Policies for operating enforcement cameras

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Key words: Optimization, enforcement cameras, speeding, road crashes, public–private partnerships, traffic police

Abstract:

This study analyzes the current Israeli public–private partnership (PPP) project of automatic enforcement cameras. There are fewer cameras than poles in Israeli law enforcement; therefore, the cameras are moved between the poles. First, we present a linear programming approach (mobility model) to determine the optimal allocation of cameras on the poles based on road crash data and geographical constraints. Second, we determine the optimal number of cameras to buy and number of movements required (camera-movement tradeoff model). Third, we use a Monte–Carlo simulation of the camera failures to define an optimal inventory policy (inventory model). We demonstrate that applying the outcomes of the mobility model results in a 25% enhancement (from 55% to 80%) of road crash coverage. The results of the camera-movement tradeoff model indicate that when the movements are relatively inexpensive (a movement costs less than 10% of the price of a camera), it is not worthwhile to buy new cameras. Finally, the results of the inventory model show that a repair period of one or two months does not seriously decrease the road crash coverage, and thus, for any future PPP project, it is unnecessary to insist that the repairs be completed within two months.

1. Introduction

Approximately 1.25 million people die each year as a result of road crashes (WHO, 2016). This is not only a humanitarian problem but also an economic problem as road crashes cost countries approximately 3%–5% of their gross national product (Elvik, 2000). The solutions and effective interventions for minimizing road crashes include designing safer infrastructures, improving the safety features of vehicles, improving post-crash care for victims, raising public awareness, and improving road user behavior by legislating and enforcing laws pertaining to key risk factors (Blais & Dupont, 2005; WHO, 2016).
The European Transport Safety Council (ETSC 1999) identified the three most significant traffic offences with a direct connection to road safety that ought to be targeted in enforcement strategies: speeding, blood-alcohol concentration above the legal limit, and the lack of safety belts. In this study, we focus on speed limit enforcement.

Speeding makes up a larger percentage of road crashes than any other violation. It has an impact on both the likelihood and severity of traffic collisions. For example, an average of 40–50% of drivers drive faster than the posted speed limit and it is a socially acceptable behavior (Pilkington & Kinra, 2005; Fleiter & Watson, 2006; OECD, 2006; Elvik, 2012; De Pauw et al., 2014), and this accounts for approximately one third of the traffic collision fatalities in the USA and for 25% of Australia’s fatal collisions (Fleiter et al., 2009; Peterso et al., 2017). Nilsson (1982) and Elvik et al. (2004, 2012, 2013) described the relationship between the number of crashes before and after a speed reduction with the following power model relationship. When the police successfully reduce the average speed on a road, the number of crashes decrease exponentially.

\[
Crashes_{after} = Crashes_{before} \times \left( \frac{speed_{after}}{speed_{before}} \right)^{exponent}
\]  

(1)

In addition to reducing injuries, lower average traffic speeds have other positive effects on health outcomes (e.g., a reduction in respiratory problems associated with car emissions) (Aarts and van Schagen, 2006; WHO, 2016).

Generally, the following relationships exist in traffic speeding policies: Enforcement increases driver deterrence, which subsequently reduces the speed, which in turn reduces road crashes. (Watson et al., 2010). In the early sixties, the world’s first speed camera was introduced to enforce traffic laws (https://en.wikipedia.org/wiki/Traffic_enforcement_camera). Since then, several countries have been using speed-limit enforcement cameras. Speed cameras make speed limit enforcement more effective and have a favorable effect on traffic safety and, in particular, on the occurrence of severe crashes (Carnis and Blais, 2013; De Pauw et al., 2014). Drivers tend to adapt their driving behavior according to speed enforcement by speeding less when limit enforcement is increased, and speeding more when enforcement is reduced. For example, the violation rate for cars passing speed cameras in Norway is close to 10% whereas almost 50% of traffic speeds in general. Bar-Gera et al. (2014) found that the average speed declined by 7.86 km/h (8.7%) at automatic enforcement cameras sites in Israel.

In most countries, the traffic police have limited resources and therefore, they attempt to maximize the benefit from their resources by using effective operation methods. For example, enforcing quality tickets according to the resources constraint (Adler et al, 2012) or allocating patrol vehicles according to collision, traffic volume, and call-for-service data (Adler et al, 2014; Hakkert et al., 1990).

