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Generation of "Biking Schedules" for Bicycle Travel Analysis

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Abstract

With an increasing focus on bicycling as a mode of urban transportation, there is a pressing need for improved tools for bicycle travel analysis and modeling. This paper introduces "biking schedules" to represent archetypal urban cycling dynamics, analogous to driving schedules used in vehicle emissions analysis. Three different methods of constructing biking schedules with both speed and road grade attributes are developed from the driving schedule literature. The methods are applied and compared using a demonstration data set of 55 h of 1-Hz on-road GPS data from three cyclists. Biking schedules are evaluated based on their ability to represent the speed dynamics, power output, and breathing rates of a calibration data set and then validated for different riders. The impact of using coarser 3, 5, and 10 s GPS logging intervals on the accuracy of the schedules is also evaluated. Results indicate that the best biking schedule construction method depends on the volume and resolution of the calibration data set. Overall, the biking schedules successfully represent most of the assessed characteristics of cycling dynamics in the calibration data set (speed, acceleration, grade, power, and breathing) within 5%. Future work will examine the precision of biking schedules constructed from larger data sets in more diverse cycling conditions and explore additional refinements to the construction methods. This research is considered a first step toward adopting biking schedules in bicycle travel analysis and modeling, and potential applications are discussed.

Cycling can be a low-cost, healthy, and fun form of transportation with diverse personal and social benefits. Promoting cycling is an increasingly common part of environmental initiatives in the transportation sector to decrease pollution emissions (*1*). As a result of these and other initiatives, bicycle facilities are increasing in many North American cities, accompanied by an increase in cycling for travel. These changes intensify a need for better understanding of real-world cycling behavior and for improved tools for bicycle travel analysis and modeling.

Bicycle speed dynamics are important for both physical and behavioral aspects of bicycle travel analysis. The human power requirements of cycling vary greatly with speed, acceleration, and road grade (*2*). Human power and energy expenditure, in turn, are linked to physical activity levels, breathing rates and pollution inhalation, and many facets of travel behavior such as speed, route, and mode choices (*3–6*). Unfortunately, detailed microsimulation and operational models of on-road urban bicycle dynamics are still in their infancy (*7–9*).

Knowledge of typical urban bicycling dynamics would be useful for a number of applications, including estimating energy expenditure and related impacts from aggregate data such as average trip speed, identifying different bicycle travel regimes such as cautious versus risky riding, and simulating cycling dynamics for vehicle development and testing such as design of electric-assist bicycle motors. Driving schedules were developed to address some similar issues for motor vehicles (*10–13*). Driving schedules, also referred to as driving cycles, are speed profiles designed to represent typical driving patterns, used in fuel and emissions modeling and in vehicle simulation and testing (*14*).

A main application of driving schedules is to enable estimation of realistic vehicle fuel consumption and emissions (which depend on driving dynamics) from aggregate travel model outputs such as average speed (*15*). Lab dynamometer testing of real-world vehicles operating on driving schedules captures the fuel and emissions effects of typical driving dynamics associated with a given average speed. Thus, the driving schedules can essentially be used to disaggregate travel model output. Similarly,

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bicycle travel analysis could benefit from the ability to estimate realistic cycling dynamics and related impacts from aggregate travel data such as average trip speed.

Like driving schedules, biking schedules can be expected to vary with travelers, topography, traffic, facility type, and more. Road grade significantly influences the speed and energy of cyclists (*4*, *16*, *17*), as well as motor vehicle emissions (*18*, *19*). However, driving schedules are typically created without synchronous grade profiles (*20*, *21*). Due to the strong influence of road grade on cycling speeds, the interdependence of speed and road grade should be included in an accurate representation of bicycle dynamics.

The objective of this paper is to introduce the concept of biking schedules along with methods for their construction. Methodologies of constructing biking schedules that integrate speed and grade dynamics are developed by building on the established driving schedule literature. The methods are evaluated using an on-road bicycling data set. Because biking schedules will most likely be generated from GPS data, the issue of required data resolution is also explored, facilitating application of the method to larger naturalistic data sets in future work.

Proposed Biking Schedule Construction Methods

Schedule construction methodologies can be classified into microtrip based, segment based, pattern based, and stochastic modal approaches (*22*). This study uses the microtrip based approach to develop biking schedules. Observed travel data are divided into small snippets, called microtrips, which form the elementary components of the biking schedules. A schedule is then constructed by appending microtrips together until a desired length is reached. Candidate schedules are evaluated for their similarity to the original travel data, based on a set of predetermined aggregate assessment parameters. Departing from driving schedule methods, the microtrips and schedules in this research include synchronous speed and grade data.

