Effects of drivers' evasive behavior on the placement of automated enforcement equipment in highway systems

Efeito do comportamento evasivo dos motoristas sobre a localização de equipamentos automáticos de fiscalização em rodovias

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ABSTRACT

The placement of automated enforcement equipment on highways is a problem of interest for many roadway infrastructure entities and law enforcement agencies. It is common that in such cases the vehicles actively try to evade enforcement, because this allows them to continue to earn profit with illegal transportation and avoid the punishment of the law. If this is not considered in the planning stages of enforcement systems, drivers can easily avoid the enforcement with the aid of route planning software. This paper seeks to investigate how such behavior changes where the enforcement equipment should be located on highway networks, by firstly reviewing how this problem has been solved in literature and then experimenting with one of the main mathematical models. The results showed that accounting for evasive behavior when locating enforcement equipment does not significantly increase the number of monitored sections that are necessary but rather optimizes their location in order to cover all the possible paths between all source-destination pairs (within a defined maximum detour from the shortest path). If planning is done without considering evasive behavior and vehicles do show this behavior, then the system may be ineffective for enforcement. On the other hand, if this tendency to avoid enforcement is considered in planning, which is greater than that shown by real vehicles, then all vehicles will be successfully captured by enforcement, without resulting in an excessive increase in cost.

RESUMO

A localização de equipamentos de fiscalização em rodovias é um problema de interesse para várias entidades responsáveis pela manutenção da infraestrutura viária e fiscalização das leis de trânsito. É possível que nesse tipo de situação os veículos busquem ativamente evadir à fiscalização, para manter o lucro associado ao trânsito ilegal ou para evitar as punições da lei. Caso esse efeito não seja considerado nas etapas de planejamento dos sistemas de fiscalização, os transportadores podem facilmente evitar a fiscalização através de aplicativos de planejamento de rotas. Este trabalho procura investigar como tal comportamento evasivo altera a forma com que os equipamentos de fiscalização devem ser localizados na malha rodoviária. Primeiramente, realiza-se uma revisão de como esse problema vem sendo resolvido na literatura, e após isso são realizados experimentos numéricos com um dos principais modelos matemáticos utilizados. Os resultados mostram que a consideração matemática do comportamento de evasão não aumenta de forma expressiva o número de equipamentos que devem ser instalados na malha, mas otimiza a sua localização para que sejam capturados todos os caminhos possíveis para cada par origem-destino (dentro de uma distância máxima de desvio em relação ao menor caminho). Caso o planejamento seja feito sem a consideração da evasão e os veículos apresentem essa tendência, a fiscalização pode ser inefetiva. Por outro lado, caso no planejamento seja considerada uma tendência à evasão maior que a real, todos os veículos serão monitorados com sucesso pelos pontos de monitoramento, sem haver aumento expressivo no custo de implantação.

1. INTRODUCTION

For any entity that is responsible for maintaining highway infrastructure, a core concern is monitoring the vehicles that use the roads in order to ensure user safety. Hazards on highways can arise, among many situations, from the presence of vehicles that are in poor maneuverability condition or from damages caused by such vehicles to the road infrastructure itself. Especially in freight-heavy traffic, overweight or speeding trucks represent a grave danger to other users, due to the increased possibility that these trucks would lose control and cause catastrophic crashes. Besides this, overweight trucks also cause exponential damage to the pavement, creating defects that can compromise the safety of other users and demand infrastructure interventions much earlier than planned, which represent an expressive cost increase for the maintenance of the service level of the highway system.

However, carriers that disobey the transport regulations often do so in a conscious manner. They seek, for instance, to optimize their costs by increasing the amount of cargo hauled in each truck over the legal limits. In doing so, however, these individuals are obtaining profit at the expense of society, since they are causing danger to other users and exponentially increasing the roadway's maintenance cost, which is ultimately paid by the users themselves via tollbooth fares or taxes (Transportation Research Board, 1990). Upon the creation of enforcement measures on the highways, such as automated weighing stations, the violating vehicles are motivated to find ways in which they can avoid enforcement and carry on with illegal transportation. In fact, a few studies have observed the practice of such evasive tendencies, which include traveling at weighing stations' closed hours or even making detours to avoid them (Cottrell, 1992; Cunagin et al., 1997; Strathman and Theisen, 2002). Another study has also applied the System Dynamics method in order to show that the practice of overloading vehicles does indeed increase productivity and profit for carriers, and that such profit comes with disadvantages to society, such as infrastructure deterioration and increased accident rates (Ghisolfi et al., 2019).

As a solution to this problem, technological advancement has allowed the creation of automated monitoring stations, which are capable of measuring various characteristics (such as size, speed, total weight and its distribution along the axles) on-track automatically. Such technologies have a potential not only for enforcement, but also for continuous data collection, since the measuring process is completely automated, and in many cases does not require additional infrastructure beyond the installation of on-track equipment (Jacob and Feypell-de La Beaumelle, 2010).

Given the possibility of creating such continuous monitoring stations and the problem of enforcement evasion by the vehicles, it is imperative to properly plan the locations of enforcement stations on the highway system, in order to effectively capture the vehicle flows without allowing simple detours to exist around the monitoring stations. This problem consists in optimally locating a minimal number of enforcement stations, with the objective of intercepting as many vehicles as possible (Mirchandani et al., 1995), while also considering that the vehicle flows might react to the installation of monitoring stations and change their original routes.

