EFFECTS OF AUTOMATED TRAFFIC ENFORCEMENT ON DRIVER BEHAVIOR AT A SIGNALIZED INTERSECTION IN SAUDI ARABIA

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ABSTRACT:

For automating road network Saudi Arabia recently introduced 'Saher Traffic Monitoring Enforcement System' (STMES) using red-light and speed-limit camera. This paper analyzes the impact of STMES on driver behavior and decision making process at signalized intersections. It proposes models for analyzing driver's probabilities of stopping and crossing decisions at signalized intersections during yellow-light interval on the basis of speed, distance from intersection and vehicle type. Models also compare STMES fitted intersections with conventional intersections without automated systems. Binary logistic regression and Artificial Neural Network (ANN) models are developed using video data at intersections in Makkah city. Analyses reveal that STMES increases stopping probability by 26 percent and distance to the stop line is the most significant factor affecting the drivers’ decisions in the yellow interval. Dilemma zone shifts closer to the stop line and the number of early stops increases due to STMES. Artificial neural network model performs better than binary logistic regression model in predicting the stopping probability at signalized intersections. Research findings suggest that ANN models can be effectively used in traffic signal design and dilemma zone reduction to improve efficiency and safety at roadway intersections.

Keywords: Traffic, Enforcement, Dilemma, Intersection, Modeling, Logistic Regression, Neural Network
1. INTRODUCTION

Intersections are the most critical component of urban roadway network systems in terms of performance and safety concerns. In 2008, the National Highway Traffic Safety Administration (NHTSA) estimated that crashes at signalized intersections in the USA caused more than 7,770 fatalities, 10 percent of which were caused by red-light running, and 97 percent of drivers feel that violation of red-lights at signalized intersections is a major safety concern [1]. In 2009, statistics indicated that traffic accidents in the Kingdom of Saudi Arabia led to 6,142 deaths, and red-light violations were a major cause of such incidents [2].

Red-light cameras (RLCs) and speed cameras at intersections are the most commonly used automated traffic enforcement technologies [3]. Urban areas are at a higher risk of crashes caused by the driver running a red light; approximately 22% of crashes at signalized intersections are caused by red-light violations [4, 5]. Many researchers recommend automated enforcement systems together with RLCs to improve safety at intersections [6, 5, 7]. Most researchers have focused on either crash severity (fatality, injury, vehicle damage, etc.), violation type (red-light running, speeding, etc.), or collision type (right-angle, rear-end, etc.). Overall, RLCs increase the proportion of rear-end crashes [8, 9] and decrease the proportion of right-angle crashes and red-light running crashes [10, 11].

In April 2010, the government of Saudi Arabia launched the automated Saher Traffic Monitoring Enforcement System (STMES), which controls and manages vehicular traffic. STMES is intended to reduce accidents and raise the overall efficiency of the road networks in Saudi Arabia. The system uses RLCs to enforce traffic laws at signalized intersections, particularly focusing on red-light signal violations. Understanding the drivers’ perception of STMES and the way it affects decision-making are significant factors to assess and enhance the system’s performance. According to studies published before STMES was implemented, drivers in Riyadh tended to be more aggressive than drivers in developed countries [12]. Driving behavior in terms of headway and gap acceptance in Riyadh and Makkah is also different, i.e., is shorter, from that of other countries [13, 14]. Although models for the probability of stopping at signalized intersections are often debated in international literature, no models that we are aware of, take local data from Saudi drivers into account.

This paper presents major findings of research on drivers’ perceptions and responses toward STMES and the resulting effect on traffic parameters. These results will assist in identifying the dilemma zone and devising ways to mitigate its effect to reduce traffic accidents. The study will also assist to develop a model for traffic characteristics and driver reaction patterns in Saudi Arabia to better understand the effect of STMES on driver behavior. After the literature review, the subsequent sections of this paper explain the analytical framework, results, discussion, and conclusion.

2. LITERATURE REVIEW

The study of drivers’ behavioral responses to traffic control devices is a classic research area in traffic engineering. Driver behavior influences the parameters that control intersections and determine the length of the dilemma zone. In addition, modeling of driver behavior can improve the safety of signalized intersections [15].

Most of the research on drivers’ behavior relates to accidents because human decisions are considered to be a contributing factor in more than 90% of total road accidents [16, 17].
NHTSA has indicated that about 67% of fatal accidents in the USA in the years 1990–1996 were caused by aggressive driving behavior [18]. Therefore, drivers’ behavior at signalized intersections, and particularly aggressive driving, may have significant implications on signal design parameters. Implementation of an enforcement system, such as the use of RLCs, complicates these scenarios and demands rigorous investigation.

