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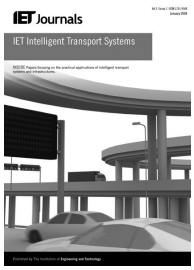


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# Effective traffic management based on bounded rationality and indifference bands

*Jaap Vreeswijk[1], Jing Bie[2], Eric van Berkum[2], Bart van Arem[3]*

[1]*Research and Development, Imtech Traffic & Infra, Basicweg 16, 3821 BR Amersfoort, he Netherlands*
[2]*Centre for Transport Studies, Faculty of Engineering Technology, University of Twente, Drienerlolaan 5, 7522 NB Enschede, The Netherlands*
[3]*Department of Transport and Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, 2628 CN Delft, The Netherlands*
*E-mail: jaap.vreeswijk@imtech.nl*

**Abstract:** Constrained cognitive abilities cause imperfections in drivers' choice behaviour and appear largely systematic and predictable. This study introduces the concept of 'effective control space' to build upon this knowledge as an opportunity to increase the effectiveness of Dynamic Traffic Management (DTM). Within the control space boundaries it is assumed that drivers do not act upon the effects of DTM measures, they behave as being indifferent to them. This study debates that: (i) drivers' ability to detect changes in attributes of their trip or the performance of a traffic system is limited, (ii) drivers make mistakes in estimating the value of such changes and (iii) drivers apply a great diversity of choice patterns but do not necessary adapt their choice. Hence, for some DTM measures to be effective effects should not exceed the control space boundaries, whereas other DTM measures need to give drivers an incentive that exceeds these boundaries. Knowledge on the effective control space may support road authorities to operationalise their measures most effectively. With the theories of indifference bands and decision-making as starting point a theoretical and conceptual framework are provided, supported by a numerical example to demonstrate how application can steer a system towards its optimal state.

## 1 Introduction

The effectiveness of Intelligent Transportation Systems and Dynamic Traffic Management (DTM) in particular is largely dependent on drivers' response to the effects of them [1]. Much research has been devoted to choice modelling, driver compliance and the influence of information, for reviews see [2–6]. In this paper, we take a fundamentally different approach. We aim to structure behavioural factors relevant for drivers' response in a general framework and converge to a new control variable for DTM. Although it appears that most research focussed on intrinsic choice behaviour (i.e. elementary route choice based on the characteristics of multiple choice alternatives), we examine drivers' response when the characteristics of the choice alternatives (slightly) change because of DTM. Moreover, we assume that drivers do not receive any information, therefore act on their senses and own experiences alone. Besides, as it seems that the final station of the majority of research is some form of modelling, we choose a more practice-oriented perspective and study the implications of drivers' response for the design of DTM. Whenever we refer to DTM we refer to systems that influence the network performance in terms of travel times, delay times, traffic density, average speed etc. such as route guidance and traffic lights. With driver response we mean second order effects that result in changes in route choice (e.g. rat run), departure time, mode choice, driving behaviour (e.g. red light violation) etc. Note that first order changes are the intrinsic responses that cause the effect on the network in reaction to the measure itself.

One important topic in traffic modelling is the predictability of choice behaviour and behavioural response. Traffic models combine demand (i.e. drivers' trips and travel choice behaviour) and supply (i.e. infrastructure and DTM) and determine the performance of the transportation system by means of traffic assignment [7]. It seems that often these models assume a fixed supply and an elastic demand which anticipates to changes in the system performance. However, to include driver response the question is how demand alters when DTM change supply? Many assumptions in conventional traffic modelling have been derived from standard economics, for example that drivers are rational decision makers and above all perfectly informed about the available choice alternatives [8, 9]. Moreover, that they can calculate the value of the different options available, that they are able to derive the optimal choice, and that they are cognitively unhindered in weighting the implications of each potential choice. In other words, people presumably make logical and sensible decisions and quickly adopt their choice to changing conditions.

These are debatable assumptions. In reality, people have limited knowledge and constrained cognitive abilities




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leading to prejudiced reasoning and certain randomness in behaviour and choice outcomes [8, 10]. It is not just the behaviour (i.e. choice outcome) that is of interest, but also the decision-making process behind such behaviour. Behavioural economics draw on the aspects of both (cognitive) psychology and economics, and studies the motives and behaviours that explain deviations from rational behaviour [11, 12]. This perspective of individual decision-making is known as bounded rationality or satisfying behaviour [13, 14], and also found its way into transportation research (e.g. [15–17]). Another recently adopted theory derived from behavioural economics and relevant in the context of this paper is prospect theory. It is based on the principle that decisions are context-dependent and alternatives are framed in terms of gains and losses relative to some common reference point, while losses weigh much more than gains of equivalent size [18–20]. Although in some cases, like random utility theory modelling, a random variable or error term is considered to somehow weaken the assumptions of perfect rationality, many models fall short in explicitly considering the predictable imperfections in drivers' choice behaviour. The development of better descriptive models of choice behaviour and empirical validation of theories derived from behavioural economics is on-going [10, 12, 21]. The aim of this paper is to structure already available evidence and make inferences of possible application for DTM. Several of the aforementioned references provide examples of models incorporating boundedly rational behaviour.

The next section introduces the general framework, followed by an overview of the theoretical background based on literature review. Next, a numerical example is presented to illustrate the principle of effective control space and its benefits. The last section of this paper concludes and presents planned future research.

## 2 Theoretical framework

A used and validated bounded rationality mechanism is the notion of indifference bands. That is, drivers will only alter their choice when a change in the transportation system or their trip, for example the travel time, is larger than some individual-situation-specific threshold [9, 10, 22–24]. To speak in earlier terms: demand is inelastic to supply-changes up to a certain threshold. There are many factors associated with bounded rationality which explain why a change in network performance not necessarily leads to a behavioural response. For example: because of the formation of habits a driver is not alert to changes, a driver may be unaware of a change if the change is small or not within the driver's periphery, drivers may be disinterested in a change if they regard it insignificant, or there is simply a lack of (knowledge of) alternatives.

