Forecasting Risk: Meteorological Impacts on San Diego Rail Grade Crossing Incidents

Chance L. Spurlin

University of California, San Diego

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Professor David Meyer

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Introduction:

In a bustling city such as San Diego, the ongoing effectiveness of its complex transportation network relies heavily on the efficiency and safety of the various traffic intersections. At many of these intersections there are varying forms of transportation that meet, in particular at highway-rail grade crossings, where road vehicles and pedestrians intersect with rail lines carrying different forms of rail, both heavy and light rail. These highway-rail grade crossings are critical points of the transportation network where the orchestrated flow of rail, pedestrian, and road traffic converge. Unfortunately, despite advancements in safety infrastructure and further implementations of safety regulations near highway-rail grade crossings in the past decade, incidents at these crossings still remain a significant safety concern. Studies show that vehicles at train crossings along with pedestrians walking on tracks contribute to 95 percent of all rail-related deaths (*Rail Safety*, n.d.). This brings to light the necessity for a more thoughtful and dynamic risk assessment model that not only accounts for constant variables such as the physical characteristics of the highway-rail grade crossings and train operations but by also considering the fluctuating traffic congestion of a big city and the meteorological factors of the region which can profoundly influence the safety dynamics involved at these crossings.

Existing models such as the Accident Prediction and Severity (*Web Based Accident Prediction Systems (WBAPS) | FRA*, 2019) model employed by the U.S. Department of Transportation, have been used to evaluate the incident risk at highway-rail grade crossings by primarily utilizing constant static variables such as the physical infrastructure characteristics of the crossings including the types of cross warnings, and by utilizing historical highway-rail grade incident data. While these models have had a substantial impact on the reduction of accidents at highway-rail grade crossings. They seem to often exclude very important region specific factors that could often have drastic and direct influence on safety at highway-rail grade crossings. The region specific factors for San Diego County that are essentially to consider are the varying vehicular traffic volume and frequency of trains per day for each crossing and the meteorological conditions of the county and its direct influence on visibility, traffic volume, road conditions, and human behavior. The variability introduced by meteorological conditions such as weather, which can range from sunshine to heavy rain, can transform a reasonably safe highway-rail grade crossing into a dangerous crossing within moments. This model aims to capture the dynamic interactions between meteorological conditions such as visibility, weather, time of day, and seasonal variations in sunlight, alongside the fluctuating volume of vehicle and train traffic to assess their direct impact on the likelihood of incidents at highway-rail grade crossings throughout San Diego county.

This research introduces a more thorough approach towards mathematically modeling highway-rail grade crossing incident risk by integrating a Meteorological Impact Score (MIS) to dynamically affect the variables used to determine the overall risk score associated with a specified highway-rail grade crossing. The MIS is a sub-model that is incorporated into the overall model to help us determine the effects of meteorological factors such as visibility, weather, time of day, and seasonal variations in sunlight. Using this new innovative approach, the MIS sub-model can dynamically influence the variables used to determine the risk score associated with the highway-rail grade crossing based on real-time weather data or forecasted weather data. Thus this approach incorporates a vital variable in highway-rail grade crossing incidents which previous models often overlooked or failed to do. This allows the model to help predict potentially hazardous risk scores for certain highway-rail grade crossings based on incoming forecasted inclement weather.

Furthermore, in addition to dynamically incorporating the meteorological impact of San Diego county, it is essential to understand the impact of both vehicular traffic and train volume and their influence on the likelihood of incidents at these critical intersections of our complex transportation network. As indicated in a study (*Rail Safety*, n.d.) that suggests that traffic volume is a major factor in accident frequency, it is essential to incorporate this crucial variable in such a highly congested city such as San Diego thus this model makes sure to account for the fluctuation in the volume of traffic utilizing each highway-rail grade crossing. This approach allows for a more reliable and accurate assessment of potential incident risk at highway-rail grade crossings in San Diego County specifically.

This type of model could be used in urban planning applications to improve transportation network efficiency or safety, while also serving as a useful tool for first responders to mitigate incidents. For instance, this model could be utilized by emergency response teams to help determine high risk incident zones based on forecasted weather reports and the assumed daily traffic volume. This would allow emergency response teams to reduce their response time for incidents that occur at highway-rail grade crossings or set-up preventative safety measures to help mitigate the effect of traffic volume and meteorological conditions at highway-rail grade crossings. Additionally, the county of San Diego could employ extra safety measures at certain crossings at definite times of the month or year based on the impact of meteorological factors alongside increased traffic volume. These are just a few of many useful cases in which this model could potentially create a substantial impact on the safety of San Diego.

