Modelling Traffic Policy with Drivers and Government Behavior using Evolutionary Game Theory

Ilia Beregovenko, Maxim Kashcheev, Yixin Wang, Sergey Kovalchuk

ITMO University, Saint Petersburg, Russia
283091@niuitmo.ru

Abstract. The article proposes a model describing the dynamics of offenses in terms of non-compliance with safety regulations and speeding, taking into account the established rules and national specifics. The method suggested in the article is a combination of game theory methods and evolutionary algorithms, where "Mild" and "Strict" government policies compete with each other in a population of governments, and law-abiding and law-breaking drivers compete in a population of motorists. The study examines the impact of penalties on driver behavior within the model.

Keywords: Evolutionary game theory, government regulation, traffic policy, speeding rate, government spendings, seatbelt wearing rate

1 Introduction

Over the past hundred years road safety has become one of the main tasks for the governments. The key factors in increasing the importance of traffic control were the growing number of drivers, both advances and limitations in technologies, as well as involvement of road policy developers.

European countries provide an example of a positive trend in road safety, manifested in a significant reduction in the number of fatal accidents [2]. However, implementing policies that would reduce the frequency of accidents is still pressing for all governments due to the cumulative economic damage [3] summarizing the cost of repairing the damaged vehicles, losses caused by transport downtime, the expenditures for reconstructing and repairing the damaged roads and road structures and of investigating a traffic accident by police officers, to name a few.

To minimize losses and expenditures, modeling road safety as a system that takes into account various forms of regulation and the social context is highly relevant.

The current study suggests an environment model, which describes the dynamics of offenses in terms of non-compliance with the speed limit and wearing a seat belt, taking into account the socio-psychological and regulatory specifics of the national environment (within, a community or a county).

Using Germany as an example, we conducted a numerical modeling of the general dynamics of law enforcement for regulating the road sector. The model refers to the government policy in terms of the original state of the road infrastructure, fixed fines

ICCS Camera Ready Version 2026
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DOI: 10.1007/978-3-032-29924-6_38

for violations of the speed limit and unbuckled seat belts and fixed parameters of national specifics and driver behavior patterns.

The study considers the impact of certain system parameters on the frequency of offenses and overall government spending, and explore the importance of penalty policies on changing the dynamics of offenses among drivers.

2 Related work

Currently, legal regulation modeling within the socio-psychological context does not appear to be amply researched. Most of the studies focus either on strategies for organizing police to minimize accidents [4], or on modeling the driver's decision-making function [5], otherwise specific traffic situations are studied using the example of games [6]. Very few studies link the forms of regulation with their impact on the dynamics of offenses. The authors in [7] discussed agent-based transportation modeling using government control standards. However, their research is mainly aimed at studying the issue of regulation of commercial transportation rather than private transport. Our work was also based on a review study [6, 8] which analyzed using game theory elements to model various traffic situations, for example, the confrontation between drivers exceeding the speed limit and the police. In addition, we referred to the studies on the driver's satisfaction with the trip [9], which revealed that one of the main factors is the duration of the latter. The reports of the European commission and public organizations [10, 11, 14, 15] and the report from the international transport forum [1], initialized the model parameters, playing a key role in the study.

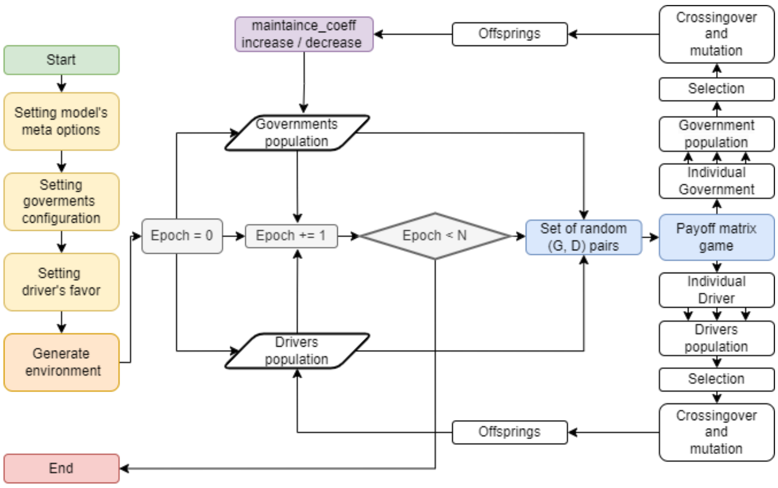

Fig. 1. Algorithm of the system for conducting a single experiment.

