Is Random Regret Minimization More Suitable in Predicting Mode Choice Decision for Indonesian Context than Random Utility Maximization?

Muhammad Zudhy Irawan[1], Sigit Priyanto[1] and Dewanti[1]
[1]*Department of Civil and Environmental Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia*

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Abstract: Since often encountered the missing prediction by using the concept of random utility maximization (RUM) for Indonesian context, this study proposed a theory of random regret minimization (RRM) aiming to more precisely predict the chosen mode and to increase the model fit. Three variances of RRM were implemented: Classical RRM, μRRM, and PRRM. Yogyakarta and Palembang were chosen as a case of the study by involving 708 respondents. A stated preference survey was carried out by offering six scenarios to the respondents. We apply the value of final log-likelihood, rho-square, Akaike and Bayesian Information Criterion, and hit rate to compare the model fit. We also calculate the value of travel time saving, and the time and cost elasticity. The result shows that by excluding the rho square, RRM outperforms RUM in both cities. The μRRM produces the best model fit in a case of travel mode choice in Yogyakarta, while there is a tendency that PRRM produces a better model fit than μRRM in Palembang. We also found that RRM tends to generate a higher VTSS, time and cost elasticity than RUM. Travellers in both cities also tend to be more sensitive to change in travel time than travel cost.

1 INTRODUCTION

To date, numerous studies worldwide concerning the choice decision use random utility maximization (RUM)-based discrete choice model in predicting the choice of several offered alternatives. This modelling approach assumes that people choose one of several options which have the highest utility (McFadden et al., 1973). In transportation studies, a logit model is the most widely used method in the discrete choice model (Ding et al., 2017) (Dong et al., 2018). The RUM based discrete choice model also applied in many studies of travel mode choice in Indonesia. (Irawan et al., 2017) applied RUM-based binary logit model to analyze the potential demand of bus mode for egress trip from railway stations in Yogyakarta, which is motivated by a situation that train passengers prefer to opt to park their owned motorcycle at destination railway station compared to they have to use bus mode for their egress trip. (Bastarianto et al., 2019) used RUM-based multinomial logit model, nested logit model, and cross-nested logit model in understanding the joint choice of travel modes and tour types for commuters from Bekasi to Jakarta, Indonesia. (Irawan et al., 2018) applied RUM-based ordered logit model in predicting the demand of hybrid car in Indonesia. Meanwhile, (Rezika et al., 2018) used bivariate ordered probit model in estimating the urban railway demand in Yogyakarta.

Regarding the choice between public transport and motorcycle mode in Indonesia, we assume that the RUM-based discrete choice model might not be appropriate. This is due to many travellers prefer to use motorcycle mode to avoid the intolerable service of public transport (PT). It is evident that even though the Indonesian government has reformed the public transport service in some cities in Indonesia, private vehicle users especially motorcyclists still reluctant to shift to public transport mode (Ilahi et al., 2015). In Yogyakarta, people who decide to use public transport must depart much earlier to minimize the lateness at the destination point, such as workplace and school (Irawan and Sumi, 2011).

It also should be noted that even though motorcycle give the high utility caused by itsflexibility (Irawan and Sumi, 2012; Irawan, 2019), the motorcycle is a transport means that is the most often involved of a traffic accident . (Soehodho, 2017) showed that

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motorcycle acts as an aggravating factor on the severity level of a traffic accident. By considering the factor of traffic death and injuries, the motorcycle could not provide the highest utility compared to public transport mode. However, Indonesian travellers are also reluctant to use public transport caused by poor service provided (Joewono et al., 2016).

As mentioned above, since we assume that RUM might not be appropriate for public transport versus motorcyclist case, we consider utilizing an alternative modelling approach to utility maximization. This alternative modelling approach contrary to RUM tries to minimize disutility. Recently, some researches have also used the disutility minimization model called Random Regret Minimization or RRM in predicting mode choice decision (Chorus, 2010) (BELGIAWAN et al., 2017). In RRM, travellers choose a specific travel mode in an attempt to minimize a disutility obtained from the other alternative travel modes (Chorus et al., 2008).