This model incorporates many interesting factors that are often overlooked in highway-rail grade crossing incident models, most uniquely, meteorological factors. At the beginning development stages of the model, much of the inspiration came from the fact that San Diego had had the most rainfall in 2023 than it did in the previous four years (*TimeAndDateAS San Diego*, n.d.). The torrential downpour of rain in San Diego County throughout 2023 alongside the author's personal fascination with passenger rail lines inspired the creation of this model.

Model Description:

As previously noted, in the field of highway-rail grade crossing safety improvement and analysis the Accident Prediction System (APS) developed by the U.S. The Department of Transportation and The Federal Railroad Administration has been a fundamental cornerstone towards reducing highway-rail grade crossing incidents in the past few decades since its deployment in 1986 (*New Model for Highway-Rail Grade Crossing Accident Prediction and Severity | FRA*, 2020). Following the creation and implementation of the APS model, highway-rail grade crossing incidents declined significantly in the following few decades (*New Model for Highway-Rail Grade Crossing Accident Prediction and Severity | FRA*, 2020) due to the increase in awareness of high risk incident zones and being able to allocate resources towards improving safety at those crossings. While this model has proved to be very useful towards improving safety at rail grade crossings, it has an achilles heel that should not be ignored. The APS model relies heavily on historical accident data and existing highway-rail grade crossing data, while this can be useful, it fails to account for many real world fluctuating factors that can directly impact safety conditions at the crossings, such as dynamic weather changes and the complex flow of traffic. This model hopes to address those limitations of existings models used to predict incidents at highway-rail grade crossings using a number of dynamically integrated variables that are often overlooked.

The first step towards addressing those limitations was to begin evaluating which factors contribute significantly towards highway-rail crossing incidents in San Diego County. Specifically, identifying what region specific variables and fluctuating conditions have the most impact on incidents occurring at these crossings throughout the county. There were many potential regional factors in San Diego county that warranted consideration such as, the variation in geography of the county, fluctuations in tourist and seasonal population, potential flood zones or unstable cliff areas that could disrupt certain roadways and rail lines among other variables.

After extensive analysis it became evident that among the plethora of regional factors, meteorological conditions such as weather conditions, changes in visibility due to the time of day, seasonal variations in sunlight, and the mitigating effects of artificial light potentially had a significant impact on the likelihood of incidents at highway-rail grade crossings. Furthermore, our model also integrates the dynamic influence of road traffic and rail traffic volume, taking into account the Average Annual Daily Traffic (AADT) and Total Daily Trains(TDT), which reflect the crossing exposure levels at each highway-rail grade crossing in San Diego. Thus to adequately capture the dynamics of these regional factors alongside physical characteristics of highway-rail grade crossings, our models approach was to compose a comprehensive model that integrates a Meteorological Impact Score (MIS) sub-model into the overall model that considers the physical characteristics, safety features and crossing exposures levels of highway-rail grade crossings.

Meteorological Impact Score (MIS) Sub-Model:

$$\textbf{Meteorological Impact Score (MIS)} = V_{\text{illuminated}} + W$$

The Meteorological Impact Score (MIS) sub-model is designed to assess the impact of meteorological conditions on the safety of San Diego county. The MIS dynamically integrates three critical environmental factors: Visibility, Crossing Illumination, and Weather. This model's innovative approach allows for the ability to adjust the MIS based on the time of day, season, weather conditions, and through the presence of artificial illumination.

The first factor we consider in our MIS sub-model is the visibility variable (V_{rating}) which is a fundamental component of our sub-model. The visibility V_{rating} is categorized into four ranks based on the natural lighting conditions present at the crossings; these ranks are Dawn, Day, Dusk, and Dark and they each reflect a different phase of natural lighting and are given an associated score based on their analyzed impact on safety. To correctly capture the complexity of sunlight through the seasons, the model considers the average sunrise and sunset times for each month to detect the range for "Day" and "Dark" ranks on that particular day. While also taking into account the nautical twilight phases which occur when the sun is between 6 and 12 degrees below the horizon, which signifies the "Dusk" and "Dawn" periods of twilight that occur right before sunrise and right after sunset. This allows for an accurate categorization of the (V_{rating}) based on the specific month and time of day.

