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Reducing Wet-Pavement Related Crashes: A Fuzzy Logic Approach

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ABSTRACT

This paper presents a fuzzy-logic model for predicting the risk of crashes that occurs on wet pavements. The statistical methods that have been used to predict wet-pavement crashes have been found inadequate due to the difficulty expressing the mathematical concepts involved with wet-pavement crashes and the uncertainty and fuzziness associated with the factors involved. Fuzzy logic model was adopted because it is easy to understand, tolerant to imprecise data, can model nonlinear functions of enormous complexity, and can be built on the experience of experts. The developed fuzzy logic model was based on the widely used Mamdani's fuzzy-inference method. The model uses skid number, speed differential, traffic volume, and driving difficulty as input variables and the number wet-pavement crashes as the output variable. The results of the prototype indicate that the fuzzy logic model performs very well, even with the limited and imprecise data available.

1. INTRODUCTION

Wet-pavement crashes occur when a vehicle's wheels lock up during braking or cornering maneuvers, leading to loss of the vehicle's directional stability. They are the result of a variety of factors from reduced tire/pavement friction to vehicular, roadway, human, and environmental factors. How to predict and prevent the occurrence of wet-pavement crashes are some of the main issues facing highway departments, especially concerning the allocation of funding. The methodologies used in identifying road sections that are in need of improvements to prevent wet-pavement crashes are the analysis of crash statistics or measurement of pavement skid resistance. Both methods have major deficiencies, the former requires that skid-related crashes occur and cluster at certain locations while the latter is not only difficult to measure but is only one of the many factors that affect wet-pavement crashes. Recent studies have found that pavement skid resistance is inadequate as it correlates very poorly with the number of wet-pavement crashes. Researchers have also found out that wet-pavement crashes are random events, and that their occurrences are related to a variety of vehicle, pavement, human, roadway, and environmental factors such as vehicle speed, road geometry, traffic density, percentage of trucks in the traffic flow, and wet-pavement exposure. The main objective of this paper is to develop a prototype fuzzy logic model for predicting wet-pavement crashes as a function of driver, vehicular, roadway, traffic, and environmental variables. Such prototype can evolve into a tool for identifying sections

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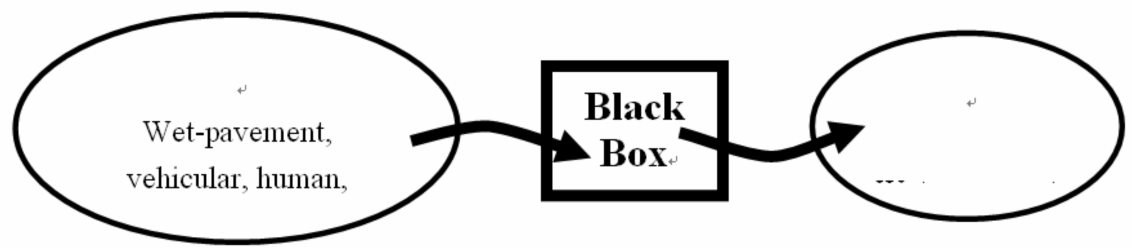
of roadway that are likely to have more wet-pavement crashes than normal for safety improvements.

2. WHY USE FUZZY-LOGIC MODEL

To justify the use of fuzzy logic for modeling the risk of wet-pavement crashes, consider Figure 1, which is mapping inputs to the appropriate outputs. In between the input and the output is a black box that does the mapping, i.e., the mechanism



underlying the system. This system could be fuzzy systems, linear systems, expert systems, neural networks, differential equations, interpolated multidimensional lookup tables, just to name a few of the possible options. It turns out that, of the different ways to make the black box work, fuzzy logic is the best.

FIGURE 1

Mechanism of Fuzzy Logic Model

Fuzzy logic is conceptually easy to understand. The mathematical concepts behind fuzzy reasoning are very simple. In addition, fuzzy logic is flexible. With any given system, it is easy to manipulate it or add more functionality on top of it without starting again from scratch. Fuzzy logic is tolerant of imprecise data and it builds on this understanding. Also, fuzzy logic can model nonlinear functions of greater complexity. You can create a fuzzy system to match any set of input-output data through adaptive techniques. Besides, it can be built on top of the experience of experts who already understand the system and can be blended with conventional control techniques to simplify their implementation.