> Example (used figures are imaginary): at a controlled intersection, increases in waiting time up to 5 s may largely go unnoticed and hardly invoke response. Presumably, this is because drivers are unable to notice the change. Increases between 5 and 10 s are more likely to be detected by drivers, but still may invoke little response. Presumably, this is because the change is not important enough relative drivers' reference point and alternatives. However, when increases in waiting time are higher than 10 s (exceeds the indifference band threshold), they may increasingly invoke substantial response. Presumably, this is because drivers do detect such changes and find them disturbing enough to favour alternatives. The same example can be applied to cases of travel time, arrival time, level of service etc.

From this simple example it becomes immediately clear that basic knowledge is needed of many factors to determine the indifference band for a specific situation. Such as, how drivers cognitively and affectively experience (waiting/travel) time, how accurately drivers are able to estimate time intervals, drivers ability to detect changes and value them correctly, the existence of alternatives and drivers' awareness of these alternatives.

We believe that the indifference band is a great opportunity for DTM as it provides road operators with certain freedom to move the performance of their network towards a state that minimises the total travel time in the network. In particular as multiple studies provide evidence that these boundedly rational behaviours are neither random nor senseless; they are systematic, consistent, repetitive and therefore predictable [8, 11, 25]. Although network-favoured measures not necessarily improve the situation of all drivers, undesirable and disproportionate behavioural response of drivers whose situation declines is limited or even absent, as long as the indifference band is respected. Hence the feasible region of DTM expands compared to the case of perfect rationality; DTM becomes more effective and the network performance benefits. In addition, the indifference band also indicates the minimum required effect of DTM to ensure driver response and likewise increase the effectiveness of the measure.

In the remainder of this paper we will refer to this region that provides extra opportunity to DTM as 'effective control space'. In the example given earlier, the indifference band was 10 s, whereas several of the aforementioned studies suggested indifference bands for the travel time of a route in the order of 5–10 min. However, it is easy to recognise that such figures strongly depend on the context. To our best knowledge no research has been done that systematically describes the relations and weights of the factors underlying and cumulatively contributing to the indifference band phenomenon.

A summary and visualisation of the general framework of the effective control space philosophy is shown in Fig. 1. It is important to distinguish that this figure is descriptive and not conclusively scaled based on quantitative data. Besides, the figure is not restricted to one specific context and DTM measure. On the horizontal axis is the time-effect of a DTM, such as a change in waiting time or travel time expressed in gains or losses. The vertical axis represents the value judgement of drivers ranging from positive to negative. The value function is taken from prospect theory [18]. In the context of difference bands this function describes the two-sided driver response probability subject to the time-effect, reference point and asymmetry of gains against losses. The reference point is marked by the dot in the centre of the figure. Evidence from time psychology research [26] adds to this framework that time feels as moving faster with gains and positive value judgments, and slower with losses and negative value judgments.

Similar to prospect theory we assume that drivers are more likely to notice and respond to changes involving losses than changes involving gains, while the effect of additional gains or losses decreases. For example, waits at traffic lights which increase by 10 s have a higher impact than waits which decrease by 10 s. In addition, the marginal impact of


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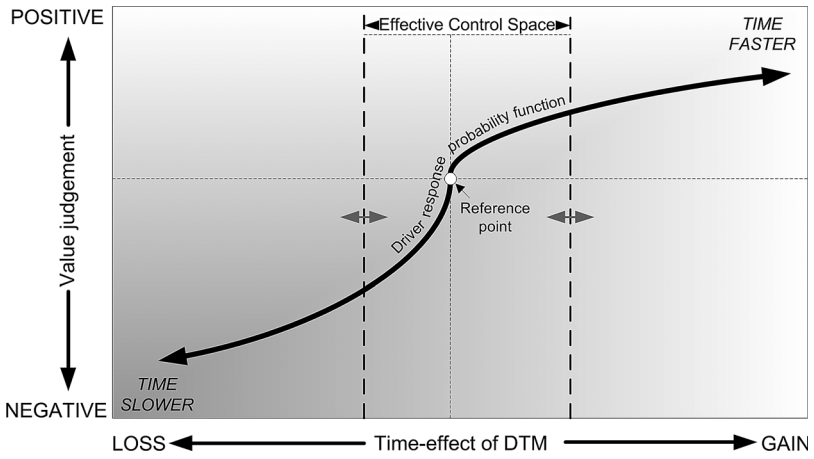


**Fig. 1** *Theoretical framework of effective control space*

the 10th second is larger than the marginal impact of the 11th second. Hence, the effective control space is asymmetrical too as indicated by the vertical dashed lines. Control space indicates an area where we expect the road user or a situation to be controllable. As it appears that DTM does not affect, or only marginally affects behaviour in the control space, the system performance might increase. An example to illustrate this will be provided later. Effective control space typically applies to day-to-day scenarios as it is strongly related to between-day decision making. Generally the experiences of the previous day and the current day are known to be dominant determinants for decision making of the next day [27]. Moreover, when a driver notices a time-effect of DTM larger than the effective control space, then it is assumed likely that the next day this driver responds in one way or another. Although, this is only relevant if the driver regards the change a loss. Where gains are concerned it only makes sense for a driver to adapt its behaviour if because of that gain an alternative has become more attractive. How drivers can become aware of improvements of non-chosen alternatives is another topic [10] and outside the scope of this paper. Finally, because of the stochastic variability of the traffic system a driver may not notice a change instantly, but requires several days to do so. If the network topology allows, only in rare cases drivers will be able to adjust their behaviour, for example their route, within a day. Empirical evidence is needed for validation and quantification of this framework, which is briefly discussed in the final section of this paper.

