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A Systematic Approach to the Optimal Planning of Energy Mix for Electric Vehicle Policy

Aritotle T. Ubando[a,*], Ivan Henderson V. Gue[b,c], Monorom Rith[b], Jeremias Gonzaga[a,b], Neil Stephen A. Lopez[a], Jose Bienvenido Manuel M. Biona[a]

[a]Mechanical Engineering Department, De La Salle University, 2401 Taft Avenue, Manila, 0922, Philippines
[b]Graduate School, Mechanical Engineering Department, De La Salle University, 2401 Taft Avenue, Manila, 0922, Philippines
[c]Mechanical Engineering Department, FEU-Institute of Technology, 839 P. Paredes St, Sampaloc, Manila, 1015, Philippines
aristotle.ubando@dlsu.edu.ph

Electric vehicle offers a cleaner and sustainable alternative to transportation as it eliminates direct carbon dioxide emission through the conventional internal combustion engine. With the increase in the global population and economic development, the demand for transportation and the adoption of electric vehicles is unprecedented. However, the adoption of electric vehicle on a national-scale requires long-term planning of infrastructure development, and energy generation and distribution. The study focuses on the development of a systematic mathematical programming approach in the optimal planning of the energy mix of the additional power generation capacity arising from the adoption of the electric vehicle in a developing country. The study considers the 2030 horizon which includes, the cost of power generation and distribution per energy mix, and the forecasted commissioning and decommissioning of energy plants. The study proposes a fuzzy mixed-integer non-linear programming model in the optimal planning of the energy mix for the adoption of EV while minimizing carbon footprint, minimizing the total capital cost, and minimizing the electricity cost. A case study in the adoption of electric vehicle in the Philippines will be utilized to demonstrate the capability of the model. In addition, a comparison of the electricity cost of the business as usual (BAU) scenario and this study has been evaluated. The results show that the various renewable energy technologies for power generation are selected initially from 2019 to 2022 and 2029 to 2030, while the fossil-fuel based power plants were utilized from 2023 to 2028. The results revealed the electricity cost from the study is relatively lower than the BAU scenario. The results of the model are intended to aid and guide policymakers in the potential adoption of electric vehicles, especially in the energy planning sector.

1. Introduction

Electric vehicles (EV) present an alternative solution for transportation without the direct dependence to fossil-based fuels. In urban areas, the reduction of exhaust transportation emissions such as carbon dioxide (CO_2) have direct relation to improving the air quality resulting to the decreasing health concerns of urban dwellers (Vienneau et al., 2015). However, Jochem et al. (2015) argued that the reduction of CO_2 emissions from shifting to EV may only be realized if the electricity is generated from either renewable energy sources or nuclear energy. To further aid the energy planning for the potential adoption of EVs in a nation, a systematic approach in the optimal planning of energy generation is needed specially in accounting the additional electricity requirements of EVs. Previous studies have been conducted in the optimal planning of energy mix. Haikarainen et al. (2019) utilized a multi-period mixed-integer linear programming (MILP) model for the optimal planning of intermittent renewable energy sources such solar and wind energy coupled with storage technologies in a region by minimizing the investment, operations, and maintenance (O&M) costs. A multi-objective evolutionary algorithm and EnergyPLAN software was used by Prina et al. (2019) for determining the additional technologies required in a district-wide scale while minimizing the investment and O&M costs. Both studies are significant in the advancement of a systematic approach in the optimal planning of the energy mix of a region and district, but