With the introduction of RRM, many studies have proven that RRM outperforms RUM in terms of model fit, prediction accuracy as well as the value of travel time savings (VTTS) and elasticities (Leong and Hensher, 2015) (Hensher et al., 2013). For the Indonesian context, previous research has compared RUM and RRM for mode choice decision in Bali (Belgiawan et al., 2017) and Jakarta (Belgiawan et al., 2019). However, their studies do not specifically study motorcycle and PT as alternative choices. Therefore, this paper aims to compare the use of utility maximization (RUM) and disutility minimization (RRM) approach in mode choice decision for Indonesian context. The mode choice alternatives that we discuss is between PT which includes Bus and Light Rail Transit (LRT), and motorcycles.

2 LITERATURE REVIEW

RRM was first introduced by (Chorus et al., 2008). It assumes that a traveller chooses a specific mode of transport to minimize anticipated regret. Since then, there are some variants of RRM. The first is the Classical RRM which is an improvement of the original RRM. By re-analysing ten datasets used to compare RUM and Classical RRM, (van Cranenburgh et al., 2015) proposed μRRM and Pure RRM (PRRM) model to improve the model fit of Classical RRM. Recently, the use of RRM is not only for mode choice decision but also for park-and-ride lot choice (Sharma et al., 2019), route choice (Mai et al., 2017) (Li and Huang, 2017), driver choice of crash avoidance maneuvers (Kaplan and Prato, 2012), freight transport (Boeri and Masiero, 2014), activity start time and duration (Golshani et al., 2018), and automobile fuel choice (Hensher et al., 2013). (Chorus et al., 2014) showed that out of 43 empirical studies, 15 studies found that RRM's performance is better than RUM, while 13 studies show that the model fit differences between RUM and RRM are generally small.

This study attempts to implement the various kinds of RRM for Indonesia context. The first study was begun by comparing Classical RRM and RUM model in term of travel mode choice decision (i.e., bus rapid transit, feeder bus, motorcycle, and car) in Denpasar Greater Area, Bali (Belgiawan et al., 2017). By considering the value of Akaike Criterion (AIC), Bayesian Criterion (BIC), rho square, and final log-likelihood, the result shows that the RUM model outperforms Classical RRM. However, both model result in the low model fit. We predict that the poor service of public transport in Bali might result in the bias data because of the difficulties experienced by the respondents when facing the stated preference survey. We also predict that comparing the mode choice between car and motorcycle regarding travel time and trip cost becomes less precise because of the respondents' characteristics of socioeconomics inherently more cause it.

To fill the research gap of the previous studies, Yogyakarta and Palembang were chosen as case studies because of the satisfying service of existing public transport (Irawan et al., 2017) (Budi and ZUSMAN, 2015). Our respondents also focus on motorcycle users since we attempt to understand the main reason of choosing motorcycle mode is more caused by the utility offered by motorcycle (RUM model) or unacceptable disutility when using bus mode (RRM model). Because the RRM could be implemented with a minimum of three alternative modes (Chorus, 2010), we added a light rapid transit mode as a choice instead of motorcycle and bus mode. In this study, we also compare the value of travel time saving, travel cost and travel time elasticities between RUM and RRM. Previous studies showed that the value of RRM-based elasticity is higher than RUM based elasticity (Belgiawan et al., 2017) (Thiene et al., 2012).

3 THEORETICAL BACKGROUND

3.1 Regret Function

In the CRRM framework, (Chorus, 2010) defined that the regret associated with an alternative m for person n is determined by:

$$RR_{mn}^{CRRM} = a_m + R_{mn}^{CRRM} + \varepsilon_{mn} = a_m + \Sigma_{z \neq m} \Sigma_q ln(1 + exp[\beta_q (X_{qzn} - X_{qmn})]) + \varepsilon_{mn} \quad (1)$$

Where R_{mn} is random regret for an alternative m for person n, R_{mn} is systematic regret for alternative m for person n, ε_{mn} is unobserved regret for alternative m for person n, a_m is alternative specific constant, β_q is the estimated parameter associated with the generic attribute X_q, X_{qzn} and X_{gft} are values associated with generic attribute Xq_q for, respectively, person n choosing alternative z and m.

