.

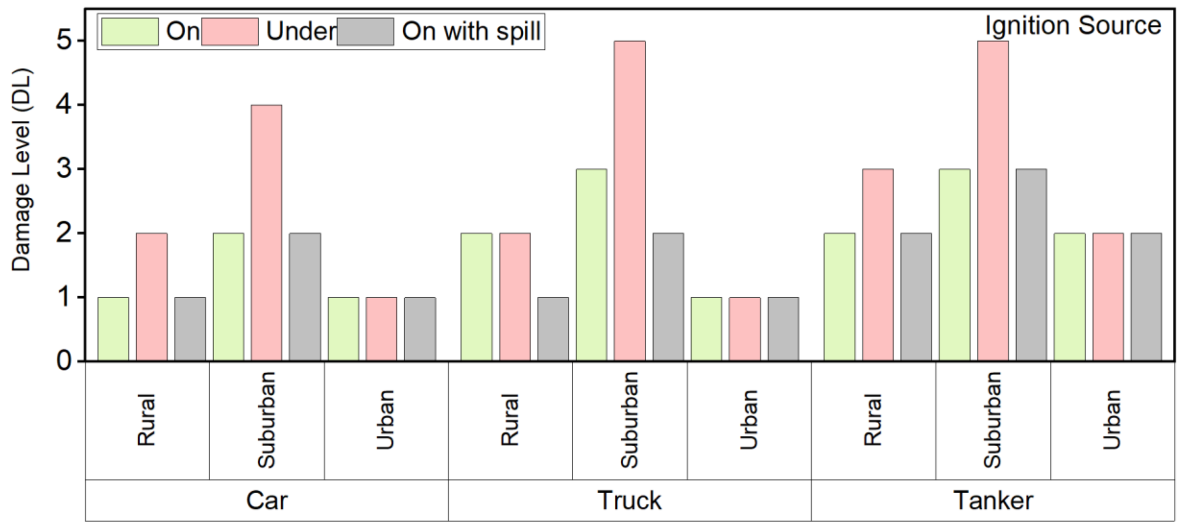


Figure 4-11 The effect of ignition source on the bridge fire incidents

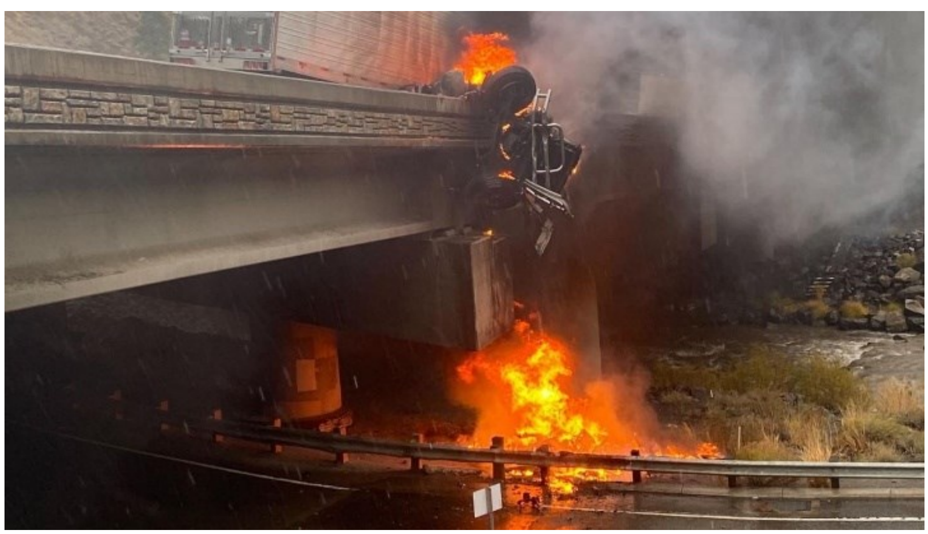


Figure 4-12 Semi-truck fire on I-80, west of Reno (FLORISTON, Calif. (KRNV & KRXI))

4.8 The effects of combustible type on bridge fires

Figure 4-13 highlights the influence of combustible types on bridge fires (i.e., gasoline, diesel, alcohol liquids, and other hydrocarbon liquids). I-girder bridges, steel, AADT 2, and tankers are the constant parameters considered in developing the results in Figure 4-13. The highest damage level (DL), is caused by alcohol liquids and hydrocarbons as the combustible types. As previously stated, hydrocarbons are typically highly flammable fuels with low flash heat, high fire severity, and a rapid heating rate within the first few minutes of a fire resulting in significant damage and bridge failure in most fire scenarios. Figure 4-13 also demonstrates that suburban areas have highest damage levels (DL) compared to rural and urban areas. A real case example is the Puyallup River in the USA where the collision of a railroad tanker transporting 113,000 liters of methanol, caused a fire incident under a prestressed girder bridge. The bridge deck and columns were constructed from concrete and mild steel. Releasing and burning on-board hydrocarbons resulted in a fire of high quick temperatures lasting over an hour. No abnormal deflections or misalignments were observed on the bridge, hence reopening the traffic flow, and commuting of legal weight trucks was approved the next day. However, heavy trucks were prohibited from commuting on the bridge and were detoured to other nearby routes. Some small stress relaxation was remarked in the prestressing steel while severe spalling occurred, resulting in temperatures as high as 500 °C in the steel. Even though the assessors concluded that the steel would maintain its basic material characteristics, they replaced the steel girders [22, 118]. Figure 4-14 illustrates a blaze from a tanker truck on the eastbound 60-freeway under the Paramount Boulevard bridge in Montebello, California, 2011. The freeway was closed indefinitely until inspectors could access bridge damage.

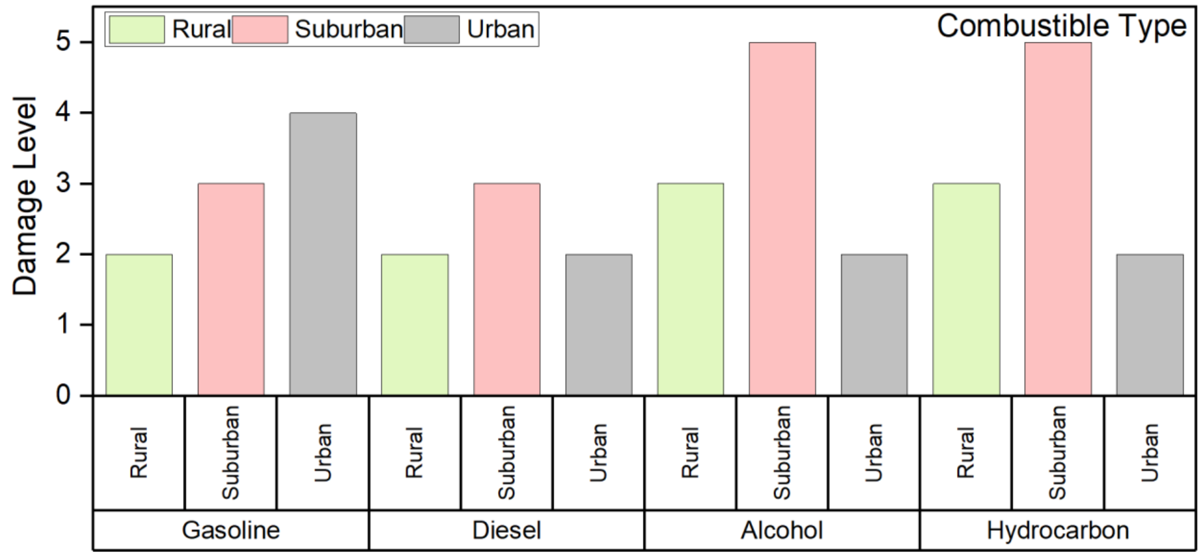


Figure 4-13 The effect of combustible type on the bridge fire incidents

Figure 4-14 gasoline tanker fire under the Montebello bridge, California, 2011 (AP Photo/Keith Durflinger, San Gabriel Valley Newspaper)