In past research on driving schedules, microtrips have been selected randomly (*21*, *23*, *24*), with sophisticated statistical methods such as Markov chain transition matrices (*12*), or with hybrid methods (*25*). In this paper, three methods of microtrip selection are presented and compared. The following subsections present detailed steps for the proposed biking schedule construction methods.

Microtrip Extraction

Approaches to defining microtrips vary across the literature. One common approach is to define microtrips between two consecutive stops (*11*, *26*), but this method poorly represents travel data with long uninterrupted segments (*25*). Other approaches involve temporal or spatial segmentations of predetermined sizes. These methods have the advantage of producing microtrips of a consistent desired length regardless of speed dynamics, but with the drawback of requiring a speed continuity criterion to produce realistically smooth speed profiles.

Microtrips in this study are delineated at fixed spatial intervals of 250 m—an approach which was demonstrated in recent research to yield the most accurate driving schedules (*27*). It is acknowledged that results from driving schedule studies are limitedly transferable to biking schedules due to differences in speed and acceleration characteristics. Investigation of alternative microtrip definitions for constructing biking schedules is left for future work.

Assessment Criteria

The role of the assessment criteria is to ensure that the developed schedules represent the important characteristics of the calibration data set. Thus, assessment criteria should be selected that are relevant to the purposes of the schedule. Target parameter values for the assessment criteria are calculated from the calibration data set, and then schedules are constructed to reproduce those parameter values as closely as possible. Table 1 lists the 12 assessment criteria proposed for developing biking schedules. These parameters were adopted from the driving schedule literature to represent speed and acceleration dynamics, with new parameters added for road grade.

The performance value (PV) is a single aggregate indicator of the set of assessment criteria, used to evaluate the biking schedules. The PV for each parameter in Table 1 is the absolute percent difference between the value calculated from the calibration data and the value calculated from the biking schedule data, with the exception of SAGPD for which the PV is the root mean square error (RMSE) between the target and schedule time fractions in each cell of the distribution matrix. A lower PV means that the schedule is closer to the target parameters and more representative of the calibration data. The total schedule PV is then the weighted average of PVs for individual parameters, PV_x. Weights are distributed equally among four sets of parameters that represent speed, acceleration, grade, and SAGPD:

$$\begin{aligned}\mathrm{PV} = {} & 0.25(\mathrm{PV_{ATS}} + \mathrm{PV_{ARS}} + \mathrm{PV_{PTI}} + \mathrm{PV_{PTC}})/4 \\ & + 0.25(\mathrm{PV_{AAA}} + \mathrm{PV_{PTA}} + \mathrm{PV_{PTD}} + \mathrm{PV_{APW}})/4 \\ & + 0.25(\mathrm{PV_{AAG}} + \mathrm{PV_{PTPG}} + \mathrm{PV_{PTNG}})/3 + 0.25(\mathrm{PV_{SAGPD}}).\end{aligned}$$

Table 1. Assessment Criteria for Biking Schedules

ID	Parameter[1]	Abbreviation	Units
1	Average trip speed	ATS	km/h
2	Average running speed ($v>0$)	ARS	km/h
3	Percentage time idling ($v = 0$)	PTI	%
4	Percentage time cruising ($v>1$, $-0.1<a<0.1$)	PTC	%
5	Average absolute acceleration	AAA	km/h/s
6	Percentage time accelerating ($a>0$)	PTA	%
7	Percentage time decelerating ($a<0$)	PTD	%
8	Average positive work per mass-distance[2] ($a>0$)	APW	m/s^2
9	Average absolute grade	AAG	%
10	Percentage time positive grade ($G > 0.5$)	PTPG	%
11	Percentage time negative grade ($G < -0.5$)	PTNG	%
12	Speed acceleration grade probability distribution[3]	SAGPD	%

Note: [1]v = speed in km/h; a = acceleration in km/h/s; G = grade in %. [2]Expressed as "positive kinetic energy" in (*21*), calculated as $\frac{\sum(v_{i+1}^2 - v_i^2)\forall v_{i+1} > v_i}{\textit{total distance}}$.
[3]Percentage time in each cell of a 3-dimensional speed-acceleration-grade probability distribution matrix with speed intervals of 5 km/h, acceleration intervals of 0.2 km/h/s (*28*), and grade intervals of 1%.