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lacks the application for the use of additional requirement for electric vehicles especially on a national scale. Most of the optimization models developed for the application of EVs are focused on vehicle energy consumption on drivetrains (Luin et al. 2019), routing and relocation with charging schedule (Iacobucci et al., 2019), projected car ownership (Du et al., 2019), and car sharing systems (Lemme et al., 2019), to name a few. A literature review was reported by Lemme et al. (2019) on the recently developed sustainability optimization models for EV planning. Other country-specific models consider the impact of electric vehicle to the energy mix. Rupp et al. (2019) assessed the carbon impact on the use of diesel and electric buses in Germany and its effect to the electricity mix. Groppi et al. (2019) evaluated the additional electricity requirements from the adoption of electric vehicles in an Island in Italy using EnergyPLAN and HOMER software. However, there have been no studies focused in the optimal planning of electricity generation on a national-scale satisfying the additional power requirements from EV adoption while minimizing the carbon footprint, capital cost, and the electricity price. In order to include these multiple objectives in the optimization model, the application of fuzzy set-theory in a linear programming model is proposed such that the partial satisfaction of the multi-objectives are achieved through a linear membership function (Zimmermann, 1978). Recent studies have shown the use of a fuzzy linear mixed-integer linear programming (FMILP) model on the optimal design of bioenergy systems for negative carbon emission (Ubando et al., 2014) and the optimal operational adjustment of an off-grid renewable energy plant (Ubando et al., 2019). A fuzzy mixed-integer non-linear programming (FMINLP) model has been utilized to evaluate the synergetic involvement of a support tenant in a biomass-based eco-industrial park (Ubando et al., 2016). Thus, this study proposes the use of an FMINLP for the optimal planning of the energy mix of a nation from 2019 to 2039 to satisfy the additional electricity requirement from the adoption of EV while simultaneously minimizing the carbon footprint of electricity generation, the total capital costs, and the electricity price. A case study on the Philippines is presented to demonstrate the developed model on the potential adoption of EV in the country. The study aims to aid the government and the EV industry on the potential adoption of EVs and hybrids in the country.

2. Fuzzy Mixed Integer Non-Linear Programming Model (FMINLP)

The fuzzy mixed-integer non-linear programming model consists of the objective function and the constraint shown in the following equations.

$$\text{Max } \lambda \quad \text{s.t.} \tag{1}$$

$$A_{ij} = x_{jk}\, y_{ik} \tag{2}$$

$$yt_k = \textstyle\sum_i y_{ik}\, b_{ik} \qquad \forall\, i = 1, 2, \ldots 7 \tag{3}$$

$$b_{ik} = \{0,1\} \tag{4}$$

$$xmax_{j,k} \geq \textstyle\sum_j x_{jk} \qquad \forall\, j \tag{5}$$

$$zt_k = \textstyle\sum_i F_i\, y_{ik} \qquad \forall\, i \tag{6}$$

$$zt_k \leq zt^u_k + \lambda(zt^l_k - zt^u_k) \tag{7}$$

$$CCt_k = \textstyle\sum_j CCa_j\, x_{jk} \qquad \forall\, j \tag{8}$$

$$CCt_k \leq CCt^u_k + \lambda(CCt^l_k - CCt^u_k) \qquad \forall\, k \tag{9}$$

$$b_{j,k} \leq b_{j,k+1} \qquad \forall\, k = 1, 2, \ldots 11 \tag{10}$$

$$EC_k = \textstyle\sum_i P_{ik}\,(y_{ik} + yc_{ik}) / (TC_k + yt_k) \qquad \forall\, i = 1,2, \ldots 7 \tag{11}$$

$$EC_k \leq EC^u_k + \lambda(EC^l_k - EC^u_k) \qquad \forall\, k \tag{12}$$

where the subscripts i represents the processes, j represents the product streams, and k is time in years; whereas the superscripts l indicates the lower limit of a factor and u indicates the upper limit of a factor; λ is the degree of satisfaction, A is the technology matrix, x is the technology scaling vector, y is the product demand vector, b is the binary technology vector, yt is the total electricity demand in MW, xmax is the maximum allowable capacity of a technology, zt is the carbon footprint vector, F is the carbon dioxide emission per technology, zt^l is the lower threshold limit of the carbon footprint, zt^u is the upper threshold limit of the carbon footprint, CCt is the total capital cost of the technologies, CCa is the unit capital cost per electricity produced, CCt^l is the lower threshold limit of the total capital cost, CCt^u is the upper threshold limit of the total capital cost, EC is the electricity cost, P is the price of electricity per technology, yc_{ik} is the current installed capacity, yc is the current installed capacity, TC is the total projected capacity of the business as usual (BAU) scenario, EC^l is the lower threshold limit of the electricity cost, EC^u is the upper threshold limit of the electricity cost.