Meanwhile, the formula to calculate the regret function for μRRM introduced by (van Cranenburgh et al., 2015) was modified by dividing the coefficient of β_q with μ. Furthermore, they also found that the formula for systematic regret of the P-RRM model is as follows.

$$RR_{mn}^{PRRM} = a_m + \Sigma_q \beta_q X_{qzmn}^{PRRM} \quad (2)$$

where:

$$X_{qzmn}^{PRRM} = \{ \frac{\Sigma_{z \neq m} max(0, X_{qzn} - X_{qmn}) if \beta_q \geq 0}{\Sigma_{z \neq m} min(0, X_{qzn} - X_{qmn}) if \beta_q < 0} \quad (3)$$

3.2 Probability Function

There is no difference in determining the probability of utility function (RUM) and regret function (RRM). The probability function of CRRM and PRRM is written as:

$$P_{mn}^{CRRM-PRRM} = exp(-Rmn) / \Sigma_{m \varepsilon Zz=1}^{z} exp(-R_{zn}) \quad (4)$$

Since the μRRM includes a scale parameter μ) as an additional degree of freedom to allows the flexibility of the regret function level attribute, the probability function of μRRM is calculated by multiplying μ with the regret value (R).

4 DATA DESCRIPTION

A household-based face-to-face interview survey was carried out from March to April 2017 and from June to July 2017 in Palembang and Yogyakarta respectively. The selected respondents were travellers whose origin and destination points are located within a radius of 500 meters from the LRT station in Palembang, while the respondents were randomly selected in Yogyakarta. The location selection purpose in Palembang was to reduce the bias data in the model since we only considered the variable of travel time and trip cost. We did not take into account several influenced variables related to the access and egress trip. We also defined the selected respondents are travellers who work and make a daily trip with a minimum distance of 5 km from home to work. It is due to the consideration that LRT can be an opt of travel mode choice and also exclude the motorcycle captive users as the respondents.

There are 401 and 307 respondents involved in Yogyakarta and Palembang respectively. The interview survey was conducted in all existing and planned train stations, and it was proportionally distributed based on population in each sub-district where the rail station is located. With the aim to obtain a better validity level of data, the questionnaire form was designed as simple as possible. We were hoping that the respondents are able to completely answer all of the questions asked by a surveyor within ten minutes interval of time. The questionnaire form was categorized into two items. The first is the characteristic of respondents (gender, age, and income), and the second is the stated preference (SP) survey. The SP questionnaire can be seen in Figure 1.

5 RESULTS AND DISCUSSION

5.1 Estimation Result

The result of the RUM and RRM based MNL model is presented in Table 1. We use PythonBiogeme (Bierlaire, 2016) in estimating the value of coefficient and calculating its model fit. The result shows that the parameter of travel time and cost are 1% significant with a negative value (as expected) for RUM, CRRM, and μRRM in both cities. However, in the case of Yogyakarta, the value of μ is significant at 10%. On the other hand, PRRM shows the insignificant coefficient regarding travel time.

Scenario 1			
	Motorcycle	Bus	LRT
Time	30 min.	45 min.	45 min.
Cost	10,000	10,000	5,000
Choice			
Scenario 2			
	Motorcycle	Bus	LRT
Time	45 min.	30 min.	60 min.
Cost	10,000	5,000	5,000
Choice			
Scenario 3			
	Motorcycle	Bus	LRT
Time	60 min.	45 min.	60 min.
Cost	5,000	5,000	10,000
Choice			
Scenario 4			
	Motorcycle	Bus	LRT
Time	30 min.	45 min.	45 min.
Cost	5,000	5,000	10,000
Choice			
Scenario 5			
	Motorcycle	Bus	LRT
Time	45 min.	30 min.	45 min.
Cost	5,000	10,000	5,000
Choice			
Scenario 6			
	Motorcycle	Bus	LRT
Time	60 min.	60 min.	45 min.
Cost	5,000	10,000	10,000
Choice			

Figure 1: The questionnaire form of SP survey.

Taking into account the model fit, we present the model fit consists of Final Log-likelihood (Final LL), Rho-square, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and hit rate. The result shows that μRRM produces the smallest final log likelihood in both cities. For Yogyakarta, the value of AIC and BIC for μRRM also indicates the best fit compared to RUM and other RRMs. However, rho-square for RUM in Yogyakarta is better than the all variances of RRM. Meanwhile, for Palembang, PRRM is the best model fit for the value of AIC, BIC, and rho-square. Looking into the hit-rate model fit, the model result for Yogyakarta produces a similar value of hit-rate by 38.53%, while μRRM and PRRM show the highest hit-rate in Palembang by 41.04%.

