Dynamic macro scale traffic flow optimisation using crowd-sourced urban movement data

Laurens Arp
Leiden Institute for Advanced Computer Science
Leiden University
Leiden, Netherlands
l.r.arp@umail.leidenuniv.nl

Dyon van Vreumingen
Leiden Institute for Advanced Computer Science
Leiden University
Leiden, Netherlands
d.van.vreumingen@umail.leidenuniv.nl

Daniela Gawehns
Leiden Institute for Advanced Computer Science
Leiden University
Leiden, Netherlands
d.gawehns@liacs.leidenuniv.nl

Mitra Baratchi
Leiden Institute for Advanced Computer Science
Leiden University
Leiden, Netherlands
m.baratchi@liacs.leidenuniv.nl

Abstract*—Urban movement data as collected by location-based social networks provides valuable information about routes and specific roads that people are likely to drive on. This allows us to pinpoint roads that occur in many routes and are thus sensitive to congestion. Redistributing some of the traffic to avoid unnecessary use of these roads could be a key factor in improving traffic flow. Many of the previously proposed approaches to combat congestion are either static (e.g. a city tax) or do not incorporate any movement data and hence ignore how citizens use the infrastructure. In this work, we present a method to redistribute traffic through the introduction of externally imposed variable costs to each road segment, assuming that all drivers seek to drive the cheapest route. We propose using a metaheuristic optimisation approach to minimise total travel times by optimising a set of road-specific variable cost parameters, which are used as input for an objective function based on Greenshields traffic flow theory. We evaluate the performance of this approach within the context of a case study on the city centre of Tokyo. An optimisation scenario was defined for this city using public spatial road network data, and movement data acquired from Foursquare. Experimental results on this case study show that, depending on the amount of cars on the road network, our proposed method has the potential to achieve an improvement between 1.35% (437 hours for 112,985 drivers) and 13.15% (925 hours for 31,584 drivers) of total travel time, compared to that of a currently operational road network configuration with no imposed variable costs.

***Keywords*-mobility modelling, traffic flow optimisation, metaheuristic optimisation, urban movements, location-based social networks**

I. Introduction

Even though extensive road networks have been developed to satisfy the high demand for vehicular transportation, overoccupancy of roads still occurs on a daily basis, causing traffic jams which hurt the environment, the economy, and the drivers' moods. Finding a solution to traffic congestion is a challenging task that has occupied many in the past century. After all, traffic dynamics are difficult to predict, due to the complex fluctuations in traffic demand, both spatially and temporally. This makes it hard to devise a protocol for traffic flow redistribution that works well in varying conditions.

To date, various approaches have been proposed to alleviate congestion in some way [14]. However, these methods tend to be either static, data-independent protocols, micro-scale solutions (on the level of individual roads) or primarily driven by theoretical models.

In this paper, which is an extension of our paper for the Future Cities Challenge at Netmob [2], we propose a data-driven method for traffic redistribution that seeks to shift traffic situation away from a state where each driver chooses the fastest or shortest route (thus causing congestion on roads that occur in many shortest routes), towards a system optimal equilibrium, as coined by Wardrop [23], where the *total travel time* for all drivers is minimised. By introducing externally imposed variable costs (e.g. tolls, or any other financial or non-financial method a policy-maker might deploy) on each road, we aim to discourage drivers from all taking the same congested roads. This approach assumes that, on average, each driver is willing to take the cheapest route from their point of departure to the destination, where the total costs to drive a route depend both on the distance travelled, through a spatial cost, and the imposed variable costs encountered along the route. We would like to point out that this variable cost can be negative and might be implemented within a rewards system where drivers receive a monetary or non-monetary reward (e.g., preferential treatment when charging electric cars) for using less congested routes.

Available data collected from traditional traffic sensing equipment (e.g. inductive loop detectors) is not suitable for proposing such a system as these sources can only provide an aggregate number of the cars passing a spatial point without capturing necessary network-level information needed for dynamic flow optimisation. New sources of urban movement data (those collected from floating cars, mobile phones, and location-based social networks) can help infer more about how people are using the road network, where the origin and destinations of their movements are, or where bottlenecks are being formed. Therefore, our objective in this paper is to propose a dynamic, macro-scale (i.e., road network level) approach to address traffic congestion by exploiting crowd-sourced urban movement datasets. In this sense, dynamic means that a solution can be adapted to new incoming movement data reflecting the traffic flows with relative ease. More specifically, our contributions in this paper are the following.

- We propose a data-driven method for traffic redistribution fuelled by metaheuristic optimisation.
- We test the effect of our proposed approach on the case of the city centre of Tokyo, using real movement data acquired as check-in records from Foursquare, a location-based social network [6].
- We evaluate this method by comparing it to the case where no optimisation has been applied. We show the amount of reduction achieved in the total amount of time spent on the road. Furthermore, we analyse this approach in terms of its fairness and the extent to which individual drivers are affected by the solution.[1]

II. Related work

The objective of combatting traffic congestion by altering road network setups has been addressed in a large body of work. The use of road pricing as a means to achieve this goal is a prevalent approach [12], [22], [25], [26]. In this context, the marginal cost of congestion is a frequently employed measure to assess optimal road pricing. A key difference between these approaches and our work is that the previously proposed road pricing policies are fixed (e.g. to charge a fee within a certain radius of the city centre) instead of being a dynamic cost-reward strategy, and do not follow from an optimisation procedure based on actual movement data.