In addition to considering the fluctuation in sunlight based on the month and time of day it was also imperative to consider the direct mitigating effects of artificial illumination at these highway-rail grade crossings. Many of these highway-rail grade crossings make use of artificial light to illuminate the crossings which can be especially useful during low vision conditions. This is why our model utilizes an adjusting visibility variable ($V_{illuminated}$) that can capture direct dynamic effects of artificial light on visibility. Because there was not any relevant data pertaining the specific kinds of artificial light that could be employed at crossings in San Diego county, our model took a more basic approach and assigned one value to all artificial crossing illuminations

$$V_{\text{Illuminated}} = \begin{cases} 0 & \text{if } I = 1 \text{ (Crossing Illuminated)}, \\ V_{\text{rating}} & \text{if } I = 0 \text{ (Crossing NOT Illuminated)} \end{cases}$$

If a crossing is illuminated (i.e. I = 1), the visibility score is adjusted to account for the mitigating effects of the artificial light. This adjusts the visibility to a score of zero which effectively changes the viability rating to optimal visibility with no impact on our MIS. On the contrary, if a specified highway-rail grade crossing lacks artificial crossing illumination then, $V_{illuminated}$ is equal to the amount of natural light at the crossing that was given by the original visibility rank (V_{rating}) which is determined by the month and time of day.

Lastly, the third critical factor that is integrated in our Meteorological Impact Score (MIS) Sub-Model is the weather (W) variable. Its very intuitive to understand the implications that adverse weather could have an many aspects of highway-rail grade crossing safety, including the visibility, the number of drivers, the actual physical dynamics in stopping changing due to the road and rail conditions being affected by rain or other adverse weather conditions which can be seen in research (*Weather and the Safety of U.S. Railways**, 2023). Therefore, based on thorough analysis and consideration of San Diego counties' ordinary weather patterns the model categories weather into three specific conditions; Clear, Cloudy, and Rainy, which are each assigned a value to signify its direct impact on highway-rail grade crossing safety.

This innovative approach in the MIS sub-model ensures that our model can adapt to real-time weather changes, or potentially forecasted weather conditions. Next our model will integrate this sub-model into the overarching model to illustrate the meteorological impact on highway-rail grade incident variables.

Meteorological-Adjusted Risk Calculator Model (MARC):

$$MARC = e^{((a(1+MIS\cdot x_1)\cdot(M-B))+b(CE_M)-c(W\cdot(1-MIS\cdot x_3)))}$$

Where:

MIS = Meteorological Impact Score

M = Average Typical Maximum Speed of Trains at the crossing.

CE = Crossing Exposure, where $CE = (AADT * TDT) CE = (AADT * TDT)$

CE$_M$ = Meteorologically Adj. Crossing Exposure, where $CE_M = (AADT \times TDT) \cdot (1 - \frac{MIS}{x_2})$

AADT = Average Annual Daily Traffic.

TDT = Total Daily Trains.

W = Warning Type at each crossing.

B = Baseline speed determined by analysis of rail grade crossings in San Diego County.

a,b,c,d = Coefficients that have been determined through model calibration.

x_1, x_2 = Adjustable coefficients that can be adjusted to account for the regional impact of meteorological effects. (Used to calibrate weather impact specifically for San Diego County)

The Meteorological-Adjusted Risk Calculator (M.A.R.C.) Model utilizes the foundation laid by the Meteorological Impact Score (MIS) sub-model and incorporates it dynamically into our overarching model to assess the overall risk at highway-rail grade crossings in San Diego County. This integration of MIS into our M.A.R.C. model allows for a refined approach that incorporates the meteorological conditions' direct affect on the safety factors of these highway-rail grade crossings in conjunction with the physical and operational characteristics and the fluctuating traffic and train volumes.

First, our Meteorological-Adjusted Risk Calculator (M.A.R.C.) model needed to consider the impact of several key physical and operational features pertaining to the highway-rail grade crossings. The key factors our research determined to be the most impactful and accessible was for one, the Average Typical Maximum Speed of Trains (M); this factor plays a vital role in determining the impact of train speed and crossing safety. This is because not only does the speed have a direct impact on the amount of time the drivers have to cross but it is evident that rail and road safety can also be impacted by weather conditions as described in a couple studies (*Weather and the Safety of U.S. Railways**, 2023) (*New Model for Highway-Rail Grade Crossing Accident Prediction and Severity | FRA*, 2020). Also as indicated by research, incident risk has an exponential relationship with speed (*The Mathematical Relation Between Collision Risk and Speed; a Summary of Findings Based on Scientific Literature*, n.d.). Thus it was imperative to indicate this in the model to demonstrate that small changes in speed after a certain threshold can lead to significant changes in collision risk especially when they are impacted by meteorological conditions.