The four primary factors that affect wet-pavement crashes and were selected as input variables for the fuzzy logic model are: pavement skid resistance (SN), speed differential (SD)—speed above the allowable speed limit, traffic volume (TV) in term of average daily traffic, and driving difficulty (DD). All of the input variables involve some degree of uncertainty, subjectivity, or fuzziness in their values because of its measurements or meaning. Skid resistance can be referred to as simply "high, medium, or low." The speed at which vehicles are traveling above the posted speed limit can be described as "high, medium, or low." Similar reasoning can be used to make a case for fuzziness of traffic volumes as "high, medium, or low." Driving difficulty is also fuzzy and can have a fuzzy meaning of low, medium, and high driving difficulty. The output variable from the system, number of wet-pavement crashes (WC) can be described in fuzzy terms of "high, medium, or low." This uncertainty or fuzziness is what makes a fuzzy logic model a suitable approach in this study. Very little knowledge of the system exists in the form of mathematical equations expressing the risk of wet-pavement crashes as a function of the input variables. On the other hand, there is considerable subjective knowledge in the form of information about the effects of the input variables on the output variable through years of research.

3. METHODOLOGY OF FUZZY LOGIC MODEL

There are two types of fuzzy inference systems, Mamdani-type and Sugeno-type. These two types of inference systems vary somewhat in the way outputs are determined. The Mamdani fuzzy logic model used in this study for estimating wet-pavement crashes is the most commonly used fuzzy methodology and was proposed by Ebrahim Mamdani in 1975, when he used fuzzy-control rules that were developed from experienced human operators to control a steam boiler based on the fuzzy-set theory formulated by Zadeh in 1973. The rules consist of a set of “if-then” rules.

Fuzzy inference is the process of formulating the mapping from given inputs to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves membership functions, fuzzy logic operators, and if-then rules. There are five parts of the fuzzy inference process:

- Fuzzification of the input variables
- Application of the fuzzy operator (AND or OR) in the antecedent
- Implication from the antecedent to the consequent
- Aggregation of the consequents across the rules
- Defuzzification.

3.1 Fuzzification of Input Variables

First, the inputs variables were examined to determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. This was done either through a table lookup or a function evaluation or from previous research. In designing the membership functions, we consulted the literature and previous research for more information on threshold values, shape of function, and sensitivity of the variables.

To fuzzify input and output domain, the number and quantification levels of each variable's membership function was estimated. A membership function is a curve that defines how each point in the variable space is mapped to a membership value between 0 and 1. In this study, the membership functions were built on three rules, and each of the rules depends on resolving the inputs into a number of different fuzzy linguistic sets: condition is low, condition is medium, and condition is high. The shape membership functions were selected from the point of view of simplicity, convenience, and efficiency. Trapezoidal and triangular membership functions were used as both are quite simple and have been used extensively in many applications. This choice of a particular shape for a membership function is a trade-off between accuracy and simplicity. Each of the input variables was fuzzified into three fuzzy sets: low, medium, and high and the membership functions are shown in Figure 2.