4.9 The effects of fire position on bridge fire damage levels

Figure 4-15 illustrates the impact of the fire location on fire damage levels. Fires occur on bridges, under bridges, and on bridges with fuel spills. Creating the results in Figure 4-15 some parameters were kept constant which are suburban areas, tankers, other hydrocarbon liquids, and AADT 2. According to Figure 4-15,the most severe damage level (DL) is caused by firesunder bridges. As mentioned before, in under-bridge fires, vertical clearance is a crucial factor, as in this case, bridge girders (RC, PC, or ST) are subjected to the fire directly. According to Figure 4-15, the highest damage levels (DL) are for steel I girder bridges when a fire occurs under bridges.

A real case can be pointed out as the Hazel Park bridge fire in Michigan in 2009. The fire incident occurred when a tanker truck carrying about 49,000 liters of gasoline and about 15,000 liters of diesel crashed under the bridge. This bridge comprised steel girders supporting a reinforced concrete deck. The collapse of the bridge occurred at temperatures over 1000 °C and resulted in a high loss of strength capacity of the exposed girders within 20 minutes of the fire incident [2, 7-10]. Figure 4-16 demonstrates a fire incident under Apongbon bridge in Lagos Island which occurred due to storing of materials under the bridge.

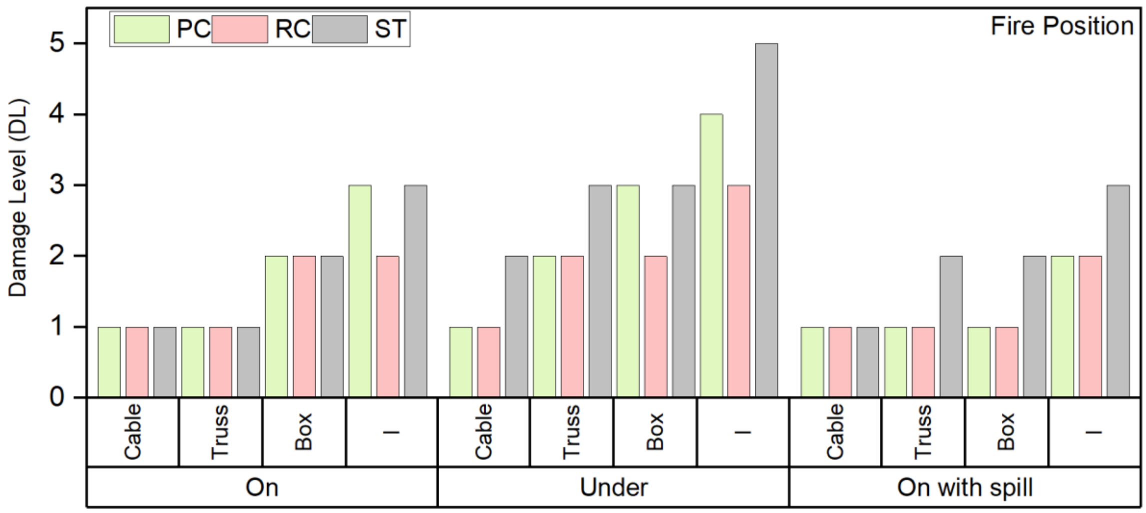


Figure 4-15 The effect of fire position on the bridge fire incidents

Figure 4-16 Fire under Apongbon bridge in Lagos Island (TVC News, Sarah Ayeku)

4.10 The effects of Annual Average Daily Traffic (AADT) on bridge fires

Figure 4-17 shows the influence of Annual Average Daily Traffic (AADT) on bridge fires. The AADT values studied in this research range from 0 to 300,000. The AADT parameter in the ANN model is divided into five ranges in an interval of 60,000. Urban areas, tankers, other hydrocarbon liquids, and fire position of under were considered constant in Figure

4-17. According to the graph, the bridges in regions with traffic volumes of 241000 to 300,000 (i.e., AADT 5 in the ANN model) have the highest damage levels (DL). It is rational to expect the probability of accidents in high-volume traffic zones to be typically higher than in low-traffic areas. The real case is the bridge fire on the I-85 bridge near Atlanta in Georgia in 2017 (Figure 4-18). During a vandalism incident underneath the I-85 bridge near Atlanta, a fire occurred due to the storage ignition of massive polyvinyl chloride (PVC) pipes and/or high-density polyethylene (HDPE) pipes under the bridge. I-85 bridge comprised three reinforced concrete piers carrying ten prestressed concrete girders, serving 243,000 vehicles per day. Based on the Georgia Department of Transportation (GDOT) report, the burning of these plastic pipes caused a rapid increase in temperature to 900 –1100 °C. The fire continued for around 2 hours, but the bridge's span fell within the first hour. Post-fire investigation revealed complete spalling of the concrete cover, causing direct fire exposure of the prestressed steel. In addition, reconstruction of the bridge imposed extra expenses for detouring commuters to alternative routes. Because of the reduced traffic flow in the area, business owners around the job site experienced a decrease in customer flow and thus lower earnings. Addressing such problems, the State of Georgia, also several other counties, revised its storing rules [21, 22].