Lum and Wong [19, 20, 21] conducted studies on the effect of signal-enforcement systems in Singapore on driver decisions regarding red-light signals. They collected data using loop sensors to and employed logistic modeling to model the stopping/crossing decisions of drivers while responding to yellow signals. The results indicated that RLCs significantly affect driver decisions at signalized intersections.

Papaioannou [22] investigated driving behavior at yellow signals as a contributing factor in safety at a signalized intersection in Thessaloniki, Greece, by classifying drivers into three categories: conservative, normal, and aggressive. The study used a logistic regression model to analyze the probability of stopping and crossing, on the basis of age, gender, vehicle speed, and the dilemma zone. A high percentage of drivers behaved aggressively, and drivers’ decisions were significantly correlate to their gender, vehicle’s speed, and the distance of the car from the stop line.

Based on video-camera data of drivers’ decisions at yellow lights, Elmitiny et al. [23] built classification-tree models to analyze the probability of stopping or crossing and of running a red light depending on traffic parameters.

Pulugurtha and Otturu [24] recently examined RLCs at 32 signalized intersections in the city of Charlotte, North Carolina, USA. They used the empirical bayes method to predict the number of crashes and then compared this predicted number with the actual number of crashes that occurred. They found that RLCs are effective in reducing the total number of crashes at signalized intersections.

Quiroga et al. [25], Yan et al. [26], and Tang et al. [27] investigated how various types of enforcement and traffic information systems (such as countdowns, flashing greens, and warning signs) affect driver behavior. To obtain a better understanding of driver decisions and behavior within the dilemma zone, majority of researchers have used the binary logistic regression model to analyze driver decisions during yellow-light intervals [28, 29, 30, 31]. Other researchers have modeled decisions with ordered-binary probit, binary probit, and fuzzy-logit models [32, 33, 34, 35]. Several studies have found that driver behavior in Riyadh tends to be aggressive [12, 13].

These local studies were published before implementation of STMES and in the absence of RLCs. The presence of an automated enforcement system at an intersection may make drivers less aggressive, as argued by Forrest et al. [36] and Shin and Washington [9].

Although automated enforcement systems at signalized intersections have been found to reduce the number of red-light violations by as much as three times[37,38], their effectiveness in terms of overall safety and their effect on decision-making at signalized intersections is still up for debate [39]. Research on the effects of automated enforcement systems on driver behavior and intersection safety in the context of Saudi Arabia is sparse.

### 3. METHODS

For assessing and analyzing driver behavior at signalized intersections, a binary logistic regression model is often suitable predicting the stopping probability based on multiple factors such as vehicle’s speed and its location [28, 29, 30, 31]. The binary model can be represented as a follows [40, 41]:

\[
P(y = \text{stop}) = \frac{e^{\beta}}{1 + e^{\beta}},
\]  

(1)
where

\[ y = \beta_0 + \beta_i \times X_i \]

is the probability of the driver choosing to stop;

- \( y \) = binary decision variable (stop = 1 and cross = 0), dependent variable;
- \( \beta_0 \) = constant coefficient;
- \( \beta_i \) = coefficients of independent variables;
- \( X_i \) = independent variables.

### 3.1. Dependent and Independent Variables

At signalized intersections, when the light changes to yellow, a driver must choose either to cross or to stop. This choice is a binary variable suitable for logistic modeling. The dependent variable is the driver’s decision regarding their behavior at a yellow signal, represented by \( y \), where

- \( y = 1 \) represents the choice to stop, and
- \( y = 0 \) represents the choice to accelerate and cross the intersection.

The independent variables include two categorical and three continuous variables. Both the continuous and categorical variables were examined in the design of the model. The factors tested for inclusion in the model were as follows:

- approaching speed (speed);
- vehicle distance from the stop line at the onset of a yellow light (distance);
- installation of an enforcement system at the intersection (STMES: with = 1, without = 0);
- vehicle type (VEH: passenger car = 1, other = 0).

The variables selected for logistic modeling are described in Table 1.

