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Exploring the potential of Neural Networks for Bicycle Travel Time estimation

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Abstract. A tool for travel time estimation of cyclists approaching a traffic light can monitor level of service of intersections in bike crowded cities. This work represents a first step in developing such a tool. Neural Network models are evaluated on how they perform in estimating individual travel time of cyclists approaching a signalized intersection. Based on simulated scenarios, in cities with low bicycle levels (deterministic scenario), Neural Networks are good travel time estimators whereas, in places with high bike volumes (where cyclists depart with a discharge rate) information on queued cyclists is crucial for travel time information.

Keywords: Bike Travel Time Estimation, Neural Networks, Signalized Intersections

1 Introduction

While some cities are struggling to increase bicycle usage, others are successful in encouraging adoption of cycling but become victims of their own success. Such 'cycling cities' struggle with high levels of bike flows, long queues at traffic lights and discontent cyclists due to the delay in their travel time. Traffic management solutions can mitigate the situation by reducing delay using adaptive traffic controllers or rerouting users to intersections with short delays. In order to deploy such systems, a tool that estimates cyclists travel times, as proxy for bike level of service at intersections, is crucial.

To develop a tool that serves the needs of a bike travel time monitoring system at intersections the following data requirements are set: 1) enabling to derive travel time 2) collected over an extensive time frame, 3) representative of user population, 4) readily and real-time available and 5) privacy proof. Some studies investigated the potential of GPS to measure delays (see [3] and references therein). However, GPS only fits the first of the five data requirements: GPS data are collected either via sport apps which enable collection over extensive time frames, but can only represent the "sport" trips, or it is collected via expensive data collection methods, which can equip a representative sample of the population with GPS trackers, but for a limited amount of time (thus not satisfying condition 2). In addition GPS data is not readily available from municipalities and stores sensitive user information. Therefore, this research will use a data set, potentially available from an intersection equipped with loop sensors, a traffic light and a bike queue measurement system because such simulated data set has the potential of meeting all data requirements. Part of this data is readily available to dutch municipalities, due to the extensive deployment of loop sensors on signalised intersections in the Netherlands. Loops are usually installed as shown in Fig. 1: 2 upstream of the traffic light (for direction measurement) and one downstream at the stop-line.

Within this work we investigate the properties of a Neural Network (NN) model, when estimating individual cyclists' travel times. Previous studies have explored the possibility of extracting travel times with more "easy to interpret" models like regressions but were not successful [1]. Our work will go one step further by exploring the potential of a more complex models like NNs.

The wide applicability of NN in the transport domain [4] and scalability would allow these models to easily scale up to incorporate more variables from the same intersection but also from other intersections in a network-oriented approach. We train and test the model on simulated data because it allows for the evaluation of both the model and its input variables.

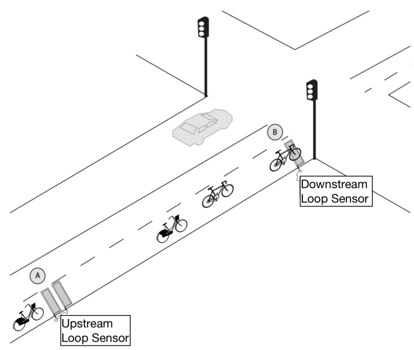


Fig. 1. Position of bicycle loop sensors at intersections

Section 2 presents the methodology describing the simulation settings, the input features and the model. Section 3 contains the performances of NNs, in order to investigate if the deployment of these models in reality is effective. Finally, the conclusions are reported in section 4.

2 Research Methodology

Our research methodology consists of 3 major steps: 1) Simulation of the arrival-departure process of cyclists at the traffic light, 2) Identification of variables to extract from the simulation to use as features for the NN, and 3) Computation of estimation error. Fig. 2 shows how the research steps interrelate. We decide to test different feature combinations on each scenario (see Table 3), in order to investigate which feature variables carry more information depending on the simulated setting.

