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By Monorom Rith, Raymund P . Abad, Alexis Fillone, Kenji Doi, HirotoInoi Jose Bienvenido M. Biona
De La Salle University

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Monorom Rith [α], Raymund P. Abad [σ], Alexis Fillone [ρ], Kenji Doi [ω], HirotoInoi [¥] & Jose Bienvenido M. Biona[§]

Abstract- Sustained economic growth coupled with inadequate public transport service are the main factors that contribute to increasing private vehicle dependency in Metro Manila. These issues exacerbate traffic congestion and spur higher energy demand resulting in more greenhouse gas (GHG) production. This paper developed a multinomial logit (MNL)-based household vehicle ownership model and a linear regression-based household energy demand model taking account of urban form attributes, gas price, and vehicle cost. The mentioned factors are hypothesized to have negative impactson household vehicle ownership and usage. The models utilized the primary dataset gathered from2,300 households surveyed from various areas within Metro Manila. The developed models were the napplied for the "what-if" scenario analysis that assumes a 25% gas price increase, a 25% vehicle cost increase, improvement of residential area accessibility to key destinations and services, and improvement of public transport line density. Had all the mentioned scenarios beencombined, the vehicle fleet and total energy demand would have been reduced by 78.95% and 84.92%among the households surveyed, respectively. Another finding highlights that a1% gas price increase would reduceCO_2emission by0.172% per household .The improvement of key destination accessibility and public transport line density are the most effective options to address private vehicle dependency toward sustainable urban transportation, rather than increasing gas and vehicle prices and road density.

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I. Introduction

The Philippines has become one of Asia's fast-growing economies with an average gross domestic product (GDP) growth of 6.8% per annum in the last three years [1]. Unhampered economic growth is an influential factor expected to fuel private passenger vehicle sales and usage, which triggers traffic congestion exacerbation, higher energy demand, air quality degradation, and greenhouse gas (GHG) production in the metropolitan area. Average travel time of one person trip in Metro Manila, the national capital region of the Philippines, was expected to increase from 1.17 hours at present up to 1.33 hours in 2030 [2]. The CO_2 emission from road passenger transport sector in the metropolis was 13.78 million tons in 2015, and it would double up to 27.9 million tons in 2040 in case of no strategic intervention from the government [3].

Metro Manila leads all the regions in the vehicle fleet with a total of 1.698 million units registered in 2016 with an average annual uptake of 204,404 new passenger vehicles from 2015 to 2016 [4]. Private vehicles were responsible for 71.3% of vehicle trips in 2012 with an average annual growth of 3.3% from 1996 to 2012 [2]. In line with this, about 50% of the metropolitan roads have already operated at a volume/capacity (V/C) ratio of 0.80 [2], and the up-trend projected private vehicle dependency is expected to saturate the roads further. An increasing private vehicle dependency over the years has rapidly degraded the effectiveness of the vehicular volume reduction schemes implemented [5, 6]. Furthermore, an increase in vehicle dependency is associated with higher road energy demand and emissions. Some literature has looked at some alternative solutions to mitigate energy demand and GHG productions through increasing accessibility of residential areas to railway stations, improvement of fuel quality, implementation of Euro 4 emission standard, expansion of the metropolitan railway network, and reduction of private vehicle kilometers traveled [3, 7, 8]. Regidor and Javier [9] and the Asian Development Bank [10] emphasized the significance of managing private vehicle ownership, usage, and energy intensity to combat GHG emissions. Moreover, Mijares et al. [11] speculated that the improvement of mass public transport service might be inefficient if car ownership cost is not increased. Recently, the government launched the Tax Reform for Acceleration and Inclusion (TRAIN) law or RA No. 10963 to raise gas

Author α: Mechanical Engineering Department, De La Salle University, 2401 Taft Ave, Manila, 1004, Metro Manila, Philippines. e-mail: rith_monorom@dlsu.edu.ph
Author σ ρ: Civil Engineering Department, De La Salle University, 2401, Taft Ave, Manila, 1004, Metro Manila, Philippines.
Author ω: Civil Engineering Department, Osaka University, 1-1 Yamadaoka, Suita, 565-0871, Osaka Prefecture, Japan.
Author ¥: Department of Urban, University of Toyama, 3190 Gofuku, Toyama, 930-8555, Toyama Prefecture, Japan.
Author §: Center for Engineering and Sustainable Development Research, De La Salle University, 2401 Taft Ave, Manila, 1004, Metro Manila, Philippines.

and vehicle price [12]. However, a reduction in energy demand for private passenger vehicles through increasing gas and vehicle prices and improving the urban form has yet to be explored in Metro Manila. A better understanding of the quantitative impact of changes in gas and vehicle prices and urban form attributes is indispensable to crafting consistent, appropriate strategic approaches toward a sustainable urban transportation system by reducing private vehicular volume and energy demand.

