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# Modeling aggressive driver behavior at unsignalized intersections

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## Abstract

The processing of vehicles at unsignalized intersections is a complex and highly interactive process, whereby each driver makes individual decisions about when, where, and how to complete the required maneuver, subject to his perceptions of distances, velocities, and own car's performance. Typically, the performance of priority-unsignalized intersections has been modeled with probabilistic approaches that consider the distribution of gaps in the major-traffic stream and their acceptance by the drivers of minor street vehicles based on the driver's "critical gap".

This paper investigates the aggressive behavior of minor street vehicles at intersections that are priority-unsignalized but operate with little respect of control measures. The objective is to formulate a behavioral model that predicts the probability that a driver performs an aggressive maneuver as a function of a set of driver and traffic attributes. Parameters that were tested and modeled include *driver characteristics* (gender and age), *car characteristics* (performance and model year), and *traffic attributes* (number of rejected gaps, total waiting time at head of queue, and major-traffic speed). Binary probit models are developed and tested, based on a collected data set from an unsignalized intersection in the city of Beirut, to determine which of the studied variables are statistically significant in determining the aggressiveness of a specific driver.

Primary conclusions reveal that age, car performance, and average speed on the major road are the major determinants of aggressive behavior. Another striking conclusion is that the total waiting time of the driver while waiting for an acceptable gap is of little significance in incurring the "forcing" behavior. The obtained model is incorporated in a simple simulation framework that reflects driver behavior and traffic stream interactions in estimating delay and conflict measures at unsignalized intersections. The simulation results were then compared against real world observations, representing an important step in validating the model of aggressive driver behavior at unsignalized intersections.


*Keywords:* Traffic; Unsignalized intersection; Gap acceptance; Stream interaction; Aggressive behavior; Forcing

## 1. Introduction

The processing of vehicles at unsignalized intersections is a complex and highly interactive process, whereby each driver makes individual decisions about when, where, and how to complete the required maneuver, subject to his perceptions of distances, velocities, and own car's performance (TRB, 1997). Unsignalized intersections include "priority-unsignalized intersection", whereby a major and a minor street intersect, and "uncontrolled intersections" where no explicit priorities exist. Typically, the performance of priority-unsignalized intersections has been modeled with probabilistic approaches that consider the distribution of gaps in the major-traffic stream and their acceptance by the minor road vehicles based on the driver's "critical gap".

Gap acceptance models have been the focus of extensive research efforts that aimed at overcoming the limitations of the basic gap acceptance theories. In this regard, researchers have investigated and modeled the concept of driver learning, but only marginally tackled the field of driver's aggressiveness that could result in reversed priorities. The New York penal law defines aggressive driving as "the unsafe operation of a motor vehicle in a hostile manner, without regard for the safety of other users of the road" (Miles and Johnson, 2003).

The objective of this research is to model the aggressive behavior of drivers at priority-unsignalized intersections that operate with partial respect for governing traffic laws.

## 2. Background

Questions about behavior at intersections have intrigued traffic engineers for a long time. Some of the earliest research

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reported in this regard was in the late 1940s by Greenshields (Lee and Hughes, 2005).

Madanat et al. (1994) used logit-modeling techniques to develop gap acceptance functions at a stop controlled intersection, and used stochastic queuing theory to evaluate the intersection's performance. They concluded that the gap length, the stop bar delay, the queuing delay, and the number of rejected gaps are "significant predictors" of gap acceptance behavior. Hamed et al. (1997) developed a set of disaggregate models to recognize the major factors affecting driver's critical gap at T-intersections. They estimated binary-probit models showing that significant variables affecting gap acceptance include the waiting time at the head of the queue, the driver socioeconomic characteristics, and the time of day.

Research efforts not only investigated driver learning while waiting for an acceptable gap, but also studied traffic stream interaction, whereby aggressive drivers force themselves into the major stream, causing a reversal in priorities and possibly serious conflicts. Sayed (1997) described a conflict simulation model for unsignalized intersections that uses "time proximity to hazard as the driver's perceived measure of safety" to simulate conflicts. The model assisted in analyzing the occurrence of conflicts as a function of driver and traffic parameters, such as driver age, gender, and waiting time.