Furthermore, the M.A.R.C. model also considers factors such as the type of cross warning (W); this variable is crucial as it represents the safety mechanisms employed at each highway-rail grade crossing that are installed specifically to mitigate safety incidents and influence the behavior of pedestrians, vehicular traffic, and rail operators. For our model to accurately assess the effectiveness of each cross warning device, we categorized the type of warning device for the highway-rail grade crossings into four categories; Highly Effective, which includes warning devices such as gates or physical barriers; Moderately Effective, encompassing warning devices like cantilevers, standard FLS (flashing light signals), and audible warnings; Minimally Effective, which includes warning devices such as crossbucks and stop signs, and lastly, No Effect, which represents the absence of warning devices at the crossing. Each category of cross warning is assigned a score that impacts the overall risk assessment of the highway-rail grade crossings. This is vital because previous models have indicated cross warning devices have a direct and substantial impact on highway-rail grade crossing incidents (*New Model for Highway-Rail Grade Crossing Accident Prediction and Severity | FRA*, 2020). Lastly, our Meteorological-Adjusted Risk Calculator (M.A.R.C.) model incorporates the Annual Average Daily Traffic (AADT), and the Total Daily Trains (TDT) as part of the Crossing Exposure (CE) variable in the model. These factors are essential in determining the amount of exposure between pedestrians, vehicular road traffic, and trains. This is paramount because research suggests that incident risk increases with increased exposure at highway-rail grade crossings (*New Model for Highway-Rail Grade Crossing Accident Prediction and Severity | FRA*, 2020). The Crossing Exposure variables calculates the exposure level by taking the Annual Average Daily Traffic (AADT) and considering the direct impact of meteorological factors on the daily traffic volume of the crossing, and then multiplying that by the Total Daily Trains (TDT) which represents the number of trains passing through the specified crossing. The rationale for including the annual average daily traffic is based on the assertion that increased vehicular traffic volume at a crossing increases likelihood of incidents between vehicles, pedestrians, and trains because of the increased interactions at the crossings. Similarly the Total Daily Trains serve as a direct indicator of rail traffic, and just as with vehicular traffic, higher frequencies of trains amplifies the chances of an incident occurring at the crossing. This dynamic representation of the daily activity of the highway-rail grade crossing through the crossing exposure variable (CE) allows for a valuable and comprehensive variable that directly emphasizes the critical role of traffic volume in determining risk assessment within the M.A.R.C. model.

Additionally the coefficients a,b,c, and d are calibrated based on empirical data to ensure that each variable within our M.A.R.C model is accurately weighted according to its impact on highway-rail grade crossing safety. While the x_1,x_2 variables act as calibration coefficients, they fine-tune the model's receptiveness to the unique regional traits and weather on crossing safety within that region by adjusting the impact of the MIS sub-model. In our research we specifically calibrate it to account for the regional meteorological impacts of San Diego County and its influence on highway-rail grade crossings. Thus this model can dynamically adjust to real-world conditions, setting our model apart from previous more statistical approaches.

Data:

The development and refinement of our dynamic model for assessing the meteorological impact on highway-rail grade crossing safety relied heavily on the extensive datasets that were derived from multiple reliable sources, most significantly from the U.S. Department of Transportation and the Federal Railroad Administration (FDA) alongside environmental data provided by Time and Date AS. The primary datasets utilized from the U.S. Department of Transportation and the Federal Railroad Administration include the Crossing Inventory Data Form 71, The highway-rail grade crossing accident data form 57, and the use of the Web-Based Accident Prediction System (APS). These datasets provided a multitude of information on the physical characteristics of rail crossings, historical incident data, meteorological conditions, and the fluctuating volume of traffic. While the dataset provided by Time and Date AS allowed us to determine the monthly and daily fluctuation in sunlight and weather patterns in San Diego county.

Among the primary datasets used, the Crossing Inventory Data (Form 71) (*Crossing Inventory Data Form 57*, 2009) dataset provides details regarding the physical characteristics and safety features of each highway-rail grade crossing in San Diego county including the Annual Average Daily Traffic, Average Train Speeds, Average Maximum Speed over crossing, and details pertaining to the physical safety features such as the types of cross warnings and artificial illumination and the number of lanes both traffic and rail lines. This is crucial in determining the baseline risks related to the physical infrastructure and safety measures employed at these crossings.

Similarly the Highway-Rail Grade Crossing Accident Data (Form 57) (*Highway-Rail Grade Crossing Accident Data*, n.d.) supplied an extensive dataset regarding all Highway-Rail Grade Crossing Accidents within the entire continental U.S.. The dataset provides records of accidents at rail-grade crossings going back to over a half century. While this plethora of data could be useful, our model only considers the last ten years of historical accident data, specifically for San Diego county to allow for a better understanding of highway-rail grade crossing incidents within the county in the past decade. The choice to go back 10 years was primarily due to many improvements in safety features that have been implemented in the past decade . Alongside the consideration that similar existing models such as the APS also only access incident data from the last ten years to consider recent improvements in physical safety features and safety regulations.

