Investigation of traffic information on route choice models considering drivers' personal characteristics

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Abstract: In this study, the types of traffic information that influence drivers' route choices in a hypothetical environment was investigated. In the numerical experiment, the expected travel times and combinations of toll information were used to create better traffic conditions, as indicated by the total travel time. These combinations include drivers' perceptions and personal characteristics such as route familiarity, information provision, and toll types under stochastic equilibrium conditions for users. Fixed, distance, and traffic-dependent tolling strategies were also implemented to illustrate the differences in outcomes imposed on the subgroups of respondents. The traffic information for an unfamiliar route has a positive effect on the traffic situation, which is reflected in a low value of total travel time. The proportion of systematic utility components changed when different traffic information were used. Variations in proportions were also found in the different sub-samples, and the best traffic conditions occurred when traffic information was provided.

Keywords: Traffic Information, Driving Behavior, Route Choice, Perceived Travel Time, Travel Time Uncertainty

1. INTRODUCTION

Traffic management is necessary to regulate traffic demand on toll road networks. Providing accurate traffic information derived from extensive traffic detectors is one tool that toll road operators (TROs) can use to regulate traffic within toll road networks. Suppose travel time prediction is no longer a problem due to the high accuracy of traffic detection systems. Compared with the previous situation, when accuracy and acceptance of traffic information is low, acceptance of the information by drivers becomes a challenge. It is argued that drivers' characteristics and socioeconomic background influence their decisions regarding the perception of traffic information.

Naturally, the driver chooses the route with the minimum utility function (minimum travel cost) to reach the destination. This definition is referred to as user equilibrium (UE) (Wardrop, 1952). However, these UE conditions occur under the assumption that drivers have complete information about the travel costs, consistently make correct decisions regarding route choice, and behave identically. Stochastic user equilibrium (SUE) was introduced to address the unrealistic assumption that users attempt to minimize their perceived utility costs (Daganzo & Sheffi, 1977). Perceived utility includes the uncertainty of tolls and travel time in traffic information. Therefore, it is assumed that this perceived benefit also influences drivers' decision behavior.

However, although traffic information enables traffic management, quantifying its influence on traffic conditions still requires explanation. Therefore, further variation in research methods is needed to gain new insights into the type of traffic information that changes drivers' choice behavior and leads to better traffic conditions. The proposed method for identifying route choice behavior and better traffic conditions when stochastic user equilibrium occurs will include the traffic information of toll and travel time ranges derived from drivers' perceptions, route familiarity, tolling strategies, and traffic congestion levels.

2. LITERATURE REVIEW

Available transportation infrastructure is more efficient when travel demand management tools, such as travel information, help drivers make better route choices (Arnott et al., 1989). (Papageorgiou et al., 2008; Sheu & Yang, 2008) have noted the importance of VMSs in managing traffic congestion and improving traffic efficiency (Shaokuan et al., 2008). A VMS is an important component of intelligent transportation systems as it provides various types of information, such as traffic conditions, speed limits, and alternative routes (Jindahra & Choocharukul, 2013).

Research has revealed several important findings on how traffic information affects route-choice behavior. As part of innovations in intelligent transportation system, traffic information systems can influence route-choice decisions (Abdel-Aty et al., 1997), but the effects are complex and influenced by many factors (Hensher & Button, 2007). Unpredictable variations in travel time are closely related to travel time reliability.(Carrion & Levinson, 2012).(Wang & Rakha, 2020) argue that expected travel time information is more effective than travel time variability. A contrary argument was made by (González Ramírez et al., 2021), who found that drivers evaluate relative travel time instead of absolute differences in their route choice, and that the decreasing accuracy of travel time information shifts drivers' choices to more reliable routes. In addition, the travel time margin influences drivers' willingness to take risks (Katsikopoulos et al., 2002). Travel time uncertainty due to drivers' perceptions has been defined using the fuzzy set theory (Ramazani et al., 2011).

Traffic information is a traffic management tool that provides drivers with valuable information such as alternative routes, incident locations, and warnings about traffic situations. It is important to provide valid traffic information based on a scientifically sound method that relies on verifiable data rather than personal intuition. Proactive traffic management should be deployed to anticipate the lag between data collection and traffic control strategies (Smith et al., 2002). However, drivers sometimes disregard messages because they are too generalized or give incorrect traffic conditions on alternative routes (Sutandi, 2008). Sutandi also argued that most drivers who ignore traffic information consider alternate routes to have similar traffic conditions. This type of driver has prior knowledge of the road network and tends to repeat previous decisions as inertial choices (Liu & Xu, 2019). In addition, driver behavior may depend type of on the road. (Gan & Ye, 2014) suggested a method to observe driver behavior when perceiving traffic messages on toll and surface roads.

Recent research on the tendency to perceive traffic information in Indonesia is limited to motorcyclists on urban road networks (Fadilah et al., 2022). (Zuna et al., 2016) and (Makmur et al., 2019) confirmed that Indonesia still lacks relevant traffic management information systems because TROs do not provide up-to-date and accurate traffic information.

Probe-vehicle data is used to estimate real-time traffic information and is used to support driver decisions and as a criterion to determine the minimum cost path in dynamic route guidance (Nanthawichit et al., 2003)

Some argue that driver experience, delays, and the number of traffic lights influence route-choice decisions (Gan et al., 2013), while others claim that familiarity with the route and the driving environment are also have the greatest influence on drivers' opinions of traffic information (Kantowitz et al., 1997). Conversely, departure time choice behavior also significantly affects travel time variability and the availability of real-time information, which in turn influences route choice (Kurauchi et al., 2019a). The latter method can also be used for transport demand management (TDM), leading to the idea that the provision of traffic information can be used as a traffic management tool.

(Dixit et al., 2019) included driver's perceptions in their analysis of route choice behavior, accounting for the travel time range. Moreover, (Tenenboim et al., 2023) considered the effect of toll payments on drivers' subjective time estimation, while others have looked at similar reactions among drivers, specific behavioral differences related to travel time variability have been found in individuals (Li & Hensher, 2013).

(Gan, 2013) examined the decision-making behavior of drivers based on VMS-displayed traffic information on arterial roads and expressways. Gan's research opens up the possibility of controlling traffic that traveling from the airport to the city and vice versa and enables better control by providing traffic information (Tanaka et al., 2014). Drivers find radio and VMS helpful to make travel decisions (Chatterjee et al., 2002; Kurauchi et al., 2019b; Wardman et al., 1997; Zhao et al., 2020), but GPS devices provide more detailed traffic information, making them more responsive to travel information.(Ramos, 2015).

This research summarizes all the above studies in the literature and thus narrows the scope. It focuses on the combination of all aspects related to traffic information as part of traffic management tools. These include travel time range, toll range, driver perceptions based on route familiarity, toll payment strategies, and traffic congestion. To the best of our knowledge, the combination of all these aspects is necessary to gain new insights into the provision of traffic information that leads to better traffic conditions.

3. METHODOLOGY

This method compares several information provisions and tolling strategies under several assumptions to balance the traffic volume and travel times of the two routes. In this sense, traffic conditions are quantified by the total travel time. The datasets come from the stated preference survey done by Sumardi,et al (2024) aimed to (1) identify awareness and acceptance of traffic information in Indonesia and Japan and (2) construct predictors sensitive to respondents' route-choice behavior. Electronic questionnaires were distributed in October 202 by surveying 508 toll road users in Indonesia regarding their preferences. However, three Indonesians did not complete the questionnaires; therefore, only 505 respondents who provided valid responses were included in the analysis. There were four subgroups of Indonesian drivers based on awareness and dependence on traffic information: aware and dependent, unaware and dependent, aware and independent, and unaware and independent. The definition of four subgroups according to Sumardi, et al (2024) : aware and dependent, unaware and dependent, aware and independent, and unaware and independent. The "aware" group responded "agree" or "strongly agree" to "I check the traffic information every time before driving." The unaware group do not always check traffic information before a trip. The dependent group obey traffic suggestions, while the independent group prefer their choice of route and neglect route suggestions. The last subsample is the group that responded: "strongly disagree," "disagree," or "neither" to the statement "I will follow the route suggestion" (see Table 1). It is assumed that the driver chooses a route based on the utility function U_{in} of option i for individual n.

