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INVESTIGATING COMMUTE MODE AND ROUTE CHOICE VARIABILITIES IN JAKARTA USING MULTI-DAY GPS DATA

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ABSTRACT

This paper reports on findings regarding the day-to-day dynamic behavior of commuters' mode and route choices in Jakarta. Ninety-three commuters using Global Positioning System (GPS) devices during a one-week period were observed. The observation proves the presence of dynamic behavior in choosing both modes and routes for commuting in Jakarta. Car drivers and motorcyclists frequently change their routes, especially during work-to-home trips. Motorcyclists were more dynamic in choosing their routes than were car drivers. This case study revealed a unique pattern of mode and route choice behavior, which can be used for developing a mode and route choice model for Jakarta.

Keywords: Global positioning system (GPS); Jakarta; Mode choice; Route choice; Variability

1. INTRODUCTION

Traffic congestion has been a part of commuters' lives in the Jakarta Metropolitan Area (JMA) for several years. Jakarta's 3-in-1 traffic regulation, implemented to reduce the number of cars travelling in busy corridors during morning and evening peak hours, has been in effect since 1992. The Bus Rapid Transit (BRT) system was established in 2004 with the intention of motivating car drivers to switch to public transport. Despite these measures, the traffic congestion problem in Jakarta has not been solved. Compounding the problem is the fact that the traffic congestion in Jakarta is made more complex by various social, economic and cultural aspects. Hence, better understanding of the dynamics of daily commuting will be advantageous in finding effective measures for reducing private vehicle use (cars and motorcycles) and for improving the appeal of public transportation in Jakarta.

Our study's purpose was to develop mode and route choice models for Jakarta using multi-day GPS data, which provides accurate and reliable travel information, especially route choice (Wagner, 1997; Wolf, 2000; Zhou & Golledge, 2000; Kochan et al., 2006; Wolf, 2006). Furthermore, multi-day GPS data enables better understanding of the day-to-day dynamics of individual travel behavior, which is crucial for modeling travel behavior.

This paper reports on the findings of the first phase of the study: investigating the day-to-day dynamic behavior of commuters' mode and route choices. These findings can be used in the next phase of the study to develop both mode and route choice models.

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Additionally, better understanding of the day-to-day variability is needed for managing travel demand and achieving more efficient use of the transport system (Pendyala & Pas, 2000; Schlich & Axhausen, 2003; Li et al., 2004; Susilo & Kitamura, 2005; Günsler et al., 2005; Elango et al., 2007). The remainder of this paper is organized as follows: section 2 presents the methodology of data collection and analysis, followed by section 3, which discusses the results. Finally, section 4 provides a summary of the findings and an evaluation on possible extensions of the research.

2. METHODOLOGY

The study consists of two parts. First, a GPS-based travel survey in Jakarta was conducted. The collected GPS data were then analyzed to identify the day-to-day variability of mode and route choices.

2.1. GPS-based travel survey

Due to budget and time constraints, the GPS-based travel survey was carried out on a small sample of about one hundred commuters during a one-week period. The survey period of one week captured the day-to-day variability of commuting behavior but obviously did not capture seasonal variations. However, the day-to-day variability of travel behavior is sufficient for modeling mode and route choices and for providing a better understanding of the dynamic behavior of daily commuting. Recruitment of the participants had a snowball effect. The author asked his acquaintances, whose workplaces are located in the central business district (CBD) of Jakarta, to participate in the survey. In turn, these acquaintances asked their co-workers to also participate in the survey. The locations of the participants' workplaces had to be inside the 3-in-1 areas or at least affected by 3-in1 regulation. The 3-in1 regulation is a traffic management policy implemented in Jakarta, which regulates certain busy corridors that can only be traveled during peak hours (i.e. from 06:30 to 10:00 and from 16:00 to 19:00) by cars with at least three passengers. A total of 105 commuters from 15 different workplace locations participated in the survey. Each participant was asked to complete a questionnaire related to information which could not be captured by GPS device, such as their socio-demographic situation, main commute mode, office hours, etc. Two types of person-based GPS devices were used for the survey: Mobitest and Holux M-1000C (see Figure 1). The devices are capable of collecting second-by-second GPS positions and times. The recorded tracking data were downloaded offline, using the relevant application software, after the survey period.