In their study, Lajunen and Parker (2001) demonstrated a relationship between driver characteristics, self-reported general aggressiveness, driver anger, and aggressive driving. Age was negatively related to aggression among men while annual mileage was negatively related to aggression among women. The study also concluded that congestion does not seem to increase driver aggression as directly as suggested in previous research.

Troutbeck and Kako (1999) examined "limited priority systems" which assume that vehicles on the major road would slow down to accommodate minor-stream vehicles, particularly under high flow conditions. They observed the frequency and ratio of "gap forcing behavior" in six traffic data sets taken from roundabout entries during high and low-saturation conditions, and concluded that the ratio of the forced gaps to the total merged gaps exceeded 9% in high-saturation conditions. They also conducted statistical tests on the data sets and concluded that in high-saturation conditions, the hypothesis that the major-stream vehicles are not affected by the merging maneuver does not hold. Troutbeck (1999) reconsidered the "limited priority systems" and studied the capacity of unsignalized intersections with limited priority merge. He concluded that in similar processes, the critical gap values are expected to decrease, resulting in an increased merging capacity.

A study by Pollatschek et al. (2001) differentiated between two groups of drivers, those who are very cautious and those who are risk-loving. The study illustrated the gap acceptance choice as a process of weighting the risk induced when accepting smaller gaps versus the penalty of losing additional time waiting for an appropriate gap. The researchers assumed that the longer the waiting time is, the higher is the willingness of the driver to take more risk, and accordingly the lower is his estimate of the critical gap. The developed model clearly shows that risky behavior is an important factor in analyzing the performance and computing the capacity of unsignalized intersections.

Iversen (2004) examined which attitudes towards safety issues are predictors for future risk behavior in traffic among the same drivers at two data collection points. Results showed a high consistent correlation between many of the attitudes measured in the first survey and risky driving behavior measured in the second survey. His study proved that driver self-reported attitudes towards "violation of traffic rules" are important predictors for future risk behavior and aggressiveness in traffic.

Kaysi and Alam (2000) explored ways to enhance the basic gap acceptance models by including driver learning and traffic stream interaction. They observed priority-unsignalized intersections that actually operate as uncontrolled intersections, and used a simple simulation model to prove the relevance of the proposed enhancements. In their model, the critical gap was assumed to decrease with the driver's waiting time, and aggressive drivers were considered to force themselves into the major-traffic stream, resulting in conflicts and delays to vehicles on the major road. They described the driver's aggressiveness as an attitudinal characteristic and studied the impact of these factors, by assuming a percentage of aggressive drivers, on the average incurred delays. They concluded that with the increase in the percentage of aggressive drivers, the average delay incurred by minor approach vehicles decreases, while that incurred by the major approach vehicles increases.

Kaysi (2001) hypothesized a behavioral framework that enables the analysis of drivers' attitudes at unsignalized intersections based on the driver's characteristics (age, gender, etc...), his past choices (familiarity, rejected gaps), and the actual conditions (intersection and traffic attributes). The framework also incorporated psychometric data that, if included in driver behavior models, "could improve the explanatory and predictive power of such models".

In their exploratory research study, Miles and Johnson (2003) proved that parameters such as the personality characteristics and attributes of people who are prone to commit aggressive driving behavior are of great interest to researchers for the purpose of understanding, predicting, and correcting or preventing such dangerous behavior. Other related parameters are the self-reported attitudes and beliefs of a known group of drivers towards some aggressive-driving traits.

Other researchers were interested in investigating the relationship between exposure to congestion (rush-hour driving) and aggressive violations. In their study over three different countries, Lajunen et al. (1999) suggest that congestion does not directly increase driver aggressive behavior.

