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Analysis and Modeling of Rural Roads Traffic Safety Data

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Abstract

Traffic accidents threaten human's safety and properties as well as restrict the management of transportation systems. Therefore, traffic accidents prediction models could help stakeholders to understand accident causes toward controlling their effects. This paper aims at developing a prediction model for a rural road in Egypt using actual accident data with survey data for pavement conditions, traffic flow presented as average hourly traffic per lane, speed, minor access, traffic signs conditions and road width. The relationship between accident number and the influencing factors is modeled using fuzzy logic algorithm which deals with nonlinear relationships between parameters. The results show that the developed model produced accurate and stable traffic accident predictions (R^2=0.79). The results indicated that average accident rate decreases as road width increases where, a reduction in accident rate of about 5.26% is reached due to road width widening by 3.5 m. The results indicate that road accidents on the studied road can be reduced by 7.38% if the speed is limited to 75 km per hour. About 17.90% reduction is achieved by improving road surface condition. Also results indicate a positive relationship between traffic volume and accidents rate.

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1. INTRODUCTION

Road traffic accidents (RTAs) are an increasing problem as they produce huge losses in lives and properties. It is reported that 1.2 million person loss their life with 50 million or more injuries, due to RTAs annually all over the world [1]. So, RTAs are an important issue and understanding their causes may have effective results to increase safety and reduce human and financial losses for road transport.

RTAs in Egypt produce about 12,000 fatalities annually [2]. Aswan-Cairo rural road has frequent RTAs especially on Aswan-Idfu section. Evaluating safety performance of highways in Aswan is important due to their high mortality rates. Traffic safety is a major concern for the public, and it is an important component of the roadway management strategies. Therefore, RTAs prediction has an important meaning to the improvement of traffic safety management. There are many factors that cause RTAs. To reduce RTAs rate, it is needed to analyze the contributing factors. RTAs modeling could help to predict their causes and occurrence probability, so the first problem of accident analysis can be fixed by using a better approach that is able to explain mechanism of such inter-related factors. However, the relationship between RTAs and their contributing causes is not linear. Fuzzy theory can deal with the uncertainty, subjectivity, imprecision and ambiguity problem, and represent the uncertain relationships.

This paper focuses on a section of Aswan-Cairo rural road (Aswan-Idfu section), which is an alternate road to decrease the flow on the Aswan-Cairo urban road. All over the road, many accidents have been recorded which have high fatality rate. In order to prevent RTAs on the rural road, the RTAs data analysis methods and measures should be used to save road users from death or serious injuries. One of the best ways to reduce future RTAs rates is developing a model forecasting accidents' rates to take suitable actions. Studying road accidents has many objectives such as studying the causes of RTAs and suggesting corrective measures and evaluating existing road design that can reduce or prevent future accidents. This paper proposed RTAs prediction model for Aswan-Idfu rural road based on fuzzy inference system. Our model is developed based on achieve traffic accident data and a field survey data.

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This paper is structured as follows. Section 2 reviewing the traffic accident prediction models developed in the literature including fuzzy logic models. The methodology is discussed in Section 3 which presents the study site and data characteristics and research methodology. Overview and analysis of RTAs, fuzzy modeling and their discussions are provided in Section 4. In Section 5, summary, conclusion, and recommendations are provided.

2. LITERATURE REVIEW

Analysis and modelling of the contributing factors may help to reduce RTAs. This paper deals with the analysis and modelling of the factors causing RTAs. Relevant studies are reviewed in this section.

Poisson's regression has been used in modelling the RTAs relationship with geometrical characteristics of rural roads [3]. While Fitzpatrick et al. [4] studied treatments of RTAs using some elements as inputs to the model. These elements are left-turn bays, intersection flashing beacons, back plates on traffic signalization, high-intensity lights, approach rumble strips, illumination, shoulder bypass lanes and advance warning for intersections. They found that advance warning for intersections was effective in reducing crashes at rural intersections. Shankar et al. [5] modeled the impact of road geometrical characteristics, rainfall and the number of rainy days on rural RTAs using binomial relationship and found that the RTAs occurrence increasing according to the frequent occurrence of these environmental factors. Also, the relationships between RTAs and many road design variables were studied by [6] who found that geometrical variables and road surface characteristics have the major contribution on RTAs occurrence. RTAs probability according to traffic flow, lighting conditions, and weather has also determined using multivariate models [7].

Sharma and Landge [8] developed regression models relating the RTAs to road geometrical and traffic characteristics for heavy-vehicles RTAs based on accident reports and field collected accident data. They found that access density and lane width have reasonable effects on RTAs occurrence. Regression models used in many studies (e.g., [9-11]) proved that RTAs occurrence is inversely correlated to the width of shoulders with reasonable prediction accuracy. Marchesini and Weijermars [11] also proved that the increase in the traffic volume leads to an associated increase in the accident rate.

