

A GIS and Fuzzy-based Model for Identification and Analysis of Accident Vulnerable Locations in Urban Traffic Management System: A Case Study of Bhubaneswar

Sarita Mahapatra

Dept. of Comp. Sc. and IT

S'O'A University, Bhubaneswar, India

Krishna Chandra Rath

PG Dept. of Geography

Utkal University, Bhubaneswar, India

Satya Ranjan Das

Dept. of Comp. Sc. and Engg.

S'O'A University, Bhubaneswar, India

Abstract—The world has seen road accident and its related societal and economical impact as one of the live, persisting problem in the last 2-3 decades and its prominence has been observed in the developing countries of the Asian subcontinent. With no exception, all major cities in India are facing the various challenges related to road accidents, mostly due to the large population density. Among the major cities in India, Bhubaneswar is a very fast growing city with aim to be the most livable city in Asia in the coming few years. With the city of Bhubaneswar as our study area, we address the issues related to road safety by determining the degree of severity of road accidents. We study the accident related data collected for the last decade using the spatial tools of Geographical Information System (GIS). Then using a GIS-map based analysis and a fuzzy-based model, we have found the spatio-temporal distribution of accident vulnerable locations with their degree of severity. Our experimental results show the accident hot-spots with values of selected contributing parameters such as timing, traffic density, vehicle speed, road intersections.

Keywords—Road traffic management; accident vulnerability; GIS; fuzzy inference; fuzzy rules

I. INTRODUCTION

Every year across the globe, the road accidents are increasing rapidly causing severe injuries and fatalities. As per the road accident data between 2004 to 2013, the accidental death is the 9th major reason of death and going to be 5th major by 2030, unless otherwise proper actions will not be taken [1]. As per [2], the global road accidental death has touched to 1.35 million in the year 2016. Hence, traffic safety is a prominent issue in the sustainable development of urban and semi-urban areas. To ensure traffic safety, road traffic accidents have been considered as one of defining components which contribute to the adverse impact on the economic growth in the developing countries, leading to social and economic concerns. In recent times death cases, severe injuries and property losses in road accidents are the major negative effects of transportation systems. The success of traffic safety programs relies on the analysis of reliable and accurate traffic accident data. Among few notable contributions towards traffic data analysis, in [3], using road accident data of UK between 2005 and 2019 for finding risk and predicting severity of accidental injuries, authors have used data analytics strategies. It can found in [4] that spatial pattern of accident distribution in a

specific study area can be analyzed and accident hot spots are identified using GIS based spatial and statistical analysis tools. In [5], authors present the performance result of spatial analysis of accident prone traffic location classification using Multi-criteria Decision Making (MCDM) approach. The study in [6], proposes a detailed spatio-temporal analysis approach combining strategies such as emerging hot spot analysis, spatial autocorrelation analysis and time-space cube analysis to identify the accident hot spots and related traffic features.

This paper analyses the present state of traffic accident information on various arterial and sub-arterial roads in the selected study area that is the city of Bhubaneswar, in the eastern region of India. This paper also discuss the determination of highly accident prone locations using QGIS Software and safety deficient areas on the major roads of the city.

This paper examines the potential use of the Geographic Information Systems (GIS) technology in executing road accident analysis in the study area with the illustration of various point-pattern techniques. Since GIS can further extend the analytical and visualization features, its implementation in urban areas like Bhubaneswar would based more on comprehensive planning and management in data acquisition and integration. A comprehensive digital database on the road structures of Bhubaneswar with an coherent and organized naming conventions is the primary need for the analysis and management of road accidents using GIS development.

In the city map of Bhubaneswar, using GIS-based analysis, locations from the periphery are to be identified in every 500metres; For each location the probability of severity of accidents are to be measured on the basis of five context-specific parameters (described in subsequent discussions); While selecting each parameter in the input interface, a supplementary value is also selected with the parameter. That supplementary value represents the “degree of impact” of each selected parameter. Five possible concepts such as very high, high, normal, low and very low are considered to the context of “degree of impact”. To control these fuzzy concepts, a fuzzy controller is used, based on Takagi-Sugeno’s fuzzy approach.

Why Fuzzy Classifier: Models based on fuzzy classification are mainly based on processing of many ambiguous, vague, imprecise input information to get some certain inference by

producing various outputs. The input information is processed through a rule-base containing a set of fuzzy if-then-else rules. Depending upon the number and structure of rules in the rule-base, the complexity and quality of fuzzy-classifier is determined.

II. RELATED WORKS

P. B. Parmar et al. [7] identified blackspot (i.e. accident-prone locations) on some specific locations of S.P. ring road, Ahmedabad with heatmap plugin and analyzed using QGIS and also suggested remedial measures for the black spot such as to find the places where enforcement steps are needed and number of particular places where sign boards for speed restriction and traffic sign are needed.

J. Choudhary et al. [8] geocoded the accident locations for five years from 2009 to 2013 over the digitized map of the city of Varanasi. The authors also evaluated and analyzed the spatial densities and clustering of accidents using heatmap plugin. The accident hot-spots were isolated with the road stretches using the heat-map using Kernel Density Estimation.

Jerome Ballarta et al. [9] have identified accident hot spots in Katipunan Avenue, Quezon city using standard GIS geoprocessing techniques.

V. Prasannakumar et al. [10] did a comparative investigation on temporal and spatial aspects of road accidents in the city of Thiruvananthapuram. Then using cluster analysis and spatial data statistics, authors have described the temporal and spatial differences of the accident vulnerable locations from the nonvulnerable locations.

Sanjay Kumar Singh and Ashish Misra [11] in their study have analyzed the road accidents in Patna city using annual data in year 1996 to 2000. It provides an overview of road accident scenario in India and deals with existing transport system in Patna.

Deesh Mandloi and Rajiv Gupta [12] have developed a GIS-based model for predicting the accident vulnerable locations using the road accident related parameters and have also given the remedial steps.

Yen Chen et al. [13] in their paper have discussed on application of geocoding technology for preparing spatial information related to the traffic accidents and presented a method which accepts potential system reducing accidents as an index to identify the black spots. The association relates the features of road network elements with the black spots, based on the GIS data-storage.