## 3 Theoretical background

Choice behaviour of drivers is very similar to consumer decision making. Buying a product involves five consecutive stages: (i) need or problem recognition, (ii) information search, (iii) evaluation of alternatives, (iv) selection or decision and (v) post decision behaviour [28, 29]. By combining 1 and 2 to 'awareness' and 4 and 5 to 'decision', a simplified three-stage sequence is the basis of the conceptual framework in Fig. 2. For reasons of comprehensivenss and readability, notable factors like

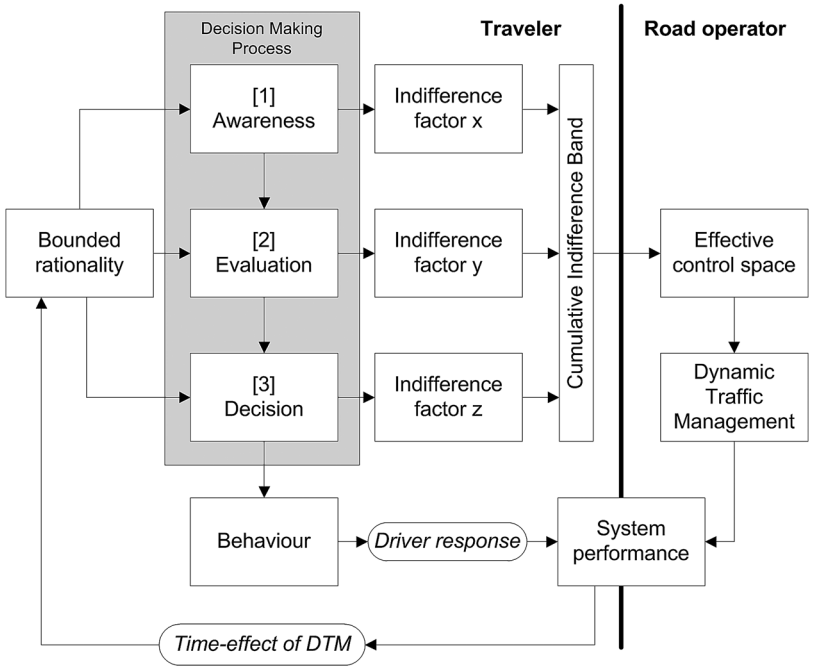


**Fig. 2** *Conceptual framework for effective control space*



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attitude, learning, perception, expectation, motivation, information and personality have been left out. Their influence is briefly discussed in the following subsections and in more detail in literature in relation to conceptual frameworks on specific themes (e.g. [27, 30–32]).

In each of three decision making stages different psychological factors are at play which together accumulate to the indifference band discussion in the previous sections. An indicative example of this philosophy is shown in Fig. 3. It is important to note that these factors are situation specific and therefore may vary from case to case. As such, any indifference band can be composed out of a different combination and weighing of factors. It is not the aim of this paper to identify all possible scenarios, but to provide a general framework that systematically captures factors and to enable practisioners to derive commonalities from scenarios that are relevant to them. It are these commonalities, that is, constant contributors to the indifference band, that define effective control space. The following three sections give an overview of factors related to awareness, evaluation and decision. Section 4 presents a numerical example to illustrate the implications that effective control space poses towards DTM and what opportunities this may offer.

### 3.1 Awareness

Research on the impact of learning shows that the awareness among drivers of changes in the transport system is limited and it grows over time as a result of direct experience and indirect learning [10]. A change could involve an improvement or degradation in the current route or an existing alternative, or the introduction of a new alternative. It concerns, for example the waiting time at traffic lights, the average speed or the travel time. In general, the larger, the more expectable the more important and the more negative a change, the sooner a driver is expected to notice the change [10, 33].

Several surveys showed that drivers' estimates of waiting times at traffic lights, on average, are fairly accurate, but widely variable, as are their perceptions [34, 35]. When a change is within the natural variation of a traffic situation with respect to an average, it seems unlikely that drivers are capable of detecting the change at all. For example, the waiting time at a traffic light with average 30 s and variation 15 s, means that measures shifting the average within the range of 15–45 s are hardly distinguishable from the natural variation. Similar findings were found in studies on user perceived level of services at signalised intersections and motorways. These studies showed that drivers are unable to perceive fine differences and only distinguish two or three levels of service rather than the six provided by the Highway Capacity Manual [36, 37]. Interestingly, this suggests that drivers' quality perception is nearly binary with only the level 'good' and 'not good'.

Derived from cognitive sciences, change blindness is the inability to detect and report changes to objects from one instant to the next that are obvious once pointed out [38]. Experiments have shown that participants are surprisingly bad at detecting even large changes, sometimes leading to change blindness in 88.5% of all cases. Change blindness increases when the changed item is not relevant for the task, when the magnitude of the change decreases, and when the change is further outside the visual periphery [38].

### 3.2 Evaluation

When drivers have been able to detect a change, the central question in the evaluation state is whether they value it properly or not? In a rational way, people have little feeling of how much things are worth. They focus on the relative advantage of one thing over another rather than the absolute difference, compare them locally to the available alternative, and estimate value accordingly [11].

Different studies confirm that the decisions and actions of drivers do not always correspond with their (perceived) observations. In one study only 12% of the drivers were able to correctly perceive their experienced travel times, and reversely, 12% perceived the opposite of their experience [33]. Similar and even larger figures were found with varying traffic volume and timing of traffic lights [21]. This led to three types of behaviour: (i) logical behaviour that reflects drivers choosing better perceived routes (perceive route A better and choose route A), (ii) cognitive behaviour reflecting drivers choosing a route in spite of not perceiving a difference between both routes; to reduce mental working