Many other researchers studied the effect of speed on RTAs such as [12] who found that 65 km/hour speed would lead to an increase to double of the risk of accident involvement. Savolainen and Mannering [13] used a multinomial logic model for multivehicle crashes and as a result of their model they also, found that unsafe speeds play important roles in crash-injury outcomes. Taylor et al. [14] and [15-17] supported the fact that speed is very important for the driver risk perception and found a strong effect of traveling speed on accident risk. In addition, Santiago et al. [18] investigated the relation between speed and RTAs and presented some countermeasures to control speed by using a dynamic speed feedback sign. Hanley et al. [19] studied RTAs in California and found that the use of rumble strips installed on freeways could decrease single-vehicle RTAs by approximately 20 percent. Also, Patel et al. [20] presented and proved the usefulness of rumble strips.

Some researchers modeled the relationship between road safety and road surface condition. Al-Masaeid [21] studied the impact of pavement condition on rural RTAs and found that the pavement condition had a considerable impact on single and multiple vehicle accident rates. Harkey [22] studied crash reduction factors under intelligent transportation system improvements and found that these improvements have a great impact on reducing accidents rate.

Machine learning and artificial intelligence applications have been widely used in RTAs modeling (e.g., Tang et al. [23], Theofilatos et al. [24] and Wang, et al. [25]). Mohamed et al. [26] provided an application for urban networks using optimum and sensitivity analyses. Mendel [27] mentioned that fuzzy logic system can be used for such complex nonlinear inter-related factors. Khodayari [28], Wang and Meng [29] and Xiaorong et al. [30] studied fuzzy learning classifier system in automatic traffic incident detection, and then they built an evaluation environment by using field traffic incident database. Also, Xiao et al. [31] modeled RTAs on wet road surfaces using different fuzzy algorithms. Pawlus et al. [32] studied vehicle to pole collision models using fuzzy logic and found that it was viable when applying to their study area. While others (e.g., [33] and [34]) used fuzzy logic models to predict the accident rate according to traffic flow, the width of the median, the number of bus stops, the percent of signalized junctions per kilometres and rain condition. Du et al. [34] established RTAs prediction model for cold areas by using fuzzy logic. They studied five factors related to highway safety level. Rossi et al. [35] studied the RTAs based on real data in Tanzania and simulation data respectively using fuzzy algorithms. These researchers proved that the fuzzy algorithms proved high prediction accuracy for RTAs occurrence in the studied locations. Detailed review on the applications of machine learning in RTAs models can be found in Tang et al. [23] and Santos et al. [36]. This paper is concerned with modeling the relationship between accident number and the influencing factors using fuzzy logic algorithm to develop relationships between multiple inter-related factors affecting the RTAs.

3. DATA AND METHODOLOGY

3.1. Data and Study locations

The paper focus is a road located on Aswan-Cairo rural road (Aswan-Idfu section). This section is a two-way section of 85 km length and the average pavement width is 11.5m with 2m shoulders in both sides. The design speed on the road is 90 km/h. This paper is concerned with the analysis and modeling of accident data of Aswan-Idfu section considering the width of the road (rw), surface pavement condition (pm), signs condition (sj), speed (sp), minor access (ma) and the average hourly traffic per lane (AHTL). Two sets of data are taken into consideration in this paper; recorded accidents data and field survey data.

3.1.1 Recorded accidents Data

The utilized RTAs dataset is an official records collected by the Egyptian General Authority for Roads, Bridges, and Land Transport (GARBLT) [37] which reported the following information:

- Road width
- Road shape (straight or curved)
- Accident severity (fatal, injury, or property damage only)
- Number of fatalities and injuries as a result of each accident.
- The time of accident occurrence (month, day, hour, and minute)
- Weather conditions (dry, rain, fog…etc.)
- The main factors lead to accident occurrence (human, vehicular, roadway and traffic characteristics, or environmental conditions)
- Accident cause according to traffic experts opinion (excessive speed, wrong overtaking, hit obstruction, tire burst…etc.)
- The number of the vehicle involved.

3.1.2. Field Survey Data

A field survey was performed in Aswan-Idfu rural road for two weeks period to collect the road geometry and traffic conditions. AHTL is observed to represent the average daily traffic (ADT) by counting the traffic flow on each direction every 15 minutes. The road geometry data is collected for each homogeneous section including pavement width and the entrances to the road. In this survey, entrances are represented by the number of entrances which equal to the sum of all paved or unpaved feeder roads that enter the road under study from the two directions.

The traffic speed was calculated every hour for each homogeneous section as shown in Table 1. The values of V1 to V24 were used as inputs to the model, where V is the mean of all days speed for every hour.

Traffic signs regulate the movement on the road and aiding the drivers by supplying them the information through there travelling along the road which may decrease RTAs. So, it was another input of the model (the number of proper signs per unit length). Some defects of road signs condition are observed as shown in Figures 1 and 2 and they were not considered in the model.