A binary logistic regression model was developed to predict the probability of stopping based on these variables with and without STMES using the following equation:

\[
\text{logit}(P) = \beta_0 + \beta_1 \times Distance + \beta_2 \times Speed + \beta_3 \times STMES + \beta_4 \times VEH,
\]

### Table 1 Variables Selected for Logistic Modeling

<table>
<thead>
<tr>
<th>No.</th>
<th>Variable</th>
<th>Variable Description</th>
<th>Codes/ Values</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Vehicle Type</td>
<td>Vehicle Type: Passenger car or other</td>
<td>P. Car = 1</td>
<td>VEH</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Other = 0</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Enforcement System</td>
<td>Saher Traffic Monitoring Enforcement System</td>
<td>With = 1</td>
<td>STMES</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Without = 0</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Distance (m)</td>
<td>Vehicle’s distance from the stop line when the yellow signal turns on</td>
<td>Continuous variable</td>
<td>Distance</td>
</tr>
<tr>
<td>4</td>
<td>Speed (km/h)</td>
<td>Vehicle’s speed when the yellow signal turns on</td>
<td>Continuous variable</td>
<td>Speed</td>
</tr>
</tbody>
</table>

### 3.2. Data Collection and Extraction

Data related to traffic flow and driver behavior was collected from 6:00 am to 9:00 am on weekdays using a video camera, which was unobtrusively mounted in a building on the roadside 16–20 meters above the ground. Among the four signalized intersections which were chosen for the analysis, two of them were with STMES and the other two without STMES.
A total of 768 vehicles facing yellow signal and having to choose either to stop or cross were sampled. In good weather conditions, the data collected from the video recording included driver’s decision, signal status, traffic conditions, and vehicle characteristics. Reference points were marked at 5-m intervals to calculate the accurate position and speed of vehicles [30]. In this research, the reference points were divided into the following two categories to obtain more accurate measurements (Figure 1):

1. **Major reference point.** This represented the stop line, the Saher cameras (STMES), and the reference line (30 m from stop line).

2. **Minor reference point.** This represented the number of curbs on both sides (each curb was a fixed space of 0.5 m), especially in the absence of STMES at signalized intersections.

![Figure 1](image1.png)

**Figure 1** Location and distance of the reference points at the intersection

Video footage was studied frame-by-frame to extract the precise timings of signal changes and stop-line crossing or stopping events. The exact time was recorded as the signal turned yellow to a precision of the 30-Hz frame rate (1/30 second). At the same time, the vehicle closest to the stop line was identified as the target vehicle and its distance to the stop line was recorded. Virtual reference lines were superimposed on the video footage, along with the major and minor reference points, using U-lead software. Figure 2 shows a screenshot with the reference lines superimposed on the video.

![Figure 2](image2.png)

**Figure 2** Reference lines superimposed on the video
The distances of the vehicles from the stop line, vehicle speeds at the onset of a yellow signal, and driver decisions when the signal turned yellow were collected from the videos. Sample data extracted from the video are shown in Table 2.

### Table 2 Sample of data extracted from the video

| N | Time (ss, ff) | Driver action | Distance To Stop Line At Onset Of Yellow (m) | Speed (m/s) = 10/Dt | Speed (km/hr) | Vehicle type | STMES
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.7 1.7</td>
<td>1</td>
<td>4</td>
<td>10.00</td>
<td>36.00</td>
<td>P.car with</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>16.1 17.2</td>
<td>1</td>
<td>6</td>
<td>9.09</td>
<td>32.73</td>
<td>P.car with</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>16.4 17</td>
<td>0.6</td>
<td>44</td>
<td>16.67</td>
<td>60.00</td>
<td>P.car with</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>14.3 15.1</td>
<td>0.8</td>
<td>6</td>
<td>12.50</td>
<td>45.00</td>
<td>P.car with</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>21.1 22.8</td>
<td>1.7</td>
<td>2</td>
<td>5.88</td>
<td>21.18</td>
<td>Other with</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>42.7 44.3</td>
<td>1.6</td>
<td>7</td>
<td>6.25</td>
<td>22.50</td>
<td>Other without</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>41.9 42.7</td>
<td>0.8</td>
<td>3</td>
<td>12.50</td>
<td>45.00</td>
<td>P.car without</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>40.3 41.5</td>
<td>1.2</td>
<td>2</td>
<td>8.33</td>
<td>30.00</td>
<td>P.car without</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>39.6 40.7</td>
<td>1.1</td>
<td>4</td>
<td>9.09</td>
<td>32.73</td>
<td>P.car without</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>56.7 57.5</td>
<td>0.8</td>
<td>6</td>
<td>12.50</td>
<td>45.00</td>
<td>other without</td>
<td></td>
</tr>
</tbody>
</table>

1. The time displayed on the counter consists of: ss: second, ff: fraction of second (1 ss = 30 ff).
2. STMES: Saher Traffic Monitoring Enforcement System

### 3.3. Estimated Logistics Model

The statistical results of the model and the probability of stopping (P) returned by the multivariate binary logistic regression model are listed in Table 3.

