A multi-agent system for distributed smartphone sensing cycling in smart cities

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Abstract

Purpose – The purpose of this paper is to propose a distributed smartphone sensing-enabled system, which assumes an intelligent transport signaling (ITS) infrastructure that operates traffic lights in a smart city (SC). The system is able to handle priorities between groups of cyclists (crowd-cycling) and traffic when approaching traffic lights at road junctions.

Design/methodology/approach – The system takes into consideration normal probability density function (PDF) and analytics computed for a certain group of cyclists (i.e. crowd-cycling). An inference model is built based on real-time spatiotemporal data of the cyclists. As the system is highly distributed – both physically (i.e. location of the cyclists) and logically (i.e. different threads), the problem is treated under the umbrella of multi-agent systems (MAS) modeling. The proposed model is experimentally evaluated by incorporating a real GPS trace data set from the SC of Melbourne, Australia. The MAS model is applied to the data set according to the quantitative and qualitative criteria adopted. Cyclists' satisfaction (CS) is defined as a function, which measures the satisfaction of the cyclists. This is the case where the cyclists wait the least amount of time at traffic lights and move as fast as they can toward their destination. ITS system satisfaction (SS) is defined as a function that measures the satisfaction of the ITS system. This is the case where the system serves the maximum number of cyclists with the fewest transitions between the lights. Smart city satisfaction (SCS) is defined as a function that measures the overall satisfaction of the cyclists and the ITS system in the SC based on CS and SS. SCS defines three SC policies (SCP), namely, CS is maximum and SS is minimum then the SC is cyclist-friendly (SCP1), CS is average and SS is average then the SC is equally cyclist and ITS system friendly (SCP2) and CS is minimum and SS is maximum then the SC is ITS system friendly (SCP3).

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Findings – Results are promising toward the integration of the proposed system with contemporary SCs, as the stakeholders are able to choose between the proposed SCPs according to the SC infrastructure. More specifically, cyclist-friendly SCs can adopt SCP1, SCs that treat cyclists and ITS equally can adopt SCP2 and ITS friendly SCs can adopt SCP3.

Originality/value – The proposed approach uses internet connectivity available in modern smartphones, which provide users control over the data they provide to us, to obviate the installation of additional sensing infrastructure. It extends related study by assuming an ITS system, which turns traffic lights green by considering the normal PDF and the analytics computed for a certain group of cyclists. The inference model is built based on the real-time spatiotemporal data of the cyclists. As the system is highly distributed – both physically (i.e. location of the cyclists) and logically (i.e. different threads), the system is treated under the umbrella of MAS. MAS has been used in the literature to model complex systems by incorporating intelligent agents. In this study, the authors treat agents as proxy threads running in the cloud, as they require high computation power not available to smartphones.

Keywords Smart city, Crowd-cycling, Distributed smartphone sensing, Intelligent Transport signaling system, Multi-agent system

Paper type Research paper

1. Introduction

In our previous work (Anagnostopoulos *et al.*, 2016), we described a system that senses cyclists and prioritizes them. Such a system, which favors cyclists, can potentially improve enjoyment and reduce accidents because of crossing a red light (B-icycle, 2015), thereby encouraging people to cycle more (Miller, 2013). Several technologies for sensing cyclists exist such as lane counters (Pai and Jou, 2014), cameras (Tan *et al.*, 2008) and road radars (Cyclemeter, 2018), but these alternatives incur costs. A more economical approach is to re-program all traffic lights to prioritize cyclists by default (Cycle-tracker, 2013). Such an approach, however, is time-consuming and works well only with sporadic vehicular traffic. We proposed sensing cyclists using their smartphones, instead of specialized hardware currently used onboard safety vehicles. Evidently, such an approach introduces a number of challenges related to power efficiency, modeling and privacy in estimating the position, speed and direction of cyclists. In another previous study (Anagnostopoulos *et al.*, 2017), we enhanced smartphone-sensing to enable efficient time-of-arrival (ToA) estimation for cyclists moving toward traffic lights in a smart city (SC) – by using GPS sensors to locate the actual position of cyclists on their way to the traffic lights. The proposed approach tackles inefficient GPS energy consumption by using velocity to estimate ToA and aims to enable efficient cycling in SCs by turning traffic lights green proactively.

In this paper, we extend prior work by assuming an intelligent transport signaling (ITS) system that prioritizes cyclists by considering the normal probability density function (PDF) and the analytics computed for certain groups of cyclists (crowd-cycling). The inference model is built based on real-time spatiotemporal data of the cyclists. As the system is highly distributed – both physically (i.e. location of the cyclists) and logically (i.e. different threads), we propose to treat the system under the umbrella of multi-agent systems (MAS) modeling (Laghari and Niazi, 2016). The MAS approach has been used in the literature to model complex systems by incorporating intelligent agents. In this study, we treat agents as proxy threads running in the cloud, as they consume high computational power not available to smartphones. The system is comprised of the following agents:

- traffic light agent (TLA);
- single cycling agent (SCA); and
- group cycling agent (GCA).