Thus, if the objective of the monitoring system is to intercept vehicles that may present evasive behavior, it is not enough to use location models that are based on maximum vehicle interception, but rather it is necessary that the evasive behavior of the vehicles also be considered in the mathematical modelling of the problem (Marković et al., 2015). Otherwise there is a risk that the system may not be effective for enforcement. This kind of mathematical problem is commonly known as evasive flow-capturing problem (EFCP).

Motivated by this scenario, this paper presents an overview of EFCP and how they have been solved in recent literature. Moreover, numerical experiments are performed with real data that allow an analysis of how effective an enforcement system is when subjected to evasive flows in relation to the number of monitoring stations that are installed and also how the number of necessary monitoring stations increases with the increase in evasive tendency of the vehicles. Other numerical experiments are also performed that investigate the effects of considering a different evasion tendency in planning than that which is shown by vehicles in practice, and show that underestimating the evasive behavior may lead to an ineffective enforcement system, whereas overestimation guarantees that the vehicles are covered, and does not require a significant increase of investment in infrastructure.

It is not the goal of this paper to advance the mathematical state-of-the-art on EFCP problems and their solution, but rather to review and discuss the practical applications of the theory and the currently existing techniques of EFCP and its solution alternatives, with special focus on transportation planners which deal with any kind of system where the users could actively try to evade enforcement by using different routes.

As such, the main contribution of this paper is to show how the evasive behavior of illegal vehicles changes the way that enforcement systems should be planned, and the consequences of not considering such behavior when planning. Another contribution of this paper is providing an up-to-date review of the currently existing formulae and solution algorithms for this problem.

The next sections are organized as follows: in Section 2, an overview of the mathematical models that deal with this problem is presented, as well as other works in which the problem of locating monitoring stations is also addressed. In Section 3, the methodology used to conduct the current study is presented. Section 4 presents and discusses the results obtained in our experiments. Finally, Section 5 presents the conclusions of this paper, along with the limitations of this study and recommendations for future works.

2. LITERATURE OVERVIEW

Many problems in transportation and logistics are well represented mathematically by "facility location problems", which are models that seek to optimally locate facilities in a given network so as to maximize an objective function. The fields in which these problems are used include the location of emergency services (Boonmee et al., 2017), refueling stations (MirHassani and Ebrazi, 2012; Yildiz et al., 2016), traffic counting equipment (González et al., 2019), distribution centers (Yan and Shuzhi, 2012) and railway stations (Xiang et al., 2010).

A subclass of location problems is called "flow capturing problems" (FCP), in which the demand is characterized by traffic flows, and the number of captured vehicles is obtained considering not only the volumes in the network, but also the routes that the vehicles take from their origin to their destinations, hence maximizing the number of vehicles that encounter at least one facility in their trip, and disregarding repeated interception of the same trips (Berman et al., 1992; Hodgson, 1990). Upon proposing the mathematical formulation for such problems, Hodgson (1990) offered a few examples of facilities for which the demand is characterized by vehicle flows instead of traffic volumes, which include: convenience stores, refueling stations, automated teller machines and billboards. For these problems, if a flow capturing model is not considered and the allocation is performed based on the links with higher volumes, then a

"cannibalism" effect may occur, in which the demand of one facility is impaired by the existence of others of the same type at nearby locations. The FCP formulation has been used to solve several applications (Gendreau et al., 2000; Hodgson et al., 1996; Liu et al., 2019; MirHassani and Ebrazi, 2012; Šelmić et al., 2010; Yang and Zhou, 1998).

An extension of flow capturing problems have been proposed by Marković et al. (2015), called "evasive flow-capturing problem" (EFCP). In this case, it is assumed that vehicles may travel by many pre-determined routes, as long as the detour from its original path is not greater than a determined distance. Furthermore, it is also assumed that vehicles choose to travel through the shortest path which is not covered by a monitoring facility. Marković et al. (2015) demonstrated that EFCP problems are structurally different from FCP problems, and that algorithms that are successfully used to solve FCP problems may not be effective in solving EFCP problems.

The problem of locating monitoring stations to capture evasive flows can be represented by a bilevel optimization problem (Hooshmand and MirHassani, 2018), which is a special case of game theory (Stackelberg, 1952). Bilevel optimization problems are typically composed of a "leader" and a "follower", which possess different, conflicting objective functions which are dependent on shared variables. The "leader" is the party which first sets decision variables in order to optimize its objective function, and the "follower" reacts to the leader's decision and sets its own decision variables in order to optimize its own objective function. A few reviews of multilevel programming problems can be found in literature (Colson et al., 2007; Hongli et al., 2011; Lu et al., 2016).

In the EFCP applied to freight monitoring on highway networks, the transportation planning and enforcement agency is the leader, and the freight carriers which are in violation of transport regulations are the followers. The goal of the leaders (enforcement agency) is to minimize the occurrence of uncaptured illegal traffic flows, and it does that by locating enforcement equipment that monitors all vehicles passing through a certain link in the network. The goal of the followers (illegal carriers), on the other hand, is to travel from origin to destination without being captured by any enforcement equipment and with the least possible transportation cost. They do that by looking for the shortest, un-monitored route from origin to destination.