Studies using dynamic movement data, such as floating car data (FCD), have been reported. Gühnemann et al. [11] report on the use of FCD generated by taxis to predict traffic flow and monitor NOx emissions. Similar work was published by Altintasi et al. [1] who show detection of traffic flow patterns extracted from corporate provided FCD. Lastly, the work of Xin et al. [24] is a field application of active traffic flow management based on a combination of toll detector and traffic sensor data. Movement data has also been used in the analysis of various aspects of urban dynamics such as visualisation and exploratory data analysis of taxi movements [5] or district classification [15]. From these works, it becomes apparent that the use of dynamic movement data is fruitful for traffic monitoring and management. Our work differs from these publications in that we adopt crowd-sourced, social network data instead of floating car data as a means to predict urban movements for traffic optimisation.

Approaches for optimising road networks and traffic flow from different viewpoints, without movement data and unrelated to cost-reward policies, include the development of intelligent traffic light systems [17], [24], metaheuristic optimisation of road improvements [7] and optimisation of road graph architectures [21]. A more exhaustive list of methods is provided by Kumar Shukla and Agrawal [14].

In this work, we explore the use of optimisation algorithms in proposing a dynamic cost-reward mechanism using actual movement data.

III. Problem statement

The problem of optimising traffic flow through adaptive road pricing has two phases: (i) predicting congestion and (ii) determining the optimal pricing strategy.

In the first phase of the problem, we need to estimate congestion in a road network, as this is the underlying cause of high total travel time when all drivers follow the cheapest routes from their origins to their destinations. To determine traffic demand, our approach requires a location dataset $\mathcal{D}_L$ and a dataset $\mathcal{D}_M$ of vehicular movements between locations in $\mathcal{D}_L$, with the following properties. $\mathcal{D}_L$ should consist of locations in the area of interest described by spatial information in terms of GPS coordinates. The movement set $\mathcal{D}_M$ should contain origin-destination-frequency tuples (A_k, B_k, N_k) with $A_k \in \mathcal{D}_L$ the origin locations, $B_k \in \mathcal{D}_L$ the destination locations, and N_k the corresponding recorded frequencies of the specific movements from A_k to B_k. Given $\mathcal{D}_L$ and $\mathcal{D}_M$ in the required form, we are interested in a figure directly related to traffic congestion, namely the total vehicular travel time T_{tot} on the road network expressed as

$$T_{\text{tot}} = \sum_{k=1}^{|\mathcal{D}_M|} T(R_k) N_k. \tag{1}$$

Here, R_k is the route we expect a driver going from origin A_k to destination B_k, and $T(R_k)$ is the time needed to drive this route (more details are given in Section IV). The assumption that each driver with the same origin and destination will drive the same route allows us to write the travel time contribution from each entry k in $\mathcal{D}_M$ as the product of the route travel time $T(R_k)$ and the frequency N_k.

As mentioned in the introduction, we base our research on the premise that route choice behaviour, and thereby overall traffic flow, may be influenced by externally imposed variable costs. As such, in the second phase of the problem, we seek to establish a relationship between these costs and the total travel time, and then optimise the cost parameters for redistributing traffic in order to achieve minimal total travel time. The complete methods for determining traffic flow and addressing the inherent optimisation problem are set out in detail in the next section.

IV. Methods

In this section, we discuss our proposed methodology to address the two facets of the traffic redistribution problem. First, we explain our model for predicting driven routes (Section IV-A1) based on variable costs, and the model for predicting

[1]The code is available at https://github.com/LaurensArp/traffic_flow_optimisation

the expected total travel time (Subsection IV-A3). Second, in Subsection IV-B, we discuss how to optimise the variable costs for minimal total travel time.

A. Traffic flow estimation

1) Road network and routing model: The first step towards prediction and minimisation of congestion is to represent the physical road network as a planar graph G that has road segments for edges, which may be traversed in order to travel from an origin to a destination. Specifically, the graph is a tuple $G = (V, E, D)$ with V the node set, E the edge set and D the set of Haversine lengths of all edges. The node set V contains intersections in the road network, as well as nodes for the origin and destination locations in $\mathcal{D}_L$.

We then introduce, for each road segment $(i, j) \in E$ in the graph, an overall cost that a driver needs to pay to traverse this segment. This overall cost is further composed of two partial costs: (i) a *variable cost*, denoted p_{ij}, and (ii) a *spatial cost*. We want to point out that the variable cost parameter can be negative (i.e. it can become a reward). This will not change the further modelling process but allows for a flexible implementation of the suggested traffic flow management. All variable cost parameters collectively form the variable cost matrix P which we seek to optimise for minimum congestion. The spatial cost, then, is an immutable base cost for travelling from node i to j which is linearly dependent on the length d_{ij} of the segment by a factor β. This spatial cost is intended as a stable upfront estimate of the travel effort that is independent of expected travel times, which may vary throughout the process. After all, in reality, drivers tend to take routes of minimal travel effort (i.e. shortest distance, shortest time or least fuel consuming), especially in the absence of externally imposed costs. Since movement data is generally aggregated into frequency numbers, and is not provided on an individual level for anonymity reasons, we take β to be equal for all drivers. Put together, the total cost for a driver to travel via a route, which is a connected set of segments $R = \{(i, j)\}$ from some origin to a destination, is given by the sum of the individual segment costs occurring on the route:

$$\text{cost}(R) = \sum_{(i,j)\in R} \beta d_{ij} + p_{ij}. \tag{2}$$

For the estimation of traffic flow, we assume that all drivers are selfish and seek to drive the route which incurs the lowest total cost. These routes can be found using a weighted shortest path algorithm. Note that if $p_{ij} = 0$ on all edges, each driver will drive the route of lowest spatial cost, which is exactly the shortest route. From the cheapest routes, which are jointed collections of segments, and the frequency numbers N_k, we can predict the vehicle count n_{ij} on each segment, from which the degree of congestion is computed.