The trade-off between travel time and toll exists in the details of the questionnaires. So, it is assumed that all drivers should choose between the given travel time and toll from the two alternative routes. In this research, we only assumed that the utility is in linear function. We started to consider the simple form of driver and traffic information provision in order to see the differences that it makes. In the future, we suggest a more complex form. This utility function is based on V_{in}, which is a systematic component of the utility and a random utility component: $U_{in} = V_{in} + \varepsilon_{in}$. V_{in} results from the sum of the multiplication of the variable coefficient (β) and a vector of observable explanatory variables X according to the following equation

$$V_{in} = \beta' X_{in} = \sum_{k=1}^{K} \beta_k X_{ink} \quad (1)$$

Therefore, the systematic utility function for respondent n who chooses option i is expressed as follows:

$$V_{in} = \beta_{n\Delta T^{min}} T_i^{min} + \beta_{n\Delta F_{12}^{max}} F_i^{max} + \beta_{T^{range}} \left(T_i^{max} - T_i^{min}\right) + \beta_{F^{range}} \left(F_i^{max} - F_i^{min}\right) + \beta_{T^{ratio}} \frac{\left(T_i^{max} - T_i^{min}\right)}{T_i^{min}} + \beta_{T^{ratio}} \frac{\left(F_i^{max} - F_i^{min}\right)}{F_i^{min}} \quad (2)$$

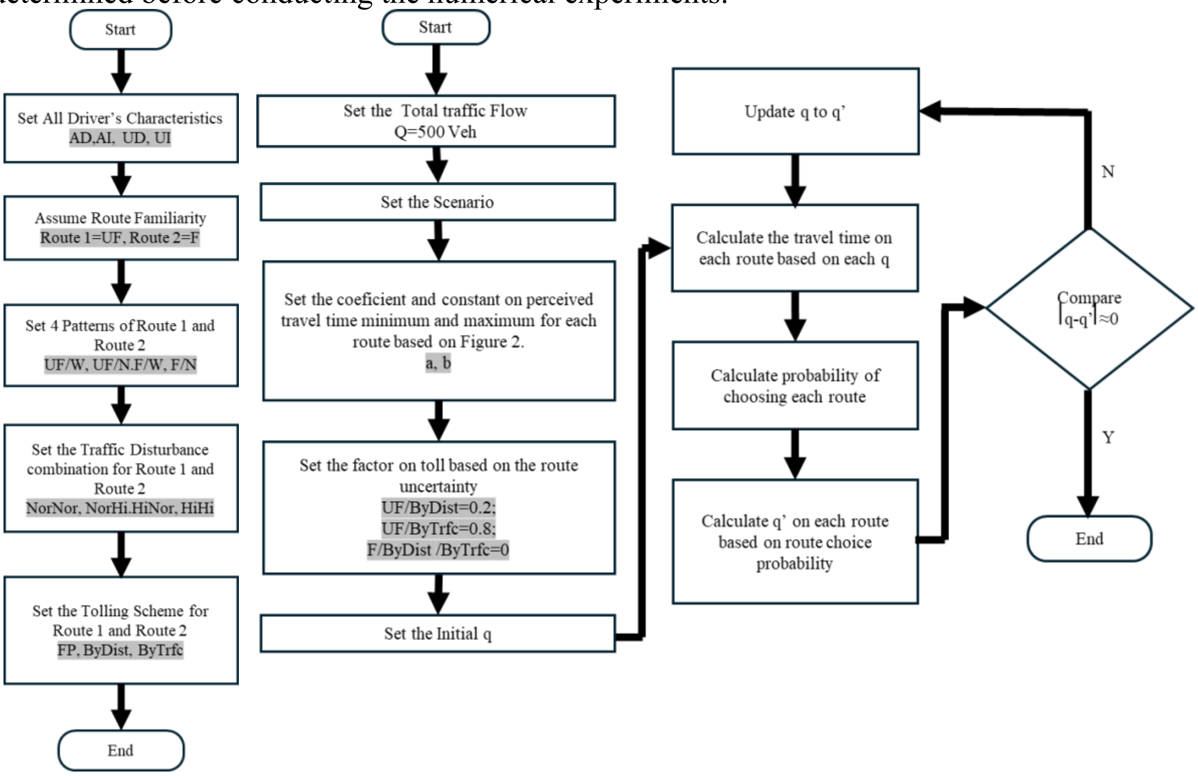
where ΔT^{min} is the minimum difference between the expected travel time on Route 1 (T_1^{min}) and the minimum expected travel time on Route 2 (T_1^{min}). The maximum toll difference (ΔF_{12}^{max}) is the maximum expected toll on Route 1 (F_1^{max}) minus the maximum expected toll on Route 2 (TF_2^{max}). The travel time range (T^{range}) is the difference between the maximum and minimum expected travel time on Route 1 ($T_1^{max} - T_1^{min}$) minus the same formula for Route 2 ($T_2^{max} - T_2^{min}$). The toll range (F^{range}) is the toll difference for Route 1 $\left(F_1^{max} - F_1^{min}\right)$ minus the toll difference for Route 2 $\left(F_2^{max} - F_2^{min}\right)$. In addition, the travel time ratio (T^{ratio}) is the ratio of the travel time range to the minimum expected travel time of Route 1 $\left(T_1^{range}/T_1^{min}\right)$ minus the ratio of the travel time range to the minimum expected travel time of Route 2 $\left(T_2^{range}/T_2^{min}\right)$. Finally, the toll ratio was derived from the ratio of the toll range to the minimum expected toll of Route 1 $\left(F_1^{range}/F_1^{min}\right)$ minus the ratio of the toll range to the minimum expected toll of Route 2 $\left(F_2^{range}/F_2^{min}\right)$. The equation (2) consist of the characteristics of drivers from their tendency of choosing route. Significant factor of variables represent the attitude towards a given traffic information.

Table 1. Results of the model estimation of the binary logit model (Sumardi et al., 2024)

Variables		Traffic Information Awareness versus Traffic Information Dependency			
		Aware & Dependent	Unaware & Dependent	Aware & Independent	Unaware & Independent
Number of Respondents =	505	253	83	77	92
		Coefficient	Coefficient	Coefficient	Coefficient
$\beta_{n\Delta T^{min}}$		0.073***	0.09***	0.11***	0.057**
$\beta_{n\Delta F^{max}}$		0.0000416***	0.0000219***	0.0000296***	0.0000243***
$\beta_{T^{range}}$		-0.056*	-0.095*	-0.117**	-0.027
$\beta_{F^{range}}$		0.0000498***	0.000083***	0.0000559*	0.0000278
$\beta_{T^{ratio}}$		2.051**	3.391*	4.062**	1.156
$\beta_{F^{ratio}}$		-1.285***	-2.118***	-1.396**	-0.846

***, **, * indicate significance at 1%, 5%, levels, and 10% respectively.

The choice models mentioned above assume a situation in which drivers know both the tolls and the travel time margins of the routes before choosing one. In real situations, the toll and travel time ranges exist only in the perception of a driver who sees the traffic information. This perception is based on several factors that the driver must take into account before deciding on a route, including drivers' choice behavior, driver characteristics, and perception of expected travel time and tolls. All factors that are influenced by the provision of traffic information are assumed to improve the traffic situation. Figure 1 shows all assumed factors that were determined before conducting the numerical experiments.