Bilevel optimization problems, however, are intrinsically very difficult to solve. Literature shows that even the simplest instances of this problem are classified as NP-hard (Colson et al. 2007). For this reason, Marković et al. (2015) have made a few assumptions that allow the problem to be reduced to a single level. The assumptions are:

1. For every trip that is made in the network, there is an associated cost, which represents two quantities simultaneously: the cost of transportation for the carrier, and the cost of illegal transportation for the planner. Both quantities are proportional to the flow volume and to the trip's distance;

2. The followers attempt to minimize the cost of travel for every origin-destination pair, by choosing the shortest, un-monitored route. The leader attempts to minimize the costs of illegal transportation in the whole network, by locating enforcement stations that capture illegal vehicles. As such, the objectives of both leader and follower models coincide;

3. The cost associated with a certain vehicle flow increases linearly with the distance traveled by unmonitored vehicles;

4. A certain vehicle flow f (defined as a set of vehicles with the same origin and destination) may travel along the k_f shortest paths between its origin and destination. The number k_f is determined so that the $(k_f + 1)^{th}$ shortest path would represent and excessive detour (that is, the cost of making such detour would exceed the benefit obtained from the illegal transportation);

5. A vehicle flow f is considered captured if there is at least one monitoring station in each of its k_f shortest paths. Furthermore, it is assumed that captured flows do not represent any cost to the highway system; and

6. An uncaptured vehicle flow travels along the shortest of its k_f shortest paths that is not covered by any monitoring station, since this minimizes its travel costs.

As a result of making these assumptions, the minimization of the travel distance of the vehicles (which is the objective of the followers) coincides with the minimization of the total cost associated with the illegal flows (which is the objective of the leader) and so the problem can be expressed as a one-level program.

The mathematical model proposed by Marković et al. (2015) is a binary integer programming model, which has an exact solution. One limitation of this model, however, is that its solution depends on the preprocessing of the shortest paths between each origin-destination (OD) pair of the network being studied, a process which has a potentially prohibitive computational cost. Other subsequent works have evolved from Marković et al. (2015) to propose more computationally efficient models and also to consider scenarios in which equipment installation spans over a long time, considered as one of the decision factors the order of equipment installation over time (Arslan et al., 2018; Hooshmand and MirHassani, 2018; Marković et al., 2017).

Another work has also approached the evasive flow-capturing problem, with the goal of relaxing assumptions made in the original paper (Lu et al., 2018). In this case, the authors dispute the assumption that the vehicles travel along one of a set of shortest paths for each OD pair, and instead consider that the route choice is made considering the whole roadway network. In order to solve this model, Lu et al. (2018) present a bilevel model and a solution algorithm based on heuristics.

Upon evaluating Marković's work, however, Lu et al. (2018) have considered a constant number of shortest paths between the OD pairs (denoted as k), chosen to represent the majority of cases. If this approach is changed, and k is chosen dynamically in relation to the route possibilities between each OD pair, then the authors' argument that the vehicles may find alternative viable paths beyond the given set of shortest paths is invalid, since there is certainty that all viable paths between origin and destination are included in the set of k shortest paths (in this case, a viable path is defined as one whose distance is within a given maximum allowed detour from the shortest path). Hence, the benefit obtained via the bilevel formulation does not compensate for the loss of certainty that the solution is going to be optimal. It can be used, however, as a good alternative to deal with large problems, where pre-processing is prohibitive.

In practical applications, the placement of enforcement stations in highway networks has been solved in various instances in literature, using various mathematical methods (AlGadhi, 2002; Ammarapala et al., 2013; Kulović et al., 2018; Mahmoudabadi and Seyedhosseini, 2013; Šelmić et al., 2010). Furthermore, the development of EFCP and its following extensions also presented as main motivation the location of enforcement stations (Arslan et al., 2018; Hooshmand and MirHassani, 2018; Lu et al., 2018; Marković et al., 2015, 2017).

3. METHODOLOGY

In order to explore the problem of positioning monitoring stations in highway networks considering evasive behavior, the deterministic EFCP model presented by Marković et al. (2015) will be used, which is presented in this section. With this model, a few numerical experiments will be carried out with a real network, which represents the highway network on the state of Espírito Santo, in Brazil.

3.1. Problem formulation by Marković et al. (2015)

Consider $G(N, A)$ as a bidirectional road network, where N is the set of nodes in the network and A is the set of links, identified by (i, j) pairs, which represent the origin (i) and destination (j) nodes of the link. Also, consider F as the set of vehicle flows, and P_f the set of possible paths for each flow $f \in F$, composed by its k_f shortest paths. In this context, a "vehicle flow" is defined as a trip with an origin, a destination, and the transported volume. A_f^p is defined as the set of links that compose the path $p \in P_f$ of flow $f \in F$. In addition, w_{ij} is the cost of installation of an enforcement station at the link (i, j), and d_f^p is the cost associated to flow $f \in F$ if it travels unmonitored along path $p \in P_f$.