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DOI: 10.1007/978-3-032-29924-6_38

3 Traffic policy modeling with evolutionary game theory

A model of the dynamics of law enforcement in the road sector (see Fig. 1) was based on the assumption that all drivers in the system drive identical cars, the police are always called to the scene in case of an accident, and drivers wait for their arrival. Based on the results of our literature review, we built a model based on the assumption that the key factor in driver satisfaction with the road is the subjective time spent on the trip [9], whereas the government is trying to decrease the average spendings per epoch including regulation enforcement and accident cost [3]. The condition of the road appears to affect the frequency of accidents [13]. Within the framework of the model, we assumed that the country we are considering has a federal structure, which makes it possible to implement different regulatory measures in different regions. During the initialization stage we generated an independent set of agents with "Driver" and "Government" types (further referred to as "D" and "G" agents, respectively).

Table 1. Payoff matrix for games

Government's Regulation strategy	Driver's speed strategy: Obeying speed limit	Driver's speed strategy: Speeding
Strict regulation	GSO, DSO	GSS, DSS
Mild regulation	GMO, DMO	GMS, DMS

Each "G" type agent is independently assigned with equal probability one of two policies ("Mild" or "Strict"). This implies a random belt penalty $feeB_s$ ($feeB_m$) from a uniform distribution with boundaries between $feeB^s_{min}$ ($feeB^m_{min}$) and $feeB^s_{max}$ ($feeB^m_{max}$) for "Strict" ("Mild") belt policy in EUR, a random speeding penalty $feeS_s$ ($feeS_m$) from a uniform distribution with boundaries between $feeS^s_{min}$ ($feeS^m_{min}$) and $feeS^s_{max}$ ($feeS^m_{max}$) for "Strict" ("Mild") speeding policy in EUR. The following parameters are set for all agents in environment: average accident cost c, EUR; the rate of infrastructure degradation Δ_{ma} ($\Delta_{ma} \in [0; 1]$); length of the road trip len, km; the coefficient of reduction of fatal outcome for belt users f_{min}. Each policy is characterized by the following parameters: car crash chance $crash_s$ ($crash_m$); chance of the fatal outcome $fatal_s$ ($fatal_m$); chance to be stopped for verification by the police $check_s$ ($check_m$); check duration d_s (d_m), hrs; initial value of the coefficient of the infrastructure of the government θ_{ma} set between 0.4 and 1; average policy spendings per driver tr_s (tr_m), EUR; mean μ_s (μ_m), standard deviation σ_s (σ_m) of police arrival time (hrs) in counties with "Strict" ("Mild") regulation policy.

Each "D" type agent can be independently and with equal probability assigned one of the two speed strategies (observing or violating the speed limit) and belt status (fastened or not), a random value of the expected travel time and a random speed $speed$ from the range between $speed^o_{min}$ and $speed^o_{max}$ in km/h, if the driver adheres to the speed limit, and from the range between $speed^s_{min}$ between $speed^s_{max}$ in km/h, if they do not. Also, during the initialization stage the driver receives a random normal distributed value of the subjective ride duration set by mean μ_{exp} and standard deviation σ^2_{exp} of the driver's ride time later defined as d_{exp} in hours.

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Finally, we set the national specific parameters: decreasing coefficient of subjective speeder's road duration θ_d; increasing coefficient of fatal outcome for speeder θ_{fc}; increasing coefficient of crash accident for speeder θ_{cr}; coefficient of subjective perception of policy expenses θ_{sp}; coefficient of fees conversion θ_{fee} and coefficient of subjective perception of the check duration θ_{ch}.

To conduct a series of games, each element from the set of agents of the "D" type was randomly assigned an element from the set of agents of the "G" type. Each pair of "D"-"G" agents participates in the game described by the payoff matrix (see Table 1). Note that all random components drop out once per pair.

Notice that payoff for "G" agents was expressed in terms of average policy expenses per driver within a single game (see Table 2), whereas payoff for the "D" agents was expressed in terms of subjective time spent for the ride (see Table 3).