Figure 1 MobiTest and Holux GPS logger

Each participant carried a GPS device every day during a one week period. Some participants were eliminated due to missing data for some days within the survey period (for example, the participant did not return the questionnaire, turn on the device during traveling, had unclear tracking data, etc.), reducing the number of participants to 93. The survey was conducted from July 29 to September 23, 2010.

2.2. Data analysis

A drawback of using GPS-based data is the huge volume of the collected information. Therefore, appropriate algorithms are needed to automate data processing. Issues related to the analysis of GPS raw data have already been tackled in several publications, which can be grouped together based on their methods: (1) using Geographical Information System (GIS) and (2) using non GIS. Stopher et al. (2005), Chung & Shalaby (2005), and Tsui & Shalaby (2006) have developed algorithms for analyzing GPS raw data using GIS. Conversely, Schüssler and Axhausen (2009) have developed the algorithms using JAVA (non GIS method). Our study, however, utilizes both methods. The entire analysis of GPS data consists of data filtering, identification of commute trips, derivations of commute trip characteristics, detection of commute main mode, and the identification of routes. A series of algorithms were developed using Visual Basic (non GIS method) in order to filter raw GPS data, identify commute trips, and derive commute trip characteristics.

The filtering process is necessary for eliminating redundant and poor quality GPS points, and elimination criteria depend on the information provided by the GPS device. This study implemented the following criteria:

- For precisely calculating three-dimensional positions and times, at least four satellites are required. Hence, GPS points recorded with less than four satellites in view were removed from the dataset.
- Sudden position jump is used to reduce multipath errors. Position jump is detected by comparing the distance between two consecutive GPS points. The distance must be not more than 42 m, which represents the distance a person could have traveled with a maximum speed of 150 km/h (i.e. traveling by train). A GPS point with a distance of more than 42 meters from its preceding point was deleted. The procedure was repeated until the distance between two consecutive GPS points was not more than 42 m.

The locations of home and workplace are represented by a Home Reference Point (HRP) and a Workplace Reference Point (WRP), respectively, which are determined using clustering methods based on speed, time stamp, time gap and the distance between two consecutive GPS points. Then, GPS points located within a buffer of 15 meters from HRP are assigned as home activity, while the points located within a buffer of 50 meters from WRP are assigned as work activity. The remaining GPS points are assigned as trips. Multipath error for the workplace is higher because there are more high-rise buildings in the target area, and an office building is normally larger than a house. Hence, a wider buffer was implemented for the workplace. A commute trip is detected if the preceding GPS point of a particular trip start is home activity and the succeeding GPS point of the trip end is work activity, or vice versa. A total of 615 commute trips could be identified from GPS raw data. Performance of the algorithms was evaluated by comparing the results against the results from the GIS platform method, which identified 601 commute trips. This means that the algorithms identified 2.3 percent more commute trips than actually occurred trips. For further analysis we considered the results of both methods, i.e. 601 commute trips including 213 trips by car (35.4%), 195 trips by motorcycle (32.5%) and 193 trips by public transport (32.1%).

Characteristics of commute trips, such as departure time, commute duration, and trip distance could be straightforwardly derived from the coordinate and time stamp of the trip start and the trip end, and the cumulative distance of two consecutive GPS points. If the movement of the GPS points approaches zero speed (i.e. lower than 3 km/h) and the duration of such records is more than 120 seconds, this stream of GPS points is grouped as an activity or intermediate stop. Commute main mode is defined as a mode used for commuting which travels the longest distance and was detected by map-matching GPS data of each commute trip on a digital road network model using ArcGIS (GIS method). The commute mode was subsequently confirmed with information from the questionnaire. The map-matching procedure was enhanced by Visual Basic for automatic processing. This procedure was used also for identifying route travelled.