Moreover, define x_{ij} as a binary variable which is equal to 1 if a monitoring station is located in the (i, j) link, and 0 otherwise. In order to allow formulation as a single-level problem, three sets of auxiliary variables are introduced. These variables are used to determine whether or not a certain vehicle flow should be considered captured, and also to determine which path is chosen, amongst all the available paths, for each vehicle flow. The auxiliary variables are defined as follows:

$$y_f^p = \begin{cases} 1 & \text{if there is at least one monitoring station} \\ & \text{located along path } p \in P_f \text{ of flow } f \in F \\ 0 & \text{otherwise} \end{cases}$$

$$y_f = \begin{cases} 1 & \text{if there is at least one monitoring station} \\ & \text{located in all paths } p \in P_f \text{ of flow } f \in F \\ 0 & \text{otherwise} \end{cases}$$

$$z_f^p = \begin{cases} 1 & \text{if flow } f \in F \text{ travels unmonitored} \\ & \text{along path } p \in P_f \\ 0 & \text{otherwise} \end{cases}$$

The auxiliary variables y_f^p and y_f have their values set by the choice made for the variable x_{ij}. However, z_f^p is also a decision variable, which represents the choice of path for each flow, and is restricted by the location of the monitoring stations. With these definitions, it is possible to write the evasive flow-capturing model as a binary programming model:

$$\min_{x_{ij}, y_f^p, y_f, z_f^p \in \{0,1\}} \sum_{(i,j) \in A} w_{ij} x_{ij} + \sum_{f \in F} \sum_{p \in P_f} d_f^p z_f^p \tag{1}$$

$$\text{s.t.} \sum_{(i,j) \in A_f^p} x_{ij} \geq y_f^p \qquad\qquad \forall f \in F, p \in P_f \tag{2}$$

$$z_f^p \leq 1 - y_f^p \qquad\qquad \forall f \in F, p \in P_f \tag{3}$$

$$\sum_{(i,j)\in A_f^p} x_{ij} \leq |A_f^p| y_f^p \qquad \forall f \in F, p \in P_f \tag{4}$$

$$y_f \leq y_f^p \qquad \forall f \in F, p \in P_f \tag{5}$$

$$\sum_{p \in P_f} z_f^p \geq 1 - y_f \qquad \forall f \in F \tag{6}$$

The objective function (1) is composed of two terms. The first term minimizes the investment cost of installing new monitoring stations. The second term minimizes the cost associated by truck flows whose paths are not covered by at least one enforcement equipment. Constraints (2)-(4) define the y_f^p auxiliary variable, by ensuring: that the path must be considered unmonitored ($y_f^p = 0$) if there aren't any enforcement stations in its links (constraint 2); that if there are any enforcement stations on a given path ($y_f^p = 1$) then the path mustn't be considered unmonitored ($z_f^p = 0$) (constraint 3); and that the path must be considered monitored ($y_f^p \geq 1$) if any of its links contain an enforcement station ($x_{ij} = 1$) (constraint 4). In constraint (4), $|A_f^p|$ denote the number of elements on the set of links that compose a path. Constraint (5) defines the auxiliary variable y_f, by stating that, if any of the paths for a certain flow $f \in F$ are un-monitored ($y_f^p = 0$ for any $\forall f \in F, p \in P_f$), then the flow must also be considered unmonitored ($y_f = 0$). Constraint (6) makes sure that all unmonitored flows ($y_f = 0$) contribute to the cost function ($z_f^p \geq 1$).

Through this formulation, it is possible to find the exact optimal solution for the location of enforcement stations on highway networks accounting for evasive behavior. In practice, the solution is obtained in two steps: first, the network must be pre-processed in order to find all k_f shortest paths within a given maximum detour from the shortest path (this can be done with Yen's algorithm (Yen, 1971). Second, the problem must be solved with any solver equipped with branch-and-bound based algorithms.

3.2. Concepts and definitions

In this section, a few concepts of interest to this study are defined in order to facilitate the explanation of the following experiments and results obtained. Firstly, we assume that the cost of transportation for each flow is equal to the distance traveled by the vehicles multiplied by the flow volume. In doing so, we assume a unitary cost per vehicle and per distance unit. As such, the cost of each path for each vehicle flow (d_f^p) is calculated as the distance traveled by the vehicles on each path multiplied by the flow volume. The origin of this definition is on weight enforcement problems, in which the damage is the loss in service-life of the pavement, which is linearly increasing with the distance traveled by overweight vehicles. This definition is still applicable on other contexts, such as hazardous material transportation, in which the cost is not related to pavement infrastructure, but rather on the risk such vehicles represent to other highway users. In this context, the risk also increases with the distance traveled by the vehicles (Šelmić et al. 2011).

For a scenario in which a certain enforcement solution is evaluated, the "resulting damage" of the solution is the sum of the cost of all unmonitored flows. This coincides with the second term of the Objective Function (1). For all the scenarios analyzed, a baseline case will be created in which there are no enforcement stations in the network (hence all vehicles travel unmonitored along their shortest paths), and the resulting total cost is noted as a reference value.

We then denote the "damage reduction" of an enforcement system as the percentual difference between the resulting damage of the system and the resulting damage of the baseline case. The complementary amount is called the "residual damage" which is the cost that still exists after the installation of the enforcement system. Therefore, if a certain scenario presents a damage reduction of 80%, for instance, that means that the enforcement system has successfully accounted for 80% of the total cost that existed in the baseline case, and the residual damage is 20%.

Vehicles that are captured by enforcement stations are considered to not represent any cost, since it is assumed that the vehicles know where the enforcement stations are and they know of the penalties of overloading, in which case they will cease their illegal practices if there is no viable unmonitored route. This is indeed a simplification; however, it is justified by considering that the planning of enforcement systems usually spans over a long timeframe, in which there would be time for carriers to learn the location of the stations and to react accordingly.

