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Personalised optimal speed advice to cyclists approaching an intersection with uncertain green time

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I. Abstract

When travelling in urban areas with signalised intersections, cyclists are currently unable to optimize their speed profile according to their preferences. By integrating information from traffic signal phase and timing and cyclists' preferences, in this paper an algorithm is developed that generates personalised optimal speed advice for cyclists. Results from the simulation experiment indicate that in spite of stochastic nature of traffic light phase and timing, with the developed algorithm based on stochastic dynamic programming, an speed profile can be advised that meets the cyclist's preferences in terms of travel time, energy consumption, or the number of stops.

II. Introduction

Apart from the health benefits and economical justification, cycling is in many cases an effort and time-efficient mode of mobility in urban areas. Thanks to its contribution in reducing air and noise pollution as well as traffic congestion alleviation, cycling mode have become an important transport policy objective in many metropolitan cities. In bicycle-friendly cities with available cycling infrastructure, cycling has become a popular mode of transportation for many citizens. The Netherlands, and Denmark are the most bicycle-friendly countries in Europe and respectively, 36, and 23 percent of their residents use cycling as of mode of transport on a typical day [11]. Nonetheless, this number in Europe is only 8% [11]. Even in China, once known to be the kingdom of bicycle, this number falls at an average yearly rate of 5% [13]. Hence, in many cities around the world, considerable growth potential remains for bicycle use.

One important factor that disfavours the use of bicycle for daily commuting compared to the motorised vehicles, is the level of convenience that the users of the latter can benefit from. In addition to the unbalanced availability of the roads for motorised vehicles compared to bikes, the policy measures mostly prioritise other infrastructures like traffic lights in favour of motorised vehicles. That being so, providing a better level of convenience for cyclist is a wise and well-justified direction for promoting this mode of transportation. For that, the required measures are not limited to allocation of roads and amenities such as parking place [9], but also includes proper measures that helps cyclists to choose the route and speed profile that matches their preferences better and make the cycling more attractive.

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Cyclists may have different preferences based on their age, gender, physical condition, and aim of travel. They may have different tendency for the speed they chose, the energy they consume and the way they consume it, and the time they tend to spend. In addition to these factors, full stop at junctions due to red light is undesirable for most of the cyclists especially elderly as they need to get off and on the bike if they stop for the red light. Cyclists also need to use extra energy to pick up the speed they used to have prior to their stop at the intersection. As an example taken from [5], on a road with stop signs every 100 m, 500 watts of power required to keep the average speed of 5.6 m/s as 100 watts would get the same speed on a road without stop signs. Moreover, cyclists may suffer from the wrong decisions made based on their incomplete knowledge of the traffic light timing, including its uncertainties. They may accelerate towards the intersection when they see a green light, hoping to reach the intersection while the light is still green. In case of fail attempt, the cyclists have used unnecessary energy without passing the intersection on time.

To make the cycling more appealing, policy-makers in bicycle-friendly cities like Copenhagen and Amsterdam used the idea of green-waves for cyclists. The idea is to adjust the traffic light timing to favour cyclists. In Copenhagen, during rush hour, cyclists get a green wave with a speed of 20 km/h through the city, without the need to stop [1]. Similarly, in a road with 11 traffic lights in Amsterdam, cyclists with the average speed of 18 km/h can travel without any stop at the junctions [2]. However, favouring the cyclists over motorised vehicles is not always possible in big cities and may result in congestion of vehicles in roads. It may also conflicts with the public transport utilities in the cities.

Motorised vehicles may also suffer from the unwanted consequences of junction signalisation. Due to inaccurate prediction of traffic light timing, drivers may accelerate but still not reach the green light. Such manoeuvres increase the fuel consumption, brake wear, and emissions. The state of the art in wireless communication in recent years has persuaded the researchers to explore the treatment of these adverse effects of traffic lights. However, most of the attention in the literature is limited to cars, oppossed to bikes, and focuses on developing advanced driver assistance systems. Infrastructure-to-vehicle (I2V) and vehicle-to-vehicle (V2V) communication allow the vehicles to have information on the traffic signal timing. With this information, the driver assistance system can provide green light speed advise for the cars. Such speed advise systems aim to reduce energy consumption by generating a smooth speed trajectory and