The objective function shown in Eq(1) ensures the degree of satisfaction is maximized. The model employs the max-min aggregation rule where λ is the lowest degree of satisfaction and it seeks for a synchronized solution which approaches the desired target of the considered multi-objectives . Different objectives indicate conflicting goals, thus, implying a compromise solution among the multi-objectives where a partial satisfaction is achieved if the λ-value is between 0 to 1. The λ-value represent an aggregated numerical representation of the compromise solution where a value of 1 indicates that all objectives are fully satisfied while a value of 0 implies that the solution has reached an undesirable state. The objective function is subject to the constraints shown in Eqs(2)-(12).

The technology matrix A_{ij} is solved through the product of the process scaling vector x_{jk} and the product demand vector y_{ik} illustrated in Eq(2). The total electricity demand yt_k is calculated with sum product of the product demand vector y_{ik} for all electricity streams from various technology ($\forall\ i = 1, 2, \dots 7$) and the binary vector b_{ik} as depicted in Eq(3). The binary vector b_{ik} is used to indicate if a technology will be used in the generation of electricity if its value is equal to 1 or if it is not considered if the value is equal to 0 as shown in Eq(4). The total power generation capacity should not exceed the maximum allowable capacity of a technology xmax as shown in Eq(5). The total carbon footprint is defined as the sum product of the carbon dioxide emission per technology F_i and the product stream vector y_{ik} as illustrated in Eq(6). A piecewise linear membership function describes the solution for the carbon footprint objective bounded by the lower (zt^l_k) and upper (zt^u_k) limits of the total carbon footprint as defined in Eq(7). The total capital cost CCt_k is represented by the sum product of the unit capital cost per electricity produced CCa_j and the process scaling vector x_{jk} as shown in Eq(8). The total capital cost CCt_k seeks to be minimized in a piecewise linear membership function bounded by the lower (CCt^l_k) and upper (CCt^u_k) limits of the total capital cost described in Eq(9). In considering a power generating technology across multiple timeframes k, it is important to ensure that an installed plant capacity on a certain timeframe will remain installed thereafter. This significant design consideration is made possible through Eq(10) where the binary value of the recent timeframe ($b_{j,k+1}$) is greater than or equal to the binary value of the previous timeframe ($b_{j,k}$). The economic potential of the electricity EC_k is equal to the sum product of the price of electricity per technology P_{ik} and the ratio of all the product streams (y_{ik} and the yc_{ik}) with the total projected electricity produced which comprise of the projected capacity of the BAU scenario and the additional power capacity for the adoption of electric vehicle (TC_k + yt_k) described in Eq(11). The price of electricity per technology P_{ik} is inclusive of the various charges such as generation, transmission, distribution, metering, and system charges as well as subsidies (life line, and cross), power rate reduction, and franchise tax. A piecewise linear membership function is used to minimize the total electricity cost EC_k with a lower (EC^l_k) and upper (EC^u_k) electricity cost target limits shown in Eq(12). The developed model seeks to satisfy the required additional power demand (y) from 2019 to 2030 with the adoption of EV while minimizing the carbon footprint (zt), the total capital costs (CCt), and the electricity cost (EC). The model was solved using Lingo 18.0 linked to MS Excel with the object linking and embedding function on a desktop with Intel Core i7 with 16 GB random access memory (RAM).