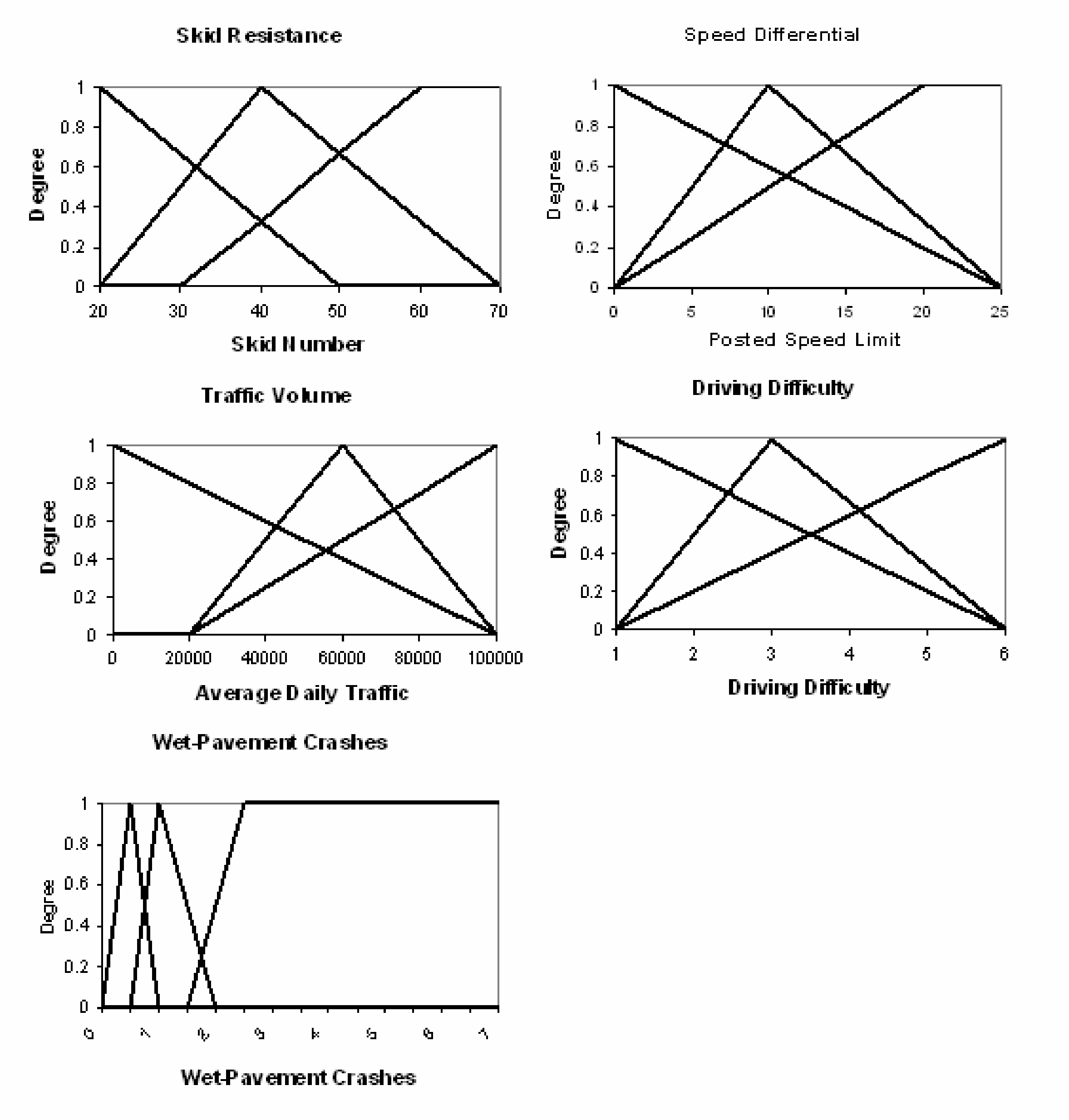


FIGURE 2
Membership Functions of the Input Variables

Skid Resistance

Skid resistance values are rarely accurate as they involve many factors that difficult to measure in the field. The most difficult parameter to estimate is the coefficient of friction between the tires of the vehicle involved in the crash and the pavement surface on which the crash occurred. The tire-pavement friction is affected by the type and condition of the vehicle tires, vehicle suspension, and vehicle load and load distribution. Water film thickness and pavement surface characteristics are also important factors that affect tire-pavement friction. The available friction depends on the pavement skid resistance which is a function of vehicle speed, road geometry, traffic characteristics, vehicle characteristics (including vehicle type and it's under steer), and driver skills. Whether or not this particular SN is high enough to prevent wet crashes cannot be determined unless the demand for friction on the section of road under consideration is known. If skid number is not available, a handbook value of the coefficient of friction is used. SN is measured at 40 mi/h. As skid number increases the pavement frictional characteristics improve. Results of skid resistance measurements provide the basis for pavement management safety decisions. In general, SN less than 30 are considered low and SN over 40 is considered acceptable. In this study, if the skid number is smaller than 30, the fuzzy value of skid resistance is low, and its degree of membership is 0.7 0r higher. At the same time, if the skid number is between 35 and 50, the fuzzy value of skid resistance is medium with 0.6 degree membership. In a similar way, the other input variables were fuzzified as well as the output membership functions.

Speed Differential

Speed is a critical factor for the balance between friction demands and supply because it: affects both. When speed increases, friction demand also increases. For instance, centrifugal forces generated during vehicle cornering must be counteracted by tire-pavement friction forces to prevent a vehicle from skidding off the road are proportional to the square of vehicle speed. At the same time skid resistance decreases with increasing speed in an approximately exponential manner. Posted speed limits serve to protect drivers under various environmental conditions. Therefore traveling over the speed limit under wet pavement conditions subjects the driver and vehicle to conditions that the road was not designed for, increasing risk of wet-pavement crashes. In this study, speed differential under 5 mph is considered low with member function of 0.8 or higher. Speed differential of 7 to 12 mph is considered medium with membership function of 0.8 or higher; 20 to 25 mph is considered high with membership function of 0.8 or higher.

Traffic Volumes

Traffic volume including its composition (cars, trucks, and buses) directly affects the number wet pavement crashes. In particular the percentage of trucks in the traffic flow has a significant effect on friction demand. This is because the stopping distances of trucks are 1.3 to 2.8 times longer than the stopping distances of passenger cars. In addition, drivers adjust for the presence of heavy vehicles by giving a larger lateral clearance and longer headway and at times driving faster or slower to avoid following or being followed by a heavy vehicle. The traffic volumes were expressed in average daily traffic (ADT). In designing the membership functions for traffic volume, ADTs under 40,000 vehicles per day is considered low with membership function of 0.8 or higher; ADT in the range 50,000 to 70,000 is considered medium with membership function of 0.8 or higher. ADT over 80,000 is considered high with membership function of 0.7 or higher.