Table 2. Government's payoff

Name	Unit	Formula
GSO	EUR	$(-c \cdot \mathrm{Bern}(\mathrm{crash}_s) - tr_s) \cdot \theta_{sp} +$ $+ (belted \cdot \mathrm{feeB_s}) \cdot \theta_{\mathrm{fee}} \cdot \mathrm{Bern}(\mathrm{check_s})$
GSS	EUR	$(-c \cdot Bern(crash_s \cdot \theta_{cr}) - tr_s) \cdot \theta_{sp} +$ $+ (belted \cdot \mathrm{feeB_s} + \mathrm{feeS_s}) \cdot \theta_{\mathrm{fee}} \cdot \mathrm{Bern}(\mathrm{check_s})$
GMO	EUR	$(-\mathrm{c} \cdot \mathrm{Bern}(\mathrm{crash_m}) - \mathrm{tr_m}) \cdot \theta_{\mathrm{sp}} +$ $+ \left(belted \cdot \mathrm{feeB}_m\right) \cdot \theta_{\mathrm{fee}} \cdot \mathrm{Bern}(\mathrm{check_m})$
GMS	EUR	$(-c \cdot \mathrm{Bern}(\mathrm{crash_m} \cdot \theta_{cr}) - tr_m) \cdot \theta_{sp} +$ $+ (belted \cdot \mathrm{feeB}_m + \mathrm{feeS}_m) \cdot \theta_{\mathrm{fee}} \cdot \mathrm{Bern}(\mathrm{check}_m)$

In a series of $\mathrm{N_{drivers}}$ games, each agent of the sets of "G" and "D" received a reward. The system then generated subsets for each of the agent types, consisting of half of the initial elements with the highest reward rates, after which it transmitted the received arrays to the crossing over.

Then the resulting set of drivers was duplicated and "D"-"D" pairs were randomly formed, each of them having an equal probability of either an exchange of the "belted" feature, or a proportional exchange of speeds, or both an exchange of the "belted" feature and a proportional exchange of speeds. A new unified population was then formed from the two subsets, which was transmitted by mutation. Simultaneously, the resulting set of policies was duplicated and "G"-"G" pairs are randomly formed, each of which was equally likely to have either an exchange of the θ_{ma} feature, or a proportional exchange of penalty policies for belts, or a proportional exchange of penalty policies for exceeding the speed limit. A new single population was then formed from the two subsets, which was transmitted by mutation.

For each element of the "D" set, with a chance equal to that of mutation m_d a new speed for the current behavior strategy can be generated, the "belted" feature can be replaced with the opposite and a new agent cab be created to replace the previous one

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from the opposite strategy class, but with the same "belted" feature. This resulted in a new population sample and the end of the driver era. For each element of the G set for the current implemented policy with a chance equal to that of mutation m_g a new penalty for violating the safety rules for the current behavior strategy can be generated, a new penalty for speeding for the current behavior strategy can be generated, the attribute can be replaced with a random value from 0.4 to 1, and a new agent can be created to replace the previous strategy from the opposite class with a random set of characteristics. After mutation, for all agents with a "Strict" management policy, the θ_{ma} indicator increases by the rate of degradation Δ_{ma}, if it does not exceed the threshold of 1, for agents with a "Mild" regulation policy, the θ_{ma} indicator drops by Δ_{ma} to at least 0.4.

After that, a new population sample was formed and the epoch for repeated states ended. The experiment finished when the epoch variable reached the parameter value *N_epochs*. After that, the system completed the experiment.