Due to this, we found that RRM performs better than RUM, in which in a case of travel mode choice in Yogyakarta, μRRM is the best model among the other RRM models. Meanwhile, it is not yet clearly detected whether μRRM or PRRM producing the best model fit in Palembang, in which μRRM produces the best model fit of final log-likelihood, whereas PRRM produces the best model fit AIC, BIC, and rho-square.

5.2 Value of Travel Time Saving

The value of travel time savings (VTTS) is used to measures the willingness to pay for a traveller due to a travel time reduction. For CRRM, the VTTS can be measured by (Leong and Hensher, 2015):

$$VTTS_{mn}^{CRRM} = 60x\frac{\delta R_{mn}^{CRRM}/\delta TT_{mn}}{\delta R_{mn}^{CRRM}/\delta TC_{mn}}$$
$$60x\frac{\Sigma_{z\neq m} - \beta_{TT}/(exp[-\beta_{TT}(TT_{zn} - TT_{mn})] + 1)}{\Sigma_{z\neq m} - \beta_{TC}/(exp[-\beta_{TC}(TC_{zn} - TC_{mn})] + 1)} \tag{5}$$

Where TTzn and TCzn represent travel time and travel cost of person n choosing mode z as the competitor of mode m, respectively. Meanwhile, the VTTS for the μRRM model is obtained by modifying the coefficient of β with β/μ in Eq. (5). Moreover, the VTTS for PRRM can be calculated by (van Cranenburgh et al., 2015).

$$VTTS_{mn}^{PRRM} = 60x\frac{\delta R_{mn}^{PRRM}/\delta TT_{mn}}{\delta R_{mn}^{PRRM}/\delta TC_{mn}}$$
$$60x\frac{-\beta TT\Sigma_{z\neq m_{TT_{zn}<TT_{mn}}}}{-\beta TC\Sigma_{z\neq m_{TT_{zn}<TT_{mn}}}} \tag{6}$$

Table 2 presents the value of travel time saving for both RUM and RRM. However, in contrast to RRM, it should be noted that the performance of the other modes does not influence the VTTS of a specific mode produced by RUM. In RRM, the VTTS measures will increase or decrease conditionally on both the number of available alternatives in the choice set and the changes in the influenced variables of chosen alternative and nonchosen alternatives. From Table 2, it can be seen that in all variance of RRM in both cities, the VTTS for LRT mode is the highest and the VTTS for bus mode is the lowest. It means that travellers in Palembang and Yogyakarta are willing to pay much more expensive when using LRT mode if there is a reduction in the travel time unit. This condition makes sense since the travellers believe that LRT is a travel mode promising timeliness of travel. However, the opposite situation occurs in bus mode representing that travellers are not willing to pay more due to the reduction of travel time. The VTSS for bus mode produced by μRRM and PRRM in both cities is approximately half of the VTSS for LRT mode. Looking into a situation that the VTTS for motorcycle mode tends to higher than bus mode in all variance of RRM, it represents that it will be challenging to shift motorcyclists to use bus mode in their daily trip as it now happens.

Variable	RUM		CRRM		μRRM		PRRM	
	Est.	t-test	Est.	t-test	Est.	t-test	Est.	t-test
Yogyakarta								
Travel time	-0.419	-4.62*	-0.283	-4.72*	-0.267	-4.78*	-0.071	-1
Travel cost	-0.203	-8.82*	-1.43	-8.74*	-0.185	-9.96*	-0.187	-9.51*
μ					0.044	1.64***		
Final LL	-2602.998		-2601.56		-2592.489		-2603.622	
Rho-square	0.403		0.062		0.018		0.014	
AIC	5209.99		5207.12		5190.98		5211.24	
BIC	5221.57		5218.70		5208.34		5222.82	
Hit rate	38.53%		38.53%		38.53%		38.53%	
Palembang								
Travel time	-0.865	-8.02*	-0.575	-8.19*	-0.535	-8.1*	-0.081	-1.05
Travel cost	-0.283	-10.94*	-2.02	-10.79*	-0.238	-12.14*	-0.243	-10.73*
μ					0.147	7.94*		
Final LL	-1948.93		-1946.58		-1939.56		-1960.01	
Rho-square	0.008		0.036		0.04		0.228	
AIC	3901.85		3897.17		3885.12		3124.02	
BIC	3912.89		3908.21		3901.67		3135.06	
Hit rate	37.46%		38.06%		41.04%		41.04%	

*Note: * 1% significant, ** 5% significant, *** 10% significant*

Figure 2: Estimation result.

