# Bali Trans Sarbagita: Comparison between Utility maximization and Regret Minimization

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**Abstract**: With the introduction of new BRT system, Denpasar Greater Area, Bali (Sarbagita), Indonesia now have a new alternative in addition to the currently available alternatives such as feeder, car, and motorcycle. We compare random utility maximization model (RUM) with random regret minimization model (RRM) using data from 526 respondents of Sarbagita. We obtain 14,055 observations in a total of three categorical distance; short, medium, and long, which each category has ten stated preference experiments. Our model fit results suggest that RUM outperforms RRM in all distance category. We found that for long distance, travel time is nearly elastic for BRT, feeder, and car, while cost is elastic for car. Thus, the implementation of a policy to reduce BRT travel time might give a substantial increase in the probability of choosing the mode, while policy to increase car cost might give a substantial reduction in the probability to choose a car.

*Keywords*: Sarbagita BRT, Random Regret Minimization, Value of Travel Time Savings, Demand Elasticities.

## 1. INTRODUCTION

In Denpasar Greater Area, Bali (Sarbagita Area), one of the agglomeration areas in Bali, Indonesia, the Ministry of Transportation has implemented a new BRT system called Trans Sarbagita (Prayudyanto et al. 2016). This new BRT system implementation was aimed to provide more high-quality service to the people. The government was hoping that this system could reduce the traffic congestion and at the same time increase the accessibility of the people of Sarbagita.

With the introduction of new BRT system, people of Sarbagita now have a new alternative in addition to the currently available alternatives such as feeder, car, and motorcycle. When facing several alternatives, it is reasonable to say that people tend to choose an alternative which maximizes their utilities. This concept is widely known as random utility maximization (RUM). In transportation research, one of the famous modeling technique to choose a mode of transportation is multinomial logit (MNL).

Recently there is a growing interest in implementing an alternative modeling technique which is called random regret minimization (RRM) (Chorus et al., 2008). There have been many studies implemented this modeling technique for transportation related choice decision. For example route choice, travel information acquisition choice, parking lot, shopping location (Chorus, 2010; 2012), automobile fuel choice (Hensher et al. 2013), willingness to pay for advanced transportation services, and salary and travel time trade off (Hess et al., 2014). According to Chorus et al. (2014), there were 43 empirical studies that compare RUM and RRM from 2010-2014. Regarding their model fit, 15 times RRM outperforms RUM and 15 times the other way around. Other 13 empirical studies show neither of these two modeling approaches outperforms each other. Adding to that list is the study by Belgiawan et al. (2017) where they compare the performance of RUM and RRM on seven Swiss data sets. They found that RRM outperforms RUM in six cases. Note that most empirical studies compared RUM and RRM regarding their model fit. Few exceptions compared the application of the model such as the value of travel time savings (VTTS), and demand elasticities.

Therefore, the aim of this study is to compare between RUM and RRM approaches for the case of Sarbagita. We would like to find which modeling approaches is best used for the area so that it can be used by the government to implement a new policy regarding public transportation system. We also present the VTTS and demand elasticities obtained from those two models as consideration for a new transport policy. Another contribution of this research is to add new RRM case study to the existing body of RRM research which to our knowledge there has not been any discussion regarding the comparison of RUM and RRM for Indonesia case, specifically Bali area.

In Section 2 we discuss the history of RRM and its implementation, while in Section 3 we describe how we collect the data and the descriptive statistics of the data. In section 4 we discuss the modeling technique and model comparison. Followed by section 5 where we compare the VTTS and demand elasticities. Finally, we conclude our study in section 6.