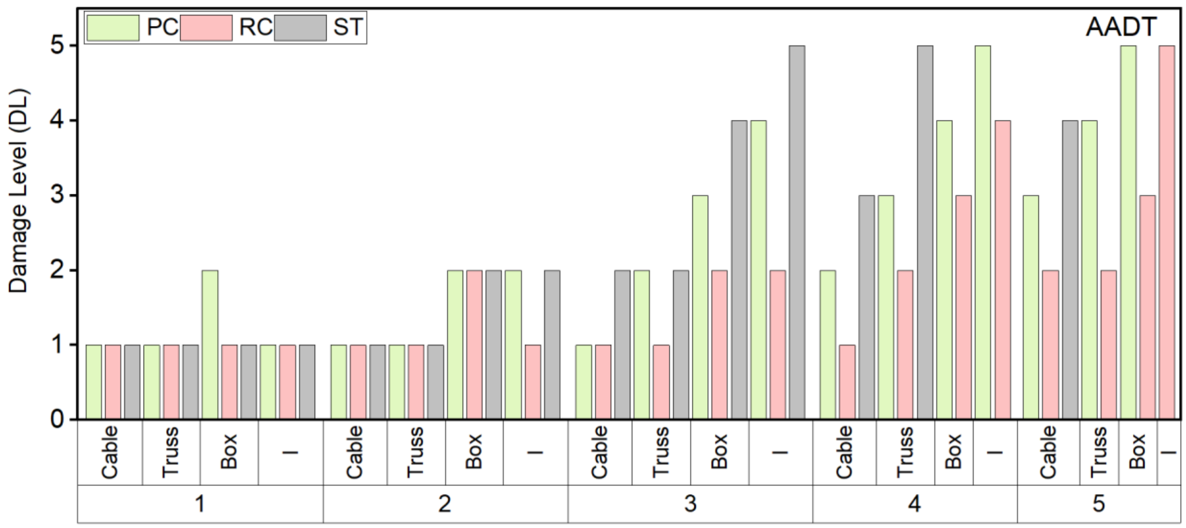


Figure 4-17 The effect of AADT (Annually Average Daily Traffic) on the bridge fire incidents

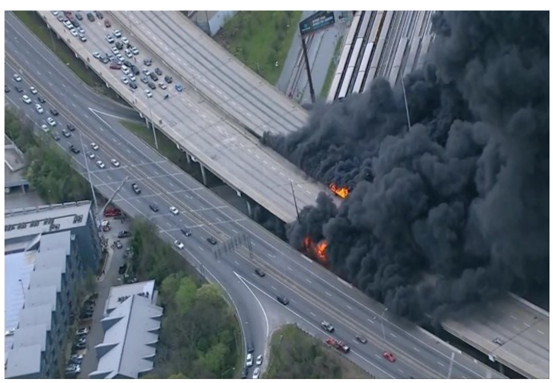


Figure 4-18 Bridge fire on I-85 bridge in Atlanta, USA, 2017 (BBC News)

Chapter 5: Conclusions and Recommendations

Near 150 bridge fire incidents were used in creating a database to develop an Artificial Neural Network (ANN) model to characterize the bridge fires. Using the ANN model, the most important parameters were selected to predict the probability of bridge fires as well as define damage levels (DL). In the proposed new dataset, the most significant parameters are:

- Area types including rural, suburban, and urban areas.
- Structural system comprising of cable bridges, truss/arch bridges, box girder bridges, and I girder bridges.
- Material including reinforced concrete, prestressed concrete, and steel.
- AADT, that is the annual average daily traffic of the vehicles across the bridges.
- Ignition source consisting of cars, trucks, and tankers.
- Combustible type which features gasoline, diesel, alcohol liquids, other hydrocarbon liquids, solids, and none of them.
- Fire position which considers the fire incidents occurring on the bridges, under the bridges, and on the bridges when fuel spills.
- Damage level (DL) which incorporates five levels of damage: minor, medium, partial, massive damages, and collapse of the brides.

The data were divided into two groups. First, in the case of cars, trucks, and tankers the ignition sources were limited to gasoline, diesel, alcohol liquids, other hydrocarbon liquids, solids, and none. In this case, AADT has been considered as it is a contributing factor when vehicles travel along bridges. In the second part of the dataset, the ignition sources were limited to electrical problems, storage, and others disregarding the AADT. For the first part of the dataset, a neural network has been trained to predict fire incidents based on the proposed parameters. For the second part as the data was not enough the research only investigated the histogram graphs to determine the possibility of some special fire incidents.

Based on the predicted Damage Levels (DL) from the developed ANN model, two other factors namely, the Average Weighted Damage Index (AWDI) and the Major Damage Index (MDI), were used to study bridge fires. The following conclusions were drawn from this research.

5.1 Conclusions and Results

The most important results based on the Major Damage Index (MDI) graphs are as follows:

1- In terms of area types, the MDI is 5, 10, and 18% in urban, rural, and suburban areas, indicating the higher probability of bridge fires in suburban areas occurring with major damage levels of 4 and 5.

2- In terms of structural systems, the MDI is 4, 8, 11, and 20% in cable bridges, truss/arch bridges, box girder bridges, and I girder bridges, respectively. This identifies I girders as the most susceptible bridges in a fire.

3- In terms of materials, the MDI in reinforced concrete, prestressed concrete, and steel is 5, 9, and 18%, respectively, which demonstrates that steel is the most vulnerable material in bridge fire occurrences.

4- In terms of ignition sources, the MDI in cars, trucks, and tankers is 8, 11, and 12%, respectively, indicating the tankers as the most susceptible source in bridge fires.

5- In terms of combustible types, the MDI is 8, 9, 10, 13, and 14% for gasoline, diesel, alcohol liquids, solids, and other hydrocarbon liquids, respectively. This shows that hydrocarbons can cause the most destructive effects in bridge fire.

6- In terms of fire position, the MDI is 5% when the fire occurs on the bridge with fuel leakage, 10% when the fire happens on the bridge, and 16% when the fire occurs under the bridge, defining the greatest vulnerability of bridges when a fire occurs under bridges.

7- In terms of AADT, the MDI in AADT 1 to AADT 5 is 2, 4, 11, 18, and 22% respectively, indicating the fires are the most destructive when they occur in areas with the highest traffic volume (i.e., AADT 5).

5.2 Recommendations for future research

While this study has produced a fundamental knowledge of bridge fires using the artificial neural network approach and the parameters that influence them, more research is needed to apply the ideas to other realistic conditions that occur in bridge fires. The following are some of the key recommendations for further research in this area:

- In the initial dataset, the combustible types were divided into seven groups (i.e., gasoline, diesel, alcohol liquids, other hydrocarbon liquids, solids, and none). Because the number of bridge fires involving gasoline, diesel, and alcohol liquid-based fuels was so high, additional hydrocarbon liquid-based bridge fires were considered individually, however grouping them all will result in higher neural network output performance.
- Seven parameters were factored in our research (area type, structural system, material, AADT, ignition source, combustible type, and fire position), and all of

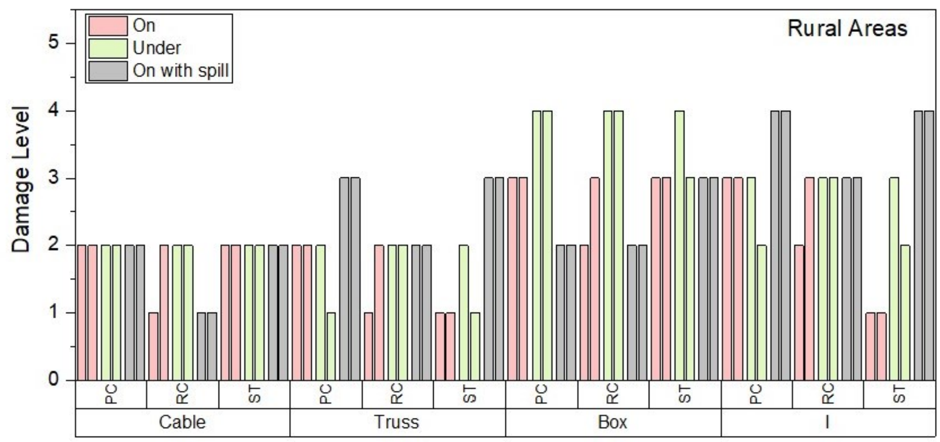
them had a significant impact on bridge fires. Another parameter that may play a vital role in bridge fires is the age of the bridges. As this parameter can determine the strength of bridges, particularly in the event of a fire, it aids assessors in more accurately investigating post-fire bridge evaluations.