Driving Difficulty

A number of conditions affect driving including but not limited to prevailing highway geometric, traffic volumes, traffic control devices, human factors, and conditions of the vehicle. As the roadway geometric conditions such as horizontal and vertical alignments become more restrictive, drivers slow down and exercise more caution. Also, narrow lanes force drivers to drive closer to one another than usual and adjust for this by driving slower arid observe longer headways. The impact of lateral obstruction also has a similar effect. The amount of driving difficulty required for safe driving is strongly affected by road geometry. Driving difficulty demand on straight sections of roads is very low if the road is level, if vehicles travel at constant speed, and if there are no intersections. The demand increases significantly if a grade or curve must be negotiated. In addition, researchers have determined that pavement crash rates are significantly higher on curves than on any other type of geometric alignment. The criteria determining driving difficulty include number of access points per segment of road, presence of turn lanes, type of surrounding land use, traffic signalization, and the roadway cross section. In addition to above-mentioned factors, lane distributions, lane use controls at intersections and on freeways also increases driving difficulty. All of these factors contribute directly to wet pavement crashes and are very difficult to quantify mathematically but can be modeled through fuzzy logic models. In this study, driving difficulty under 2 is considered low or easy with member function of 0.8 or higher; driving difficulty between 3 and 4 is considered medium with membership function of 0.8 or higher; driving difficulty of 5 or more is considered high with membership function of 0.8 or higher.

3.2 Application of Fuzzy Operators

Once the inputs were fuzzified, a fuzzy operator was applied to combine the antecedent of each rule to obtain one number that represents the result of the antecedent for that rule. It is this number that was applied to the output function. In other words, the input to the fuzzy operator is the four membership values from the fuzzified input variables, and the output is a single truth-value that is the weight of that rule. The weight of a rule is mathematically expressed as:

$$W_i = \mu_{sni} \wedge \mu_{sdi} \wedge \mu_{tvi} \wedge \mu_{ddi}$$

where, W_i = weight of Rule i

μ_{sni} = degree of membership of pavement skid resistance

μ_{sdi} = degree of membership of speed differential

μ_{tvi} = degree of membership of traffic volume

μ_{ddi} = degree of membership of driving difficulty

For example the four different pieces of the antecedent (skid resistance is good and traffic volume is low and speed is low and driving difficulty is low) may yield fuzzy membership values of say 0.1, 0.5, 0.3, and 0.7 respectively. The fuzzy AND operator simply selects the minimum of the four values, 0.1.

3.3 Implication of Rule

A three-rule fuzzy control system was designed based on experience and understanding of the system. All of the rules are evaluated in parallel using fuzzy reasoning (Figure 3). Before applying the implication method, we examined the rule's weight. Every rule has a weight, a number between 0 and 1, which is applied to the number given by the antecedent. Once proper weighting were assigned to each rule, the implication method was implemented. The input for the implication process is a single number given by the antecedent of a rule, and the output is a fuzzy set, a consequent represented by a membership function which is reshaped using a function associated with the antecedent, a single number. Implication is implemented for each rule using the AND method: minimum, which truncates the output fuzzy set, was used. The out of the implication method, mathematically is expressed as:

$$\Delta i = W_i A_i$$

where, Δi = Implication of Rule i

W_i = Weight of Rule i

Ai = Area of truncated membership function

3.4 Aggregation of Outputs

The decisions made from fuzzy logic models are based on the testing of all of the rules in a fuzzy inference system. Because there many rules involved, they must be combined in some manner in order to make a decision and that process is called aggregation. Through aggregation the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set and they occur once for each output variable. The input of the aggregation process is the list of truncated output functions returned by the implication process for each rule and the output of the aggregation process is one fuzzy set for each output variable. In Figure 3, all rules have been placed together to show how the output of each rule is aggregated, into a single fuzzy set whose membership function assigns a weighting for every output value. The aggregation process is mathematically expressed as:

$$\Delta = \sum \Delta i$$

where, $\Sigma\Delta i = W_i Ai$, the implication fired for Rule i.