The area contained by a traffic light is considered the environment of the MAS and is assigned with a certain active range. Due to the dynamic nature of cycling, the agents are designed to be stateless, and therefore, the system does not apply learning and stochastic algorithms.

Based on normal PDF and GCA, three different policies (Ps) are defined (P1, P2 and P3); these policies should be evaluated by GCA to trigger the TLA and turn a traffic light green. Only a single policy can be applied on a certain normal PDF per evaluation. Certain evaluation metrics combining multiple satisfactions of the cyclists, system and SC are defined to evaluate the proposed inference model. We evaluated the proposed model experimentally by incorporating a real GPS trace data set from the SC of Melbourne, Australia (Project-Victoria, 2009) and by applying the proposed MAS model and the policies to the data set. The results are promising and indicate that an integration of the system with contemporary SC infrastructure would be successful in meeting the overall objectives.

The structure of the paper is as follows. In Section 2, prior work is presented. We define the theoretical formulation of the model in Section 3 and present the inference model in Section 4. In Section 5, we present an analytic description of the introduced policies. In Section 6, the evaluation metrics used to assess the model are discussed. The experiments and their results are presented in Section 7. In Section 8, we discuss the results and provide solutions to be incorporated by SCs, while in Section 9, we conclude the paper and we propose future work to extend the current.

2. Related work

In the literature, there is a variety of smartphone sensing cycling in SCs. Specifically, BikeNow (Frohlich *et al.*, 2016) is a system, which predicts the moment of the next green phase of the traffic light to recommend the best speed for a cyclist to pass. To obtain data about location and signaling state of traffic lights, it relies on a traffic open-data system connected to all the traffic lights in a city area. Although BikeNow can help cyclists to decide a suitable speed, it has no control of traffic lights to provide cyclist-aware intelligence to optimize the signaling state of traffic lights. Cyclists may still experience an unnecessary wait. In addition, multiple strategies exist to sense cyclists, which have also prohibitive drawbacks. For example, the city of Assen in The Netherlands has programed traffic lights to give priority to cyclists by default, unless vehicles are present (Cycle-tracker, 2013). However, this approach only works well when vehicular traffic is low.

Location prediction of cyclists is feasible using a variety of sensors, including GPS, available on smartphones. Typically, location prediction for outdoor settings is achieved either by analyzing the relative position of movement handovers within a cellular network (Bike-Computer, 2017) or by exploiting the recorded GPS position of a moving entity. In the latter case, analysis of GPS position data may rely solely on GPS coordinates (Caceres *et al.*, 2007), GPS coordinates enhanced with time (Eagle and Pentland, 2006) or GPS coordinates along with velocity and direction. In fact, predicting the future location of a cyclist is the first step toward predicting the ToA to particular locations of interest, which in our case are the traffic lights of a city. The current literature on ToA estimation contains a variety of computational approaches based on, namely, historical trajectories, real-time map matching, shared locations and mobile phone participatory urban sensing (Chen *et al.*, 2009; Zhou *et al.*, 2012).

A number of projects have attempted to accurately reconstruct general mobility patterns by using people's mobile devices. Mobile phone tracking has been used as an approach to measure the flows of passengers between parts of a city and for estimating speeds and travel times (Graham, 2014). The results typically have low spatial resolution and are most

effective for long-distance segments such as highways. Overall, cyclists prefer cycling infrastructures that are segregated from vehicular traffic, regardless of their cycling confidence (Giommo *et al.*, 2013). In Europe, for example, research has highlighted the need to enhance safety and mobility by minimizing the waiting time for pedestrians and cyclists at crossings; providing them with the same rights as motorized traffic; and prioritizing walking and cycling in urban areas (Li *et al.*, 2011). One of the reported technical recommendations is the use of detectors that provide pedestrians and cyclists with green light priority. Of course, motorists may experience inconvenience and delays if cyclist priority is not well calibrated for the flow of cyclists.

Furthermore, the use of communication technology for capturing city-scale mobility is not new. Multiple smart-city initiatives have explored city-scale instrumentation of major infrastructure including energy networks (e.g. electricity, gas and water), building monitoring in terms of environmental and structural performance and transport including urban mobility, energy costs and environmental impact. Some notable initiatives include IBM's Smarter Planet (www.ibm.com/smarterplanet/), the European Union's Smart Cities and Communities (www.eu-smartcities.eu) and the Smart Santander project in Spain (www.smartsantander.eu) and Korea's Songdo city (www.songdoibd.com) to name a few. Particularly in the context of urban mobility and transport, a number of previous projects have considered ways to estimate road traffic (Map-Ride, 2018) and travel patterns using cellular (Bike-Computer, 2017) or proximity (Johnson *et al.*, 2013) technologies.