As previously mentioned, the number k_f of shortest paths will be chosen for every OD pair as a function of a parameter called "maximum allowed detour". The maximum allowed detour quantifies the tendency of the vehicles to evade monitoring stations. The meaning of this parameter is that, if a maximum deviation detour of $D\%$ is prescribed, then all vehicles will accept traveling distances up to $D\%$ greater than the shortest possible distance between origin and destination in order to avoid the monitoring stations. This means that k_f is such that the $(k_f + 1)$th shortest path have a distance at least $D\%$ greater than the shortest possible path.

3.3. Numerical experiments

A few experiments will be carried out, in which some input parameters will be controlled in order to study the sensitivity of the optimal solution and investigate the problem. The experiments will be described in this section, and their results presented in Section 4.

3.3.1. Experiment 1: reduction of total damage in relation to the number of stations located.

The goal of this experiment is to verify the efficiency of locating a variable number of monitoring stations in the damage reduction of the system. The model will be adapted in order to locate a given maximum number of stations. In order to achieve this, the installation costs w_{ij} will be considered null, and Constraint (7) will be added to the model:

$$\sum_{(i,j)\in A} x_{ij} \leq N \tag{7}$$

The k_f shortest paths will be found using a modified version of Yen's algorithm (Yen 1971), that finds not a given number of shortest paths, but all shortest paths within a maximum allowed detour. The modified model will be solved repetitively, varying the number of monitoring stations in the system (N) and observing the final value of the objective function.

3.3.2. Experiment 2: effects of the increase of the evasion tendency on the number of monitoring stations needed to cover all flows.

In this case, the goal is to study the impact of the variation of maximum allowed detour (in practical terms, this varies the tendency of the vehicles to evade enforcement) in the number of monitoring stations that is necessary to cover all flows in the network.

To this end, the installation costs w_{ij} receive much lower (but non-zero) values than the cost associated with unmonitored flows. Thus, the second term on the Objective Function (1), that represents the cost associated with unmonitored flows have a much greater importance than the term that represents installation costs. Therefore, the model will locate the least possible number of stations that are needed in order to eliminate the occurrence of unmonitored traffic.

With the model modified in this way, the maximum allowed deviation will be varied and the number of stations necessary to eliminate unmonitored traffic will be observed.

3.3.3. Experiment 3: consequences of planning without considering evasive behavior.

In order to investigate the need to consider evasive behavior on the planning of automated monitoring systems for enforcement, another experiment is carried out, in which an initial planning is made with a maximum allowed deviation of 0%. Thus, only the shortest paths for every OD pair will be considered in this initial planning, which reflects the way the problem has been solved in a few works (AlGadhi, 2002; Mahmoudabadi and Seyedhosseini, 2013; Šelmić et al., 2011). When solving this model, the installation costs w_{ij} are set in the same way as Experiment 2. Hence, the minimum amount of stations necessary to capture all flows will be located. After this, the location of the monitoring stations from this initial planning will be kept constant, and a simulation carried out in which the vehicles receive a greater maximum allowed detour than the one considered in planning (up to 50%).

Furthermore, additional instances of this experiment will be carried out, in which the initial maximum allowed deviation also varies between 0% and 50%, and the resulting locations are used in the simulation of flows with varying maximum allowed detours. With this, it is possible to observe the effects of evasive behavior in a system that did not completely account for it in the planning of the stations' locations.

4. RESULTS AND DISCUSSION

The experiments described previously were carried out on a personal computer with an Intel® Core™ i5-8400 processor with 2.80GHz frequency, with RAM memory of 16.0 GB and Windows 10 64 bits operational system. The models were implemented with the "PuLP" python library (Mitchell et al., 2011). This library allows for the modelling of the optimization problem and provides an interface to a few solvers, of which the COIN-OR CBC solver was used (Forrest et al., 2018).

The results obtained allow a few observations to be traced regarding the effects of evasive behavior in the problem of optimally locating monitoring stations for enforcement purposes. As a first point of discussion, it is possible to observe the potential that the model presented by Marković et al. (2015) has in being used for the planning of the locations of monitoring stations for evasive flow capture. The usefulness of this model is mainly in the fact that the optimal solution to this otherwise very complex problem is possible to find, limited only by network complexity and computing capacity. Finding the optimal solution means that all the possible paths contained in the input vector P_f will be accounted for. The pre-processing of all the viable paths between each OD pair, however, can be prohibitive.

4.1. Results of Experiment 1

The network used in this experiment represents the federal, state and municipal highway