3.5 Defuzzification

The input for the defuzzification process is a fuzzy set consisting of the aggregate output fuzzy set. The aggregate output fuzzy set encompasses a range of output values and so must be defuzzified in order to resolve a single output value from the set. The popular defuzzification method, the centroid calculation, which returns the center of area under the curve, was used in this study. Mathematically, the defuzzification process is express as:

$$Wc = \frac{\sum \Delta i}{\sum Wi}$$

where, Wc = percent of wet-pavement crashes

$\sum \Delta i$ = sum of all implications

$\sum W_i$ = the implication fired for Rule i.

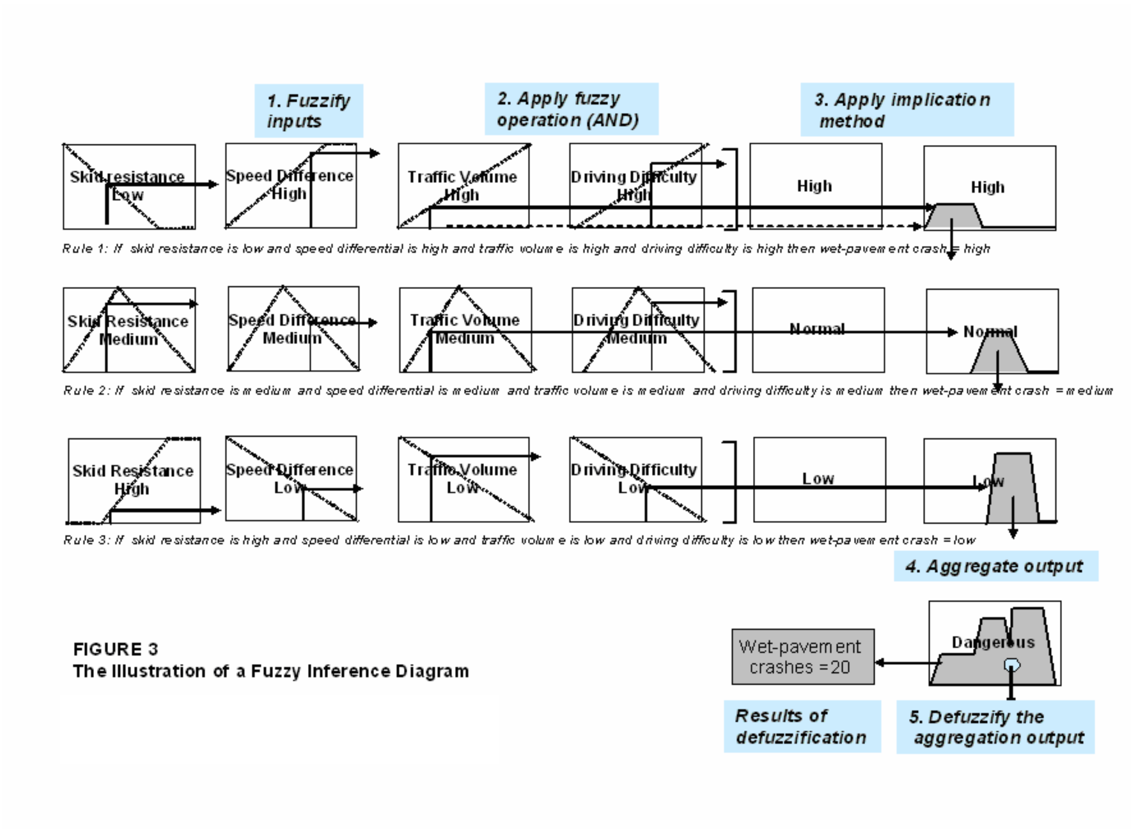


FIGURE 3
The Fuzzy Inference Diagram

4. DATABASE CONSTRUCTION

The data used in testing the fuzzy logic model this study came from the Department of Transportation highway crash database. The wet-pavement crashes were extracted along with other information such as speed of travel and class of road. Because the database did not include information on skid resistance and traffic volumes a proxy variable, road class, was used for traffic volume. It was also assumed that high-level road classes such as freeways and principal highways receive high priority maintenance and consequently their pavements have good skid resistance. Table 1 shows the distribution of wet-pavement crashes from the database. Each row total in Table 1 comprises of the total wet pavement crashes resulting from the total combinations of skid resistance, speed deferential, traffic volume, and driving difficulty. It must be emphasized that certain combinations of the input variables are impossible for certain row totals in Table 1. From Table 1, it can be seen that the higher class highways have lower wet-pavement crashes, even though, they have higher speeds—a direct result of the high maintenance priority that are assigned to those classes of roads. The results also reflect exposure of each road class in terms of mileage and vehicles miles of travel. The observed and expected number of wet-pavement crashes is shown in Table 2 where a close examination shows some association among the wet-pavement crashes with speed and road class.