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increasing the chance for catching a green light. This goal could be achieved in different ways. Model predictive control [3], dynamic programming [6], [7] or other optimization-based algorithms [4] have been developed to address eco-driving in urban traffic networks. Although the simulation-based results of these algorithms are promising in mitigating the aforementioned environmental and economical effects, their underlying assumption on the *fixed* traffic light timing makes the applicability of these algorithms in real-world questionable, as advanced traffic lights do not have fixed timing but are adaptive with respect to the traffic conditions. Interesting results have been developed in [6], where signal phasing probability is embedded in the cost function and *deterministic* dynamic programming is suggested for speed planning that reduce the idle time and increase the energy efficiency of the vehicles. Although, in [6], some level of uncertainty in signal timing is considered, however, the cycle time and structure of traffic light is assumed to be fixed. Moreover, the probability of green light is predicted only based on the current color (red or green) of the traffic light and the average length of the green light, but ignoring the time duration that the signal was showing the given color.

The unique contribution of this paper is the use of stochastic dynamic programming to provide speed advice planning for cyclists aiming to increase (1) the chance to catch the green light when they arrive at the intersection, (2) minimise energy consumption, (3) travel at preferred speeds, (4) minimise travel time, or a combination of these. The traffic lights at the intersection are assumed to change adaptively with the traffic condition and hence, the transition from one phase to the other is assumed to be stochastic. Therefore, the algorithm could be used for real-world application. The problem has been formulated as Markov Decision Process (MDP) and the associated transition probability matrix is assumed to be known. This is indeed not a strong assumption because this matrix can be extracted from historical data.

This paper is organised as follows. The system description is presented in the next section, which is followed by a description of the cyclists' preferences in Section IV-B. The formulation and algorithm for the optimal speed advice is presented in Section IV. A simulation case study with multiple scenarios is presented in Section V, which is followed by the concluding remark in Section VI.

III. System description

Our goal is to find a speed advice for the cyclists with the aim of favouring a behaviour that e.g. minimises the travel time, or avoids full stop at the intersection, or minimises the total energy used during the travel. We may also look for a behaviour that makes a trade-off between these targets. To provide such speed profile, it is not enough to have knowledge of the cyclist's position and speed. In addition to the cyclist's current state and knowledge of the cyclist's dynamics, information about the current state of the traffic signal, its structure and also the probabilities of the signal phase and timing are needed.

Let us start with characterising a cyclist's movement by its speed $v(k)$ (m/s), and its position $x(k)$ (m) with respect to the upstream end of the road that leads to the intersection, for time step k. By choosing the constant sampling time Δt (s), we can describe the kinematics of the bike by the following set of discrete-time equations:

$$\begin{aligned} x(k+1) &= x(k)+v(k)\Delta t+\frac{1}{2}u(k)\Delta t^2, \\ v(k+1) &= v(k)+u(k)\Delta t, \end{aligned} \tag{1}$$

where $u(k)$ (m/s^2) is the acceleration of the bike. Hence, let us define the cyclist's state in time step k as $s_\mathrm{c}(k) \in \mathscr{S}_\mathrm{c}$ where

$$s_\mathrm{c}(k) = (v(k), x(k)). \tag{2}$$

Clearly, $\mathscr{S}_\mathrm{c}$ is defined based on the constraints on the speed and position of the cyclist: $0 \le v(k) \le v^{\max}$ and $0 \le x(k) \le x^{\max}$, where $x^{\max}$ is the distance between the start and the end point. The state of the cyclist in time step $k+1$ will change according to (1) and as a result of acceleration $u(k) \in [u^{min}, u^{max}]$ that is the control input in this note. However, as already mentioned, this information is not enough to produce an optimal speed advice for the cyclist. It should be complemented with the prediction of the future signal phase and timing of the traffic light in the intersection.

An intersection is composed of multiple streams (also called movements), each is a unique combination of an incoming and a leaving travel direction. Streams at junctions may conflict, which means that the streams are not allowed to have green at the same time. Phase control of traffic lights determines the sequence and the time duration of each stream for using the conflict area. In Figure 1a, an intersection with 6 steams is depicted, where the streams are coded according to the Dutch standard. The flow diagram in Figure 1b exemplifies the sequence of prioritising streams in one cycle time for phase control of this intersection. Each block in this figure corresponds to a set of non-conflicting streams. Table I enumerates each block with the associated streams for this intersection. From Figure 1b, it is clear that B_4 can be reached either via B_1, B_2 or B_3. Depending on whether stream 8 or 2 ends earlier, one of the conflicting streams 3 or 9 can be given green before B_4 starts.