3. RESULTS AND DISCUSSION

3.1. Commute trip characteristics

Table 1 presents descriptive statistics of the respondents' characteristics and will be used in the next phase of the study as determinants of mode and route choices. The respondents were mostly male (69.9%), 21-30 years old (51.6%), university graduate (89.2%), married (83.9%), family head/husband (62.4%), government employee (64.5%), office staff (73.1%), middle income (60.2%), and possess a driving license (88.2%). Fifty-three and eight-tenths percent of the respondents own one or more cars, while 77.4 percent own one or more motorcycles. Sixty percent of the respondents own both a car and a motorcycle. Thirty-five and five-tenths percent of the respondents use a motorcycle as their primary mode for commuting, followed by using a car (31.2%), bus (18.3%), train (12.9%) or taxi (2.2%).

Table 1 Socio-demographic characteristics of the respondents

Characteristics		Observation
Gender	Male	65 (69.9%)
	Female	28 (30.1%)
Age	≤ 20	29 (31.2%)
	21-30	48 (51.6%)
	31-40	15 (16.1%)
	41 - 50	1 (1.1%)
Education	Junior H. School	1 (1.1%)
	Senior H.School	8 (8.6%)
	University	83 (89.2%)
Marriage Status	Single	14 (15.1%)
	Married	78 (83.9%)
	Divorce	1 (1.1%)
HH-member Status	Husband	58 (62.4%)
	Wife	21 (22.6%)
	Adult child	14 (15.1%)
Type of Occupation	Govt. Employee	60 (64.5%)
	Private Comp.	33 (35.5%)
Job Position	Office Staff	68 (73.1%)
	Supervisor	12 (12.9%)
	Manager	13 (14.0%)

Characteristics		Observation
Individual Income	< 5 Mio IDR*)	17 (18.3%)
	5 – 10 Mio IDR	56 (60.2%)
	> 10 Mio IDR	20 (21.5%)
Motorcycle Ownership	No Motorcycle	21 (22.6%)
	Have Motorcycle	72 (77.4%)
Car Ownership	No Car	43 (46.2%)
	Have Car	50 (53.8%)
Driving License Own	No Dri- Lic.	11 (11.8%)
	Have Driv-Lic.	82 (88.2%)
Home Location	DKI Jakarta	36 (38.7%)
	Bogor	13 (14.0%)
	Depok	11 (11.8%)
	Tangerang	18 (19.4%)
	Bekasi	15 (16.1%)
Primary Mode	Car	29 (31.2%)
	Motorcycle	33 (35.5%)
	Taxi	2 (2.2%)
	Bus	17 (18.3%)
	Train	12 (12.9%)

** 1 USD = 8,750 IDR*

Figure 2 shows the home and workplace locations of the participants. Home locations spread across the JMA, which reflects the share of commuters residing in each region of the JMA. The mean distance of direct commute trips is 24.11 kilometers, while the mean commute distance with trip-chaining is 25.06 kilometers. Thus, trip chaining increases the commute distance by about four percent. A large percentage of the commute trips cover a distance between 5 and 35 kilometers; however, a commute distance between 25-30 kilometers has the highest share (19-22%). The highest percentage of commute trips show a trip duration between 60 and 90 minutes.

The mean commute duration, including trip-chaining stops, is 82.10 minutes, while the mean commute duration without trip-chaining stops is 76.10 minutes. Thus, trip-chaining stops increase commute duration by about eight percent. The highest percentage of workers leaves home between 05:00 and 06:59, and leaves their office between 16:00 and 17:59.

Figure 2 Home and work locations of the participants

3.2. Mode choice

3.2.1. Number of commute main modes

Eighty-two and seven-tenths percent of the samples used one main mode for commuting during the survey period (see Table 2), while the remaining 17 percent used at least two main modes. This proves the existence of dynamic behavior in the selection of commute main modes.