In their recent research, Shinar and Compton (2004) investigated three types of behavior that are commonly characterized as "aggressive driving", namely, honking, cutting across one or more lanes in front of other vehicles, and passing on the shoulders. They extended the results of previous studies that had looked at similar aggressive driving behaviors by adding two significant attributes. First, they analyzed observational data of realistic driving in order to simultaneously assess both individual differences/characteristics (such as gender and age of the driver, presence or absence of passengers in the car, type and perceived status of the vehicle) and environmental/situational variables (such as congestion) then explore the relationship between aggressive driving and these correlating factors. They concluded that, since men have lower level of motivation to comply with traffic laws than female drivers, they were more likely to commit aggressive actions. Age also appeared to correlate negatively with aggressive driving; drivers 45 years-old or older were less likely to drive aggressively than younger ones. Moreover, the presence of passengers was associated with slight but consistent reduction in aggressive driving of all types. On the other hand, drivers of passenger cars and drivers of old cars were no more aggressive than drivers of commercial vehicles and drivers of high-status cars. Second, their study provided a first attempt to distinguish between the effects of congestion and the effects of time of observation, which in real-life are often confounded. The separate analyses of the effects of congestion and period of observation showed that delay in travel relative to the value of time seems to be an important determinant of aggressive behavior since delays are by their nature frustrating but more so when the value of time is high. Thus, the study concluded that congestion by itself does not necessarily induce aggressive behavior. However, when congestion is coupled with a sense of urgency, aggressive driving was found to increase. The effects of the period of observation—after adjusting for the number of vehicles in the traffic—were clear-cut in the study: drivers were most likely to behave aggressively during the weekday rush hours and least likely to behave aggressively during the weekend.

Finally, Liu and Lee (2005) highlighted a significant parameter in aggressive driving – that of car-phone use during critical driving maneuvers. Their study on the effect of car-phone use and aggressive disposition on braking response at signalized intersections resulted in confirming the notion that the combination of decision making and car-phone communication increases accident risk since distraction causes drivers to react later.

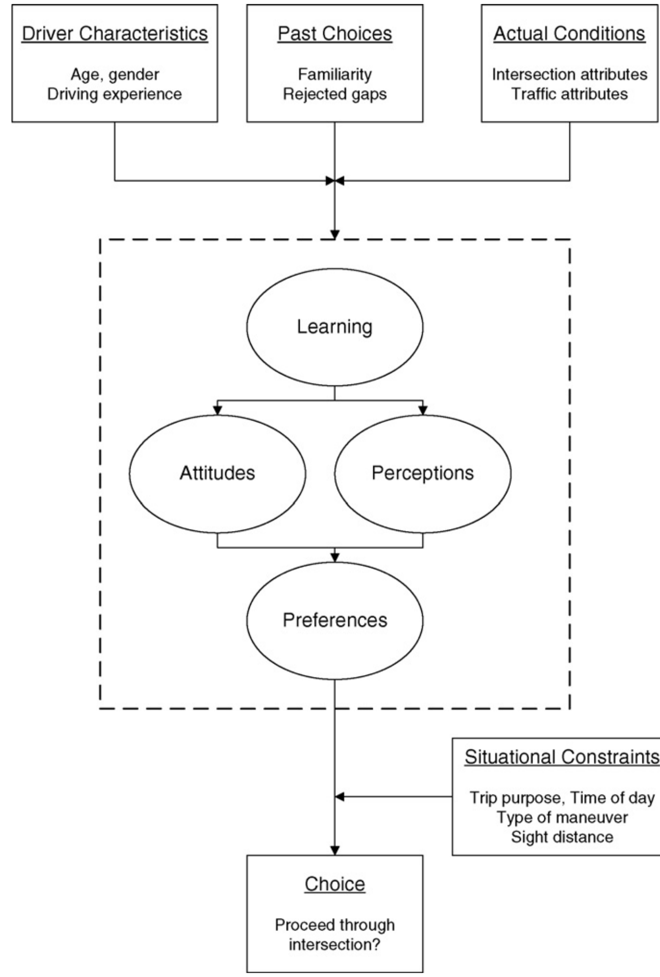


Fig. 1. Behavioral framework.