(a) Setting up scenarios (b) Calculation steps

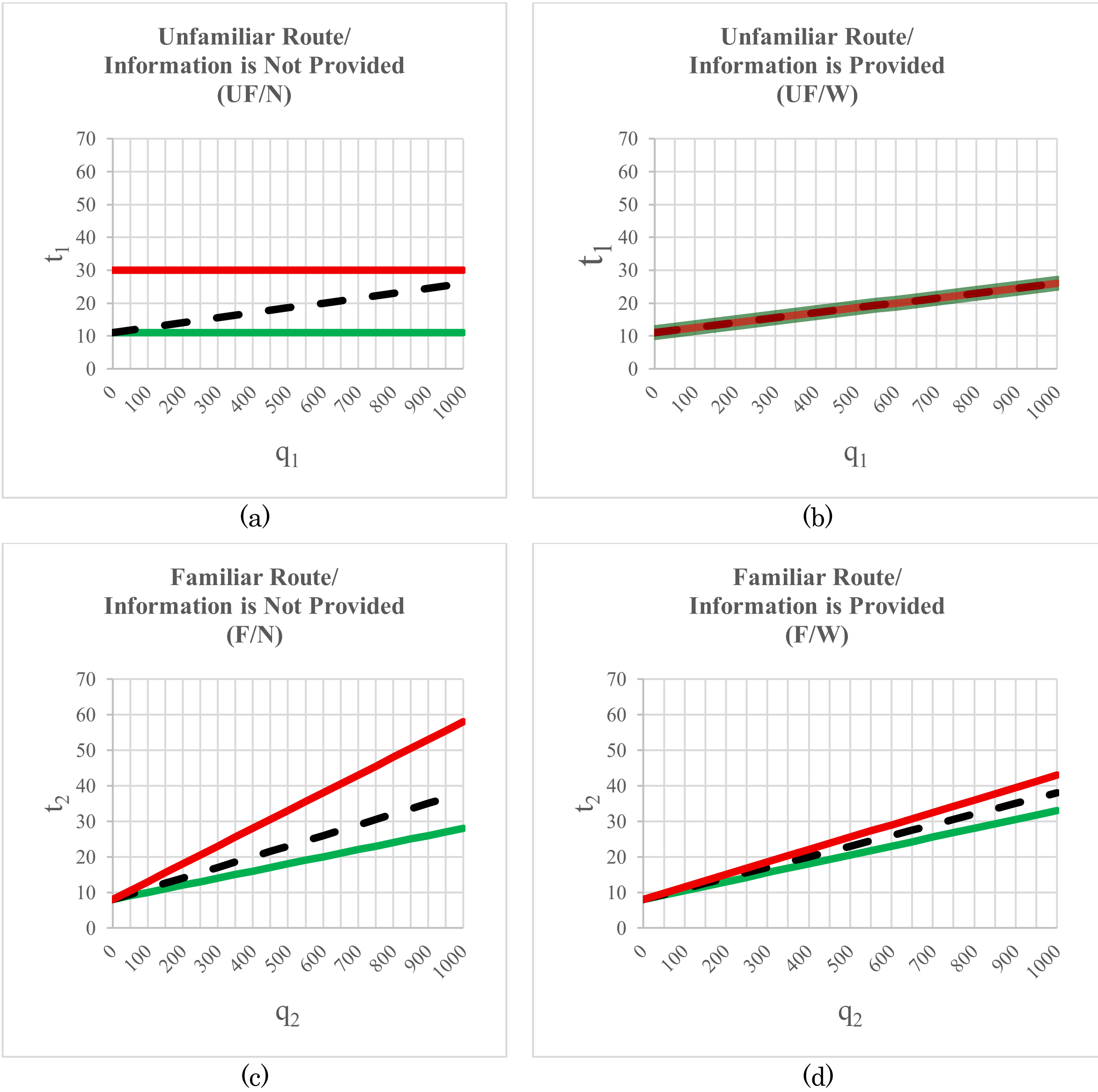
Figure 1. Setting up the assumptions

The conceptual assumption of perceived travel time and fare is based on familiarity with the route and the provision of traffic information. When the driver sees a route option, we assume that there are two options: a familiar or an unfamiliar one. Route familiarity creates a range of perceptions between minimum and maximum travel time and fares. Subsequently, the perceived travel time is assumed based on the familiarity of the route. In addition, traffic information also plays a role in the perception of route travel time, regardless of whether it is provided. The information provided makes the deviation of the perceived travel time and fare smaller than under the uniform condition. However, in certain situations, the provision of traffic information leads to drivers' perceptions being similar to those of real travel times and fares.

The following assumptions were made: Compared to normal traffic disruptions, a route with a high traffic congestion will also result in a high travel time. This factor leads to different patterns in perceived travel time. Finally, toll payment scenarios were applied based on fixed-price, distance-based, and traffic-dependent toll types. To observe the variation in the results, we also compared the four groups of drivers and several values of traffic demand that went into the two route options. The numerical experiment used different combinations of expected travel times and toll information, including driver perceptions. First, the actual travel time is defined for a given route. The expected travel time changes depending on the traffic volume on that route and creates the link cost function. In addition, it is assumed that there may be traffic disruptions within the route during this time, such as traffic incidents, bad weather conditions, or road works. Normal and severe traffic disturbances affect the magnitude of the perceived link cost function. From the driver's perspective, the expected travel time may vary depending on their perception. Their perceptions are based on their familiarity with the route. In addition, the provision of traffic information makes the choice dependent on this. The experiments were conducted based on several assumptions. Today's travel time is the travel time information provided to users by the toll road operators. It is assumed that the travel time is derived from the field and is considered to be an accurate travel time. Table 2 lists the parameters that have been simplified using the codes representing the imposed parameter variations.

Table 2. Variables in the numerical experiment

<table>
<tr><th>No</th><th>Parameter</th><th colspan="2">Variable</th><th colspan="2">Code</th></tr>
<tr><td>1</td><td>Toll type</td><td colspan="2">The toll based on fixed price
The toll based on the distance
The toll based on traffic</td><td colspan="2">FP
Bydist
Btrfc</td></tr>
<tr><td>2</td><td>Nationality</td><td colspan="2">Indonesian</td><td colspan="2"></td></tr>
<tr><td>3</td><td>Driver Type</td><td colspan="2">Aware Dependent
Aware Independent
Unaware Dependent
Unaware Independent</td><td colspan="2">AD
AI
AD
UI</td></tr>
<tr><td rowspan="5">4</td><td rowspan="5">Information Provision</td><td>Route 1</td><td>Route 2</td><td>Route 1</td><td>Route 2</td></tr>
<tr><td>No Info</td><td>No Info</td><td>N</td><td>N</td></tr>
<tr><td>No Info</td><td>With Info</td><td>N</td><td>W</td></tr>
<tr><td>With Info</td><td>No Info</td><td>W</td><td>N</td></tr>
<tr><td>With Info</td><td>With Info</td><td>W</td><td>W</td></tr>
<tr><td rowspan="5">5</td><td rowspan="5">Traffic Disturbance</td><td>Route 1</td><td>Route 2</td><td>Route 1</td><td>Route 2</td></tr>
<tr><td>Normal</td><td>Normal</td><td>Nor</td><td>Nor</td></tr>
<tr><td>High</td><td>High</td><td>Hi</td><td>Hi</td></tr>
<tr><td>Normal</td><td>High</td><td>Nor</td><td>Hi</td></tr>
<tr><td>High</td><td>Normal</td><td>Hi</td><td>Nor</td></tr>
<tr><td>6</td><td>Traffic Flow</td><td colspan="2">500 vehicles</td><td colspan="2"></td></tr>
<tr><td>7</td><td>Route Familiarity</td><td colspan="2">Route 1: Unfamiliar
Route 2: Familiar</td><td colspan="2">Route 1: U
Route 2: F</td></tr>
</table>



Legend:

Perceived Minimum Travel Time
Real Travel Time
Perceived Maximum Travel Time

Figure 2 shows a graph explaining the perception of travel time when drivers encounter route choices based on route familiarity and traffic information. To create a real link cost function, the expected travel time on a given route depends on traffic flow. A person who is unfamiliar with this route will estimate the minimum travel time because it does not depend on the traffic flow. The perceived minimum travel time corresponded to the travel time under conditions of free-flow of traffic. The maximum travel time was also estimated by respondents based on their experience. However, if they are familiar with the route, but do not receive any traffic information, they perceive the travel time to be similar to the actual one. However, there will be a deviation between the minimum and maximum perception, and the pattern will be the same with information, but with a slight deviation.

If Q is the total traffic flow from Route 1 (q1) and Route 2 (q2),

$$Q = q_1 + q_2 \tag{3}$$

and the travel time on route 1 (T1) is a linear function of the constant (a) and the coefficient (b) according to the flow,

$$T_1 = a_1 + b_1 q_1 \tag{4}$$

$$T_2 = a_2 + b_2 q_2 \quad (5)$$

The probability that a driver chooses Route 1 (P1) is the traffic flow on Route 1 divided by the total traffic flow.

$$P_1 = \frac{q_1}{Q} \quad (6)$$

$$P_2 = \frac{q_2}{Q} \quad (7)$$

Figure 3 shows the pricing as a function of the tolling strategy, the drivers' knowledge of the route, and provision of traffic information. The actual fare (F) is perceived as the minimum (Fmin) or maximum fare (Fmax). The fare is expressed in Rupiah, the Indonesian currency, and is set depending on to the traffic volume. In the fixed-price tolling scenario, the cost is the same for both routes. The fare was therefore the same for all route familiarities and traffic information provisions.