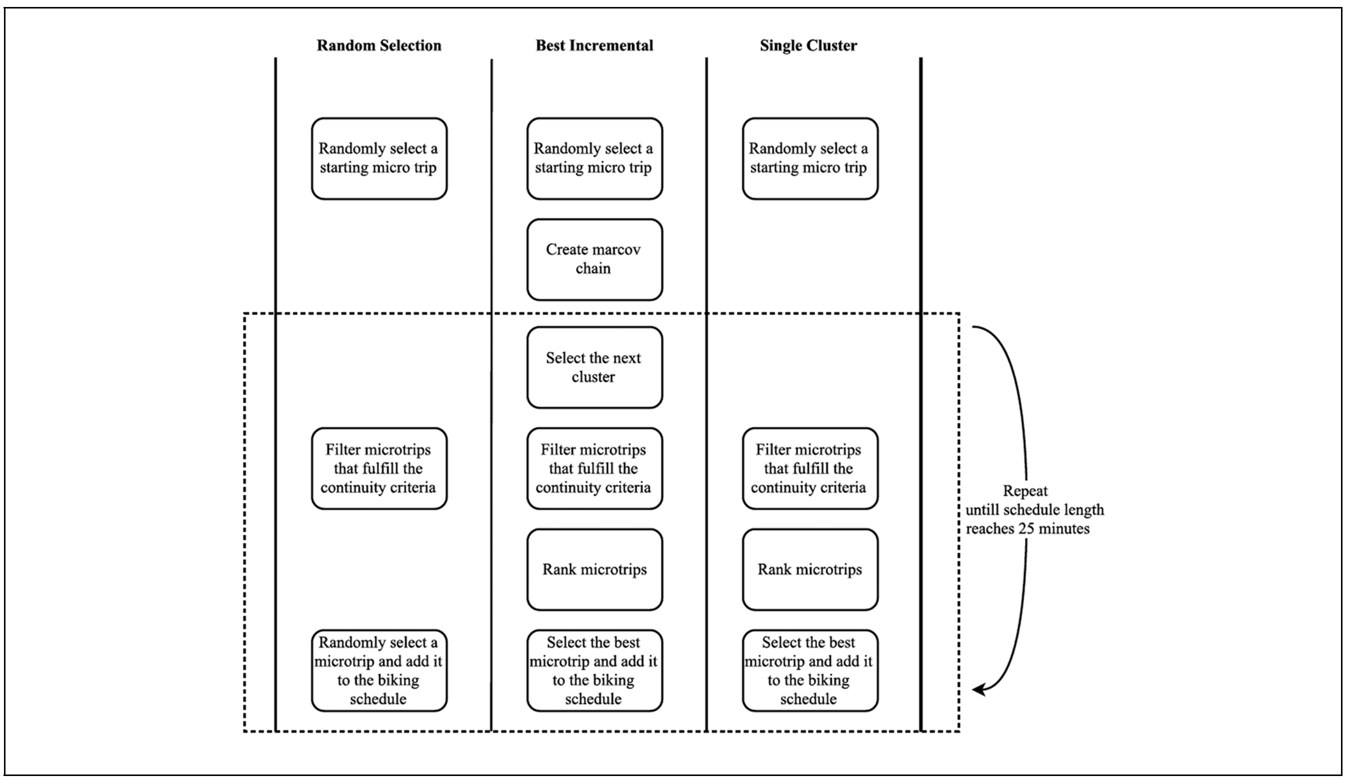

Figure 1. Framework for constructing biking schedules with three different methods.

Biking Schedule Construction

Biking schedules were constructed from the microtrips using three different methods: random selection, best incremental, and single cluster. The details of each method are described in the following subsections. Figure 1 summarizes the overall framework for constructing biking schedules.

For all three methods, the first microtrip in the biking schedule is randomly selected from a subset of trip-starting microtrips. Then, additional microtrips are appended, without repetition, until a schedule duration of 25 min is reached, consistent with the 10–30 min driving schedules common in the literature (*24*). Each subsequent microtrip must meet continuity criteria of an initial speed within 2 km/h and initial grade within 2%

of the end of the previous microtrip. The methods differ primarily in how they select the next microtrip from among those meeting the continuity criteria. For each method, several candidate biking schedules are constructed and the best schedule selected based on lowest PV.