Evidence from the existing literature in developed countries suggests that a number of household vehicles and vehicle type choice are significantly influenced by vehicle cost [13–15]; these are considered to be more significant than increases on gas taxes [15]. Penalty taxes on older SUVs could reduce emissions by inducing people to hold on to their existing sedans or purchase new SUVs in lieu of second-hand units [13]. Lower-income households are more responsive to gas prices than higher-income households [15]. As to urban form attributes, households living in higher density area are less likely to own more vehicles and put on miles [16, 17] and more inclined to use smaller vehicles [14, 18]. A similar finding reported that building compact cities or encouraging urban densification contributes to a reduction in mobile CO_2 emissions [19, 20]. One explanation could be that the access to or use of parking lots is prohibitive [14] and expensive in urban high-density areas [21]. Vehicle users that originated from central business districts (CBDs) are willing to own small and luxury vehicles, presumably on account of ease in parking, and in addition to that those living in CBDs have high income [22]. Japanese households residing in high-density areas in the vicinity of railway stations have lower propensity to own more vehicles as the railway system in Japan is systematic, convenient, and sufficient to use [21]. A similar finding in Dublin, Ireland, also showed that households located close to more bus stops are less likely to own more vehicles [23]. Households living in a neighborhood with high bike lane density have a lesser likelihood to acquire vehicles, while those located in a high street block density community are more inclined toward holding smaller vehicle types [14].

However, the state of the public transport system in Metro Manila is apparently different from that of developed countries. The Public Utility Jeepney (PUJ), whose features are like a minibus, is the dominant mass transit mode in Metro Manila. PUJ stops are practically non-existent because passengers are loaded and unloaded anywhere along the roads. There are bus stops along the roads, but the buses (standard buses) also operate the same way as the PUJs. Correspondingly, the impact of bus stop density in the metropolis is hypothesized to have no impact on household vehicle ownership and usage, unlike in developed countries. The empirical finding in Ho Chi Minh City was reported that the bus stop density had no impact on vehicle type choice and usage [24]. In this context, we should consider the road public transport line density rather than the bus stop density. Additionally, on-street parking is rampant in Metro Manila. Higher block density or road density is associated with more on-street parking space, which in turn probably encourages private vehicle ownership. The proximity of residential areas to critical destinations (i.e., hospitals, schools, markets, and recreational centers) and the accessibility to CBDs have not been known how these factors affect household energy consumption for private vehicle usage. The impact of an increase in one percent of gas price on household vehicle ownership and usage in developing countries is not known to be higher or lower to some extent, compared with that of developed countries, because for developing countries the per-capita GDP is relatively even lower, but the public transport service is relatively much inefficient and inadequate.

This paper intends to identify the impact of vehicle and gas price and urban form attributes on household vehicle ownership and energy demand within Metro Manila, using the sample data of 2,300 households gathered from various traffic analysis zones (TAZs) in the metropolis in April and May 2017, based on a simple random sampling technique. For the urban form characteristics, a multi-criteria accessibility index of communities to essential destinations, road public transport line density, road density, and accessibility of residential areas to CBDs took into account important peculiarities and measures. The multinomial logit (MNL) regression and linear regression were applied to develop the models. Also, the developed models were used in a sensitivity analysis by varying the significant variables captured by the models. The findings of this study provide insights on effective solutions on how to lower private passenger vehicles and energy demand in Metro Manila toward a sustainable urban transportation system.

II. Methodology

This section provides a brief description of the model formulation followed by the sample data, the mathematical framework, the scenario formulation, and the elasticity of energy demand and CO_2 emission with respect to the gas price increase.

a) Model Formulation

We classified household vehicle holdings (vehicles and types owned by households) into five different bundles (alternatives). The description of the dependent and independent variables is provided in Table 1. Car refers to a small vehicle (i.e., hatchback, sedan, and multipurpose vehicle (MPV)), whereas UV (utility vehicle) refers to a large vehicle (i.e., SUV, minivan, van, pickup, and Asian utility vehicle (AUV)). Correspondingly, the UV has a larger seating and luggage capacity than the Car. Households owning two UVs or more than two vehicles are very few (less than 0.1%) in our data sample, and we thus removed those households to avoid problems arising during the model estimation. The likelihood value of the model estimation cannot be maximized if an alternative has very few observations in the data sample, specifically the household energy demand model.

A multi-criteria gravity-based accessibility function was taken into account to approximate the accessibility of household residential areas to key destinations or facilities (see Equation (1)). The center point of a TAZ was used as the coordinate of a residential area, and the TAZs are based from [25].

$$Multi-criteria\ accessibility = \sum_j w_j \sum_i \frac{1}{e^{d_{j,i}}} \qquad (1)$$

The key destinations are categorized as Educational Institutions, Hospitals and Medical Care Centers, Public Markets, and Recreational and Shopping Areas. Distance $d_{j,i}$ represents kilometer travel required to reach a point of interest i of a destination category j, while weight W_j refers to the importance of a destination category j. The weights W_j were adopted from [26] and are provided in Table 2.

Soltani [27] identified the impact of distance from home to CBD on household vehicle holding using the cut-off approach. The impact of distance to CBD is changed if the distance cut-off is varied. Using the gravity-based accessibility approach (see Equation (2)) is likely to be more reliable to understand the impact of distance from a residential area to CBD on household vehicle holding and energy demand. If the distance linearly increases, the accessibility to CBD exponentially decreases.

$$CBD\ Accessibility = \sum_i \frac{1}{e^{d_i}} \qquad (2)$$

where distance d_i represents kilometer travel required to reach CBD point i.

