


Article

Impact of Large-Scale Electric Vehicles' Promotion in Thailand Considering Energy Mix, Peak Load, and Greenhouse Gas Emissions

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Abstract: Thailand's policies are in accord with the global drive to electrify transportation vehicle fleets due to climate concerns. This dedication is evident through its adoption of the 30@30 initiative and the planned ban on new internal combustion (IC) engine vehicles by 2035, showcasing a strong commitment. The objective of this study was to utilize the Low Emission Analysis Platform (LEAP) software to model the transition possibilities for electric vehicle (EV). Emphasis was placed on the future of the light-duty vehicle (LDV) sector, encompassing the energy sources, electric power demands, and greenhouse gas (GHG) emissions. Two scenarios were evaluated: one involving rapid economic growth and the other characterized by a more-gradual expansion. The former projection foresees 382 vehicles per thousand people by 2040, while the latter estimate envisions 338 vehicles. In the scenario of high growth, the vehicle stock could surge by 70% (27-million), whereas in the case of low growth, it might experience a 47% rise (23.3-million) compared to the base year (15.8 million). The increased adoption of EVs will lead to a decrease in energy demand owing to improved fuel efficiency. Nonetheless, even in the most-extreme EV scenarios, the proportion of electricity in the energy mix will remain below one-third. While GHG emissions will decrease, there is potential for even greater emission control through the enforcement of stricter emission standards. Significant EV adoption could potentially stress power grids, and the demand for charging might give rise to related challenges. The deployment of public fast charging infrastructure could provide a solution by evenly distributing the load across the day. In the most-rapid EV penetration scenario, a public charging program could cap the demand at 9300 MW, contrasting with the 21,000 MW demand for home charging. Therefore, a recommended approach involves devising an optimal strategy that considers EV adoption, a tariff structure with incentives, and the preparedness of the infrastructure.

Keywords: electric vehicle promotion; Thailand; load demand; LEAP; vehicle driving distance; energy demand; emission; zero-emission vehicles



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1. Introduction

In this century, a major challenge is reducing GHG emissions and implementing climate-change-mitigation measures. Global communities are striving for net-zero commitments to achieve sustainability. Actions such as decarbonizing electrical power, promoting green manufacturing, and enforcing the control of emissions are underway worldwide to achieve net-zero goals. Concerns about the GHGs and micro-pollutants from vehicle exhaust are driving countries to craft policies encouraging zero-emission vehicles (ZEVs). Electric vehicles (EVs) are gaining popularity, with the IEA projecting them to constitute 7% of the vehicle fleet under standard policies and 12% under sustainable policies by 2030 [1]. The Clean Energy Ministerial's "30@30" campaign aims for 30% of new vehicle registrations to be ZEVs by 2030 [2]. Notably, global EV sales rose from 9% in 2021 to 14%

in 2022, a ten-fold increase from 2017 [3]. China leads the EV market, followed by the European Union and the United States.

Countries worldwide are implementing diverse policies to boost EV adoption and establish new EV industry supply chains. Despite variations in their strategies, three common approaches emerge in EV-promotion policies globally. First, direct cash subsidies are offered at the point of sale. Second, incentives and tax rebates are provided to the industry to keep the EV costs affordable and stimulate a burgeoning industry. Third, non-monetary incentives, such as parking access, streamlined registration processes, and exemptions from congestion and pollution restrictions, are utilized. Examples of direct cash transfer schemes include New Zealand’s Clean Car Discount, as well as purchase subsidies in France, Germany, the U.K., Canada, the U.S., Japan, and China. India’s Faster Adoption and Manufacturing of Hybrid and EVs (FAME) scheme and Australia’s Future Fuels Fund are industry-focused incentives. Indonesia and Malaysia have similar policies to attract EV parts and component investment. France’s Green Pass and China’s Green Sticker scheme are non-monetary promotional initiatives improving road and parking access for EV users. The increasing EV market penetration in these countries suggests that these schemes are effective in achieving their objectives. Notably, some countries such as China are reducing or eliminating point-of-sale subsidies, while Japan has recently increased such incentives. Table 1 summarizes incentives across regions and socio-economic levels to promote EV and ZEV adoption. Common approaches include cash subsidies, tax benefits for manufacturers, and non-monetary perks such as parking access and pollution-related congestion exemptions. The growing EV market share in these countries indicates policy success.

Table 1. Illustrative promotion of EVs in selected countries.