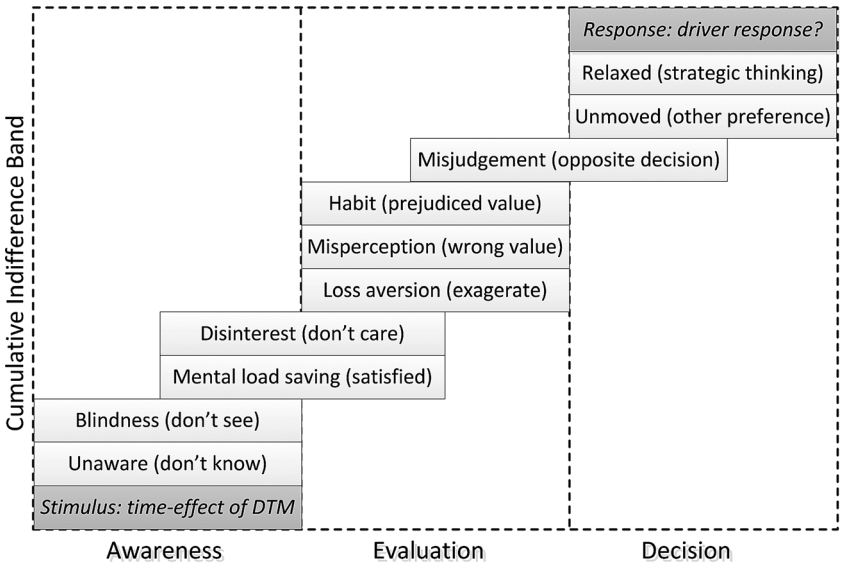


**Fig. 3** *Illustration of separate factors accumulating of indifference towards effective control space*


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load (perceive no different, choose any route) and (iii) irrational behaviour that reflects drivers choosing worse perceived routes (perceive route A better and choose route B). For the last type, cognitive scientists use the term 'choice blindness' to explain such failures to detect mismatches between intention and outcome of a simple task [39]. Most surprisingly, in a choice blindness paradigm, participants are still able to offer arguments why their choice was the most logical. An interesting insight on this aspect is that drivers are better in perceiving travel speeds than travel times; perceived travel speeds seem to influence choice outcomes more than perceived travel time [33].

Previous experiences are known to serve as an anchor in the memory of drivers and strongly affect choice behaviour, in particular when bad experiences are involved [11, 20]. Loss aversion refers to the fact that people treat gains and losses differently as they tend to be more sensitive to decreases in wealth than increases, whereas people become less sensitive for every marginal gain or loss [18, 25]. In general, bad experiences involving loss, weigh two times a similar size good experience involving a gain [12]. Figuratively, good experiences create a certain 'acceptability-buffer', which may be emptied again by far less bad experiences (e.g. unacceptable DTM measures). In the mind of the driver the reference point determines to a large extent how things are valued. Earlier research concluded that the perception of the reference point in the mind of the driver is vague and fuzzy rather than crisp; they may not necessarily consider their actual experience to be the reference point [20].

To value a choice option or a change in any of its attributes, the option and/or its attributes need to be within the area of interest of an individual. As a result of driver's bounded rationality there are multiple factors which narrow this area of interest and make drivers appear indifferent concerning the evaluation of alternatives. For example habitual behaviour, which evolves in trips that are often repeated and causes cognitive processes to reach automaticity and eventually result in making choices in a more or less mindless fashion [10, 40]. Besides, drivers tend to be near-sighted which means that experiences of the previous day as well as short-term gains dominate choice processes [27]. Satisfying behaviour, stating that people are happy with a good solution instead of finding the best solution, is regarded as another major cause for drivers' indifference [10, 27]. It means that humans tend to minimise their cognitive efforts, and follow simple heuristics to reach decisions which are both satisfactory and sufficient, especially under uncertainty and time constraints [9, 33]. Empirical research on the indifference band showed that drivers may be uninterested in other choice options until their current situation worsens by 22% (e.g. extra travel time), or a choice alternative improves by 22% [9].

### 3.3 Decision

Changes in traffic conditions may be observed and correctly valued or not, but do they provide sufficient motive to affect the decision outcome? Generally, studies on decision behaviour focus on decision outcomes, apart from few exceptions which shifted interest to the analysis of underlying cognitive mechanisms. Such studies, for example showed that drivers think much more strategically than usually presumed [41, 42]. Based on the analysis of verbal reports, at least four decision strategies can be considered: the comparison strategy, the exploitation strategy, the exploration strategy and the anticipation strategy [41]. The great diversity in applied strategies proves that a certain level of awareness and acceptance of changes affect choice decisions. Another study showed that route switching occurs more frequently when the traffic conditions fluctuate randomly than when they are stable [9]. This type of behaviour is largely influenced by risk attitude (i.e. risk aversion and risk seeking), which determines the amount of risk somebody is willing to take. Many factors such as travel purpose, length of the trip and preferred arrival time have a big impact on a driver's risk attitude and choice outcomes (e.g. [27]). In terms of choice outcomes, roughly four route choice patterns can be distinguished: fixed choice, single trial, preferred switching and random switching [40].

## 4 Numerical example

This section illustrates by means of a numerical example the principles of effective control space and its implications for DTM and the resulting system performance. The objective of applying the effective control space framework is to move away from user equilibrium (UE) state and thereby improve system performance. Through identification of indifference bands the resulting effective control space will be determined. It is important to note that the purpose of the examples is illustrative and therefore simplified. They are based on the assumption that the indifference bands are constant and known, while the decision of a driver against a change is taken as a one-off process. Follow-up research should bring finer details to further improve the framework suggestions are given in Section 4.

Consider a network as shown in Fig. 4. There are two origin-destination (OD) pairs: A–B and C–D, with fixed demands of 2000 and 1000 vehicles per hour, respectively. Two routes exist from A to B: a north route (R1) and a south route (R2). From C to D there is only one route (R3). R1 and R3 intersect at a signalised intersection. The traffic signal has a cycle length of $C$, with an effective green time of $g$ for R1 and an effective green time $C$–$g$ of for R3 (thus assuming no lost time because of all-red time). Route travel times consist of link travel times and intersection delays. Bureau of Public Roads (BPR) function is adopted for link travel times, with the form

$$tt = \left[1 + \alpha\left(\frac{f}{F}\right)^{\beta}\right]T \tag{1}$$

where $tt$ is the actual link travel time, $f$ is the actual link flow, $F$ is the link capacity, $T$ is the free flow travel time and $\alpha$ and $\beta$