Speed offences can be enforced manually by a police officer with a laser gun that measures an upcoming vehicle’s speed, who stops the vehicle on the spot and gives the offender a ticket, or automatically, wherein the vehicle is caught speeding on camera, and the owner of the vehicle receives a ticket in the mail. Several problems can occur when a police officer enforces the speed limit. Firstly, traffic
collisions have been the leading cause of death for law enforcement officers in the USA, and this a primary occupational hazard in the policing vocation (Gustafson, 2015). Secondly, drivers perceive police officers who enforce traffic laws rather unfavorably (Yagil, 1998). Thirdly, the most frequent type of citizen complaint filed against police officers involves how the officer uses interpersonal communication. The most common location for police–citizen contact is the traffic stop. In a time of community-oriented policing, it is important for law enforcement agencies to improve their relationships with the public and avoid causing citizen complaints (Johnson, 2004). Fourthly, using automatic enforcement equipment reduces the time a police officer spends handing out tickets to speed offenders. This enables police officers to concentrate on other tasks. Therefore, the automatic procedure is more effective for reducing speed and crashes, and thus, the traffic police should use human resources for other tasks that cannot be automated (Li et al., 2016; Wijers, 2013, Wilson et al., 2010)). As in most countries, the higher the percentage of the fines that go to court, the greater the workload of the court system. Dreyfuss and Nowik (2018) developed a method for decreasing the average driver speed without increasing the number of fines. This helps the Israeli police to reduce the occurrence of speeding without increasing the court system’s workload.

In 2012, a new Public-Private Partnership (PPP) for enforcement cameras was established in Israel to purchase and operate new digital cameras and poles for automatic static enforcement. Owing to economic and public reasons, a limited number of poles and cameras were installed with fewer cameras than enforcement poles, and therefore, the cameras are moved between the poles. The actual location of the poles is determined by a public committee.

In this paper, we make the following contributions: First, we present three models for improving the actual operation of the camera-enforcement project. For each of the three models, we present the possible decisions, the objective function and the technique for how to solve the model. The mobility model uses an integer programming approach that determines an optimal mobility schedule using a predefined objective and satisfies all the constraints. The results of this model are presented in the numerical application section. The damages that occur in the car collisions (road crash value, RCV) are used to determine allocation of the cameras on the poles. The camera-movement tradeoff model and inventory model serve as bases for planning the next PPP contract. The camera-movement tradeoff model includes the economic considerations as well as a sensitivity analysis. Every camera has a cost, and every movement of the camera incurs a cost to the system. However, by moving the cameras and buying new cameras, the RCV might be reduced. The sensitivity analysis shows the tradeoff between the number of cameras and number of movements of the cameras between the poles. The inventory model depicts the tradeoff between the maximum utility of the project and the number of cameras in the inventory, which are used in the case of camera failure. Finally, we applied these models to real data from the Israeli police and demonstrate which insights can be gleaned from the results of applying these models.
2. Current operating system

The characteristics of the system and the data were obtained from the Israel Traffic Police. The police supervise the enforcement camera system, which is a PPP project. A private company is in charge of purchasing and installing all the equipment and moving the cameras between the poles. The actual contract ends in 2021.

Each of the enforcement cameras includes a brightly colored orange pole topped with a box that has a reflective sticker. A camera with a computer can be installed in the box. The system is connected to two electronic detectors embedded in the road surface of each lane. The wide angle of the camera lens is pre-determined according to the number of lanes. When a car passes over the first detector, an electronic signal activates the camera. When the car passes over the second detector, the speed is calculated, and if it exceeds the pre-determined enforcement limit, a digital picture of the vehicle is taken. The vehicle’s speed is determined by the time elapsed between when the car touches the first and second detector. In multi-lane conditions, each lane has its own detectors while all the lanes are observed using one wide-angle camera. The enforcement system records the date, time, location, lane, car license plate number, direction of travel, speed, and the enforcement speed level.

In the Israeli speed-limit enforcement camera system, speed cameras at intersections enforce red light compliance as well. In this case, two photos spaced one second apart are captured to prove the violation. The locations of the poles are selected based on a cost-benefit analysis at each site. It is based on road crash data, the effect of enforcement on drivers’ behavior, and the relationship between the average speed reduction and a decrease in casualties, which is based on the extant literature (see Eq. (1)).