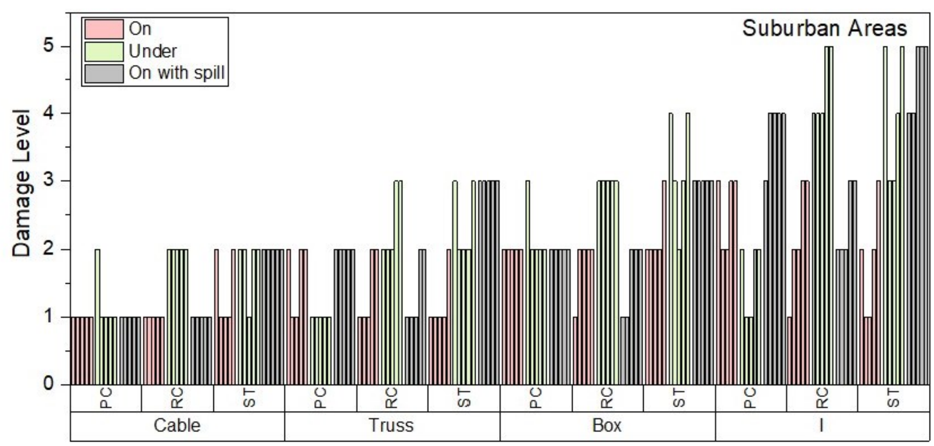
- Special bridge fires that occurred many times were recorded in our database. The reasons for these bridges were also analyzed based on the researched parameters, however, it is possible that structurally and more specifically investigating these situations would be preferable.
- Utilizing the proposed network to evaluate the fire performance of existing bridges as real case studies is recommended.
- Investigating the effect of driving culture on the probability of bridge fire incidents could be an efficient factor.

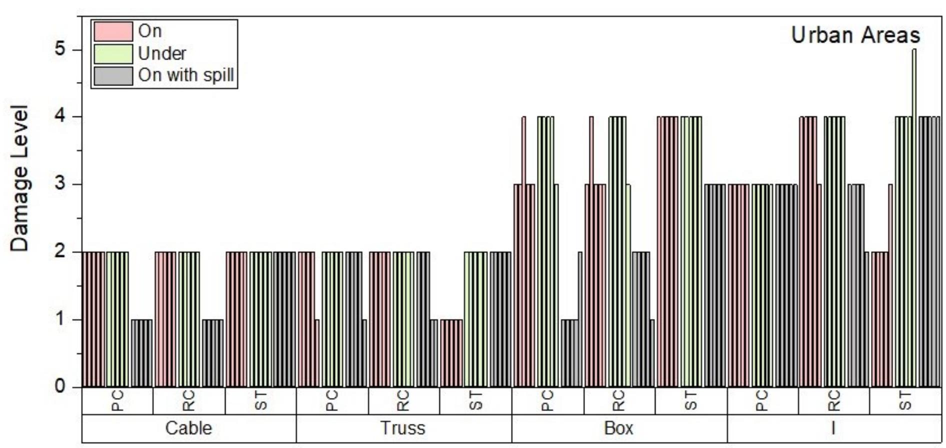
Appendices

Appendix A The effect of the selected seven parameters on the bridges fire incidents

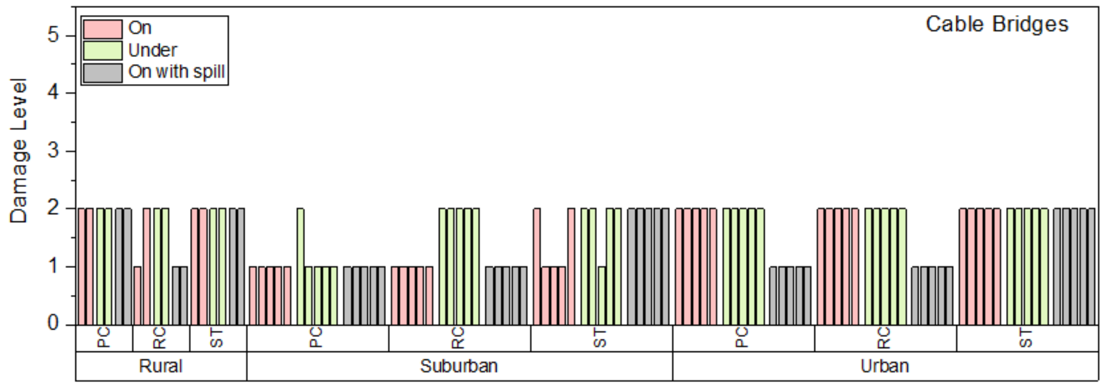
A.1 The effect of Area Types on the bridge fire incidents

