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Using MATSim to test sensitivity towards vehicle ban enforcement

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Abstract

In recent years many authorities have considered heavy vehicle restrictions, or complete bans, in certain parts of the city to alleviate both congestion and other externalities. But such restrictions are often implemented without regard for the true impact, both intended and unintended. One reason is because anticipating the effects, through modelling, is not easily achieved. As but one consequence, such bans are often implemented but not well-enforced. In this paper we show how an agent-based simulation is used to study the efficacy of truck bans. That is, studying if the combination of the probability of being caught, and the size of penalty *if caught* violating the restriction, has the intended effect of getting heavy vehicles to abide by the restriction(s). The results show that the behaviour of heavy vehicles is more sensitive to enforcement efficiency than the size of the penalty. In other words, using the proverbial *stick* as a motivator instead of a carrot, just *using the stick* has more effect than the size of the stick, no matter how much you wave it around.

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1. Introduction

City authorities have to consider a growing arsenal of initiatives to manage the increasing demand placed on transport infrastructure. With urbanisation comes higher levels of congestion, and its associated increase in externalities. One tool at the city authority's toolbox, vehicle (access) restrictions, has been studied more and more over the past decade [1, 9]. A specific focus of many of these restrictions are heavy goods vehicles since the higher population is concomitant with increases in the demand (density) for goods, and larger quantities of waste to be removed. Bontempo et al. [3] note that emerging countries, especially, has seen a rise in implementing truck bans due to the explosive growth of private car ownership. Even though heavy vehicles account for a small proportion of the overall vehicle population, they contribute disproportionately to congestion, infrastructure damage and environmental externalities.

But vehicle restrictions are mainly representative of the *authority's* point of view, and is rarely cognisant of the (often conflicting) objectives of the freight carriers, shippers, and receivers [9]. One reason is that it is hard to study

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even the direct, intended consequences of a truck ban during the morning peak, answering for example “*by how much will emissions go down in the central business district?*” It is even harder to anticipate the *unintended* consequences [2, 10] like carriers opting for smaller, but *many more* vehicles in their fleet to maintain their contractual agreements [3], or travelling further to avoid restricted areas [7], which results in higher overall emissions for freight. Increased logistics costs ultimately manifest itself in higher prices for consumer goods on the shelf.

Few companies in practice, at least in many developing countries, have the sophistication to perform vehicle routing, let alone using software or algorithms that can take truck bans into account like those proposed by [11].

Another problem with vehicle restrictions, and truck bans specifically, is that they are often ill-informed and the result of increased political pressure from the commuting population. Bontempo et al. [3] note that

“[o]ftentimes, these constraints are defined, decided and implemented in very short notice, in a typically, ‘Brazilian mode’, with neither regard for technical and logistic arguments, nor long term effects and impacts. Also, medium and small cities have been implementing truck bans in a crescent way, even when they do not face significant heavy traffic or congestion issues, as trucks bans are ‘fashionable’ ”.

Consequently, and confirmed by European cases [4], some of these vehicle restrictions exist on paper but are poorly enforced.

Recent advances in agent-based transport models allow us to model large-scale urban scenarios [6] at a high resolution so that one can study the distributional effects [12]. That is, when you model at the individual vehicle/person level it is easier to answer questions like “*who gets the congestion benefit of truck restrictions?*” and “*who pays for those benefits?*”

Like [8], [7], and many others, this paper will use the MATSim [5] toolkit to study the impacts on specific vehicles of different classes. The purpose of this paper is to lay the foundation for studying the efficacy of vehicle restrictions. Results show that people, based on vehicle type, respond to the efficiency of enforcement of vehicle-based restrictions, and the extent of the penalty *when* enforced. MATSim is indeed capable of capturing these sensitivities, opening the door for larger scale investigations.