The pavement condition evaluation was based on visual inspection of paved surface defects to determine the severity, area and total length and the use of curves to determine the values of the deduct value and then finding the pavement condition index (PCI), which ranges from 0 to 100 [38].

TABLE 1. SPEED OBSERVATION

Hour of the day	First day1	Second day2	…	Average hourly speed
1	v11	v21	…	V1
2	v12	v22	…	V2
3	v13	v23	…	V3
:	:	:	:	:
:	:	:	:	:
23	v123	v223	…	V23
24	v124	v224	…	V24

Fig 1. Improper position of road signs.

Fig 2. Damaged road sign.

3.2. Development of the Model

The Output Variable is the total number of accidents occurred in a road section during a certain hour (AAA), equation 1. Input variables are AHTL, rw, pm, sj, sp, and ma. AHTL was collected manually for 24 hours a day continuously. Pm was calculated based on the PCI, and rw was manually measured. Sp was observed by selecting two points 50m apart and using a stopwatch to calculate the spot speed at every hour of the day of survey. Sj and ma were calculated by counting traffic signs and minor access along a road section length and dividing them by the length of the road section using Equations 2 and 3, respectively.

$$AAA = \frac{\text{Total number of accidents occurred in a certain hour}}{R\text{oad length}*\text{Number of years}} \quad (1)$$

$$sj = \frac{\text{Total number of traffic signs in a road section}}{Length\ of\ \text{road section}} \quad (2)$$

$$ma = \frac{\text{Total number of minor access in a road section}}{Length\ of\ \text{road section}} \quad (3)$$

In fuzzy logic, the crisp is a set of data that has a certain characteristics and each data point has to be checked regarding inclusion within a crisp or not [39, 40]. Collan et al. [41] mentioned that the crisp consists of infinite grades of membership lies between 0 and 1. Inputs are represented in a way such that the closer the value to 1, the relevance to be a member of the crisp based on a membership function (mf). A fuzzy-set has a qualitative (linguistic) identification and a value. The fuzzy-set may approximate the relevance of a data point to be a member with a certain percent based on the mf.

According to Passino, et al. [42], an mf is the base of fuzzification and defuzzification of inputs and outputs and usually associated with the fuzzy rules [27]. There are many types of membership functions; the popular types used in relevant studies are the "triangular" and "trapezoidal" mf as recommended by Cartwright and Sztandera [43]. They are simple waveforms and can be used for a variety of applications so they are used in this paper as shown in equations 4 and 5, respectively.

$$\begin{aligned} f(x{:}a{,}b{,}c) &= 0 && a > x \\ &= \frac{y-a}{b-a} && a \le x \le b \\ &= \frac{c-y}{c-b} && b \le x \le c \\ &= 0 && c < x \end{aligned} \quad (4)$$

$$\begin{aligned} f(y,l,m,n,z) &= 0 && z < y < l \\ &= \frac{y-l}{m-l} && l \le y \le m \\ &= 1 && m \le y \le n \\ &= \frac{z-x}{z-n} && n \le y \le z \end{aligned} \quad (5)$$

According to Zimmermann et al. [44], there are mainly two models used frequently in literature; Mamdani and Sugeno fuzzy models. The former is widely used for human behavior inputs. The Mamdani's inference method [45] is used in this paper that consists of fuzzification, assessing rules evaluation, aggregation and defuzzification, as shown in Figure 3 [46]. In fuzzification, the mf is derived based on Equations 4 and 5. The mf works on measuring the distribution of input and output data. For rules evaluation, calculations are performed to construct fuzzy-sets members. To take the fuzzified input and apply them to "if-then" fuzzy rules, the union operations (A OR B; A AND B) were applied as shown in equations 6 and 7 [45]. "If-then" rule was applied for fuzzification of inputs, i.e. resolve all inputs to an mf degree (0 and 1).