Research in (Lu and Liu, 2012) categorizes past research on geospatial analysis into three groups as follows:

(1) in a data-driven approach where spatiotemporal patterns are mined from trajectory data;

(2) research that aims to analyze and model dynamic interactions between people; and

(3) "urban studies" that focus on modeling human and vehicular flows in cities.

The third category best describes the aim of our work, as we focus on techniques to establish comprehensive urban traffic mobility data from multi-modal sources. Cycling has important positive outcomes on health and the environment by reducing air pollution and greenhouse emissions (Tan *et al.*, 2008; Miller, 2013). For many cities, it is vital to promote cycling and improve the urban center cycling experience. However, many studies have consistently found cyclists performing a red light infringement (B-icycle, 2015; Calabrese *et al.*, 2011), leading to accidents and even death. For instance, 37 per cent of Australian cyclists reported that they had ridden through a signalized intersection during a red light phase (B-icycle, 2015), while in Taiwan, the short red light duration at intersections is one of the main reasons for cyclists to exhibit risky behavior (Bike-Computer, 2017; Pucker *et al.*, 2010).

Most urban mobility work has been demonstrated in the context of short-lived research projects and pilots. Our approach paves the way for the establishment of an open API for third-party applications who could provide a means to make cyclist sensing sustainable in the long run. Effectively, this API allows any third-party app (e.g. fitness apps, music apps and maps) to request green light priority from the local city. To the best of our knowledge, no previous work has considered the use of distributed smartphone sensing to directly influence traffic light priorities for cyclists in an urban setting. The USA Department of Transportation has developed the IntelliDrive program, focused on the creation of interoperable connectivity among all types of vehicles, the traffic management infrastructure and mobile devices (Cyclemeter, 2018). However, this requires individual drivers, pedestrians and cyclists to carry specialized hardware, which is cost-inefficient.

Similarly, lane counters (Pai and Jou, 2014) and camera systems (Tan *et al.*, 2008) have high hardware and installation costs.

The cognitive traffic management system (CTMS) (Miz and Hahanov, 2014) describes an intelligent traffic approach based on the internet of things. With the connectivity on each person's smartphone, it monitors both bicycles and cars on the road to optimize traffic control, rather than causing bias to cyclists or drivers. However, CTMS is a conceptual design without providing a workable mechanism to support varying numbers of bicycles and cars. Compared to the case of a single cyclist, CTMS cannot give special treatment to a group of cyclists for optimal road traffic management. Popular approaches for sensing mobile phones have incorporated the use of proximity-based technologies such as Bluetooth or Wi-Fi traces (Balazinska and Castro, 2003; Gonzalez *et al.*, 2008). However, this approach suffers from strong privacy concerns (Johnson *et al.*, 2011) and the need for a dense network or urban "scanners".

Cybernetics theoretical framework is used to consider the smartphone as an integrated platform (Kanarachos *et al.*, 2018). Lack of consistency between current approaches and metrics used in large-scale deployment of ITS is addressed. In addition, areas such as the fusion of heterogeneous information sources, deep learning and sparse crowdsensing are identified as promising research directions for further study. Smart traffic monitoring and control architecture is also proposed in the literature incorporating a sensor-enabled algorithm (Lah *et al.*, 2017). Sensors are strategically placed along the road to detect traffic volume. Information is transmitted via low power wide area network to a dedicated control center, for further analyzes, where a server controls the traffic lights scheduling process at the road junctions. A testbed for testers to validate their intelligent traffic light control programs at pedestrian crossings on a road is also proposed (Tian *et al.*, 2018). Given the traffic light controls the testbed conducts the simulation and provides visualized performance measures including the waiting time of vehicles and pedestrians. To reflect the lifetime cost of vehicle brake systems, the proposed testbed measures how many times vehicles stop.

In our approach, we use modern smartphones' internet connectivity through 4G and Edge, where users have control over the data they provide to us and there is no need for installation of additional sensing infrastructure. We extend the related work by assuming an ITS system, which is modeled with MAS modeling. Such a system is able to turn the traffic light to green by considering the normal PDF and the analytics computed for a certain group of cyclists. The MAS model is built based on the real-time spatiotemporal data of the cyclists, which are highly distributed with regards to the location of the cyclists and the agents' functionality. Specifically, we treat agents as proxy threads running in the cloud, as they consume high computation power that smartphones are not able to afford.

3. Theoretical formulation

Let us assume a terrain of certain road segments and junctions with traffic lights in the SC of Melbourne, Australia. Let us also assume that a group of cyclists (crowd-cycling) cycle toward traffic lights. Let the ITS system handle their spatiotemporal GPS location data. Assume that the real-time location data of the cyclists' group, per traffic light, can be fitted to a certain normal PDF. The following quantiles are defined as follows:

- 1st quantile, i.e. 25 cyclists;
- median (2nd quantile, i.e. 50 cyclists); and
- 3rd quantile, i.e. 75 cyclists.