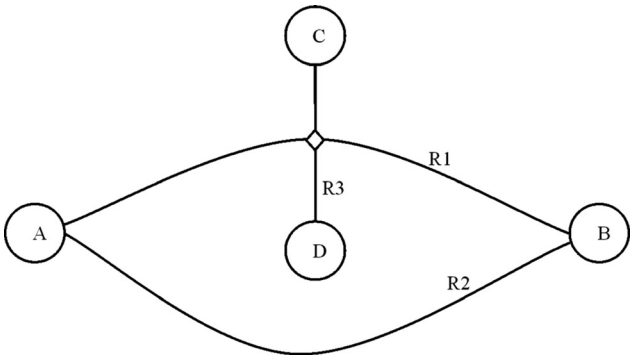


**Fig. 4** *Two-OD network with three routes*



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are the coefficients. Delays at the intersection are assumed to follow the function (note here that this delay function follows the Webster formula; the formula may not apply in practice when the saturation level is high)

$$\text{delay} = \frac{(1-\lambda)^2}{2(1-\rho)}C \tag{2}$$

where the average delay for a movement, delay, is dependent on its effective green ratio $\lambda$ and the flow saturation rate $\rho$. As a result, the route travel times are given as

$$t_1 = \left[1 + \alpha\left(\frac{f_1}{F_1}\right)^{\beta}\right]T_1 + \frac{\left(1-g/C\right)^2}{2\left(1-f_1/F_1\right)}C \tag{3}$$

$$t_2 = \left[1 + \alpha\left(\frac{2000-f_1}{F_2}\right)^{\beta}\right]T_2 \tag{4}$$

$$t_3 = \left[1 + \alpha\left(\frac{1000}{F_3}\right)^{\beta}\right]T_3 + \frac{\left(g/C\right)^2}{2\left((1-1000)/F_3\right)}C \tag{5}$$

Consider the case where $\alpha = 0.15$, $\beta = 4$, $T_1 = 5$ min, $T_2 = 6$ min, $T_3 = 5$ min, $C = 60$ s and $F_1 = F_2 = F_3 = 1800$. The traffic system then has two degrees of freedom:

- $g$ (seconds): determined by the traffic network manager;
- $f_1$: determined by the behaviour of the drivers.

The state of the traffic system can then be represented by these two variables, $(g, f_1)$.

### 4.1 System optimal (SO) and UE

Different settings of $(g, f_1)$ result in different system performances. On the one hand, DTM aims to reduce the system travel time, $T$, as much as possible, by changing the signal setting $g$. On the other hand, the drivers want to reduce their own travel time, by switching route and thus changing $f_1$, through which process $|t_1 - t_2|$ will become as small as possible.

The system travel time is computed as

$$T(g, f_1) = f_1 t_1 + (2000 - f_1)t_2 + 1000t_3 \tag{6}$$

The SO is achieved when the system travel time is minimised, through changing the signal setting and the route choice. This is given by the following programme

$$\min_{f_1, g} T \tag{7}$$

$$\text{s.t.} \begin{cases} 0 \le f_1 \le 1800 \\ 0 \le g \le 1 \end{cases}$$

The solution of SO lies at $(g, f_1) = (34.556, 1133)$ (Table 1). Other combinations of $(g, f_1)$ will have higher system travel times. This is illustrated by the contour chart in Fig. 5. Note here that in reality the SO scenario is unlikely to occur, because drivers' actual route choices are not based on the SO principles.

UE occurs when $t_1 = t_2$, that is, the travel times on R1 and R2 are equal. The gap function, defined as

$$H(g, f_1) = |t_1 - t_2| \tag{8}$$

describes how far away a system state is from the equilibrium condition. It is easy to see that $H(g, f_1) = 0$ if and only if $(g, f_1)$ is a UE state. The SO solution $(g, f_1) = (34.556, 1133)$ is not UE because it has a $|t_1 - t_2|$ of 41 s (Table 1). Given the signal design of $g = 35$ s, the UE condition is achieved at $(g, f_1) = (35, 1540)$ (Table 1). Under other signal designs, the UE solution will change accordingly. The contour chart in Fig. 6 illustrates the location of different combinations of $(g, f_1)$ that fulfil the UE condition; they are located within the thin stripe that characterises the curve $H(g, f_1) \le 2$ s, which is surrounded by two other stripes characterising $2 \le H(g, f_1) \le 4$.

**Table 1** Scenarios of system variables and performance measurements

| Scenarios | System variables | | System performance | |
|---|---|---|---|---|
| | $g$, s | $f_1$ | $T$, min | $\lvert t_1 - t_2 \rvert$, s |
| SO | 34.556 | 1133 | 16762 | 41 |
| UE under SO design ($g = 35$ s) | 35 | 1540 | 17460 | 0 |
| scenario 1A: if we increase $g$ by a few seconds without drivers reacting to the change, the system is better off | 36 ( + 1) | 1540 | 17410 ( − 50) | 2.9 |
| | 37 ( + 2) | 1540 | 17363 ( − 97) | 5.6 |
| | 38 ( + 3) | 1540 | 17320 ( − 140) | 8.2 |
| | 39 ( + 4) | 1540 | 17280 ( − 180) | 10.7 |
| | 40 ( + 5) | 1540 | 17244 ( − 216) | 13.0 |
| scenario 1B: if we increase $g$ by a few seconds and drivers react by switching route (to UE condition), the system is worse off | 36 ( + 1) | 1554 ( + 14) | 17481 ( + 21) | 0 |
| | 37 ( + 2) | 1568 ( + 28) | 17503 ( + 43) | 0 |
| | 38 ( + 3) | 1582 ( + 42) | 17528 ( + 68) | 0 |
| | 39 ( + 4) | 1596 ( + 56) | 17554 ( + 94) | 0 |
| | 40 ( + 5) | 1609 ( + 69) | 17576 ( + 116) | 0 |
| scenario 2A: if we decrease $g$ by a few seconds without drivers reacting to the change, the system is worse off | 34 ( − 1) | 1540 | 17514 ( + 54) | 2.9 |
| | 33 ( − 2) | 1540 | 17572 ( + 112) | 5.9 |
| | 32 ( − 3) | 1540 | 17633 ( + 173) | 9.1 |
| | 31 ( − 4) | 1540 | 17698 ( + 238) | 12.4 |
| | 30 ( − 5) | 1540 | 17766 ( + 306) | 15.8 |
| scenario 2B: if we decrease $g$ by a few seconds and drivers react by switching route (to UE condition), the system is better off | 34 ( − 1) | 1526 ( − 14) | 17441 ( − 19) | 0 |
| | 33 ( − 2) | 1512 ( − 28) | 17424 ( − 36) | 0 |
| | 32 ( − 3) | 1497 ( − 43) | 17403 ( − 57) | 0 |
| | 31 ( − 4) | 1482 ( − 58) | 17384 ( − 76) | 0 |
| | 30 ( − 5) | 1467 ( − 73) | 17366 ( − 94) | 0 |