$$mA \cup B(x) = \max\{mA(x), mB(x)\} \tag{6}$$

$$mA \cap B(x) = \min\{mA(x), mB(x)\} \tag{7}$$

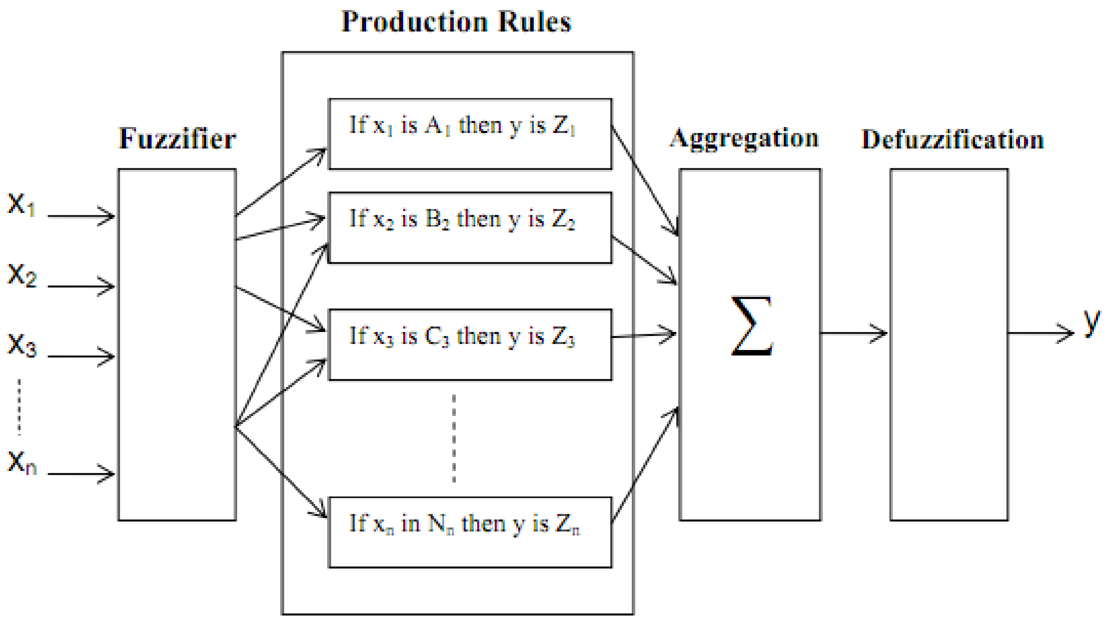

Fig. 3. Fuzzy inference system [28].

The defuzzification retranslates the resulted data values into their original form before fuzzification. There are many defuzzification methods that are used in the relevant literature, in this paper, the center of gravity function is applied as shown in Equation 8 [47] and [48].

$$y = \frac{\sum_{k=1}^{n} \text{yi}*\mu*(\text{yi})}{\sum_{k=1}^{n} \mu*(\text{yi})} \tag{8}$$

where y is the linguistic variable value, *k=1* to *n* are its range and μ is the membership function of the variable.

4. RESULTS AND DISCUSSION

4.1. Accidents' Data Analysis

RTAs data analysis shows that the number of accidents varied from day to another during the week. Figure 4 shows that RTAs occurrence during Tuesdays was lower than during other days and the large percent of total RTAs about 20.73% occurred in Mondays. As a result of reviewing the crash reports, RTAs can be classified according to its type to single vehicle accidents, double vehicle accidents, and more than two-vehicle accidents. It is found that 62% of RTAs involved single vehicle while 36% of RTAs involved double vehicles. RTAs were classified into type of severity according to fatal, injury or property damage only (pdo) accidents. Figure 5 shows that fatal accident occupied about 57.4% where injury accidents took 39% and pdo occupied 3.6% of total RTAs that occurred on the studied road.

RTAs occur due to driver, vehicle, roadway, and environmental reasons. Based on the RTAs data analysis, human factors caused about 81% of all RTAs occurrence on the road while vehicle and roadway factors are 15.85% and 2.44%, respectively. The main human factors recorded are over-speeding and overtaking. The greater a vehicle speed exceeds design speed, the greater the probability of involving in RTAs. The analysis shows that 96% of RTAs in the studied road are because high speeds and 4% of accidents were due to improper overtaking by the driver that may be due to limited pavement width. The analysis shows that RTAs occurred at night were 38% where 62% of road accidents occurred at daylight. Horizontal curves on the studied road do not affect accident rates, RTAs data analysis shows that all RTAs occurred in straight road sections. Since the drivers are being mindful and decreasing their speeds during curves. The majority of RTAs happened under clear weather condition. This may be because drivers tend to be more careful while driving during bad conditions of weather. So this factor was not taken into consideration while processing the model. It is noticed that speed is primary factor of RTAs so we used it as input in our model, the majority of RTAs occurred at midday and few accidents occurred at night with the over-speeding reason so, road's lightening was not an important factor on our model. All accidents happened in straight road sections that mean road curves did not have obvious effect on accidents rate because of that we did not expose to it in the model.