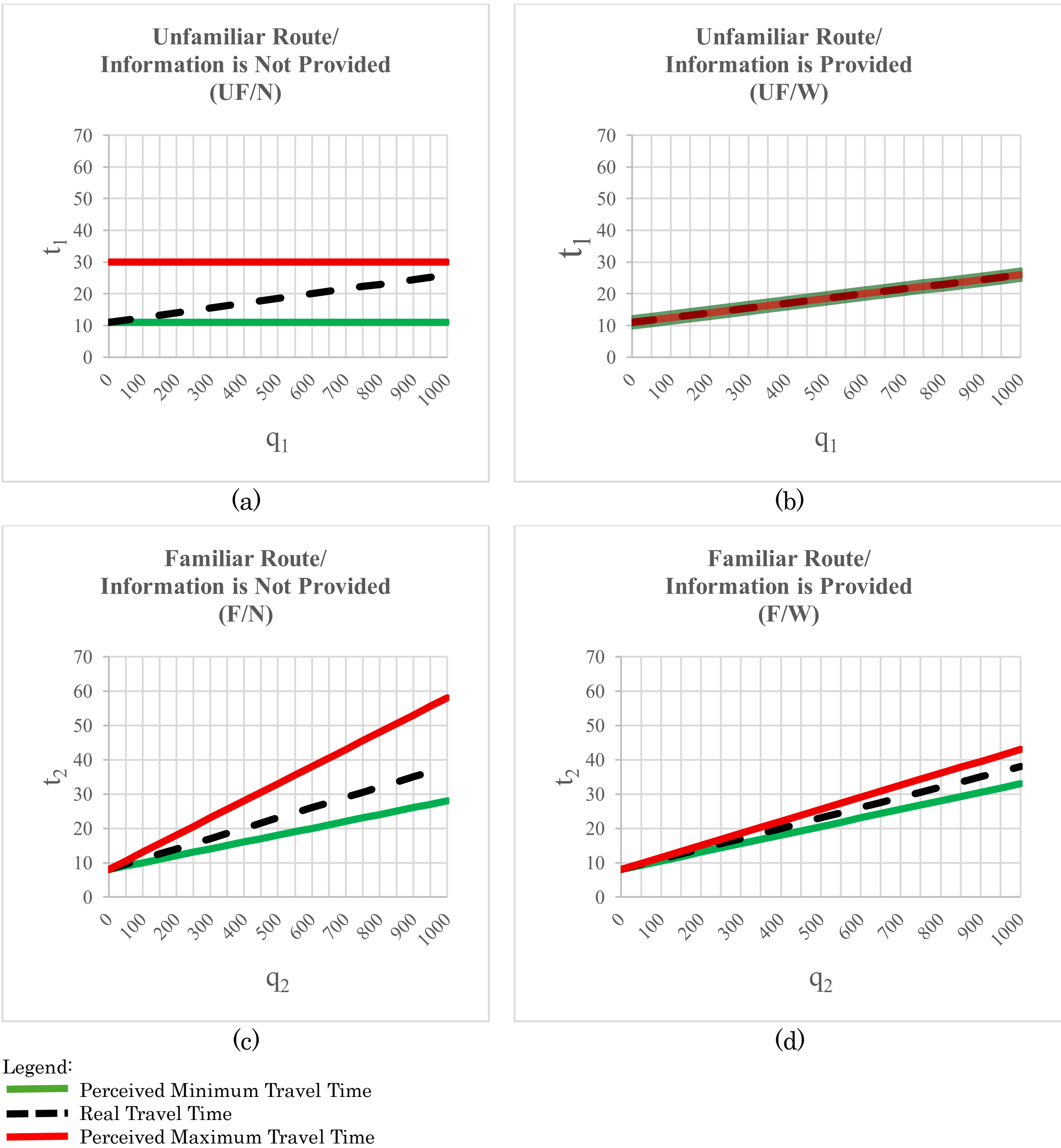


Figure 2. Distribution of travel time perception

In the distance-based strategy, there are two types of fare distributions: one with an unfamiliar route and the other with a familiar route. Unfamiliar routes give drivers a perception of the fare, which is reflected in minimum and maximum fares. However, the deviation in fares in this scenario was not significant. Drivers know the exact fare on a known route, so the perceived fare would be the same as the actual fare. The traffic-dependent tolling strategy differentiates the fare distribution according to familiarity with the route and the provision of information On the unfamiliar route without information, there was a large deviation. It is understood that the driver has to assume the fare as the traffic volume increases, and this assumption could show a large difference from the actual fare. Similar conditions also occurred on routes that were familiar with the traffic information provided. However, the deviation is not as large as that in a uniform situation as the driver has historical knowledge of fares based on their experience. The fare profiles of the informed drivers show the same patterns, and the assumed fare corresponds to the actual fare based on the traffic flows. Each calculation of the scenario was done as if all the toll users were homogeneous (i.e. All AD or AI or UD or UI).
The steps in this numerical experiment are as follows:

1. Assumptions about the distribution of travel time according to the traffic flow on each route. These travel time assumptions are based on the current travel time. It is assumed that this travel time is derived from the number of traffic detectors and that it is accurate. The travel time distribution follows a linear equation:
   a is a constant indicating the travel time on route i in free-flow traffic, and b is a coefficient based on the traffic flow.
2. Assume minimum and maximum travel times based on the traffic disruptions of the route (Normal or High), route familiarity (Unfamiliar or Familiar), and the provision of traffic information (No Information or With Information).
3. Assume the fare according to the toll payment strategy: fixed-price, distance-based, and traffic-dependent.
   In a traffic-dependent toll strategy, uncertainty is introduced based on the familiarity with the routes.
4. Assume the minimum and maximum fare based on the uncertainty of the route.
5. Calculate the utility cost based on each sub-group route choice model

$$
\begin{aligned}
V_i(q_i) = {} & \beta_{n\Delta T^{min}}\left(T_i^{min}(q_i)\right) + \beta_{n\Delta F_{12}^{max}}\left(F_i^{max}(q_i)\right) \\
& + \beta_{T^{range}}\left(T_i^{max}(q_i) - T_i^{min}(q_i)\right) \\
& + \beta_{F^{range}}\left(F_i^{max}(q_i) - F_i^{min}(q_i)\right) \\
& + \beta_{T^{ratio}}\frac{\left(T_i^{max}(q_i) - T_i^{min}(q_i)\right)}{\left(T_i^{min}(q_i)\right)} \\
& + \beta_{T^{ratio}}\frac{\left(F_i^{max}(q_i) - F_i^{min}(q_i)\right)}{\left(F_i^{min}(q_i)\right)}
\end{aligned} \tag{8}
$$

Where the probability that route i is chosen according to its traffic flow is:

$$
P_i(q_i) = \frac{1}{1 - e^{\left(V_i(q_i) - V_j(Q^{Total} - q_i)\right)}} \tag{9}
$$

The recalculated traffic flow under stochastic user equilibrium is therefore:

$$
q_i^* = Q^{Total}.P_i(q_i^*) \tag{10}
$$

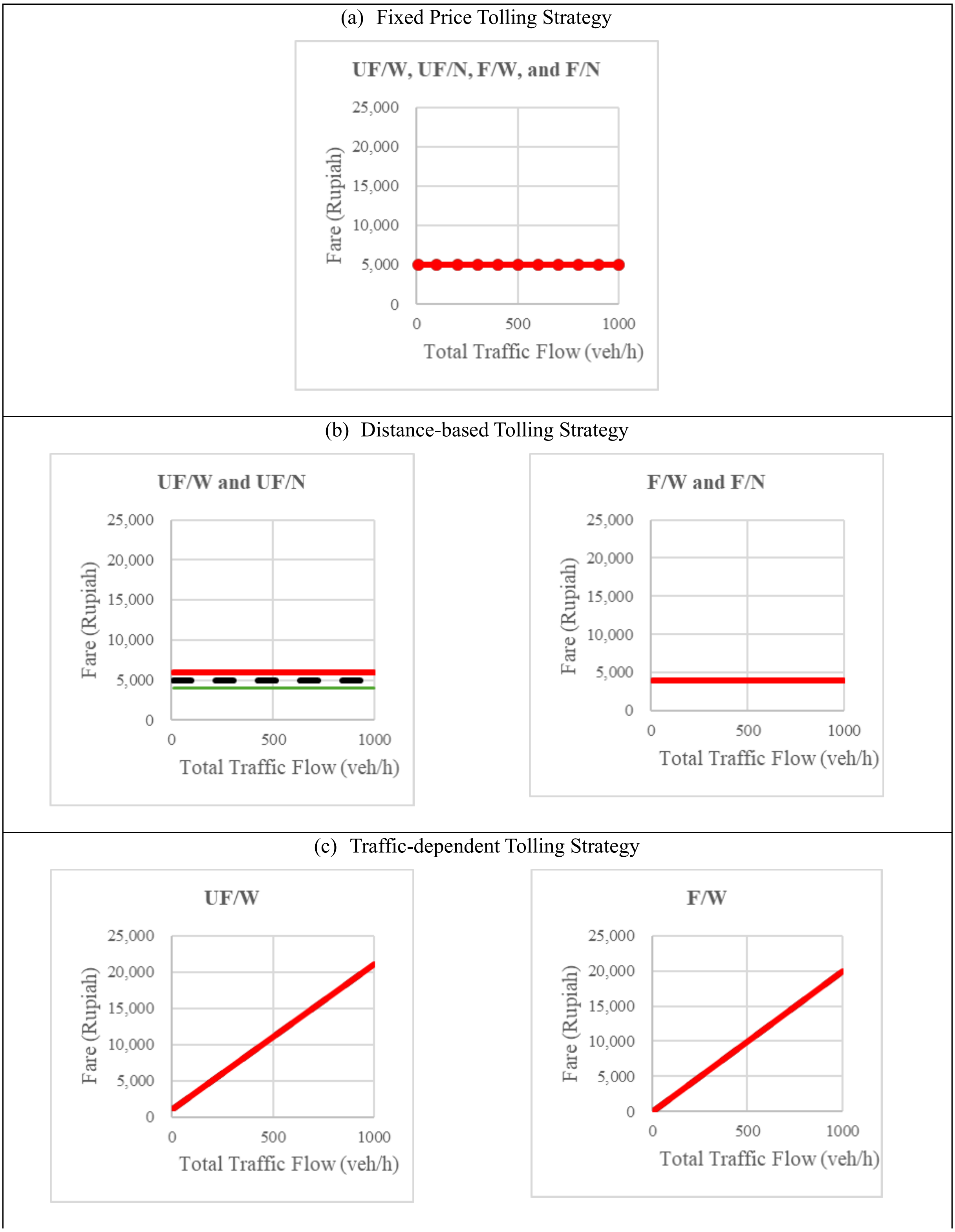
The total travel time for Route 1 and Route 2 is calculated as the sum of the travel time for the flow on both routes.