2.1 Simulation for Data Generation

We use simulation and not real data from a signalised intersection with sensors because of 4 main reasons. 1) Simulation allows a controlled environment to

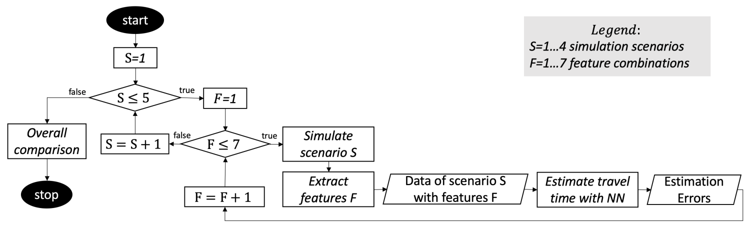


Fig. 2. Flow of the research steps

measure the performances of NNs as complexity is added. 2) We can simulate data not yet available (like queue of cyclists) and assess if collecting such data is valuable for a NN. 3) It allows us to train the model on correct ground truth data that loop sensors alone are not able to deliver, due to occlusion error (see [2] for the definition) in the downstream loop. 4) Based on the NN performance on simulated data, it will be clear if to pursue testings on real data.

Data is simulated based on four scenarios which vary depending on the cycling time, queuing model of cyclists, and high demand of cyclists. Hereafter the four scenarios simulating arrival-departure process of cyclists are described (from simple to more complex):

– Deterministic scenario: cycling time is the same for all individuals and cyclists depart from the stop line as soon as the traffic light turns green.
– Discharge Rate scenario: similar to the deterministic scenario with the added complexity that cyclists do not depart from the downstream sensor all at the same time but with a discharge rate.
– Stand over queues scenario: road capacity constraints are considered and arrival rate is modelled to simulate high cyclists demand, so more cyclists are in the queue than can be discharged in one cycle. Cyclists may stay in the queue for more than one red light cycle.
– Stochastic scenario: based on a random arrival-departure process, cycling time between 2 loops is not fixed but modelled according to a normal distribution .

2.2 Selection of Feature Variables

Hereafter, a set of five features has been defined based on the data potentially available, the moment a cyclist approaches the upstream senors of bicycle intersections, in the Netherlands.

– Arrival time: this variable contains date-time information of the moment a cyclist reaches the upstream loop sensor.
– Upstream traffic light: carries a 0-1 information to represent green (0) and red light (1) state when the cyclist reaches the upstream sensor.
– Downstream traffic light: carries a 0-1 information to represent green (0) and red (1) light state when the cyclist reaches the upstream sensor (this data might not be available in real settings, but is used as a check).

– Elapsed time from traffic light change: defines, at the arrival time of the cyclist, the seconds passed since the last change in state of the traffic controller.
– Bike queue: defines the number of cyclists waiting for a green light.

Seven combinations of these five features define the data-sets used for the different experimental scenarios (see Figure 3).

2.3 The Model

NN models have shown to be extremely versatile and perform well even without a priori assumption on the variable distribution. Their generalization properties make NNs suitable for our purpose. Like all data driven models that learn by minimising the predicted error, NNs need labels (i.e. travel time) of past observations in order to learn how to estimate future ones. Once the NN is trained on past travel time observations (in this case simulated), it will be able to estimate travel time of never seen before observations.

3 Numerical Results

In this section we report results form the numerical experimentations. For reproducibility, we first describe the structure and parameters of the NN used, as resulting form the numerical experiments. Follows, a description of the NN performance, based on mean square errors in the different scenarios tested on the various feature variable combinations.

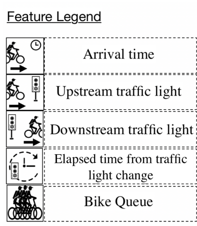
3.1 Neural Network Structure

Throughout the numerical experiments, a shallow Feed-forward Neural Network, with 6 neurons, emerged as the architecture with the smallest validation error. The NN was implemented in MATLAB software. A structured investigation indicated that the network architecture is adequate, because increasing the number of layers or neurons per layer on average did not improve test performances. Where performances were measured through the mean square error (MSE) as performance function.

3.2 Model Performance

Via simulation, a data set of 7200 instances is generated, 70% of which is used for training, 15% for validation and 15% for testing the NN model. Estimation performance of the NN on the different scenarios is reported in Fig. 3.