2. Model

A first step in studying people’s behavioural response is to set up an experiment in which one can validate that the model is indeed behaviourally sensitive. For this purpose we use an adaption of a well-known model, referred to as the *equil* network, of MATSim [5]. The circular network, shown in Figure 1, is made up of 15 nodes connected by 23 (directional) links. Two vehicle types are used, namely *light* vehicles with a passenger car equivalent (pce) value of 1 and a maximum free speed of 120km/h, and *heavy* vehicles with a pce value of 2 and a maximum speed of 80km/h. Links represented by solid lines may be traversed by any type of vehicle during any time of the day, while links represented by dashed lines are subject to restrictions based on vehicle-type and time of day. More specifically, heavy vehicles are not allowed during the morning peak of 07:00–08:00. The experiment is set up so that all vehicles have to traverse from node 1 to 13 via one of 9 possible routes connecting nodes 2 and 12. The three routes via links 5–7, that is, link combinations 5→14, 6→15 and 7→16, are subject to the restrictions.

For the travel demand we create a population of 10 000 people, or *agents*, all initially located at node 1, with a typical home-work-home activity chain. Each agent’s sequence of activities, referred to as a *plan*, sees it leaving node 1 (home), travelling to node 13 (work) where it spends approximately 8 hours before returning to node 1 (home). Every agent is randomly assigned a vehicle type and initial departure time. An agent is assigned either a light or heavy vehicle with equal probability. The reason for this is so that we have a control group (light vehicles) that is insensitive to the vehicle restrictions and only changes its behaviour based on the overall system state, namely congestion in this case.

With the restrictions being active in the period 07:00–08:00, referred to as the *peak*, we assign the departure time randomly again, and over the two-hour period 06:30–08:30 so that each agent is equally likely to travel during the peak or off-peak period in the morning. One can ignore for now that the 10km link 1 will indeed incur approximately 5min travel time under free speed conditions. Although not necessary in a MATSim configuration, the travel demand is initialised with a given route. Each agent is assigned a random route from node 1 to node 13 with each of the 9 possible routes being equally likely. The return route from node 13 to node 1 is fixed via links 21→22→23.

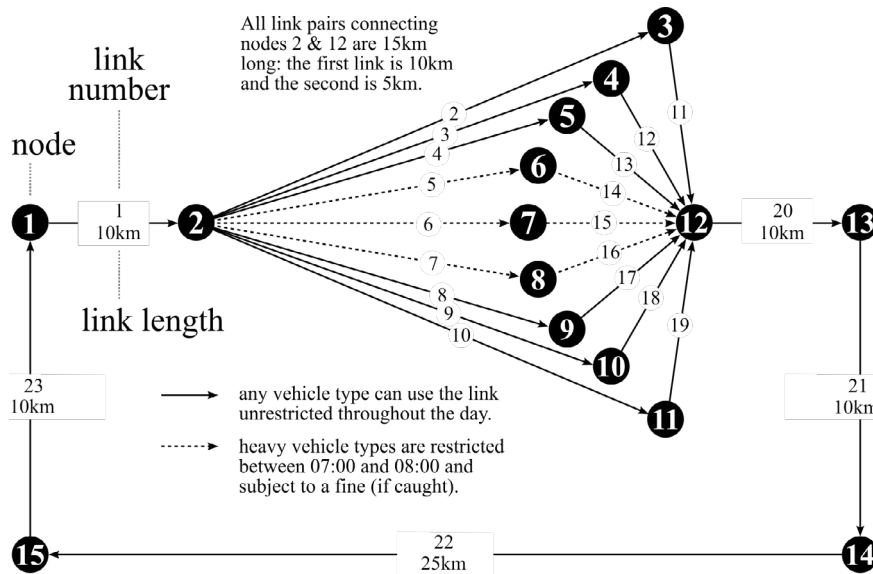


Fig. 1: Layout of the equi1 network noting the three links (dotted lines) that are subject to a vehicle-type ban during the morning peak.

A simulation instance can now be started with each agent executing its one (and only) initial plan on the road network. During the mobility simulation MATSim's efficient queue-based model is used, and agents follow the route between activities link by link. Whenever an agent enters a link, the mobility model checks if the specific link, the agent's vehicle, or the time at which the link is entered, falls within the link restrictions. An agent is flagged when all three these conditions are met. An agent is only flagged once for an entire leg. That is, a single journey between two consecutive activities.