Table 2 Number of commute main modes distribution

Number of Commute Main Modes	Number of Commuters	Percentage (%)
1	77	82.7
2	14	15.1
3	2	2.2

3.2.2. Commute main modes

This study identified nine types of modes used as commute main modes (see Table 3). During observations, the majority of commute trips used private vehicles (33.3 percent used cars and 32.4 percent used motorcycles), while 17.6 percent used buses and 12.6 percent used trains. This reflects that commuters in Jakarta still prefer to use private vehicles, i.e. car or motorcycle, even though the 3-in-1 regulation and the BRT have been implemented. However, from another perspective, we can see a great potential for motivating private vehicle users to switch to public transportation. The study determined that 21.6 percent of commute trips originated in suburban areas via cars and 16.0 percent via motorcycles. These trips could be diverted to public transport if the performance of commuter trains, feeder buses, and BRT buses were improved. Table 3 shows that commuters more heavily use private vehicles because the commute is faster and the duration more certain than with public transport (i.e. bus and train). Therefore, commuters could be attracted to public transportation if the uncertainty of the commute duration could be reduced, for example by applying a fixed time schedule for buses.

Although the commute trip is a routine trip, Table 4 shows the dynamic behavior in choosing commute main modes. If we define the most frequently used commute main mode during the survey period as a commuter's primary mode, a total of 571 out of 601 (95.0%) commute trips used the primary modes, while the remaining trips used alternative modes. Company buses and informal transit services were never used as primary modes. Taxis were used as a primary mode rather than an alternative mode. Car/motorcycle drivers utilized trains or buses as alternative modes, while train users used a car as an alternative mode. Bus users and, car or motorcycle ridesharing commuters utilized more alternative modes, such as company buses, trains, informal transit services, and personal cars.

Table 3 Commute main mode distribution

No.	Commute Mode	No. of Trips	Mean Travel Time [minutes]	Median Travel Time [minutes]
1	Motorcycle	189 (31.4 %)	63.7	60.5
2	Car	165 (27.5 %)	78.5	74.1
3	Bus	106 (17.6 %)	103.8	92.8
4	Train	76 (12.6 %)	72.6	98.3
5	Car Sharing	34 (5.7 %)	96.6	92.7
6	Taxi	14 (2.3 %)	62.6	68.2
7	MC Sharing	6 (1.0 %)	27.5	26.3
8	Company Bus	6 (1.0 %)	107.8	106.6
9	Informal Transit	5 (0.9 %)	89.8	87.6
	Total	601 (100 %)	77.3	75.6

Informal transit services, which compete with regular buses was used as an alternative mode for commuting. Even though informal transit services are illegal, they are necessary. Rather than banning informal transit services, transportation authorities could legalize and control their operations, providing a much needed additional (and more organized) commute mode.

Table 4 Commute main mode choice matrix

Primary Main Modes	Alternative Main Modes								
	MC	Car	Bus	Train	Car Sharing	Taxi	MC Sharing	Company Bus	Informal Transit
Motorcycle	189	-	-	2	-	-	-	-	-
Car	-	162	-	1	-	-	-	-	-
Bus	-	1	99	3	-	-	-	6	2
Train	-	2	-	68	-	-	-	-	-
Car Sharing	-	-	5	2	33	-	-	-	-
Taxi	-	-	-	-	-	14	-	-	-
MC Sharing	-	-	2	-	1	-	6	-	3
Company Bus	-	-	-	-	-	-	-	-	-
Informal Transit	-	-	-	-	-	-	-	-	-

3.2.3. Variability of commute main mode choice

For a deeper understanding of the dynamics of commute main mode choices, this study examined the day-to-day variations in the selection of main mode for AM-commute (home-to-work trips) and PM-commute (work-to-home trips). If there was no variation (using one main mode), then it was labeled "No", whereas if using at least two main modes, then it was labeled "Yes". Table 5 shows that the number of commuters using at least two main modes for AM-commute is 11.8 percent, while for PM-commute is 12.9 percent. Approximately 17 percent of the commuters used at least two main modes during the survey period.