## 2. MODELLING APPROACHES

### 2.1 Random Regret Model

Random regret minimization was first introduced by Chorus et al. (2008) for a model of travel choice. According to Chorus et al. (2008) in RRM, individual bases his/her choice between alternatives wishing to avoid a situation where a non-chosen alternative turns out to be more attractive than the chosen one, which causes regret. Thus, the individual when choosing between alternatives is assumed to minimize anticipated regret as opposed to maximizing his/her utility. Chorus (2010) stated that this first RRM approach has two limitations. Therefore, he improvised the technique to alleviate those limitations with the new RRM-approach. In RRM framework, the regret associated with alternative *i* is obtained by the following formula (Chorus, 2010):

$$RR_{in} = R_{in} + \varepsilon_{in} = \alpha_i + \sum_{j \neq i} \sum_{k} \ln\left(1 + \exp\left[\beta_k \cdot \left(\chi_{kjn} - \chi_{kin}\right)\right]\right) + \varepsilon_{in} \tag{1}$$

where,

$RR_{in}$ : random (or total) regret for an alternative *i* for person *n*

$R_{in}$ : observed regret for an alternative *i* for person *n*

$\varepsilon_{in}$ : unobserved regret for an alternative *i* for person *n*

$\alpha_i$ : alternative specific constant

$\beta_k$ : estimable parameter associated with generic attribute $\chi_k$

$\chi_{kin}$ , $\chi_{kjn}$ : values associated with an attribute $\chi_k$ for, respectively, person *n* choosing alternative *i* over alternative *j*.

Similar to RUM formulation of choice probabilities (McFadden, 1974), the RRM framework assumes the error term in Eq. 1 be identically and independently distributed (i.i.d) Extreme Value Type I-distributed with a variance of $\pi^2/6$. In the RRM setting, the formulation of choice probabilities is as follow:

$$P_{in} = \frac{\exp(-R_{in})}{\sum_{j=1\ldots J}\exp(-R_{jn})} \tag{2}$$

The result from MNL and RRM models can be used to calculate the value of travel time savings (VTTS) and demand elasticities.

## 2.2 Value of Travel Time Savings

The value of travel time savings (VTTS) measures how much money (e.g. Indonesian Rupiah - IDR) a person is willing to pay for a reduction of travel time unit (e.g. hour). To measure the VTTS for MNL model we can use the formula below.

$$VTTS_{in}^{MNL} = 60 \times \frac{\partial V_{in}/\partial T_{in}}{\partial V_{in}/\partial C_{in}} = 60 \times \frac{\beta_T}{\beta_C} \tag{3}$$

Where $V_{in}$ represents systematic utility for an alternative $i$ for person $n$, $T_{in}$ represents travel time for the person $n$ choosing an alternative $i$, and $C_{in}$ represent the cost for the person $n$ choosing an alternative $n$. The parameters of time and cost are represented by $\beta_T$ and $\beta_C$ respectively.

We use the formula taken from Chorus (2012) to measure the VTTS for RRM, as shown below.

$$VTTS_{in}^{RRM} = 60 \times \frac{\partial R_{in}/\partial TT_{in}}{\partial R_{in}/\partial TC_{in}} = 60 \times \frac{\sum_{j\neq i} -\beta_T \big/ \left(\exp\left[-\beta_T \cdot \left(T_{jq} - T_{iq}\right)\right] + 1\right)}{\sum_{j\neq i} -\beta_C \big/ \left(\exp\left[-\beta_C \cdot \left(C_{jq} - C_{iq}\right)\right] + 1\right)} \tag{4}$$

Note that, in contrast to RUM, RRM is a context-dependent model, which means the performance of other alternatives influences the VTTS for a chosen alternative. Therefore, as shown in Eq.4, VTTS measures will change when the number of available alternatives in the choice set increases/decreases. Changes in the attributes of chosen alternative as well as non-chosen alternatives will also influence the VTTS. The derivation of the formula to measure VTTS for RRM can be seen in Belgiawan et al. (2017)

## 2.3 Demand elasticities

Direct elasticity shows the relationship between a percentage change in the magnitude of the attribute and the percentage change in the probability of choosing an alternative based on the respected attribute. The formula to measure the disaggregate direct point elasticities for RUM model is shown below (Ben-Akiva and Lerman, 1985)

$$E_{in\chi_{kin}} = \frac{\partial P_{in}}{\partial \chi_{kin}} \cdot \frac{\chi_{kin}}{P_{in}} = (1 - P_{in}) \cdot \beta_k \cdot \chi_{kin} \tag{5}$$

Hensher et al. (2013) derived for the first time an equation to measure the elasticity of RRM Eq.6 below. The derivation of the formula can also be seen in Belgiawan et al. (2017).

$$E_{in\chi_{kiq}} = \left( -\frac{\partial R_{iq}}{\partial \chi_{kiq}} + \sum_{\substack{i \in J \\ j \neq i \\ j=1}}^{J} P_{jq} \cdot \frac{\partial R_{jq}}{\partial \chi_{kiq}} \right) \cdot \chi_{kiq} \tag{6}$$

In this paper, we are comparing the model fit, VTTS and demand elasticities of standard RUM model (MNL) with the RRM (Chorus, 2010) to see which model is suitable for the Sarbagita case.