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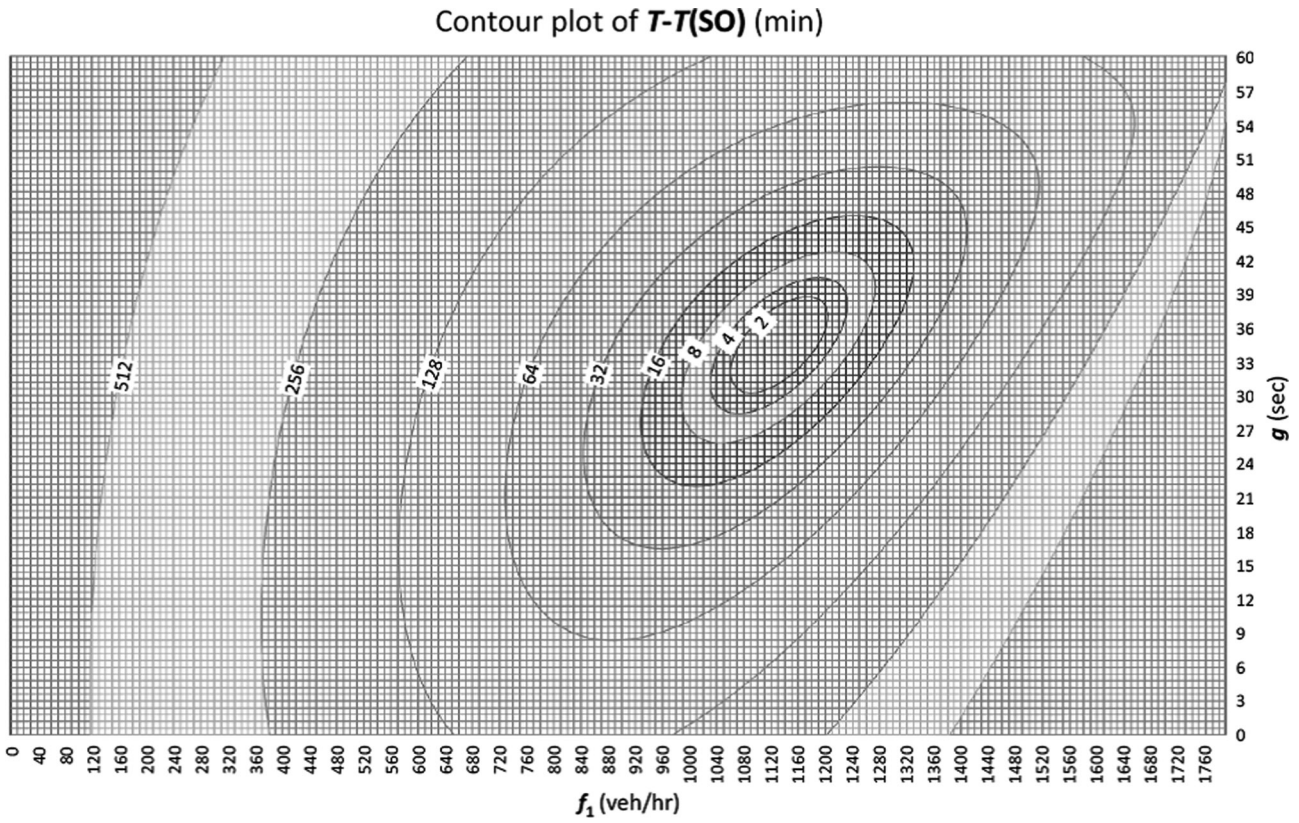


**Fig. 5** *Contour plot of T–T(SO) (min), that is, the system travel time T minus the system travel time at SO, T(SO)*
The log-scale of base 2 is chosen for better visual presentation of the wide range of T–T(SO)