2) Clustering: We modify the travel data by selecting the locations occurring in the C most popular (i.e. frequent) routes, and cluster all other locations together with their nearest neighbour (by Haversine distance) in the set of most popular locations. The routes are clustered accordingly, going between location clusters instead of individual locations. This is done in order to substantially reduce the number of routes and therewith the computational complexity of the problem, accepting a decrease in accuracy in return for higher efficiency. More precisely, we obtain a best-case multiplicative complexity reduction of $\Omega(C^2/|V|^2)$ on the routing calculation, averaged over all possible choices of cluster points (i.e., most popular locations). This can be seen as follows. For a random clustering, each cluster contains on average $|V|/C$ points, and the travel data can contain at most $|V|^2/C^2$ route records between two such clusters (one for each point pair). When all points in a cluster are combined into one, all route records between points from two clusters are merged into a single record, thus reducing execution time multiplicatively by $C^2/|V|^2$. Furthermore, routes within a cluster are ignored, and the complexity gain from this scales similarly. As these are best-case gains, we have the lower bound given above. The upper bound is 1, since the data might contain records only for precisely those vertices which were chosen as cluster points.

We define the cluster number C by

$$C = N/\bar{d}\rho_c l \tag{3}$$

with ρ_c the critical density, l the number of lanes on each road segment and $\bar{d}$ is the average road segment length (Subsection V-C). The idea behind this definition is that a single movement cluster should not place more vehicles on a road segment than its average critical occupancy, in order to prevent congestion from a single cluster, which is difficult to alleviate through redistribution.

3) Congestion model: For our congestion model, we adopt Greenshields traffic theory [9] as the means to predict traffic flow on each road segment. The Greenshields model is an elegantly simple yet powerful model for describing traffic dynamics in a macroscopic way, fitting the aim of the paper. It considers traffic in terms of the macroscopic variables flow f (vehicles passing by per unit time) and density ρ (vehicles present per unit road length). Despite its simplicity, the model has been shown to be surprisingly accurate and compatible with field studies [16]. Furthermore, it allows us to extract average travel times from the presence of vehicles, as is discussed below. For these reasons, we deemed this theory to be an appropriate choice for our congestion model.

The theory assumes that the flow of traffic on a road segment is fully described by a fundamental traffic flow curve that directly relates flow and density (see Figure 1). In this curve, there exists a *maximum density* ρ_m that the road can support, beyond which the total flow is taken to be zero. Furthermore, there is a *critical density* ρ_c at which the flow reaches its maximum value: $f(\rho_c) = f_m$. Naturally, $f(0) = 0$, as no flow exists when no cars are present.

A basic curve that fits this description, which was originally proposed by Greenshields, is a concave quadratic function, with zero flow at $\rho > \rho_m$. We take this function to be

$$f(\rho) = \frac{f_m}{\rho_c^2} \max\bigl(0,\ \rho[2\rho_c - \rho]\bigr), \tag{4}$$

where we note that, since f is quadratic in ρ, $\rho_m = 2\rho_c$. The maximum flow is directly related to the critical density; assuming that the traffic is able to drive at the maximum allowed speed v_m when the density is at its critical point, we set $f_m = \rho_c v_m$.

From this density-flow dependence, we can extract the *space mean speed* $v(\rho)$, the average speed of all vehicles on the road segment, given by [9]

$$v(\rho) = \max\big(v_{\text{jam}},\, \min[v_m,\, f(\rho)/\rho]\big), \tag{5}$$

where again the maximum speed enters the relation, this time as a bound on the space mean speed. Finally, the *space mean travel time* $t(\rho)$ on the segment, taken to have length d, is computed as

$$t(\rho) = \frac{d}{v(\rho)}. \tag{6}$$

Note the introduction of a *jam velocity* v_{jam}, which is a slight deviation from the original Greenshields model. The reason for this addition is that the Greenshields flow curve tends to break down close to the maximum density, as the traffic undergoes a phase transition into a jammed state [13]. After all, following the flow curve up to zero flow and thus zero velocity would lead to infinite travel times. As field observations show average speeds of approximately 15km/h at the phase transition [10], we chose $v_{\text{jam}} = 15$km/h to be a lower bound on the velocity function.

From the expected number of vehicles n_{ij} on each road segment, we obtain the segment density as $\rho_{ij} = n_{ij}/d_{ij}$. For multi-lane roads, we divide this number by the number of lanes. By inserting the segment density into the density-time relation described above (Equation 6), we find the space mean time t_{ij} spent on the segment. The collection of these segment space mean travel times then leads to the definition of the objective function for optimisation by a metaheuristic algorithm.

B. Parameter optimisation

1) Objective function: The objective function computes the measure $\text{obj}(\mathrm{P})$, which reflects the extent to which the system

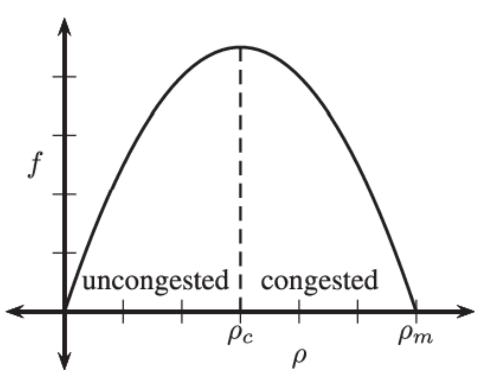


Fig. 1. A Greenshields fundamental traffic flow diagram. Below a critical density ρ_c, traffic flows freely and traffic flow f increases with ρ. At densities beyond ρ_c, traffic becomes congested and traffic flow decreases.