5. EXPERIMENTAL DESIGN

Because of the association and randomness of wet pavement crashes, it would be inappropriate to apply one fuzzy logic model to model the four classes of road. A separate model has to be developed for each road class or some kinds of factors must be used to extend one fuzzy logic model to the other road class. In this study, the factorization approach was used. The developed factors reflect exposure in terms of miles of road in each class of road, the relative degree of difficulty in driving on each class of road, the amount of traffic that use each class of road, and many others that are embedded in the wet-pavement crash data. Using the results in Table 1, the following conversion factors, presented in Table 3, were developed for each road class. With is in mind, the fuzzy logic model was developed and customized for freeways. Thus, the fuzzy logic model developed represented crashes on Freeways for which a factor of 1.0 is associated. The fuzzy logic model predicts wet-pavement crashes for each combination of the input variables. An experimental design was used to set up the input variables. Using 3 membership functions (low, medium, and high) for each of the four input variables will results in 81 different cells shown in the Table 4 in the Appendix. The 81 different combinations cover all the conditions that can be expected for each road class. The sum of the wet-pavement crashes (output) in the 81 cells gives the estimate of wet-pavement crashes for Freeways. To estimate the total crashes for the other road classes, the appropriate factor is applied to the freeway estimate to convert it.

6. RESULTS AND DISCUSSION

The plot of the observed and expected wet-pavement crashes is shown in Figure 4. The observed and expected crashes do not correlate, showing randomness in wet-pavement accidents. Statistically, using the Chisq test statistic indicates that the crash data shows some kinds of associations between the observed crashes and the variables speed and road class. Higher-class roadways usually have lower wet-pavement crashes due to the high maintenance priority they receive. Exposure in terms of miles of road in each class of road, the relative degree of difficulty in driving on each class of road, the amount of traffic that use each class of road, and many others that are embedded in the observed wet-pavement crash data. The results of the fuzzy logic model are presented in Table 5 in which the predictions of the fuzzy logic model and the corresponding observed numbers of wet-pavement crashes are presented. The predictions have a relatively good correlation with the observed numbers of wet-pavement crashes. Figure 5 show the surface view of the fuzzy logic model for freeways under various axes. The surface view provides the full spectrum of the relationships between the input variables and the output variable and can be used to examine the sensitivity of the model.

7. CORRECTIONAL STRATEGIES

One of the objectives of this research is to develop recommendations for efficient and effective ways of improving the safety conditions for wet-pavement crashes. To evaluate these correctional strategies quantitatively, a sensitivity analysis was carried out. To see how each input variable affects the safety of the roadway, one of the input variables is varied over a certain range each time, and the rest controlled. Through this technique, the effect of each variable can be examined and its impact on reducing wet-pavement crashes. It is therefore not difficult to choose an effective and efficient way to improve the safety condition at a location if the existing conditions are known. The remedial strategy could involve increasing the skid resistance, reducing speed to posted speed limit, decreasing the driving difficulty (information that must be processed by drivers during navigation)—or any combination of these.

8. CONCLUSIONS AND RECOMMENDATIONS

Modeling wet-pavement crashes is a very complex and challenging task. Wet-pavement crashes are caused by complex interactions among many roadway, vehicle, human, and environmental factors. They also occur because of random variables such as driver inattentiveness, misjudgment, and recklessness and other unexpected events, to name a few. These events are embedded in the observed number of wet-pavement crashes and contribute significantly to the modeling error. Because of these events of wet-pavement crashes, it is unlikely to expect the developed methodology to predict the exact number of wet-pavement crashes. However, fuzzy logic modeling is a promising methodology for predicting and preventing the occurrence of wet-pavement crashes. It can express the relationships between the input and output and clearly show the mechanism of occurrence of wet-pavement crashes. The methodology can be used to identify those road sections where wet-pavement crashes are high for more attention.

To improve on the reliability and efficiency of the fuzzy-logic models, further research is necessary, such as comprehensive and extensive datasets to provide the basis for constructing a high-quality fuzzy logic models as well as testing and training the model. In addition, further research is needed on adding more functionality on top of the current model to improve its prediction capabilities and uses.