## 3. DATA COLLECTION AND DESCRIPTION

The data was collected in 22nd – 25th of January 2016 in Sarbagita by SUTIP (Sustainable Urban Transportation Improvement Project) part of GIZ (Deutsche Gesellschaft für Internationale Zusammenarbeit) project in Indonesia with total respondents of 526 respondents (Prayudyanto et al. 2016). The survey was conducted by distributing the questionnaire proportionally based on population in each region in Sarbagita area. By proportionally, it means that we weighted our sample with the Bali population based on 2010 population census (Statistics of Bali Province, 2016).

The characteristics of our respondents can be seen in Table 1 below. We present the gender, age, and income proportion of our 526 sample. In the right column, we present the gender and age proportion of 3,890,754 Bali population from 2010 population census.

Table 1. Sample Descriptive Analysis

| Variable | Value | Sample | Population |
|---|---|---|---|
| | Male | 50.00% | 50.41% |
| | Female | 50.00% | 49.59% |
| Age | 1-24 | 59.89% | 40.27% |
| | 25-39 | 17.68% | 26.37% |
| | 40-54 | 17.11% | 19.16% |
| | 55-65 | 4.18% | 7.63% |
| | 65+ | 1.14% | 6.57% |
| Income (in IDR per month*) | Less than IDR 1,000 K | 34.62% | NA |
| | IDR 1,000 K - 2,000 K | 28.54% | NA |
| | IDR 2,000 K - 6,000 K | 30.16% | NA |
| | IDR 6,000 K - 10,000 K | 5.87% | NA |
| | More than IDR 10,000 K | 0.81% | NA |

*At the time of the survey, USD 1 = IDR 13,600.

We have almost equal gender proportion in our sample which is similar to the population. The biggest part of our respondents belongs to undergraduate students age (1-24), almost similar to the population proportion where the biggest part of the population is also under 25. Since the proportion of age category of our sample is not similar to the population proportion, we calculate the weight using "post-stratified weights." The weight calculation is necessary to calculate the aggregate direct point elasticities in Section 5. The proportion of monthly income is almost equal for the three lowest categories, while we have a small percentage of higher income.

In the survey, each of the respondents is given sets of scenarios where they need to choose between four alternatives modes: Trans Sarbagita Bus Rapid Transit (BRT), feeder, car, and motorcycle. Each of the alternative is given some attributes. For BRT and Feeder, the attributes are travel time (in minute), travel cost (in IDR 1K), waiting time (in minute), and walking distance to the shelter (in meter). While for car and motorcycle the attributes are travel time (in minute), travel cost (in IDR 1K), parking cost (in IDR 1K), and the ease of parking (binary response; 1=easy, 0=otherwise). Each scenario has different attribute characteristics which can be seen in Figure 1.

Scenario 1

| Attributes | BRT | Feeder | Car | MC |
|---|---|---|---|---|
| Travel Time (min) | 30 | 60 | 60 | 60 |
| Travel Cost (IDR) | 5,000 | 9,000 | 15,000 | 3,000 |
| Waiting Time (min) | 10 | 15 | - | - |
| Walking Distance to Shelter (meter) | 100 | 150 | - | - |
| Parking Cost (IDR) | - | - | 2,000 | 8,000 |
| Easiness of Parking | - | - | Easy | Easy |
| **My Mode Choice** | ☐ | ☐ | ☐ | ☐ |