Country	Activity and Promotion	Ref.
India	(i) Faster Adoption and Manufacturing of Hybrid and EVs (FAME) scheme; (ii) Offers tax incentives in the manufacturing of EV parts and sub-parts.	[4]
Australia	(i) Future fuels fund; (ii) AUD 250-million in funds support industries to develop EV charging stations and hydrogen refueling infrastructure.	[5]
New Zealand	(i) Clean car discount; (ii) Offers rebates and punishes with fees depending on per-kilometer carbon emission during vehicle registration.	[6]
France	(i) Ecological bonus scheme; (ii) Subsidizes up to 27% of purchase price; (iii) 50–100% rebate of registration fee; (iv) EVs are eligible to receive a green pass, allowing them to be parked up to 2 h free of charge in a few municipalities.	[7]
Germany	(i) Purchase subsidy; (ii) Discount on registration fees; (iii) Investment in public charging infrastructure.	[8]
U.K.	(i) Grants towards the purchase of light commercial vehicles, taxis, and heavy-duty vehicles; (ii) Investment in charging infrastructure; (iii) Ban on petrol and diesel cars by 2030.	[9]
Canada	(i) Grants towards EV purchase, lease, as well as installment of charging stations; (ii) Phase out plan for buses and HEVs.	[10]
U.S.	(i) Various states have announced a ban on the sale of IC cars after 2035; (ii) States have prepared their fuel transition activities and budgeting; (iii) Up to USD 7500 federal tax credit from 2023 to 2032.	[11,12]

Table 1. Cont.

Country	Activity and Promotion	Ref.
Indonesia	(i) More focused on developing EV ecosystem; (ii) Offers tax benefit to manufacturers depending on amount of local components used in the final product; (iii) Manufacturing of electric two wheelers is given more importance in the short term.	[13]
Malaysia	(i) Fully green transport by 2030 including LPG, CNG, biofuel, and EVs; (ii) Primary focus is on parts and component development and manufacturing.	[14]
Japan	(i) The 2021 Green Growth Strategy aims for 100% LDV electrification by 2030; (ii) Offers purchase subsidies to buyers and tax incentives to manufacturers; (iii) Maximum purchase subsidy limit: JPY 800,000.	[15,16]
China	(i) China has been subsidizing new energy vehicles since 2009, adjusting subsidies based on market conditions; (ii) A formula considers factors such as range, battery energy density, and energy consumption to determine subsidy amounts; eligibility criteria are regularly adjusted, and the subsidy program, initially set to end in 2022, has been extended to 2027; (iii) Many cities and local governments offer non-monetary benefits such as parking access and exemptions from congestion and pollution restrictions.	[16,17]

Thailand, the second-largest ASEAN economy, is a significant player in the automobile industry, with approximately 6% of newly registered LDVs being EVs in 2022 [18]. In 2015, Thailand launched an EV promotion roadmap to enhance EV usage, manufacturing, and capabilities [19]. Thailand is committed to the 30@30 campaign and plans to ban IC vehicle registration after 2035, aligning with more-ambitious goals [20]. Furthermore, Thailand is pursuing policies to boost EV adoption and develop the EV ecosystem. The Thailand Board of Investment (BOI) offers tax incentives for EV manufacturing [21], and a THB 2.9-billion EV subsidy program supports new EV buyers [22]. This subsidy ranges up to THB 150,000 based on passenger and battery capacity. These policies, successful in other countries, are expected to drive increased EV adoption in Thailand, potentially impacting existing energy management policies outlined in the Thailand Integrated Energy Blueprint (TIEB) (2015–2037), which faces challenges in meeting the rising electrical demand from EVs.

By 2030, official energy consumption is projected to be 151 Mtoe, potentially reduced by 30 Mtoe through successful the EEP implementation [20]. Transportation is expected to consume 31% of energy and industry 41%, with the EEP projecting transport's energy-saving potential at 44%. Achieving efficiency targets relies on electrifying fleets, fuel economy improvements, enforcing standards, and eco-driving policies. PDP-2018 guides power systems, adding 52,431 MW generation capacity, including 18,833 MW of renewables. By 2037, there will be an estimated 77,200 MW installed capacity, 54,000 MW peak load, and 367 TWh annual energy demand. The EV transition must align with the TIEB framework, considering its impact on load, stability, and emissions.

The generation composition in the PDP2018 is crucial. In 2018, renewables made up 18% of total capacity, with the rest from fossil fuels. Natural gas accounted for 60% and coal for 19%. By 2037, renewables will comprise 30% of total capacity and coal will drop to 11%, but natural gas will remain dominant at 53%. A concern is the potential addition of new coal-fired power plants after 2030, conflicting with global efforts to discourage them. This may change in future policy revisions. CO₂ emissions from power generation are expected to increase by just over 18% from 2018 to 2037.