Ela Ertung et al. [14] have carried out a GIS-based analysis of intersection road accidents by creating a database using fatal-injury traffic accident data at intersections in Antalya City Center, Turkey between years 2009 and 2010. They have also determined hot spots for intersection accidents and have conducted statistical evaluations of accidents.

Anik Vega and Dwi Cahyono [15] have used Multiple-Attribute Utility Theory (MAUT) strategy to map dense and accident-vulnerable traffic roads so as to analyze attribute and spatial data. This method helps in finding alternative new road to minimize the traffic density.

Michal Bil et al. [16] in their paper have evaluated and organized clusters of traffic accidents based on their significance. They have also suggested a better strategy for detecting cluster, based on standard Kernel Density Estimation (KDE), suitable to find the most hazardous spots by verifying the importance of the clusters and then ordering the most hazardous spots.

Hao Yu et al. [17] have conducted a comparative investigation of spatial analysis techniques for identifying hot-spots. They collected data from a 622.2-km section on the A1 highway in the UK. From 2001 to 2010, where 7930 crashes were found at the selected highway zones.

Gholam A. Shafabakhsh et al. [18] have conducted spatial analysis of traffic accidents for the city of Mashhad, Iran using GIS methods. Based on the spatial aspect, authors have given a detailed study on various types of road accidents, which is the first attempt in the Mashhad city corporation and also analyzed the accident types using spatial patterns in GIS tool. accidents.

A. Research Contributions

The followings are the list of our contributions in this paper:

- 1) To study the road accidents data in Odisha from the year 2010 to 2020.
- 2) To estimate the distribution and incidence of road accidents in the city of Bhubaneswar using GIS.
- 3) To design a fuzzy rule base with selected set of road accident parameters.
- 4) To identify the accident vulnerable locations using fuzzy classifier.

III. STUDY AREA

Odisha has registered a sharp rise in road accident fatalities in the five years ending in 2020 against the target reduction in deaths by 50% during same period. A total of 107732 accidents occurred that led to 47884 fatalities. In the road accident statistics of the state of Odisha given in the Fig. 1, the major contributing city is Bhubaneswar, the capital of Odisha. It is seen that the year 2019 has the highest number of fatal accidents, a year which is taken as the starting of the “UN Decade of Action for Road Safety”.

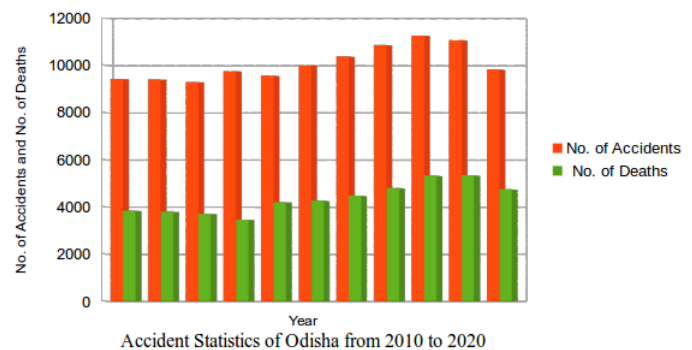


Fig. 1. Year-Wise Accident and Death Statistics of Odisha

Bhubaneswar, the capital of the state of Odisha and one of the popular tourist locations in India, is fast growing city which has organized various international events like International Mega Trade Fair, Men's Hockey Champions Trophy in 2014, Asian Athletics Championships in 2017, Men's Hockey World Cup in 2019, Men's FIH Hockey Junior World Cup in 2021 and also going to organized many more global events including Men's Hockey World Cup in 2023. It is on its way to be India's one of the most well-built cities and selected as a prominent city for the smart-city plan. Hence the crowd density is increasing alarmingly day-by-day leading to more accident cases. The objective of this paper is to evaluate and show hot-spots in Bhubaneswar using information modeling for identifying the statistical locations of accidents using GIS technology and a fuzzy classifier. Spatial-temporal analysis is needed for effective identification of hot spots and can be used to improve the safety of these spots.

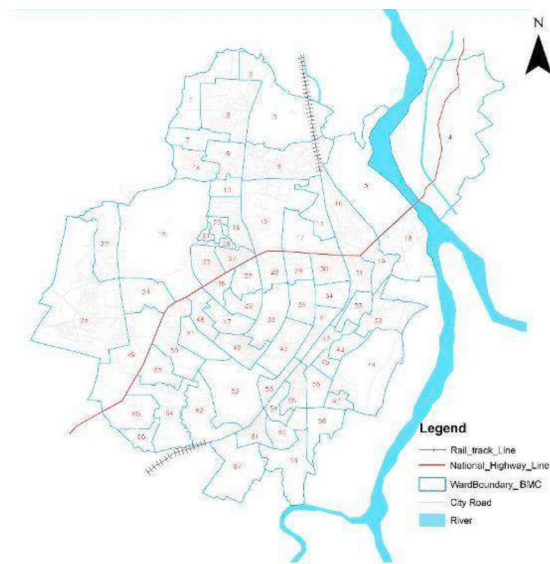


Fig. 2. Road Map of Bhubaneswar

Here Bhubaneswar is considered as the study area which is governed by Bhubaneswar Municipality Corporation. The city of Bhubaneswar sees rapid urbanization with both planned and unplanned way in all sides of the city such as towards Cuttack, Puri and Khurda. In the last three decades, Bhubaneswar has become the business as well as the educational hub of the state along with the best medical facilities available. As a result of which people from all corners of the state and the country as well, are coming to Bhubaneswar for their livelihood. It has a great impact to the population growth, urban environment and most importantly traffic congestion in the city. Nowadays, the traffic issues in the city has become a major concern. In Fig. 2, we have given the road map of Bhubaneswar prepared using QGIS, an open-source GIS software.