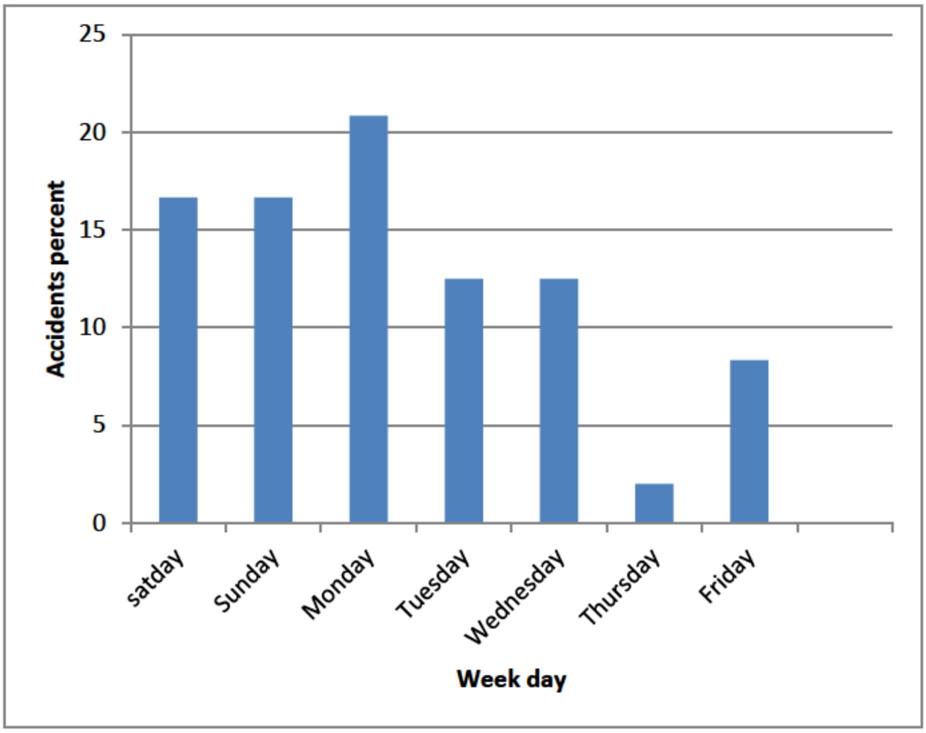

Fig. 4. Percent of accidents during weekdays.

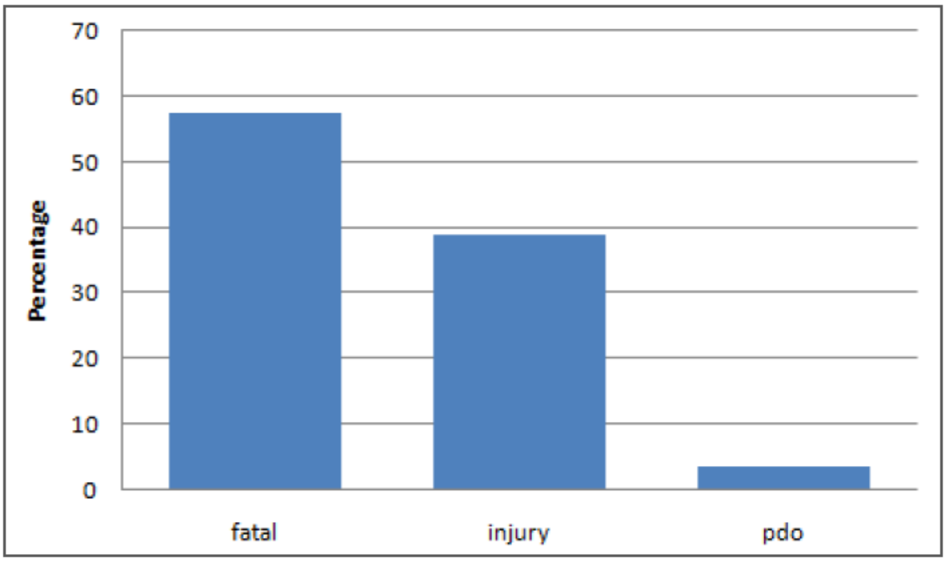

Fig. 5. Classification of road accidents according to the severity.

4.2. Modeling of Accidents Data

To develop and calibrate the model, data split was performed; the training data is a random 50% of the whole data which were used for the model construction and the remaining data will be the testing data for the model calibration. Each data set consists of 168 data points (24 hours*7 days=168 data point). Figure 6 shows the overall representation of the proposed fuzzy algorithm. At first, this study established the membership function for every selected variable which are AHTL, rw, sp, sj, ma and pm then choose the linguistic variables. Next, the general rules were built by using the significant rules. After that, aggregation process was applied and the defuzzification was used to invert the output of the proposed model to crisp set. Then the results of RTAs prediction modeling were calibrated by comparing the true AAA values with their model-estimated values using the testing data. The estimation goodness of fit of the model proves a reasonable determination coefficient (R^2) of 0.79 as shown in Figure 7.