systems of the state of Espírito Santo (ES), Brazil. It includes all paved highways in this state. Urban streets are not included, neither are dirt roads. The network is composed of 368 nodes, 902 links and 451 OD pairs (Figure 1). The origin and destination nodes (which correspond to municipalities), the OD pairs and the transported volumes were obtained from official data for the state of Espírito Santo in 2017. The shortest paths for all OD pairs were pre-processed for a maximum allowed detour of 20% (it is possible to consider lower values simply by filtering the input set P_f). This resulted in a total of 107,920 considered paths. The number k_f has varied in the following way: 61% of the flows had fewer than 10 viable paths, 25% between 10 and 100 viable paths, 10% between 100 and 1000 viable paths, and 4% of the flows had more than 1000 viable paths, including two OD pairs with over 26,000 viable paths.
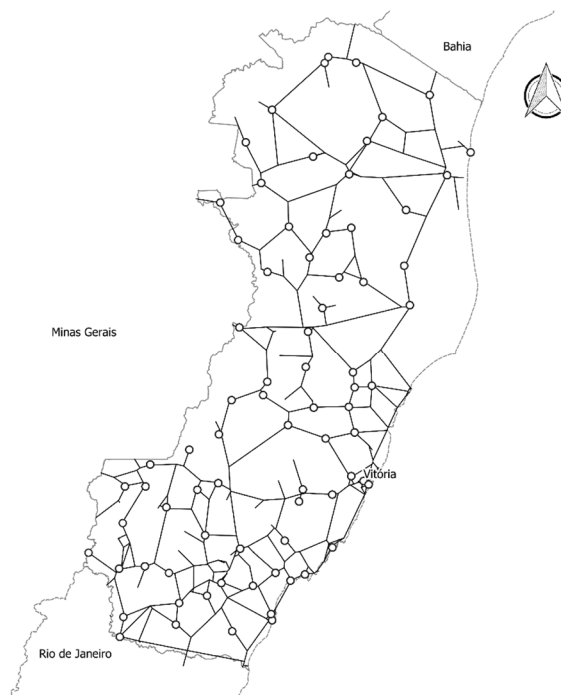

Figure 1. Network of the highway system in the state of Espírito Santo, Brazil. (circles denote the origin or destination nodes for OD pairs.)

The solution of the model was obtained with three computational processes running in parallel. Each process executed a sequence of processing tasks that correspond to instances of the problem solution. A common queue of processing tasks was created, and each one of the three processes pulled from the same queue.

For each processing instance, a number N of located monitoring stations was prescribed. The average time needed to solve the model with the COIN-OR CBC solver (Forrest et al., 2018) was 14 hours. This time does not include the time it took to pre-process the k_f shortest paths, which was of approximately 13 hours for the maximum allowed detour of 20%. Figure 2 shows the damage reduction obtained as a function of the number of monitoring stations located in the network.

It is observed that, in the three cases of maximum allowed detours, a reduction of more than 95% on the damage associated with unmonitored flows was obtained with 20 monitoring stations, with 78 stations needed to increase this reduction to 100%. This may be explained by the fact that the highest damages are associated with the longest trips, which possess a greater

number of links in common between themselves. Besides which, a concentration of the highest volume flows in a few origins or destination nodes is observed in reality, which can also contribute to the majority of the damage being eliminated with a few stations, since covering these regions would account for a large part of the traffic.
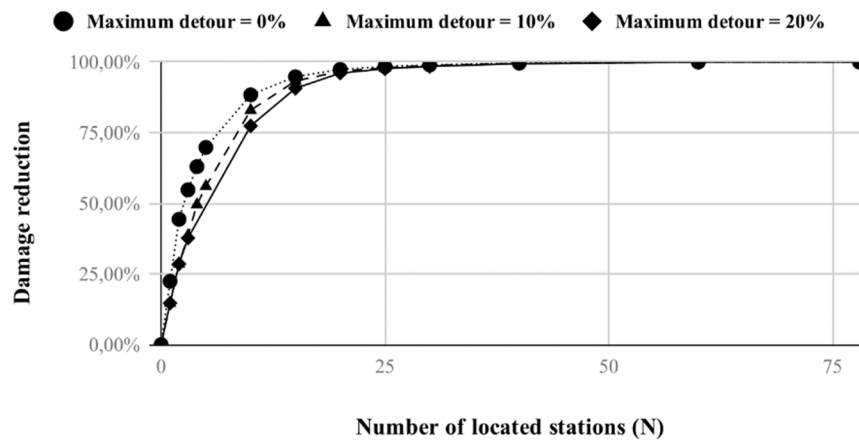

Figure 2. Damage reduction in the ES network by number of located stations

4.2. Discussion of Experiment 1

An analysis of the results presented on Section 4.1 (Experiment 1) shows the efficiency of increasing the number of monitoring stations on reducing the damage associated with unmonitored flows. Figure 2 shows a drastic reduction on the resulting damage with a relatively low number of monitoring stations. This observation is due to the fact that the model's exactness guarantees that in any scenario the maximum possible damage reduction will be obtained, so even with a low number of stations, the solution will prioritize locations where it finds the best results with the limited number of stations. Another fact that collaborates this result is that, usually, highway systems present a clustering of nodes with high volumes, which may be located near production or consumption centers, large cities or large transportation terminals such as ports, railway stations, etc.

Note that, for Experiment 1, every number of located stations was run as a new solution to the model, independent from the ones found previously. Therefore, the increase in number of stations does not represent the evolution of a system that is gradually built, but rather the increase in effectiveness of increasing the total investment on the system.

4.3. Results of Experiment 2

The network used in this experiment represents the south-central region of the state of Espírito Santo, Brazil. This network includes the largest cities of the state and the OD pairs with the highest volumes. The reduction in network size was performed in order to lower the computational cost of the analysis, since pre-processing of the ES network with more than 20% maximum allowed detour was inviable.