Over the years the Ministry of Road Transport and Highways (MoRTH) has been in the process of identifying the accident black spots on the National Highways passing through Bhubaneswar. Most of these spots located on NH-5 (now is NH-16) are mainly because of faulty road designs during ongoing of road projects. Inside the city of Bhubaneswar,

Aiginia Chowk and Khandagiri Chowk are found to be two major black spots of NH-16 where 30 and 36 accidental death case occurred respectively between 2017 and 2020. Hence there is an immediate need of micro-level analysis of accident vulnerable locations in Bhubaneswar.

IV. METHODOLOGY USED FOR IDENTIFYING ACCIDENT VULNERABLE LOCATIONS IN URBAN TRAFFIC

Road traffic accidents are now considered as one of the major concerns in India. Authors in [19] mentioned that around 0.4 million accidents are occurring in India almost every year, hence leading to an ever-increasing accident rate. Since accidents are uncertain and unpredictable, hence there is high possibility that this increasing rate of accidents may sustain. Hence there is extreme need of identification of different accident-prone geographical locations and finding the different features related to accidents occurring at these locations which will monitor the different scenarios of road accidents.

In [20], authors suggested that to identify potential measures to prevent road accidents, there is a need for systematic correlation between frequency of accidents and attributes such as traffic information, road-side features, vehicle information, road structure. Lee et al. [21] suggested to use statistical models for analyzing road accidents to determine the correlation among the spatial features and road accident features.

However, [22] found certain demerits of using regular statistical methods for analyzing datasets with large dimensions. In addition to problems like sparse data in large dimensional tables, statistical methods can also give some incorrect results mainly due to the assumptions based on the specific models. Hence some techniques based on artificial intelligence and data mining are adopted to handle the large datasets in road accidents.

In [23], authors described some specific data mining applications for road accident analysis, pavement analysis and roughness analysis of road. Authors in [24] narrated the potential data mining strategies like classification, clustering, association rule mining etc. for the effective analysis of road accident data.

As per authors in [25], for effective data analysis the accidents reports available in the police stations are not complete and sufficient for research. At the same time, these basic data can be used and analysed for some specific road segments with the help of statistical approaches, as described in [26], [27].

This paper uses fuzzy logic based classification technique to determine the high-frequency accident spots and subsequent analysis to identify various factors that affect road accidents at these spots. We first identify the parameters for the analysis of the accident vulnerable locations. Then using the fuzzy rule base, we compute the degree of vulnerability of the specific locations by correlating between the characteristics features of these locations and the various attributes in the accident data. Here our main focus is to interpret the results.

A. Proposed Model

The work is basically based on the classification and analysis of traffic data of the city of Bhubaneswar. The

proposed smart traffic management system is going to provide a systematic analysis of data. User has to give the required information like timing (early morning, morning, noon, afternoon, evening, night, late-night), road-condition (i.e. road-friction-density), level-of-road-intersections, existence of crowd-pulling-centers (such as school, bank, shopping mall, etc.) within 200metres periphery and traffic-calming-measures (such as speed-breakers, rumble-strips, bollards), etc. through selecting suitable icons given on the user-interface.

Then the sequence of selected attributes gets associated with values signifying the degree of intensity. The set of user information are then to be stored in a fuzzy rule base which is in the back-end of the system. The fuzzy rule base contains some generalized traffic information and more importantly a set of rules in the form of IF-THEN. In each of the rule the IF-part contains a set of premises which are nothing but the conditions required for finding the degree of accident vulnerability, and the THEN-part contains the response after vulnerability analysis. Hence the response selected by the user is now matched with the premises of the rules in a sequential manner. The rule, for which the inputs matched with all of its premises, will be selected. Then the result part of the selected rule is considered as the response to the user as the result of the vulnerability analysis.

An overview of the proposed system is shown in Fig. 3.

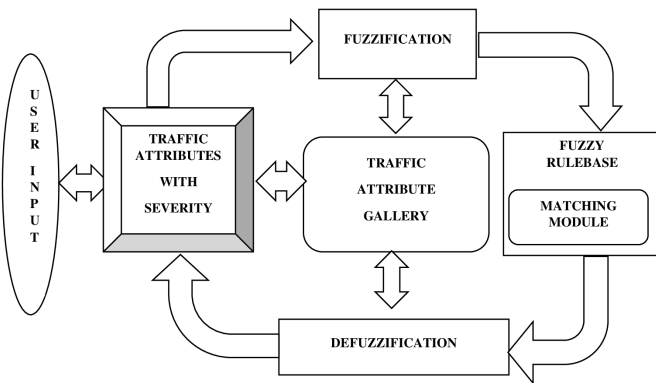


Fig. 3. Framework of Fuzzy-Based Accident-Vulnerability Location Identification

B. Rule-Based Fuzzy Inference System

A rule-base basically consists of the following components:

- a collection of knowledge, in the form of facts
- a set of rules-of-logic, in the form of “if-then”, and
- an inference mechanism, which decides what rule is to be used and when.

The knowledge-base in the model consists of these if-then rules which represent conditional statements. Each rule has a premise (P) and a conclusion (C) in the form “if P then C”. Based on these rules, the rule-base systems are broadly categorized into two types such as forward-chaining-system which is data-driven and backward-chaining-system which is goal-driven. A forward chaining system is based on first

processing the initial data and the using the rules to form the valid conclusions based on the given initial data. A backward chaining system is based on first processing the goals and then searching for rules that can be used for getting the set goals.

C. Rule-based System

The working of the fuzzy controller is described with the following example: The reasoning method in a fuzzy-inference-model is based on the processing of a large set of if-then rules, leading to a knowledge-base. Each rule has a premise, that is the “if” part and a conclusion, that is the “then” part. The knowledge-base in the fuzzy-inference-system (FIS) consists of a large set rules of the form ‘if x_1 is P_1 AND x_2 is P_2 AND... x_n is P_n then y is C ’ where P_1, P_2, \dots, P_n and C are linguistic variables that take fuzzy values from the interval $[0,1]$, and x_1, x_2, \dots, x_n are the input parameters and y is the output parameter that is $y = f(x_1, x_2, \dots, x_n)$. There are two popular FIS such as Mamdani FIS and Takagi-Sugeno FIS.