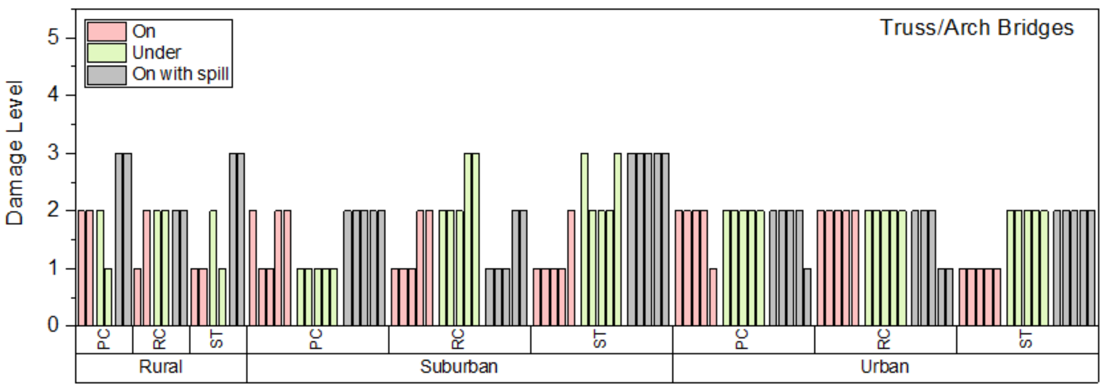


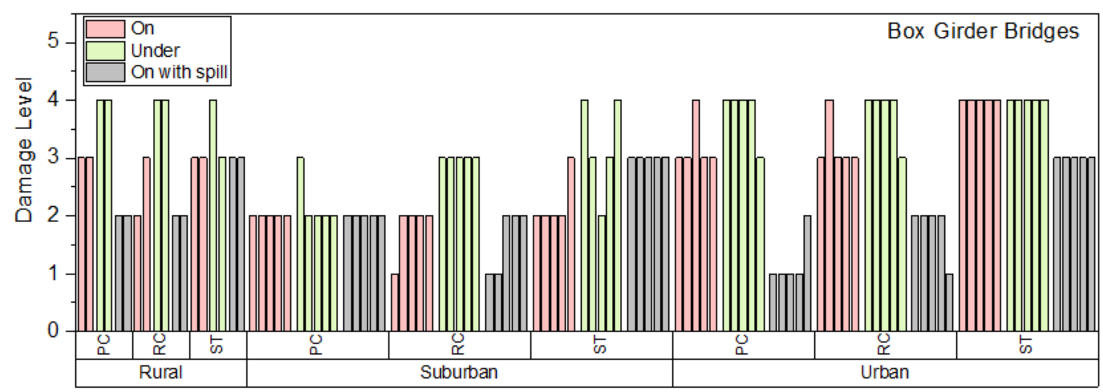


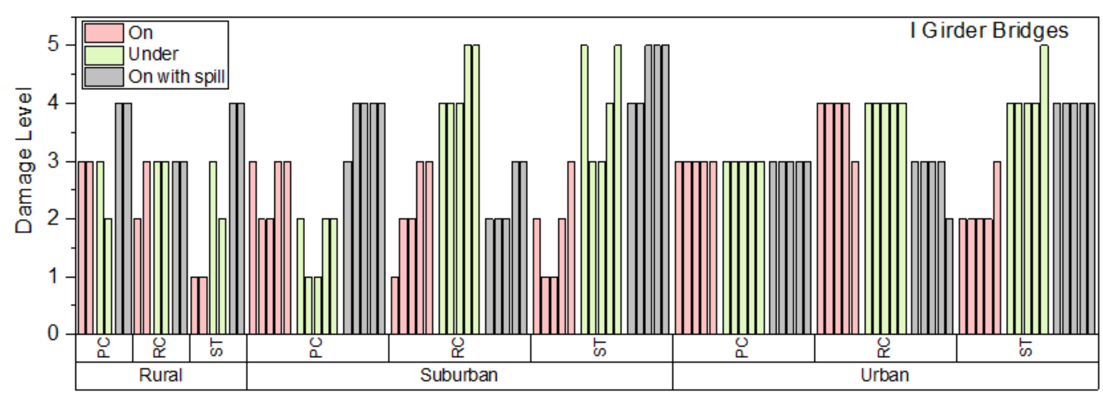


A.2 The effect of the Structural System on the bridge fire incidents