	Yogyakarta			Palembang		
	Motorcycle	Bus	LRT	Motorcycle	Bus	LRT
RUM	12,384			18,339		
CRRM	13,303	11,085	13,674	20,860	15,039	22,682
μRRM	17,862	6,668	20,666	15,445	9,852	20,005
PRRM	22,836	15,187	26,352	13,333	9,395	17,849

Figure 3: Value of travel time saving (IDR per hour).

Comparing the VTTS produced by RUM and RRM in a case of Yogyakarta, all variances of RRM produces the higher VTTS than RUM except in bus mode. Meanwhile, by excluding the bus mode in Palembang, the VTTS for CRRM is higher than RUM, and the VTTS for PRRM is lower than RUM. However, since we have not the VTTS of each respondent either from the questionnaire survey or secondary data, we cannot check what the best model between RUM and RRM which could precisely estimate the VTTS is.

5.3 Demand Elasticity

Elasticity is used to measure the percentage change of probability value caused by the change of correlated attributes. (Ben-Akiva et al., 1985) showed the equation used to calculate the direct elasticities of RUM model is as follows.

$$E^{RUM}_{mn.X_{qmn}} = \frac{\delta P_{mn}}{\delta X_{qmn}} x \frac{\delta X_{qmn}}{P_{mn}} = (1 - P_{mn})\beta_q X_{qmn} \quad (7)$$

Where $E^{RUM}_{mn.X_{qmn}}$ is RUM-based elasticity for traveller n on mode m which is related to variable $X_q.X_{qmn}$ and β_q are specific attribute x for traveller n by mode m and estimated the parameter of attribute x. p_{mn} is the probability of traveller n chooses mode m. For RRM based elasticity value, the formula for PRRM and μRRM is similar as follows (van Cranenburgh et al., 2015).

$$E^{PRRM-\mu RRM}_{mn.x_{qmn}} = \left(-\frac{\delta R^{PRRM-\mu RRM}}{\delta X_{qmn}} + \Sigma^{p}_{m\in Zz\neq mz=1} P_{pn} \frac{\delta R^{PRRM-\mu RRM}_{zn}}{\delta X_{qmn}}\right) \quad (8)$$

Meanwhile, the equation to calculate the elasticity for CRRM is as follow (Hensher et al., 2013).

$$E^{CRRM}_{mn.X_{qmn}} = \left(-\frac{\delta R^{CRRM}_{mn}}{\delta X_{qmn}} + \Sigma^{p}_{m\in Zz\neq mz=1} P_{pn} \frac{\delta R^{CRRM}_{zn}}{\delta X_{qmn}}\right) .X_{qmn} \quad (9)$$

Figure 4 presents the measurement of cost and travel time elasticities. As we expected, the sign of all the travel time and cost elasticities produced by RUM and RRM in both cities are negative, means that a reduction of travel time and cost of an alternative mode will increase the percentage of probability in choosing of that alternative mode. However, it should be noted that the value of elasticity of costs and travel time cannot provide an idea of whether RUM is better than RRM or vice versa. These findings will be more useful related to policy implementation. For example: as the policymakers, they hope that the resulted elasticity value is large enough to ease them to make decisions to increase the demand for public transport.

Looking into the cost elasticity, both RUM and RRM produce the lowest cost elasticity for motorcycle modes in both cities. It means that with the change in travel costs, the motorcycle users will be the most reluctant travellers to switch to bus and LRT modes. For example: in the case of μRRM in Palembang City, a 10% increase in out of pocket would only cause a 10% decrease in the probability of using a motorcycle, while for bus and LRT modes could decrease the probability of modal usage by 12% and 14% respectively.