In Mamdani-type FIS, the rule-base grows with the increase in parameters in the premise part which leads to difficulty in comprehending the co-relationships between the premises and consequences. In Sugeno-type FIS (or Takagi-Sugeno-Kang method), with fuzzy inputs and a crisp output, It is computationally suitable and efficient to work with adaptive and optimization methods, hence very effective for control problems. Takagi-Sugeno method gives a systematic way to produce fuzzy rules from a given data set. Mamdani-type FIS follows the technique of defuzzification of a fuzzy output where as Sugeno-type FIS follows the computation of crisp output using weighted average. Both the FIS have the same structure in the first two parts such as fuzzifying the inputs and execution of the fuzzy operator. The main difference is in the output membership functions of Sugeno FIS which are either constant or linear.

D. Input Parameters

Based on the data collected for road accidents in the study area, five input parameters are taken which are found to be potential parameters for the prediction of accident vulnerability. Input: $I_1, I_2, I_3, I_4, I_5, a_1, a_2, a_3, a_4, a_5$ where I_1, I_2, I_3, I_4, I_5 represent five parameters which affects vulnerability of locations towards accident, such as traffic density, vehicle speed, presence of crowd-gathering-centers, number of road intersections and timing. The inputs a_1, a_2, a_3, a_4, a_5 are described later in this section.

1) *Traffic Density*: (I_1) As per the Indian Road Congress (IRC), traffic density can be defined as the average number of vehicles that are present or available in one mile or one kilometer of a road segment, expressed in number of vehicles per kilometer or per mile. Then traffic density (I_1) is computed by:

$$trafficedensity = vehiclecount / segmentlength$$

The survey was conducted two times per hour on selected road portions.

The traffic density (I_1) is computed by the following formula: $I_1 = (1 * C_1 + 2 * C_2 + 3 * C_3 + 4 * C_4) / 10$

where C_1, C_2, C_3 and C_4 represent the number of pedestrians, the number of two-wheelers, the number of four and six wheelers, the number of heavy vehicles, respectively.

2) *Vehicle Speed: (I_2)* Vehicle speed is one important parameter which has taken fuzzy values from [0,1] based on the range of speed.

3) *Presence of Crowd Gathering-Centers: (I_3)* This parameter is considered as it is including shopping malls, hospitals, educational centers which mainly responsible for crowd gathering and hence leading to accidents and congestions as well.

4) *Road Intersections: (I_4)* Road intersections can be several types such as 3-ways, 4-ways and multi-ways. Each intersection can affect differently based on the shape, structure, scope, use of channelization and other varieties of traffic-control-devices.

5) *Timing: (I_5)* Timing of road accidents is one of the most important parameters in the computation of degree of accident vulnerability of locations.

E. Degree of Intensity

We represent the degree of intensity of the accident by a numeric value in between 1 and 5 in the increasing order of the intensities that is from very low to very high. The value of the degree of intensity is based on the values of the input parameters I_1, I_2, I_3, I_4, I_5 and a_1, a_2, a_3, a_4, a_5 represent the degree of intensities of road accidents which are as follows:

- $a_j = 5$ for $I_i =$ very high(VH), implies highly probable for severe accidents leading to death/fatal cases,
- $a_j = 4$ for $I_i =$ high(H), implies probable for accidents leading to severe injuries,
- $a_j = 3$ for $I_i =$ normal(N), implies for probable accidents leading to property loss,
- $a_j = 2$ for $I_i =$ low(L), implies for probable accidents leading to minor injuries,
- $a_j = 1$ for $I_i =$ very low(VL), implies for very low probability of accidents,

where $i = 1, \dots, 5$ and $j = 1, \dots, 5$. In Table I, the range of values for each input parameter is given with respect to their degree of intensities.

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section includes the result analysis of the different stages of the input parameter selection and the calculations of the fuzzy output of the rules.

A. Accident Dataset

To test the proposed model, traffic accident data are used which are collected from all districts of Odisha State with special focus on Bhubaneswar. The dataset, provided by the Department of Road Transportation, Odisha and Office of the Police Commissionerate, Bhubaneswar, contains 50,540 traffic accidents that occurred between the year 2011 to 2020. The

dataset includes accidents that occurred on national highways such as NH16 and NH203, state highways in Bhubaneswar and its nearby rural areas. The attributes in the dataset include information about the accident timing, vehicle speed, road condition, nearby crowd-gathering centers and traffic density of the road during accident. In the dataset, some attributes are collected from the sensors deployed in the roads. Information, such as actual reason of the accident, light condition, visibility, and road conditions of the accident spot are collected from visibility sensors, traffic surveillance cameras, and tachographs. Hence, due to different modes of data collection, the dataset led to a very complex preprocessing of data. Here we have considered the severity of accident in terms of injury, loss of property, death cases as the dependent variable. Then we have translated these numerical variables into variables with ordinal values. We have considered records of 9640 accidents after preprocessing.

B. Fuzzy Rule-Base

The fuzziness add better and more accurate prediction to the whole system. While selecting value of each parameter as the input, a supplementary value is also selected with the input parameter. That supplementary value represents the “degree of intensity” of each selected parameter. Five possible concepts such as very low, low, normal, severe/high, very severe/very high are considered to the context of “degree of vulnerability”. To control these fuzzy concepts, a fuzzy controller is used which is based on Takagi-Sugeno’s fuzzy approach. The working of the fuzzy controller is described with the following example:

Input: $I_1, I_2, I_3, I_4, I_5, a_1, a_2, a_3, a_4, a_5$.

where I_1, I_2, I_3, I_4, I_5 represent five parameters, eg. five parameters which affects vulnerability of locations towards accident, eg. traffic density, vehicle speed, presence of crowd-gathering-centres, number of road intersections, timing., and a_1, a_2, a_3, a_4, a_5 represent the degree of intensity of road accidents.

Output: $y_i = f(I_1, I_2, I_3, I_4, I_5) = a_1 * I_1 + a_2 * I_2 + a_3 * I_3 + a_4 * I_4 + a_5 * I_5$

where y_i represents the degree of vulnerability based on the input parameters (I_i s) and their degree of intensities (a_j s).