The Deterministic process is the one the NN can estimate better, as expected, since the process is simple. This is deduced by the very small test error, of tenth of a second, on all the scenarios, compared to the other three processes. The data in the feature combination 2 will not be available in real cases; we use it as



Scenario / Feature combinations	Deterministic	Discharge Rate	Stand Over Queue	Stochastic
1)	0.15	5.64	396.34	19.19
2)	0.00	6.10	300.91	1.58
3)	0.16	5.08	306.26	19.34
4)	0.13	5.00	391.82	18.66
5)	0.14	6.70	315.25	19.18
6)		1.13	2.23	
7)		1.28	2.08	

Fig. 3. Mean square error for bicycle travel time estimation: Estimation performance (on test data) of the NN on the 4 scenarios, tested on different feature combinations. Feature combinations with queue information are not considered in the Deterministic and Stochastic case, since these scenarios are simulated without cyclists' discharge rate.

a check case to see how well the model can predict if we provide it with signal of the traffic light at the time the cyclist would arrive at the downstream (in real life the time the cyclist arrives downstream is not known). The second lowest error in the deterministic scenario is with features: arrival time and elapsed time from traffic light change. This means that, the model estimates better when knowing how many seconds have passed since the change in traffic light state, because it is a FIFO based scenario.

If the process incorporates a queue discharge rate of cyclists, as in the Discharge Rate and Stand Over Queue scenario, feature combinations with bike queue have the smallest estimation error. Having the queue as feature reduces the estimation mean square error up to 2 orders of magnitude. The main reason is that the queue feature incorporates the dynamic information of the arrival-departure process at signalised intersections (i.e. a cyclist has to wait for the queue ahead to discharge, before it can depart again). The Stand Over Queue scenario, incorporated high peak of cyclists arriving at the intersection and Fig. 4 shows how accurately the model can estimate travel times in high peak (longer waiting time) when queue information is provided and how it would perform without it. Without queue information the NN can not reproduce the longer travel times that occur when cyclists need to stand in the queue for more than one traffic light cycle. Among the feature combinations that have queue information including the elapsed time form traffic light change improves estimation error in the Stand Over Queue but not in the Discharge rate process. The reason being that in the former process a cyclist is always discharged within the first traffic light cycle, thus elapsed time does not provide as useful information as when the cyclist stays more than one cycle.

Overall, in the Stochastic process, the reached performances are not sufficiently accurate. As information used in the second data-set is not available, on average the error reached by the NN is of 19 seconds. This indicated that, as the process is more complex, the information considered is not enough for the NN to reproduce the underlying process that generated the data.

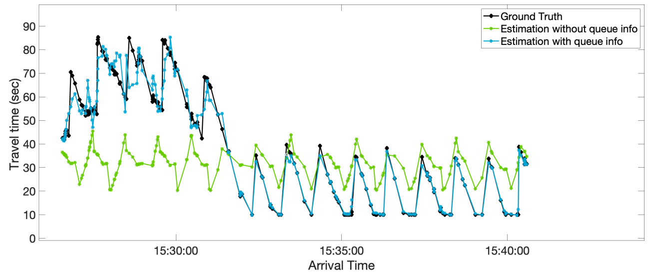


Fig. 4. Visualization of model performance in the Stand Over Queue scenario, considering feature combination 3 (without queue info) and 7 (with queue info).

4 Conclusions

This work provides a structured investigation, based on a simulation methodology, on how Neural Networks perform for individual travel time estimation. This is the first study on bicycle travel time estimation at intersections, in order to develop real-time bike level of service measures. The investigation of effectiveness of Neural Networks made clear the potentials and limitations of these models. In cities with low bicycle levels (deterministic scenario), NNs are good travel time estimators since with all data sets the reached error is of tenth of a second. Whereas, in places with high bike volumes (where cyclists depart with a discharge rate), only data sets with information on queued cyclists lead to acceptable error of 1 to 2 seconds. The main limitation of using NN models to estimate individual bicycle travel time is the availability and richness of the data.

The results enable us to quantify the estimation error in the four scenarios with the different input data. As a consequence, this quantitatively encourages us in future research to develop queue estimation algorithms (of cyclists) that can improve overall travel time estimation. Moreover, future steps should look into the opportunity to cover more complex processes, and more intersections with this methodology.

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