At the end of the mobility simulation each agent scores its executed plan using a utility function based on generalised cost [5]. To affect the restrictions we introduce two parameters. Firstly, there is a probability p , that when an agent was flagged as violating a link restriction, the agent is *actually caught*. This is to capture enforcement efficiency. Secondly, there is a monetary fine f imposed on the agent if indeed caught.

During the scoring stage each agent evaluates the goodness of its executed plan based on the time spent travelling (negative utility), time actually performing an activity (positive utility), and the fine (negative utility). Instead of working with some expected fine, each agent exactly evaluates its plan. Agents violating link restrictions will be imposed a fine, but only if caught. The score is then associated with the plan, the plan is put into *memory*, and the iteration ends.

During every iteration a randomly selected portion of agents are allowed to *replan* by choosing another plan from its memory, or adapting the current plan in its memory. In this experiment agents have three replanning options. Firstly, another plan from memory can be chosen with a probability based on the goodness of the plan. The better the past performance of the plan, the higher chance of being picked. Secondly they can choose an alternative, randomly selected route (on the first leg from node 1 to 13), or thirdly, change the time of departure from an activity. This adapted plan is then used during the next iteration. Once an agent's memory is full (in this study it was limited to five plans), the worst performing plan is removed. This iterative process is repeated until some relaxed state is achieved and no agent can improve its own set of plans in memory.

3. Results

Each simulation instance was executed with 10 000 agents over a total of 200 iterations. Different simulation instances considered different probabilities of being caught, p , and different penalties, or fines, f . The set of probabilities evaluated was in increments of 10%, $\mathbf{P} = \{0.0, 0.1, 0.2, \dots, 1.0\}$, while the set of fines was in increments of 100 monetary units, $\mathbf{F} = \{0, 100, 200, \dots, 1000\}$.

In the results that follow we report both how agents adapt their behaviour within a simulation instance, specifically, and also how agents respond overall to the restrictions.

3.1. Behavioural sensitivity to restrictions

The initial travel demand was set up to be random between the control (light vehicle) and experimental (heavy vehicle) groups. That is, random route choice among links 2–10, and random departure times. The cohort of agents' route choices as it changes over a simulation instance's iterations are shown in Figure 2. The results given here, as an