Meanwhile, the highest travel cost elasticity is for LRT mode for the RUM, CRRM, and μRRM models, and the bus mode for the PRRM model showing that those mentioned travel mode will be easy to leave by its passengers if there is a slight increase in ticket costs. From Table 3, it also can be found that people living in Palembang are more elastic in changing travel mode caused by a variable of the trip cost compared to people living in Yogyakarta.

On the travel time elasticity, the value produced by the variances of RRM is not consistently higher than RUM. Even though μRRM results in the highest travel time elasticity in Yogyakarta, both RUM and CRRM produces a higher value than μRRM and PRRM in Palembang. Different from the cost elasticity, bus mode has the lowest travel time elasticity in both cities meaning that with the change in travel time, bus users are the most resistant travellers to use the current mode. It is reasonable because people use motorcycle or LRT mode is more caused by travel time saving so that if there is a small increase of travel time, motorcyclists and LRT passengers are the most vulnerable travellers from the additional travel time. Similar to the previous finding in cost elasticity, the change in travel time is felt more significant for people living in Palembang than people in Yogyakarta.

Comparing between the elasticity of cost and travel time, the travel time elasticity generated by RUM and all variances of RRM is higher than the cost elasticity, except for motorcycle and bus mode in Yogyakarta produced by the μRRM model. This situation represents that the change in the travel time factor makes the traveller more sensitive to switch to other modes compared to the shift in travel cost that must be spent. Meanwhile, in a case where the elasticity of cost is higher than the travel time, the authors cannot find the reason why did it happen. Therefore, in further research, a more in-depth analyzis is needed to reveal the phenomena that occur.

Finally, comparing among the elasticity values produced by the RUM and RRM model, all variances of RRM produces a higher elasticity than RUM. In a more specific case, μRRM and CRRM result in the highest elasticity value in a case of travel mode choice in Yogyakarta and Palembang respectively.

		RUM	CRRM	μRRM	PRRM
Yogyakarta	Motorcycle	-0.09 (-1.28)	-0.96 (-1.20)	-2.76 (2.71)	-0.17 (-0.45)
	Bus	-0.10 (-1.14)	-1.16 (-1.19)	-3.34 (2.43)	-0.24 (-0.36)
	LRT	-0.11 (-1.53)	-1.28 (-1.62)	-3.63 (-3.71)	-0.22 (0.63)
Palembang	Motorcycle	-0.12 (-2.76)	-1.34 (-2.43)	-1.04 (-1.63)	-0.22 (-0.51)
	Bus	-0.13 (-2.27)	-1.65 (2.41)	-1.20 (-1.43)	-0.31 (-0.41)
	LRT	-0.16 (-3.38)	-1.88 (-3.53)	-1.39 (-2.32)	-0.30 (-0.72)

Note: Value in parenthesis is an elasticity value of travel time

Figure 4: Value of travel time saving (IDR per hour).

6 CONCLUSIONS

This study implements all variances of RRM consisting of CRRM, μRRM, and PRRM. To compare which results are better between RUM and RRM, we use the statistic tests of Final Loglikelihood, Rho-square, Akaike and Bayesian Information Criterion, and Hit Rate. Our modelling result indicates that RRM outperforms RUM. Even though RUM still produce the better rho square, RRM could produce the lower of Final Loglikelihood and Akaike and Bayesian Information Criterion. The probability of choice generated by RRM could estimate more precisely shown by the value of hit rate and the average probability value for chosen mode and non-chosen mode. Among all variances of RRM, it can be generally concluded that μRRM could produce the best model fit although there is a propensity that PRRM delivers a better model fit than μRRM in a case of travel mode choice in Palembang.

The value of travel time saving produced by RUM and RRM shows that RRM tends to provide a higher VTTS than RUM. The highest VTTS in both cities generated by RRM is on LRT mode indicating that people are willing to pay more when using LRT if there is a reduction in the travel time unit. Meanwhile, the demand elasticity shows that the travel time elasticity generated by RUM and all variances of RRM (except μRRM in Yogyakarta) is higher than the cost elasticity showing that travellers are more concerned with the travel time than travel cost in deciding what kind of transport means that they use. Both RUM and RRM produce the lowest cost elasticity for motorcycle mode and lowest travel time elasticity for bus mode, saying that motorcyclists and bus users are the most unwilling travellers to shift to other modes due to the change of travel cost and travel time respectively.

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