## 3. Research objectives and methodology

The objective of this research is to formulate a behavioral model that takes into account the framework developed by Kaysi (2001) as shown in Fig. 1, and that predicts "forcing" as a function of a set of driver and traffic attributes. Forcing is the behavior whereby aggressive drivers "force" themselves into the major stream, causing a reversal in priorities. The adopted methodology consists of the following steps:

(a) Data collection and analysis.
(b) Model formulation and testing.
(c) Incorporating the obtained driver aggressiveness model in a simulation framework that replicates traffic operation and driver behavior at an unsignalized intersection.

Parameters that will be tested and modeled include *driver characteristics* (gender and age), *car characteristics* (performance and model year), and *traffic attributes* (number of rejected gaps, total waiting time at head of queue, and major-traffic speed). The model is formulated as binary probit, and will be based on data collected from an unsignalized intersection within the city of Beirut. The resulting model will be used to enhance the work of Kaysi and Alam (2000) by predicting the probability that a driver is aggressive based on personal and traffic characteristics, rather than simply assuming a percentage of aggressive drivers among the whole population and introducing that number in the simulation model.

### 3.1. Data collection

Data was collected from a U-turn on a coastal boulevard in the city of Beirut (Fig. 2). This intersection is priority-unsignalized, with no stop or yield signs, but with an inherent understanding that traffic laws assign priority to through-moving vehicles over turning vehicles. However, in reality, this intersection functions with little respect of the priority rule, and in many circumstances, U-turning vehicles force themselves through and oblige through-moving vehicles to slow down. In some instances, the latter vehicles do slow down to accommodate the "forced" maneuver; in other instances, they stick to their priority and continue their initial movement, thus, "re-forcing" U-turning vehicles to respect the priority rule.

Two data collection processes were undertaken for the same approach on two different weekdays in order to obtain an accu-

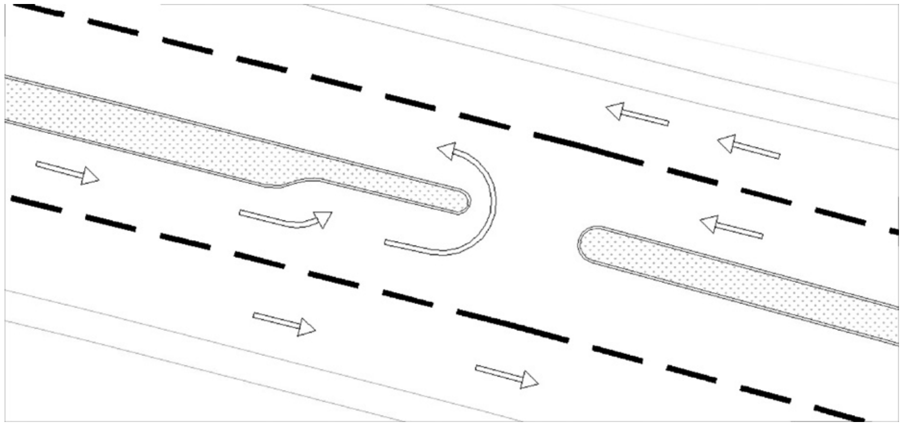

Fig. 2. U-turn illustration.

rate representation of normal traffic conditions. The field studies were conducted between 8:30 AM and 10:30 AM, on a typical Thursday and Friday. Because of the proximity of two schools to the survey location, these times were chosen to fall between the morning and the noon traffic jams caused by the students of both schools. The data to be sampled on the minor approach (U-turning traffic) included *driver characteristics* (gender and age), *car characteristics* (type and model year), and *traffic attributes* (number of rejected gaps, total waiting time at head of queue, and through-traffic speed). Vehicle types were characterized based on the size of the engine, i.e. small, medium, big, or sport cars. The intersection was videotaped during the data collection process to assist in recording information and to double check the collected information.

A member of the survey team recorded the driver and car characteristics on site. The number of rejected gaps and the total waiting time were obtained through a gap study that conforms to the methodology recommended in *Transportation Engineering Basics* (Murthy and Mohle, 1993). The through-traffic speed was estimated from playbacks of the video recording, whereby the time required by through vehicles to travel a pre-determined distance was recorded on screen, and the estimated speed was calculated as the ratio of distance over time.

The sample sheet used in the data collection process is presented in Fig. 3.