Algorithm 1. Routine for computing the objective function for a given variable cost matrix P.

Data: road graph $G = (V, E, D)$ with node set V inferred from location data $\mathcal{D}_V$, E and D inferred from road network data;
movement data $\mathcal{D}_M$;
spatial cost factor β
Input: variable cost matrix P
Result: objective function value $\text{obj}(\mathrm{P})$

Initialise $n_{ij} \leftarrow 0$, $t_{ij} \leftarrow 0$, $\rho_{ij} \leftarrow 0$ for all $(i, j) \in E$

```
// Compute predicted vehicle counts n_ij on each segment
forall origin-destination-freq. tuples (A_k, B_k, N_k) in D_M do
    Find cheapest route R_k from A_k to B_k according to β
      and P using weighted shortest-path algorithm
    forall (i, j) ∈ R_k do
        n_ij ← n_ij + N_k
    end
end
// Find mean travel times t_ij on each segment
forall (i, j) ∈ E do
    ρ_ij ← n_ij / d_ij              (segment density)
    t_ij ← t(ρ_ij)                  (segment travel time, Eqs. 4–6)
end
obj(P) ← Σ_{(i,j)∈E} n_ij t_ij      (total travel time, Eq. 7)
return obj(P)
```

optimal equilibrium is reached by a variable cost matrix P, the entries of which form the parameter vector for the optimisation algorithm. This equilibrium occurs when the total travel time of all drivers on their routes, as introduced in Equation 1, are minimal. Since the traffic flow model yields expected travel times (in the form of space mean travel times), we define the objective function as the total space mean travel time over all routes driven on the road network. This total travel time can be conveniently expressed using the segment vehicle counts n_{ij}, which are directly dependent on P:

$$\text{obj}(\mathrm{P}) = \sum_{(i,j)\in E} n_{ij}(\mathrm{P})\, t_{ij}(\mathrm{P}). \tag{7}$$

Note that each segment mean travel time t_{ij} is also a function of P since it is dependent on the vehicle count n_{ij}. Algorithm 1 shows, in pseudocode, the routine to compute the objective function. The purpose of the optimisation algorithm is to find an optimal variable cost configuration such that the value of the objective function, the total travel time, is minimised. Since we are considering an entire road network, optimising the variable cost matrix for this network is a complex high dimensional problem. Furthermore, it is not clear beforehand where the minima in the objective landscape could lie. Black-box metaheuristic algorithms have been developed to tackle precisely these kinds of problems. In principle, any such algorithm could be used to search for local optima of variable cost configurations, in hopes of approximating a system optimal equilibrium. That said, for these purposes, an algorithm that is robust for high dimensional problems is preferred, as the number of parameters increases proportionally to the number of edges in the graph.

For our implementation, we employ a genetic algorithm (GA) adapted for continuous optimisation. GAs are a class of high dimensional optimisation algorithms loosely based on biological evolution, which optimise by 'evolving' a population of candidate solutions. For this optimisation problem, we use a population size of 20 and an offspring size of 20, with elitist selection. Mutations are generated using a normal distribution with zero mean and a standard deviation of 4, at a mutation rate of 0.2 per parameter.

V. Case study: Tokyo city centre

In order to test our traffic flow optimisation method, we applied it to movements in the city centre of Tokyo (i.e. excluding the Greater Tokyo area). Since the optimisation method of this paper is general, it is intended to be suitable for use within any urban area for which movement and road network data are accessible. In our case, the choice for the city of Tokyo was motivated by the availability of road network data which captures the most important roads in the vicinity of the considered movement records, while also being of low enough resolution (i.e. having few enough edges) for the cost function to be computed in reasonable time on a regular PC processor.

In this section, we briefly discuss the movements and road network data used for the case study and further present our experimental results.

A. Movement data

In principle, any type of movement data in the city that reflects movements of cars over the network, and can be expressed in the forms of $\mathcal{D}_L$ and $\mathcal{D}_M$ introduced in Section III, is suitable. We used crowd-sourced data in the form of movement data collected by Foursquare, a location-based social network platform. We made this choice in order to show the feasability of an alternative to floating car data, which is generally not freely available due to either privacy concerns or commercial interests. With Foursquare, users can share their check-ins at numerous venues, which allows identification of movements between these venues. Aggregated data from the years 2017-2019 were made available as part of the *Future cities challenge 2019* [6]. We selected only those parts related to the Tokyo city centre. Within this region, the data provides a list of approximately 25,000 locations together with their GPS coordinates and venue category (restaurant, railway station etc.), as well as a movements list, containing movements of the same form as the tuples in $\mathcal{D}_M$, but with additional indications of the month during which the movement occurred, and the time of the day (periods of 4 to 6 hours). Because the amount and type of movements made could be different depending on the time of day (e.g., due to commutes to and from work), we considered only movements made in the afternoon (15:00 – 19:00 o'clock), and aggregated the frequencies N_k for the same movements in all 24 months into a single frequency, for a total of nearly 135,000 movement records. This is summarised in Table I.

Longitude interval	[139.705, 139.862]
Latitude interval	[35.594, 35.727]
Period	Apr 2017 – Mar 2019
Time of day	15:00 – 19:00
Locations	25,000
Movement records	135,000

TABLE I. Properties of the Foursquare movement data as used in this research.