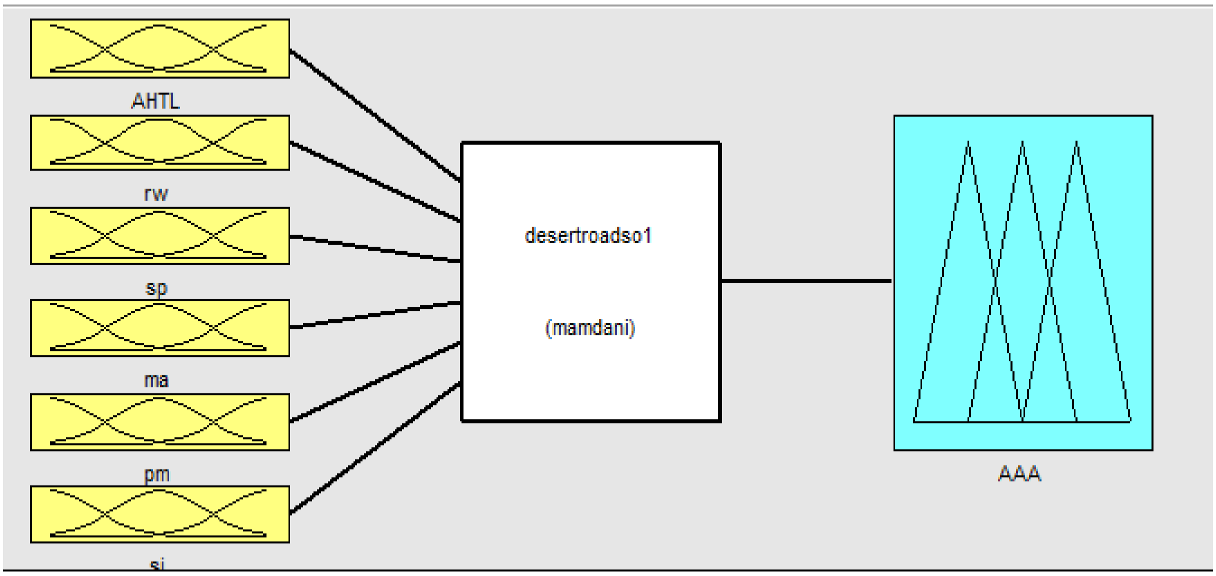

Fig. 6. The model structure.

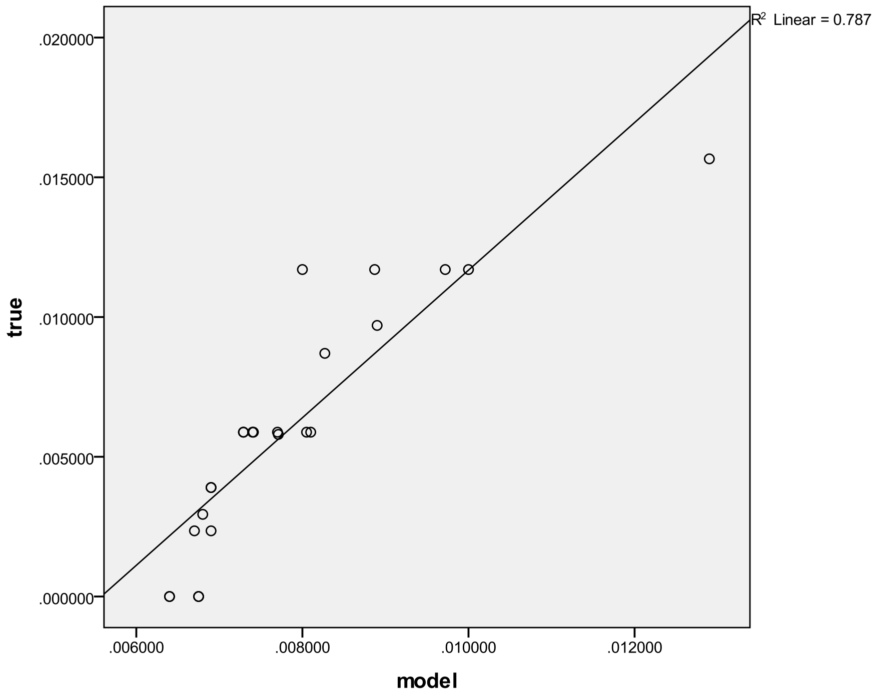

Fig. 7. The true AAA values with their model-estimated values using the testing data.

The surface shape of the model using center of gravity defuzzification method provides some insights for the possible improvements to decrease accidents number. Figures 8 and 9 show the 3-D plot between AAA and different variables. Figure 8 shows the relationships between AAA with (rw) and AHTL, and Figure 9 shows relationships between AAA with sp and pm. Figure 8 shows that the RTAs decrease as the average flow decreases and road width increases. Moderate traffic conditions had increased RTAs with limited pavement width while at congested zones the number of accidents is high but it seems constant. Figure 9 shows that RTAs rapidly increased with speed increase for different pavement conditions.