Table 3. Driver's payoff

Name	Unit	Formula
DSO	hrs	$d_{exp} - \frac{\mathrm{len}}{speed \cdot \theta_{ma}} - \mathrm{Bern}(\mathrm{check_s}) \cdot \mathrm{d_s} \cdot \theta_{\mathrm{ch}} - $ $- \mathrm{Bern}\left(\mathrm{fatal_s} \cdot \left(1 - belted \cdot (1 - \mathrm{f}_{min})\right)\right) \cdot 10^6 -$ $- \mathrm{Bern}(\mathrm{crash_s}) \cdot (\mathrm{N}(\mu_\mathrm{s}, \sigma_\mathrm{s}^2) + \mathrm{d_s} \cdot \theta_{ch})$
DMO	hrs	$d_{exp} - \frac{len}{speed \cdot \theta_{ma}} - \mathrm{Bern}(\mathrm{check_m}) \cdot \mathrm{d}_m \cdot \theta_{\mathrm{ch}} - $ $- \mathrm{Bern}\left(\mathrm{fatal}_m \cdot \left(1 - belted \cdot (1 - \mathrm{f}_{min})\right)\right) \cdot 10^6 -$ $- \mathrm{Bern}(\mathrm{crash}_m) \cdot (\mathrm{N}(\mu_m, \sigma_m^2) + \mathrm{d}_m \cdot \theta_{\mathrm{ch}})$
DSS	hrs	$d_{exp} - \frac{len}{speed \cdot \theta_{ma}} \cdot \theta_d - \mathrm{Bern}(\mathrm{check_s}) \cdot \mathrm{d}_s \cdot \theta_{\mathrm{ch}} - $ $- \mathrm{Bern}\left(\mathrm{fatal_s} \cdot \theta_{\mathrm{fc}} \cdot \left(1 - belted \cdot (1 - \mathrm{f}_{min})\right)\right) \cdot 10^6 -$ $- \mathrm{Bern}(\mathrm{crash_s} \cdot \theta_{\mathrm{cr}}) \cdot (\mathrm{N}(\mu_s, \sigma_s^2) + \mathrm{d}_s \cdot \theta_{\mathrm{ch}})$
DMS	hrs	$d_{exp} - \frac{len}{speed \cdot \theta_{ma}} \cdot \theta_d - \mathrm{Bern}(\mathrm{check}_m) \cdot \mathrm{d}_m \cdot \theta_{\mathrm{ch}} - $ $- \mathrm{Bern}\left(\mathrm{fatal}_m \cdot \theta_{\mathrm{fc}} \cdot \left(1 - belted \cdot (1 - \mathrm{f}_{min})\right)\right) \cdot 10^6 -$ $- \mathrm{Bern}(\mathrm{crash}_m \cdot \theta_{\mathrm{cr}}) \cdot (\mathrm{N}(\mu_m, \sigma_\mathrm{m}^2) + \mathrm{d}_m \cdot \theta_{\mathrm{ch}})$

4 Case study: modeling of traffic policy environment in Germany

As part of the study, we defined Norway and Germany traffic regulation policies as "Strict" and "Mild" respectively, as Norway has the highest fees for speeding and unbelted driving and is leading among all EU countries in road safety rating [1, 2]. The chances of accidents and fatalities were calculated as the ratio of the number of accidents to the number of registered cars [1, 14]. For Norway, the chance of an accident

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DOI: 10.1007/978-3-032-29924-6_38

was calculated from the chance of fatal outcomes [11] in proportion to the German data. Pairs of $\mu_s - \mu_m$, $d_s - d_m$, $\sigma_s - \sigma_m$ are equal for all policies and taken from American research [12].

The boundaries of penalty policies for exceeding the speed limit were defined as a minimum fine for exceeding the limit by 5 km/h and a maximum fine for exceeding the limit by 50 km/h for the current traffic policy in Germany and Norway. As part of the experiment, we modelled the case of driving in rural areas where speed limits in Germany and Norway allow acceleration to 100 km/h. Then experiment set speed initialization limits between 70 km/h and 100 km/h for the drivers who follow the speed limit, and between 100 km/h and 150 km/h for those who do not. We do not consider higher speeds, because for exceeding the speed limit above 50 km/h, their license is withdrawn. The ride length is set at 100 km, the average expected travel time is 1 hour with an average deviation of 0.1 hour. The average spending on policy implementation for each country was calculated as the sum of government expenditures on Police services and R&D Public order and safety in EUR divided by the total number of the population of the country in 2023 [15]. Finally, assuming that the average cost of an accident is the same for all countries and only cases with severe and mild injuries are included (without fatal outcomes, since they are quite rare), the cost of an accident was amounted to 1.539.328 NOK or 137.008 EUR [11]. Since the model has a pronounced stochastic nature, we set 10 launches with 300 epochs per launch in one experiment. The Δ_m was determined to be 0.05. We set the m_d and m_g equal to 0.09. The f_{min} indicator will be 0.6. The parameters of Germany's national specifics were selected through a series of launches with an attempt to approximate the values of indicators expressed in the percentage of drivers who do not use a seat belt, which is 98%, and in the percentage of drivers who exceed the speed limit, which is 74% [10]. With the current parameters for an average of 300 epochs with trajectories averaged over 10 launches 90.4% of drivers fasten seat belts (with an average deviation of 4.9%), and 74.6% of drivers exceed the speed limit (with an average deviation of 4.9%).