3. The Philippines: a case study

The Philippine case study considers an extended technology matrix A_{ij} shown in Table 1 where various technologies are considered to produce power such as biomass, coal, diesel, gas, hydro, solar, and wind. Table 1 consists of the material flow required to produce the electricity given the chosen technologies. An identity matrix is considered as an extension of Table 1 to represent the electricity stream produced from different technologies such as biomass, coal, diesel, gas, hydro, solar, and wind. The heating values of biomass and coal are 19.8 MJ/kg and 32.2 MJ/kg, respectively. The typical energy density of diesel and natural gas is 38,600 MJ/m^3 and 36.4 MJ/m^3, respectively. The energy density of the hydropower is expressed in terms of volume of water required at 14.71 MJ/m^3. The energy density for solar and wind are expressed in terms of land requirement with 44.93 MW/km^2 and 83.31 MW/km^2, respectively. The amount of water required for the hydropower plant is The projected target for the electricity generation of the Philippines for each power generating technology from 2019 to 2030 is adapted from DOE (2019). The study includes a detailed projection of the installation and decommissioning of power plants across the 2019-2030 timeline adapted from Kuryente (2019). The additional electricity requirement for EV is assumed to be one-third of the forecasted electricity power demand from DOE (2017). The maximum capacity allocation per technology across the 2019 to 2030 timeline adapted from DOE

(2019). The projected price of electricity per technology together with the price of the material stream to produce electricity from 2019 to 2030 is shown in Figure 1. The capital cost for the considered technologies per MW of electricity generated and the CO_2 emission of electricity generation from different technologies is shown in Table 2 (adapted from Turconi et al., 2013). The lower limit for the capital costs (CCt^l) per year is USD 0 while the upper limit for the capital costs (CCt^u) per year is USD 2,885 (x 10^6), which are both exogenously defined. The total allowable CO_2 emissions range from zt^l = 0 to zt^u = 6.2 $MtCO_2$ per year based on the historical CO_2 emissions of the Philippines (adapted from IEA, 2017).

A business as usual (BAU) scenario has been used to compare the electricity cost resulting from this study. The BAU scenario excludes the additional power generation requirement form the adoption of electric vehicle. While the electricity cost for this study is quantified by Eqs.(11)-(12).

Table 1: The technology matrix A.

Extended A Matrix	Biomass	Coal	Diesel	Gas	Hydro	Solar	Wind
Biomass (t/d)	-18.98	0	0	0	0	0	0
Coal (t/d)	0	-7.24	0	0	0	0	0
Diesel (t/d)	0	0	-4.85	0	0	0	0
Gas (x10^3 m^3/d)	0	0	0	-6.79	0	0	0
Water (x10^3 m^3/d)	0	0	0	0	-7.05	0	0
Solar (km^2)	0	0	0	0	0	-0.11	0
Wind (km^2)	0	0	0	0	0	0	-0.03

Table 2: The capital cost and CO_2 emissions of each technology.

Power Generation Technologies	Capital cost per technology, CCa (USD/MW x10^6)	CO_2 emissions for the power generation adapted from Turconi et al. (2013), F (t_{CO2}/MJ)
Biomass	2.90	6.58 x 10^{-5}
Coal	5.81	2.99 x 10^{-4}
Diesel	0.66	1.81 x 10^{-4}
Gas	0.89	1.22 x 10^{-4}
Hydro	2.14	2.78 x 10^{-6}
Solar	1.26	1.61 x 10^{-5}
Wind	1.45	1.39 x 10^{-6}

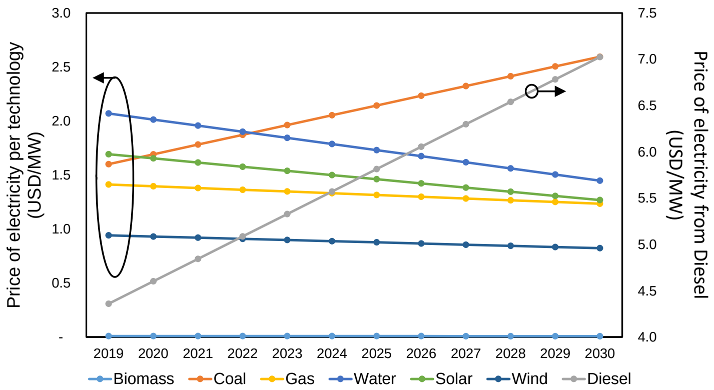

Figure 1: The price of electricity (P) per technology (adapted from Lazard 2018).