Since the used dataset includes movements besides vehicular journeys (such as subway and walking trips), and gives no indication about transportation mode proportions, we chose to adjust the frequency distribution to reflect the routes likely to be made by car. For this we followed the McFadden logit choice model [19], which is a commonly used behavioural theory with applications in econometrics [18] and transportation forecasting [3]. We discriminate between walking, driving, and railway transport. In the model, the probability $p_m(A_k, B_k)$ of choosing transportation mode m on a journey between locations A_k and B_k is given by a logistic distribution:

$$p_m(A_k, B_k) = \exp[u(m, A_k, B_k)] \Big/ \sum_m \exp[u(m, A_k, B_k)] \tag{8}$$

where $u(m, A_k, B_k)$ is the *utility function* which models the desire to take transportation mode m on the given movement. The most straightforward form of the utility function which we applied is a linear dependency on the total distance as well as the distances to the closest train stations. For clarity, denote $\mathcal{S} \subset \mathcal{D}_L$ as the set of all station locations. Then, we defined u separately for each mode, as follows:

$$u(\text{walk}, A, B) = -\alpha_1\, d(A, B) - \gamma_1 \tag{9}$$

$$u(\text{auto}, A, B) = -\alpha_2\, d(A, B) - \gamma_2 \tag{10}$$

$$\begin{aligned} u(\text{train}, A, B) = &-\alpha_1[d(A, S_A) + d(B, S_B)] \\ &- \alpha_3\, d(S_A, S_B) - \gamma_3 \end{aligned} \tag{11}$$

where d is the Haversine distance between two locations, $S_A \in \mathcal{S}$ is the train station closest to the origin location A and $S_B \in \mathcal{S}$ is the station closest to the destination location B. Furthermore, $\gamma_1 \ldots \gamma_3$ model the base reluctance for a person to take the corresponding transportation mode. Note the use of α_1 as the scaling factor for the origin-station and station-destination distances, which we assume to be walked based on the high density of stations in Tokyo. The scaling factors in the utility functions were chosen to match transportation choice ratios [8] for trips between a set of randomly sampled origin-destination pairs within the perimeter of the Tokyo city centre, as well as the assumption that short distances (up to ∼500 metres) are

α_1	α_2	α_3	γ_1	γ_2	γ_3
0.5	0.1	0.1	-0.4	3.7	2.8

TABLE II. Tuned scaling factors for the transportation mode choice utility functions (Eqs. 9–11).

mostly walked. The right choice of scaling factors incentivises walking on short distances through a low γ_1 as compared to γ_2 and γ_3, but a high α_1; meanwhile, for longer distances, taking either car or train is encouraged by low α_2 and α_3, with the availability of nearby stations being in favour of the train. Table II shows the scaling factors we chose to satisfy these requirements.

Having found the vehicle probabilities $P_{\text{auto}}(A_k, B_k)$ for each origin-destination pair (A_k, B_k) from Equation 8, we corrected the corresponding frequencies N_k with these probability values, which reduced the total number of original frequencies by 71.7%. Finally, the so-obtained vehicle frequencies were normalised to sum to unity and multiplied by a variable total number of vehicles N that the road network graph we constructed could support (see Subsection V-C).

B. Road network data

The road network data used is based on the Asia shapefile provided by the Earthdata *Global roads open access data set* [4]. It contains information on the road networks of the entirety of Asia with a variable resolution (i.e., edge density). The resolution of the Tokyo city centre is well suited for the algorithm, in the sense that the number of edges is both low enough for the problem to be tractable in terms of computational complexity; and high enough to have multiple road segments present in the vicinity of the clustered locations. The latter is needed, since the presence of too few segments leads to overuse of single segments by routes from too many locations, causing unrealistic congestion.

The road data is translated into a graph representation by finding intersections between lines and turning these into intersection nodes. The lines themselves are used to create edges between intersections. Location nodes are created by identifying the coordinates of the locations from $\mathcal{D}_L$, which are connected to the nearest intersection node.

The road network representation was simplified in a number of ways. Since there was no data for the number of lanes per individual road segment, we set the number of lanes $l = 2$ for all roads, in both directions. For similar reasons, we set a constant speed limit $v_m = 100$km/h for all roads. Since the network data contains only major roads, these are reasonable simplifications that do not significantly impact our results. Furthermore, for the occupancy of the roads, we did not take temporal aspects into account, and instead considered a car to be on all roads of its path simultaneously. In reality, the occupancy of roads would therefore be more spread out over the paths taken. However, the results we present still stand, for the reason that, given the high number of vehicles on the road in reality, we can expect multiple vehicles to be at different points along a single (approximate) route at the same time, especially those routes that appear in the relatively low-resolution road network we use.

C. Experimental results

The analysis of the results of our case study will be split into an evaluation of the proposed method through improvement percentages, a closer look at the optimisation progress over iterations for a specific solution, the evaluation

of the fairness of the proposed method using an example, and a visualisation of what a good solution would look like in practice. The improvement percentages were computed by taking the situation without viariable costs as a baseline. The GA in our experiments used a population size of 20, with a mutation rate of 0.2, elitist (plus) selection, and random single-point crossover.

1) Achieved improvements: Because the true total number of cars N on the network is unknown, we ran our algorithm several times, setting N to random values. This approach allowed us to evaluate our method without committing to a single estimation of the number of cars on the network at the same time. Since the number of cars on the road tends to be dynamic depending on factors such as the time of day or special events, it could therefore be useful to be able to estimate how much our method could improve on the default situation of no variable costs, for any number of cars that might actually be on the roads in a given scenario.