### 3.2. Data analysis

The obtained total number of valid observations was 266, out of which 85 maneuvers were denoted as "aggressive". In this respect, a maneuver was considered aggressive if it forces major-stream vehicles (through traffic in this case) to slow down in order to accommodate turning vehicles. The "forcing" behavior was recorded on site but then double-checked on the videotape by observing the reaction of cars on the major road. The following main statistics were derived from the collected data set:

(a) 32% of the turning movements were recorded "aggressive".
(b) 72% of aggressive drivers were male (28% were female).
(c) 29% of aggressive drivers forced themselves through in the first available gap, 33% waited less than 5 s, 28% waited between 5 and 10 s, and the remaining 10% waited for longer than 10 s.
(d) Almost 50% of aggressive drivers were subject to less than one rejected gap, and a little less than 25% had faced more than four rejected gaps.
(e) 36% of aggressive drivers owned medium size cars, and 31% owned sport cars.

A complete statistical summary of the obtained data is shown in Table 1. Two main conclusions can be drawn from the collected data. First, the occurrences of aggressive behavior (32% of total observations) are relatively frequent and can't be neglected in any performance study of the subject intersection. Second, there does not seem to be a direct relation between the number of rejected gaps (or delay at head of queue) and the aggressive behavior, since many of the "forcing" observations occurred with zero rejected gaps and total delay. Accordingly, the aggressive behavior of minor street drivers is more of a personal attitude rather than a result of the driver losing his patience while waiting for an acceptable gap.

### 3.3. Model calibration

The driver's attitude is treated in this research as a binary choice of either being aggressive or not. In this respect, binary probit model will be used to estimate the utility function that would be attributed to the aggressive behavior of drivers, based on parameters relating to their personal characteristics, car performance, and prevailing traffic conditions. Based on the framework developed by Kaysi (2001), the main parameters that are expected to influence the aggressiveness of drivers include age, gender, car type, car model year, number of rejected gaps, total waiting time at head of queue, and major-traffic average speed.

A number of binary probit models were tested to determine the significance of each of the above parameters on the driver's aggressive behavior. The estimation was done using the *Statistical Software Tools* (*SST*) version 2.0, and some 40 combinations of the independent variables were tested. Most of these models were either statistically insignificant, or the estimated coefficients were unrealistic with respect to their sign and magnitude.

Date: ................... Day: ..................... Weather: ..................................

Recorder: ............... Starting Time: ................................... Ending Time: ...............................

| Observation No. | Forcing | No. of Rejected Gap | Driver Gender | Driver Age Group | Car Type | Model Year | Total Waiting Time | Major Traffic Speed (km/h) |
|---|---|---|---|---|---|---|---|---|
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Fig. 3. Sample data sheet.

One of the developed models reasonably explained the aggressive behavior of drivers as a function of their young age, their ownership of a sport car, and the major-traffic speed. In this model, the probability that a specific driver makes a forcing maneuver is given by:

$$P_i(\text{forcing}) = \frac{1}{(1 + \exp^{-u_i})}$$

where:

$$u_i = 1.45 + 0.29 \times \text{age } 1825 + 0.63 \times \text{carsport} - 0.04 \times \text{majrspee}$$

“age 1825” is a dummy variable with a value of 1 a sport car was being driven and 25 years, and 0 otherwise. “carsport” is a dummy variable with a value of 1 if a sport car was being driven, and 0 otherwise. “majorspee” is the average speed on the major road, in km/h.

The complete results obtained in SST for this model are shown in Fig. 4.

### 3.3.1. *Quasi t-test of coefficients*

At 95% confidence level:

(a) H0: $\beta_{\text{one}} = 0$; test statistical = 2.413 > $t_{0\cdot 05}$ = 1.96; reject null hypothesis.
(b) H0: $\beta_{\text{age1825}} = 0$; test statistical = 1.426 < $t_{0\cdot 05}$ = 1.96; can’t reject null hypothesis.
(c) H0: $\beta_{\text{carsport}} = 0$; test statistical = 2.903 > $t_{0\cdot 05}$ = 1.96; reject null hypothesis.
(d) H0: $\beta_{\text{majrspee}} = 0$; test statistical = 3.538 > $t_{0\cdot 05}$ = 1.96; reject null hypothesis.