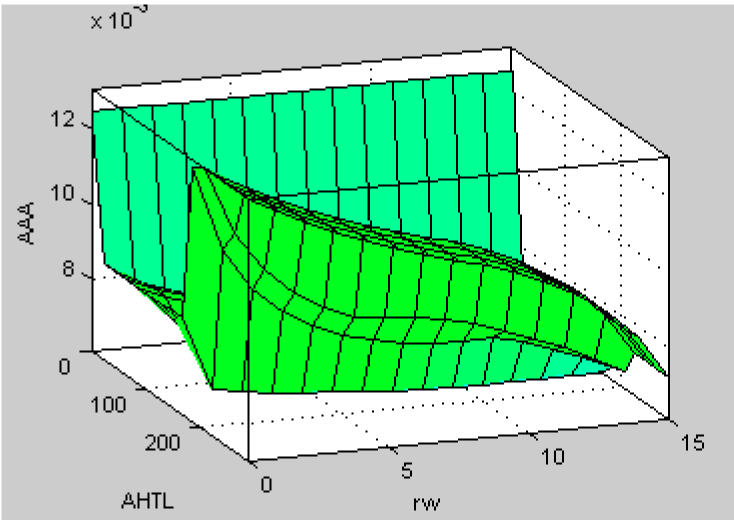

Fig. 8. AAA, AHTL and rw relationships after defuzzification process.

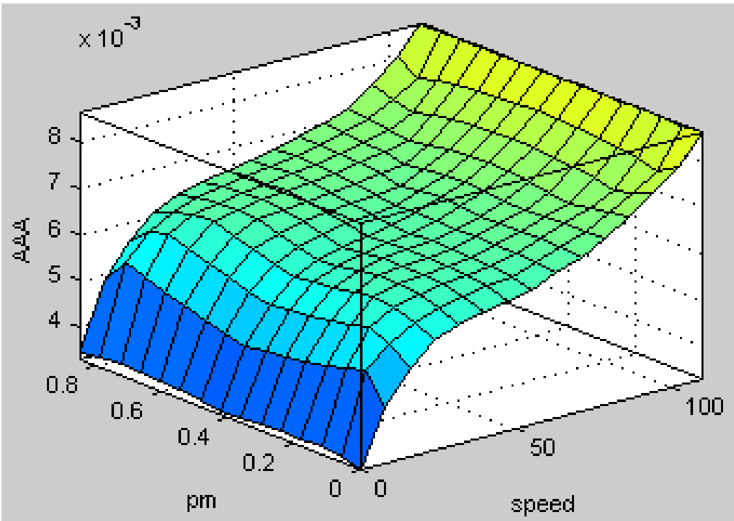

Fig. 9. AAA, speed and pm relationships after defuzzification process.

An important application of the model is to predict the effect of improving different variables on the number of accidents. The impact of speed limit on AAA was checked for speeds between 20 and 90 km/h and fixing the values of other variables as shown in Figures 10 and 11. These figures show that there is a reduction in AAA of about 7.38% is reached due to controlling speed limit at 75 km/h.

The same procedure is applied by changing the value of rw between 11.5 and 15 m;, the value of ma between 0 and 0.05 minor access / km, the value of pm between 0.1 and 0.8, the value of sj between 0 and 0.8, the value of AHTL between 160 and 176 and fixing the values of other variables in each case. The results of the model show that AAA is inversely correlated to road width. Increasing road width by 3.50 m reduced AAA by 5.26%. AAA is directly correlated with minor entrances intensity, and AHTL. AAA increases due to the increase of traffic volume and conflict points. This is due to high traffic flow which restricts the freedom of drivers for maneuvering. The results of the model show that AAA is inversely correlated to pavement and road signs conditions. There is a reduction in AAA of about 17.90% due to improving road surface condition. AAA reduced by about 5.9% due to improving signs condition.

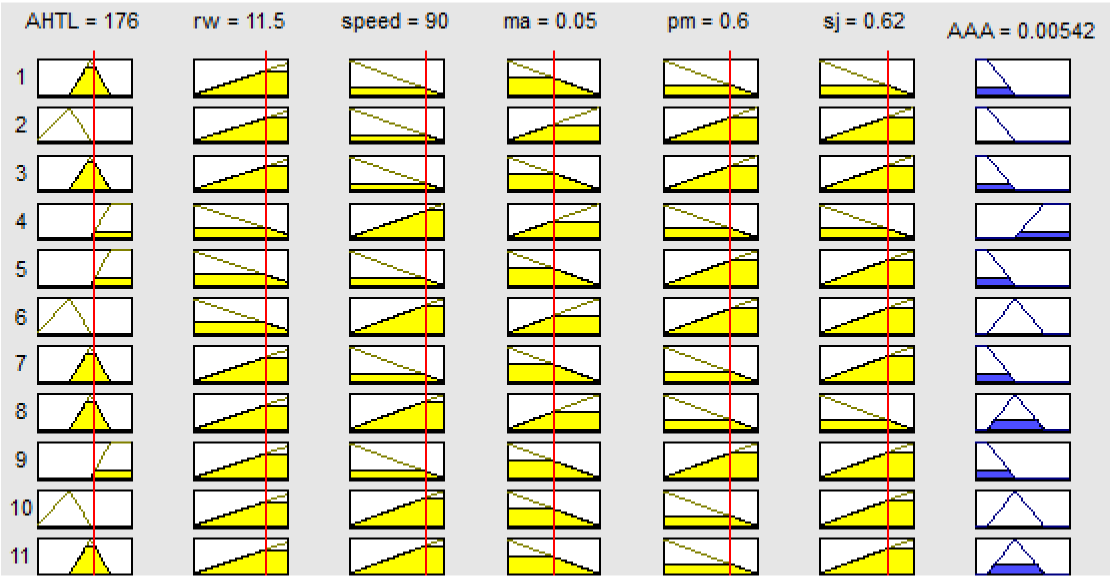

Fig. 10. Defuzzification of the data (sp =90).