Scenario 2

| Attributes | BRT | Feeder | Car | MC |
|---|---|---|---|---|
| Travel Time (min) | 30 | 45 | 45 | 45 |
| Travel Cost (IDR) | 9,000 | 7,000 | 10,000 | 3,000 |
| Waiting Time (min) | 20 | 10 | - | - |
| Walking Distance to Shelter (meter) | 100 | 150 | - | - |
| Parking Cost (IDR) | - | - | 5,000 | 6,000 |
| Easiness of Parking | - | - | Easy | Easy |
| **My Mode Choice** | ☐ | ☐ | ☐ | ☐ |

Scenario 3

| Attributes | BRT | Feeder | Car | MC |
|---|---|---|---|---|
| Travel Time (min) | 75 | 30 | 60 | 60 |
| Travel Cost (IDR) | 5,000 | 3,000 | 10,000 | 9,000 |
| Waiting Time (min) | 5 | 10 | - | - |
| Walking Distance to Shelter (meter) | 150 | 200 | - | - |
| Parking Cost (IDR) | - | - | 5,000 | 6,000 |
| Easiness of Parking | - | - | NotEasy | Easy |
| **My Mode Choice** | ☐ | ☐ | ☐ | ☐ |

Scenario 4

| Attributes | BRT | Feeder | Car | MC |
|---|---|---|---|---|
| Travel Time (min) | 60 | 60 | 60 | 60 |
| Travel Cost (IDR) | 7,000 | 3,000 | 20,000 | 12,000 |
| Waiting Time (min) | 15 | 15 | - | - |
| Walking Distance to Shelter (meter) | 100 | 50 | - | - |
| Parking Cost (IDR) | - | - | 2,000 | 6,000 |
| Easiness of Parking | - | - | NotEasy | Easy |
| **My Mode Choice** | ☐ | ☐ | ☐ | ☐ |

Figure 1. Examples of scenarios for stated mode choice experiments

This survey consists of six blocks which designed using orthogonal fractional factorial Hensher et. al. (2005). There are three different categorical scenarios in each block, which based on distance; short (less than 5 km), medium (between 5 km and 15 km), and long (more than 15 km). There are ten stated preference (SP) experiments for each respondent in one categorical distance, therefore, in total, each respondent faces 30 SP experiments and for all blocks, we have180 combination of different attributes. There are 526 respondents that we use in our analysis. There are some respondents that did not complete the questionnaire, thus, in total, we have 4,928 observations for short-distance, 4,528 for medium-distance, and 4,599 for long-distance. Detailed attributes and values in each alternative is shown in Table 2.

Table 2. Attribute and values of the alternatives in stated choice survey

| Alternatives | Attribute | Values |
|---|---|---|
| BRT | Travel time (minutes) | 5, 10, 15, 30, 45, 60, 75, 105 |
| | Travel cost (IDR 000) | 2, 3, 5,7,9 |
| | Waiting time (minutes) | 5, 10, 15, 20 |
| | Walking distance to shelter (meter) | 50, 100, 150, 200 |
| Feeder | Travel time (minutes) | 5, 10, 15, 30, 45, 60, 75, 90 105 |
| | Travel cost (IDR 000) | 2, 3, 5, 6, 7, 9, 12 |
| | Waiting time (minutes) | 5, 10, 15, 20 |
| | Walking distance to shelter (meter) | 50, 100, 150, 200 |
| Car | Travel time (minutes) | 5, 10, 15, 20, 30, 45, 60, 75, 90, 105 |
| | Travel cost (IDR 000) | 2, 4, 5, 6, 8, 10, 15, 20, 25 |
| | Parking Cost (IDR 000) | 2, 4, 5, 8 ,10 |
| | The ease of parking | 0 1 (easy) |
| Motor cycle | Travel time (minutes) | 5, 10, 15, 30, 45, 60, 75 |
| | Travel cost (IDR 000) | 1, 2, 3, 4, 6, 9, 12, 15 |
| | Parking Cost (IDR 000) | 2, 4, 6, 8 |
| | The ease of parking | 0 1 (easy) |

# 4. MODEL ESTIMATION

## 4.1 Model Specification

RRM is a context-dependent model, which means choosing an alternative is influenced by the presence of other alternatives in term of their attribute values, therefore for this study, we only use a parsimonious model formulation with only generic attributes travel time and cost. The generic attribute is an attribute that is available across all alternatives. Those generic attributes are sufficient to measure the VTTS and demand elasticities. In this section, we present the utility function for the MNL and RRM. The estimation is maximum likelihood using PythonBiogeme (Bierlaire, 2016).