In 2015, the Israeli enforcement camera system had 115 poles and 60 cameras. To improve coverage at dangerous and high-cost locations, the cameras were moved between the poles according to operational policy and constraints (Israel Police website, 2016).

3. Models and methods

In this section, we present the new models that were developed in this research. The first model (3.1) is the *mobility model* for the optimal operation of the project. The second and third models are used for the next PPP contract (3.2). The second model is the *camera-movement tradeoff model* (3.2.1) as the cameras’ number of movements between the poles and the required number of cameras depend on the cost of the cameras, cost of moving a camera, and the current or predicted road crash data for calculating the objective function of the system. The third model is an inventory model (3.2.2) that determines the inventory level and maximum repair time for the cameras for each period of time in the case of camera failure as per the service level agreement for the new contract.

3.1 Mobility model
Consider a camera enforcement system with $N$ cameras, $L$ poles, where $L > N$, and a planning horizon of $t = 0, 1, ... T$ periods. At the beginning of each period, a camera might be removed from the current pole and installed on a different pole. We assume that the setup time is negligible. The objective is to allocate cameras at poles and at periods with the most fatal collisions. The additional constraints are as follows. Firstly, there are poles installed at dangerous road sections and are thus defined as hotspots and require a camera for the entire planning period. Therefore, the cameras and poles are eliminated from the problem, which reduces the magnitude of the problem. Secondly, there are areas that have more than one pole, and the police require that in such areas, there is at most one camera operational simultaneously. There are also areas that require at least one camera per period.

We use the following notations:

- $U_{l,t}$ is the utility value of installing a camera at pole $l = 1, ... L$ at time $t = 1, ..., T$. In this paper, we use the $RCV$ as the utility function.
- $M$ is the maximum number of movements for the entire planning period according to the PPP contract. It should be noted that $M \leq T \times N$.
- $R_t$, $t = 1, ..., T$ is the maximum number of cameras that the police can remove at time $t$. It should be noted that $R_t \leq N$.
- $A_t$, $t = 1, ..., T$ is the maximum number of cameras that the police can install at time $t$. $A_t \leq N$.
- $P = \{P_i\}, i = 1, ..., I$, is the set of groups of poles that require one camera at most per group for all periods. There are $I$ groups in the set.
- $Q = \{Q_j\}, j = 1, ..., J$, is the set of groups of poles that require one camera at least per set for all periods.

We now define the following variables:

- $X_{l,t} \in (0,1), l = 1, ... L, t = 1, ..., T$ is a decision variable. $X_{l,t} = 1$, if a camera should be installed on pole $l$ at the beginning of time $t$, and $X_{l,t} = 0$, if nothing changes.
- $Y_{l,t} \in (0,1), l = 1, ... L, t = 1, ..., T$ is a decision variable. $Y_{l,t} = 1$, if a camera should be removed from pole $l$ at the beginning of time $t$, and $Y_{l,t} = 0$, if nothing changes.
- $S_{l,t}$ denotes the assignment of a camera at pole $l = 1, ... L$ at time $t = 1, ..., T$. $S_{l,0}$ represents the initial positioning of the cameras.

The objective function is the overall coverage of the $RAV$ in the system and is denoted by

$$
\max \left( \sum_{l=1}^{L} \sum_{t=1}^{T} U_{l,t} \cdot S_{l,t} \right)
$$

(2)
In Table 1, we present the problem constraints.