The graph used in this experiment has 146 nodes, 368 links and 147 OD pairs (Figure 3). Pre-processing of this network was carried out with up to 50% maximum allowed detour, which resulted in a total of 78,137 possible paths between OD pairs. Figure 4 shows the results obtained in this experiment.
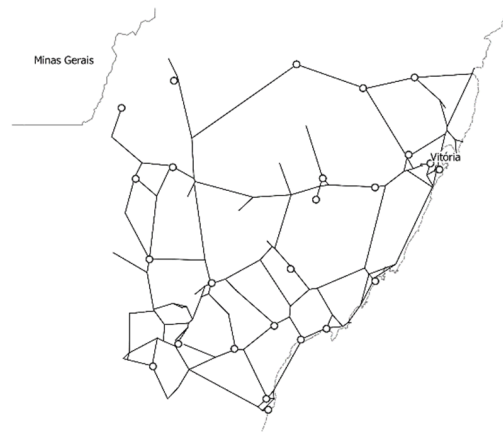
Figure 3. Network used in experiment 2. (circles denote the origin or destination nodes for OD pairs.)
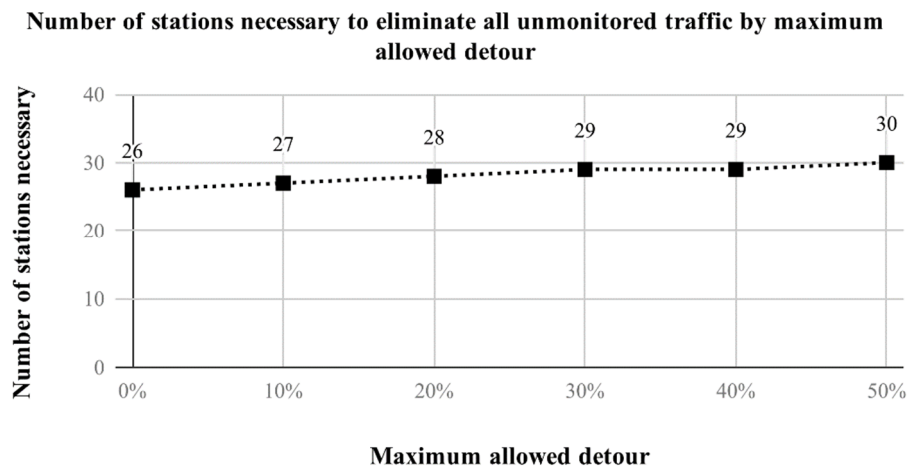

Figure 4. Number of stations necessary to capture all flows by maximum allowed detour

4.4. Discussion of Experiment 2

Looking at results from Section 4.3 (Experiment 2), it is possible to observe that considering evasive behavior on the planning of automated monitoring systems did not significantly increase the number of monitoring stations needed in order to achieve total coverage. This result is due to the fact that many of the possible paths between origin-destination pairs, including those with high detours, have a great number of common links. Especially if there is some kind of junction between origin and destination, the increase in the maximum allowed detour would still be covered by a monitoring station located in the appropriate link. As such, it is possible to observe that the consideration of evasive flows in the planning of automated monitoring systems does not mean that a significantly greater investment would be needed on building new stations, but rather that the choice of installation links would be performed in a more intelligent way, so that the links that cover a greater number of paths are chosen.

Another important consideration on this Experiment is the fact that, in order to consider the allowed detour with values up to 50%, it was necessary to reduce the network to a smaller region. The reason is that with such high values of allowed detour percentage, the number of paths that are possible for each vehicle flow increases greatly and makes it prohibitive to carry out this experiment on a larger network. This is also due to the model that was chosen to perform

this study. This paper uses the deterministic model presented in Marković et al. (2015) because it presents an exact solution and is simple to implement. However, there are different models to solve the same problem, including the one presented by the authors of Arslan et al. (2018), which also presents an exact solution without preprocessing.

4.5. Results of Experiment 3

The same network used in Experiment 2 was used in this case. An initial planning was carried out with 0% maximum allowed detour, and the total cost associated to flows with an increasing maximum allowed detour was observed. The residual damage of the system was observed with the varying flows. Results are found in Figure 5.
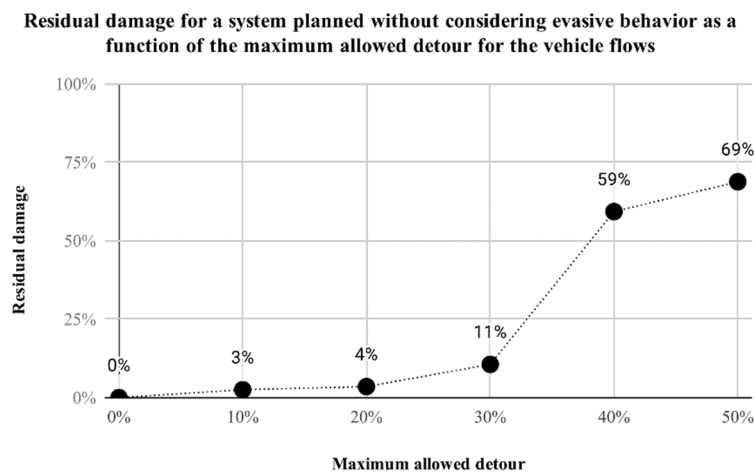

Figure 5. Residual damage for a system planned without considering evasive behavior as a function of the maximum allowed detour considered for the vehicle flows.

