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Optimising Random Breath and Drug Tests Scheduling in Networks

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Abstract

This paper presents a genetic algorithm (GA)-based approach to optimise the scheduling of breath and drug tests to maximise general deterrence and positive test results. Driving under influence is a major cause of road tolls, and roadside testing is a crucial countermeasure. The roadside tests deter potential offenders from further driving under influence of alcohol and illicit drugs and thus reduce related traffic accidents. First, we introduce the mathematical equations to formulate test scheduling as an integer programming problem, which is subject to constraints on working hours and the number of test sites. Then, we resort to using Genetic Algorithm (GA) as a heuristic optimization procedure. Temporal and spatial segments of testing are defined as genes and permutation and mutation are used to produce new generations. A fitness function is defined to take previous positive test results and captured traffic flows (as a proxy of general deterrence) into account. A number of hypothetical driving-under-influence scenarios are designed. We use numerical examples to demonstrate how the optimised testing (test locations, time and duration) outperforms randomly generated test schedules.

1. Introduction

Drivers may infer the likelihood of apprehension by the level of intensity of police enforcement reflected by the variation in checkpoint time, duration and frequency. Regarding the likelihood of encountering roadside DUI checkpoints from the perception of drivers, New Zealand Transport Agency conducted two rounds of Public Attitudes to Road Safety Survey in 2016 and 2020 (Agency, 2016, 2020). The 2016 survey results indicated that drivers had recognized 10pm-12am as the riskiest period in terms of the possibility of roadside breath tests. The 2020 Survey results reinforced this finding. Harrison (2001) and Wundersitz et al. (2009) state that high profile roadside breath test operations that commence early in the evening (before 6pm) and are observed by potential drink drivers on their way to drinking venues would affect their subsequent decisions to drink and drive.

Duration of checkpoints refers to the duration of one checkpoint operation (generally measured in hours). Morrison et al. (2021) defined the duration as the time elapsed between the first and the last breath test conducted in a checkpoint and used the number of devices available in the checkpoint as a proxy of checkpoint size. The frequency of checkpoints should be adjusted to seasonal and holiday effect. A study in Fargo city, France sought out noticeable seasonal variation in DUI counts in 2005 and 2006. In 2005, fall days had 29% higher and 36% higher expected DUI arrest counts than did summer days. Mobile breath testing tends to have higher successful detection rates since officers rely on their discretion to stop and test target drivers (Terer and Brown, 2014). In a study in South Australia, Wundersitz and Woolley (2008) reported that mobile patrols could capture 29 drivers whose BAC had exceeded legal limits per one thousand breath tests performed, while fixed checkpoints could detect only 5.7 drivers.

In addition, the unpredictability of mobile tests weakens the 'grapevine effect' which nullifies the deterrence achieved by highly observable statutory checkpoints, and thus they are suitable to be used in conjunction with fixed location tests (Wundersitz and Woolley, 2008). In rural areas, surprise checks by mobile patrols or car-based RBT can achieve better efficiency and can sustain deterrence grounded on limited resources available (Delaney et al., 2006, Ferris et al., 2015). The Indian study proposed a control experiment to detect if effects differ between checkpoints fixed at the best location and randomized rotating checkpoints across many potential locations (Banerjee et al., 2019). Fixed checkpoint operations are powerful, they can be resource-intensive, so it is often difficult to generate as much use as is desired. NHTSA proposed alternative enforcement tactics-flexible check-points, sometimes referred to as 'phantom checkpoints' or 'mock' check-points, to supplement the traditional checkpoints (National Highway Traffic Safety Administration, 2017).

2. Problem Formulation

In this section, we introduce the mathematical description of the road network and test schedules. We consider vehicular flow and driving under influence and design the fitness function. Mutation and crossover are used to generate new test schedules in the genetic algorithm.

Figure 1. Map of the network (Sydney, approximately 50 km by 50 km area).

Driving under influence happens randomly in space and time. The origins could be evenly distributed; sometimes, they are more likely to center around certain high-risk hot spots. We use two examples to represent the two scenarios. On the right In Fig. 1, there are six hot-spots, numbered 59950, 121285, 36942, 83876, 58282 and 108752; the latitudes and attitudes of the spots are (151.2001,-33.8864), (150.9186,-33.7356), (151.1016,-33.9333), (150.9498,-33.8290), (150.8936,-33.8890), (151.1157,-33.7649). Paths are the blue lines and the origins are red circles. The paths stretch from these hot spots and spread across the network. Alternatively, the origins could be evenly distributed in space, as is shown in Fig. 1 left.