Table 1: Problem constraints and descriptions

<table>
<thead>
<tr>
<th>#</th>
<th>Constraint</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\sum_{l=1}^{L} S_{l,t} \leq N, \forall t$</td>
<td>For each time period, the sum of cameras assigned must be smaller or equal to the total number of available cameras.</td>
</tr>
<tr>
<td>2</td>
<td>$\sum_{l=1}^{L} X_{l,t} \leq A_t, \forall t$</td>
<td>For each period, the sum of cameras for installation must be smaller or equal to the total number of permitted allocations.</td>
</tr>
<tr>
<td>3</td>
<td>$\sum_{l=1}^{L} Y_{l,t} \leq R_t, \forall t$</td>
<td>For each period, the sum of cameras to be removed must be smaller or equal to the total number of permitted removals.</td>
</tr>
<tr>
<td>4</td>
<td>$\sum_{t=1}^{T} \sum_{l=1}^{L} X_{l,t} \leq M$</td>
<td>The sum of installations must be smaller than the total number of permitted installations for the entire planning period.</td>
</tr>
<tr>
<td>5</td>
<td>$\sum_{t=1}^{T} \sum_{l=1}^{L} Y_{l,t} \leq M$</td>
<td>The sum of removals must be smaller than the total number of permitted removals for the entire planning period.</td>
</tr>
<tr>
<td>6</td>
<td>$S_{l,t} = S_{l,t-1} + X_{l,t} - Y_{l,t} \forall l, t$</td>
<td>A camera is assigned to pole $l$ at time $t$ if it was assigned at time $t-1$ without removal or it was added at time $t$.</td>
</tr>
<tr>
<td>7</td>
<td>$X_{l,t} + Y_{l,t} \leq 1 \forall l, t$</td>
<td>At each time $t$ and for each pole, we can either add, remove, or retain a camera.</td>
</tr>
<tr>
<td>8</td>
<td>$\sum_{l \in P_i} S_{l,t} \geq 1 \forall i, t$</td>
<td>The set of poles that require at least one camera per set.</td>
</tr>
<tr>
<td>9</td>
<td>$\sum_{l \in P_j} S_{l,t} \leq 1 \forall i, t$</td>
<td>The set of poles that require at most one camera per set.</td>
</tr>
<tr>
<td>10</td>
<td>$0 \leq S_{l,t} \leq 1 \forall l, t$</td>
<td>For each time and pole, there must be one or no camera assigned.</td>
</tr>
</tbody>
</table>

In our actual system, $A_t = R_t, t = 1,..,T$, which means that we have the same capacities for removing and adding cameras at each time period. The first movement (addition or removal) is performed at time $t = 1$. When $A_t \neq R_t$, the model has different capacities for the addition and removal of cameras at each time period. This enables the model to output an implementation of the system in which a camera is removed at a certain time and added a month or two later. This might be done for the purpose of maintenance or repair or if no collisions have occurred. The values of the variables $S_{l,t}, X_{l,t},$ and $Y_{l,t}$ are
set endogenously by optimizing the model. The output of the optimization model represents the optimal allocation policy for the entire planning period. The numerical application is described in Chapter 4.

### 3.2 Models for the next PPP agreement

In a few years, the current PPP project will be terminated, and a new PPP agreement will be signed. The cooperation parameters in the new PPP agreement are based on the current data analysis. We developed two models to support the decision makers in their negotiations with the external company. The camera-movement tradeoff model is presented in subsection 3.2.1 and the inventory model in subsection 3.2.2.

#### 3.2.1 Camera-movement tradeoff model

In the mobility model (3.1), \( N \) (number of cameras) and \( M \) (number of movements) are fixed according to the current PPP contract. However, for the future PPP contract, the police intend to re-evaluate the optimal values for \( N \) and \( M \) to maximize a predefined objective function of the system. In this model, \( N \) and \( M \) are decision variables while the cost of a camera and of moving a camera are given.

We use the following constants:

- \( p^c \) is the cost (in units of money) of a camera
- \( p^m \) is the cost (in units of money) of moving a camera

Thus, (2) becomes

\[
\max \left( \sum_{l=1}^{L} \sum_{t=1}^{T} U_{l,t} \cdot S_{l,t} - N \cdot p^c - M \cdot p^m \right)
\]

The use of (3) as an objective function allows us to determine the optimal ratio between the number of cameras to be purchased and the optimal number of movements to be performed. The constraints of the mobility model are still valid, and in the numerical application, we demonstrate the insight gleaned from this model in Chapter 4.

#### 3.2.2 Inventory model

An important clause in the PPP contract is the inventory and the repair time required until a failed camera becomes functional. Camera failure is unpredictable and is thus a stochastic process. When a camera fails, it is sent for repair. After the camera is repaired or replaced (in the case of serious damage), the camera is reinstalled on the “best” pole, which is determined using the objective function. Meanwhile, a serviceable camera might be moved from another pole. Generally, the police are interested in achieving zero repair time whereas the private company in the PPP partnership prefers a longer time that allows them to order a new camera from the supplier, which might be based abroad, and thus, does not require them to hold any inventory.
Therefore, we define the following variable and cost function:

- \( \tau = 0, 1, ..., T \) is the time until a failed camera becomes serviceable either after repair or replacement. \( \tau = 0 \) implies that there are sufficient cameras in stock for replacement.
- \( g(\tau) \) is the overall cost for any option of \( \tau \) for an average number of camera failures. We assume that \( g(\tau) \) is a decreasing function with \( \tau \). We also assume that the replacement is made at zero cost to the police when a camera fails, and the setup time is negligible.