The ITS system turns the traffic light to green by considering the PDF and the analytics computed for a certain group of cyclists. The inference model is build based on the real-time spatiotemporal data of the cyclists. As the nature of the system is highly distributed both physically (i.e. location of the cyclists) and logically (i.e. different threads) it is proposed to treat the system under the umbrella of MAS.

4. Inference model

MAS has been used in literature to model complex systems by incorporating intelligent agents. In the current study, we treat agents as proxy threads running in the cloud, as they consume high computation power that smartphones cannot afford. Specifically, the system is built on certain agents, namely,

- TLA;
- SCA; and
- GCA.

The environment is considered the area contained by a traffic light assigned with a certain active range. The proposed agents are memoryless due to the dynamic nature of cycling so the system does not apply learning algorithms. Specifically, every traffic light is associated with a TLA, which receive GCA's request to control the traffic light. A GCA is associated with the TLA of a certain traffic light and when a group of cyclists is approaching, GCA will trigger a "change to green light" event to TLA. In addition, GCA will receive SCA's request for providing the distance between the cyclist and the traffic light. A GCA will send control traffic light request to one TLA and communicated with many SCA according to whether the SCA is in the active range of the traffic light. Each SCA is associated with a cyclist, when the cyclist is moving, the distance between SCA (i.e. cyclist) and the traffic light will change time by time.

4.1 Traffic light agent decision algorithm

TLA decision algorithm describes the communication interface by means of triggering between the group of cyclists handled by GCA and the traffic light. When TLA is triggered by GCA a condition whether the traffic light is red is validated. If the traffic light is red then TLA turns it to green for 15 s. During that period cyclists have priority to pass the junction while vehicles are forced to stop. After that period of the time traffic light is turned to red again and the cyclists are forced to stop while vehicles can pass the junction. TLA decision algorithm presents the TLA decision algorithm as follows:

```
TLA: decision algorithm
Require: GCA trigger event
Actions: traffic light, GCA trigger event
Begin
   If (GCA trigger event is Activated) Then
      If (traffic light = red) Then
      traffic light ← green//traffic light is set to green
      wait(15)//Set timer to 15 seconds and decrease it down to 0 seconds
      traffic light ← Red//Traffic light is set to red
   End if
 End If
  GCA trigger event ← Deactivated
 return (traffic light, GCA trigger event)
End
```

4.2 Single cycling agent decision algorithm

SCA decision algorithm describes the location data transmission to GCA regarding a certain active range per traffic light. Specifically, an active range around a certain traffic light is set experimentally to 5 m. It is assumed that consecutive traffic lights have adequate distances such as preventing overlapping active ranges. While the traffic light is red and the cyclist is within the active range SCA transmits the location of the cyclist to GCA. Subsequently, the process waits for a certain amount of time (i.e. 1 s), the system not to collapse from the many location invocations and then SCA transmits the new location to GCA. SCA decision algorithm is presented in the SCA decision algorithm as follows:

```
SCA: decision algorithm
Require: traffic light, SCA cyclist location, traffic light active range
Actions: SCA cyclist location
Begin
  While ((traffic light = red)AND(SCA cyclist location is within a certai n traffic light active range)
  Do
        //By means of pseudocode's simplicity it is assumed that SCA is examined per certain traffic light.
    return (SCA cyclist location)
      Wait(1)//set timer to 1 second and decrease it down to 0 second
  End While
End
```

4.3 Group cycling agent decision algorithm

GCA decision algorithm describes the analytics performed to evaluate a policy to trigger the TLA and activate the traffic light (Section 5). While the traffic light is red and no cyclist has reached it, GCA receives the location from each SCA. Subsequently, the GCA creates a normal PDF and apply the selected policy. The process terminates when GCA evaluates the policy for the specific normal PDF. Then, GCA triggers TLA to turn the light green. GCA decision algorithm presents the GCA decision algorithm as follows:

```
GCA: decision algorithm
Require: traffic light, SCA cyclist location, traffic light active range, policy
Actions: GCA trigger event
Begin
  While
  ((traffic light = red) and (There is a SCA cyclist location belongs to certain traffic light active range) Do
      GCA cyclist location ← For each SCA cyclist location//Store all SCA cyclists' locations
                                  //to GCA cyclist location vector
    distribution ← create fitted normal PDF(GCA cyclist location)
    apply certain policy (policy, distribution) //Apply certain policy to fitted normal PDF
    return (GCA trigger event ← Activated) //Trigger TLA
  End While
End
```

4.4 Mas infrastructure overview

The proposed MAS infrastructure overview is presented in Figure 1 according to the definition of the TLA, SCA and GCA functionality as discussed in Sections 4.1, 4.2 and 4.3. Each traffic light has a TLA, while each single cyclist is assigned to an SCA. TLA is responsible for traffic light behavior i.e. turn green or red, while SCA is responsible for the single cyclist behavior. SCA access the GPS sensor of the cyclist's smartphone, through a mobile app, to be aware of the cyclist's movement trajectory. SCA of each single cyclist provides location information to the GCA, which is responsible to handle the dynamics of the group of cyclists. When cyclists' approaching the active range of a certain traffic light the control is passed from GCA to the TLA according to a certain policy. Note that this study focuses on the proof of concept of such a system, thus, it does not consider the information of other vehicles and/or people moving on the road. This is an issue of further future research.