### Table 3 Multivariate Binary Logistic Regression Model Statistics on Predictions (Stop/Cross)

| Coefficients | \( \beta \) | Std. Error | z value | Pr(|z|) | Odd Ratio |
|---|---|---|---|---|---|
| Intercept | 1.4432 | 1.0338 | 1.396 | 0.163 |
| Distance | 0.1995 | 0.0419 | 4.765 | <0.001 *** | 1.22 |
| Speed | −0.1039 | 0.0272 | −3.815 | <0.001 *** | 0.90 |
| STMES | 2.1897 | 0.6765 | 3.237 | <0.01 ** | 8.93 |
| VEH | −1.4421 | 0.8683 | −1.661 | 0.097 | 0.24 |

Direction of the binary response variable ("0" indicates crossing / "1" indicates stopping)
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for binomial family taken to be 1)
Null deviance: 193.62 on 139 degrees of freedom Residual deviance: 140.11 on 134 degrees of freedom

Most of the parameters considered in the model are logical and significant (at the 5% significance level). A relatively low level of confidence for vehicle type (VEH) may be attributed to a relatively lower number of observations. These predictions are expected to become significant with an increased number of observations of decision for heavy vehicles. Analysis of variance (ANOVA) results show that traffic factors, including distance (p < 0.001), speed (p < 0.001) and STMES (p < 0.001), have a significant effect on drivers’ decisions. This finding supports the results of other studies indicating that a driver’s decision...
to stop or to cross is affected by both the approach speed and the distance from the stop line during the yellow phase at intersections[15, 19]. Results revealed that for the same vehicle location and velocity at the onset of yellow, the odds for stopping at a signalized intersection with STMES are 8.93 times those of a signalized intersection without STMES, and results in improving intersection safety by reducing red-light violations when STMES is present.

The probability curve for a vehicle stopping, as plotted in Figure 3, suggests that the average probability of a vehicle stopping is significantly increased when STMES is present and the vehicle is less than 10 meters from the stop line when the signal changes to yellow.

![Figure 3](image)

**Figure 3** Probability of stopping during yellow light

Figure 3 shows the effect of distance to stop line on probability to stop for with and without STMES cases. With increasing distance to the stop line, the difference between the two curves quickly diminishes until the two curves merge. Vehicles are almost always less likely to stop when STMES is absent. In the yellow interval, when vehicles are at the same distance from the stop line, the average probability of stopping at intersections with STMES is significantly higher than without STMES by approximately 26%. This suggests that STMES is effective in deterring red-light violations, as evidenced by the large difference in stopping probability between these scenarios. As shown in Table 4, the model under-predicts crossing probability and aggregate prediction accuracy of the logistic model is 72.9 percent.

<table>
<thead>
<tr>
<th>Predicted Decision</th>
<th>Observed Decision</th>
<th>Percentage Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stop</td>
<td>Cross</td>
<td>68.2</td>
</tr>
<tr>
<td></td>
<td>Stop</td>
<td>77.0</td>
</tr>
<tr>
<td>Aggregate Accuracy</td>
<td></td>
<td>72.9</td>
</tr>
</tbody>
</table>

### 3.4. Estimated Artificial Neural Network Model

In order to enhance model prediction accuracy, application of artificial neural network (ANN) is examined. ANN works like a collection of biological neurons. These neurons receive inputs from the source, perform a nonlinear operation, and predict an output [42]. An artificial neural
network takes the basic structure of the human brain [43], which is essentially very complex, nonlinear, and capable of parallel processing [44].

Recently, with developments in computer technology, artificial neural networks have been applied to many engineering problems such as automotive applications [45, 46] and transportation planning [47]. Moreover, artificial neural networks have the ability to model all kinds of traffic violations and traffic patterns as long as an appropriate structure is implemented [48].

An artificial neural network comprises many simple and highly interconnected processing elements like the neurons in the human brain. The model can be defined as a black box comprising a series of equations for the calculation of outputs from given input values [49].

The block diagram of a neuron model is shown in Figure 4 and forms the basis for designing an artificial neural network [44]:

![Figure 4 Block diagram of nonlinear model of a neuron](image)

Mathematically, a neuron $k$ can be described by the following equations:

$$ u_k = \sum_{j=1}^{m} w_{kj} x_j, \quad (3) $$

$$ y_k = \varphi(u_k + b_k), \quad (4) $$

Where

- $b_k =$ Bias (increasing or decreasing the net input of the activation function);
- $x_1, x_2, ..., x_m =$ inputs;
- $w_{kj1}, w_{kj2}, ..., w_{km} =$ weights of the neuron $k$;
- $u_k =$ linear combiner output due to input signals;
- $\varphi(\cdot) =$ activation function;
- $y_k =$ output signal of the neuron.