Table 1: Description of the model formulation and the explanatory variables

Variable	Description
	Dependent variable
Household vehicle holdings: Alternative 1 Alternative 2 Alternative 3 Alternative 4 Alternative 5	Zero-vehicle owned by a household One car owned by a household One UV owned by a household Two cars owned by a household One car and one UV owned by a household
Energy demand: Energy 2 Energy 3 Energy 4 Energy 5	Energy demand by a one-car household Energy demand by a one-UV household Energy demand by a two-car household Energy demand by a car-UV household
	Independent variable
Household size	Continuous variable (the total number of family members)
Age of household head	Dummy variable (1 = if the household head is 40 years old or above; 0 = otherwise)
Multi-criteria accessibility[a]	Continuous variable (TAZ-based accessibility to key destinations)
Line density	Continuous variable (road public transport line density at TAZ level taking into account Jeepneys (minibusses), public utility vans, and buses)
Road density	Continuous variable (road density at TAZ level)
Population density	Continuous variable (population density at TAZ level)
CBD accessibility [a]	Continuous variable (TAZ-based accessibility to CBD)
Vehicle cost/ income [b]	Continuous variable (an average purchasing cost of one vehicle divided by annual household income)
10 x Gas expenditure/ income[b]	Continuous variable (an average monthly expenditure on gas for one vehicle divided by monthly household income)
	TAZ : Traffic analysis zone; CBD: Central business district [a] See Equations (1) and (2) [b] Based from [14]

Table 2: Destination importance weights

Facility	Weight
Hospital and medical care center	20.9%
Educational institution	32.9%
Public market and supermarket	10.7%
Social, eating and recreational facility	35.5%
adopted from [26]	

b) Data Source

A total number of 2,300 households were selected through various TAZs in Metro Manila to participate in the face-to-face interview from April to May 2017, using a simple random sampling technique. The status of each randomly selected household had not been known. Such a technique is the ease of assembling the sample, and every household gets an equal probability of being selected. Furthermore, Metro Manila has no baseline statistical data of household vehicles and types owned by households. After cleaning the data, only 2,140 observations were used for data modeling. Based on the Cochran formula, the size of 2,140 samples provided a confidence level of 99% with a margin of error of 2.79%. Table 3 presents the distribution of households vehicle holdings and the descriptive statistics of energy demand by household vehicle holdings. The household energy demand is converted from the monthly household expenditure on gasoline and diesel. The data sample shows that 47.29% of households have no vehicle, and this figure corresponds to a report of Nielsen Global Survey of Automotive Demand that about 47% of Philippine households have no four-wheeler [28].

Table 3: Distribution of household vehicle holdings and descriptive statistics of energy demand

Alternatives	Household vehicle holdings	Energy demand (GJ/month)			
	Frequency (%)	Min	Mean	Max	SD
No vehicle	1,012 (47.29)	–	–	–	–
One car	711 (33.22)	0.312	2.968	9.899	1.184
One UV	288 (13.46)	0.593	4.731	14.848	2.640
Two cars	69 (3.22)	3.119	6.917	15.593	2.117
Car & UV	60 (2.81)	3.119	8.246	16.136	2.738

Table 4 shows the descriptive statistics of the independent variables. All the independent variables have 2,140 observations, except vehicle cost and monthly expenditure on gas having 344 observations. As mentioned earlier, we use the average vehicle cost and monthly gas expenditure to capture the impact of gas price and vehicle cost on household vehicle holdings and energy demand, and any vehicle purchased before the year 2012 was removed to avoid data inconsistency. To explain, for instance, some vehicles purchased in the year 2000 or 2005 cost much cheaper than those of the current year and using the actual vehicle cost in the former year relative to the household income in the survey year might not make sense. Specifically, vehicle average lifespans for car and UV in Metro Manila are 14.225 and 13.929 years, respectively [29]. Additionally, vehicle cost and gas expenditure are considerably varied from household to another (see the last two rows of Table 4).

Table 4: Descriptive statistics of the explanatory variables

Variables	Frequency	Min	Mean	Max	SD
Household size	2140	1	3.322	11	1.230
Age of household head	2140	0	0.679	1	0.467
Multi-criteria accessibility	2140	1.126	8.743	13.129	2.507
Line density (km/km^2) [a]	2140	0	28.18	154.22	31.210
Road density (km/km^2) [a]	2140	0.419	9.456	28.201	4.167
Population density (10^3	2140	1.524	41.257	147.848	17.976

perons/ km^2) [a]					
CBD accessibility (10)	2140	0	0.835	8.601	1.312
Monthly household income	2140	0.412	6.891	41.343	5.968
(10^4 PHP)					
Vehicle cost for one vehicle	344	200,000	819,287	3,615,000	349,643
(PHP)					
Monthly expenditure on gas for one vehicle (PHP)	344	716	4,086	12,857	1,321
[a] Based from [25]					

c) *Mathematical Framework*

The existing literature has applied various joint discrete-continuous choice algorithms to develop the household vehicle ownership and usage model to capture the dependency between the discrete choice and the continuous choice; however, the estimated percentage shares of the discrete choice component and the estimated output variables of the continuous choice component were inaccurate [16, 17, 30–34]. If we apply the developed model using those algorithms to simulate the total vehicle fleet and vehicle usage of each alternative as numerical values in response to variation of the input variables, those algorithms cannot perform well. Accordingly, all the existing literature simulate the percentage changes of the output variables in place of numerical values under changes in the input variables for the sensitivity analysis. Therefore, this study developed the household vehicle ownership model and energy demand model separately but estimate the two models simultaneously.