Table 5 Distribution of main mode choice variation

Main Mode Choice Variation	Number of commuters		
	AM-commute	PM-commute	AMxPM-commute
No	82 (88.2 %)	81 (87.1 %)	77 (82.8 %)
Yes	11 (11.8 %)	12 (12.9 %)	16 (17.2 %)

The variation of commute main mode choices is categorized as shown in Table 6:

- Category 0: no main mode variation (used one main mode during survey period).
- Category 1: no main mode variation for either AM-commute or PM-commute, but used different main modes for both the AM-commute and the PM-commute.
- Category 2: main mode variation for PM-commute only.
- Category 3: main mode variation for AM-commute only.
- Category 4: main mode variation for both AM-commute and PM-commute.

Table 6 Distribution of main mode choice variation categories

Category	Commute Main Mode Choice Variation			No. of Commuters
	AM-commute	PM-commute	AMxPM-commute	
0	No	No	No	77 (82.8 %)
1	No	No	Yes	2 (2.2 %)
2	No	Yes	Yes	3 (3.2 %)
3	Yes	No	Yes	2 (2.2 %)
4	Yes	Yes	Yes	9 (9.6 %)

Eighty-two and eight-tenths percent of the commuters used one main mode during the survey period (category 0). Around two percent of the commuters used one main mode for either the AM-commute or the PM-commute, but they used different main modes for both the AM-commute and the PM-commute (category 1). Three and two-tenths percent of the commuters used different main modes for the PM-commute only (category 2), while 2.2 percent of the commuters used different main modes for the AM-commute only (category 3). Nine and six-tenths percent of the commuters used different main modes for both the AM-commute and the PM-commute (category 4).

3.3. Route choice

In a road and transit network, there are a large number of possible alternative routes between the home and the workplace. Some commuters use a single route while others choose multiple routes. Some chosen routes had shared (overlapped) links, and others had no overlap. This chapter summarizes the general findings of the route choice patterns of car and motorcycle trips. Car trips cover 35 O-D pairs (home-workplace), while motorcycle trips cover 33 O-D pairs.

3.3.1. Number of commute routes

If the most frequently used route between an O-D pair during the survey period is defined as a commuter's primary route, 105 car trips (49.5 %) were on primary routes while the remaining car trips were on alternative routes. For motorcycle trips, 84 trips (43.1 %) were on primary routes. Around 20 percent of car trips and 6 percent of motorcycle trips used a single commute route during the survey period (see Table 7), while the remaining trips used at least two routes (multiple routes) for their commute.

3.3.2. Route deviation pattern

Depending on the commuter's familiarity of the road network, deviation can occur anywhere along the route. Li (2004) defined route deviation pattern based on where the deviation occurs:

near home, near work, or in the middle of the route, and identified eight types of deviation patterns from the GPS data of the Commute Atlanta Project (see Table 8: types 0-6 and 8). However, this study detected a new type of deviation pattern (type 7 in Table 8), which was not identified by Li (2004). Visual examples of each category are shown in Figure 3.

Table 7 Number of commute routes distribution

Number of Routes	Car Trips		Motorcycle Trips	
	No. of Commuters	[%]	No. of Commuters	[%]
1	7	20.0	2	6.1
2	5	14.3	9	27.2
3	9	25.7	8	24.2
4	5	14.3	6	18.2
5	3	8.5	4	12.1
6	4	11.4	2	6.1
7	1	2.9	2	6.1
8	1	2.9	-	-
Total	***35***	***100***	***33***	***100***

Table 8 Distribution of route deviation pattern

Dev. Type	Route Deviation Pattern	Car Trips		Motorcycle Trips	
		No. of Commuters	[%]	No. of Commuters	[%]
0	No Deviation, one route	7	20.0	2	6.1
1	Near home Deviation	-	-	-	-
2	Mid-route Deviation	-	-	-	-
3	Near work Deviation	6	17.1	2	6.1
4	Near home & mid-route Dev.	1	2.9	4	12.1
5	Near work & mid-route Dev.	2	5.7	6	18.2
6	Near home & work Dev.	7	20.0	3	6.1
7	Near home, mid-route, near work	12	34.3	14	39.4
8	Complete different Deviation	-	-	2	9.1

