CHEMICAL ENGINEERING TRANSACTIONS

VOL. 81, 2020

A publication of AIDIC

The Italian Association of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Petar S. Varbanov, Qiuwang Wang, Min Zeng, Panos Seferlis, Ting Ma, Jiří J. Klemeš

ISBN 978-88-95608-79-2; **ISSN** 2283-9216

DOI: 10.3303/CET2081129

Spatial Decomposition Of Drivers Of Household Energy Use in Metro Manila Using LMDI

Ana Karmela Lopez[a,*], Neil Stephen Lopez[a], Anthony Chiu[b], Jose Bienvenido Manuel Biona[a,c]

[a]Mechanical Engineering Department, De La Salle University, Manila, Philippines
[b]Industrial Engineering Department, De La Salle University, Philippines
[c]Enrique K. Razon Logistics Insitute, De La Salle University, Philippines
ana_karmela_lopex@dlsu.edu.ph

The trend on the migration to home-based work environment as an option for the global workforce implies that the Philippines' residential energy use is as significant as in the industrial and commercial sectors. Improving efficiency and reducing energy intensity in these sectors are as important in the context of sustainability. Little to no studies have looked into the potential drivers to household energy consumption in a developing country such as the Philippines. Using a spatial decomposition analysis approach, various drivers to increasing household energy consumption in Metro Manila are estimated. Household size, income levels, energy intensity and energy use structure are considered in the study. The use of spatial decomposition techniques provides a new way to compare drivers between individual regions. The results are used to identify priority areas for electricity management and to draw insights for curbing household energy use. Policy implications are provided to conclude the study.

1. Introduction

Energy utilization efficiency impacts environment and economy on a global scale. At an average yearly growth rate of 2.4 % for energy per capita from 2007 to 2017 (Department of Energy, 2017a), developing economies such as the Philippines benefit from understanding energy consumption efficiency. Existing government data show the consumption for various sectors, specifically; industry, residential, transport and commerce. Analyses of information is done on key areas of improvement for reasons of: (1) technological development and (2) policy making, (3) augmentation and (4) implementation.

In the same year, the Philippine Energy Efficiency Roadmap (Department of Energy, 2017b) focused on these four areas. In 2017, DOE launched policy bridges to foster energy efficiency on a national level. Plans for execution of the roadmap shows actual monitoring of real-time data and the goal of initializing enabling technologies to make the proper changes.

The 10 y data (2007 to 2017) shows that bulk of the total energy fuel consumption is allocated to transportation, industry, and residential sector. Transportation sector, ranges from 34.4 % in 2007 to 34.8 % in 2017; the industrial sector total fuel energy consumption remains relatively the same at 34.4 % to 34.9 %; and the residential total fuel energy consumption ranges from 31.7 to 27.2 %. This trend shows consistency for the averaged data. The total of approximately 85 % to 89 %, impact on the overall energy efficiency management of all three sectors require a detailed analyses.

Evaluation of energy efficiency and economic performances provide insights on consumer behaviour, and other driving mechanisms that may have an effect on future projections. Impacts of these factors, tied in with their environmental implications and causes give way to how sustainable end goals can be achieved.

Previous studies have focused on drivers to energy use and emissions in transportation (Lopez et al. 2018) and industrial (Sumabat et al., 2016) sectors.

The importance of studying residential energy use is much more evident in the face of a globalized economy. Shifting demographics for some developing and developed countries, tied with the increased demand for a

Paper Received: 30/04/2020; Revised: 05/06/2002; Accepted: 09/06/2020
Please cite this article as: Lopez A.K., Lopez N.S., Chiu A., Biona J.B.M., 2020, Spatial decomposition of drivers of household energy use in Metro Manila using LMDI, Chemical Engineering Transactions, 81, 769-774 DOI:10.3303/CET2081129

better lifestyle suggests a need allowed for shifts from office to home working environments to be done. Case studies have been proven that some employees who prefer to work at home can improve productivity that translates to benefits for both employer and employee (Bloom et al., 2015). In relation to this, Lopez and Biona (2019) assess accessibility in Metro Manila using a cumulative approach.