The household vehicle ownership model was developed using the MNL regression, on account of its simple form and ease in interpretation. The probability of an alternative *T* chosen by a household *n* is expressed as Equation (3) below [35]:

$$Pr(T) = \frac{\exp(\beta_T' x_{nT})}{\sum_{t=1}^{M} \exp(\beta_t' x_{nt})} \quad (3)$$

Let *n* (*n = 1, 2 . . . N*) and *t* (*t = 1, 2 . . . M*) be the indices representing households and household vehicle holdings, respectively, T∈t. x_{nt} is a column vector of explanatory variables including a constant, and $\boldsymbol{\beta}_t$ is a column vector of the corresponding coefficients.

The parameters of the utility functions can be estimated using the maximum likelihood function (*LL*), as seen in Equation (4):

$$LL_{discrete} = \sum_{n=1}^{N} \sum_{t=1}^{M} R_{nt} \left[\log(Pr(t))\right] \quad (4)$$

where R_{nt} defines the dummy variable of choice indicator, taking the value 1 if an alternative *t* is made by a household *n* and 0 otherwise.

We assumed the energy demand for the bundle *T* chosen by a household *n* is a linear function, as seen in Equation (5).

$$E_{nt}{}' = \alpha_t' y_{nt} + \eta_{nt} \quad (5)$$

The column vector of the coefficients are estimated by maximizing the term "$-\sum_{n=1}^{N} \sum_{t=1}^{M} R_{nt}\ [\eta_{nt}^2]$" ,based from [13], using the maximum likelihood function, as seen in Equations (6), (7), and (8):

$$\eta_{nt} = E_{nt} - \alpha_t' y_{nt} \quad (6)$$

$$-\sum_{n=1}^{N} \sum_{t=1}^{M} R_{nt}\ [\eta_{nt}^2] = -\sum_{n=1}^{N} \sum_{t=1}^{M} R_{nt}\ [(E_{nt} - \alpha_t' y_{nt})^2] \quad (7)$$

$$LL_{continuous} = -\sum_{n=1}^{N} \sum_{t=1}^{M} R_{nt}\ [(E_{nt} - \alpha_t' y_{nt})^2] \quad (8)$$

where y_{nt} is a column vector of explanatory variables including a constant, $\boldsymbol{\alpha}_t$ is a column vector of the corresponding coefficients for an alternative t, and an error term $\boldsymbol{\eta}_{nt}$ is the unobserved part.

d) *Scenario Formulation*

Five different scenarios were formulated to simulate the percentage changes in household vehicle holdings and energy demand based on the "what if" concept rather than the intrinsic forecast method for the sensitivity analysis as follows:

- Scenario 1: High accessibility to key destinations (all TAZs = maximum multi-criteria accessibility);
- Scenario 2: High public line density (all TAZs = maximum line density);
- Scenario 3: a 25% vehicle price increase;
- Scenario 4: a 25% gas price increase;
- Scenario 5: Integration of scenarios 1 through 4.

The percentage changes of the total energy demand of all the above scenarios relative to the actual total energy demand are expressed as follows (Equations (9), (10), and (11)):

$$Total\ energy_{t,scenario} = \sum_{n=1}^{2140} R_{nt}\,[\alpha_t' y_{nt}] \tag{9}$$

$$Total\ energy_{scenario} = \sum_{t=2}^{5} \left(\frac{\%\ share_{t,scenario}}{\%\ share_{t,actual}}\right) \times total\ energy_{t,scenario} \tag{10}$$

$$\%\ Energy\ change = 100 \times \left(\frac{Total\ energy_{scenario} - Total\ energy_{actual}}{Total\ energy_{actual}}\right) \tag{11}$$

For the gas price scenario analysis, the retail gas prices in April 2017 in Metro Manila were used as the reference values because the survey was carried out during the mentioned period. The retail pump prices were 47Php/liter (for gasoline RON97) and 30Php/liter (for diesel) during that period [36].

e) Elasticity

Once we obtain the energy demand model by household vehicle holdings, we calculate the elasticity of energy demand (GJ/household-month) with respect to a 1% gas price increase to capture the marginal effect of gas price, as seen in Equation (12). The elasticity of CO_2 emissions (Tons/household-month) with respect to 1% gas price increase is calculated using Equation (13):

$$Energy\ elasticity_t = \frac{Total\ energy_{t,1\%\,gas} - Total\ energy_{t,actual}}{Total\ households_t} \tag{12}$$

$$CO_2\ elasticity = Emission\ Factor_{CO_2} \times Energy\ elasticity_t \tag{13}$$

where *Total energy*$_{t,\ 1\%\ gas}$ defines the total energy demand of 1% gas price increase for bundle *t* and *Total households*$_t$ is the total number of households for bundle *t*. The CO_2 emission factor is 74.10 tons/TJ [37].