The general utility function for MNL model is as follow:

$$V_i = \alpha_i + \beta_T \cdot T_i + \beta_C \cdot C_i \tag{7}$$

where,

$V_i$ : utility for BRT ($i$=1), feeder ($i$=2), car ($i$=3), motorcycle ($i$=4)

$\alpha_i$ : alternative specific constant (ASC) associated with $i$ (fixed at 0 for $i$=1)

$\beta_k$ : estimable parameter associated with attribute $\chi_k$

$T_i$ : travel time for alternative $i$

$C_i$ : cost for alternative $i$

For the classical RRM, the general regret function is as follows:

$$R_i = \alpha_i + \sum_{j \neq i} \ln\left(1 + \exp\left(\beta_T \cdot \left(T_j - T_i\right)\right)\right) + \sum_{j \neq i} \ln\left(1 + \exp\left(\beta_C \cdot \left(C_j - C_i\right)\right)\right) \tag{8}$$

where,

$R_i$ : regret for alternative $i$

$i$ : the chosen alternative

$j$ : the competing alternative

## 4.2 Model Estimation

We present the result of the MNL and RRM in Table 3. The reference choice is Trans Sarbagita. As mentioned in Section 3, we divided our observations into three categories according to the distance.

For the RUM case, we can see that almost all parameters are significant with a negative sign. In the case of RRM, all the parameters are significant, with all attributes have a negative value, and the ASCs have a positive value.

Table 3. Model comparison between MNL and RRM

| Variables | MNL Short | | RRM Short | | MNL Medium | | RRM Medium | | MNL Long | | RRM Long | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Est. | t-test | Est. | t-test | Est. | t-test | Est. | t-test | Est. | t-test | Est. | t-test |
| Travel time | -0.04 | -14.1* | -0.02 | -13.9* | -0.02 | -16.3* | -0.01 | -16.1* | -0.02 | -17.2* | -0.01 | -17.0* |
| Cost | -0.17 | -16.7* | -0.08 | -16.5* | -0.09 | -13.8* | -0.04 | -13.7* | -0.06 | -11.5* | -0.03 | -11.5* |
| ASC Feeder | -0.54 | -12.9* | 0.54 | 12.9* | -0.44 | -11.1* | 0.44 | 11.0* | -0.49 | -12.0* | 0.49 | 11.9* |
| ASC Car | -0.82 | -17.6* | 0.82 | 17.6* | -0.70 | -13.0* | 0.72 | 13.3* | -0.39 | -6.5* | 0.42 | 7.1* |
| ASC Motorcycle | -0.26 | -6.5* | 0.25 | 6.3* | -0.31 | -7.5* | 0.31 | 7.6* | -0.50 | -10.1* | 0.49 | 10.3* |
| Observations | 4928 | | 4928 | | 4528 | | 4528 | | 4599 | | 4599 | |
| Final-LL | -6213.34 | | -6215.40 | | -5706.62 | | -5714.87 | | -5907.65 | | -5911.00 | |
| Rho-square | 0.091 | | 0.090 | | 0.091 | | 0.090 | | 0.073 | | 0.073 | |
| AIC | 2.52 | | 2.52 | | 2.52 | | 2.53 | | 2.57 | | 2.57 | |
| BIC | 2.53 | | 2.53 | | 2.53 | | 2.53 | | 2.58 | | 2.58 | |

*p value <0.01.

All of the parameter estimate (time and cost) are significant (p value < 0.01) with expected sign. Note that the interpretation of MNL result is different than the interpretation of RRM results. For example, in short distance MNL, increasing of a unit of one attribute, travel time, decrease 0.04 unit of utility associated with mode alternative, similar interpretation also applies to travel cost. However, for the RRM parameter estimate, an increase in travel time refers to the potential decrease in regret associated with comparing a chosen mode alternative with other non-chosen mode alternatives. Therefore we cannot just compare the magnitude of parameter estimate of an attribute between MNL and RRM. For direct comparison of the influence of an attribute, we need to compare the elasticities (in Section 5), which give the percent change in the choice probability of an alternative as a result of a percent change in one of its attributes.