The above tests show that the “constant”, “carsport”, and “majrspee” variables are significant predictors of the aggressiveness of a specific driver. Moreover, the test failed to reject the null hypothesis for “age1 825” variable, at 95% confidence level. However, this variable will be kept in the model, assuming a lower level of confidence for the statistical significance of this parameter.

### 3.3.2. *Log-likelihood test*

For 95% confidence level:

(a) L(0) = −184.38
(b) L(C) = −166.66
(c) L($\beta$) = −152.22

```
Independent        Estimated            Standard             t-
 Variable          Coefficient           Error             Statistic

      one            1.44891             0.60052             2.41274*
  age1825            0.29458             0.20663             1.42566
 carsport            0.62854             0.21654             2.90258*
 majrspee          -4.01430e-002         1.13471e-002       -3.53774*

auxiliary statistics               at convergence       initial
log likelihood                        -152.22           -184.38
number of observations                    266

(*) Significant at 95% confidence level
```

Fig. 4. Model estimation results.

Table 1
Summary statistics of the obtained data

| | Forcing (%) | No forcing (%) | Total (%) |
|---|---|---|---|
| Percent of total observations | 31.95 | 68.05 | 100 |
| Distribution by gender | | | |
| Male | 52.26 | 15.79 | 75.19 |
| Female | 22.93 | 9.02 | 24.81 |
| Distribution by age | | | |
| 18–25 | 9.40 | 10.90 | 20.30 |
| 26–30 | 3.01 | 14.66 | 17.67 |
| 31–35 | 5.26 | 11.65 | 16.92 |
| 36–40 | 6.39 | 7.89 | 14.29 |
| >40 | 8.07 | 22.75 | 30.47 |
| Distribution by number of rejected gaps | | | |
| 0 | 9.40 | 7.14 | 16.54 |
| 1 | 6.02 | 15.79 | 21.80 |
| 2 | 4.51 | 12.41 | 16.92 |
| 3 | 4.14 | 7.14 | 11.28 |
| 4 | 3.38 | 9.02 | 12.41 |
| 5 | 2.63 | 7.52 | 10.15 |
| >5 | 1.87 | 9.03 | 10.90 |
| Distribution by total waiting time (s) | | | |
| 0 | 9.40 | 7.14 | 16.54 |
| $0 \ll = 5$ | 10.53 | 28.20 | 38.72 |
| $5 \ll = 10$ | 9.02 | 23.31 | 32.33 |
| $10 \ll = 15$ | 1.88 | 4.51 | 6.39 |
| $15 \ll = 20$ | 0.75 | 3.76 | 4.51 |
| >20 | 0.38 | 1.13 | 1.50 |
| Distribution by car type | | | |
| Small | 3.01 | 13.16 | 16.17 |
| Medium | 11.65 | 30.08 | 41.73 |
| Big | 7.52 | 16.92 | 24.44 |
| Sport | 9.77 | 7.89 | 17.67 |
| Distribution by car age | | | |
| ≥20 years | 1.13 | 4.78 | 6.02 |
| 15–19 years | 7.14 | 10.90 | 18.05 |
| 10–14 years | 5.64 | 12.03 | 17.67 |
| 5–9 years | 9.77 | 18.80 | 28.57 |
| <5 years | 8.27 | 21.43 | 29.70 |
| Distribution by major-traffic average speed (Km/h) | | | |
| 40 | 3.01 | 4.89 | 7.89 |
| 45 | 8.65 | 11.28 | 19.92 |
| 50 | 8.27 | 10.53 | 18.80 |
| 55 | 7.52 | 17.29 | 24.81 |
| 60 | 3.76 | 13.16 | 16.92 |
| 65 | 0.38 | 7.89 | 8.27 |
| 70 | 0.38 | 2.63 | 3.01 |
| 75 | 0.00 | 0.38 | 0.38 |

(d) $-2 \times \{L(0) - L(\beta)\} = -2 \times (-184.38 + 152.22) = 64.32$; $\chi^2(4) = 9.488$ (critical value); $64.32 > 9.488$; Reject hypothesis that all parameters are zero.
(e) $-2 \times \{L(C) - L(\beta)\} = -2 \times (-166.66 + 152.22) = 28.88$; $\chi^2(4-1) = 7.815$ (critical value); $28.88 > 7.815$; Reject hypothesis that all parameters, except the constant term, are zero.