Random Selection Method. In this method, microtrips are randomly selected and appended, restricted only by the continuity criteria, until the target duration (25 min) is reached. Consistent with previous studies (*23*), new biking schedules are repeatedly constructed until 20 candidate schedules with PV $< 15\%$ have been generated, and then the preferred schedule selected from those candidates based on lowest PV.

Best Incremental Method. In this method, also adapted from previous studies (*12*, *29*), microtrips are first clustered by average speed, average acceleration, and average grade using a K-means clustering algorithm. The number of clusters is selected based on the sum of squared errors (SSE) within clusters, as illustrated in Figure 2. The SSE decreases with more clusters (i.e. they become more similar), but with the trade-off of fewer microtrips in each cluster which can create problems for meeting the continuity criteria. The optimal number of clusters is likely context-dependent. In this study, microtrips are grouped into nine clusters.

After grouping the microtrips into clusters, a transition matrix is generated to represent the probability of transitioning between clusters, based on observed sequences of microtrip clusters in the calibration data. A stochastic Markov chain process then generates a sequence of clusters starting from the cluster of the (randomly selected) initial microtrip (*30*). Then, for each successive cluster

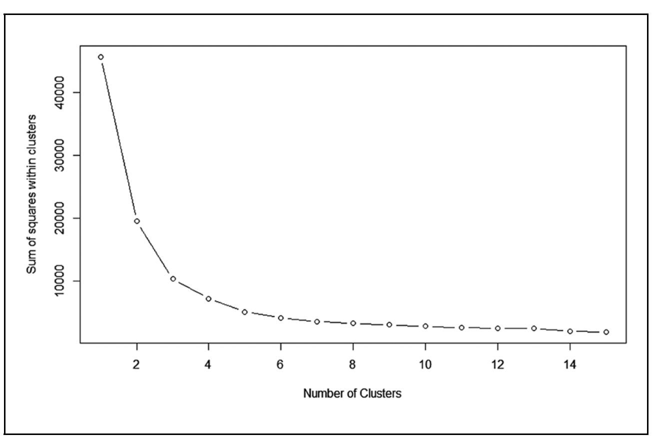

Figure 2. Relationship between number of clusters and SSE within clusters.

1. Microtrips in the cluster are filtered to identify candidate microtrips that meet the continuity criteria;
2. Candidate microtrips are individually appended to the schedule and a provisional PV calculated for each;
3. Candidate microtrips are ranked by lowest provisional PV; and
4. The best microtrip is appended to the schedule.

This process is repeated for each successive cluster in the sequence until the desired schedule length is reached. Consistent with the random selection method, 20 biking schedules are generated using this method and the best schedule selected based on lowest PV.

Single Cluster Method. This method is similar to the best incremental method, but discards the Markov process by combining all microtrips into a single cluster. After selecting the first microtrip randomly, successive microtrips are appended based on fulfilling continuity and lowest provisional PV. Because this is no longer a stochastic process, each starting microtrip generates a single deterministic schedule. Hence, the number of unique candidate biking schedules from this method depends on the number of starting microtrips in the pool. As with the other methods, the best biking schedule is selected from among the candidates based on lowest PV.

Evaluation of Methods

An existing on-road cycling GPS data set is used to demonstrate and evaluate the proposed biking schedule methods. The data set includes 55 h of 1-Hz speed and grade data from three cyclists (A, B, and C) in Portland, Oregon (*3*). Speed and grade data were processed using a kernel smoothing algorithm with bandwidths of 3 and 10, respectively (*28*). Biking schedules are generated for cyclist A (for which the most data are available) and then validated in two ways: by testing application to estimates of cyclist power and breathing rate, and by testing transferability to the other two riders and lower data resolutions. A total of 1,530 microtrips were extracted from the cyclist A data; partial microtrips were discarded.