Drivers use roads to travel to different locations. We use nodes N to represent a set of such locations.

$$N = \{n_1, n_2, \dots\}.$$

We picked 144, 055 nodes, as is shown on the left in Fig. 1. There are roads connecting close nodes, and the set of all links/arcs is I.

$$I = \{1, 2, \dots\}$$

A sequence of linking nodes can be used to represent a path. We use path p_{ij} to represent the shortest path from node $i \in N$ to $j \in N$,

$$i \to i_1 \to i_2 \to \cdots \to j.$$

The length of path p_{ij} is l_{ij}, and we have L below.

$$L = \begin{bmatrix} 0 & l_{12} l_{13} \dots \\ l_{21} & 0 \; l_{23} \dots \\ l_{31} l_{32} & 0 \; \dots \\ \vdots & \vdots \; \vdots \; \ddots \end{bmatrix}.$$

Note that we assume $l_{ij} = 0$ for $i > 0$.

3. Fitness Function

We use path and travel time to represent the states of drunk drivers. Assume that a drunk driver starts driving at t_1 from node i_1 at speed v. The path is $i_1 \rightarrow i_2 \rightarrow \dots i_k$. Then, we have

(1) the time interval the drunk driver is on link $i_1 \rightarrow i_2$ is $(t_1, t_1 + \frac{l_{i_1 i_2}}{v})$;

(2) the time interval on link $i_2 \rightarrow i_3$ is $(t_1, t_1 + \frac{l_{i_1 i_2}}{v}, \; t_1 + \frac{l_{i_1 i_2}}{v} + \frac{l_{i_2 i_3}}{v})$;

... ...

Of all available drink driver states, we find $c_{i,t}$, which is the number of drink drivers anytime during interval t anywhere on link $i \in I$. Thus, we have C as below considering a day is partitioned into 96 15-min intervals:

$$C = [c_{i,t}] = \begin{bmatrix} c_{1,1} \cdots c_{1,96} \\ \vdots \quad \ddots \quad \vdots \end{bmatrix}.$$

The more drink drivers are identified by tests, the larger the elements in C become. Assume $c' = \max c_{i,t}$ and to avoid overflow, we normalise C and obtain $\bar{C}$.

$$\bar{C} = [\bar{c}_{i,t}] = [\frac{c_{i,t}}{c'}].$$

Given the flow in the links, we obtain F.

$$F = [f_{i,t}] = \begin{bmatrix} f_{1,1} \cdots f_{1,96} \\ \vdots \quad \ddots \quad \vdots \end{bmatrix},$$

where $f_{i,t}$ is the flow along link i during time interval t. Similarly, assume that $f' = \max f_{i,t}$ we normalise F and obtain $\bar{F}$.

$$\bar{F} = [\bar{f}_{i,t}] = [\frac{f_{i,t}}{f'}].$$

We take the number of positive results and the flow into account and use the following function T to obtain the fitness of test schedules.

$$T = \sum_{96 \geq t \geq 1} \sum_{i \in I} s_{i,t} \left(\alpha \bar{c}_{i,t} + (1 - \alpha) \bar{f}_{i,t} \right).$$

In above, α regulates the trade-off balance between the two sub-objectives of the fitness function. In addition, $s_{i,j}$ denotes the binary decision variable indicating a testing procudere during j-th time interval on link i.

4. Schedule Optimisation

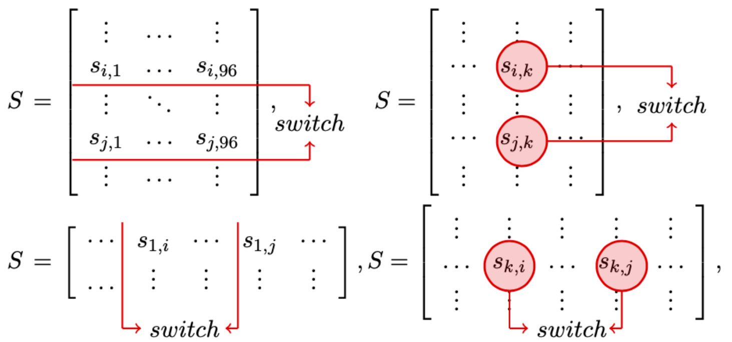
The genetic algorithm (GA) is a heuristic optimisation method for solving constrained optimization problems. GA repeatedly modifies the genes of the population to obtain new generations. The algorithm uses natural selection to reserve the individuals that are most fit such that the population evolves toward an optimal solution over successive generations.

In this research, we aim for the optimal test schedule that includes tests' locations, times and durations. There are 24 hours in a day and we divide it into 96 15-minute intervals. Schedule of random breath tests and mobile drug tests is represented by S.

$$S = \begin{bmatrix} s_{1,1} s_{1,2} \cdots s_{1,96} \\ s_{2,1} s_{2,2} \cdots s_{2,96} \\ \vdots \quad \vdots \quad \ddots \quad \vdots \end{bmatrix}.$$

At the j-th time interval, $s_{i,j} = 1$ if there is test scheduled on link i; otherwise $s_{i,j} = 0$.