5. Policies

According to the normal PDF described in Section 3 and GCA described in Section 4.3, three different policies are defined, which should be evaluated by GCA to trigger the TLA and turn traffic light to green. Specifically, we distinguish the following policies, namely, P1, P2 and P3. Only a single policy can be applied on a certain normal PDF per evaluation.

5.1 P1

P1 defines that the traffic light turns green when an amount of 1st quantile number of cyclists has arrived to the traffic light. This means that the system promotes the quickest cyclists within the active range. Specifically, in P1 the system gives priority to first arrived cyclists without taking care of the rest of cyclists in the group. The rationale behind this is that the following cyclists might slow down their velocity due to an obstacle or even change their direction and leave the active range. In such, a case the system gives priority to quickest cyclists not to spend time waiting for cyclists that might change their behavior and produce delays. However, it does not treat equally the slow cyclists, which might cause queues in the junctions, as they do not catch up the green traffic light on time Figure 2.

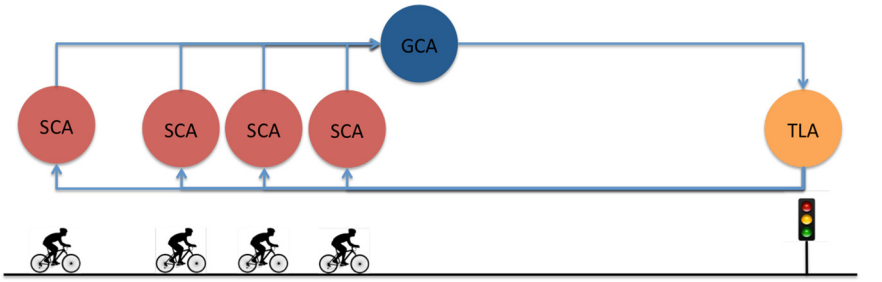

Figure 1.
MAS infrastructure overview

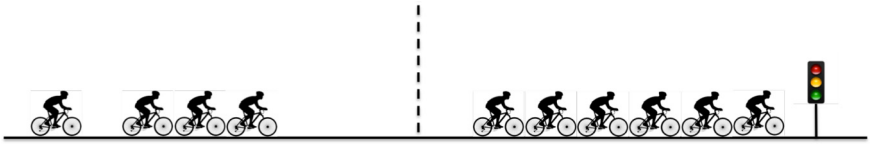

Figure 2.
P1 policy

5.2 P2

P2 defines that the traffic light turns green when an amount of median (i.e. 2nd quantile) number of cyclists have arrived to the traffic light. In such a case the system gives priority to the average population of cyclists. In P2, the rationale is to handle the average amount of cyclists and be fair to the whole population of cyclists. This means that quickest cyclists have to wait some more time and slower cyclists should speed up to catch the rest of the group Figure 3.

5.3 P3

P3 defines that the traffic light turns green when an amount of 3rd quantile number of cyclists have arrived to the traffic light. The rational of this decision is that TLA should be triggered when all the cyclists have approached the traffic light. In such a case the system takes care of the whole population of cyclists and makes sure that all the cyclists should be served by the system. However, this approach might lead to queues to the junctions and even to lead to delays to the group of cyclists Figure 4.

6. Evaluation metrics

To evaluate the proposed inference model certain evaluation metrics are defined, combining multiple satisfaction criteria of the, namely, cyclists, system and SC. Cyclists' satisfaction (CS) is defined as a function, which measures the satisfaction of the cyclists based on the following:

- waiting average time (WAT) to the traffic lights; and
- cyclists' average speed (AS) per route from cyclist origin to destination in the SC.

CS is maximum in case that WAT is minimum and AS in maximum. This is the case where the cyclists wait the minimum time to traffic lights while at the same time they move as fast as they can toward their destination. WAT and AS values are normalized such as it holds that they take values in the interval [0, 1] as follows:

$$CS = f(WAT, AS), \ such\ that: \{WAT\ is \quad \min \ \cap \ AS\ is\ max\} \tag{1}$$

ITS system satisfaction (SS) is defined as a function, which measures the satisfaction of the ITS system based on the following:

- Number of cyclists served per traffic light transition (NCS); and
- Number of traffic lights transitions per time (NTL).