Artificial neural networks use learning algorithms to simulate the function of the human brain [50]. A multilayer perceptron trained with a backpropagation algorithm is the simplest and the most widely used neural network method [47, 51]. The multilayer perceptron comprises three layers: input and output layers and one or more hidden layers.
A backpropagation algorithm was used as the learning algorithm for multilayered feedforward networks. The vehicle’s distance from the stop line when the yellow signal turns on (Distance), vehicle’s speed (Speed), presence of STMES, and vehicle type (VEH) were used as input parameters.

3.4.1. Artificial Neural Network results

The neural network package in the R software package was used to implement the artificial neural network model. The main structure of the artificial neural network is shown in Figure 5.

![Figure 5 Main structure of artificial neural network](image)

We checked the implementation of neuralnet using the training and test data sets, and assessed model performance and prediction accuracy following the steps and pseudo code shown below:

**Step 1**: Read Data – Input variables (Speed, Distance, STMES, VEH) and Output (Decision).

**Step 2**: Model Calibration – Using Neuralnet package in R and saving output as ‘nnnn’ object.

**Step 3**: Check accuracy of neural network model with test data set.

```r
R>nnnn$net.result[[1]]
R>nnn2 = ifelse(nnnn$net.result[[1]]>0.5,1,0)
R>misClasificationError = mean(DataFrame$Decision !=nnn2)
R>accuracy<- (1-misClasificationError)*100
R>accuracy
[1] 84.29
```

3.4.2. Performance of existing traffic management systems

The performance of existing traffic management systems was evaluated considering the ANN model's predictions. The evaluation focused on the accuracy and reliability of the ANN model in predicting traffic conditions.

**Results**

The ANN model showed a high level of accuracy in predicting traffic conditions, with an overall accuracy of 84.29%. This indicates that the ANN model has the potential to be a reliable tool for traffic management systems.
4. MODEL COMPARISON

The two models described above were compare on the basis of prediction accuracy. The artificial neural network model is clearly more accurate than the logistic regression model. The artificial neural network model made 11% more accurate predictions than the logistic regression model.

The estimated error values of both models show that the artificial neural network is more accurate than the binary logistic regression model for predicting the stopping probability at signalized intersections. The prediction accuracy for the logistic regression model was about 73 percent, whereas it was more than 84 percent for artificial neural network model. This might be caused by the ability of neural network model to account for the interaction effect among the input variables.

5. CONCLUSION

In the paper we compared the effectiveness of using binary logistic regression and artificial neural network models to assess traffic characteristics, safety implications, and performance at intersections with and without STMES. Major findings of the study are summarized below:

- The distance to the stop line is the most significant factor affecting drivers’ decision at the onset of yellow light.
- Vehicles are 26 percent more likely to stop at an intersection with STMES compared to intersection without STMES.
- The dilemma zone moved closer to the stop line, and its length decreased to from 35 to 10 m with installation of STMES.
- STMES increases the number of early stops as drivers try to avoid red-light violations. This finding supports findings reported elsewhere that the use of RLCs as automated enforcement devices increases the number of rear-end collisions (up to approximately 45 percent) [5, 52, 53, 54, 55].
- Comparison of two predictive modeling approaches show that artificial neural network is more accurate for predicting stopping behavior than binary logistic regression model. The artificial neural network model is 84.29 percent accurate, whereas binary logistic regression model accuracy is 72.86 percent.

The presence of STMES affects driver decisions about whether to slow down at a yellow signal thereby determines the boundary of dilemma zone, and in turn, affects the safety and performance at intersection. Increase in propensity to stop due to STMES induced perceived risk of penalty enhances perception of safety, and such systems are supported by 75 percent of road users in USA [56]. Predictive models can be used to enhance safety and assist drivers in decision making by dynamically updating the parameters of intersection operations and adjusting the yellow-light period to reduce the effect of the dilemma zone at signalized intersections. Further research is required to integrate predictive models with real-time signal operations and advanced warning systems. Future research with more field data could further improve predictive accuracy of the neural network model.

REFERENCES


Effects of Automated Traffic Enforcement on Driver Behavior at a Signalized Intersection in Saudi Arabia


[25] Quiroga C.; Kraus E.; Schalkwyk I.V.; Bonneson J. Red light running—A policy review. Texas Transportation Institute, College Station, TX, 2003


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