We use test schedules as genes and get new genes from mutations. There are two basic mutations. We randomly select two links $i, j>0$ and switch their testing schedule to get a new schedule; the testing schedule include either all the time intervals or a random one. In addition, we randomly select two of its time intervals $1 < i, j < 96$ and switch their testing schedule to get a new schedule; the testing schedule include either all the links or a random one.



There is a limited number $\bar{n}$ of police officers and they cannot work longer than $\bar{\tau}$ at one testing site. We have the following constraints.

$$\begin{cases} \begin{cases} \sum\limits_{t \geq j}^{t \leq k} s_{i,t} \leq \bar{\tau}, \\ s_{i,t} = 1|_{j \leq t \leq k}, \end{cases} & \text{for } i \geq 1, \\ \\ \sum\limits_{i \geq 1} s_{i,t} \leq \bar{n} & \text{for } 1 \leq t \leq 96. \end{cases}$$

5. Numerical Examples

In this section, we use simulation scenario to demonstrate the performance of optimised test scheduling. One random schedule and one optimised schedule are used for comparison. The offenders have spatial distribution similar with that in Fig. 1 on the right. There are more offenders at night than during the day, as is shown in Fig. 2.

The numbers of positive results are given in Fig. 3. It can be seen that there are more identified offenders at night. A total number of 64 offenders are identified by the optimised schedule and 24 offenders are identified by the random. Moreover, the total traffic flow at all test sites are plotted in Fig. 4 for the optimised and random schedules. It can be seen that the optimised schedules has captured more traffic flow (more general deterrence).

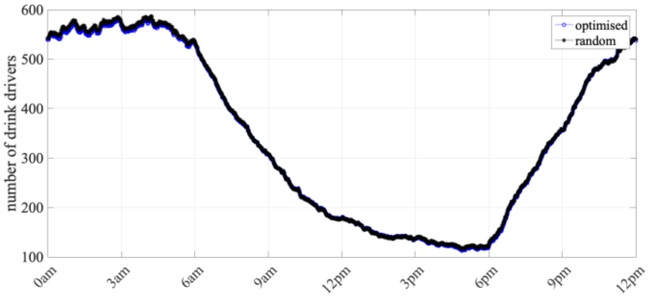


Figure 2. Number of offenders in time.

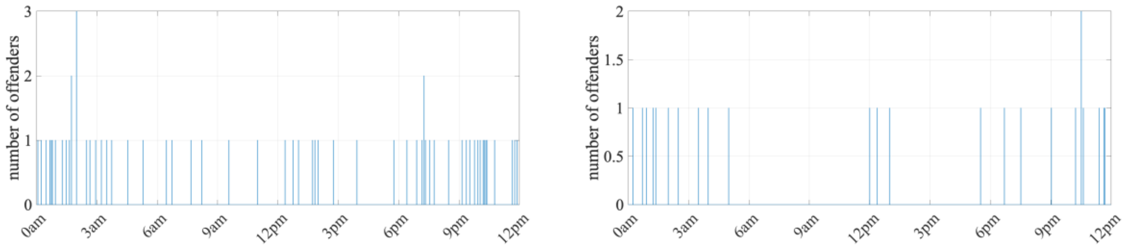


Figure 3. Number of identified offenders (positive test results). Optimised schedule is on the left and random schedule is on the right.

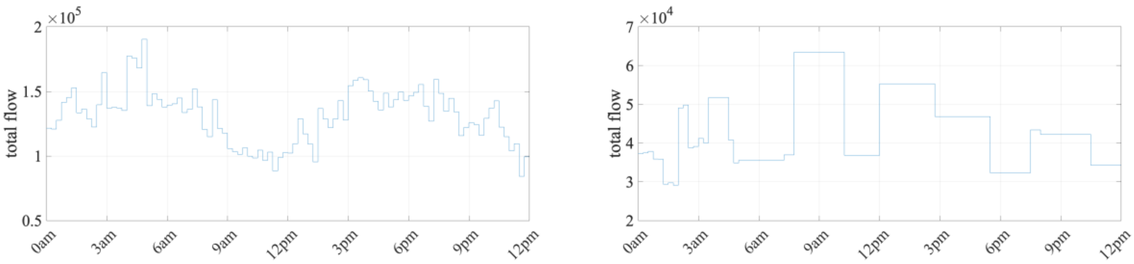


Figure 4. Total traffic flow at all test sites. Optimised schedule is on the left and random schedule is on the right.

6. Closing Remarks

In this paper, GA is used to optimise roadside alcohol and drug test schedules to maximise the positive test results and general deterrence. Schedules are formulated into binary matrices and are used in GA as genes. Permutation and mutation are used to produce new schedules. In numerical experiments, the optimised and random schedules are benchmarked, and the optimised schedule captures more traffic flow and positive results in performance. For future work, we will investigate how periodic patterns can be reflected in test schedules. We will investigate how the optimal schedule can be modified to adapt to the time-varying uncertainty.

7. Acknowledgment

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