If all the cameras are new, and they all have the same probability of failure at any given \( t \), then the number of failures will follow a binomial distribution. Nevertheless, in practice, old cameras behave differently from new ones, and more failures occur in winter than in summer owing to weather conditions, and thus, the number of failures does not follow any known distribution. Therefore, a list of scenarios is defined (the list may be arbitrarily large) with the corresponding probabilities. We define the following functions:

- \( f(c_t, t), t = 1, ... T, c = 0, 1, ... N_t \) is the probability that \( c_t \) cameras fail in period \( t \), and \( N_t \) is the number of available cameras at time \( t \).
- \( \vec{f}(c_1, ..., c_T) \) is the sequence of the number of cameras that failed at time \( t \). This sequence forms a scenario.

We neglect the location of the failure and assume that for any failure, a camera is moved from another pole free of charge (the company is obligated to move a functional camera to the failed camera’s pole) if necessary. The failures of cameras at each time \( t \) is assumed to be independent, and thus, the probability of scenario \( \vec{f}(c_1, c_2, ..., c_T) \) is given by

\[
P \left( \vec{f}(c_1, c_2, ..., c_T) \right) = \prod_{t=1}^{T} f(c_t, t).\]

We illustrate this idea with the following example. Let us assume that \( T = 2 \), that only one camera can fail at any time \( t \), and that the probability of failure is 0.05. Thus, we have the following four scenarios: \( \vec{f}(0,0), \vec{f}(0,1), \vec{f}(1,0), \) and \( \vec{f}(1,1) \) with their respective probabilities 0.9025, 0.0475, 0.0475, and 0.0025.

Now, we derive an algorithm that determines the optimal value for \( \tau \). For this, we simulate all the various scenarios and select the best \( \tau \). When \( \tau = 0 \), it does not affect the availabilities of the cameras in the system. But when \( \tau > 0 \), it affects the availability at time \( t, t + 1, ..., t + \tau \). Thus, we adjust the mobility model and change the constraint 1 (of Table 1) as follows.
\[
\sum_{l=1}^{L} S_{l,t} \leq N_{t} - \sum_{i=0}^{t-1} c_{t-i}, \forall t
\]

If, for example, \( \tau = 2 \), then the cameras that failed in the periods \( t \) and \( t - 1 \) are missing as they did not return after repair. In addition, the objective function itself must be adjusted to include the cost of the solution, and it thus becomes

\[
\max \left( \sum_{l=1}^{L} \sum_{t=1}^{T} U_{l,t} \cdot S_{l,t} N \cdot p^c - g(\tau) \right)
\]

Thus, the following algorithm is used to determine the optimal \( \tau^* \).

1. For each \( \tau = 0, 1, ..., T \)
   
   For each of the scenarios \( \hat{f} \)
   
   - Solve the model and calculate the optimal \( RCV \rightarrow RCVFT(\hat{f}, \tau) \).
   - Calculate the expected value of \( \tau \) using \( RCVT(\tau) = \sum_{\hat{f}} P(\hat{f}) \cdot RCVFT(\hat{f}, \tau) \)

2. \( \tau^* = \arg\max(RCVT(\tau)) \)

In step 2, \( \tau^* \) is the value of \( \tau \) that maximizes the \( RCVT(\tau) \) function.

The complexity of this algorithm is \( O(T \times \text{number of scenarios}) \).

4. Numerical applications

In this section, we use data from the Israeli police system for the years 2011–2014 and the values from Elvik and Bar-Gera to demonstrate the insights of the models presented in this paper.

4.1 Data collection

To apply the models, we collected road crash data for the years 2011–2014 within 1 km from the poles and summarized the severity of the injuries according to the Israeli Transportation projects procedure (Table 2: Israel Transportation Ministry 2012). The total \( RCV \) for all poles is 1.33 billion ILS, and the location (pole) with the highest \( RCV \) has a value of 54.66 million ILS. We calculate the \( RCV \) for each of the \( T = 12 \) months for each of the 115 poles, yielding 1,380 poles–months, which we analyzed.