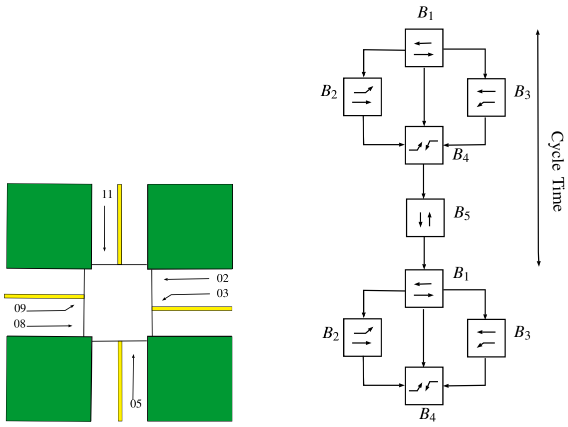
Block	B_1	B_2	B_3	B_4	B_5
Streams	(2,8)	(2,3)	(8,9)	(3,9)	(5,11)

TABLE I: Blocks and the associated streams' pairs

The duration of each block and also the transition from one block to the other is of stochastic nature. To model this transition in mathematical terms, let us define the state vector s_l from the state set $\mathscr{S}_l$ as follows to represent the status of the traffic light

$$s_l = (B_b, n_1, n_2). \tag{3}$$

In (3), $b \in \{1, \dots, N\}$ represents the current block selected from N possible blocks associated with the intersection. Accordingly, if $n_i^{\max}$ is the maximum number of time steps



(a) (b)

Fig. 1: A hypothetical intersection with its streams (a) and the corresponding flow diagram (b)

that light associated to the i-th stream in B_b can be green, $n_1 \in (0, n_1^{\max}]$ and $n_2 \in (0, n_2^{\max}]$ indicate how long a light has been green for the first and the second stream of B_b respectively. As an example, according to Table I associated with the intersection in Figure 1a, the triple $(B_3, 10, 5)$ refers to the state that pair of streams (8,9) have the permission to use the intersection and the lights associated to these two streams have been green for 10 and 5 time steps respectively. Having the states associated with the signal timing and phase as in (3), their evolution can be defined by specifying the transition probability $p(s_l \mid s_l')$ for all s and s' in $\mathscr{S}_l$ as follows:

$$p(s_l \mid s_l') = Pr\{S_l(k+1) = s_l \mid S_l(k) = s_l'\}. \tag{4}$$

The one-step dynamics (4) displays the Markov property of the process as it enables us to predict the next state of the traffic light independent of the past and by only knowing the current state. Obviously, the transition probabilities depend on the signal control strategy and the typical demand levels. In the real world, the transition probabilities for all s_l and s_l' in $\mathscr{S}_l$ can be extracted from historical data.

For mathematical formulation of the problem, let us introduce state vector $s(k)$ as

$$s(k) = \big(s_l(k), s_c(k)\big), \tag{5}$$

that concatenates $s_l(k)$ and $s_c(k)$ defined in (3) and (2) respectively. Therefore, the evolution of state s can be described by the deterministic cyclist kinematics in (1) using the acceleration input, and the stochastic traffic signal evolution of (4).

IV. Speed Advice

Having the system described as in Section III, the goal is to design a personalised speed advice based on the cyclist's preference. The problem can be formulated as a finite horizon Markov Decision Process where the state of the system is defined as in (5). For this stochastic process, Stochastic Dynamic Programming (DP) summarised in the following subsection is used to define the optimal policy π^* [10] .

A. Stochastic dynamic programming

A policy π in DP is a mapping from states to actions, $\pi : S \to A$, and it determines which action should be executed at each state. After execution of an action a, a transition from state s' to state s will be made. This transition is rewarded with a scalar called reward r, obtained from the reward function R and reflects on the quality of this transition, in terms of the selected action as well as the new state s that this transition leads to.