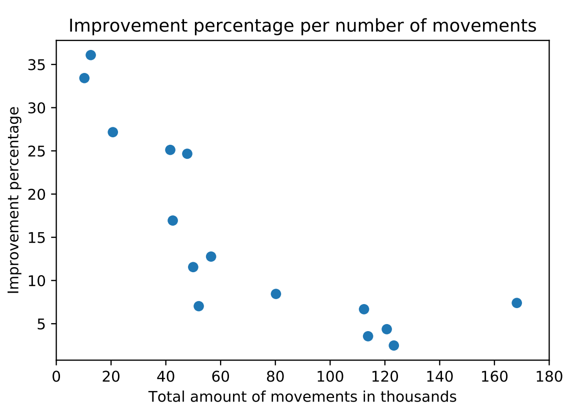


Fig. 2. Percentage of improvement plotted against the amount of cars N on the road network.

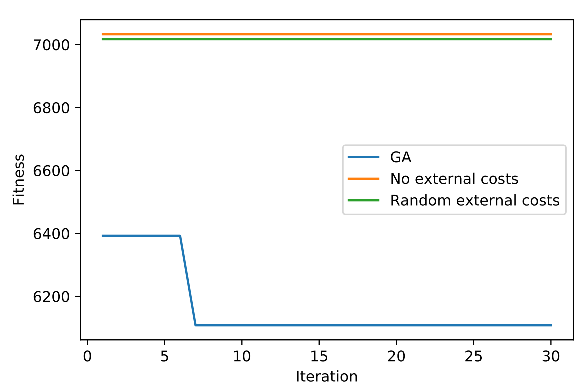
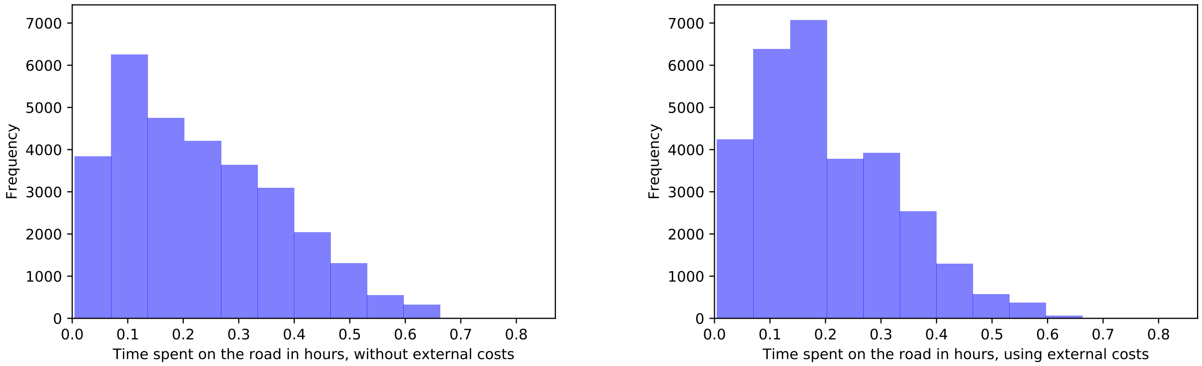
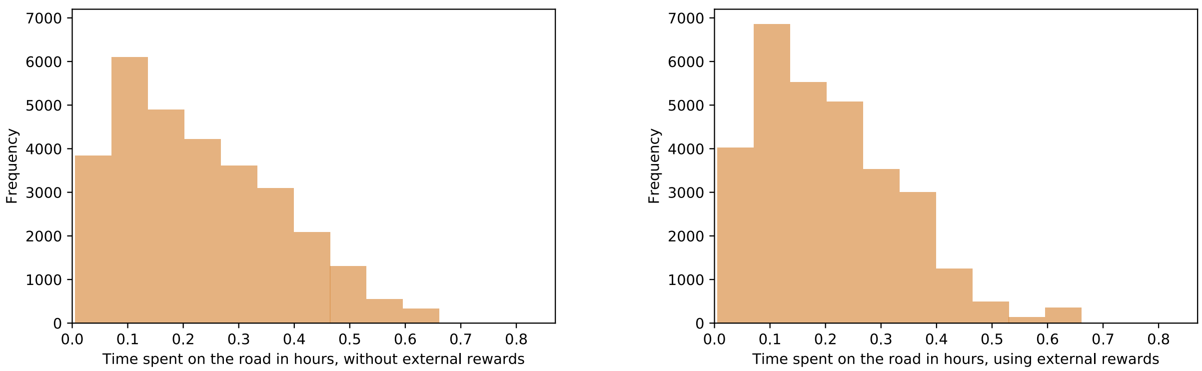


Fig. 3. Objective function value plotted to the number of GA iterations. Values are the total time spent on the roads.



(a) (b)

Fig. 4. Histograms of the distribution of times spent on the road, (a) without variable costs (b) with variable costs.



(a) (b)

Fig. 5. Histograms of the distribution of times spent on the road, (a) without variable rewards (b) with variable rewards.

For each value of N the number of movement clusters C was determined using Equation 3. After running the algorithm we stored the value of N, along with the resulting percentage of improvement the algorithm was able to achieve compared to a scenario with no variable costs. A scatter plot of these two variables, as shown in Figure 2, can give some insight into how well the algorithm is expected to perform on this road network for a given number of cars on the road. As Figure 2 shows, better results are achieved by the algorithm when there are fewer cars on the network. The highest amount of improvement of any run was 13.15% for $N = 31{,}584$, resulting in a total time gain of 925 hours under the current model and parameter settings. Conversely, the lowest amount of improvement was 1.35% for $N = 112{,}985$, with a total time gain of 437 hours. Thus, even though the improvement percentage is more modest when there are more cars on the road network, a relatively small improvement for many cars can still result in a large number of hours spent on the road in total being saved, even if the percentage itself might not be that high. A possible reason for the algorithm achieving higher improvements with a low value of N could be that there is simply more to optimise in those situations; when there are too many cars on the network at once, not all the cars of a route will fit on a single road. Consequently, once the shortest route is already fully occupied, those cars would overflow onto the next shortest path, which makes those roads less attractive as alternatives for other cars. When N is low, however, there are many relatively empty roads available to redirect traffic to, thus allowing for large improvements compared to scenarios where drivers only take the shortest path.