Figure 1 shows the distribution of the poles with respect to their \( RCV \). There are 445 months (32.2%) without crashes and 609 months (44.1%) with a small number of crashes (less than a million ILS). Thus, 76.3% of the data points have no crashes or a small number of crashes. However, there are a few months with serious casualties with a value higher than 10 million (0.8%; 11 out of 1,380).
Table 2: Israeli Transportation projects procedure to classify injury costs

<table>
<thead>
<tr>
<th>Injury Description</th>
<th>Cost in million ILS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fatalities</td>
<td>6.6</td>
</tr>
<tr>
<td>Very seriously injured</td>
<td>4.376</td>
</tr>
<tr>
<td>Seriously injured</td>
<td>1.675</td>
</tr>
<tr>
<td>Moderately injured</td>
<td>1.117</td>
</tr>
<tr>
<td>Mildly injured</td>
<td>0.142</td>
</tr>
<tr>
<td>Very mildly injured</td>
<td>0.025</td>
</tr>
</tbody>
</table>

Figure 1: Number of months that have a specific Road Crash Value (in thousands of ILS).

In Figure 2, the RCV distribution per pole is presented. There are six poles (5.2%) that recorded no crashes and the majority (67 poles, which represents 58% of the poles) had an RCV of less than 10 million. There are a limited number of locations that are considered very dangerous. Generally, this data is used to declare red locations that the police then focus on to limit driving speeds and consequently increase road safety.
4.2 Mobility model

We executed the mobility model using the above-mentioned data: $L = 115$ and $N = 55, \ldots, 95$, and set the limitations on the number of movements $A_t = R_t = M = 1,000$. To estimate the importance of the model, we obtained information on the number of cameras used in 2015. At the beginning of the year, 55 cameras were available. Additional cameras were added during the year, which resulted in a total of 95 cameras by the end of 2015.

In 2015, the police covered a $RCV = 0.73$ billion ILS, which represents a coverage percentage of 55% (= 0.73/1.33). On applying the mobility model using the same data ($RCV$ and the number of cameras), we obtain a percentage of 80% and a coverage of $RCV = 1.07$ billion ILS, which reflects a 25% increase by assigning the cameras optimally. Furthermore, in 2015, there were 99 movements whereas the mobility model requires only 65 movements, which represents a 34% improvement. The results are summarized in Table 3.

Table 3: Results of the model versus the actual data

<table>
<thead>
<tr>
<th></th>
<th>Actual system</th>
<th>Model results</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Movements</td>
<td>99</td>
<td>65</td>
<td>−34%</td>
</tr>
<tr>
<td>Annual cost coverage</td>
<td>0.73 billion</td>
<td>1.07 billion</td>
<td>+0.34 billion</td>
</tr>
<tr>
<td>Cost coverage percentage</td>
<td>55%</td>
<td>80%</td>
<td>+25%</td>
</tr>
</tbody>
</table>
Figure 3 shows an example of the inefficient assignment of the cameras before using the model. For this purpose, five poles were arbitrarily selected and entered into the figure, where the size of the bullet represents the RCV, the black circle represents the actual assignment, and the grey circle represents the optimal assignment. Of the 1,380 months (12 months for each of the 115 poles) we analyzed, only 760 (55%) are identical (with both systems (model/real) with either a camera or none). For example, the first pole has a camera for 9–12 months, but the model dictates that a camera should be set up from month 7–11. It is evident from the size of the bullets that this makes sense and improves the objective function. For example, pole 2 in period 4 has a small RCV, but the model selected this pole to allocate a camera.

Figure 3: Five examples of different poles with cameras showing the real situation and the results of the model. The Road Crash Value is also added.

4.3 Camera-movement tradeoff model

To calculate the profit of an additional movement or camera, we calculate the improvement achieved by installing a camera on a pole. Elvik (2013) provides a relationship between the reduction of the velocity and the severity of the collisions and the value of the exponent of (1) for highways as shown in section 2.2. Bar-Gera et al. (2014) found that there is a 9% reduction in the velocity when there is a pole at a section of the road. On combining the findings of Elvik and Bar-Gera et al. and using (1), we obtain
\[ Benefit = Crashes_{before} - Crashes_{before}((1 - 0.09)^{2.2}) \]
\[ = Crashes_{before} * (1 - (0.91)^{2.2}) = Crashes_{before} * 0.19 \]

Obviously, the 9% speed reduction is an average value (by Bar-Gera et al.) and might differ for different locations (urban roads, highways, etc.), weather conditions, and other factors. We use it to connect the number of collisions with the installation of a camera. Thus, the benefit of assigning a camera at pole \( l \) is a 19% reduction in the \( RCV \). Therefore, we have two factors that influence the optimal solution:

The trade-off is as follows. If there are sufficient cameras such that all poles can always be covered then the value of an additional movement/camera is zero. However, because we do not have a sufficient number of cameras, there will be a positive value for every additional camera/movement. Installing an additional camera reduces the location’s \( RCV \) by 19% but increases the cost to the system. Thus, the goal of this model is to provide the decision-makers in the Israel Police with a tool for determining the optimal number of cameras/movements that are required from the PPP based on actual data.