Negative ASCs in MNL case tells us that ceteris paribus BRT is preferred compare to other modes. Similarly, positive ASCs for RRM indicates that those modes give more regret than choosing BRT. Overall we can say that BRT is the most preferred mode for all distance categories while car is the least preferred mode for short and medium distance. Interestingly car is more preferred for the case of long distance compare to feeder and motorcycle which make sense.

Regarding model fit, we can compare log-likelihood, Rho-squared as well as Akaike Criterion (AIC) and Bayesian Criterion (BIC). From the final-LL, we can see that MNL is better than RRM. From the Rho-square, MNL is slightly better than RRM for the short and medium distance. From the AIC comparison, it appears that MNL is better than RRM for the medium distance. For internal validation, we performed out-of sample model estimation and formulation, where we choose 2/3 of the sample for estimation and simulate the model on the rest of 1/3 sample. For all distance categories, MNL outperforms RRM.

# 5. MODELS APPLICATION

## 5.1 Value of Travel Time Savings

We present the mean value and standard deviation of the value of travel time savings for three distance categories for RRM model in Table 4. MNL is not a context-dependent model. Therefore the VTTS of an alternative is not influenced by the performance of other alternatives in contrast to RRM. It is quite interesting that overall the VTTS of medium distance is lower than the short distance VTTS. The VTTS for long distance is the highest which makes sense. Normally we would expect that the VTTS for car is higher than public transport. However, it appears that it is not the case for Bali.

Table 4. Value of travel time savings (in IDR/hour*)

| Alternatives | Short distance | | | Medium distance | | | Long distance | | |
|---|---|---|---|---|---|---|---|---|---|
| | MNL | RRM | | MNL | RRM | | MNL | RRM | |
| | | Mean | Std. D | | Mean | Std. D | | Mean | Std. D |
| BRT | 15,358 | 15,414 | 1,760 | 12,786 | 14,823 | 1.545 | 18,421 | 22,680 | 2,360 |
| Feeder | | 15,102 | 1,931 | | 14,942 | 1.610 | | 22,817 | 2,347 |
| Car | | 14,877 | 1,717 | | 12,761 | 1.699 | | 19,202 | 2,224 |
| Motorcycle | | 16,728 | 1,845 | | 13,183 | 1.572 | | 18,133 | 2,131 |

*At the time of the survey, USD 1 = IDR 13,600.

To give a better depiction of the VTTSs distribution, we plot the VTTS by alternative modes for short, medium and long distance in Figure 2, Figure 3, and Figure 4. On the x-axis, we present the alternatives modes. At the y-axis, we present the VTTS in IDR 1,000 per hour. The reference line attaches to the y-axis represents the MNL VTTS for that distance category. For short distance travel, we can see that the median value RRM of BRT, feeder, and car are below the MNL line. For the medium and long distance travel, the median value RRM of BRT and feeder are above the MNL line.

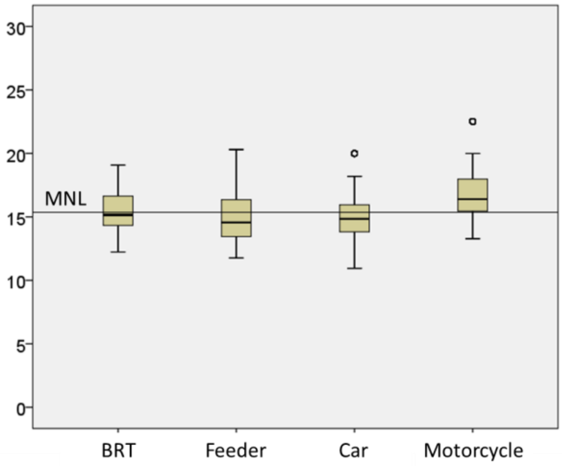


Figure 2. Value of travel time savings for short distance travel RRM (IDR 1,000/hour)