4. Results and discussion

The results yielded an objective function of λ = 0.1238 solving a total variable of 895 with 589 total constraints under a total number of 114 iterations. Since the resulting λ-value is within 0 to 1, a partial satisfaction of the multi-objectives has been achieved representing a compromise solution between the carbon footprint, the capital cost, and the electricity cost. The additional electricity capacity needed for the rise in the electricity demand arising from the adoption of EVs in the Philippines is shown in Figure 2a. For 2019, the installation of a hydro and a natural gas power plants mainly provides for the 1,568 MW of electricity requirement until 2022. From 2023 to 2028, the majority of the additional power demand from the EV adoption is generated from the coal-fired power plant with supporting power plants such as diesel-fired power plant in 2024 and from 2027 to

2028, and from biomass and hydro in 2024 and 2026 to 2027. For 2029, the hydropower plant delivers 1,147 MW of electricity supported by the gas-fired plant at 82 MW. The additional requirements in 2030 is mainly satisfied by mostly renewable energy technologies such as natural gas at 1,033 MW, hydro at 656 MW, solar at 69 MW, and wind at 33 MW with the support from the diesel-fired power plant at 102 MW.

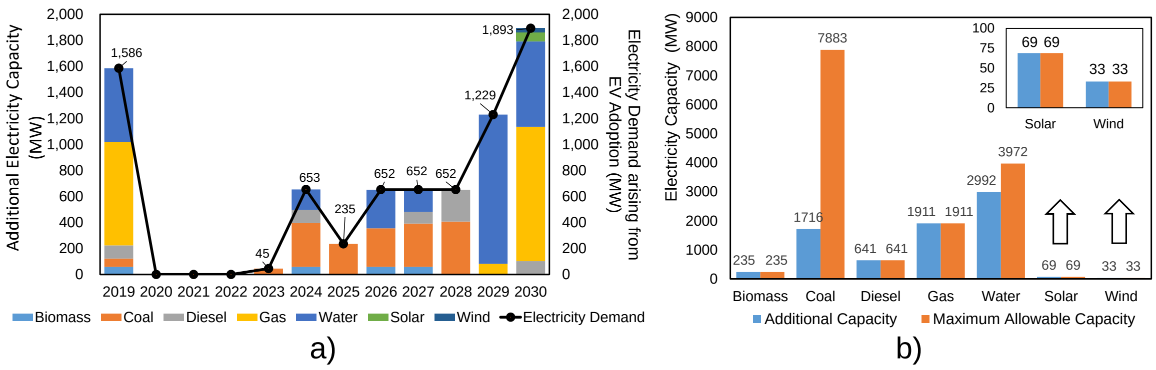

Figure 2: The a) additional electricity capacity needed for the EV adoption, and b) the comparison of maximum allowable capacity and the additional capacity.