Table 1. Residual damage for scenarios varying the maximum allowed detour for the initial planning and for the simulated vehicle flows.

Maximum detour for vehicle flows	Maximum allowed detour in initial planning					
	0%	10%	20%	30%	40%	50%
0%	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%
10%	2.512%	0.000%	0.000%	0.000%	0.000%	0.000%
20%	3.521%	0.286%	0.000%	0.000%	0.000%	0.000%
30%	10.604%	1.304%	0.022%	0.000%	0.000%	0.000%
40%	59.309%	59.395%	0.026%	52.780%	0.000%	0.000%
50%	68.838%	76.938%	0.028%	67.426%	0.001%	0.000%

The same analysis was also run with varying values of maximum allowed detour both for the initial planning and for the vehicle flows. The results of this analysis are shown in Table 1. This table is structured in the following way. Each column represents the value of maximum allowed detour that was used in order to plan the system and locate the enforcement equipment. In turn, each row represents the maximum allowed detour that was used to simulate the flows' response to the initial planning. The value in each cell represents the residual damage in the network, which quantifies the ability of the vehicles to evade the system. For instance, the first column represents a case where the location of the equipment was chosen without considering evasive tendencies. The values in this column mean that, for instance, if the vehicles are willing

to perform detours of up to 50% their total travel distance, then 68.8% of the flow is able to continue travelling without being captured. The last column shows, however, that if the initial planning is done considering a 50% tolerance on the vehicle's detours, then all the vehicles which are willing to perform detours of up to 50% their total distance will be captured.

4.6. Discussion of Experiment 3

Results from Section 4.5 (Experiment 3) show that, in the event that carriers do have a disposition of avoiding enforcement stations by changing their routes, and such behavior was not considered in planning, the system might be ineffective in capturing these vehicles, and the investment made in installing monitoring stations might not have an adequate return. For the network considered in Experiment 2, it is seen that the system planned without consideration for the evasive behavior (maximum allowed detour in planning was 0%) suffered a significant loss of efficiency when the vehicles had an allowed detour greater than 30%. In reality, the profits obtained by vehicles with illegal practices such as truck overloading might compensate for a 30% detour in routes.

The results from Table 1 show that if, during planning stages, the maximum allowed detour is considered to be less than the detours that the vehicles might perform in reality, the effectiveness of the system is unpredictable. Because the effectiveness of the system depends on choices of location for the monitoring stations, it is possible that the choice made for lower allowed detours is already a good candidate for dealing with more evasive flows, which was the case for the scenarios planned with 20% maximum allowed detour in Table 1.

The same table shows, however, that all the flows with a maximum allowed detour lower than the value considered in planning were completely captured. For this reason, it is possible to say that, in the planning of monitoring stations' locations for enforcement purposes, the evasion tendency must be overestimated. Doing this, there is no doubt that all the considered flows along the accounted paths will be captured by the enforcement stations. The cost of such overestimation is not in excessive investments needed in the system (as seen by Experiment 2), but rather on the computational effort that is needed for proper planning of the system. This computational effort, however, is minimal when compared to the magnitude of the timeframes that are considered in the planning of transportation systems, which usually span for multiple decades.

5. CONCLUSIONS

The goal of this study was to show how the evasive tendencies of illegal vehicles change the way that the placement of enforcement equipment in highway networks should be performed. It was also the goal of this paper to present relevant references as to how this placement may be performed in order to address evasive behavior. By analysis of literature and the performance of numerical experiments, this paper has arrived at the following conclusions:

- Considering evasive behavior in the positioning stages of automated monitoring systems does not significantly increase the number of stations that are needed to cover the flows, but rather optimizes the chosen locations;
- With the evasive flow-capturing model, a significant reduction in the cost associated with unmonitored flows can be obtained even with a reduced number of monitoring stations. For instance, in the real case of the state of Espírito Santo, Brazil, the location of 20

stations reduced the total network cost in more than 95%, while 78 monitoring stations were needed to further increase this reduction to 100%;

- If the targeted flows for a certain enforcement system do present an evasive behavior, and such behavior was not accounted for in the planning stages, then it is possible that there are escape routes which allow the vehicles to avoid enforcement by making relatively short detours, and the enforcement system might not be effective in promoting compliance to traffic regulations; and

- On the other hand, if the planning of the enforcement stations locations considers an evasion tendency that is greater than the one actually presented by the vehicles, then all the vehicle flows will still be accounted for, and such consideration will not generate excessive costs in infrastructure. Therefore, evasion tendencies must be overestimated in practice.

This study also presents a few limitations, that are listed below, along with recommendations for future works.

- Firstly, the model that was used to perform the studies (Marković et al., 2015) requires that all the possible paths considered between each origin-destination pair be preprocessed. This is very costly, and as such, the size of the networks that were analyzed was limited. Future studies in this subject might consider using different models, which in turn could allow larger networks to be considered;

- This study did not consider real costs of transportation or equipment installation, rather used proportional quantities that guaranteed the optimality of the solution for the experiments that were performed. As such, future studies could factor in the real installation and transportation costs for a specific application, in order to obtain more specific insights regarding the financial planning of said application; and

- Future studies could further expand on this work by also considering scenarios in which the installation of the enforcement equipment occur in a gradual manner, which more closely reflects the way that real systems are gradually installed over time. This would allow for observations regarding which locations should be prioritized, for example.

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