In addition, our model also utilized the data provided by Web-Based Accident Prediction System (APS) (*Web Based Accident Prediction Systems (WBAPS) | FRA*, 2019). The Web Based APS or WBAPS, is a predictive analytical tool that ranks Highway-Rail Grade crossings based on the expected collisions. This tool utilizes a combination of historical inventory data along with a ten year collision history to determine the rank of each crossing. While WBAPS ranks all the highway-rail grade crossings within the entire continental U.S, our model only focuses on San Diego county so our model only acknowledges the data associated with San Diego county in the past ten years. This dataset was a useful tool to determine the accuracy of our model and validate the findings in our model's risk identification capabilities.

Lastly, the data provided by the Time and Date AS (*TimeAndDateAS San Diego*, n.d.)served as a critical dataset in determining the meteorological impact on Highway-Rail Grade Crossing incidents. The Time and Date AS website provided regional sunlight information pertaining to San Diego County. In order to capture the average timespan for each visibility category, our research analyzed the data to consider the fluctuation of natural light to allow for a dynamic variable that can change depending on the visibility at the time of the year and day that the model chooses.

Average Monthly Timespan of Each Visibility Category:

Month	Dawn	Day	Dusk	Dark
January	5:54 am - 6:50 am	6:50 am - 5:05 pm	5:05 pm - 6:02 pm	After 6:02 pm, Before 5:54 am
February	5:37 am - 6:31 am	6:31 am - 5:34 pm	5:34 pm - 6:28 pm	After 6:28 pm, Before 5:37 am
March	6:05 am - 6:59 am	6:59 am - 6:56 pm	6:56 pm - 7:49 pm	After 7:49 pm, Before 6:05 am
April	5:23 am - 6:19 am	6:19 am - 7:18 pm	7:18 pm - 8:14 pm	After 8:14 pm, Before 5:23 am
May	4:50 am - 5:49 am	5:49 am - 7:40 pm	7:40 pm - 8:40 pm	After 8:40 pm, Before 4:50 am
June	4:36 am - 5:40 am	5:40 am - 7:58 pm	7:58 pm - 9:01 pm	After 9:01 pm, Before 4:36 am
July	4:49 am - 5:51 am	5:51 am - 7:57 pm	7:57 pm - 8:59 pm	After 8:59 pm, Before 4:49 am
August	5:15 am - 6:12 am	6:12 am - 7:33 pm	7:33 pm - 8:30 pm	After 8:30 pm, Before 5:15 am
September	5:38 am - 6:32 am	6:32 am - 6:54 pm	6:54 pm - 7:48 pm	After 7:48 pm, Before 5:38 am
October	5:59 am - 6:52 am	6:52 am - 6:15 pm	6:15 pm - 7:09 pm	After 7:09 pm, Before 5:59 am
November	5:22 am - 6:18 am	6:18 am - 4:47 pm	4:47 pm - 5:43 pm	After 5:43 pm, Before 5:22 am
December	5:45 am - 6:43 am	6:43 am - 4:44 pm	4:44 pm - 5:42 pm	After 5:42 pm, Before 5:45 am

The datasets provided by The U.S. Department of Transportation and the Federal Railroad Administration (FRA) are extremely reliable datasets as they are provided by and updated by government agencies in the United States. These datasets provided by The U.S. Department of Transportation and the FRA are updated monthly. In addition, train conductors are required to submit an incident report any time an incident occurs on the rail lines. This allows for constant modernizing and improving of data. Similarly, the Time and Date AS is also updated monthly. This dataset is also considerably reliable as it contains a multitude of datasets for different meteorological conditions. Our research specifically focused on the meteorological data in San Diego which was easily accessible through the Time and Date AS dataset. The Time and Date AS began collecting data and providing datasets online beginning in 1995 (*TimeAndDateAS San Diego*, n.d.), proving this data is fairly reliable and robust.

Analyze Model:

The model needed to somehow quantify the impact of meteorological conditions on the many variables that influence rail grade crossing safety. Therefore, our MIS sub-model consists of two primary variables which are visibility and weather.

Visibility(V_{rating}):

Our first variable which is visibility was categorized into four ranks, which were then each assigned a numerical value reflecting the typical light conditions they represent; 'Dark' is given a score of (1.00), acknowledging the highest impact on vision due to lack of light and the visual impairment on vision. 'Dawn' and 'Dusk' are both ranked closely to 'Dark' with an impact score of (0.90). This score is attributed to the suboptimal lighting conditions during these times. 'Dawn' and 'Dusk' both occur when the lighting conditions are adjusting considerably and this can affect the vision in many ways such as sun glare and reduced light. On the contrary, 'Day' suggests complete daylight and no impact on vision thus it suggests the least risk with a score of (0.0).