$$
TT_{R1+R2} = T_1 q_1 + T_2 q_2 \tag{11}
$$

$$= (a_1 + b_1 q_1)P_1 Q + (a_2 b_2 (1 - P_1)Q)(1 - P_1)Q$$
$$= (b_1 + b_2)Q^2 P_1^2 + \left((a_1 - a_2)Q\right) - 2b_2 Q^2)P_1 + a_2 Q + b_2 Q^2$$
$$= P_1 Q T_1(P_1 Q) + (1 - P_1)Q T_2\left((1 - P_1)Q\right) \quad (12)$$

Assuming Q=500 vehicles, then:

$$TT_{R1+R2} = P_1 500 T_1(500 P_1) + (1 - P_1)500 T_2\left((1 - P_1)500\right) \quad (13)$$



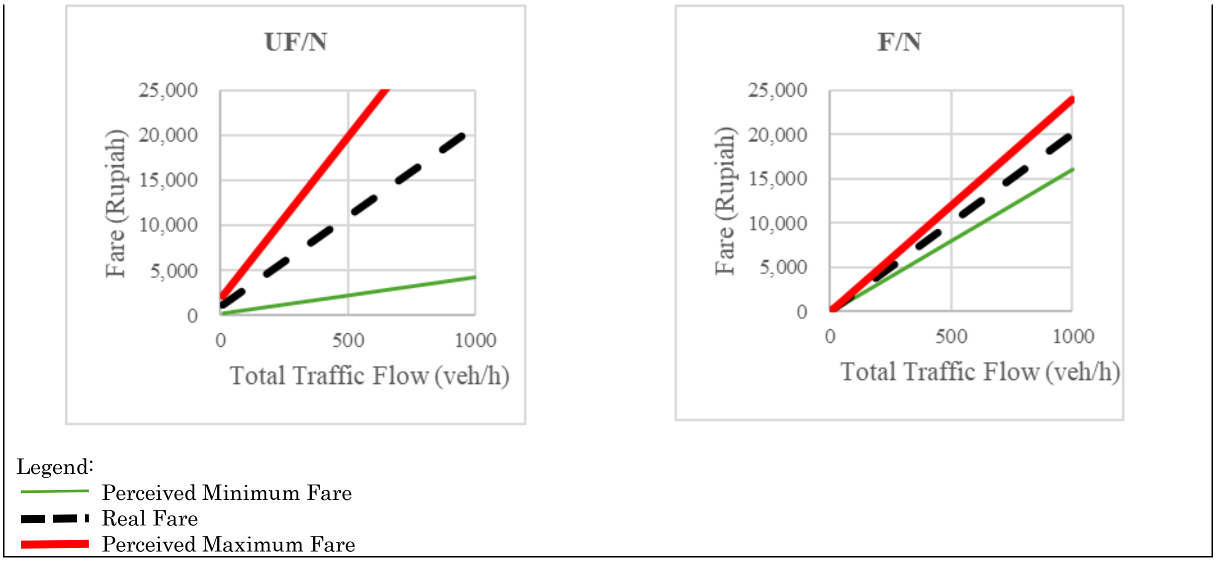


Figure 3. Perceived fare setting

4. RESULTS

Figure 4 shows the total travel time and the probability that the Indonesian AD group chooses R1 (unfamiliar route) when the fixed price (FP) toll strategy is applied for the four combinations of traffic disturbances on both routes. Providing traffic information for the unfamiliar route (Route 1) has a positive effect on the traffic conditions, which is reflected in a low value of the total travel time. Figure 4 shows four combinations of traffic information: No information on Route 1 and No information on Route 2 (NN), No information on Route 1 and With information on Route 2 (NW), With information on Route 1 and No information on Route 2 (WN), and With information on both Route 1 and Route 2 (WW).

The provision of traffic information affects all tolling strategies, even under high traffic disruptions conditions. The graph confirms that most of the best traffic conditions occurred when the traffic information was provided.

The probability of choosing a route indicates the total travel time in an equilibrium state based on the provision of traffic information. The best conditions vary even though the probability sequence is the same. The reason for this is because of the traffic performance. In the fixed-price strategy, the best condition occurs when the customer is unfamiliar or when both routes are informed. In a traffic-dependent strategy drivers will choose Route 1 (the unfamiliar route) 100% of the time if no traffic information is available for Route 1. The tendency to provide traffic information to improve traffic conditions was shown for each strategy and each group of drivers (see Appendix). However, when there was no information on Route 2, the drivers tended to change their choices from Route 1. As the disturbance on Route 2 was high, the route performance was worse. For the traffic-dependent tolling strategy, the results are slightly different. Better traffic conditions indicated that there was no traffic information on unfamiliar routes.

The proportion of utility systematic components that determine choice behavior is different for each tolling strategy (see Figure 5). This calculation indicates the main contributions of each systematic components of each utility to different traffic information provisions, tolling strategies, and observed groups. The utility systematic components are explained as follows: ΔT^{min} is the minimum difference, the maximum toll difference (ΔF_{12}^{max}), the travel time range (T^{range}), the toll range (F^{range}), the travel time ratio (T^{ratio}) and the toll ratio (F^{ratio}).

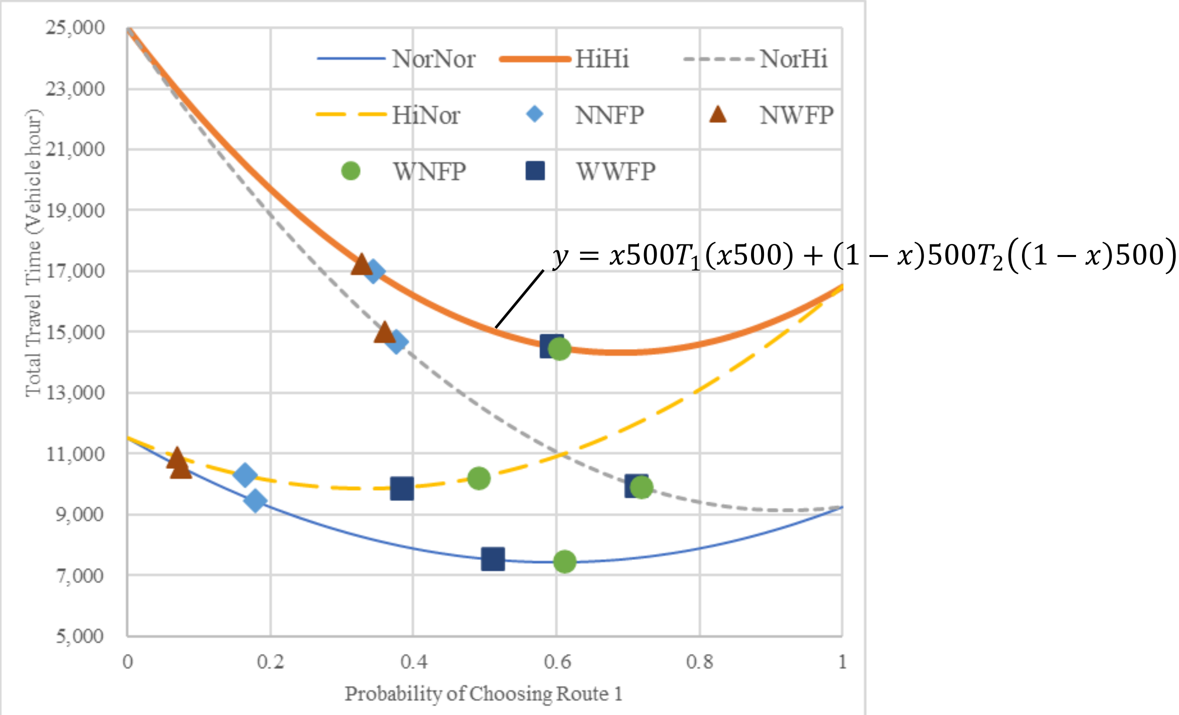
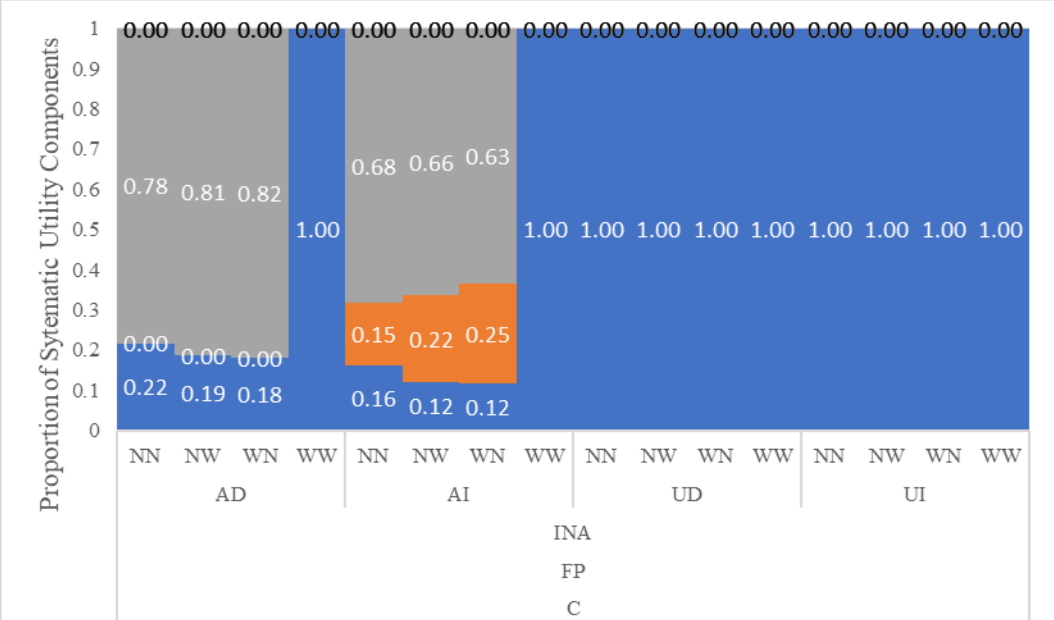