1.1. Related Publications

After the introduction of the EV promotion roadmap, several studies have analyzed various aspects related to EVs in Thailand. These studies have explored public perceptions of EVs and their popularity [23,24], the potential of charging stations [19], and the socioeconomic consequences of promoting EVs [23,25,26]. Together, these articles indicate a consensus that the Thai population is leaning towards adopting EVs. Young people in Thailand are increasingly favoring EVs over IC vehicles due to factors such as vehicle performance, environmental concerns, and social considerations. Yet, significant challenges persist, encompassing insufficient public infrastructure, limited driving range, cost considerations, and concerns about battery lifespan. In response to the insufficient charging infrastructure, potential solutions have been suggested. These solutions mainly involve incentivizing existing gas stations to install charging infrastructure and fostering collaborations between startups and major businesses, such as shopping centers. Furthermore, technical studies have investigated the impact of EV charging on the grid and power quality, with results suggesting that an off-peak charging strategy may be more favorable from a technical standpoint [27]. Studies related to vehicle-to-grid (V2G) and smart-home-based energy management have also surfaced, concentrating on strategies such as time-of-use (ToU) and real-time pricing (RTP) to address domestic demand from the consumer's perspective [28]. While this strategy can assist in managing daily load demand, its overall impact on the entire power system is challenging to assess since smart home technology has not yet widely penetrated the market in Thailand. This suggests that the domestic charging management strategy may not have a significant impact on peak demand or its timing in the near future. Despite these efforts, there is a relative scarcity of macro-level studies addressing long-term energy demand and fuel transition in relation to the growth of EVs and their impact on the electrical generation and supply system. Previous research has frequently focused on the potential emission reductions resulting from increased EV adoption, but it has lacked insights into the enduring effects on the electricity generation and supply system [29–31]. Article [31] criticized the potential emissions benefits of EV promotion, as it could lead to increased emissions from the power sector. However, other studies endorse the electrification of the transportation sector, especially in light of the rapid growth of renewable integration in the power system. Only a handful of studies in the literature have made predictions about the potential transition to EVs and the resulting peak load caused by EV charging. For example, in a scenario involving 1.5-million cars, roughly 35-million motorcycles, and a few thousand electric buses, a scenario with free charging would necessitate approximately 6000 MW of peak demand [27]. In a study spanning the period from 2010 to 2030, it was estimated that approximately 11.5 TWh of electrical energy would be required to charge a fleet consisting of 18.5-million motorcycles and 1.1-million cars, resulting in a peak demand of 10,000 MW [32]. While current conditions differ significantly from those assumed in the article, it is still important to analyze the academic interest in this sector. Extensive energy modeling of the Bangkok metropolitan area demonstrates the potential for introducing EVs and their positive impact on energy-conservation and emission-reduction efforts. Moreover, the expansion of mass rapid transport systems significantly contributes to emission reduction [33,34]. The latest study, utilizing the PDP2018, examined scenarios involving diverse levels of EV adoption, ranging from 1.2-million in 2030 to 15-million in 2037 [35]. The findings suggest that increased electrification of the transportation fleet substantially decreases overall energy demand. Nevertheless, the increased electricity generation still depends on natural gas, underscoring the importance of a robust transition towards renewable energy sources in the final energy mix. Similar doubts about the transition to EVs without simultaneously decarbonizing the electricity-generation sector are widespread, as emphasized in [36,37]. The article [38] contended that, although people generally hold positive views on the potential of EVs to reduce emissions, their skepticism is amplified by the slow integration of renewables into the grid system. Moreover, there are concerns regarding the socio-economic aspects of private car ownership and their sustainability impact, along with the

environmental implications of rare earth mining for battery production and disposal, which require attention. In-depth analyses of vehicle electrification effects in Abu Dhabi City and the Netherlands can be found in [39,40]. A substantial infrastructure investment would be needed if there is excessive demand from EV charging. Moreover, the article [41] examined how EV adoption can foster the development of sustainable communities. Similar analyses in Thailand are vital for evaluating existing policies, formulating new ones if needed, and assessing electrical demand and peak load variations with varying EV penetration. These data will inform optimal charging strategies and long-term power development policy adjustments.