Also, to further provide a more accurate model when assessing the impact of different amounts of sunlight on visibility, our model uses the average sunrise and sunset times along with the nautical twilight hours of each month to define the time spans for Day, Dusk/Dawn, and Dark. These adjusted time spans are crucial for assessing visibility at these crossings because depending on the time of the year such as in December, the sun can set as early as 5pm in San Diego.

Weather(W):

The weather variable was also categorized and ranked into three ranks to reflect the impact of the typical weather conditions in San Diego county. Each condition was assigned a score based on the determined meteorological impact on safety at crossings. 'Clear' is given a score of (0.0) and this represents the absence of any inclement weather suggesting no impact on safety at highway-rail grade crossings. 'Cloudy' conditions, which represents overcast skies may slightly hinder the visibility conditions and the drivers ability to notice certain physical safety features such as stop signs. The final condition is 'Rain' which can significantly affect visibility, along with road traction, and driver behavior. Because of the multitude of factors rain can influence it has the highest weather-related risk score with a (.25), recognizing its substantial potential to escalate incident likelihood.

Below the MIS combines these components to create a cumulative score, formulated as:

$$\textbf{Meteorological Impact Score (MIS)} = V_{\text{illuminated}} + W$$

Where $V_{illuminated}$ represents the adjusted visibility score in case of the existence of artificial lighting, and W is the weighted score of the weather conditions.

Whereas the overarching model, the Meteorological Adjusted Risk Calculator (M.A.R.C) model, dynamically calculates the risk at highway-rail grade crossings by integrating in the MIS sub-model along with the physical safety features and traffic volume variables.

The M.A.R.C model variables consist of the MIS Score, Crossing Exposure (CE_M), Max Speed of Train (M), Baseline Speed(B), Cross Warning Type (W), along with the coefficients a, b, c, x_1, x_2, and x_3.

Below is the M.A.R.C. exponential function that displays the relationship between variables:

$$MARC = e^{((a(1+MIS \cdot x_1) \cdot (M-B)) + b(CE_M) - c(W \cdot (1-MIS \cdot x_3)))}$$

Including the impact of the MIS score from the sub-model.

Crossing Exposure (CE_M):
This variable is a critical component of the model because it quantifies the potential interaction between vehicles and trains at each crossing. It's calculated by considering the Average Annual Daily Traffic (AADT) and Total Daily Trains (TDT), reflecting the potential frequency of conflict events between these two modes of transportation. The model also considers the meteorological impact on the crossing exposure at each crossing, thus using our MIS score and our calibration coefficient x_2 we can reduce the amount of driver/train interactions based on the assumed impact that certain meteorological conditions can have on the traffic volume for each region.

$$CE_M = (AADT \times TDT) \cdot (1 - \frac{MIS}{x_2})$$

Max Speed of Train (M):
This is the maximum speed limit on trains at the crossing. This is crucial to determine the potential danger there is associated with higher speed versus lower speed trains. We are under the assumption that higher speeds generally increase the risk of incidents due to a reduced reaction time for both trains and drivers.

Baseline Speed (B):
This is just a baseline speed used to normalize the rain speeds across various crossings. This was determined to be 5 M.P.H. as it could be assumed that most incidents are avoidable at those speeds under most meteorological conditions.

Cross Warning Type (W): $MARC = e^{((a(1+MIS \cdot x_1)\cdot(M-B))+b(CE_M)-c(W\cdot(1-MIS\cdot x_3)))}$

Including the impact of the MIS score from the sub-model.

Crossing Exposure (CEM):
This variable is a critical component of the model because it quantifies the potential interaction between vehicles and trains at each crossing. It's calculated by considering the Average Annual Daily Traffic (AADT) and Total Daily Trains (TDT), reflecting the potential frequency of conflict events between these two modes of transportation. The model also considers the meteorological impact on the crossing exposure at each crossing, thus using our MIS score and our calibration coefficient x2 we can reduce the amount of driver/train interactions based on the assumed impact that certain meteorological conditions can have on the traffic volume for each region.

$$CE_M = (AADT \times TDT) \cdot (1 - \frac{MIS}{x_2})$$

Max Speed of Train (M):
This is the maximum speed limit on trains at the crossing. This is crucial to determine the potential danger there is associated with higher speed versus lower speed trains. We are under the assumption that higher speeds generally increase the risk of incidents due to a reduced reaction time for both trains and drivers.