Special cases such as need for isolation, lack of transportation, infrastructure limitations, domestic requirements and other prospects that could limit productivity from office-related factors can be remedied by household-based work. These cases, could also give rise to increased residential energy consumptions at any given period in time. So for these cases, industry-related emissions and energy consumption are offsetted towards residential sector.

Methodology of analyses such as the logarithmic mean Divisia index (LMDI) help to develop policies and design products to direct towards goals for energy efficiency. Various decomposition techniques have already been used to identify areas for policy and technological changes. Methods linked to Divisia Index and Laspeyres Index have been used for various policy recommendations by institutions, academics and various agencies alike (Ang, BW., 2004). Other than the sectors, spatial-related effects and their interactions with known driving forces can be confirmed using the spatial variety of decomposition methods. Ang et al. (2015) discuss this variety of LMDI for spatial decomposition. Previously, Rapal et al. (2017) performed a spatial analysis for site selected in renewable energy projects in the Philippines.

This study aims to uncover the characteristics or driving factors influencing high household emissions in various cities in Metro Manila, Philippines using the spatial LMDI method. Differences in economic and energy efficiency performance between cities offer discernment on how to best prioritize implementation of policies with economic and environmental cost-benefit in mind.

2. Methods and data

The household energy consumption data is modeled by the authors from the Family Income and Expenditure Survey (Philippine Statistics Authority, 2015). The identity function used for decomposition analysis is shown in Eq(1).

$$\Delta HHe = \sum_i population \times \frac{income}{population} \times \frac{energy}{income} \times \frac{energy_i}{energy} = \sum_i pop \times inc \times int \times str \tag{1}$$

Where ∆HHe is the change in household energy consumption; pop refers to population; inc refers to household income per capita; int refers to household energy intensity; and str refers to the household energy use structure, i.e. the breakdown of energy use into components such as electricity use, direct use for transport (private), indirect use transport (public), and other miscellaneuos fuel use.

The individual effects are calculated as follows in Eq(2) to Eq(5). The variable C refers to a specific city. As seen below, in spatial decomposition analysis, the comparison is between places instead of between time periods. The variable μ is the average of all cities considered in the study. This approach is taken from Ang et al. (2015).

$$\Delta pop = \frac{HHe^C - HHe^\mu}{ln\,HHe^C - ln\,HHe^\mu} ln\left(\frac{pop^C}{pop^\mu}\right) \tag{2}$$

$$\Delta inc = \frac{HHe^C - HHe^\mu}{ln\,HHe^C - ln\,HHe^\mu} ln\left(\frac{inc^C}{inc^\mu}\right) \tag{3}$$

$$\Delta int = \frac{HHe^C - HHe^\mu}{ln\,HHe^C - ln\,HHe^\mu} ln\left(\frac{int^C}{int^\mu}\right) \tag{4}$$

$$\Delta str = \sum_i \frac{HHe_i^C - HHe_i^\mu}{ln\,HHe_i^C - ln\,HHe_i^\mu} ln\left(\frac{str_i^C}{str^\mu}\right) \tag{5}$$

The direct comparison between two cities is done using Eq(6),

$$\Delta HHe_j^{(C1-C2)} = \Delta HHe_j^{(C1-\mu)} - \Delta HHe_j^{(C2-\mu)} \tag{6}$$

3. Results and discussion

Figure 1 shows the estimated effects from the study per city. The main driving factors are income per person and energy intensity. The most significant effects are not the same for all cities. Figure 2 breaks down energy use per city into electricity, miscellaneous, transport (direct) and transport (indirect). The impact of structure difference is apparent in the cities of Pateros, San Juan, and Paranaque. It is observed that these are the top three cities with the most direct transportation energy consumption as can be seen in Figures 1 and 2. Variations in the trend for energy use per city suggests that the drivers for each city.