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TABLE 1

Distribution of Wet-Pavement Crashes by Speed and Road Class

Road Class	Speed (Km/hr) ≤30	≤60	≤90	≤120	Total
Freeway	0 0	15 0.23	89 1.36	60 0.92	164 2.51
Principal	24 0.37	948 14.51	121 1.85	0 0	1093 16.73
Urban	124 1.89	4257 65.16	29 0.44	2 0.03	4412 67.53
Local	72 1.10	783 11.99	9 0.13	0 0	864 13.23
Total	220 3.37	6003 91.89	248 3.80	62 0.95	6533 100

Shown in bold italics is the percentage of crashes

TABLE 2

Distribution of Observed and Expected Wet-Pavement Crashes by Speed and Road Class

Road Class	Speed (Km/hr)				Total
	≤30	≤60	≤90	≤120	
Freeway	0 6	15 150	89 6	60 2	164
Principal	24 36	948 1004	121 42	0 10	1093
Urban	124 149	4257 4054	29 167	2 41	4412
Local	72 29	783 793	9 33	0 8	864
Total	220	6003	248	62	6533

Shown in bold italics is the expected number of crashes

TABLE 3

Road Class Factors

Road Class	Number of Crashes	Percentage	Factor
Freeway	164	2.51	1.0
Principal Highway	1093	16.73	6.6
Urban Street	4112	67.53	26.9
Local Street	864	13.23	5.3

APPENDIX

TABLE 4

Results of the Fuzzy Logic Model for Freeways

Numbe r	Skid Resistance	Speed Differential	Traffic Volume (x1000)	Driving Difficulty	Number of Wet Pavement Crashes
1	30	5	30	2	2.72
2	30	5	30	3	2.64
3	30	5	30	5	2.64
4	30	5	60	2	2.72
5	30	5	60	3	2.72
6	30	5	60	5	2.80
7	30	5	80	2	2.72
8	30	5	80	3	2.72
9	30	5	80	5	2.80
10	30	10	30	2	2.64
11	30	10	30	3	2.64
12	30	10	30	5	2.64
13	30	10	60	2	2.72
14	30	10	60	3	2.96
15	30	10	60	5	3.12
16	30	10	80	2	2.92
17	30	10	80	3	3.04
18	30	10	80	5	3.12
19	30	20	30	2	2.64
20	30	20	30	3	2.64
21	30	20	30	5	2.64
22	30	20	60	2	2.80
23	30	20	60	3	3.12
24	30	20	60	5	3.20
25	30	20	80	2	2.80
26	30	20	80	3	3.12
27	30	20	80	5	3.28
28	40	5	30	2	2.32
29	40	5	30	3	2.40
30	40	5	30	5	2.48
31	40	5	60	2	2.48
32	40	5	60	3	2.48

33	40	5	60	5	2.80
34	40	5	80	2	2.48
35	40	5	80	3	2.56
36	40	5	80	5	2.72
37	40	10	30	2	2.30
38	40	10	30	3	2.32
39	40	10	30	5	2.48
40	40	10	60	2	2.48
41	40	10	60	3	2.64
42	40	10	60	5	2.88
43	40	10	80	2	2.56
44	40	10	80	3	2.80
45	40	10	80	5	2.88
46	40	20	30	2	2.40
47	40	20	30	3	2.48
48	40	20	30	5	2.48
49	40	20	60	2	2.64
50	40	20	60	3	2.96
51	40	20	60	5	2.96
52	40	20	80	2	2.64
53	40	20	80	3	2.96
54	40	20	80	5	2.96
55	60	5	30	2	0.64
56	60	5	30	3	0.72
57	60	5	30	5	0.8
58	60	5	60	2	0.72
59	60	5	60	3	0.72
60	60	5	60	5	0.88
61	60	5	80	2	0.8
62	60	5	80	3	0.8
63	60	5	80	5	0.88
64	60	10	30	2	0.64
65	60	10	30	3	0.64
66	60	10	30	5	0.8
67	60	10	60	2	0.72
68	60	10	60	3	0.8
69	60	10	60	5	0.88

70	60	10	80	2	0.8
71	60	10	80	3	0.8
72	60	10	80	5	0.88
73	60	20	30	2	0.8
74	60	20	30	3	0.8
75	60	20	30	5	0.8
76	60	20	60	2	0.8
77	60	20	60	3	0.64
78	60	20	60	5	0.8
79	60	20	80	2	0.8
80	60	20	80	3	0.8
81	60	20	80	5	0.8
				TOTAL	168.02

TABLE 5

Results of the Fuzzy Logic Model

Road Class	Observed Number of Wet-Pavement Crashes	Predicted Number of Wet-Pavement Crashes
Freeway	164	168
Principal Highway	1093	1108
Urban Street	4112	4519
Local Street	864	890
Total	6554	6685