Baseline Speed (B):
This is just a baseline speed used to normalize the rain speeds across various crossings. This was determined to be 5 M.P.H. as it could be assumed that most incidents are avoidable at those speeds under most meteorological conditions.

Cross Warning Type (W):
This variable is vital in determining the physical safety features and their impact on reducing incidents. The Cross Warning types are categorized into four groups and each assigned a score based on their analyzed and researched impact on incident reduction. The first category 'High Effect' which includes physical crossings or barriers such as gates. 'High Effect' cross warnings are given a score of (0.5), which can significantly reduce the likelihood of incident risks at crossings. Next, the 'Moderate Effect' category given a score of (0.25) includes physical safety features such as Cantilevers, Standard Flashing Light Signals (FLS), and Highway Traffic Signals. These are any device that provides visual and auditory alarms about approaching trains. These are effective safety devices but they do not physically provide any prevention and thus are not as effective as physical barriers. We also have to consider the 'Minimal Effect' category scored at (0.1), which includes crossbucks and stop signs. These are passive safety devices whose effectiveness relies entirely on the drivers ability to visualize and comprehend the sign. Thus they are considerably less effective then the previous categories but they are still substantially better than no safety measures. Which leads us to our final category, 'No Effect' which represents a crossing without any crossing warning device. In the absence of a warning device, there would be no mitigating effects on the crossing risk level.

Discussing the coefficients:

$$MARC = e^{((0.005(1+MIS\cdot(2))\cdot(M-5))+0.000001(CE_M)-0.05(W\cdot(1-\frac{MIS}{5})))}$$

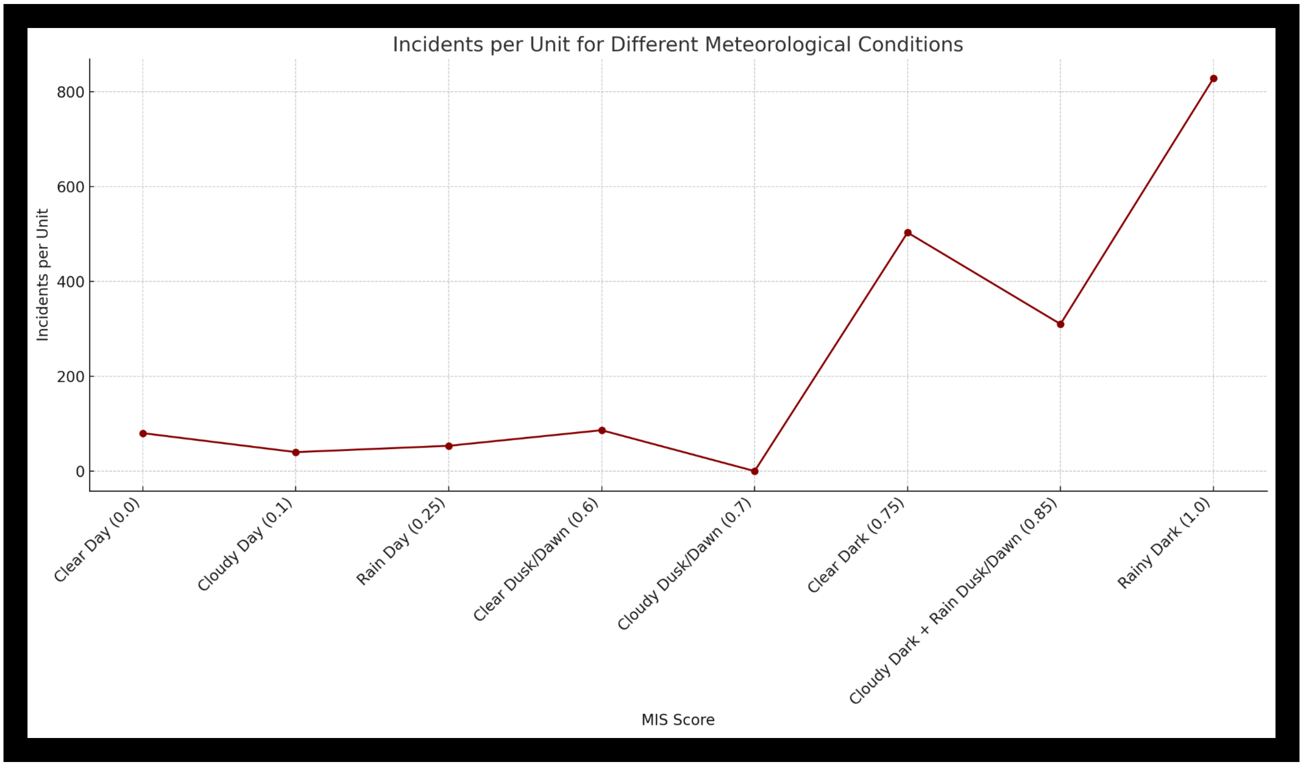
a,b,c coefficients as seen above were used to weight the relative influence of the speed component of the model, the crossing exposure, and crossing warning type relative to each other. Our model used regression analysis on existing incident data to determine the impact of each of these coefficients and determine the impact on each portion of the function. For our speed component, our coefficient 'a' was chosen to be (0.0005) to calibrate the model to account for the overall speed risk impact on the MARC score. Similarly, for our crossing exposure, because of the potential for extremely large exposure values and utilizing the data from regression analysis to best fit the model we determined that the coefficient 'b' should be (0.000001). And lastly, for our cross warning device segment of our function we used partial assumption along with analysis to determine that our 'c' coefficient should be (0.05) to account for the reduction in risk that is introduced by the cross warning devices.