To find the optimal policy, DP makes use of a state-dependent function called value function $V^\pi(s)$. It represents how *good* it is, in terms of expected return, to be in state s and follow policy π thereafter. The value function $V^*(s)$ of the optimal policy is defined as the one that $\forall s \in \mathscr{S}$:

$$V^*(s) = \max_\pi V^\pi(s). \tag{6}$$

The value function of the optimal policy will satisfy the Bellman optimality equation expressed as follows:

$$V^*(s) = \max_{a \in \mathscr{A}(s)} \sum_{s',r} p(s', r | s, a) \Big(r + \gamma V^*(s')\Big), \tag{7}$$

where γ is the discount factor and $\mathscr{A}(s)$ is the set of all actions possible to take at state s; all the possible values for acceleration that cyclist with the current state s can take without violating constraints on the speed and acceleration. Thanks to (7), optimal policy can be found in an iterative procedure using algorithms like the value iteration algorithm expressed in Algorithm 1. The update rule in Algorithm 1 depends on the reward function R, $V(s')$, and the transition probability $p(s', r | s, a)$ that describes the evolution of the process from state s to state s' taking action a and receiving reward r.

As it is mentioned, the reward function R indicates what we want accomplished in our problem. Hence, depending on the selected performance criterion, or a combination of them, the reward function may vary. Therefore, we need to first identify the cyclist preferences and then properly relate to these preferences in the reward function.

B. Cyclist preferences and the reward function

Cyclists may have different preferences, depending on their age, gender, physical condition, how much they are in a hurry, and possibly other personal preferences. In the following, we discuss some of the typical preferences.

1) Minimising required cycling energy: Rate of energy usage or the cycling power P_{cyc} produced by the rider is composed of five terms associated with the acceleration, P_{ac}, aerodynamic drag P_{dr}, tire rolling resistance P_{tr}, and also change in the road slope P_{rd} [8]. Hence, if the effective headwind speed is $v_{\mathrm{w}}(m/s)$, the simplified equation of output power required for cycling at speed v and having acceleration

u takes the following form:

$$P_{\mathrm{cyc}}(k) = P_{\mathrm{ac}}(k) + P_{\mathrm{dr}}(k) + P_{\mathrm{tr}}(k) + P_{\mathrm{rd}}(k) \quad (8)$$

$$= \underbrace{(m+m_{\mathrm{w}})u(k)v(k)}_{P_{\mathrm{ac}}} + \underbrace{0.5\rho v(k)\big(v(k)+v_{\mathrm{w}}(k)\big)^2 C_{\mathrm{dr}}F}_{P_{\mathrm{dr}}}$$

$$+ \underbrace{C_{\mathrm{tr}}mgv(k)}_{P_{\mathrm{tr}}} + \underbrace{mgv(k)e(k)}_{P_{\mathrm{rd}}} \quad (9)$$

where m (kg) is the mass of the bicycle and the rider, m_w (kg) is the effective rotational mass of the wheels and the tyres, g (m/s^2) is the acceleration due to gravity, F (m^2) is the frontal surface, ρ (kg/m^3) is the density of the air, e is the slope of the road, and C_{dr} and C_{tr} are the coefficients of the aerodynamic drag, and rolling resistance respectively. To generate a speed trajectory which reflects on the energy consumption of the cyclist, in the reward function, we can use (8) to penalise energy consumption in each time interval.

2) Minimising total travel time: Some cyclists may prefer to minimise their total travel time to reach their destinations. The gain in travel time for a cyclist is expected when the cyclist can travel faster (than normally) at the right moments e.g. just before it gets red, to catch the end of green, or just before the end of red, when he/she knows that he/she does not have to slow down, or can accelerate in advance because the light will be green when the cyclist reaches to the intersection. To reflect on the total travel time in the optimisation algorithm, we can penalise taking each control action with a constant negative number $-R_t$ in the reward function. Since in our problem, the control action is taken each Δt seconds, the lower the number of total control actions, the lower the total travel time.

3) Avoiding full stop at the intersection: As it is mentioned earlier, due to physical and also psychological reasons, majority of cyclists dislike full stop at the intersection. To dissuade the algorithm from taking actions leading to reaching to the intersection when the light is red, we penalise stoping at the junction with constant negative number $-R_r$.