Power output and breathing rate are calculated using speed and grade from the biking schedules applied to the equations and fixed parameters (mass, resistance factors, etc.) given in (*3*). Transferability to other riders is tested by generating biking schedules for cyclists B and C based on their aggregate travel characteristics (assessment parameters), but using the microtrips from cyclist A. The rationale for this approach is to test the possibility of developing biking schedules for other riders and conditions knowing only aggregate riding characteristics. To

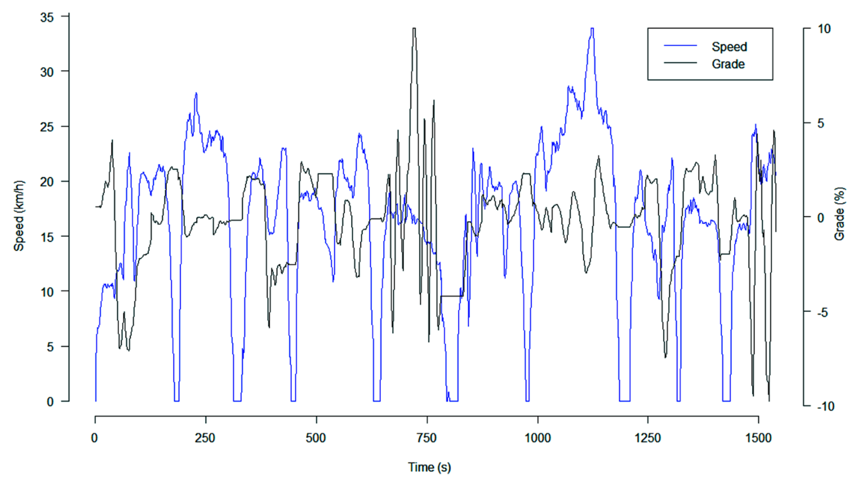

Figure 3. Biking schedule with the best overall PV, generated from the single cluster method.

Table 2. Overall and Parameter PV of Biking Schedules from Each Construction Method

		Construction method		
		Random selection	Best incremental	Single cluster
Individual-parameter PV_x (%)	ATS	8.91	1.40	0.39
	ARS	8.70	0.89	0.08
	PTI	1.94	4.99	3.03
	PTC	6.04	1.19	0.86
	AAA	7.26	0.42	1.57
	PTA	0.96	1.21	1.75
	PTD	3.21	2.60	2.66
	APW	3.04	1.06	2.26
	AAG	2.52	1.03	1.05
	PTPG	4.77	1.15	0.06
	PTNG	21.4	2.78	1.29
	SAGPD	0.15	0.13	0.13
Overall PV (%)		4.93	1.31	1.02

evaluate the effect of GPS data resolution on biking schedule generation, coarser logging intervals of 3, 5, and 10 s are simulated from the original data set by removing observations. Acceleration is recalculated as the difference between consecutive velocity observations, and new biking schedules generated from the revised microtrips and assessment parameters.

Evaluation Results

Processing time to generate the biking schedules varied between methods but was similar among data resolutions. The random selection method took the longest: up to 3 h to identify 20 candidate schedules with PV $<$ 15%. On average, 70 schedules were created to reach 20 candidate schedules. The processing time for this method would increase with more microtrips, more desired candidate schedules, or a lower PV threshold. In contrast, the best incremental method required the least processing time, 10–20 min. The processing time for the single cluster method is mainly determined by the number of microtrips in the trip-starting pool. This method took the most time to develop each schedule, but was still more time efficient than the random selection method because it required fewer iterations to identify 20 candidate schedules. Failure to find microtrips that met the continuity criteria was an issue for all methods, but predominantly a problem for the best incremental method which is restricted to microtrips within clusters rather than the entire pool.

Table 2 gives the overall and individual-parameter PV for the biking schedules generated from each construction method. Based on the PV, the single cluster method yielded the best biking schedule (illustrated in Figure 3), followed closely by the best incremental method. The random selection method substantially underperformed the other two methods according to the PV. Inspecting all generated schedules, there was no clear pattern of certain parameters having consistently higher PV than others.

Figure 4 shows the evolution of PV for each method with biking schedules of increasing length (measured by the number of microtrips). The last data point in each series is the target 25-min schedule. In general, PV improves (decreases) with increasing schedule length, but not monotonically, and the optimum length depends on the construction method. Longer schedules can in some cases degrade the PV due to the constraints of the continuity criteria when selecting microtrips to append.