1.2. Motivation and Contributions

Given the recent EV penetration targets, it is essential to reevaluate the potential energy demand and peak load associated with EV growth. Determining future charging demand based on the EV penetration pace is crucial for power system planning and reliability. Additionally, assessing the impact of EV promotion on reducing tailpipe emissions is important. This study introduced a scenario-based LEAP model to project future energy demand, fuel mix, and GHG emissions, considering EV growth potential and penetration. Compared to the existing works, the salient features of this paper are listed below:

1. Using econometric data, we constructed a vehicle ownership model to project vehicles per thousand population, contingent upon various future economic growth scenarios.
2. We analyzed energy consumption, fuel mix, and LDV emissions in different scenarios, factoring in the transition pace using the LEAP software tool.
3. Each vehicle type possesses distinct operational traits. In this study, we focused on LDVs primarily used for commuting, excluding taxis. In such instances, charging LDVs concurrently with larger vehicles could lead to excessive demand.
4. Additionally, we also assessed the potential impact of various charging schemes on peak load. Here, Monte Carlo simulation was employed to derive the EV charging load profiles.

1.3. Paper Organizations

The rest of the paper is structured as follows. Section 2 explains the methodology implemented in this paper. The details of the proposed scenarios and simulation setup are described in Section 3. Section 4 contains the obtained simulation results. Finally, Section 5 concludes the paper.

2. Methodology

Several tools exist for energy system modeling, including TIMES, HOMER, MESSAGE, and LEAP. This study opted for LEAP due to its convenience and independence from a specific environment, unlike the general algebraic modeling system (GAMS) [42]. It is a scenario-focused energy system modeling software from the Stockholm Environment Institute [43]. LEAP, as an optimization framework, finds widespread application in diverse fields including integrated energy modeling, water resource management, emission estimation, and generation expansion planning [44–48]. LEAP employs the accounting method for energy-related activities simulation. Its standout qualities are its flexibility and versatility, serving as a model-building platform adaptable to user needs. Diverse modeling approaches (bottom-up, top-down, end-use, macroeconomic) are feasible. Planning horizons vary from short to long, but LEAP excels in medium-term operational and long-term expansion planning. A key feature is its inbuilt Technology and Environment Database (TED), containing standards and techno-economic, socio-economic, and environmental data from organizations such as IEA and the IPCC. This streamlines analysis, minimizing data input through internal library linkage.

2.1. LEAP Models

LEAP employs the stock turnover method for calculating energy demand (ED). It necessitates vehicle driving distance (VKT), fuel economy (FE), and the number of vehicles for a specific year, N_{stock} . The ED model is mathematically defined as

$$ED_{i,j} = N_{stock\ i,j} \times VKT_i \times FE_{i,j}, \quad (1)$$

where i represents the consumed fuel and j denotes the vehicle type, such as car, SUV, or taxi.

Total energy consumption is the aggregate of all vehicle types' energy consumption and their associated fuel. Focusing on the LDV segment, the study considered cars (up to seven passengers), SUVs, personal trucks, and taxis as the vehicle types. The Department of Land Transport registers similar vehicles in various categories based on the service designation, such as fixed-route taxis and hotel taxis. To simplify the model, these categories are merged and treated as distinct vehicle types.

The total stock of each vehicle and fuel type can be calculated based on vehicle sales and the vehicle's survival rate as

$$N_{stock\ i,j} = \sum_{v=1}^t N_{sale\ i,t}(v) \times S_{i,j}(a), \quad (2)$$

where $N_{sale\ i,j}(v)$ is the quantity of new vehicles sold in the given vintage year v and $S_{i,j}(a)$ is the survival rate of the j -th vehicle type with fuel i with age a so that $a = t - v$.

The survival rate pertains to the anticipated likelihood of a specific vehicle enduring in operational use, while the survival profile was derived from prior research and documented information [49,50].

Each vehicle type's driving characteristics differ significantly based on urban or rural settings, alongside its utility, which impacts annual mileage. Driving characteristics' data were gathered from prior publications [51,52]. Data related to the vehicle number, annual new registration, fuel type classification, age, etc., was collected from Thailand's Department of Land Transport (DLT) government web portal.