III. Results and Discussion

This section discusses the model estimation results, scenario analysis, and elasticity of energy demand and CO_2 emissions with respect to a 1% gas price increase.

a) Model Estimation Results

The estimation results of the household vehicle holding model and the energy demand model are listed in Table 5.

i. *Household vehicle holdings*

For the household vehicle ownership model, the parameter estimates are shown from rows 2 through 11, and the zero-vehicle bundle was used as the reference category. The McFadden R^2 was 0.396 that is higher than the critical value of 0.3 [38]. The intercept coefficients of the MNL model have no interpretable meaning, but they are included to capture the average unobserved effect [35]. The household size coefficients are negative for all the alternatives, which indicate that households with more family members are less likely to hold vehicles, unlike previous studies. One explanation may be that large-sized families have low income, relative to small-sized families in Metro Manila, and therefore large size families have a lower vehicle purchasing power. The coefficients of the age of household head demonstrate that older households (household head aged 40 years old and above) have a higher propensity to hold more and large-sized vehicles (UVs), compared with younger households (household head aged below 40 years old). That household heads reach the mid-age (40 years and older) is just about the time their children become adults; therefore, the older households need vehicles with large seating and luggage capacity (i.e., UVs). For wealthy households, it is the stage when the kids are provided with their own vehicles.

The high accessibility of residential areas to the key facilities and the high road public transport line density have negative impacts on household vehicle holdings, and the impact of the multi-criteria accessibility was at a higher degree relative to the road public transport line density. As hypothesized, the high road density encourages household vehicle holdings for all the bundles, on account of larger on-street parking space and generally no law reinforcement related to on-street parking in residential areas in Metro Manila. Unlike the findings in other countries [16–18, 21, 34], the population density has no effect on household vehicle holdings. This could be explained that the multi-criteria accessibility has a stronger impact on household vehicle holdings than the population density, and all the studies in the existing literature have never considered the factor of multi-criteria accessibility to the key facilities. Households with high accessibility to CBDs are more likely to hold more vehicles. It is intuitive that those located close to CBDs have higher income, which means higher purchasing power for more vehicles. A similar finding in China was also reported by Jiang et al. [22].

The coefficients of vehicle cost-to-annual household income ratio factor are negative for all the alternatives, which indicates that high-income households are likely to hold more and large vehicles. Inversely, households are more prone to hold fewer and small-sized vehicles, if the vehicle cost is increased.

ii. *Energy Demand*

The parameter estimates of the energy demand model for all the bundles are demonstrated in the last ten rows of Table 5. As explained previously, zero-vehicle households have no energy demand. The positive intercept coefficients indicate that household holding vehicles are more likely to consume energy. Larger household size is associated with higher energy consumption for one-UV households and one-car households but has no statistically significant effect on households owning two cars. Generally speaking, households with more members are associated with more trips, which in turn requires more energy demand. It is surprising to see that car-UV households with more family members are likely to consume less energy. Age of household head has an effect on bundle 5 (i.e., car-UV households) only, and older households for this bundle are associated with less energy consumption, relative to younger households intuitively having more small child-related trips.

The multi-criteria accessibility has a negative impact on energy demand for one-car households but has a positive effect on energy demand for two-car households. Such a factor has no effect on energy demand for the one-UV and car-UV households. The road public transport line density has a negative impact on energy demand for one-car households, but a positive effect on energy demand for one-UV households. The line density has no effect on two-vehicle households. One-car households located in high road density area are more likely to consume more energy, probably owing to the fact that high road density is associated with more moving vehicles and narrow road space wherein traffic flow is slower. Additionally, an average fuel economy of a private vehicle in Metro Manila was 8.97km/l at 39.79km/h speed and 5.26km/l at 16.25km/h speed [39]. Contrary to one-car households, the other households are likely to consume less energy, and this could be explained that households holding larger and more vehicles might put on fewer miles, probably because a higher road density area has more convenience stores, supermarkets, and other facilities resulting in fewer private vehicle trip activities. It is not surprising to see that households of all the bundles having higher accessibility to CBDs require lower energy demand since the CBD area is the proximity of land-mixed use, pedestrian-friendly street, and better public transport accessibility.

The negative coefficients of expenditure on gas-to-income ratio factor were found for all the bundles, and most significant for one-UV households. Generally speaking, households with higher income are more like to consume more energy; and inversely, an increase in gas price has a negative impact on energy consumption.

Furthermore, the developed models for household vehicle holdings and energy demand are applied to estimate the output variables and then compared with the actual output variables as discussed below.

Table 6 presents the estimated output variables and the actual output variables. As seen in columns 2 and 3, the predicted percentage shares exactly matched the actual percentage shares for all the bundles. As apparent from columns 4 and 5, the predicted total energy demands are equal to the actual ones for all the bundles. The root mean square errors (RMSEs) of the estimated energy demand (the last column of Table 6) are very small for all the bundles (except bundle 2), as compared to the corresponding mean energy demands (see column 4 of Table 3). The RMSEs of bundles 3 and 5 were higher than those of bundles 2 and 4, on account of the relatively higher standard deviations of bundles 3 and 5 (see column 6 of Table 3).