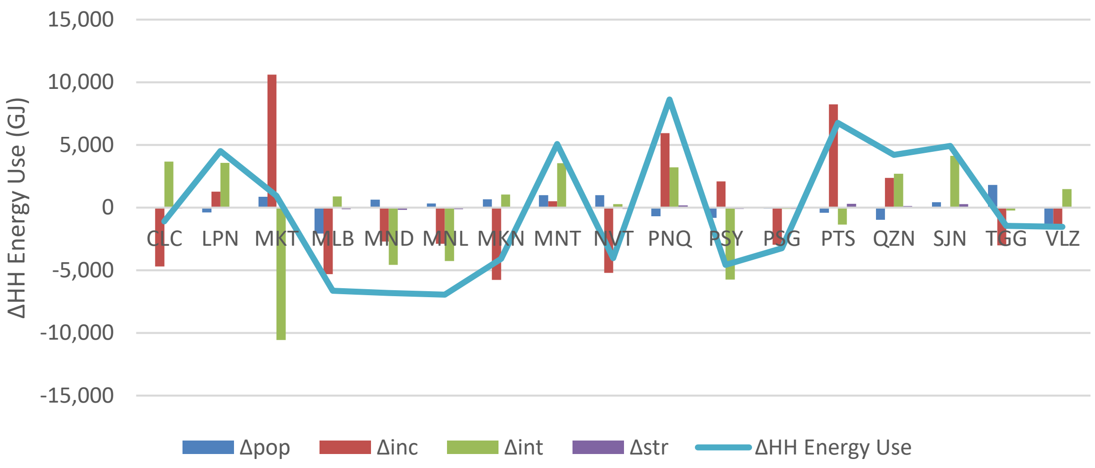

Figure 1: Estimated effects per city, measured against the group average

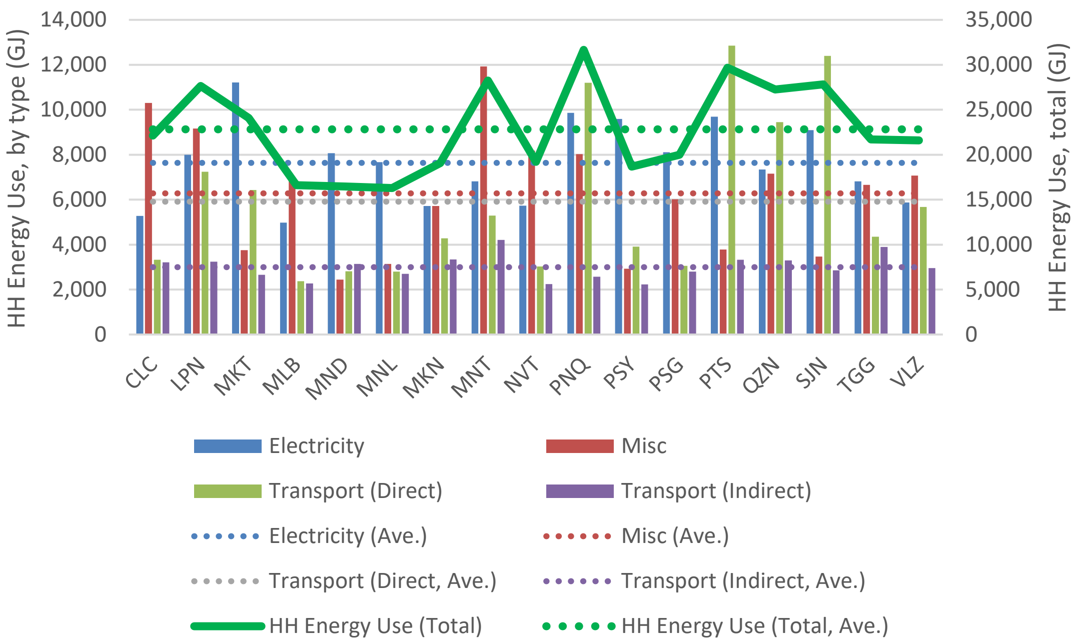

Figure 2: Breakdown of energy use per city, modelled from Family Income and Expenditure Survey (PSA, 2015)

Proximity of residents to major areas of commerce may attribute to the negative intensity offsetting the energy consumed of households in the area. Low use of miscellaneous type of energy source may suggest availability of infrastructure for electricity distribution. This finding contrasts high miscellaneous energy use of areas in the city at the outskirts of Manila. These are areas of development with infrastructure improvements implemented only after 2015.

In Figure 3, it is observed that as income per capita and energy intensity increases, household energy use also increases. Las Piñas, Muntinlupa, Parañaque and Quezon City have above average miscellaneous energy consumption. Possible interactions in the proximity of areas of commerce and type of industries existing in and neighboring areas could potentially contribute to the positive effects of income and household energy use.