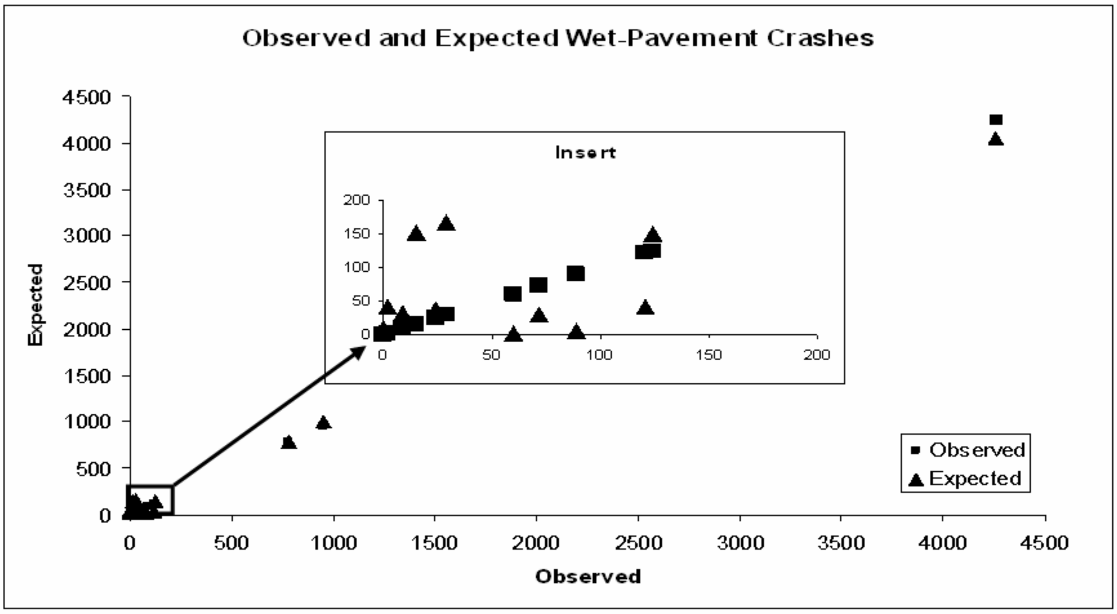

FIGURE 4
Observed and Expected Number of Wet-Pavement Crashes

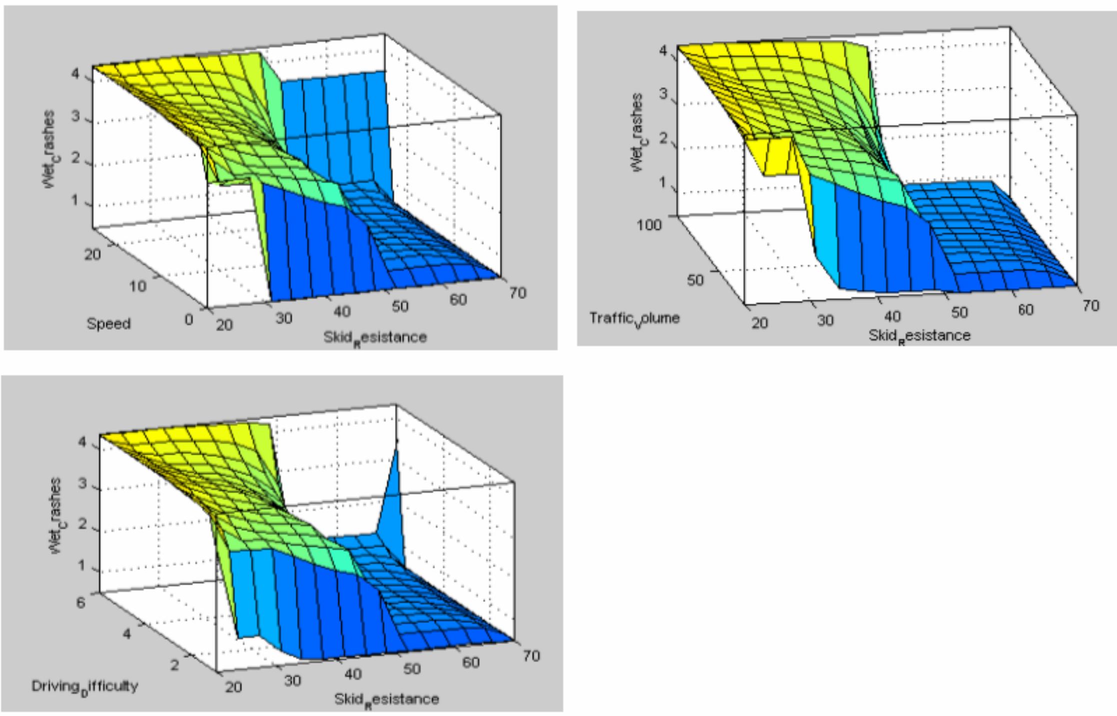

FIGURE 5
The Surface Viewer of Wet-Pavement Crash Fuzzy Logic Model