Figure 4. Total travel time in the SUE environment under the fixed price tolling strategy

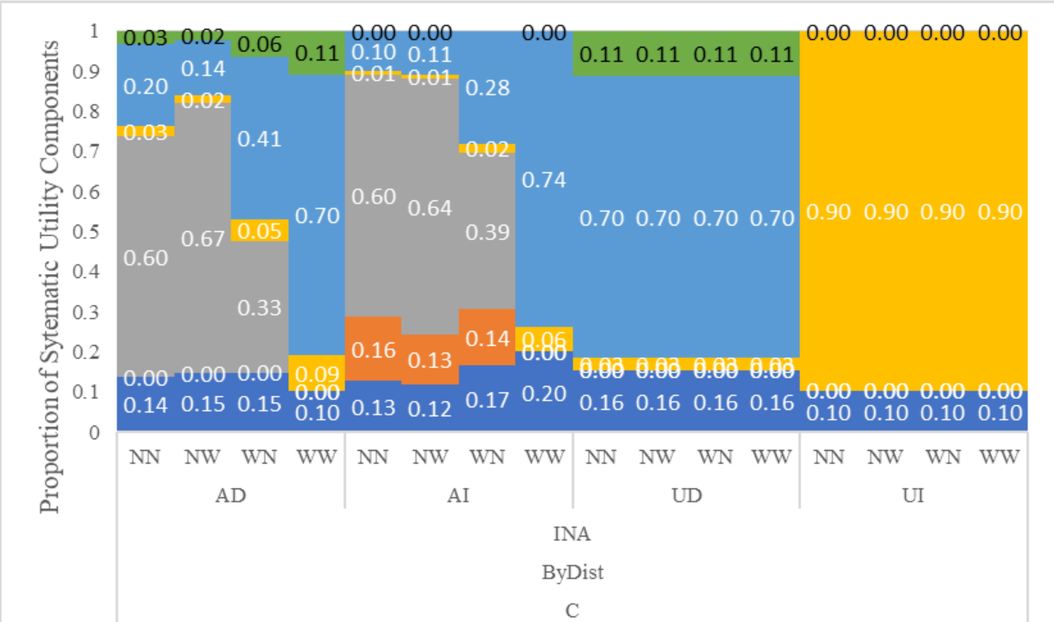
The graph in Figure 5 shows the combination of the systematic utility components for one group of respondents when the distance-based tolling strategy is applied. Five out of six components play an important role in the route choice decision: ΔT^{min}, ΔF_{12}^{max}, F^{range}, T^{ratio} and F^{ratio}. As depicted in the graph, the proportion of the components changed when different traffic information provisions were applied. Variations in proportions were also found in the different sub-samples. If we consider the AD group, unfamiliar and familiar routes are not provided with traffic information in this part of the traffic information provision. For the aware and dependent groups, the route choice was mainly based on the travel time ratio for each route. This factor accounted for approximately 80% of the decisions.

Judging from the proportion of utility systematic components, Indonesian drivers exhibit dynamic route choice behavior. The main proportion of utility components may have led to different outcomes when using a particular tolling strategy, even for the same group of drivers. For the unaware group, drivers considered only the minimum travel time the route offered for each piece of traffic information. In addition, each group of drivers had different dominant factors on their preferred routes. The unaware groups (UI and UD) were used to compare the minimum travel time for each route when applying the FP strategy. The other strategies (traffic- and distance-based) compare the maximum and ratio of each fare.

When we compare the three tolling strategies, it is evident that there are shifting tendencies in the systematic utility components that lead to route decisions. For example, consider an aware dependent group when all route options are provided with traffic information. Indonesian drivers exhibit dynamic behavior when deciding on a route. The most important decision factor may be different if applied to certain strategies, even for the same group of drivers.



(a) Fixed-time Tolling Strategy



(b) Distance-based Tolling Strategy

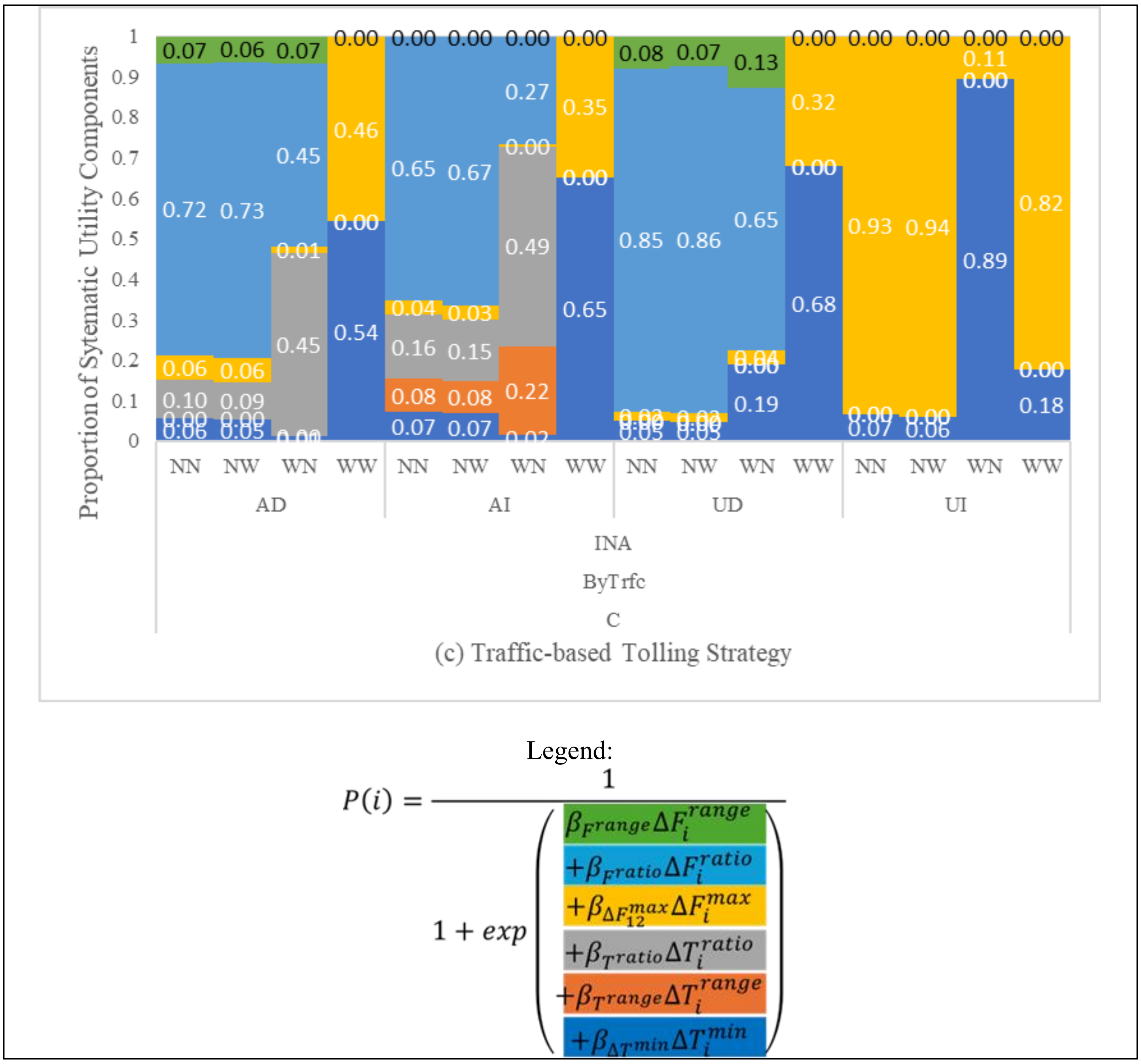


Figure 5. Utility systematic components of on Indonesian respondents' choosing behavior

5. CONCLUSIONS

In this study, the types of traffic information that change drivers' route choices in a hypothetical environment were investigated. Various combinations of expected travel times and toll information were used in numerical experiments, including drivers' perceptions and personal characteristics. The scenario resulting from the combination of route familiarity, information provision, and toll type under stochastic user equilibrium behavior was implemented.