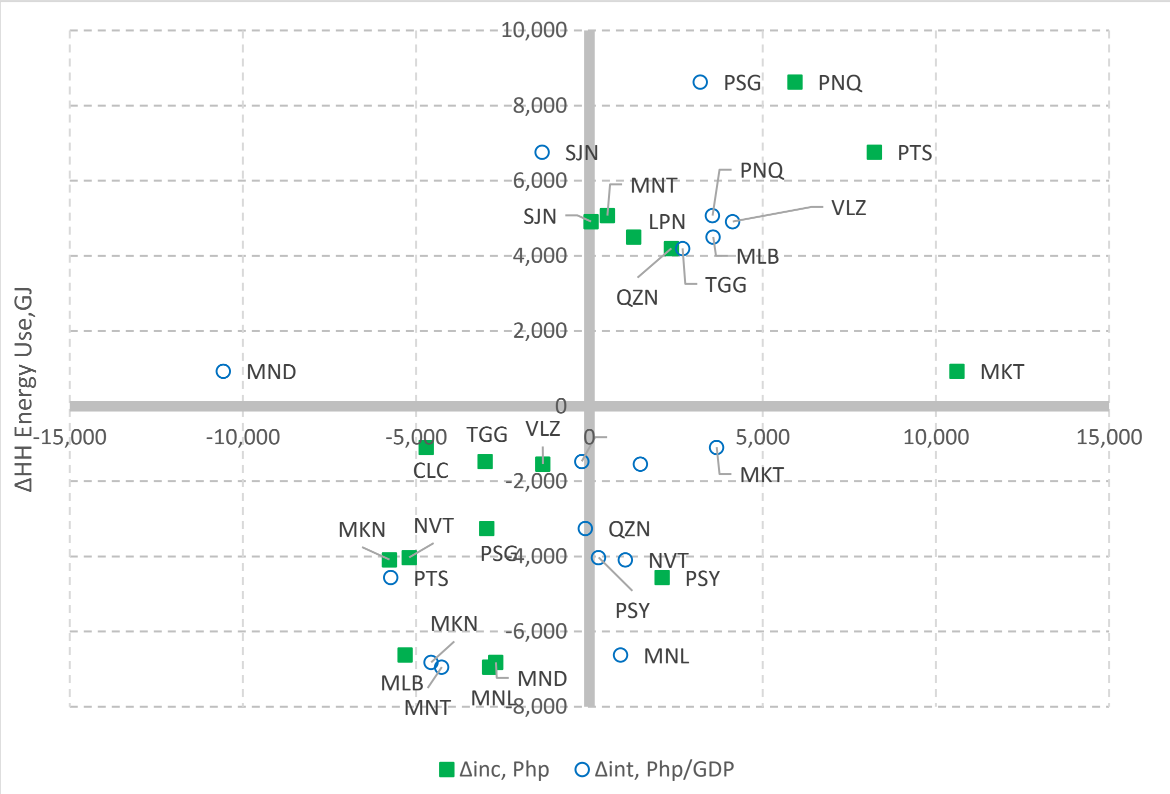

Figure 3: Difference in household energy use versus difference in income and difference in energy intensity

The drivers to household energy use are further investigated in Figures 4a to 4c. In Figure 4a, it is surprising to see that electricity consumption is not the primary driver of high energy consumption in households. Makati is the only city with both above-average energy use and above-average electricity share in total consumption. Based on Figure 4b, household energy consumption is more directly proportional to direct energy consumption from transport. The household energy consumption is inversely proportional to indirect energy consumption from transport (i.e. from patronage of public transport) according to Figure 4c. This means that the primary characteristics of most high energy consuming households are high private transport use and low public transport use. Interesting areas of comparison are cities with overlapping values for effect of structure. Marikina and Navotas are cities at the far ends of Manila. Low energy use may be attributed to electricity infrastructure developments. Muntinlupa City shows high sensitivity on the stuctural effect (public transportation) as the highest energy consumer for this sector. The benefits of using private transportation in this case may be offsetted by distance-to-work, traffic route conditions and availability of public transportation options. Infrastructure developments from 2015 onwards should allow for improvements for the cities at the southern part of Metro Manila. Neighboring cities such as Mandaluyong and Manila also have negative structural effect on direct transportation this potentially resulted in low energy use. This shows that there are varying primary drivers for each city. Mechanisms for each driver may also include behavior-related factors. These mechanisms may manifest in some areas in the city. The conclusive identification of the effect of these factors is not directly investigated in this study. The study of these factors may be more relevant for areas not behaving according to trend observed.