2) Closer look at the best solution found: In order to gain an insight into the details of the optimisation process, we selected the run with the highest percentage improvement as a best-case example, where the effects of the optimisation can be observed most clearly. This example considers $N = 31{,}584$ and $C = 48$.

A logical aspect to look at in detail would be the progress of the GA fitness values over iterations. This progress was plotted in Figure 3, with a horizontal line for the fitness value when there are no variable costs as reference. Of interest, as well, would be how optimised solutions compare to randomly generated variable cost configurations; we do this to ensure that simply adding any weights to road segments is not sufficient, and instead optimised weights are required. We therefore added an extra horizontal line representing the average fitness value of five random variable cost configurations.

Figure 3 shows that the GA successfully optimises its solutions to improve the total travel time compared to when no variable costs are used. In the case of this run, it was able to achieve an improvement of 13.15%, which under this model and these parameter settings amounts to 925 hours saved for 31,584 drivers. Another salient observation would be that the figure illustrates the importance of the optimisation algorithm, as using a solution with random variable costs produced an objective function value comparable to not using variable costs at all. This particular run was unusual in that regard, as in most runs random solutions not only did not manage to improve over the baseline, but actively achieved worse objective function values than those not using variable costs. The reason the first iteration of the GA already produces better results than random costs is that, in each iteration, the objective function value of the best solution of a total population of 40 is plotted, rather than the average.

3) Fairness of the proposed method: A possible concern when redistributing traffic to reduce congestion is the fairness of the method. For instance, some individual drivers might be forced to spend a far longer time to get to their destination in order to allow the majority of drivers to experience roads with less congestion. To see whether our solutions caused a disproportionately high delay to individual drivers, we created histograms of the total travel time it took drivers to get to their destination, in the unoptimised and optimised scenario. These histograms are shown in Figures 4a and 4b.

The histograms show a modest difference in the travel time distributions between the presence and absence of variable costs. The optimised solution does show higher frequencies of drivers spending little time on the road compared to the scenario without variable costs, as well as a sharper drop in frequency for higher travel times. For other runs with lower improvement percentages, the difference between the histograms tended to be smaller as well, but for some of those, there was also a slight increase in the number of drivers spending a relatively longer amount of time on the road. Overall, these distributions could be seen as positive results. Although it does appear that the effectiveness of the total travel time improvements being achieved came at the expense of a higher delay for few individuals in some runs, as in the case of the run from Figure 5b, this effect is very small when it happens. Moreover, the amount of individual drivers who spend less time on the road has increased substantially. Nonetheless, if this effect was considered as a large problem, a possible solution would be to add a weighted penalty term to the objective function, corresponding to the sum of the extra time spent on the road by individual drivers who are slower when the variable costs of a solution are used. Higher weights for the penalty term would result in these cases being avoided more assiduously.

4) Solution visualisation: As an instance of an optimised solution, a visualisation of the road network graph displaying optimised variable costs is shown in Figure 6. In the figure, black edges are roads with a variable cost of 0, and red edges are roads with a high variable cost. Further, black nodes signify road intersections, whereas green nodes are locations from the location dataset $\mathcal{D}_L$. Looking at the figure, it is interesting to see that high-quality solutions appear to favour imposing high variable costs onto short, central roads connecting their larger neighbours, leaving the outer roads mostly untouched. This does not apply to all such roads, however, and thus rather than discouraging using central roads altogether, the algorithm dynamically selects roads to impose such costs based on movement data. The resulting solutions are such that, when balanced to the cost of alternatives, these central roads will be most attractive only to a subset of drivers, while others will prefer alternatives, thus optimally distributing the drivers over all available routes.

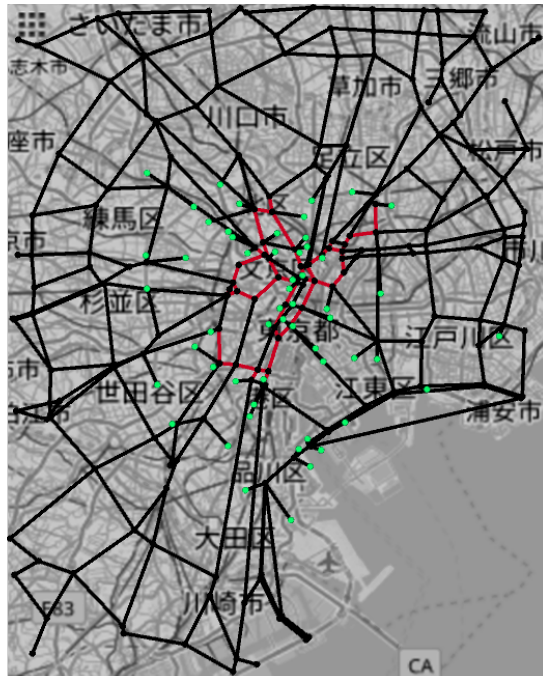


Fig. 6. Visualisation of the road network, as an overlay on a map of Tokyo, with edges coloured according to their associated variable costs. Red edges have high costs, while black edges have a cost of 0. Map source: OpenStreetMap [20].

5) Viability of rewards instead of costs: While the emphasis of our analysis has been on using variable costs to reduce the total amount of hours spent on the road, we have stated repeatedly throughout the paper that using variable rewards (negative variable costs) could be equally effective at improving the traffic flow of a city. This generality offers decision-makers with more flexibility with regard to a real-life implementation of this type of method. To support our claims, we performed a run with identical settings to that of the best solution found ($N = 31{,}584$, $C = 48$), with the only difference being that the optimisation algorithm now uses solutions of negative costs, or rewards, instead of costs.