The above results from the log-likelihood tests indicate that the fitted model does a very good job at explaining instances of driver aggressiveness since the value of the test-statistic is much greater than the associated Chi-square critical value.

### 3.3.3. Interpretation of coefficients

The positive constant term that appeared in the model reflects an inherent tendency towards being aggressive that increases if the driver is young (age between 18 and 25) and if he drives a sport car. This is reflected in the positive coefficients that are attributed to both variables. Moreover, driving a sport car seems to increase the probability of performing a "forcing" maneuver twice as much as the young age does (as reflected in the higher variable coefficient). As for the major-traffic speed, the coefficient implies that the probability of "forcing" decreases with the increase in the opposing traffic speed, primarily because with higher speeds, the conflicts caused by the "forcing" maneuver become significant. Summarizing, the signs of the obtained coefficients are reasonable and conform well to what was expected.

## 4. Simulation model

Kaysi and Alam (2000) developed a computer simulation model that replicates "traffic operation and driver behavior at an uncontrolled intersection", using the *General Purpose Simulation Software* (*GPSS*) by Minuteman Software (1992). The concept of this model is fairly simple. Minor and major stream vehicles are generated according to a negative exponential distribution, and the time of generation is recorded for each one of these vehicles. Generated minor street vehicles enter in a queue, and are only allowed to proceed when they arrive at the head of the queue. An initial critical gap size is assumed and is updated with each rejected gap. The gap between the arrival of the minor street vehicle and the major street vehicle is tested relative to the minimum acceptable gap. If it exceeds the critical gap, the minor vehicle is allowed to proceed without any delay. If not, the driver is tested for aggressiveness based on a pre-determined percentage of aggressive drivers among the studied population. If the driver is aggressive, he will proceed with the maneuver and cause a conflict. Otherwise, he will wait for a next gap. The critical gap is updated at this stage (Kaysi and Alam, 2000).

In this research, the above model is enhanced to better reflect the influence of personal and traffic attributes on the aggressiveness of a specific driver. In the previous model, forcing maneuvers are performed based on a fixed probability of aggressiveness, no matter what the characteristics of the driver, or those of the traffic, are. The "aggressiveness" probit model that was estimated in the previous sections will be included in the simulation to estimate, for each driver, a "particular" probability of being aggressive, based on a set of generated parameters. Accordingly, for each minor street vehicle, the following variables are generated:

(a) A dummy variable reflecting the age group. This variable takes a value of 1 if the driver is younger than 26 years, and 0 otherwise.

Table 2
Summary of the GPSS simulation runs

| | Conflicts | Minor approach average stopped delay (s/veh) | Major approach average stopped delay (s/veh) |
|---|---|---|---|
| Flow on major approach | 1150 *vehicles per hour* | | |
| Flow on minor approach | 350 *vehicles per hour* | | |
| Observed | 69 | 5.3 | 4.9 |
| Simulated | | | |
| Run 1 | 80 | 7.15 | 3.80 |
| Run 2 | 89 | 6.68 | 2.80 |
| Run 3 | 86 | 6.75 | 4.50 |
| Run 4 | 90 | 6.66 | 4.38 |
| Run 5 | 83 | 6.60 | 3.70 |
| Run 6 | 86 | 7.33 | 3.74 |
| Run 7 | 83 | 7.01 | 3.57 |
| Run 8 | 88 | 6.81 | 4.48 |
| Run 9 | 91 | 6.77 | 6.01 |
| Run 10 | 84 | 7.13 | 3.83 |
| Average of runs | 86 | 6.89 | 4.08 |

(b) A dummy variable representing the vehicle type. This variable takes a value of 1 if the car is a sports one, and 0 otherwise.
(c) An estimate of the opposing major-traffic average speed.