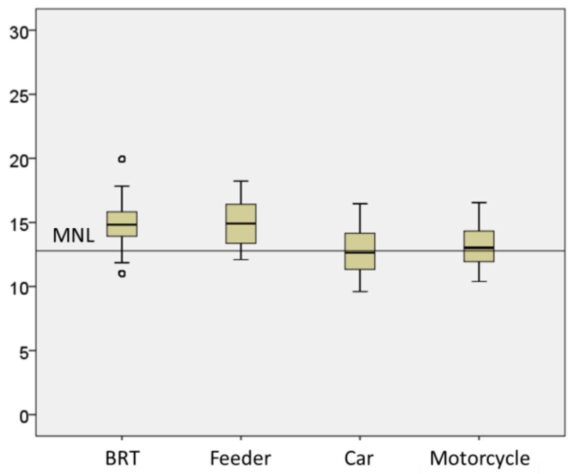


Figure 3. Value of travel time savings for medium distance travel RRM (IDR 1,000/hour)

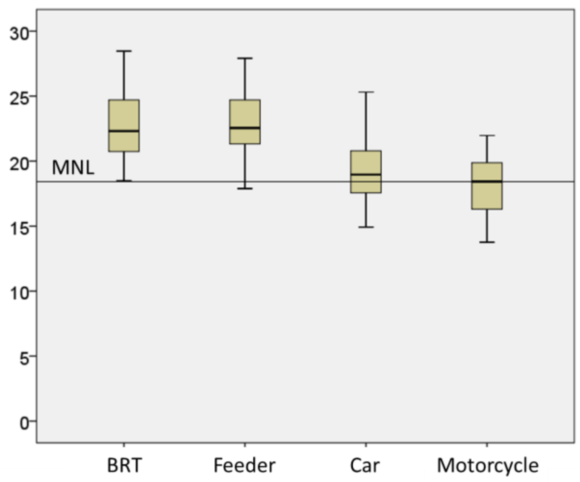


Figure 4. Value of travel time savings for long distance travel RRM (IDR 1,000/hour)

## 5.2 Demand Elasticities

To compare elasticities between models, we have to calculate the aggregate direct point elasticities for each model. The measurement formula, presented in Atasoy et al. (2013), is shown below:

$$E^{W_i}_{inX_{kin}} = \sum_{n=1}^{N_s} E_{inX_{kin}} \frac{w_n P_{in}}{\sum_{n=1}^{N_s} w_n P_{in}} \qquad (9)$$

Where $w_n$ represents the sample weight for an individual $n$ from sample $N_s$ from population $N$ and $E_{inX_{kin}}$ is the disaggregate elasticity of demand of individual $n$ for variations in the attribute $x_{kin}$. We weighted each observation on our data sets according to the representation of its age and gender category in Bali population data set (Statistics of Bali Province, 2016) as discussed in Section 2.

We present the aggregate direct point elasticities for travel time and cost for three distances category for MNL and RRM in Table 5. Travel time and cost for all models are relatively inelastic except for feeder travel time and car travel time in the long distance category. The percentage differences for short distance travel are substantially high, higher than the medium and long distance. The travel time and cost elasticities for RRM are greater than RUM for short distance. As for the medium and long distance, the travel time elasticities for RRM are greater than RUM for BRT, feeder, and car. For motorcycle travel time elasticities and all cost elasticities for medium and long distance, MNL elasticities are higher than RRM.

For the interpretation of the elasticities, we can take one example, for short distance MNL, a 10% increase in the travel time of BRT makes, on average ceteris paribus, a 1.4% reduction in the probability of choosing BRT. At the same time, 10% increase in BRT travel time in the context of RRM takes into account the travel time associated with other three alternative modes. A 10% increase in BRT travel time, results in 3.3% reduction in the probability of choosing BRT, which explicitly accounts for the difference in travel time in the set of available alternatives. The difference is 135.7% with RRM being higher than MNL, suggesting that the possibility of the wrong choice is taken, may have been made amplifies the behavioral responses.