4) Avoiding very low speed: Cyclists may feel unstable if they cycle in a very low speed. Hence, by use of a speed dependant function $-f_s(v)$, the algorithm should discourage actions leading to such situation. $f_s(v)$ should be chosen to have respectively higher value in lower speed. We have selected $f_s(v)$ to be $\kappa/(v+\kappa)$ in this paper where κ is a constant parameter.

5) Cycling at a desired speed: Many of cyclists prefer a desired speed v_d to cycle in. To discourage the algorithm from taking actions which make the cyclist's speed deviates from the desired speed, a function $-f_d(v,v_d)$ can be added to the reward function to penalise this divergence. Qualitatively, $f_d(v,v_d)$ should have low value when the speed is close to v_d and gradually increase as we get far from v_d. A possible choice for $f_d(v,v_d)$ selected in this paper is $(v-v_d)^2$.

6) Safety: The algorithm should always prevent the case when the cyclist pass the junction while the light is red. Hence, these situations are penalised with a very high negative values $-R_s <<< -R_r$. Note that having this safety factor in the cost function can result in conservative actions.

In order to encounter all the above preferences for the cyclist and make a trade-off between them, let us define the reward function R as:

$$R = \begin{cases} R_c - W_1 P^{\mathrm{norm}}, & \{\forall s \in \mathscr{S} | x \neq x^{\max}\}, \\ 0, & \{\forall s \in \mathscr{S} | x = x^{\max}\}, \end{cases} \quad (10)$$

with R_c defined as:

$$\begin{cases} -R_t - W_2 f_s - W_3 f_d^{\mathrm{norm}} - R_r, & \text{If cyclist waiting behind the red light,} \\ -R_t - W_2 f_s - W_3 f_d^{\mathrm{norm}} - R_s, & \text{If cyclist passes the junction and the light is red,} \\ -R_t - W_2 f_s - W_3 f_d^{\mathrm{norm}} & \text{Otherwise} \end{cases} \quad (11)$$

where P^{norm} and f_d^{norm} are the normalised value of P_{cyc} and f_d respectively. The weights W_1, W_2 and W_3 are introduced in the reward function to make the desired balance between the preferences. Moreover, the color of the light at the intersection needed in (11) can be determined from the term b in s_l defined in (3). As an example, let us consider a cyclist traveling in the same direction as direction 02 illustrated in Figure 1a. Hence, according to Table I, the light for this cyclist is green if when reached at the intersection, $B_b \in \{B_1, B_2\}$, otherwise, the light is red.

```
Initialize the value function V(s)=0 ∀s ∈ 𝒮;
δ = 10^(−8), Δ = 0;
while Δ > δ do
    Δ = 0;
    forall the s ∈ 𝒮 do
        vs ← V(s);
        V(s) ← max_{a∈𝒜(s)} Σ_{s′,r} (p(s′,r|s,a)(r + γV(s′)));
        Δ ← max(Δ, |vs − V(s)|)
    end
end
forall the s ∈ 𝒮 do
    π*(s) = argmax_{a∈𝒜(s)} Σ_{s′,r} (p(s′,r|s,a)(r + γV(s′)))
end
```

Algorithm 1: Value iteration algorithm

V. CASE STUDY

The case study aims at evaluating different speed profiles of cyclist and their effects on travel time, energy consumption and also probability of catching green when the cyclist is at the junction. For the case study, we simulate a cyclist traveling in direction of stream 02 towards a junction shown in figure 1a, but in general, the direction of the cyclist can be known if the bike is equipped with a navigation system. The total travel distance is assumed to be 110 meters and the intersection is located 70 meters from the start point. The phase and timing of the traffic light is assumed to be stochastic. The parameters defined in (8) have been taken from [8] and can be found in Table VI. Note that if the wind speed and the slope are not zero, proper identification algorithm should be used to find their values. Moreover, $v^{\max}$,