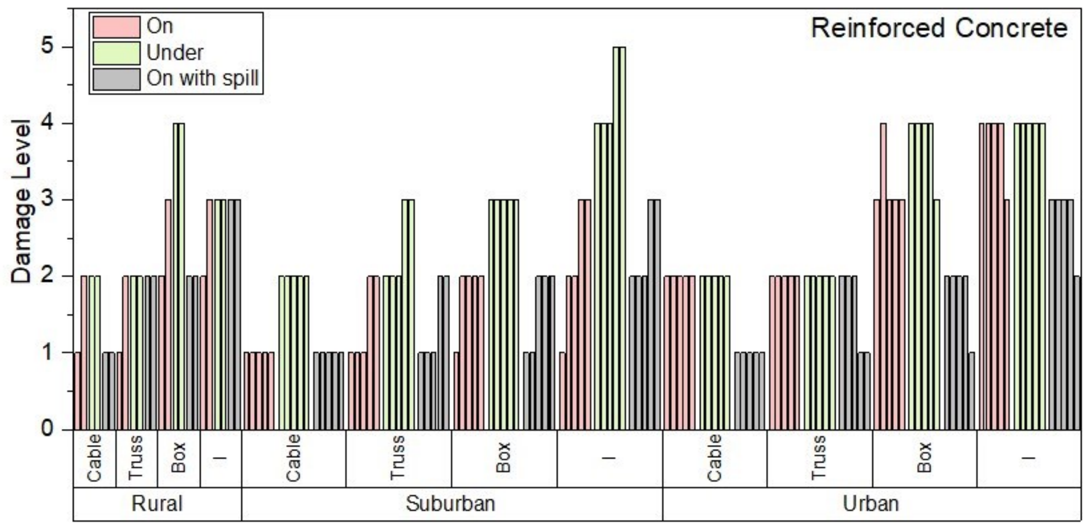


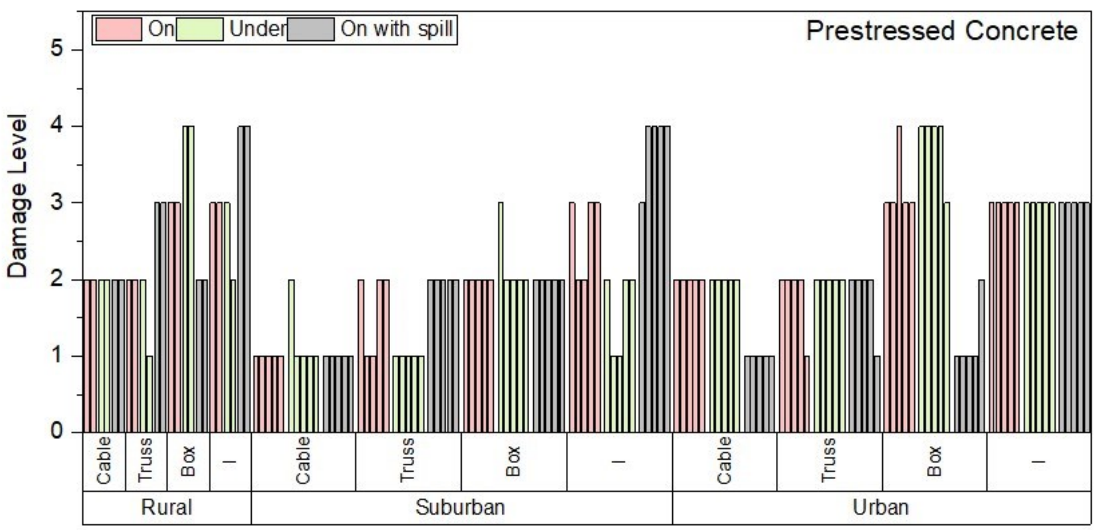


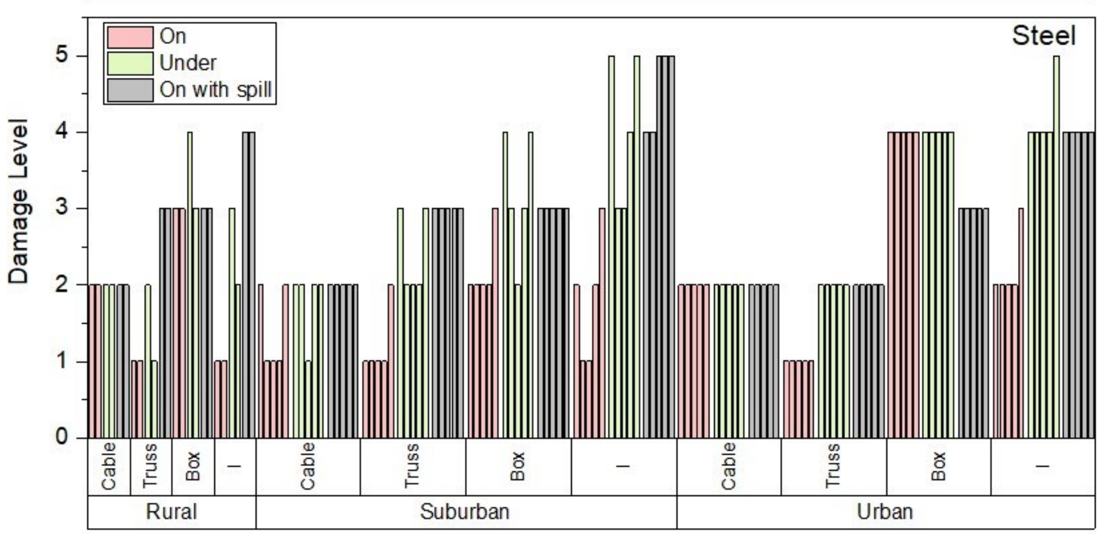




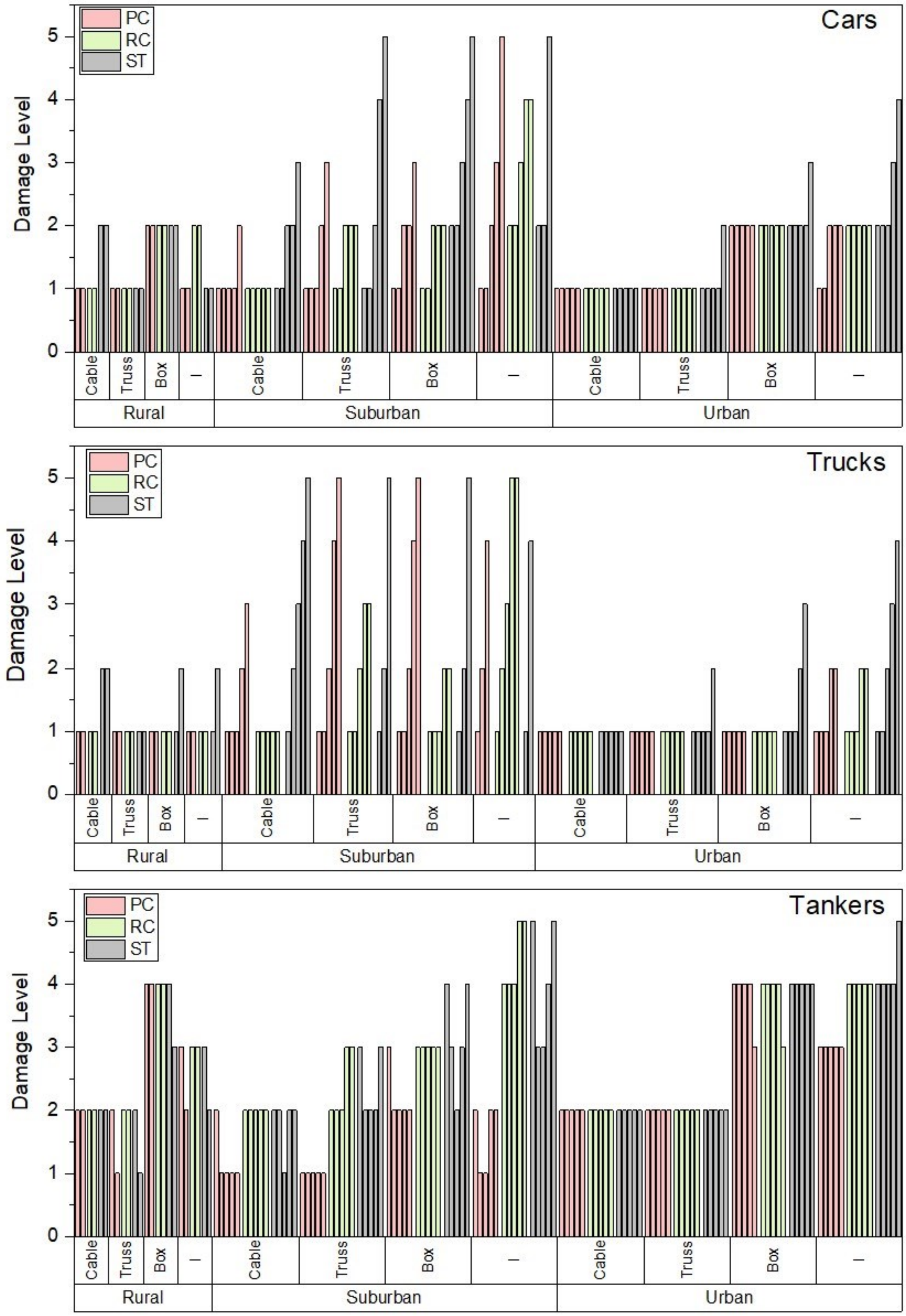
A.3 The effect of Material on the bridge fire incidents