For medium and long distance, changes in travel time of BRT, feeder, and car might give a substantial impact on the reduction/increase of probability of choosing those modes. Policy to reduce travel time of BRT and feeder might increase the probability of choosing those modes for medium and long distance travel. Therefore, accelerate development of the rest planned corridors, as (Governor of Bali regulation, 2010) stated that there are 17 corridors are planned, might be highly important to support all commuting activities in Sarbagita area. Alternatively, policy maker could also think about the implementation of road pricing or congestion charging to reduce the probability to use car since the cost of car for long distance is nearly elastic. However, it should be proofed by future research.

Table 5. Travel time and cost elasticities

| | Alternatives | Short distance | | | Medium distance | | | Long distance | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | MNL | RRM | % dif-ference | MNL | RRM | % dif-ference | MNL | RRM | % dif-ference |
| Travel time | BRT | -0.14 | -0.33 | 135.71 | -0.56 | -0.57 | 1.79 | -0.95 | -0.98 | 3.16 |
| | Feeder | -0.19 | -0.42 | 121.05 | -0.66 | -0.67 | 1.52 | -1.14 | -1.18 | 3.51 |
| | Car | -0.21 | -0.42 | 100.00 | -0.73 | -0.74 | 1.37 | -1.20 | -1.23 | 2.50 |
| | Motorcycle | -0.12 | -0.32 | 166.67 | -0.43 | -0.42 | -2.33 | -0.63 | -0.60 | -4.76 |
| Cost | BRT | -0.22 | -0.43 | 95.45 | -0.32 | -0.29 | -9.38 | -0.32 | -0.28 | -12.50 |
| | Feeder | -0.31 | -0.58 | 87.10 | -0.35 | -0.32 | -8.57 | -0.37 | -0.33 | -10.81 |
| | Car | -0.38 | -0.62 | 63.16 | -0.76 | -0.75 | -1.32 | -0.83 | -0.81 | -2.41 |
| | Motorcycle | -0.13 | -0.26 | 100.00 | -0.40 | -0.37 | -7.50 | -0.40 | -0.36 | -10.00 |

## 6. CONCLUSION

In this paper, we try to compare the widely used modeling technique MNL which belong to the Random Utility Maximization framework with the recently introduced Random Regret Minimization framework. To check the sensitivity to distance, at the time of the survey our respondents were given ten scenarios for each of three distance category, short (below 5 km), medium (5-15km), and long distance (more than 15 km). We perform MNL and RRM for each of those distance categories with only two generic attributes travel time and cost. We compare model fit, the value of travel time savings and demand elasticities of those two models. Comparing final-LL, MNL outperforms RRM in all distance category.

Regarding the VTTS, using only generic attributes, travel time and cost, RRM can give richer interpretation compare to MNL. For MNL we obtain one VTTS for all alternative modes, while for RRM we can obtain VTTS for all alternatives. We found an interesting result that the VTTS for car overall is lower than BRT/feeder. The VTTS results obtained for these modeling approaches can be used for policy makers to do cost benefit analysis for the transportation related project.

As for the demand elasticities, we found that for short distance travel, the direct elasticities for travel time and cost are nearly inelastic, that means the increase on both attributes might not resulting in substantial reduction for the probability of choosing the particular mode. However, we found that in the medium and long distance categories, travel time is nearly elastic (elastic for feeder and car long distance), while cost is nearly inelastic for car. That means the implementation of a policy to reduce BRT and feeder travel time might give a substantial increase in the probability to choose those modes, at the same time, policy to increase car cost might give a substantial reduction in the probability to choose a car.

This research is the first one to compare RUM and RRM for Indonesian context. There are several limitations to this study. We realize that low model fits that we obtain might be because we only use generic attributes. We did not utilize other non-generic attributes such as waiting time, walking distance to shelter, parking cost and easiness of parking. We also do not use interaction variable with socio-demographic. Regarding the data collection, we realize that stated preference survey (SP) tend to give the lower VTTS than revealed preference survey (RP) since the travel time and cost used in the calculation are hypothetical time and cost which strongly depends on the experimental design (Brownstone and Small, 2005). Therefore, further research in the framework of RRM, possibly using RP data, is necessary so that RRM can also be implemented in Indonesia in general as an alternative to RUM modeling technique.

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