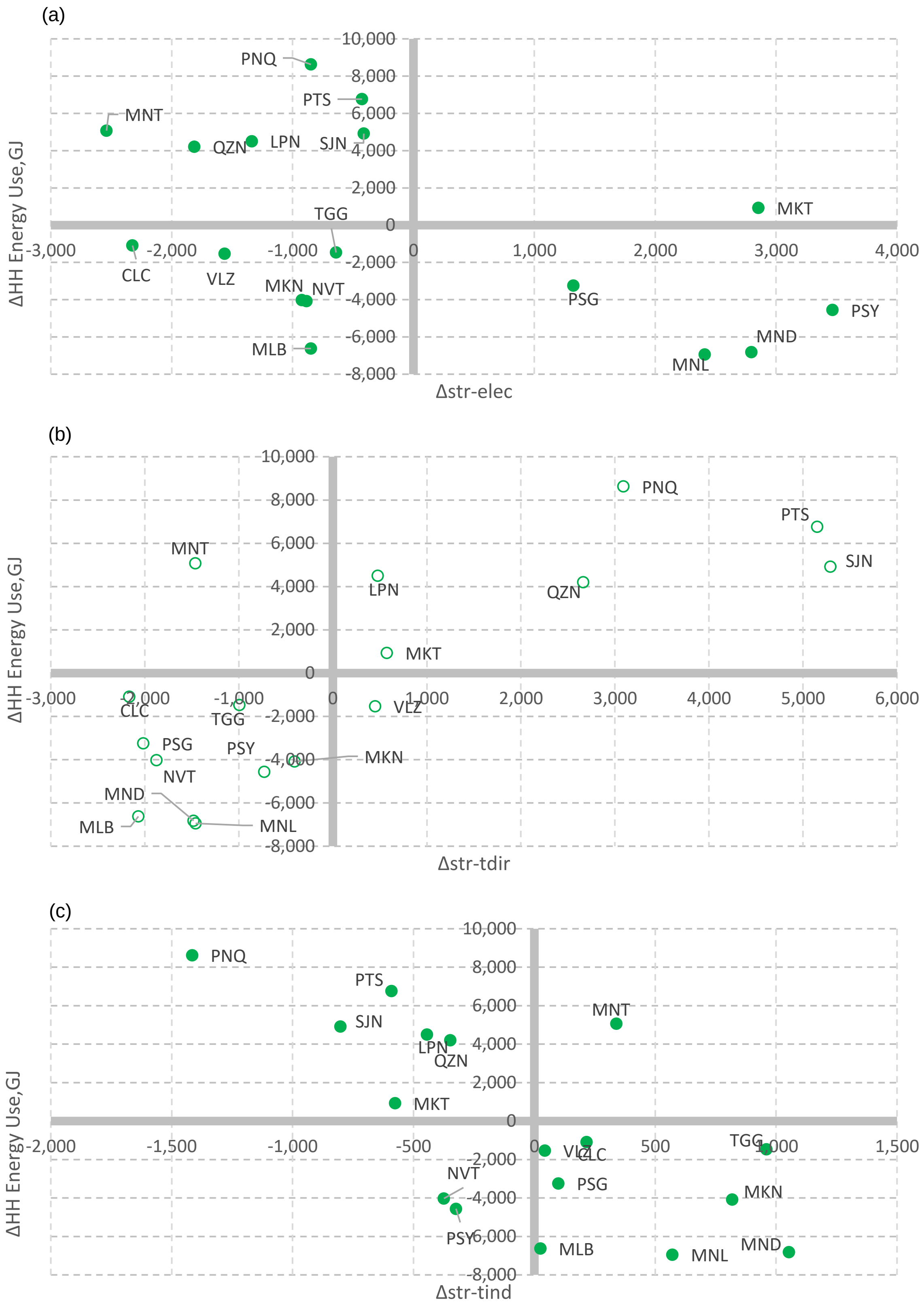

Figure 4: Difference in household energy use versus energy use structure: a) energy use as electricity ; b) direct energy use for transport (private transport); and c) indirect energy use for transport (public transport)

4. Conclusion

In this study, the use of spatial decomposition using LMDI to analyze drivers of high household energy consumption in Metro Manila was demonstrated. High household energy consumption is driven primarily by high income per capita and high energy intensity, but it is important to note that the primary driver for each city is not the same. Looking at the utilization, it is surprising to see that electricity consumption is not the primary driver, but rather private transport use. Potential interactions for cities in proximity with each other may also be looked into.