We estimate the annual cost of a camera to be 30,000 ILS per year (300,000 for a lifetime of 10 years). We execute the model for various costs of movements. The cost is a percentage of the camera cost (0% = 0 ILS, 10% = 3,000 ILS, etc.). We present the results in Figure 4. When the movement is free of charge, then with 60 cameras, 150 movements are required to achieve optimal coverage (\( RCV = 1.07 \) billion) of road crashes. When the movement is expensive (the annual cost of a movement is equal to the annual cost of a new camera), it is worthwhile to have 75 cameras but only 30 movements. The findings support our intuition that the more expensive the movement, the more worthwhile it is to invest in additional cameras. These results gleaned from the model will help the police in their negotiations for the new PPP contract to restrict speeding offences and achieve better road safety at a minimum cost.
4.4 Inventory model

The next PPP contract will also involve negotiations over how long the private partner company can wait until a failed camera is serviceable. The options in the negotiations are $\tau = 0, 1, 2, 3$ periods, and the cost incurred by the police is not known. In this example, we assume that there are 60 cameras, that there are no limitations as to the number of movements, and that the probability of a camera failing is 10% for each period. We arbitrarily chose to execute 350 scenarios using the Monte–Carlo method and calculated the average $RCV$ for each $\tau$. Obviously, the greater the number of scenarios that we execute, the more reliable the results of the model will be. The optimal $RCV$ of the mobility model is 1.07 billion (section 4.2). Figure 5 shows the difference between the obtained value and the optimal value of the mobility model and thus represents the cost to the system of having a delay of $\tau$ units of time. The longer $\tau$ is, the greater the cost to the system. During negotiations, this graph will help decision-makers at the police to decide what value of $\tau$ is acceptable, which will be used to optimize the $RCV$ of the system.
5. Discussion and conclusions

In this paper, we presented three different models for improving the operation of the speed camera-enforcement project and an application for the allocation of the Israel Traffic Police’s camera resources. The presented models improve the Police’s capabilities in their effort to reduce speeding offences on the road and increase road safety. We use the model with actual data and demonstrate that using the model significantly improves the coverage of collisions (from 55% to 80%). In addition, these models will help the Israel Police in their PPP contract negotiations. The results of the camera-movement tradeoff model indicate what should be the best policy in terms of cameras and movements. When the movement costs more than 6000 ILS, then it is preferable to buy more cameras. If the number of cameras is fixed by the government, then it is preferable to insist on an inexpensive movement of the cameras. If the costs for different camera repair times are available, the Israel Police can choose its optimal strategy. Without these costs, the model shows that a brief repair time (one month or two months) does not seriously affect the road crash coverage.

6. Areas of further research

A similar model can be developed to achieve a certain objective by assigning the position of police patrol cars and moving them between different locations. Additionally, the models do not include the next generation of enforcement cameras, which control sections and calculate point-to-point average
speed (Soole et al., 2013). Our models will need to be adjusted to these types of new technologies to ensure the cameras’ maximum efficiency.

We have left the following topics to further research. Evaluating the impact of enforcement cameras on reducing road crashes using various statistical methods can be further improved using methods of a before-and-after approach, the propensity score matching method, or the empirical Bayes method (Haojie et al., 2013). Furthermore, our cameras mobility model is based on road crash data under the assumption that offences are the cause of these collisions. Until recently, collecting traffic speed data was expensive using dual magnetic loop detectors, which were installed only on a relatively small portion of the roadway system and thus provided limited coverage of the entire transportation network. Today, there are technologies available such as information from cellular phone service providers and floating car measurements (Bar-Gera, 2007) that are gradually being introduced in public traffic control. These systems exist on a network-wide range and can help to evaluate the best location and time period for speed-limit enforcement cameras.
References