The DLT database indicates diverse fuel registrations, primarily gasoline and diesel, with CNG and LPG also used. Some vehicles have dual-fuel registrations such as CNG = -gasoline or CNG = -diesel. Older vehicles use benzene. Newer registrations include hybrid (gasoline hybrid), plug-in hybrid, and battery electric vehicles (BEVs) in distinct categories. Thailand pioneered the introduction of biodiesel and bioethanol applications and associated policies in Asia [53]. Gasohol, commonly known as ethanol-blended gasoline, is required and offered in various blends, including 5%, 10%, and 20%. Likewise, various biodiesel blends exist, each with slightly different energy content, emission coefficients, and fuel economy compared to gasohol grades. Accounting for these nuances is challenging due to limited data and computational constraints. Thus, these fuels were classified into the following simplified groups.

1. **Gasoline:** This category includes all vehicles registered under the gasoline designation.
2. **Diesel:** Vehicles registered with diesel as their primary fuel.
3. **CNG:** Vehicles with CNG as the primary fuel, including those with dual-fuel options such as CNG–gasoline, are grouped due to the government's promotion of CNG through subsidies and tax rebates, driven by its affordability.
4. **LPG:** The primary fuel is LPG, with the addition of dual-fuel capabilities.
5. **Gasoline (Hybrid):** Gasoline–electric vehicles overwhelmingly dominate the hybrid electric category, leading to the assumption that all hybrid electric vehicles are powered by gasoline.
6. **Electricity:** This category includes both battery electric and plug-in EVs.

Fuel economy (FE) is a pivotal factor in determining vehicle energy demand, influenced by factors such as manufacturer, model, fuel type, vehicle type, utility, driving conditions, and age. Regulators typically set minimum fuel economy standards for road-worthiness. In Thailand, these standards are not strictly defined by regulations, but rather influenced by market forces, as vehicles with lower fuel efficiency might not be market-friendly. Given the dominance of Japanese manufacturers in the Thai automaker sector and market, the expected fuel efficiency is comparable to that of non-European members of the IEA, which is 9 km/l [54]. Conversely, the ASEAN fuel economy roadmap forecasts Thailand's LDV fuel efficiency to be 13.3 km/lge [55]. As Thailand leads in both vehicle manufacturing and market, a range of brands are offered. Notable gasoline and plug-in hybrid brands include Toyota, Mazda, Hyundai, and Nissan. In the battery electric market, leading brands encompass Nissan, BYD, Tesla, etc. Table 2 provides the utilized FE values in this study.

Table 2. Fuel economy taken from [55].

Vehicle	Fuel Economy, FE (km/lge)		
	IC	HEV	BEV
LDV	12	18	47

Emissions are calculated based on travel distance and energy consumption, where total emission for a specific vehicle type and fuel is the product of consumed energy, emission factor, and degradation factor. The emission factor adheres to regulating authority limits set according to country-specific environments. Thailand adopted Euro-IV in 2012, following Euro-III (2005) and Euro-II (1999); Euro-V is upcoming. Emission degradation is influenced by aging engines, but is complex to gauge for diverse vehicle types due to driving, road, and environmental variables. Predicting old vehicle emissions is limited; thus, the emission factor was assumed constant throughout their service. The mathematical formula used to calculate emissions is given as

$$Emission_{i,j,k} = ED_{i,j} \times EF_{i,j,k} \times \phi_{i,j,k,\alpha}, \quad (3)$$

where $Emission_{i,j,k}$ is the k -th emission from the i -th fuel of the j -th vehicle type; $EF_{i,j,k}$ is the emission factor; and $\phi_{i,j,k,\alpha}$ is the emission degradation factor for type k emission from the i -th fuel of the j -th category vehicle on the α -th year such that $\alpha = t - v$.

2.2. Estimation of New Vehicle Registration

The number of vehicles in a specific year stands as one of the utmost critical factors in (1). This study examined the time frame from 2016 to 2040. Given the extended forecasting period, precise short-term forecasting methods might not be advantageous. A vehicle ownership model was created for future registration predictions. The time series forecasting technique is extensively used for long-term prediction tasks. In the articles [56,57], ARIMA models forecast upcoming car sales. Holtz's method might surpass ARIMA in accuracy due to its exponential smoothing approach, which could comprehensively assign weights to past data [58]. Due to its simplicity and relatively low data requirements, log-linear regression stands as the predominant approach for crafting vehicle ownership models [35,59,60].