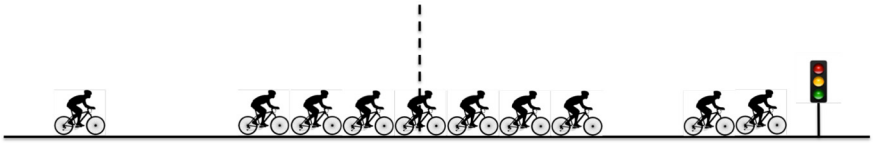

Figure 3. P2 policy

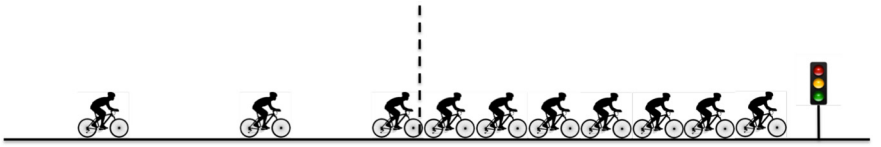

Figure 4. P3 policy

SS is maximum when NCS is maximum and NTL is minimum. This is the case where the system serves the maximum number of cyclists while at the same time the traffic lights perform the minimum number of transitions to serve the cyclists. NCS and NTL values are normalized such as it holds that they take values in the interval [0, 1].

$$SS = f(NCS, NTL),\ such\ that: \{NCS\ is\ \max\ \cap\ NTL\ is\ min\} \tag{2}$$

Smart city satisfaction (SCS) is defined as a function, which measures the overall satisfaction of the cyclists and the ITS system in the SC based on the following: CS and SS. SCS defines three SC policies (SCP) based on the following: CS and SS values. Specifically, in the case of:

- CS is maximum and SS in minimum then the SC is cyclists' friendly, case of SCP1;
- CS is average and SS is average then the SC is equally cyclists' and ITS system friendly, case of SCP2; and
- CS is a min and SS is max then the SC is ITS system friendly, case of SCP3.

$$SCS = f(CS, SS) : \begin{cases} SCP1: \{CS\,is\,max\ \cap\ SS\,is\,\min\} \\ SCP2: \{CS\,is\,average\ \cap\ SS\,is\,average\} \\ SCP3: \{CS\,is\,min\ \cap\ SS\,is\,\max\} \end{cases} \tag{3}$$

7. Experiments and results

Experiments are performed by incorporating a real GPS trace data set from the SC of Melbourne, Australia. We apply to the data set the MAS model and the policies P1, P2 and P3. Results are evaluated with the metrics CS, SS and SCS. We also assess the proposed SC policies SCP1, SCP2 and SCP3, respectively. Specifically, we update the real data set with synthetic traffic light locations. The data set was fed to the simulator we implemented. The simulator is built with Python 3.6 and implements the proposed MAS. Python code and real GPS trace data set used to implement the proposed research is available in a public GitHub domain (Cyclist-Simulator, 2019). The parameters to the simulator are as follows:

- the number of GPS points of the real data set;
- the number of cyclists incorporated; and
- the number of traffic lights' locations.

The real data set has 4,297 GPS points covering a total area of 16.780896 km^2 from minimum GPS coordinate: (−37.830853, 144.951303) to maximum GPS coordinate: (−37.783272, 144.987318) in the SC of Melbourne, Australia. The number of cyclists is increased from 1 to 100, moving on the real GPS trace. The number of traffic light locations is increased from 1 to 10, incorporated within the real GPS data set (Table I).

We applied the evaluation metrics for each policy and results are discussed in the following paragraphs. Specifically, in the case of CS, the results for WAT are that policy P1 receives minimum values, policy P2 receives average values, while policy P3 receives maximum values for the given experimental setup (Figure 5). The x-axis represents the number of cyclists, which increases from 1 to 100. The y-axis represents the number of traffic lights, which increases from 1 to 10, while the z-axis represents the normalized values

of WAT within the interval [0, 1]. We can observe that WAT values are distributed equally with respect to the number of cyclists. This is explained, as the values of WAT are not aggregated in relation with the number of cyclists i.e. each cyclist has an equivalent WAT in each traffic light. However, WAT values are increasing with respect to the number of traffic lights. This is explained, as the values of WAT are covariate positively in relation with the number of traffic lights i.e. the more the traffic lights the more the aggregated WAT per traffic lights setup.

Consequently, the results for AS are that policy P1 receives maximum values, policy P2 receives average values, while policy P3 receives minimum values for the given experimental setup (Figure 6). The *x*-axis represents the number of cyclists, which increases from 1 to 100. The *y*-axis represents the number of traffic lights, which increases from 1 to 10, while the *z*-axis represents the normalized values of AS within the interval [0, 1]. We can observe that AS values are distributed equally with respect to the number of cyclists. This is explained, as the values of AS are not aggregated in relation with the number of cyclists i.e. each cyclist has an equivalent AS in each traffic light. However, AS values are increasing with respect to the number of traffic lights. This is explained, as the values of AS are

Parameters	Values
Trace length (GPS points)	4,297
Total coverage area (km^2)	16.780896
Minimum GPS coordinate	(−37.830853, 144.951303)
Maximum GPS coordinate	(−37.783272, 144.987318)
Number of cyclists	100
Number of traffic lights	10