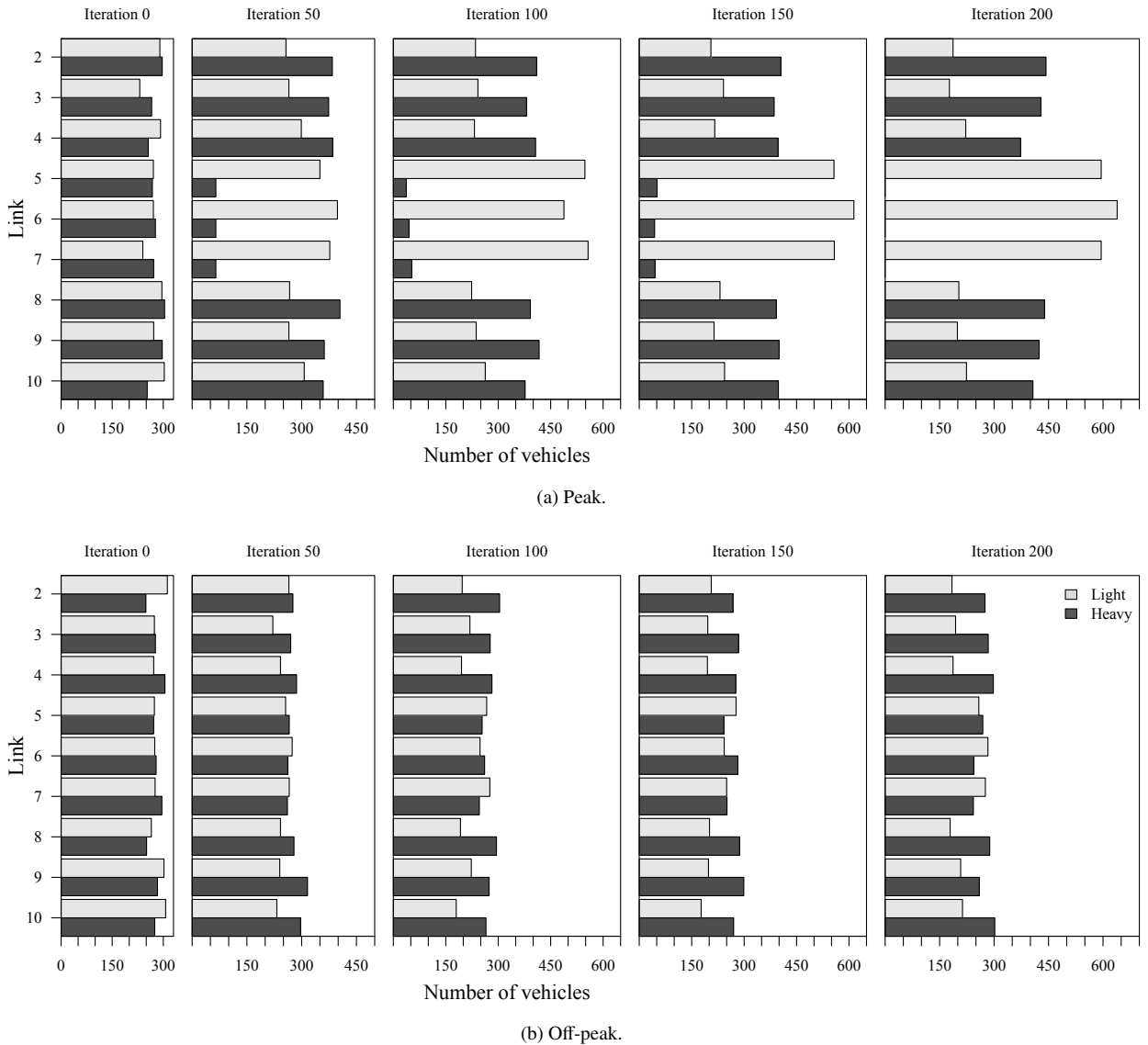


Fig. 2: Progression showing how individuals' route choice behaviour changes over the simulation iterations during both peak and off-peak periods.

example, is using a probability to being caught of $p = 0.50$ (50%) and a fine of $f = 500$. At the start, in iteration 0, there is an expected, homogenous spread over all route choices, both in the peak (Figure 2a) and off-peak (Figure 2b) case.

As the simulation progresses, we quickly see (iteration 50) that heavy vehicles start avoiding the restricted links during the peak period. To interpret the results more specifically the actual proportions of the two vehicle types are

given in Table 1. The table distinguishes between peak and off-peak period, as well as the use of open or restricted

Table 1: Percentage of the two vehicle types using the open and restricted links during different periods over the course of the simulation run

| Iteration | Period ¹ | Open links ² | | Restricted links ³ | | Total | |
|-----------|---------------------|-------------------------|-------|-------------------------------|-------|-------|-------|
| | | Light | Heavy | Light | Heavy | Light | Heavy |
| 0 | Peak | 33.5 | 33.6 | 15.6 | 16.4 | 49.1 | 50.0 |
| | Off-peak | 34.5 | 33.0 | 16.4 | 17.0 | 50.9 | 50.0 |
| 50 | Peak | 33.0 | 45.6 | 22.4 | 3.9 | 55.4 | 49.5 |
| | Off-peak | 28.7 | 34.6 | 15.8 | 15.9 | 44.6 | 50.5 |
| 100 | Peak | 28.5 | 47.9 | 31.7 | 2.7 | 60.2 | 50.6 |
| | Off-peak | 24.0 | 34.1 | 15.7 | 15.3 | 39.8 | 49.4 |
| 150 | Peak | 26.9 | 47.8 | 34.4 | 2.8 | 61.3 | 50.6 |
| | Off-peak | 23.4 | 33.8 | 15.3 | 15.6 | 38.7 | 49.4 |
| 200 | Peak | 24.1 | 50.5 | 36.4 | 0.0 | 60.5 | 50.5 |
| | Off-peak | 23.2 | 34.3 | 16.3 | 15.2 | 39.5 | 49.5 |

¹ The period ‘Peak’ refers to 07:00–08:00 while ‘Off-peak’ refers to any other time.