The histograms of this run are shown in Figure 5; its characteristics, seem very similar to that of the best solution using costs. To compare costs and rewards more empirically, we

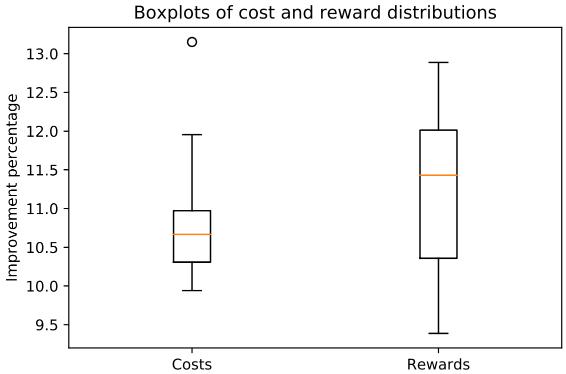


Fig. 7. Comparison of improvement percentage distributions for using variable costs or rewards visualised by boxplots, based on a sample of 20 runs for each condition for $N = 31{,}584$ and $C = 48$.

ran the two conditions 20 times (with $N = 31{,}584$ and $C = 48$ for both, as we have looked into runs with these settings in more detail), and created boxplots of the resulting sample of improvement percentages in Figure 7. The figure shows that both samples contain values within a similar range, although the spread of the rewards sample appears to be greater than that of the costs sample. Though not identical, the highly comparable distributions of both conditions seem to be encouraging signs that the rewards would indeed be a viable alternative to costs.

VI. Ethical considerations

When working on a project explicitly aimed at having some impact on the lives of people in the real world, it is advisable to dedicate some time to the reflection on the ethical implications of the applications or methods being considered. In our case, we identified the following points on which ethical objections could be made:

- A few specific routes might be disproportionately targeted, which would be unfair even if it results in greater benefits for the population as a whole.
- The method could unfairly affect some groups or social classes of people, as the costs or rewards could have a different value for different people depending on, for example, their financial situation.
- Directing how individuals behave could be considered a violation of their individual freedom.
- The result of the redistribution depends on the data source. The choice of the input data can disadvantage groups of citizens.
- Location information is sensitive personal data, using those data for the greater good needs to be balanced against preserving citizens' privacy.

For the first point, we would refer to Figure 4, where we show that the change to the distribution was modest in this instance, and to Section 5.3, where we discuss the possibility of a penalty term for solutions where individual routes are worse off than they were before. To the second point, we would like to emphasise that our variable costs do not have to be monetary in nature, nor are they necessarily absolute values rather than relative to some property of the drivers (such as income). The variable costs do not depend on any particular implementation, as long as the value of the variable costs compares predictably to that of the spatial costs, and is consistent for all drivers. With regard to the third point, while we acknowledge that some people might feel strongly about the freedom of driving a car as independently as possible, we would also like to point out that individual driving behaviour is already being directed (far more forcibly and directly) by speed limits and traffic lights. Those measures, too, limit the drivers' freedom to determine their own behaviour, but they fulfil a vital role in keeping traffic as safe and functional as possible, to the benefit of traffic flow and safety as a whole. Regarding the input data, we would like to argue that city administrators are in charge of choosing data that represents car movement in their city best. Transparency about which data is used and how this influences the redistribution is a core task of administrators and data scientists when putting data-driven policies into practice. On a similar note, we would like to note that administrators will need to consider which level of detail of location information is needed to achieve a good redistribution. For this case study, aggregated and anonymised location information offered enough detail necessary to improve overall travel time. Individual trajectories were not necessary, which addresses all privacy-related concerns.

VII. Conclusion and future directions

We have shown that we can successfully reduce traffic congestion by redistributing traffic using variable road segment costs, and optimising this cost configuration using a meta-heuristic algorithm, based on crowd-sourced urban movement data. In a case study of the Tokyo city centre, our algorithm was able to find configurations reducing the total time spent on roads by up to 13.15%, resulting in a total time gain of 925 hours. When the number of cars on the road was larger, the improvement percentage decreased, but the total time gain tended to be higher, as those relatively small improvements could be used by more drivers.

Though the practical implementation of the variable costs may be another non-trivial problem to address first, the positive results show that, at least conceptually, this method could result in improved traffic flow when applied in practice.

In order to improve the applicability of our approach, future work could include addressing the simplifications we made, in particular with regard to the road network representation. Case studies on other cities, particularly those with different morphological properties than Tokyo, would also be beneficial to show the method's generalisability. Furthermore, it could be insightful to adopt traffic simulations in place of our occupancy estimation and Greenshields traffic flow model, thus introducing a temporal component. Other future work might focus on selecting the best possible metaheuristic optimisation algorithm with the best possible parameter settings, as well as employing vehicular movement data, such as floating car data.

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We would like to extend special thanks to Foursquare and Netmob for the movement data provided as part of the Future cities challenge [6]. The challenge provided researchers with a movement dataset from the social network Foursquare, which could then be used to carry out research that might shape future cities. Topics for the Future cities challenge included location intelligence, urban growth and dynamics, mobility and transport and more. Given the proprietary nature of many sources of movement data (including the dataset from Foursquare), and as a result the difficulty for independent researchers of obtaining this type of data, the challenge provided us with opportunities that might otherwise not have been possible. In particular, this work is an extension of an "unpublished" proposal that was submitted to the Future cities challenge, and thus would not have been possible without it.

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