Table I. Experimental setup

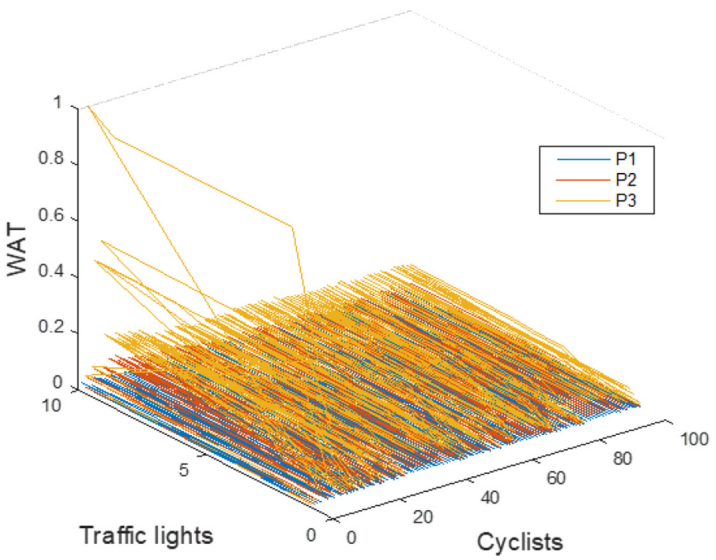

Figure 5. WAT result values

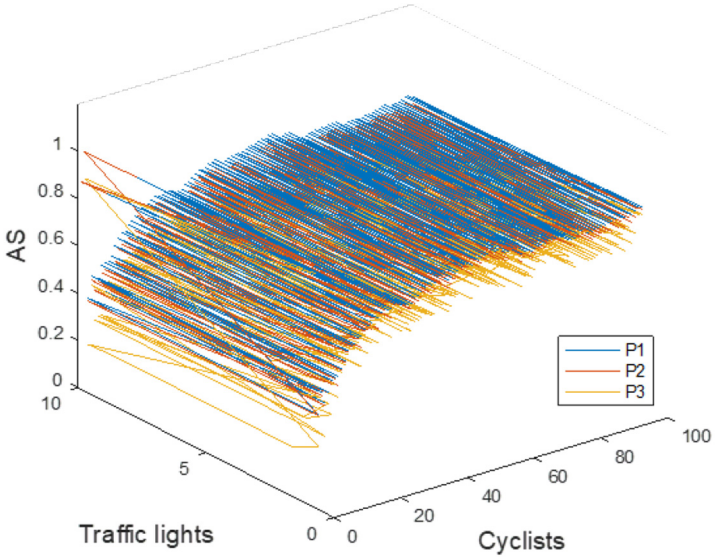

Figure 6.
AS result values

covariate positively in relation with the number of traffic lights i.e. the more the traffic lights the more the aggregated AS per traffic lights setup.

Concretely, in the case of SS, the results for NCS are that policy P1 receives minimum values, policy P2 receives average values, while policy P3 receives maximum values for the given experimental setup (Figure 7). We can observe that NCS values are increasing with respect to the number of cyclists. This is explained, as the values of NCS are aggregated in

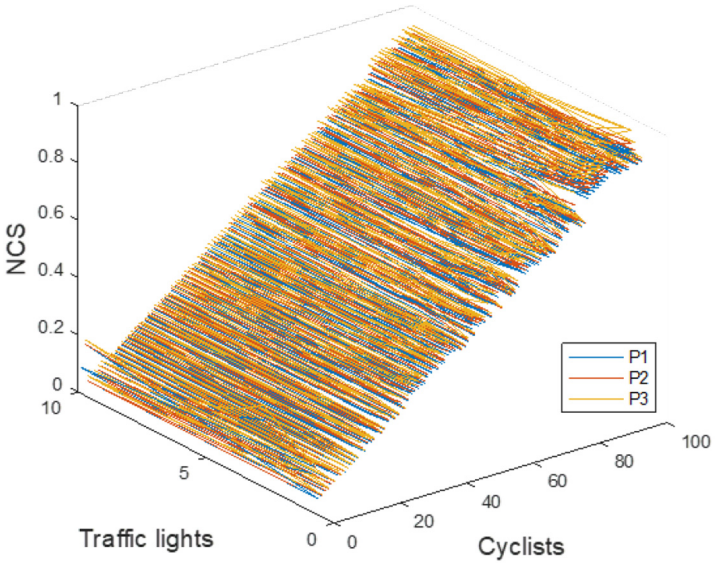

Figure 7.
NCS result values

relation with the number of cyclists i.e. a number of cyclists' served is aggregated per traffic light. However, NCS values are distributed equally with respect to the number of traffic lights. This is explained, as the values of NCS are not aggregated in relation with the number of traffic lights i.e. the number of cyclists' served per traffic light is not covariate with respect to the number of the traffic lights.