With this information, should the government aim to manage energy consumption in households, the correct driver can be targeted. High energy intensity in households should be addressed. Other than high private transport use, it is also observed that energy-intensive households consume a lot of fuelwood and charcoal. In succeeding studies, more validating information can be discussed to support the findings and the study can be extended to estimate emissions. Potential applications of this study may be done to developing megacities.

Acknowledgement

The authors would like to acknowledge the financial support in the conduct of this study from the Department of Science and Technology, Philippines, Engineering Research and Development for Technology program, the Office of the Vice Chancellor for Research and Innovation of De La Salle University, and the Commission on Higher Education, Philippines, Grants-in-Aid program.

Nomenclature

CLC	Caloocan	PNQ	Parañaque
LPN	Las Piñas	PSY	Pasay
MKT	Makati	PSG	Pasig
MLB	Malabon	PTS	Pateros
MND	Mandaluyong	QZN	Quezon
MNL	Manila	SJN	San Juan
MKN	Marikina	TGG	Taguig
MNT	Muntinlupa	VLZ	Valenzuela
NVT	Navotas		

References

Ang B.W., 2004, Decomposition analysis for policymaking in energy: which is the preferred method? Energy Policy, 32, 1131-1139.

Ang B.W., 2015, LMDI decomposition approach: A guide for implementation, Energy Policy, 86, 233-238.

Ang B.W., Xu X.Y., Su B., 2015, Multi-country comparisons of energy performance: The index decomposition analysis approach, Energy Economics, 47, 68-76.

Bloom N., Liang J.,Roberts J., Zhichun J.Y., 2015, Does Working from Home Work? Evidence from a Chinese Experiment, Quarterly journal of Economics, 130(1), 165-218.

Department of Energy, 2017a, Key Energy Statistics <doe.gov.ph/sites/default/files/ pdf/energy_statistics/ 2017_key_energy_statistics.pdf> accessed 29.04.2020.

Department of Energy, 2017b, Philippine Energy Efficiency Roadmap 2017-2040 <doe.gov.ph /sites /default/files/pdf/announcements/epower_fontana_03_04_phillippines_energy_efficiency_roadma_2017-2040.pdf> accessed 30.04.2020.

Lopez N.S., Soliman J., Biona J.B.M., 2020b, Cost-benefit analysis of alternative vehicles in the Philippines using immediate and distant future scenarios, Transportation Research Part D, 82, 102308.

Lopez N.S., Biona J.B.M., 2019, Assessing transport equity through a cumulative accessibility measure and Google Maps: a case for healthcare in Metro Manila, Philippines. In R. Hickman et al. (Eds.), A Companion to Transport, Space and Equity, Edward Elgar Publishing, UK, 136-146

Lopez N.S., Chiu A.S.F., Biona J.B.M., 2018, Decomposing drivers of transportation energy consumption and carbon dioxide emissions for the Philippines: the case of developing countries, Frontiers in Energy, 12, 3, 389-399.

Philippine Statistics Authority, 2015, Family Income and Expenditure Survey (FIES) <psa.gov.ph/sites/default/files/FIES%202015%20Final%20Report.pdf> accessed 06.06.2020.

Rapal B.K.A.L., Sumabat A.K.R., Lopez N.S.A., 2017, Analytic hierarchy process for multi-criteria site selection of utility-scale solar and wind projects, Chemical Engineering Transactions, 61, 1255-1260.

Sumabat A.K., Lopez N.S., Yu K.D., Hao H., Li R., Geng Y., Chiu A.S.F., 2016, Decomposition analysis of Philippine CO2 emissions from fuel combustion and electricity generation, Applied Energy, 164, 795-804.