² Paths connecting nodes 2 and 12 via links 2, 3, 4, 8, 9 or 10.

³ Paths connecting nodes 2 and 12 via links 5, 6 or 7.

links. For example, 33.5% of light vehicles use open links (those connecting nodes 2 and 12 via links 2–4 or 8–10) during the peak period (07:00–08:00).

The split between heavy vehicles travelling between the peak and off-peak period remains fairly constant, and equal. That said, there is a general shift of heavy vehicles towards the open links, and mainly during the peak period. A total of 84.8% of heavy vehicles use the open links at the end of the simulation compared to the 66.6% at the start. This was expected as one should recall that there is double the number of open link route choices than restricted ones.

What was somewhat of a surprise, yet plausible, is the shift of light vehicles towards the peak period. The proportion of light vehicles using the restricted links during the off-peak remains near-constant over the course of the simulation, from 16.4% in iteration 0 to 16.3% in iteration 200. But the light vehicles using the open links generally shift to the restricted links *during the peak period*. By the end of the simulation 60.5% of light vehicles travel during the peak, likely because of the additional capacity resulting from the void left by the heavy vehicles.

3.2. Efficacy of truck bans

The purpose of heavy vehicle restrictions is to affect behaviour change in agents. More specifically, to let them use alternative routes and times. We specifically exclude ‘not travelling at all’ as a choice option as this study assumes that heavy vehicles are obliged to still deliver the goods, i.e. participate in their chosen activities. Next we therefore report on the impact that enforcement efficiency and the size of the penalty has on changing agents’ behaviour. The combination of these two elements is what is referred to as *efficacy*: the ability to produce the desired result.

Figure 3 shows the trade-off between the enforcement efficiency, represented as the probability of being caught, and the size of the penalty. Each value on the grid represents the percentage of the heavy vehicles that actually violates the restriction. That is, the percentage of heavy vehicles that uses a restricted link during the peak period. When executing these simulation instances, the exact same random seed was used so as to capture the effect of the two variables, and not mere randomness in the simulation.

The two extreme cases are quite self-explanatory. If either there is *no chance* of being caught, or there is *no penalty* when you *are caught*, the probability of violating (ignoring) the truck ban remains the same. What is quite clear from

the figure is that the behaviour of agents is a lot more sensitive to the enforcement efficiency than the size of the penalty. Although the percentage of violators decrease as the penalty increases, it is by quite a small margin.

The absolute values should not be interpreted too directly. This is because these remain experiments to illustrate phenomena of behaviour when comparing an experimental group against a control.

4. Conclusion

In this paper it was illustrated that MATSim can be effectively used to study the efficacy of truck bans. It has the ability to capture the co-evolutionary behaviour of road users since it is sensitive to the user’s vehicle type, time of day, and the specific network links. Two main avenues of research now opens. Firstly, to make the results more useful and take a step closer to the policy level we need to extend the small equilibrium experiment to a large-scale urban environment. This will allow one to study metrics like total vehicle kilometres travelled, and emissions, and interpret the results in a more absolute sense, with practical interpretations.

Secondly, the behaviour of carriers (those stakeholders using heavy vehicles to convey goods) is more complex than just route choice and changing activity timing. Very often the time windows are imposed by the receivers of the goods. Consequently, one needs to study alternative behaviour dimensions. For example, understand how carriers might change their fleet from few heavy vehicles to (many) more small and medium-sized vehicles that are not, or at least less affected by the restrictions.