It was confirmed that Indonesian drivers' route choice depends on group and tolling strategies and that providing traffic information that helps improve traffic conditions. Some groups only respond to toll fluctuations, that influence the route choice in the traffic-dependent tolling strategy. Traffic information helps improve traffic conditions when an option includes both unfamiliar and familiar routes. An unfamiliar route is preferred when traffic information is provided. Route preferences can be changed by providing traffic information to manage traffic.

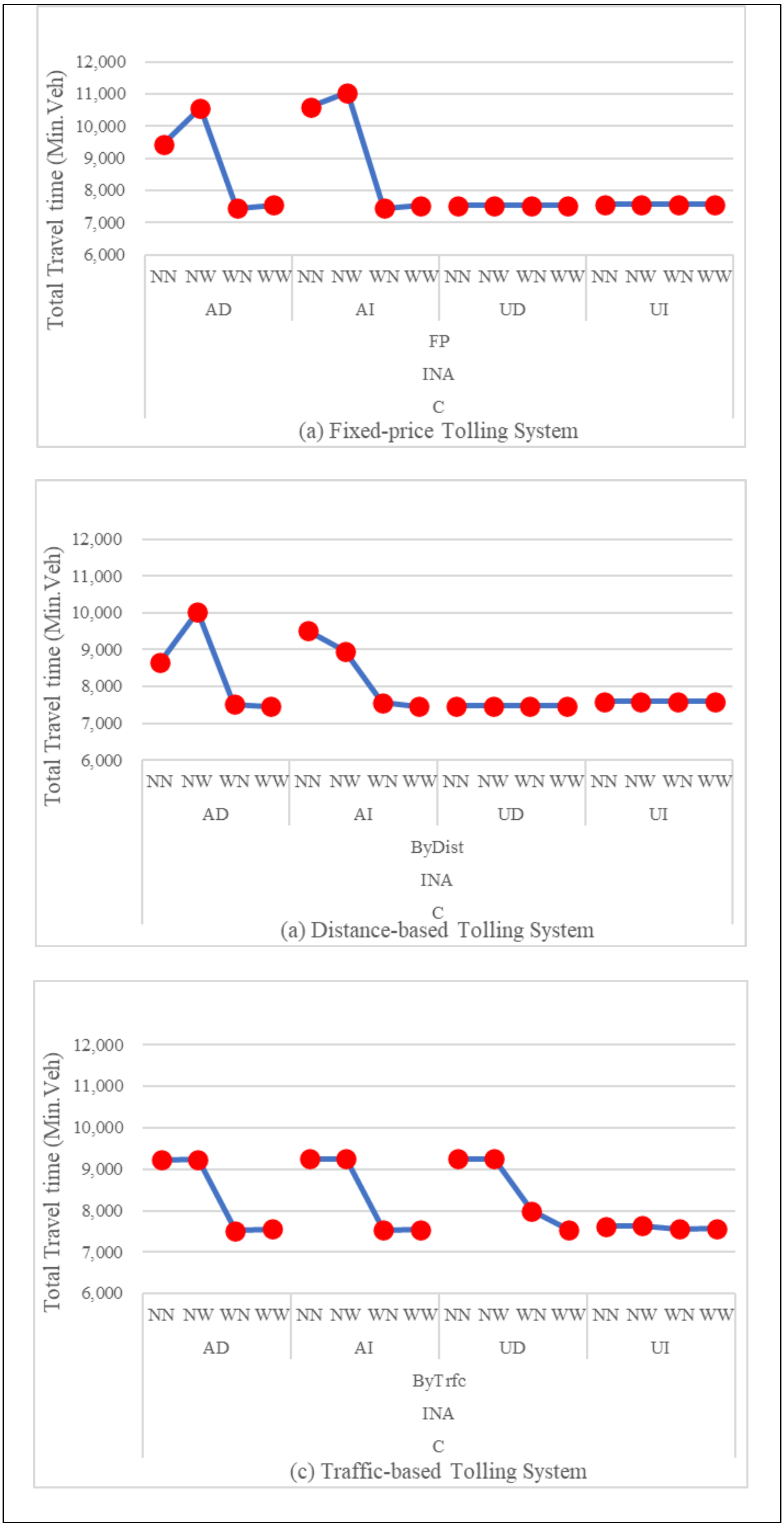


Figure 6. Calculated total travel time according to the tolling strategies

For the fixed-price strategy, the best condition is when the customer is unfamiliar or when both routes are informed. In the traffic-dependent strategy, drivers choose Route 1 (the unfamiliar route) 100% of the time when traffic information for Route 1 is unavailable. The tendency to provide traffic information to improve traffic conditions was shown for each strategy and each group of drivers.

However, when there was no information about Route 2, the drivers tended to change their choices from Route 1. The elevated disruptions on Route 2 adversely affected its performance. The results showed that traffic conditions are better as long as toll road users are adequately informed. Most tolling strategies, traffic disturbances, and driver groups show similar results when traffic information is supported via route alternatives. These criteria suggest that the TRO must consistently communicate the user of the travel duration and toll expenses involved in its traffic information delivery. The choice models are derived from a situation in which the drivers know both the routes' tolls and travel time ranges before deciding on a route. In real situations, the toll and travel time ranges exist solely from the viewpoint of a driver observing the traffic information. This perception is based on several factors that the driver must consider before deciding on a route. These include the drivers' choice behavior, driver characteristics, and perception of expected travel time and tolls. All factors that are influenced by the provision of traffic information are assumed to improve the traffic situation.

This research highlights the importance of providing accurate information on travel times and fares to the right group of toll road users, as they will optimize their route choices. The findings from the application of distance- and traffic-dependent tolling scenarios make attitudes toward traffic information more relevant. Providing traffic information would influence the awareness of toll road users, as it contributes to better traffic conditions. This will facilitate the implementation of toll pricing strategies on Indonesian operators.

The results suggest that different types of management should be applied to different driver groups, depending on the variation of their characteristics in traffic information provision. Therefore, there is a need to propose a better strategy that can identify the users so the toll road operator can easily impose measures in order to manage the traffic with traffic information provision. These specific scenarios open the opportunity of making more complex situation. Future research is expected to explore other predictors that constitute route-choice behavior. Diverse settings, such as imposing dynamic traffic flows, will provide additional insights.

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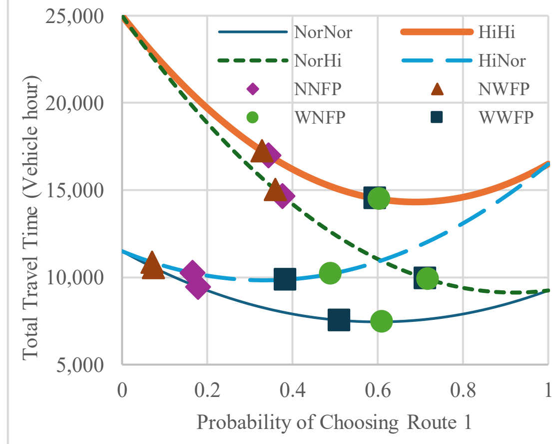
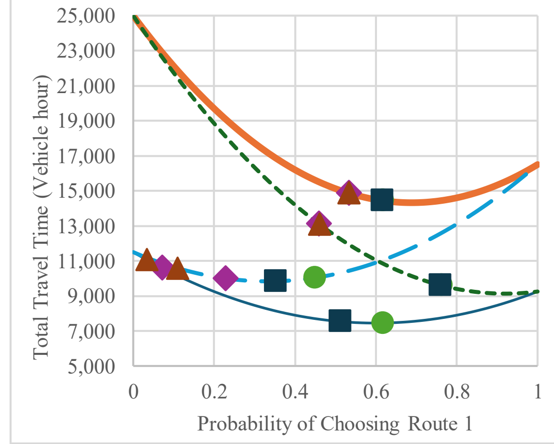
Appendix. Route Choosing Probability