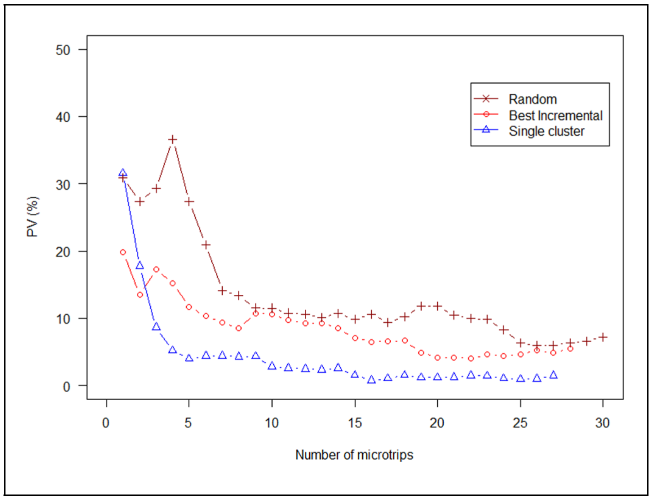

Figure 4. Relationship between PV and drive schedule length for each method.

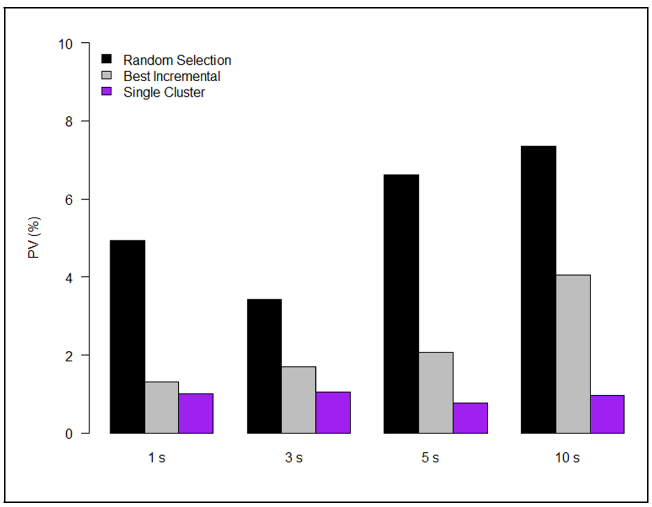

Figure 5. PV across methods using data resolutions of 1, 3, 5, and 10 s.

Substantially shorter schedules generate similar PV for the best incremental and single cluster methods, but the random selection method is less efficient at attaining a low PV. The question of optimal schedule length for biking schedules requires further investigation.

Figure 5 gives the PV results for all three methods using data resolutions of 1, 3, 5, and 10 s (the 1-s results are the same as in Table 2). The ordering among the three methods is consistent across all four data resolutions, with single cluster performing best (lowest PV), followed by best incremental and random selection. The accuracy of the best incremental method degrades at coarser data resolutions. The single cluster method has the most consistently good performance, and no clear relationship with data resolution.

Table 3 gives the cyclist power output and breathing rate results. Biking schedules generated by all methods and data resolutions provide power output and breathing rate estimates within 10% of the estimates from raw data, and most are within 5%, suggesting that biking schedules can plausibly be used for these applications. Somewhat surprisingly, there is no clear relationship between the accuracy of the power and breathing estimates and the PV (shown in Figure 5). If desired, the assessment criteria could potentially be refined to more specifically reflect the determinants of power and breathing, or power and breathing estimates could even be used directly as assessment parameters.

The PV for the biking schedules generated for cyclists B and C (using cyclist A's microtrips) were 2% and 6%, respectively, by the best incremental method, and 1% and 2%, respectively, by the single cluster method. The biking schedules are less precise, as expected, when constructed from a different cyclist's GPS data. Still, the biking schedules are able to represent the cycling dynamics reasonably well based on the assessment criteria. The single cluster method was markedly better for this application, likely because it draws from a larger pool of microtrips and does not rely on a transition matrix that was generated from a different cyclist's data.

Calculated power outputs from these single cluster biking schedules are 11% and 18% higher than from the raw data for cyclists B and C, respectively, and breathing rates are 4% and 8% higher. These differences are likely larger for cyclist C than cyclist B because the dynamics of cyclist C were more distinct from cyclist A. For example, cyclists A, B, and C had mean power outputs of 114, 77, and 57 W, respectively, and mean breathing rates of 21, 20, and 16 L/min. The observation of similar PV but markedly different power/breathing rate accuracy for cyclists B and C supports the idea that the assessment criteria might not well reflect the determinants of cyclist power, and further refinements should be explored.