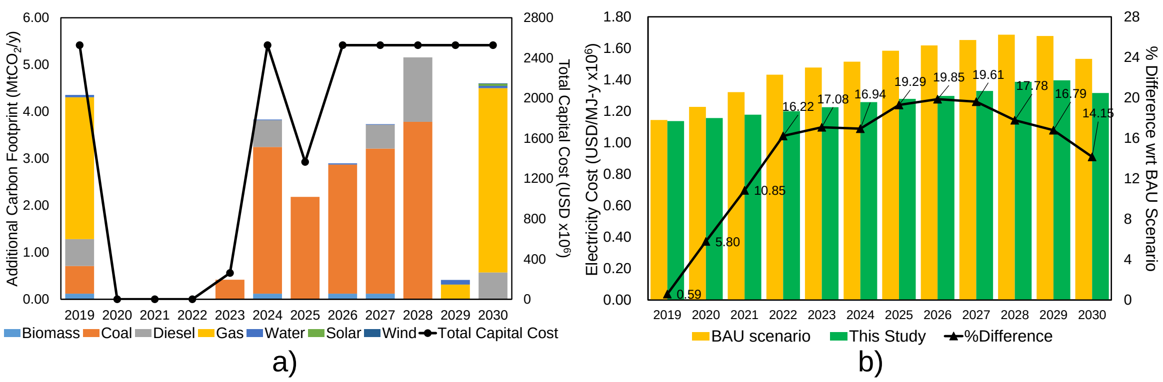

Figure 3: The resulting a) carbon footprint, and b) the electricity cost comparison from 2019 to 2030.

The additional capacity per technology (shown in Figure 2a) versus the maximum allowable capacity based on available resources in the Philippines is shown in Figure 2b. All of the renewable energy technologies have been fully maximized except for the hydro with an ending capacity utilization of 75% by 2030. As shown in Table 2, the capital cost for the coal-fired power plant is relatively higher compared to the gas-fired power plant by a factor of ~2.5. Moreover, the carbon emission for a coal-fired power plant is relatively higher compared to that of the gas-fired power plant by a factor of ~6.5. However, the maximum allowable capacity of the gas-fired plant is significantly lower by almost a factor of 4 compared to the coal-fired power plant as shown in Figure 2b. In addition, the trend for the electricity price from coal is an uptrend from 2019 to 2030 while the electricity price for gas is a downtrend. With the simultaneous solution of the multi-objective, the results suggest installing the coal-fired power plants from 2024 to 2028 together with other renewable energy technologies such as hydro and biomass as well as the diesel power plant. Moreover, the results suggest maximizing the capacity of the natural gas by installing the remaining 1,033 MW by 2030. The installation of fossil-fuel based power plants mainly the coal-fired has driven the increase of the carbon footprint from 2023 to 2028 as shown in Figure 3a. The carbon footprint accounted in Figure 3a only accounts for the CO_2 emissions generated from the additional capacity shown in Figure 2a. The total capital cost of the additional electricity capacity is shown in Figure 3a. The electricity cost comparison between the BAU scenario and the results of this study together with the percent difference with respect to the BAU scenario are shown in Figure 3b. The electricity cost shown in Figure 3b is a composite electricity cost among all the technologies used to generate electricity for each year. With the variation of the electricity price P for each of the technologies shown in Figure 1, the resulting electricity costs shown in Figure 3b has an increasing trend from 2023 to 2028 attributed to the use of fossil-based technologies such as coal and diesel. Further, a down-trend of the electricity cost is observed from 2029 to 2030 due to the use of renewable energy technologies where its production price is relatively low compared with coal and diesel on these years.

5. Conclusions

A fuzzy mixed-integer non-linear programming has been systematically developed for the optimal planning of the additional power requirement emanating for the adoption of electric vehicles in the Philippines. The model consists of multi-objectives such as satisfying the electricity requirement with the additional power demand for the electric vehicle from 2019 to 2030 while minimizing the carbon footprint, the total capital cost of the installation of the power plants, and the electricity price. The study considered the actual maximum capacity installed for a certain power generating technology based on the available natural resources in the Philippines. The results indicate the optimal energy mix for the additional electricity requirement for the adoption of electric vehicles in the Philippines. Partial satisfaction of the multi-objectives has been achieved representing a compromise solution among the capital costs, the carbon footprint, the electricity price, and the generation of electricity. Future studies include the analysis of various electric vehicle scenarios in the Philippines which considers the preferred transportation mode of the various classes of society.

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