Consequently, the results for NTL are that policy P1 receives maximum values, policy P2 receives average values and while policy P3 receives minimum values for the given experimental setup (Figure 8). We can observe that NTL values are increasing equally with respect to the number of cyclists. This is explained, as the values of NTL are aggregated in relation with the number of cyclists i.e. the cyclists' number affects the number of traffic light transitions per each traffic light. In addition, NTL values are increasing with respect to the number of traffic lights. This is explained, as the values of NTL are covariate positively in relation with the number of traffic lights i.e. the more the traffic lights the more the aggregated number of traffic light transitions per traffic lights setup.

8. Discussion

The results are promising and highlight the proposed approach impact in distributed smartphone sensing cycling in SCs with the incorporation of MAS. Specifically, the decision table as it formed for the case of CS implies that CS values are maximized for policy P1, where WAT is minimum and AS is maximum (Table II). This means that for policy P1 we achieve low values of WAT and high values of AS, which results to high CS levels. This result implies that the current set up sponsors cyclists' friendly policies in certain SCs.

Consequently, the decision table as it formed for the case of SS implies that SS values are maximized for policy P3, where NCS is maximum and NTL is minimum (Table III). This means that for policy P3 we achieve high values of NCS and low values of NTL, which results to high SS levels. This result implies that the current set up sponsors the ITS system's friendly policies in certain SCs.

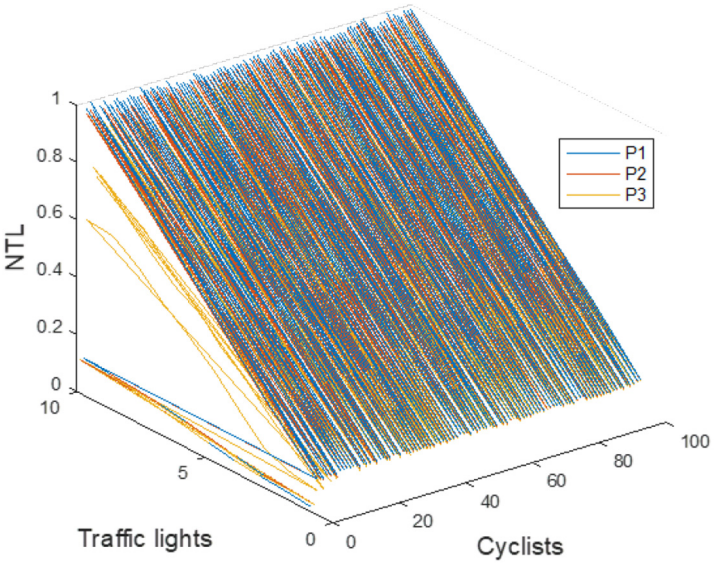

Figure 8.
NTL result values

Concretely, applying SCP policies in the observed results leads to different mutual exclusive use cases. Each use case is expressing the willingness of an SC to promote either the CS, SS approach or a combination of them. So, in the case of SCP1, we observe that adopting P1 leads to maximum CS values and minimum SS values. In this use case, the SC promotes an SC policy, which is cyclists' friendly. Consequently, in the case of SCP2, it is adopted P2, which leads to average CS and SS values. In this use case, the SC promotes an SC policy, which is equally cyclists' and ITS system's friendly. In the case of SCP3, we observe that adopting P3 leads to minimum CS values and maximum SS values. In this use case, SC promotes an SC policy, which is the ITS system's friendly (Table IV).

9. Conclusions and future work

Research in this paper extends prior work in the literature by assuming an ITS system, which turns the traffic light to green by considering the normal PDF and the analytics computed for a certain group of cyclists. We model the ITS system with MAS modeling. The proposed approach is by definition a simplification of ITS system for group cycling in SCs. ITS systems generally tend to be more complex and taking into consideration more parameters such as the vehicles running in the road, people walking across the road and cyclists in other directions in the road. However, our aim was to study the simplified case where we have a stream of a group of cyclists toward traffic lights, which is a generalization of our previous publications where we studied one cyclist at a time. Although the study of an extended ITS is not in the context of the current paper we intend to do such research in future studies, where we will generalize the proposed model to the greater area of the SC, while incorporating the dynamics of the mutual exclusive benefits of adversarial vehicles' policies within the SC traffic area. We also provided a proof of concept of the proposed system. Future research will target in applying such an ITS system in real conditions by implementing a mobile app available in Google Play that the cyclists will have while they

Table II. CS Evaluation

P	WAT	AS
P1	min	max
P2	average	average
P3	max	min

Table III. SS Evaluation

P	NCS	NTL
P1	min	max
P2	average	average
P3	max	min

Table IV. SCS Evaluation

SCP	CS	SS
SCP1	max	min
SCP2	average	average
SCP3	min	max

are cycling in the SC. In such a real scenario MAS agents will be implemented as code threads in the cloud.

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