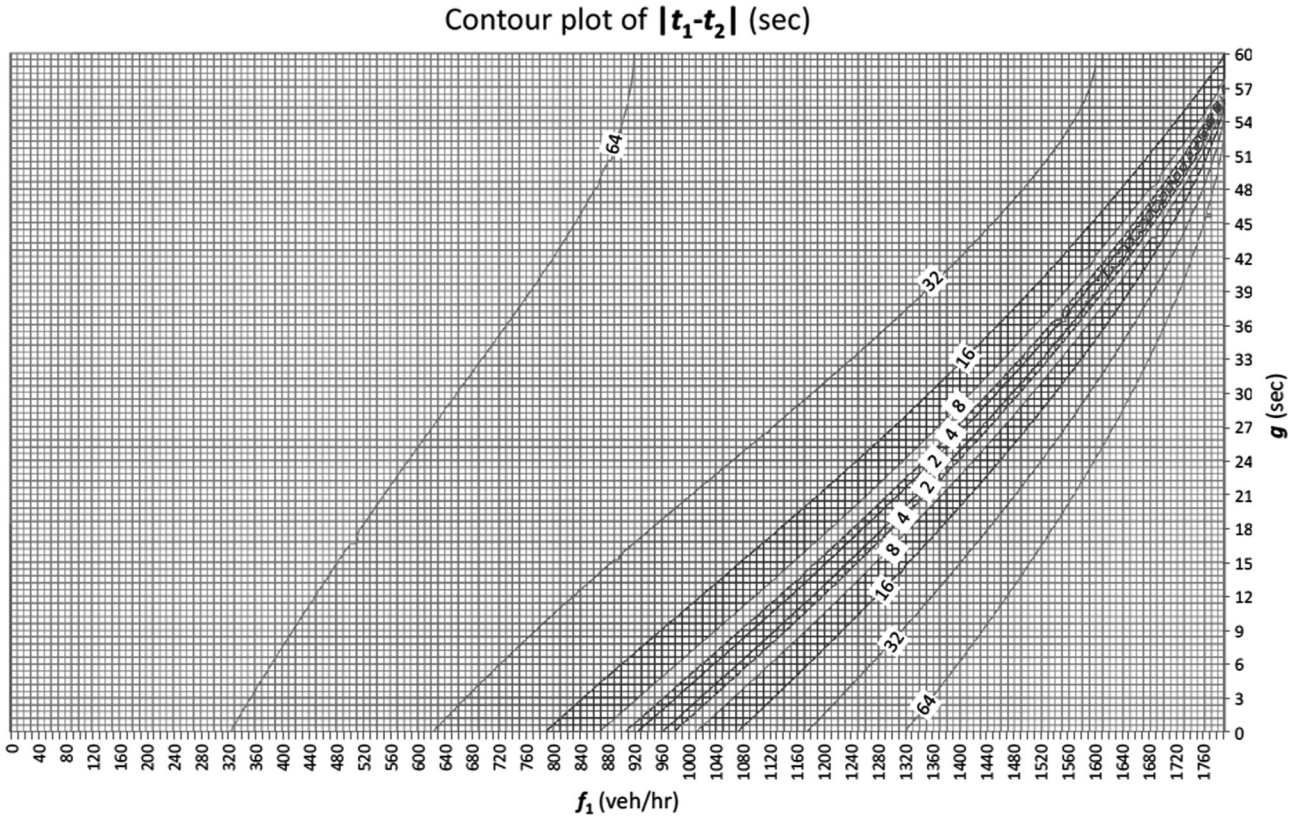


**Fig. 6** *Contour plot of travel time differences between R1 and R2, $|t_1 - t_2|$ (seconds)*
The log-scale of base 2 is chosen here for a better visual presentation



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**Table 2** Scenarios of management measures/changes and their outcome

| Scenarios | Change | Driver response | System travel time | UE condition? |
|---|---|---|---|---|
| 1A | increase $g$ | no reaction | decrease | no longer UE |
| 1B | increase $g$ | route switching | increase | new UE |
| 2A | decrease $g$ | no reaction | increase | no longer UE |
| 2B | decrease $g$ | route switching | decrease | new UE |

### 4.2 Scenarios of network changes and behavioural responses

Consider the current scenario of the traffic network at $(g, f_1) = (35, 1540)$ (a UE state). This situation is not optimal for the system. From a DTMs point of view, the signal setting may be changed to improve the system performance. There are two ways: either to increase $g$ (Scenario 1), or to decrease $g$ (Scenario 2). Drivers' response to this change falls into two categories: either they do not react to the change and keep with their original route choice (Scenario A), or they react by switching route and therefore settle down with the new UE solution (Scenario B). Four combinations of these scenarios, as well as their potential outcome on the system performances are shown in Table 1, with a schematic summary in Table 2.

### 4.3 Indifference to changes in network

In Scenarios 1A and 2A, drivers do not perceive the changes and stay on their current routes. The route flows remain the same before and after the changes. It implies that the system state will move along the straight line of current flow in Fig. 7. The system travel time, plotted in contours in Fig. 7, is apparently varying along this line: going up (Scenario 1A) reduces system travel time; going down (Scenario 2A) increases system travel time. Therefore, from the traffic manager's point of view, the green time should be increased.

In Scenarios 1B and 2B, drivers always notice and act on the changes and switch routes in search for a new UE. This implies that the system state will move along the UE curve in Fig. 7. The system travel time is again varying along this curve: going up (Scenario 1B) increases system travel time; going down (Scenario 2B) reduces system travel time. Therefore, from the traffic manager's point of view, the green time should be reduced.

Compare Scenarios A and B, whether drivers will notice the change or not leads to contrary conclusions. Effective control space comes into play in determining whether a change will be noticed or not: any changes within the indifference band are ignored; only changes exceeding the indifference band are recognised.

Consider the special case where the indifference band is $\pm 1.5$ s. The system travel time is reduced when $g$ is either increased by 1 s (scenario 1A) or decreased by 2–5 s (Scenario 2B). Decreasing $g$ by 5 s brings a larger reduction than increasing $g$ by 1 s. Therefore the traffic manager should decrease $g$ by 5 s.

Consider another special case where the indifference band is $\pm 2.5$ s. The system travel time is reduced when $g$ is either increased by 1–2 s (Scenario 1A) or decreased by 3–5 s (Scenario 2B). Increasing $g$ by 2 s is the most effective and should be preferred by the traffic manager.

These two cases illustrate the pivotal role of the indifference band in determining the system outcome of a network change. They also support the idea of effective control space as discussed earlier: unnoticeable