Our observation shows that none of the commuters deviate their routes near home only (type 1) or in the middle of route only (type 2). The majority of car drivers (34.3%) and motorcyclists (39.4%) deviates their routes near home, at mid-route, and near work simultaneously. This reflects the dynamic behavior of car drivers and motorcyclists in selecting routes to avoid congested roads and 3-in-1 corridors near workplaces, as well as to maintain trip-chaining activities/stops. Motorcyclists were more dynamic than car drivers because motorcyclists had no restrictions (except for not being allowed on toll roads), such as 3-in-1 regulation, travelling on local roads and even travelling on the BRT-lanes. These findings indicate that using a motorcycle can increase the commuter’s mobility in Jakarta. However, because of the poor driving behavior of the motorcyclists, the presence of motorcycles on the roads often causes traffic jams and accidents.

Nevertheless, motorcycles are the most flexible and the cheapest travel mode. Based on these findings and on the fact that the number of motorcycles on the road is increasing, we suggest developing a route choice model for motorcycles, or motorcycle network. Appropriate roads will have to be determined and facilitated with special lanes for motorcycles. By separating the lanes for motorcycle from lanes for other modes, the mobility system in Jakarta can be increased and thus traffic congestion and accidents can be reduced.

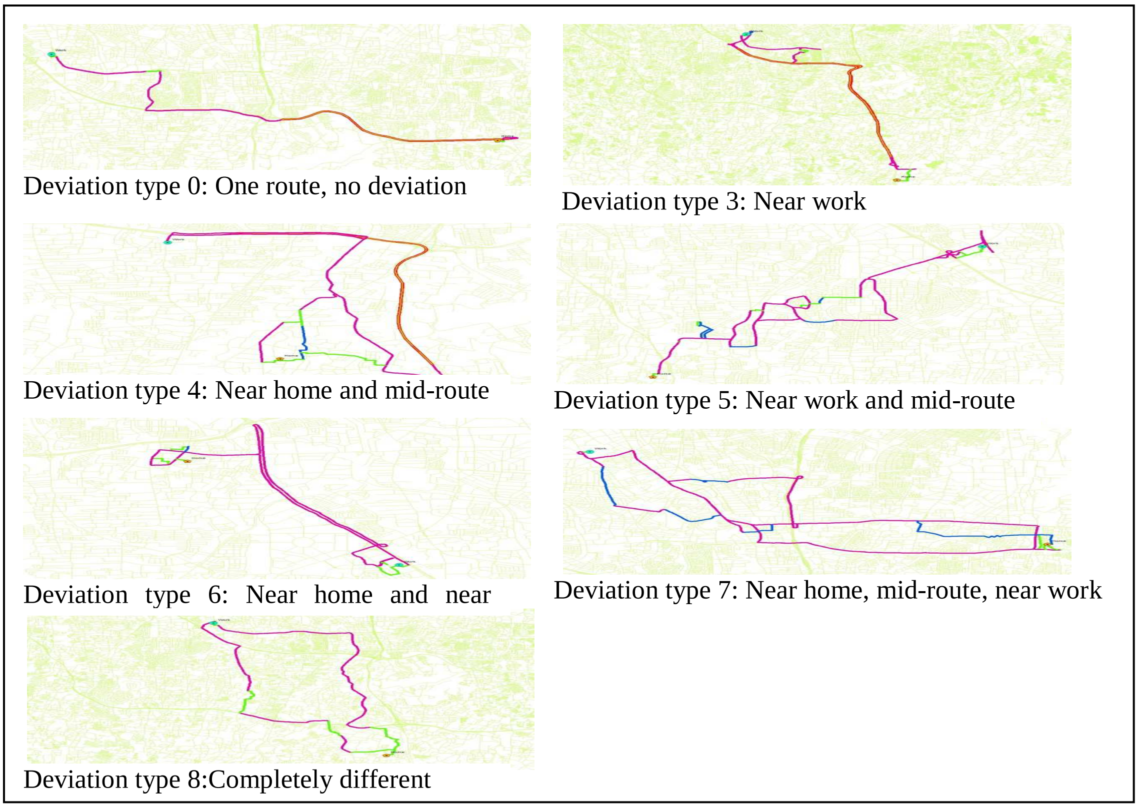

Figure 3 Visual examples of route deviation pattern

3.3.3. Route choice variability

The variation of route choice deviations during the AM-commutes and the PM-commutes were examined. If a commuter employed route deviations (used multiple routes), then he/she was labeled “Yes”. Commuters that did not employ route deviations (used a single route) were labeled “No”. The distribution of route choice deviations is shown in Table 9.

Table 9 Distribution of route choice deviation

Mode	Route Choice Deviation	Number of Commuters (%) AM-commute	PM-commute	AMxPM-commute
Car	No	34.5	25.9	10.3
	Yes	65.5	74.1	89.7
Motorcycle	No	45.5	22.6	3.0
	Yes	54.5	77.4	97.0

Route choice deviations can be categorized as shown in Table 10:

- Category 0: no route deviation (used a single route during the survey period).
- Category 1: no route deviation during either the AM-commute or the PM-commute, but used different single routes for both the AM-commute and the PM-commute.
- Category 2: used multiple routes during PM-commute only.