Table 5: Estimation results of the MNL regression and linear regression – parameters (t-value)

Variables	One car	One UV	Two cars	Car & UV
Household vehicle holdings				
Intercept	5.442	5.521	5.039	4.720
	(12.62)**	(10.71)**	(5.64)**	(4.82)**
Household size	-0.443	-0.279	-0.346	-0.147
	(-6.47)**	(-3.35)**	(-2.29)*	(-0.96)
Age of household head	0.049	0.239	1.038	1.576
	(0.30)	(1.15)	(2.47)*	(2.80)**
Multi-criteria accessibility	-0.513	-0.554	-0.524	-0.707
	(-11.56)**	(-10.69)**	(-6.30)**	(-8.01)**
Line density (km/km2)	-0.019	-0.016	-0.008	-0.015

Global Journal of Researches in Engineering (J) Volume XIX Issue VI Version I Year 2019

	(-4.69)**	(-3.74)**	(-1.50)	(-2.69)**
Road density (km/km2)	0.260	0.226	0.230	0.287
	(8.87)**	(6.79)**	(5.14)**	(6.34)**
Population density (10^3/km2)	0.002	-0.003	-0.004	-0.004
	(0.41)	(-0.45)	(-0.37)	(-0.40)
CBD accessibility (10^{-1})	0.999	0.974	1.093	1.245
	(10.12)**	(8.89)**	(7.96)**	(9.25)**
Vehicle cost/annual income	-1.590	-2.478	-5.699	-5.977
	(-13.98)**	(-13.04)**	(-10.53)**	(-10.01)**
Energy demand				
Intercept	3.059	4.996	8.116	15.923
	(21.12)**	(24.42)**	(13.29)**	(25.66)**
Household size	0.074	0.425	0.147	-0.335
	(2.71)**	(11.05)**	(1.26)	(-3.57)**
Age of household head	0.038	0.149	0.467	-2.613
	(0.65)	(1.50)	(1.66)	(-6.89)**
Multi-criteria accessibility	-0.035	-0.039	0.414	-0.067
	(-2.54)*	(-1.69)	(5.87)**	(-1.11)
Line density (km/km2)	-0.007	0.011	-0.005	-0.002
	(-7.90)**	(6.65)**	(-1.85)	(-0.63)
Road density (km/km2)	0.035	-0.069	-0.099	-0.07
	(4.83)**	(-5.54)**	(-3.60)**	(-2.80)**
Population density (10^3 people/km2)	-0.001	0.004	-0.055	-0.013
	(-0.67)	(1.56)	(-7.88)**	(-1.69)
CBD accessibility (10)	0.052	-0.044	-0.276	-0.171
	(2.21)*	(-1.18)	(-2.82)**	(-3.40)**
10 x Gas expenditure/income	-0.342	-2.509	-5.293	-6.493
	(-3.90)**	(-16.46)**	(-8.90)**	(-8.77)**

No vehicle alternative was used as the reference category for the discrete choice model.
Discrete choice component: LL = -1553.1; McFadden R^2 = 0.396
Continuous choice component: LL = -3203.7

Table 6: Comparison of the estimated and actual output variables

Bundles	% Shares		Total Energy Demand (GJ/month)		RMSE
	Actual	Estimated	Actual	Estimated	
Zero vehicle	47.29%	47.29%	–	–	–
One car	33.22%	33.22%	2110.19	2110.19	1.15
One UV	13.46%	13.46%	1362.52	1362.52	2.44
Two cars	3.22%	3.22%	477.27	477.27	1.77
One car & one UV	2.80%	2.80%	494.77	494.77	2.34
RMSE: Root mean square error					

As can be seen in Table 6, the separate estimations of the discrete choice model and the continuous choice model using the maximum likelihood function performed well in terms of accuracy of the estimated output variables, as compared with other algorithms. Those algorithms include the two-step approach proposed by Dubin and McFadden [40], the multiple discrete-continuous extreme value (MDCEV) model proposed by Bhat [41], the Bayesian Multivariate Ordered Probit & Tobit (BMOPT) model proposed by Fang [34], the copula-based MNL-linear regression model proposed by Bhat and Eluru [33], and the integrated multinomial logit-multinomial probit-linear regression model proposed by Liu et al. [16].

In summary, improvement of accessibility of residential areas to the key destinations, improvement of road public transport line density, and increases in gas and vehicle prices have negative impacts on household vehicle holdings and energy demand. These factors are considered for scenario analysis in the subsection below, whereas a 1% gas price increase is taken into account of investigating the elasticity of energy demand and CO_2 emissions.

b) Scenario Analysis

The simulated percentage changes in household vehicle holdings are illustrated in Figure 1. The positive sign means an increase, and the negative sign means a decrease. Scenario 1 shows the percent changes in household vehicle holdings if all the TAZs have the same highest accessibility to the integral destinations and services. The percentage share of the zero-vehicle households would have increased by 26.43% that could be traced to a decrease in the households owning vehicles had all the TAZs been maximized. The percentage share of the zero-vehicle households would have increased by 21.09% shall all the TAZs have been introduced with the same highest road public transport line density (see scenario 2). A marginal increase in percentage change in two-car households could be traced from a decrease in percentage changes in one-UV households and car-UV households. It is also evident from scenario 3 that a 25% increase in vehicle cost would have reduced the vehicle-owning households by 4.88% only.