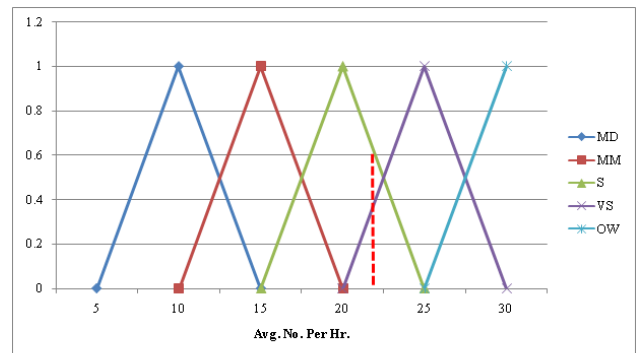


Fig. 4. I_1 :Traffic Density

TABLE I. FACTORS OR PARAMETERS WHICH AFFECT VULNERABILITY OF LOCATIONS

Parameters	Very High(0.9-1.0)	High(0.7-0.8)	Normal(0.6)	Low(0.3-0.4)	Very Low(0.1-0.2)
traffic density	0.9-1.0	0.7-0.8	0.5-0.6	0.3-0.4	0.1-0.2
vehicle speed	> 80	60-80	40-60	20-40	0-20
road-intersections	> 6	6	5	4	3
crowd-gathering-centers	> 5	4	3	2	1
timing	15:00-21:00	9:00-15:00	6:00-9:00	3:00-6:00	00:00-3:00

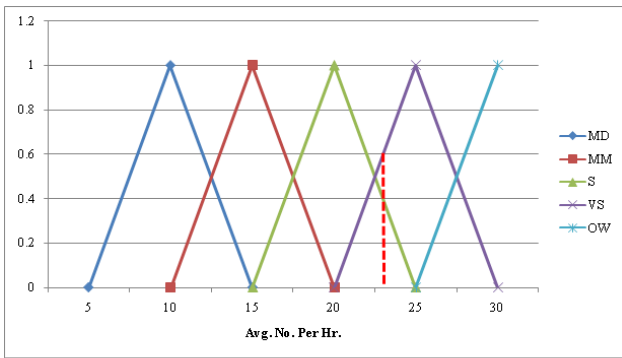


Fig. 5. I_2 : Vehicle Speed

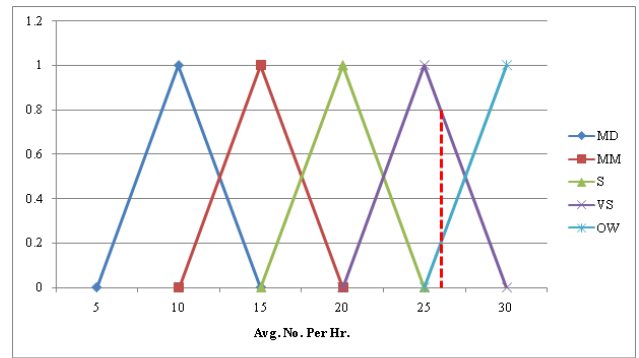


Fig. 7. I_4 : Number of Road Intersections

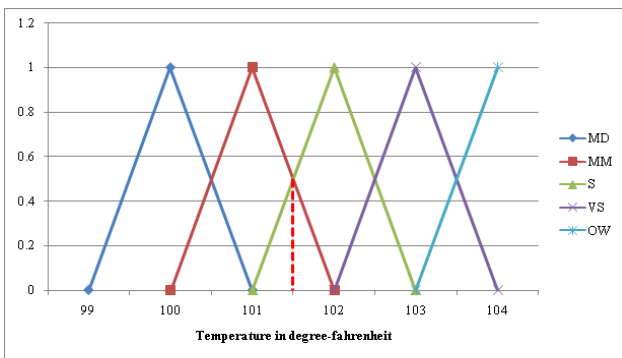


Fig. 6. I_3 : Presence of Crowd-Gathering-Centres

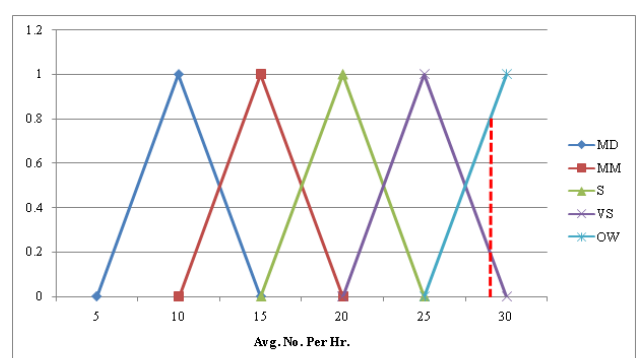


Fig. 8. I_{51} : Accident Timing

We have taken an example scenario, which is as follows. Let $I_1 = 0.6$ per kilometer, from the Fig. 4 using triangle formula we get:

$$\mu_H(0.6) = 0.6$$

$$\mu_{VH}(0.6) = 0.4$$

Let $I_{82} = 82$ kilometers per hour, from the Fig. 5 using triangle formula we get:

$$\mu_H(82) = 0.7$$

$$\mu_{VH}(82) = 0.8$$

Let $I_3 = 3$ number of crowd-gathering-centre, from the Fig. 6 using triangle formula we get:

$$\mu_N(3) = 0.5$$

$$\mu_H(3) = 0.5$$

Let $I_4 = 4$ number of road intersections, from the Fig. 7 using triangle formula we get:

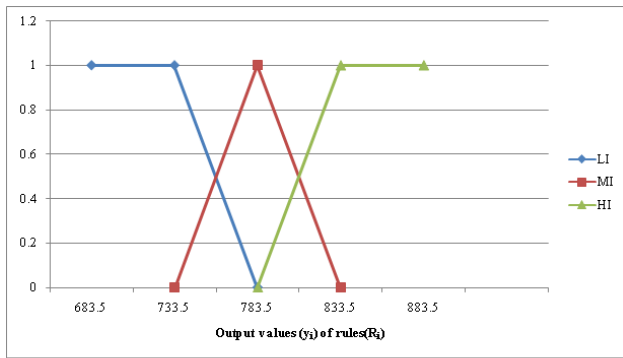


Fig. 9. Fuzzy Output of Rules

$$\mu_H(4) = 0.8$$

$$\mu_{VH}(4) = 0.2$$

Let $I_5 = 20$, from the Fig. 8 using triangle formula we get:

$$\mu_{VH}(20) = 0.9$$

$$\mu_N(20) = 0.6$$

From the above analysis, we get 32 numbers of rules. For each rule R_i , the corresponding y_i and ω_i (represents weight of rule R_i) value is computed as below:

Rule R_1 : (I_1 is H)(I_2 is S)(I_3 is S)(I_4 is H)(I_5 is H)
 $\omega_1 = \mu_H * \mu_S * \mu_S * \mu_H * \mu_H = 0.6 * 0.4 * 0.5 * 0.8 * 0.2 = 0.0192$
 $y_1 = 4 * I_1 + 3 * I_2 + 3 * I_3 + 4 * I_4 + 4 * I_5 = 681.5$

Rule R_2 : (I_1 is H)(I_2 is S)(I_3 is S)(I_4 is H)(I_5 is VH)
 $\omega_2 = \mu_H * \mu_S * \mu_S * \mu_H * \mu_{VH} = 0.6 * 0.4 * 0.5 * 0.8 * 0.8 = 0.0768$
 $y_2 = 4 * I_1 + 3 * I_2 + 3 * I_3 + 4 * I_4 + 5 * I_5 = 710.5$

Rule R_3 : (I_1 is H)(I_2 is S)(I_3 is S)(I_4 is VH)(I_5 is H)
 $\omega_3 = \mu_H * \mu_S * \mu_S * \mu_{VH} * \mu_H = 0.6 * 0.4 * 0.5 * 0.2 * 0.2 = 0.0048$
 $y_3 = 4 * I_1 + 3 * I_2 + 3 * I_3 + 5 * I_4 + 4 * I_5 = 707.5$

Rule R_4 : (I_1 is H)(I_2 is S)(I_3 is S)(I_4 is VH)(I_5 is VH)
 $\omega_4 = \mu_H * \mu_S * \mu_S * \mu_{VH} * \mu_{VH} = 0.6 * 0.4 * 0.5 * 0.2 * 0.8 = 0.0192$
 $y_4 = 4 * I_1 + 3 * I_2 + 3 * I_3 + 5 * I_4 + 5 * I_5 = 736.5$

Rule R_5 : (I_1 is H)(I_2 is S)(I_3 is H)(I_4 is H)(I_5 is H)
 $\omega_5 = \mu_H * \mu_S * \mu_H * \mu_H * \mu_H = 0.6 * 0.4 * 0.5 * 0.8 * 0.2 = 0.0192$
 $y_5 = 4 * I_1 + 3 * I_2 + 4 * I_3 + 4 * I_4 + 4 * I_5 = 783.0$

Rule R_6 : (I_1 is H)(I_2 is S)(I_3 is H)(I_4 is H)(I_5 is VH)
 $\omega_6 = \mu_H * \mu_S * \mu_H * \mu_H * \mu_{VH} = 0.6 * 0.4 * 0.5 * 0.8 * 0.8 = 0.0768$
 $y_6 = 4 * I_1 + 3 * I_2 + 4 * I_3 + 4 * I_4 + 5 * I_5 = 812.0$

Rule R_7 : (I_1 is H)(I_2 is S)(I_3 is H)(I_4 is VH)(I_5 is H)
 $\omega_7 = \mu_H * \mu_S * \mu_H * \mu_{VH} * \mu_H = 0.6 * 0.4 * 0.5 * 0.2 * 0.2 =$

0.0048
 $y_7 = 4 * I_1 + 3 * I_2 + 4 * I_3 + 5 * I_4 + 4 * I_5 = 809.0$

Rule R_8 : (I_1 is H)(I_2 is S)(I_3 is H)(I_4 is VH)(I_5 is VH)
 $\omega_8 = \mu_H * \mu_S * \mu_H * \mu_{VH} * \mu_{VH} = 0.6 * 0.4 * 0.5 * 0.2 * 0.8 = 0.0192$
 $y_8 = 4 * I_1 + 3 * I_2 + 4 * I_3 + 5 * I_4 + 5 * I_5 = 838.0$

Rule R_9 : (I_1 is H)(I_2 is H)(I_3 is S)(I_4 is H)(I_5 is H)
 $\omega_9 = \mu_H * \mu_H * \mu_S * \mu_H * \mu_H = 0.6 * 0.6 * 0.5 * 0.8 * 0.2 = 0.0288$
 $y_9 = 4 * I_1 + 4 * I_2 + 3 * I_3 + 4 * I_4 + 4 * I_5 = 704.5$

Rule R_{10} : (I_1 is H)(I_2 is H)(I_3 is S)(I_4 is H)(I_5 is VH)
 $\omega_{10} = \mu_H * \mu_H * \mu_S * \mu_H * \mu_{VH} = 0.6 * 0.6 * 0.5 * 0.8 * 0.8 = 0.1152$
 $y_{10} = 4 * I_1 + 4 * I_2 + 3 * I_3 + 4 * I_4 + 5 * I_5 = 733.5$

Rule R_{11} : (I_1 is H)(I_2 is H)(I_3 is S)(I_4 is VH)(I_5 is H)
 $\omega_{11} = \mu_H * \mu_H * \mu_S * \mu_{VH} * \mu_H = 0.6 * 0.6 * 0.5 * 0.2 * 0.2 = 0.0072$
 $y_{11} = 4 * I_1 + 4 * I_2 + 3 * I_3 + 5 * I_4 + 4 * I_5 = 730.5$

Rule R_{12} : (I_1 is H)(I_2 is H)(I_3 is S)(I_4 is VH)(I_5 is VH)
 $\omega_{12} = \mu_H * \mu_H * \mu_S * \mu_{VH} * \mu_{VH} = 0.6 * 0.6 * 0.5 * 0.2 * 0.8 = 0.0288$
 $y_{12} = 4 * I_1 + 4 * I_2 + 3 * I_3 + 5 * I_4 + 5 * I_5 = 759.5$