$p(s_l \mid s_l')$ — s_l / s_l'	$(B_1,\ n_1^+,\ n_2^+)$	$(B_2,\ n_1^+,\ 1)$	$(B_3,\ n_1^+,\ 1)$	$(B_4,\ 1,\ 1)$
$(B_1,\ 0 < n_1 \le n^{min},\ 0 < n_2 \le n^{min})$	1	0	0	0
$(B_1,\ n^{min} < n_1 \le n^{min}+3,\ n^{min} < n_2 \le n^{min}+3)$	0.8	0.2	0	0
$(B_1,\ n^{min}+3 < n_1 \le t^{max},\ n^{min}+3 < n_2 \le n^{max})$	0.1	0.7	.2	0
$(B_1,\ n_1 = n^{max},\ n_2 = n^{max})$	0	0	0	1

TABLE II: Transition probability of s_l' when $B_b = B_1$

$p(s_l \mid s_l')$ — s_l / s_l'	$(B_2,\ n_1^+,\ n_2^+)$	$(B_4,\ n_2^+,\ 1)$
$(B_2,\ 0 < n_1 < n^{max},\ n_2)$	0.3	0.7
$(B_2,\ n_1 = n^{max},\ n_2)$	0	1

TABLE III: Transition probability $p(s_l|s_l')$ when $B_b = B_2$

$p(s_l \mid s_l')$ — s_l / s_l'	$(B_4,\ n_1^+,\ n_2^+)$	$(B_5,\ 1,\ 1)$
$(B_4,\ 0 < n_1 \le t^{min},\ n_2 < n^{max})$	1	0
$(B_4,\ n_1 \le n^{max},\ 0 < n_2 < n^{min})$	1	0
$(B_4,\ n^{min} < n_1 < n^{max},\ n^{min} < n_2 < n^{max})$	0.3	0.7
$(B_4,\ n_1 = n^{max},\ n_2)$	0	1
$(B_4,\ n_1,\ n_2 = n^{max})$	0	1

TABLE IV: Transition probability $p(s_l|s_l')$ when $B_b = B_4$

$p(s_l \mid s_l')$ — s_l / s_l'	(B_5, n_1^+, n_2^+)	$(B_1, 1, 1)$
$(B_5, 0 < n_1 \le n^{min}, 0 < n_2 \le n^{min})$	1	0
$(B_5, n^{min} < n_1 \le n^{min}+3, n^{min} < n_2 \le n^{min}+3)$	0.8	0.2
$(B_5,\ n^{min}+3 < n_1 \le n^{max},\ n^{min}+3 < n_2 \le n^{max})$	0.2	0.8
$(B_5, n_1 = n^{max}, n_2 = n^{max})$	0	1

TABLE V: Transition probability $p(s_l|s_l')$ when $B_b = B_5$

m	ρ	C_{dr}	A	C_{tr}	m_{w}	e	v_{w}
95	1.226	1.2	0.616	.008	0.95	0	0

TABLE VI: Values of parameters in (8)

$n^{\min}$, $n^{\max}$, $u^{\min}$, $u^{\max}$ and γ have been chosen as 7.75 m/s, 4, 10, -0.75, 0.75 and 0.98 respectively and the sets of speed and acceleration have been discretised with step size of 0.25.

We consider three scenarios in this case study. In scenario I that we call No-control scenario, the cyclist does not follow any optimal speed plan and if the rider does not face the red light at the junction, he/she travels the whole distance with a constant speed, which is the same as his/her initial speed. If the cyclist is forced to stop at the junction due to the red light, the rider's behaviour is simulated as follows: in each time step, the cyclist chooses deceleration of -0.5 m/s^2 if he/she is at least 25 m far from the junction and sees the red light. If the light is still red when the rider reaches the intersection, the cyclist will have to stop. Moreover, when the cyclist who is waiting behind the red light gets permission to pass the junction, he/she will accelerate based on a two-term sinusoidal model taken from [12] to reach the desired speed the rider initiates the travel with.

In the second and third scenarios, the cyclist's acceleration is controlled through the algorithm explained in Section IV. In order to implement the algorithm, we first need to describe the transition probability matrix of the signal phase and timing. In this note, practical values have been chosen to represent this transition probability in a hypothetical intersection depicted in Figure 1a. Table II-V exemplify a transition distribution of s_l, defined in (3) and (4). Transition probability in B_3 is similar to the one in Table III. In these tables, we use n_i^+ to indicate $n_i + 1$.