Fixed Price Tolling Strategy



AWARE AND DEPENDENT GROUP



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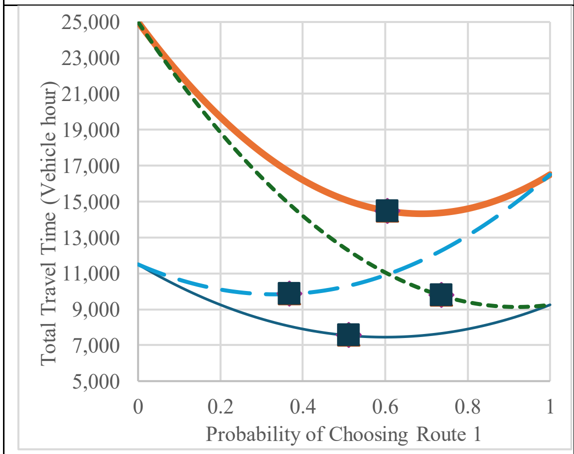

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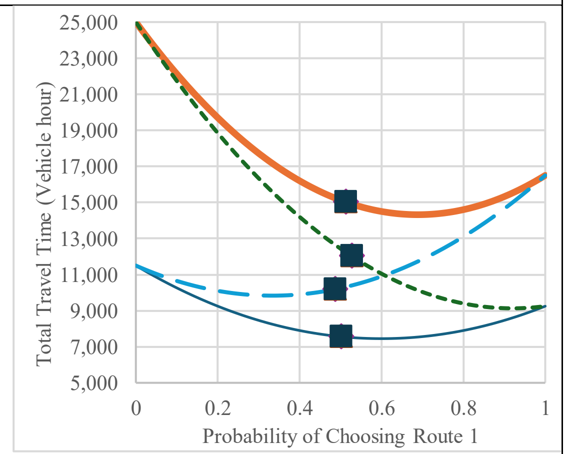

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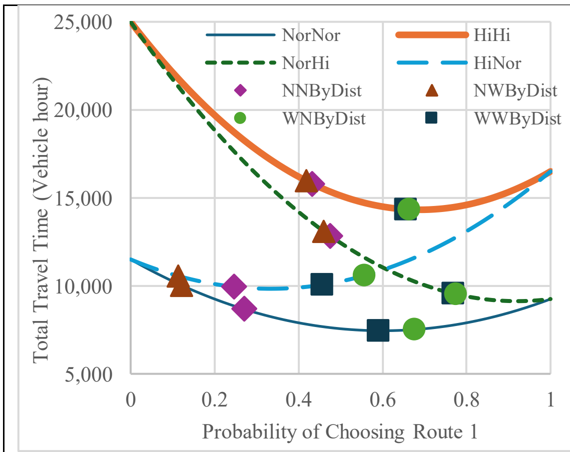
Distance-based Tolling Strategy



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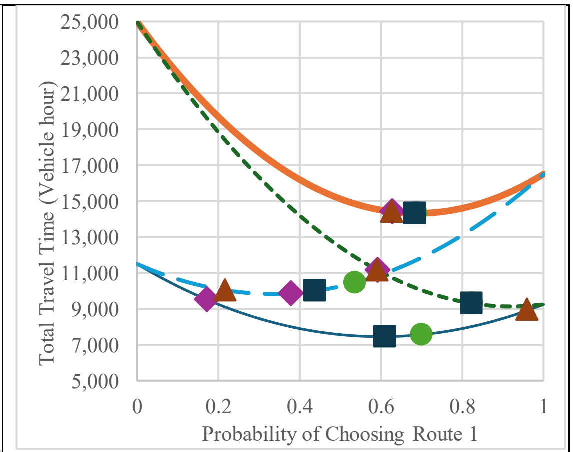

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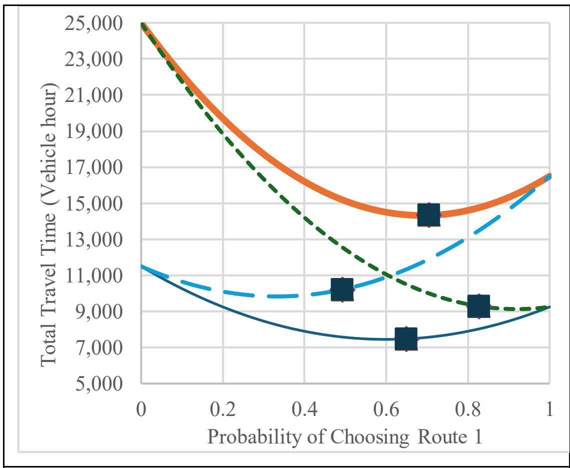

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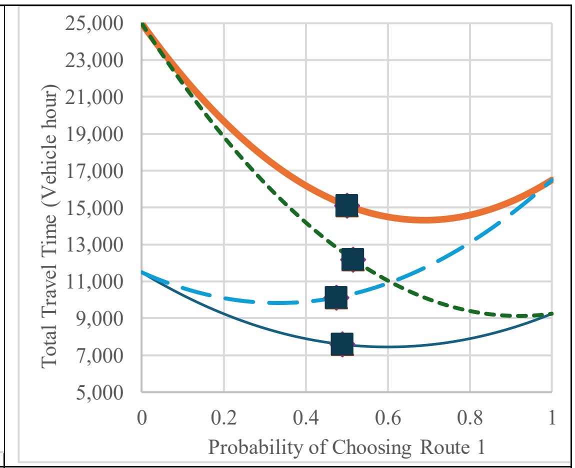

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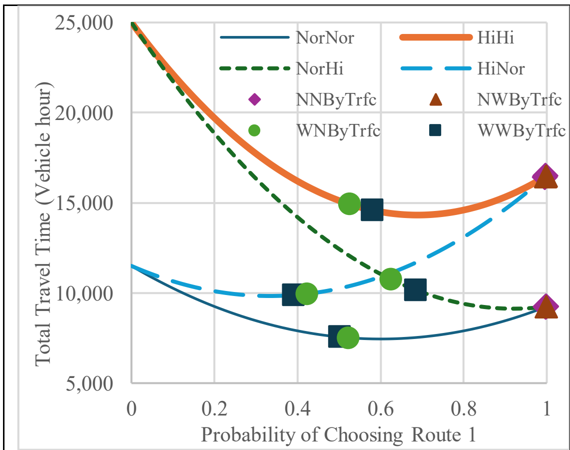
Traffic-dependent Tolling Strategy



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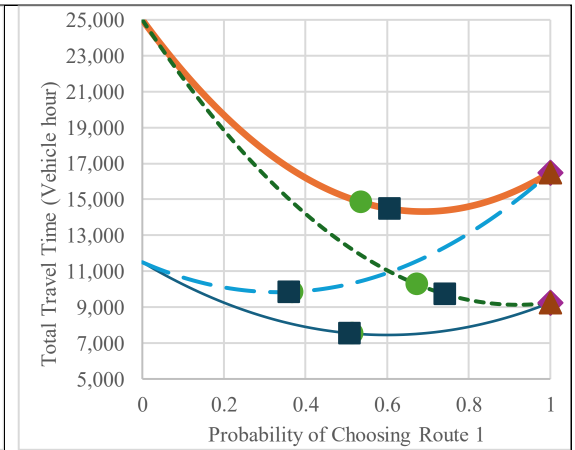

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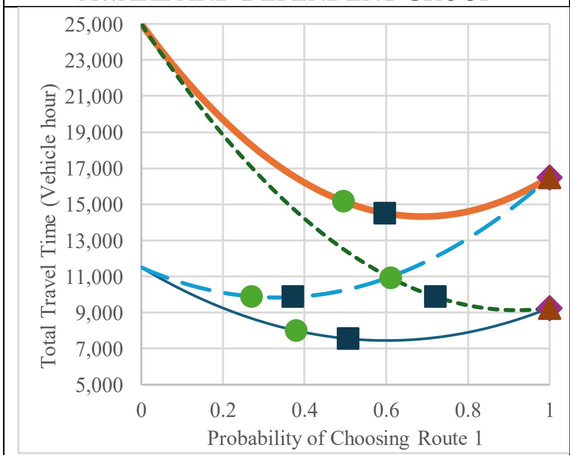

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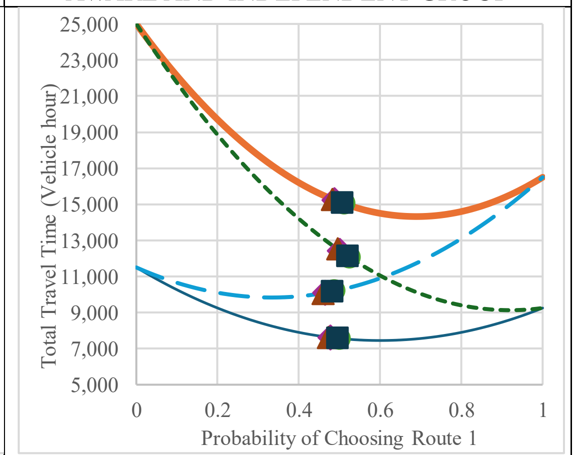

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