Comparably, the x_1, x_2, and x_3 coefficients which are used to calibrate the model for regional data were based on research along with educated hypotheses. For instance, the x_1 coefficient which modulates the influence of MIS on the train speed component of the function was determined to be (x_1=2), this is because we hypothesized that inclement weather would have a fairly substantial impact on speed related risks and driver safety at crossings. While the value for x_2 coefficient is (x_2=50) this is because while weather can affect exposure volumes due to the fairly mild weather in San Diego the meteorological impact was determined to be less impactful then compared to the speed component. And finally, to accurately calibrate the model's cross warning component, it was determined that the x_3 coefficient is (x_3=5). This reflects that there is a modest impact on the effectiveness of cross warning devices. This is because inclement weather can reduce the ability to visualize or hear many of the cross warning devices and thus can be quite impactful in reducing the effectiveness of these safety measures.

Results:

After running the model through a few different simulations in python it was determined that different meteorological conditions, especially inclement weather and darkness can have a significant impact on the overall incident risk associated with a crossing.

Utilizing the MIS sub-model along with incident data from the past ten years and frequency of weather conditions, the model was able to determine that clear and daylight conditions resulted in lowest incident rates, which is expected given the optimal visibility. While, the incident rates climbed significantly under dark and rainy conditions. Which emphasizes the heightened risk associated with inclement weather and poor visibility.



Similarly, the M.A.R.C. further solidifies the results for the MIS sub-model. After simulating the M.A.R.C. model in two different python programs, one that runs a simulation to determine the M.A.R.C. score of a particular crossing under different MIS scores or meteorological conditions to determine the impact of MIS on the over risk assessment score. First when graphing the exponential function with crossing exposure as the x-axis, our results indicated that the M.A.R.C. score increases along with the growth of the crossing exposure (CE). Thus to now determine the impact of meteorological conditions on our overarching risk assessment calculator we ran a simulation. The simulation simulates different fluctuating MIS values for a particular crossing. The simulation demonstrated that when there are inclement weather conditions the M.A.R.C. score significantly increased even when the CE level remained the same. This suggests that poor weather conditions amplify the inherent risks, possibly turning crossings with moderate risk into possible hot-spot zones that are high-risk.

Conclusion:

The outcomes of this model clearly demonstrate that meteorological conditions, including weather and visibility, alongside the effects of crossing exposure volumes, significantly influence the risk levels at highway-rail grade crossings. The results showed that lower MIS scores, which are indicative of clear and moderate weather conditions, have a discernible but controlled impact on safety due to optimal lighting conditions and more predictable traffic conditions. On the contrary, the risk associated with higher MIS scores, which are reflective of inclement weather showed a substantial increase in risk escalation or M.A.R.C. score. Indicating that severe weather conditions greatly exacerbate safety risks at highway-rail grade crossings.

This research and model demonstrate the critical need for a dynamic risk assessment model that goes beyond static variables such as physical safety characteristics and historical data, to include real-time forecasted meteorological conditions and traffic volume.

There are several improvements that could be made to improve the accuracy and relevancy of the M.A.R.C. model. For example, to further enhance the predictive accuracy of the model we could corporate real-time traffic data and the number of active trains or cars by the hour. Additionally, considering further meteorological variables that are customary to the region such as wind speeds or sea fog which is extremely common in San Diego county especially along the coastline where many rail lines reside. Moreover, including pedestrian traffic data along with driver decision making predictions could improve the risk assessment capabilities of this model. Finally, having an expert's opinion on meteorological impacts on traffic could help calibrate the model to be more accurate and relevant would be extremely useful. Overall these improvements would not only enhance the predictive capabilities of the model, but also broaden its applicability and utility in improving highway-rail grade crossing safety in a multitude of ways.

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