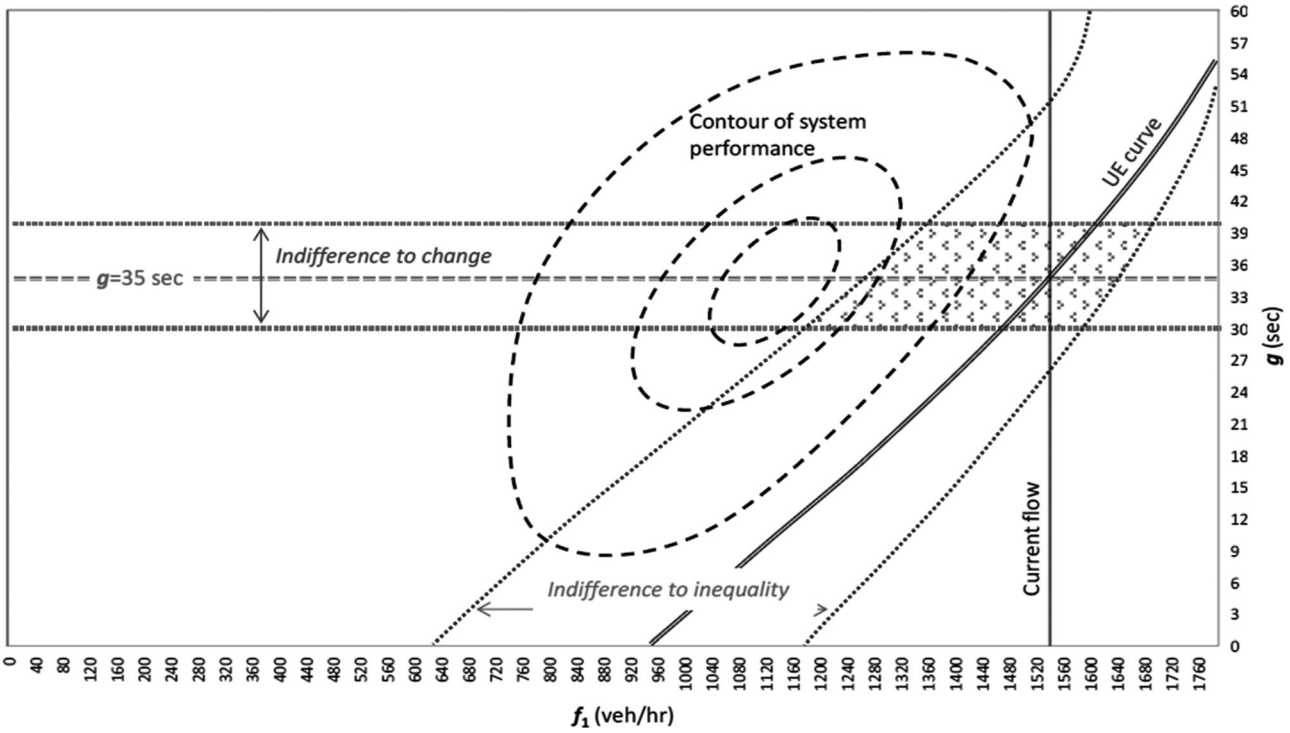


**Fig. 7** *Schematic plot of system state and indifference bands: indifference band of green time change (±5 s) and indifference band of travel time inequality (±32 s)*

The current system state is located at $g = 35$ s, $f_1 = 1540$ veh/h, which is a UE situation


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changes can be introduced which do not affect driver behaviour but may improve system performance; if behavioural response is needed for improving the system performance, then the introduced changes have to be noticeable.

### 4.4 Indifference to travel time inequality

The above discussion for Scenario B assumes that, once drivers notice the change, they have perfect information on the network situation and will strive for the new UE condition. This is often not the case. The indifference band in travel time inequality suggests that drivers are willing to accept, or simply not perceive, a non-UE situation if the difference in travel time between the alternative routes is within a threshold. The case of an indifference band equal 32 s is illustrated in Fig. 7: any system situation within this band is accepted by the drivers, in the same way that UE is accepted. For the given green time of $g = 35$ s, this implies that an acceptable system state can be any point that is on the straight line of $g = 35$ s and between the two curves representing indifference to inequality. The system travel time is apparently varying along this line segment. A natural question to ask is then how can the traffic manager 'move' the system state towards the left-hand side (lower $f_1$), which has lower system travel time.

When this indifference band in travel time inequality is combined with the indifference band of limited change awareness, an area of effective control space is formed (the shaded area in Fig. 7). Given the current system state of $(g, f_1) = (35, 1540)$, drivers are indifferent to any other (non-UE) system states within this area. The size of this area depends on the bandwidths of the two types of indifference: the wider the indifference bands are, the more effective control space the traffic manager has.

## 5 Conclusion and future research

Intuitively it is not right to assume that drivers respond to all changes in the characteristics of their choice alternatives caused by DTM which make their current choice suboptimal. Notions of bounded rationality and indifference bands acknowledged that, stating that factors like limited awareness, misperception and disinterest make that drivers only alter their choice if a change exceeds a certain threshold. In parallel road operators' interest in finding synergies between human factors and DTM recently started increasing [43]. The main purpose of this paper is to introduce a new dimension in the design of DTM strategies that may serve as a tool for road authorities. Taking indifference bands as a starting point, this paper introduced and demonstrated the concept of 'effective control space' which aims to increase the effectiveness of DTM. By means of a simple numerical example the implications of effective control space for DTM and the system state were explained. The green split of traffic lights was used as control mechanism and showed that application of effective control space can successfully steer the system towards its optimal state. We believe that the introduced framework is general and can also be applied to other DTM measures like dynamic speed limits, ramp metering installations, route guidance, road pricing etc. In all cases, effective control space helps to understand the feasible region of a measure (i.e. with minimal driver response), as well as a measure's minimum required effect to ensure response.

It is important that these mechanisms become part of traffic models to realistically capture choice behaviour in dynamic situations. However, it requires more empirical research to fully understand and quantify the underlying phenomena. To the best knowledge of the authors there is yet no related work that structures factors related to the philosophy of effective control space and shows practical application as done in this paper. To further improve the presented framework there are several avenues for future research worth mentioning. First of all, rather than a one-off process, the process of repeated decisions including learning and adjustment should be considered to more realistically capture day-to-day dynamics. Secondly and following the previous point, it is relevant to examine the implications of asymmetry in decision making and related irreversibility of network state. Thirdly, in a dynamic context the use of a probabilistic indifference band seems more opportune than a deterministic one. It mainly requires empirical research to determine such a distribution, which may also contribute to the improvement of for example random utility models and the definition of the random component in particular. Finally and as also pointed out by the referees, it is not always evident which strategy based on the effective control space yields the best outcome, especially not in a dynamic day-to-day context. Moreover, there might be important implications for solution uniqueness that need to be explored. Therefore a control strategy based on the proposed framework might be set up with the help of some optimisation approach, such as dynamic programming.

Future empirical research will involve a driving simulator experiment and a field study. The field study aims to investigate in a natural setting drivers' estimation of time and how accurately they are able to guess time intervals. Literature review showed that for such analysis field studies yield the most valid data as subjects are in their natural environment with same perceptions, behaviour and awareness as they normally have [44]. In the selected approach, subjects will be randomly selected and interviewed at the nearest down-stream intersection or parking area of the studied intersection or series of intersections. They will be asked about their waiting time experience and challenged to value this single experience in comparison to what they regard as average (their expectation). Objective data such as the actual waiting time will be collected for every individual user to allow study of the correlation between actual measurements and user perception. In addition, a driving simulator experiment will be set up for two reasons. First of all to evaluate if the findings from the field study can be reproduced in different conditions and collect more detailed evidence in order to formulate a general theory. Secondly to determine effective control space quantitatively and indicate the moment when drivers adapt their behaviour as the result of changing conditions. Together, the field study and driving simulator study gain a quantitative understanding of drivers' ability to detect changes and value them correctly as well as their response to these changes.

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