As assumed earlier for scenario 4, gas price changes have no impact on household vehicle holdings. Had all the scenarios been integrated, the percentage share of zero-vehicle households would have increased from 47.29% up to 89.78% (a 42.49% increase), which translates to a 78.95% decrease (55.42% of car and 23.53% of UV) in the vehicle fleet.

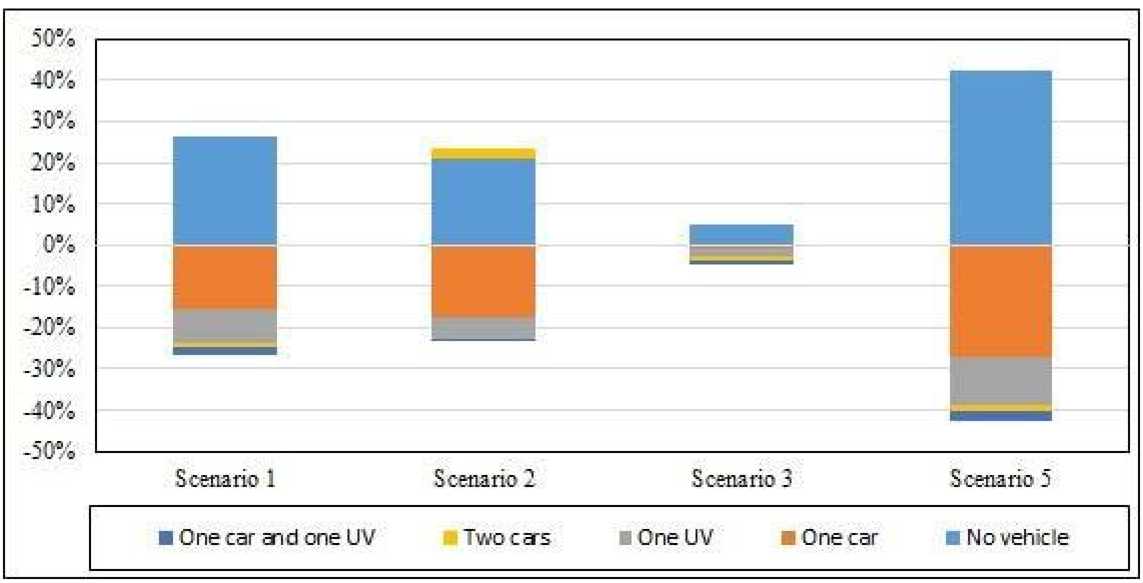

Figure 1: What-if scenario analysis of percentage changes in household vehicle holdings

The simulated percentage changes in energy demand based on the various scenarios are shown in Figure 2. If the key facility accessibility and the road-based public transport line density for all the TAZs had been improved, the energy demand would have decreased by 37.45% and 50.43%, respectively (see scenarios 1 and 2). An increase in vehicle and gas prices would cut down the energy demand by 12.81% and 4.30%, respectively, and the impact of vehicle and gas prices is much smaller than that of the improvement of the urban form attributes. An increase in vehicle price is more effective than an increase in gas price by 2.97 times, which is slightly smaller than a finding in the USA wherein an increase in vehicle price is more effective than an increase in gas price by 3.19 times [13]. Had the four scenarios been coupled, the energy demand would have lowered by 84.92%. Based on the "what if" scenarios analysis, the improvement of accessibility to the key facilities and public line density could be the chosen solutions for the adoption of strategic options to suppress household vehicle ownership and usage, rather than controlling household vehicle ownership via an increase in gas and vehicle prices.

For a 25% gas price increase, the energy demand in Metro Manila would have been reduced by 4.30%, which is smaller than the vehicle usage decrease of 9.91% in the USA [16]. Generally speaking, households living in developing countries are less sensitive to a gas price increase, presumably owing to "forced vehicle usage" compared to those living in developed countries, as a result of inadequate public transport service in the former even though the households residing in developing countries have a relatively lower income. Thus, an increase in gas price to reduce vehicle usage, vehicular energy demand, and CO_2 emissions is more effective in a developed country relative to a developing country. For more clarification, the elasticity of CO_2 emission with respect to a 1% gas price increase is shown in the subsection below.