As it is already mentioned, the speed advice can be customised using the proper weights in the reward function. In scenario II called Power-Pref, we find a speed advice for a cyclist who prefers not to stop at the junction but also cares about the power output needed to use during cycling. In scenario III named as Speed-Pref, we consider a cyclist with the desired speed of 5.5 (m/s) who also dislikes being stop by the red light. To reflect on these cyclist's preferences in each scenarios, let us choose the weights and parameters in (10) and (11) as shown in Table VII. The experiment has been repeated 20000 times for each scenario. In each time, respecting the possible speed range, normal distribution with

	W_1	W_2	W_3	R_r	R_t	R_s
Scenario II (Power-Pref)	10	3	0	15	0.1	10^5
Scenario III (Speed-Pref)	0	3	10	15	0.1	10^5

TABLE VII: Weights used in scenarios II and III

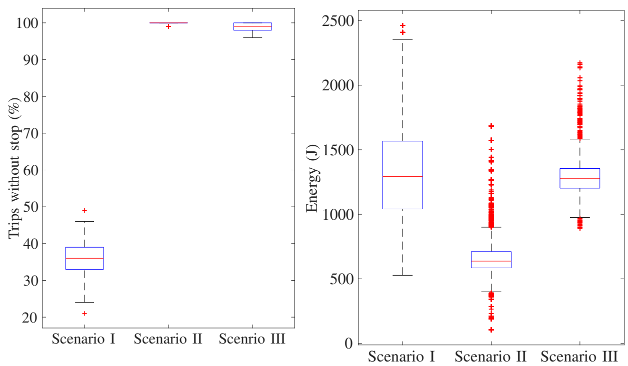


Fig. 2: The rate of trips without stop and power output for the three scenarios

mean of 5.3 and standard deviation of 1.2 has been used to randomly choose the initial speed of the cyclist [12] while uniform distribution has been used to randomly select the initial phase, and also the initial timing for the traffic light. We have used multiple indices like energy consumption, travel time, average speed, and rate of full stops to compare the scenarios. The latter indicates the percentage of the experiments in which the cyclist needs to stop during his/her travel. The results of the simulations have been compared in Figure 2 and Figure 3 and indicate the applicability of the suggested method to generate a customised speed advice. From Figure 2, it is clear that the suggested speed advice can significantly decrease the need for full stop for the cyclist. As expected, Scenario II has the lowest energy consumption among the three. Moreover, the distribution of the speed in Scenario III is the closest to the desired speed. The success rate in Scenario I is very low and with high probability,

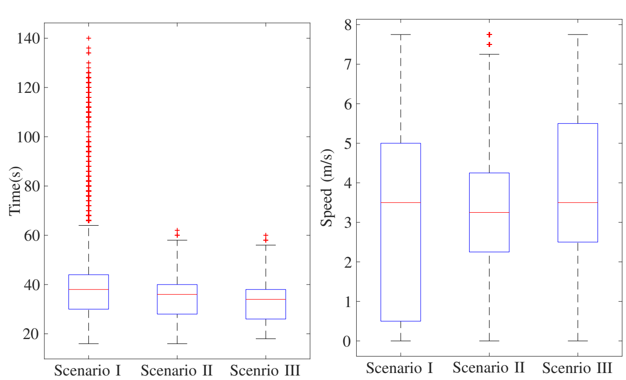


Fig. 3: Travel time and speed for the three scenarios

the cyclist needs to wait behind the red light to pass the junction. Hence, this scenario has the highest travel time. Moreover, as it is already mentioned, retaining the constant speed for the cyclist after full stop is a hassle and requires extra energy consumption which is inferred in relatively high energy consumption profile of Scenario I in Figure 2.

VI. Conclusions and Future Direction

An approach is developed for dynamic speed advice to cyclists who approach a traffic signal with uncertainty in its timing. The approach is based on stochastic dynamic programming, and can take into account various cyclist objectives, such as minimising energy consumption, the number of stops, or travel time, or the preference to travel at some speed. The transition probabilities of traffic light phase and timing are modeled as a Markov Decision Process. Three scenarios are evaluated 20000 times in simulation to assess the viability of the suggested method and evaluate its performance as a customised speed advice. In future work, speed advice for the cyclist to achieve green wave for multiple intersection will be investigated. We will also analysis the sensitivity of the algorithm to compliance of the cyclists. Implementation of the algorithm in real field is the next experimental step.

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