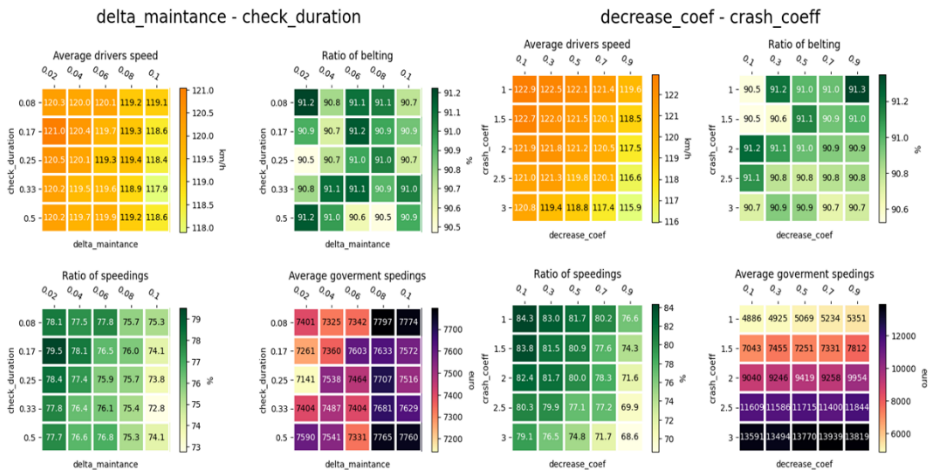

Fig. 2. Mapped effects

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DOI: 10.1007/978-3-032-29924-6_38

5 Conclusion and future work

As part of the experiments, we considered the impact of the right-hand boundaries of penalty policies on the dynamics of law violations in terms of the speed limit and respecting the seat belt rules and conducted a series of two two-way ANOVA tests. For one case, we fixed all the parameters except for pairs of values $feeB^s_{max} - feeB^m_{max}$ (set between 600 and 2200 with step 400 and between 200 and 600 with step 100, respectively). In the other case we fixed all the parameters except the pair $feeS^s_{max} - feeS^m_{max}$ (set between 200 and 400 with step 50 and between 50 and 200 with step 50, respectively). All other parameters remained fixed. After that 2 series of experiments were launched, each of them with 25 independent experiments on a grid of 5 for each of the modifiable parameters, fixing the average values of the percent of belted and speeding drivers in each of the 10 iterations of the experiment. Based on the collected data, a two-way ANOVA showed that the factors $feeB^s_{max}$, $feeB^m_{max}$ and their combination did not affect the frequency of violations. However, factor $feeS^m_{max}$ effects speeding with p-value of 5%, but its combination with the $feeS^s_{max}$ factor did not produce any effects, which partially confirms the early studies [6]; showing that amount of penalties has no effect on speed limit violation.

Table 4. two-way ANOVA tests results.

Factor name	P(>F) Influence on ratio of belt usage	P(>F) Influence on ratio of speeding
C($feeB^m_{max}$)	0.467	0.8985
C($feeB^s_{max}$)	0.84043	0.6211
C($feeB^m_{max}$):C($feeB^s_{max}$)	0.6738	0.1159
C($feeS^m_{max}$)	0.1917	$\mathbf{0.011}$*
C($feeS^s_{max}$)	0.7595	0.521
C($feeS^m_{max}$):C($feeS^s_{max}$)	0.1093	0.674

* p<0.05

As shown in Fig. 2, a decrease in the rate of degradation Δ_{ma} does not reduce the frequency of speeding or the average driver's speed. On the other hand, the national specific factors, namely the accident probability coefficients θ_{cr} and the decreasing coefficient θ_d, had the greatest effect on reducing the frequency of speeding. Noteworthily, an increase in the reduction coefficient leads to a gradual but significant increase in the average driver expenses. Additionally, an increase in the accident probability coefficient resulted in a significant increase in the average expenses.

Further work would include testing the approach in other countries. The quality of the model can also be improved by increasing the number of factors affecting the driver's speed, which in turn will lead to additional balancing indicators. Also, in the future, it would be interesting to consider the impact of the cost of an accident on the dynamics of key parameters. To strengthen the validation claims we will run the model for

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DOI: 10.1007/978-3-032-29924-6_38

Norway. To increase the descriptive accuracy of the model, we will refer to additional information to select the optimal parameters. Also, it would be important to consider generalizing the model, which allows for the transition between different driving zones (city, highways, and rural areas) and introducing a public opinion component that would allow drivers to explicitly influence regulatory policy.

Acknowledgements. The research was supported by The Russian Science Foundation, agreement №24-11-00272, https://rscf.ru/project/24-11-00272/.

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DOI: 10.1007/978-3-032-29924-6_38