References

- [1] Allen, J., Browne, M., 2010. Sustainable strategies for city logistics, in: McKinnon, A., Cullinane, S., Browne, M., Whiteing, A. (Eds.), *Green Logistics: Improving the environmental sustainability of logistics*. Kogan Page. chapter 14, pp. 282–305.
- [2] Arvidsson, N., 2013. The milk run revisited: A load factor paradox with economic and environmental implications for urban freight transport. *Transportation Research Part A: Policy and Practice* 51, 56–62.
- [3] Bontempo, A.P., B.Cunha, C., Botter, D.A., Yoshizaki, H.T., 2014. Evaluating restrictions on the circulation of freight vehicles in Brazilian cities. *Procedia - Social and Behavioral Sciences* 125, 275–283.
- [4] Dablanc, L., Montonen, A., 2015. Impacts of environmental access restrictions on freight delivery activities - examples of low emissions zones in Europe. *Transportation Research Record: Journal of the Transportation Research Board* 2478, 12–18.
- [5] Horni, A., Nagel, K., Axhausen, K.W. (Eds.), 2016. *The Multi-Agent Transport Simulation MATSim*. London: Ubiquity Press.
- [6] Joubert, J.W., Fourie, P.J., Axhausen, K.W., 2010. Large-scale agent-based combined traffic simulation of private cars and commercial vehicles. *Transportation Research Record* 2168, 24–32.
- [7] Kickhöfer, B., Kern, J., 2015. Pricing local emission exposure of road traffic: An agent-based approach. *Transportation Research Part D: Transport and Environment* 37, 14–28.
- [8] Nagel, K., Kickhöfer, B., Joubert, J.W., 2014. Heterogeneous tolls and values of time in multi-agent transport simulation, in: *The 3rd International Workshop on Agent-based Mobility, Traffic and Transportation Models, Methodologies and Applications (ABMTRANS)*, pp. 762–768.
- [9] Quak, H.J., 2014. Access restrictions and local authorities’ city logistics regulation in urban areas, in: Taniguchi, E., Thompson, R.G. (Eds.), *City logistics: Mapping the future*. CRC Press.
- [10] Quak, H.J., de Koster, R., 2006. The impacts of time access restrictions and vehicle weight restrictions on food retailers and the environment. *European Journal of Transport and Infrastructure Research* 6, 131–150.
- [11] Qureshi, A.G., Taniguchi, E., Thompson, R.G., Teo, J.S.E., 2014. Application of exact route optimization for the evaluation of a city logistics truck ban scheme. *International Journal of Urban Sciences* 18, 117–132.
- [12] Ziemke, D., Joubert, J.W., Nagel, K., 2018. Accessibility in a post-apartheid city: Comparison of two approaches for accessibility computations. *Networks and Spatial Economics* 18, 241–271.

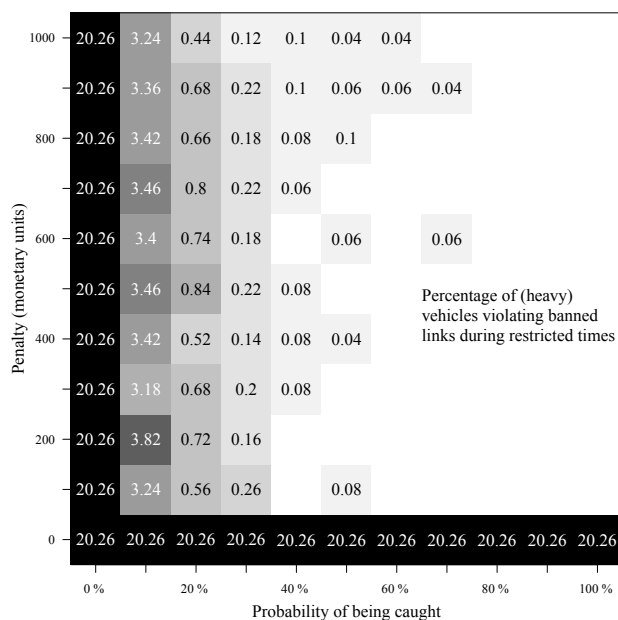


Fig. 3: Results showing the trade-off between enforcement efficiency and the penalty.