- Category 3: used multiple routes during AM-commute only.
- Category 4: used multiple routes during both the AM-commute and the PM-commute.

Table 9 shows that more than 50 percent of car drivers and motorcyclists used multiple routes. Route deviation occurred more during the PM-commute than the AM-commute. This reflects that traffic congestion in the evening peak hours is higher than in the morning. Motorcyclists executed more route deviations than car drivers. Table 10 shows that the majority of car drivers

(58.6%) and motorcyclists (45.5%) used multiple routes during both AM-commute and PM-commute (category 4).

Table 10 Distribution of route choice deviation categories

Mode	Category	AM-commutes	PM-commutes	AMxPM-commutes	Number of Commuters (%)
Car	0	No	No	No	10.3
	1	No	No	Yes	6.9
	2	No	Yes	Yes	17.2
	3	Yes	No	Yes	6.9
	4	Yes	Yes	Yes	58.6
Motorcycle	0	No	No	No	3.0
	1	No	No	Yes	12.1
	2	No	Yes	Yes	30.3
	3	Yes	No	Yes	9.1
	4	Yes	Yes	Yes	45.5

4. CONCLUSION

This paper presents the day-to-day dynamic behavior of commuters' mode and route choices using multi-day GPS data observed from 93 commuters in Jakarta during the period of a one-week survey using person-based GPS devices. A series of algorithms was developed to analyze the GPS raw data. The analysis consisted of data filtering, identification of commute trips, derivation of commute trip characteristics, detection of commute main modes, and identification of routes. Day-to-day dynamic behavior was investigated by analyzing mode and route choice variations during the AM and PM-commutes.

The observation data proves the presence of dynamic behavior in choosing both modes and routes for commuting. Route deviations are more common in the afternoon. In fact, using a motorcycle can increase the mobility system in Jakarta if motorcyclists are better regulated by establishing a "motorcycle network". Furthermore, the study identifies a great potential to attract private vehicle users to public transportation if the performance of the public transport system can be improved, for example, by applying a fixed time schedule for reducing the uncertainty of the travel time.

The limitations of this study are that the results are based on a small sample size and a survey of short duration. Validation studies could be undertaken, using larger samples and a longer survey period to test the reliability of the findings. Nevertheless, this study has provided valuable insight into the real day-to-day dynamic behavior of commuters in Jakarta observed over a one-week period.

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