Conclusion

This paper presents and compares three methods for constructing biking schedules to be used in bicycle travel analysis. The selection of the best method depends on several factors. First, data set size is crucial to the process. A larger data set is preferable for all methods, but particularly for the best incremental method which further segments the microtrips into clusters. For smaller data sets the single cluster method would be preferred. The single cluster method also performed better than other methods with coarser data resolutions. The random selection method is unlikely to be optimal because it generates relatively low-accuracy schedules.

Table 3. Cyclist Power Output and Breathing Rate Calculated from Raw Data and Biking Schedules

		Power output (W)		Breathing rate (L/min)	
		Mean	Difference from raw data (%)	Mean	Difference from raw data (%)
1 sec data	Raw data	114	–	20.8	–
	Random selection	114	0.2	20.8	0.2
	Best incremental	103	9.8	19.1	8.0
	Single cluster	116	1.7	21.1	1.5
3 sec data	Raw data	115	–	20.9	–
	Random selection	113	1.9	20.6	1.1
	Best incremental	112	2.7	20.4	1.7
	Single cluster	123	7.2	22.3	7.0
5 sec data	Raw data	115	–	20.9	–
	Random selection	120	3.9	21.7	3.4
	Best incremental	111	3.6	20.4	3.0
	Single cluster	118	2.6	21.5	2.2
10 sec data	Raw data	116	–	21.1	–
	Random selection	108	7.4	19.8	6.2
	Best incremental	121	4.1	21.9	3.6
	Single cluster	116	<0.1	21.1	<0.1

The accuracy of the method depends on the proximity of the calibration data to the application conditions. In this study, GPS data from one cyclist was able to generate reasonable biking schedules based on the aggregate travel data of two other cyclists in the same 55-hour data set, albeit with less accuracy. Transferability to more remote conditions (other cities, seasons, etc.) requires further investigation. It is expected that larger calibration data sets encompassing more variability (of riders, terrain, trip purposes, bicycle types, weather conditions, facility types, etc.) would have greater utility for generating realistic biking schedules for other contexts. The transferability of biking schedules, however, depends on the consistency of cycling dynamics across contexts, for which we still have little evidence in the literature.

The proposed biking schedules can have a variety of applications. Biking schedules can be used to estimate cyclist power, energy, and breathing rate from aggregate travel data (collected through travel surveys, bikeshare systems, smartphone applications, etc.), and thus improve health effects estimates including physical activity and pollution inhalation. Biking schedules could be segmented by rider type (age, experience), equipment (e-bike, cargo bike, road bike), season or weather conditions, or facility type (bike lane, cycle track, multi-use path) to explore and represent systematic, archetypal differences in urban cycling styles and dynamics among population segments, cities, or facilities. In addition to modeling cycling outcomes, biking schedules could potentially be used to represent the typical energy "costs" of network links and thus applied as inputs to route choice models.

Biking schedules can also be used by bicycle designers and manufacturers, particularly of e-bikes and other human or electric hybrid vehicles, similar to the way driving schedules are used in motor vehicle modeling and design. Representative schedules could be implemented in simulation models and laboratory testing to investigate power consumption and battery life, for example. Segmented biking schedules could provide more customized performance information for specific market segments (sport vs. leisure riders, for example), similar to the city and highway fuel economy information supplied to motor vehicle shoppers. Biking schedules could also be used in research and clinical laboratories to investigate human performance under more realistic cycling conditions than traditional tiered-workload exercise tests.

The proposed biking schedules are a promising new tool for bicycle travel analysis, but further work is needed to develop robust construction methods. Much of the proposed approach was drawn from driving schedule methods, which likely have limited transferability to cycling. The selection of assessment criteria requires further investigation, including the most appropriate parameters to represent outcomes of interest such as energy expenditure, and alternative weighting schemes to adjust the influence of individual assessment parameters on the overall PV. As this is the first known attempt to develop biking schedules, the 12 assessment measures used in this study should be viewed as preliminary. Different microtrip definitions and methods of determining schedule length should also be explored. Delineating microtrips between consecutive stops would eliminate the need for continuity criteria, which could improve the performance of the best incremental method. Lastly, this study used a limited demonstration data set, and the methods should be further validated on larger data sets encompassing more diverse cycling conditions. Transferability should also be tested by comparing biking schedules and assessment criteria from cycling data in multiple cities.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: AB, AM; data collection: AB; analysis and interpretation of results: AM, AB; draft manuscript preparation: AM, AB. All authors reviewed the results and approved the final version of the manuscript.

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