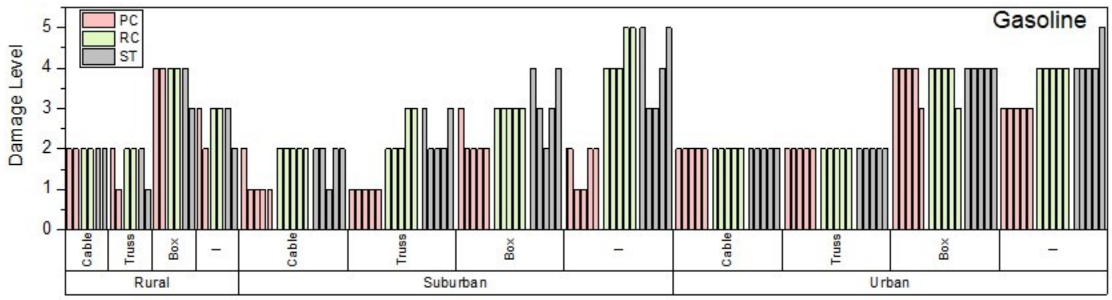


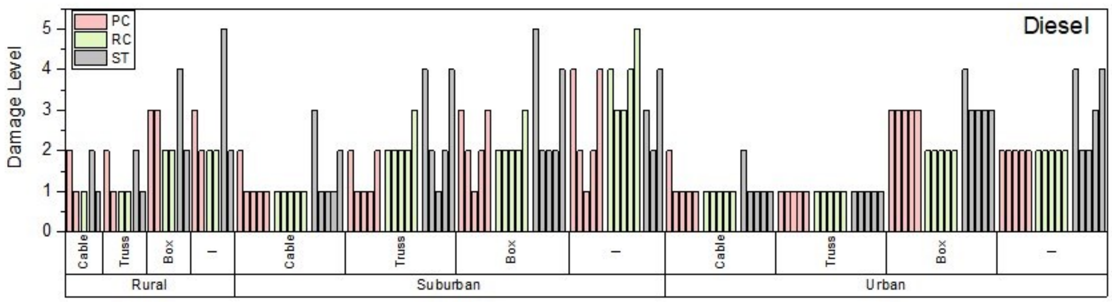


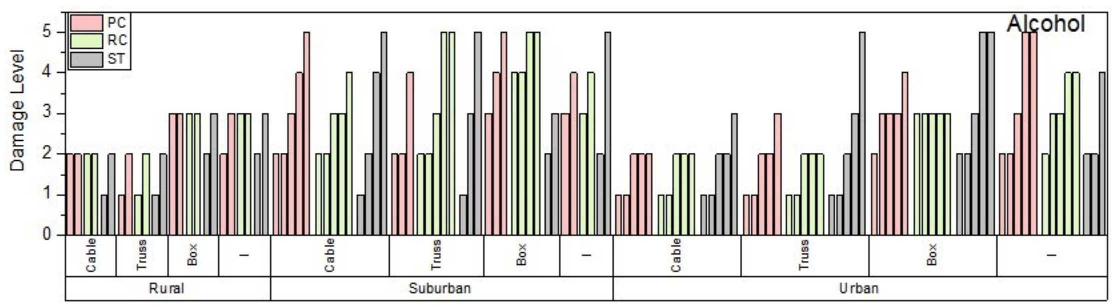
A.4 The effect of Ignition Source on the bridge fire incidents

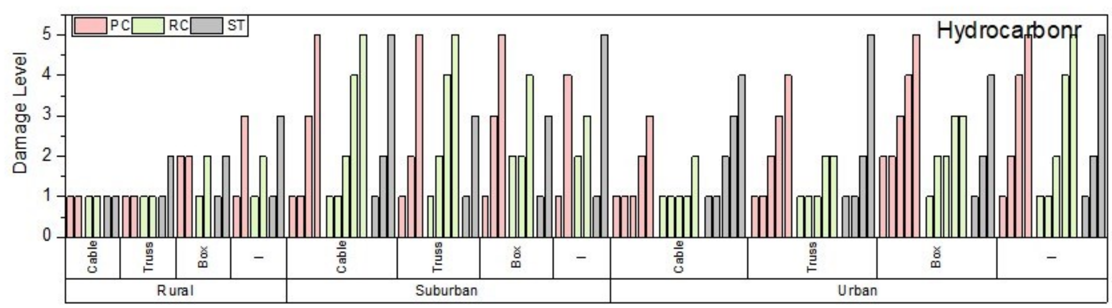


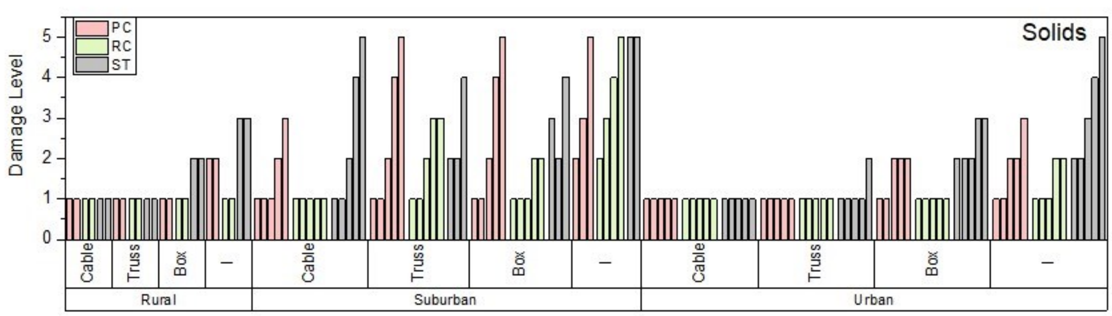
A.5 The effect of Combustible Type on the bridge fire incidents