Rule R_{13} : (I_1 is H)(I_2 is H)(I_3 is H)(I_4 is H)(I_5 is H)
 $\omega_{13} = \mu_H * \mu_H * \mu_H * \mu_H * \mu_H = 0.6 * 0.6 * 0.5 * 0.8 * 0.2 = 0.0288$
 $y_{13} = 4 * I_1 + 4 * I_2 + 4 * I_3 + 4 * I_4 + 4 * I_5 = 806.0$

Rule R_{14} : (I_1 is H)(I_2 is H)(I_3 is H)(I_4 is H)(I_5 is VH)
 $\omega_{14} = \mu_H * \mu_H * \mu_H * \mu_H * \mu_{VH} = 0.6 * 0.6 * 0.5 * 0.8 * 0.8 = 0.1152$
 $y_{14} = 4 * I_1 + 4 * I_2 + 4 * I_3 + 4 * I_4 + 5 * I_5 = 835.0$

Rule R_{15} : (I_1 is H)(I_2 is H)(I_3 is H)(I_4 is VH)(I_5 is H)
 $\omega_{15} = \mu_H * \mu_H * \mu_H * \mu_{VH} * \mu_H = 0.6 * 0.6 * 0.5 * 0.2 * 0.2 = 0.0072$
 $y_{15} = 4 * I_1 + 4 * I_2 + 4 * I_3 + 5 * I_4 + 4 * I_5 = 832.0$

Rule R_{16} : (I_1 is H)(I_2 is H)(I_3 is H)(I_4 is VH)(I_5 is VH)
 $\omega_{16} = \mu_H * \mu_H * \mu_H * \mu_{VH} * \mu_{VH} = 0.6 * 0.6 * 0.5 * 0.2 * 0.8 = 0.0288$
 $y_{16} = 4 * I_1 + 4 * I_2 + 4 * I_3 + 5 * I_4 + 5 * I_5 = 861.0$

Rule R_{17} : (I_1 is VH)(I_2 is S)(I_3 is S)(I_4 is H)(I_5 is H)
 $\omega_{17} = \mu_{VH} * \mu_S * \mu_S * \mu_H * \mu_H = 0.4 * 0.4 * 0.5 * 0.8 * 0.2 = 0.0128$
 $y_{17} = 5 * I_1 + 3 * I_2 + 3 * I_3 + 4 * I_4 + 4 * I_5 = 703.5$

Rule R_{18} : (I_1 is VH)(I_2 is S)(I_3 is S)(I_4 is H)(I_5 is

VH)

$$\omega_{18} = \mu_{VH} * \mu_S * \mu_S * \mu_H * \mu_{VH} = 0.4 * 0.4 * 0.5 * 0.8 * 0.8 = 0.0512$$

$$y_{18} = 5 * I_1 + 3 * I_2 + 3 * I_3 + 4 * I_4 + 5 * I_5 = 732.5$$

Rule R_{19} : (I_1 is VH)(I_2 is S)(I_3 is S)(I_4 is VH)(I_5 is H)

$$\omega_{19} = \mu_{VH} * \mu_S * \mu_S * \mu_{VH} * \mu_H = 0.4 * 0.4 * 0.5 * 0.2 * 0.2 = 0.0032$$

$$y_{19} = 5 * I_1 + 3 * I_2 + 3 * I_3 + 5 * I_4 + 4 * I_5 = 729.5$$

Rule R_{20} : (I_1 is VH)(I_2 is S)(I_3 is S)(I_4 is VH)(I_5 is VH)

$$\omega_{20} = \mu_{VH} * \mu_S * \mu_S * \mu_{VH} * \mu_{VH} = 0.4 * 0.4 * 0.5 * 0.2 * 0.8 = 0.0128$$

$$y_{20} = 5 * I_1 + 3 * I_2 + 3 * I_3 + 5 * I_4 + 5 * I_5 = 758.5$$

Rule R_{21} : (I_1 is VH)(I_2 is S)(I_3 is H)(I_4 is H)(I_5 is H)

$$\omega_{21} = \mu_{VH} * \mu_S * \mu_H * \mu_H * \mu_H = 0.4 * 0.4 * 0.5 * 0.8 * 0.2 = 0.0128$$

$$y_{21} = 5 * I_1 + 3 * I_2 + 4 * I_3 + 4 * I_4 + 4 * I_5 = 805.0$$

Rule R_{22} : (I_1 is VH)(I_2 is S)(I_3 is H)(I_4 is H)(I_5 is VH)

$$\omega_{22} = \mu_{VH} * \mu_S * \mu_H * \mu_H * \mu_{VH} = 0.4 * 0.4 * 0.5 * 0.8 * 0.8 = 0.0512$$

$$y_{22} = 5 * I_1 + 3 * I_2 + 4 * I_3 + 4 * I_4 + 5 * I_5 = 834.0$$

Rule R_{23} : (I_1 is VH)(I_2 is S)(I_3 is H)(I_4 is VH)(I_5 is H)

$$\omega_{23} = \mu_{VH} * \mu_S * \mu_H * \mu_{VH} * \mu_H = 0.4 * 0.4 * 0.5 * 0.2 * 0.2 = 0.0032$$

$$y_{23} = 5 * I_1 + 3 * I_2 + 4 * I_3 + 5 * I_4 + 4 * I_5 = 831.0$$

Rule R_{24} : (I_1 is VH)(I_2 is S)(I_3 is H)(I_4 is VH)(I_5 is VH)

$$\omega_{24} = \mu_{VH} * \mu_S * \mu_H * \mu_{VH} * \mu_{VH} = 0.4 * 0.4 * 0.5 * 0.2 * 0.8 = 0.0128$$

$$y_{24} = 5 * I_1 + 3 * I_2 + 4 * I_3 + 5 * I_4 + 5 * I_5 = 860.0$$

Rule R_{25} : (I_1 is VH)(I_2 is H)(I_3 is S)(I_4 is H)(I_5 is H)