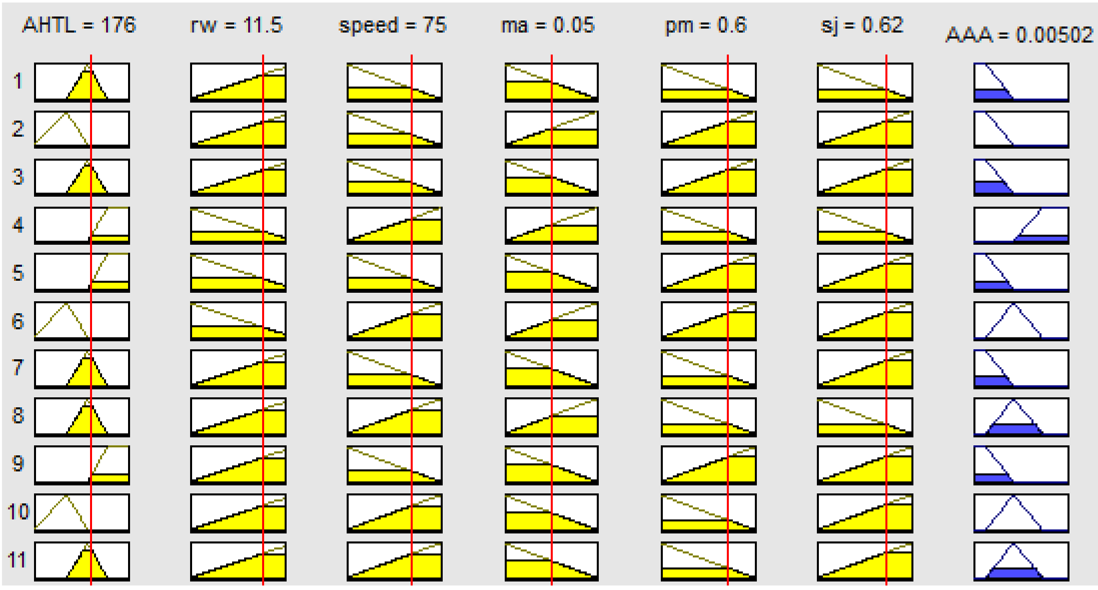

Fig. 11. Defuzzification for (sp=75).

5. SUMMARY, CONCLUSION AND RECOMMENDATIONS

The current paper analyzed traffic accidents data in order to determine their determinants and modeling their causes, the paper focused on a section of Aswan-Cairo rural road (Aswan-Idfu section), which is an alternate road to decrease the flow on the Aswan-Cairo urban road but has high fatality rate. The Mamdani's fuzzy algorithm is used for correlating accidents to their determinants. Calibration test showed that the results of the algorithm is promising ($R^2 = 0.79$). Based on traffic accident analysis and modeling on the studied road, this paper suggested some improvements in road characteristics and traffic operation. The following conclusions were obtained:

- 81.7% of accidents are due to human behavior. While vehicular, road and traffic shared about 15.9%, 2.4% respectively of all accidents occurred on the road.
- About 96% of all accidents occurred on the desert road were due to exceeding speed limit, on the other hand, about 4% of all accidents were due to improper overtaking by the driver. Traffic speed must be controlled by traffic agencies using order signs and radar controlling traffic speed on the studied road.
- Majority of accidents happened at a good and clear weather conditions because the driver takes full care while driving during bad weather conditions.

- The results of the model show that AAA is inversely correlated to road width. Increasing road width by 3.50 m reduced accidents by 5.26%.
- Accidents are directly correlated with minor entrances intensity, and AHTL. Their occurrence increase with the increase of traffic volume and conflict points. This is due to high traffic flow which restricts the freedom of drivers for maneuvering.
- The results of the model show that accidents are inversely correlated to pavement and road signs conditions. There is a reduction in accidents of about 17.90% and 5.9% are reached due to improving road surface and signs conditions.
- Accidents are proportionally correlated to excessive speed and could be reduced by 7.38% with applying a speed limit of 75 km/h.

Accordingly it is recommended to pave extra 3.5 m, decrease the speed limit to be 75 km/h, perform the needed road surface and signs maintenance. Future research need to investigate the countermeasures which help in decreasing accidents at the zone of contact between the desert road and the side roads.

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