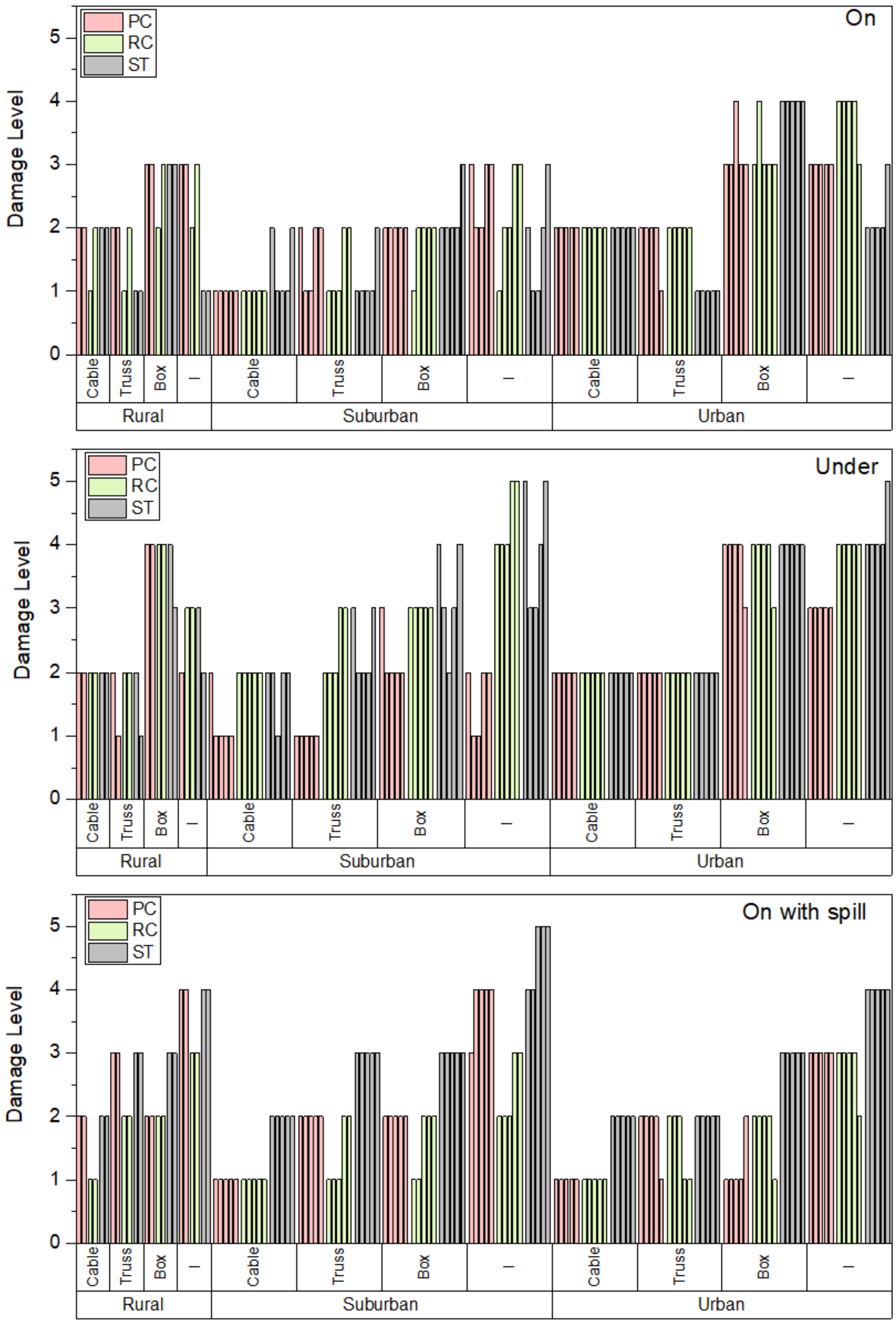




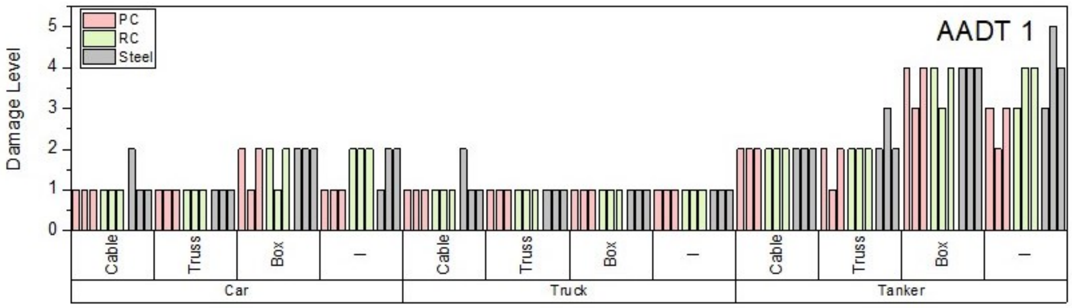


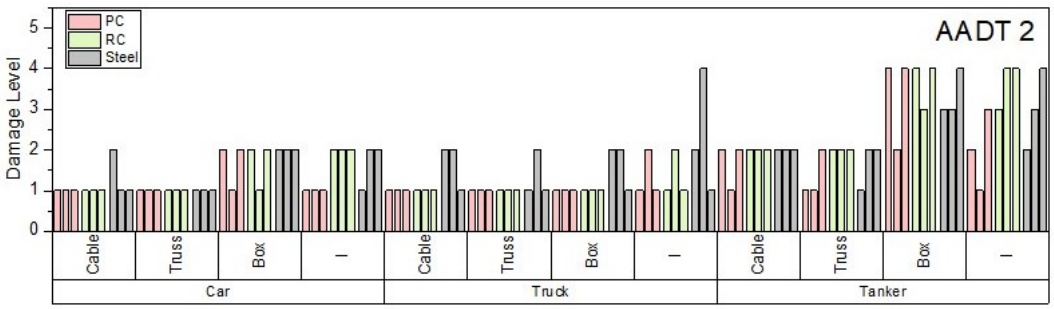


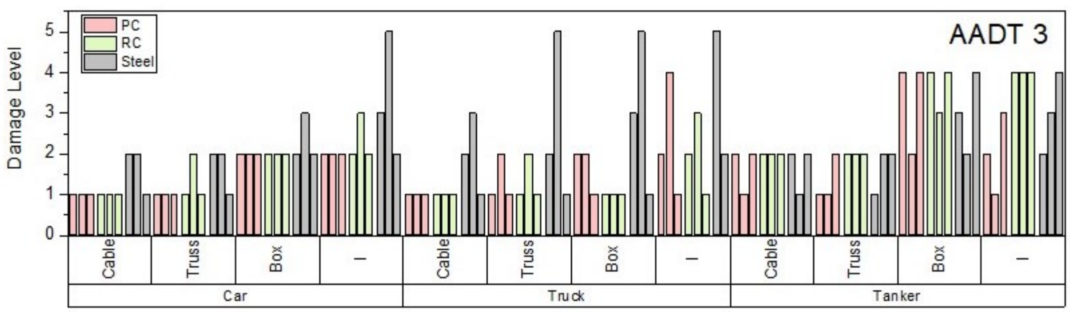
A.6 The effect of Fire Position on the bridge fire incidents

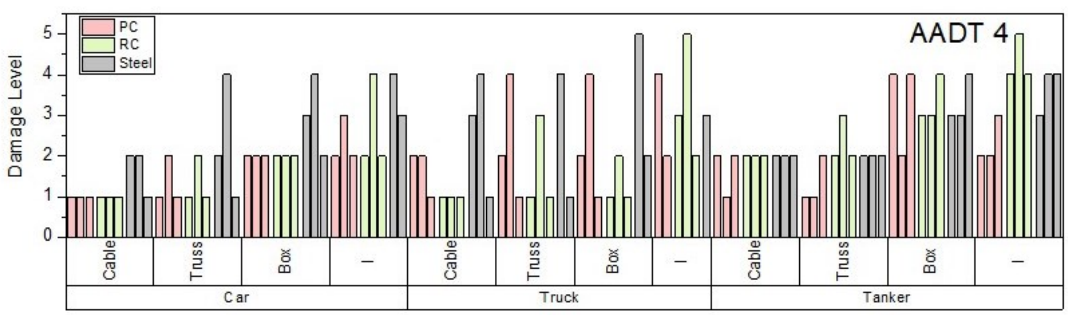


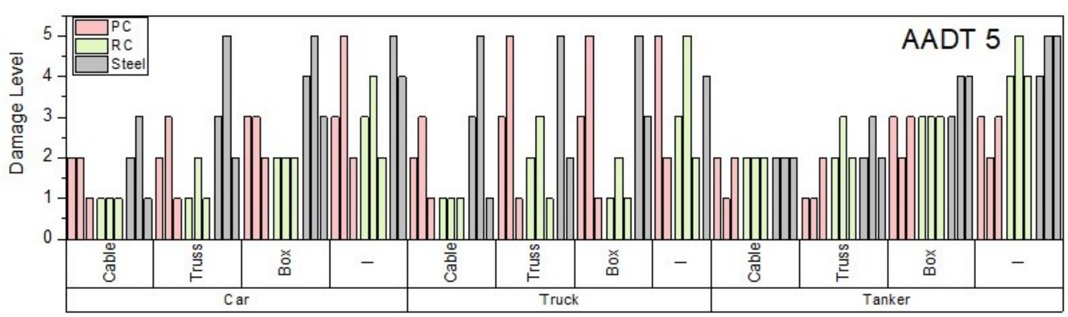
A.7 The effect of AADT on the bridge fire incidents











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