All the variables were generated as per the distributions that were observed on site. The probability of performing a "forcing" maneuver was calculated from these parameters based on the utility function developed previously, and the obtained value was used in simulating the response of the driver when faced with a gap that is less than the minimum acceptable. The simulation will permit testing and validation of the developed probit model by comparing the conflict and delay figures obtained from the simulation with those observed on site. In this regard, an intersection at Hamra area within the city of Beirut will be considered, and the model-simulated results will be compared to those observed on that specific intersection.

Different runs of the model were performed in order to check the consistency and the stability of the obtained results. The input was not changed in any of the runs, and the only variance is that of the random number generators. The results were quite satisfactory, and they were indeed statistically stable. Table 2 presents a summary of the results of each of these runs, including the estimated conflicts and the average stopping delay on each of the minor and major street approaches.

As can be seen in Table 2, the simulated average delay for major stream vehicles conforms well to the observed figure (4.08 s as compared to 4.9 s). The average delay for minor stream vehicles and the number of conflicts were not as accurate but are relatively close to the observed values (6.89 s and 86 counts compared to 5.3 s and 69 counts). The values are also consistent with those obtained by Kaysi and Alam (2000) whereby the count of conflicts and the average stopped delay for minor and major stream vehicles were 80, 7.0, and 4.3 s, respectively. These figures were obtained for an assumed 40% of aggressive drivers among the sampled population. This conforms well to the results of the different simulation runs, whereby the average probability of aggressive behavior was calculated from the utility function as 43%.

The results of the simulation accordingly validate the developed probit model and confirm that the estimated parameters are indeed good estimators of the aggressive behavior of drivers at unsignalized and uncontrolled intersections. Although the simulated and observed values do not perfectly match, they remain close enough to be considered as valid estimators of the drivers' behavior.

## 5. Conclusions

This paper has investigated the aggressive behavior of minor-approach drivers at intersections that are nominally priority-unsignalized but operate with partial respect of traffic laws. At these intersections, some minor street drivers, characterized as aggressive, will force their cars into the major stream, obliging conflicting vehicles to slow down in order to accommodate the maneuver. This type of behavior may result in lower total delays at the expense of higher risks. Accordingly, modeling of similar types of intersections depends highly on the behavioral characteristics of minor street drivers, and advanced types of models that incorporate aggressive driver attitudes and traffic stream interaction are more appropriate than the basic gap acceptance model.

This paper is an extension of the work accomplished by Kaysi (2001) whereby binary probit modeling was used to interpret the aggressive attitude of a driver based on personal, car, and traffic characteristics. Such relevant parameters include driver's age and gender, car's type and model year, as well as the number of rejected gaps, total waiting time at head of queue, and major-traffic average speed. The study has proven that the occurrences of forcing maneuvers are significant (more than 30%) and accordingly they can't be neglected in any performance study. The obtained model revealed that the major parameters to affect the probability that a driver will attempt a forcing maneuver are his young age (below 26), driving a sport car, and the average speed on the major road. A simple simulation program was used to test and validate the obtained model. The results of the performed simulations agreed well with the observed conflicts and delay figures, and proved satisfactory the representation of drivers' aggressive behavior by the estimated utility function.

The most important conclusion that one can draw from the obtained model is that aggressive behavior of the observed sample is not, as had been stipulated, dependent on the driver's total waiting time while waiting for an acceptable gap. Rather, forcing is mainly the outcome of attitudinal characters, and a driver might be aggressive at the first available gap.

This paper can only be considered as a first step on the way to understand and model the aggressive behavior of drivers at unsignalized intersections. More extensive data collection processes are needed to validate and enhance the obtained model, and possibly to investigate the significance of other parameters in explaining the aggressiveness of drivers. Finally, the problem of aggressive driving behavior and road rage may be a worldwide problem. Cross-cultural research should be conducted to explore whether a profile of an aggressive driver (and/or a "road rager") developed in one country or culture would be consistent with a similar profile developed in another country or culture (Miles and Johnson, 2003); more effort should be brought to bear on changing the attitude of road users aiming at changing aggressive and risky driving behaviors.

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