$$\omega_{25} = \mu_{VH} * \mu_H * \mu_S * \mu_H * \mu_H = 0.4 * 0.6 * 0.5 * 0.8 * 0.2 = 0.0192$$

$$y_{25} = 5 * I_1 + 4 * I_2 + 3 * I_3 + 4 * I_4 + 4 * I_5 = 726.5$$

Rule R_{26} : (I_1 is VH)(I_2 is H)(I_3 is S)(I_4 is H)(I_5 is VH)

$$\omega_{26} = \mu_{VH} * \mu_H * \mu_S * \mu_H * \mu_{VH} = 0.4 * 0.6 * 0.5 * 0.8 * 0.8 = 0.0768$$

$$y_{26} = 5 * I_1 + 4 * I_2 + 3 * I_3 + 4 * I_4 + 5 * I_5 = 755.5$$

Rule R_{27} : (I_1 is VH)(I_2 is H)(I_3 is S)(I_4 is VH)(I_5 is H)

$$\omega_{27} = \mu_{VH} * \mu_H * \mu_S * \mu_{VH} * \mu_H = 0.4 * 0.6 * 0.5 * 0.2 * 0.2 = 0.0048$$

$$y_{27} = 5 * I_1 + 4 * I_2 + 3 * I_3 + 5 * I_4 + 4 * I_5 = 752.5$$

Rule R_{28} : (I_1 is VH)(I_2 is H)(I_3 is S)(I_4 is VH)(I_5 is VH)

$$\omega_{28} = \mu_{VH} * \mu_H * \mu_S * \mu_{VH} * \mu_{VH} = 0.4 * 0.6 * 0.5 * 0.2 * 0.8 =$$

0.0192

$$y_{28} = 5 * I_1 + 4 * I_2 + 3 * I_3 + 5 * I_4 + 5 * I_5 = 781.5$$

Rule R_{29} : (I_1 is VH)(I_2 is H)(I_3 is H)(I_4 is H)(I_5 is H)

$$\omega_{29} = \mu_{VH} * \mu_H * \mu_H * \mu_H * \mu_H = 0.4 * 0.6 * 0.5 * 0.8 * 0.2 = 0.0192$$

$$y_{29} = 5 * I_1 + 4 * I_2 + 4 * I_3 + 4 * I_4 + 4 * I_5 = 828.0$$

Rule R_{30} : (I_1 is VH)(I_2 is H)(I_3 is H)(I_4 is H)(I_5 is VH)

$$\omega_{30} = \mu_{VH} * \mu_H * \mu_H * \mu_H * \mu_{VH} = 0.4 * 0.6 * 0.5 * 0.8 * 0.8 = 0.0768$$

$$y_{30} = 5 * I_1 + 4 * I_2 + 4 * I_3 + 4 * I_4 + 5 * I_5 = 857.0$$

Rule R_{31} : (I_1 is VH)(I_2 is H)(I_3 is H)(I_4 is VH)(I_5 is H)

$$\omega_{31} = \mu_{VH} * \mu_H * \mu_H * \mu_{VH} * \mu_H = 0.4 * 0.6 * 0.5 * 0.2 * 0.2 = 0.0048$$

$$y_{31} = 5 * I_1 + 4 * I_2 + 4 * I_3 + 5 * I_4 + 4 * I_5 = 854.0$$

Rule R_{32} : (I_1 is VH)(I_2 is H)(I_3 is H)(I_4 is VH)(I_5 is VH)

$$\omega_{32} = \mu_{VH} * \mu_H * \mu_H * \mu_{VH} * \mu_{VH} = 0.4 * 0.6 * 0.5 * 0.2 * 0.8 = 0.0192$$

$$y_{32} = 5 * I_1 + 4 * I_2 + 4 * I_3 + 5 * I_4 + 5 * I_5 = 883.0$$

Now the combined action of all the rules can be obtained as follows:

$$y = \frac{\sum_{i=1}^{32} \omega_i y_i}{\sum_{j=1}^{32} \omega_j} = 783.25/1.0 = 783.25$$

Hence from the above computations we infer that: the rules (R_i s) with output values (y_i s) greater than the value of y are cases with high vulnerability and hence alertness is to be given in the output interface. The output of the fuzzy-controller, that is the degree of vulnerability is defined using fuzzy values as, given in the Fig. 9:

$$b_i(y_i) = \begin{cases} 1(LV) & \text{for } y_i < 733.5 \\ 2(MV) & \text{for } 733.5 \leq y_i \leq 833.5 \\ 3(HV) & \text{for } y_i > 833.5 \end{cases}$$

Here LV, MV and HV represent low vulnerable, medium vulnerable and high vulnerable respectively. Hence, sequence of control is as follows:

parameters selected \Rightarrow for each input parameter, the degree of intensity selected \Rightarrow corresponding fuzzy ruled fired \Rightarrow with the output of the fuzzy rule, the degree of vulnerability notified.

Based on the values of the selected input parameters, the degree of vulnerabilities are computed for some specific locations in our study area. It is found that in addition to Khandagiri and Aiginia square, the other black spots identified includes Patrapada, Palasuni and Hanspal within the limits of our study area Bhubaneswar.

VI. CONCLUSION

Fuzzy Inference Systems have been reliable strategies for the analysis of accident data sets taken from various countries of the globe. In several attempts, different authors have used the Mamdani and Sugeno FIS for finding the causes of road accident severity. In this paper, we have taken an integrated

approach of GIS data modeling with fuzzy inference mechanism to analyze and identify the accident vulnerable locations with their degree of vulnerability in the study area.

The present study have used fuzzy-based technique on different sections of accident locations. The rules generated for each section expressed the various reasons associated with road accidents in the specific locations. Each section may contain some similar rules, but they have different values for each group. The dataset for road accident and its analysis using fuzzy-based method shows that this method can be applied on other accident data having larger number of attributes to find more number of parameters linked with road accidents. It is observed that this fuzzy-based method has adequately found reasonable information from the given data set, with the outcomes produced at very general level because of some missing information such as the victim information, road surface condition, weather related information. The data with higher number of attributes can extract additional information using the present strategy.

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