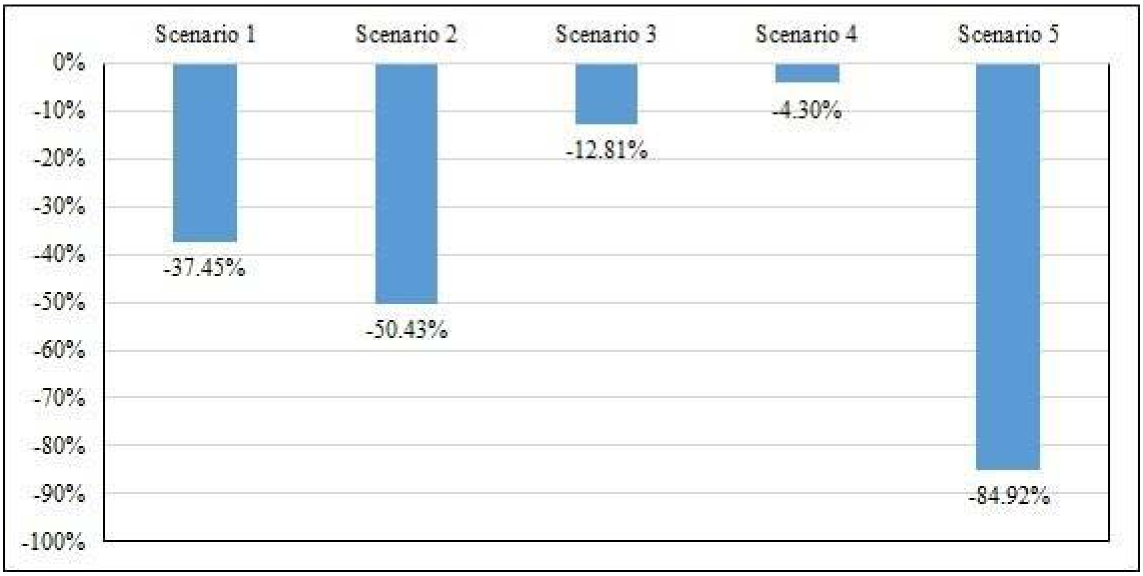

Figure 2: What-if scenario analysis of percentage changes in energy demand

c) *The elasticity of Energy Demand and CO_2 Emissions in terms of Gas Price*

The elasticity of energy demand and CO_2 emission with respect to a 1% gas price increase are listed in Table 7. As apparent in the last column of the table, one-UV households are most responsive to the gas price increase, followed by two-car households, car-UV households, and one-car households. The energy demand and CO_2 emission would decrease by 3.57 x 10^{-3}GJ/ household-month and 0.27 x 10^{-3}tons/ household - month, respectively, among vehicle-owning households in response to a 1% gas price increase (see the last row of Table 7). A 1% gas price increase would reduce the energy demand and CO_2 emission by 0.172%, this value is marginally lower than a 0.211% emission reduction in the USA [13].

Table 7: The impact of 1% gas price increase in energy demand and CO_2 emission

Household vehicle holdings	Energy (GJ/household-month)	CO_2 emission (tons/household-month)	% changes
One car	-2.19 x 10^{-3}	-0.16 x 10^{-3}	-0.074%
One UV	-12.99 x 10^{-3}	-0.96 x 10^{-3}	-0.274%
Two cars	-16.96 x 10^{-3}	-1.26 x 10^{-3}	-0.245%
Car & UV	-19.69 x 10^{-3}	-1.46 x 10^{-3}	-0.238%
Overall	-3.57 x 10^{-3}	-0.27 x 10^{-3}	-0.172%

IV. Conclusions and Recommendations

This study develops the MNL-based household vehicle ownership model and the linear regression-based energy demand model using the sample data of 2,300 households gathered from various areas within Metro Manila. Unlike findings in other countries, households in Metro Manila with more members are most likely not to own vehicles because most large-sized families have lower income associated with lower purchasing power. However, vehicle-owning families with more members consume more energy conceivably as a result of more trip activities. Households with older family heads are more likely to own more and large vehicles but less likely to consume energy. Households with high income have a higher propensity to hold more and large vehicles and require more energy demand. An increase in gas price and vehicle cost have a negative impact on household vehicle ownership and usage. In terms of urban form factors, population density has no statistically significant effect on household vehicle holdings, while an increase in road density would encourage households to own vehicles as a result of the availability of more on-street parking spaces. Households located in an area with high accessibility to CBDs are more induced toward holding more small vehicles but consume less energy. Households located in an area with high accessibility to the key destinations and high public transport line density are most likely not to own vehicles.

A 1% increase in gas price would reduce energy demand and CO_2 emission by 0.174%. The elasticity of CO_2 and energy demand reduction from private vehicles in term of the gas price increase was lower for Metro Manila relative to the USA. The developed models were also applied using the "what if" scenario analysis as explained earlier. Results showed that if the accessibility to the key facilities and the road-based public transport line density for all the TAZs had been maximized, the energy demand would have been reduced by 37.45% and 50.43%, respectively, while a 25% vehicle price increase and a 25% gas price increase would have cut down the energy demand by 12.81% and 4.30%, respectively. Therefore, improvement of both the key facility accessibility and the public transport line density are the most effective solutions toward a sustainable urban transportation system rather than increasing gas and vehicle prices. Shall all the mentioned scenarios have been combined, the vehicle fleet and energy demand would have decreased by 78.95% (55.42% of car and 23.52% of UV) and 84.92%, respectively.

It is evident from the empirical findings that transportation planners and policymakers should consider the improvement of accessibility to the core facilities and public transport line density rather than increasing gas and vehicle taxes in order to mitigate traffic congestion, energy consumption, worsening urban air quality, and GHG emissions in metropolitan areas of developing countries.

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