Models commonly employ macroeconomic indicators (e.g., per capita income (PCI), population density (POPden), urbanization, fuel price, and taxation) to predict vehicle ownership per thousand population. In this paper, we used three dependent variables (nominal per capita income, population density, and average retail fuel price) and introduced the concept of saturation level, rendering the model quasi-logistic. Testing multiple saturation levels (400, 500, 600, 700, and 800) showed 600 to yield the best-fitting accuracy; thus, it was

chosen for final simulation. The mathematical expression of the vehicle ownership model used in this article is given by

$$\ln \left(\frac{VO_{1000}}{S - VO_{1000}} \right) = \beta_0 + \beta_1 \ln PCI + \beta_2 \ln POPden + \beta_3 \ln FP + \epsilon, \quad (4)$$

where VO_{1000} is the vehicle ownership per thousand population; S is the saturation level (600); and β_0 , β_1 , β_2 , and β_3 are the coefficients of the respective variables.

The vehicle inventory at year-end, spanning 1995 to 2020 and acquired from the Department of Land Transport, can be employed to address (4). The World Bank database gathers data on PCI and population density [61]. Ultimately, the historical fuel price record was sourced from the records of the Bank of Thailand [62]. Table 3 encapsulates the outcomes derived from solving (4). The model exhibited R2 and adjusted R2 values of 0.982 and 0.98, respectively.

Table 3. Parameters of the vehicle ownership model.

Parameter	Coefficient	p-Value
β_0	−44.365	1.33770×10^{-8}
β_1	0.70569	6.9×10^{-4}
β_2	7.4199	3.79×10^{-5}
β_3	−0.43314	1.0354×10^{-6}

2.3. Estimation of Charging Load and Charging Scenarios

Understanding charging behavior is crucial for determining system peak load. Yet, calculating multi-decade peak load and driving traits is challenging due to evolving EV technology and changing parameters such as charging rate, battery capacity, driving behavior, and infrastructure. Short-term strategies and public supercharging shape charging patterns and the ensuing peak load. This article employed a Monte Carlo simulation to derive EV charging load profiles, focusing on three key parameters: daily driving distance, charge start time, and rate. Distance and start time were treated as normally distributed random variables, with their probability density functions (PDFs) in (5) and (6) [63,64]. Charging rate varies based on infrastructure and scheme. Type I is slow charging; Type II is fast; home chargers were all assumed to be Type II. In this article, public fast charging was regarded as supercharging and represented by

$$f_d(x_{i,j}) = \frac{1}{\sigma_{d,j}\sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x_{i,j} - \mu_{d,j}}{\sigma_{d,j}} \right)^2}, \quad (5)$$

$$f(T_{st,i,j}) = \frac{1}{\sigma_{st,j}\sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{T_{st,i,j} - \mu_{st,j}}{\sigma_{st,j}} \right)^2}, \quad (6)$$

where μ_d and σ_d are the mean and standard deviation of the j -th-type vehicle driving distance, respectively. Similarly, μ_{st} and σ_{st} represent the mean and standard deviation of the starting time of charging of the i -th type of vehicle, respectively.

The state-of-charge (SoC) is determined using driving distance and the range provided by the vehicle manufacturer. This can be expressed as

$$SoC_{i,j} = 1 - \frac{d_{i,j}}{D_j \eta}, \quad (7)$$

where d is the covered distance; D signifies the complete driving capacity with a fully charged battery (100%); and η denotes the battery efficiency during discharging.

The duration for the battery to reach 100% SoC is presented as

$$t_{ch_{i,j}} = (1 - SoC_{i,j}) \frac{BP_{i,j}}{CP_{i,j} \times \eta}, \quad (8)$$

where $t_{ch_{i,j}}$ is the charging time; $BP_{i,j}$ is the battery capacity (Whr); $CP_{i,j}$ is the charging rate; and η is the charger efficiency or overall charging efficiency.

With the known starting time of charge and charging duration, the ending time of charge (T_{end}) can be computed as

$$T_{end_{i,j}} = T_{st_{i,j}} + t_{ch_{i,j}}. \quad (9)$$

Now, demand caused by the i -th vehicle at time t can be given by

$$P_{EV_{i,j}}(t) = \begin{cases} CP_{i,j} : & T_{ST} < T < T_{end} \\ 0 : & \text{otherwise.} \end{cases} \quad (10)$$

Finally, total demand at a particular time can be calculated as

$$P_{EV}(t) = \sum_{j=1}^{N_{types}} \sum_{i=1}^{N_{EV}} P_{EV_{i,j}}(t). \quad (11)$$

3. Simulation Setup and Proposed Scenarios

This study included cars (up to seven passengers), pickup trucks, taxis, and minivans. Historical vehicle stocks for each category in Thailand's seven regions were obtained from DLT—Bangkok for the eastern, central, northeastern, northern, western, and southern regions. The total vehicles in the country were first calculated using a vehicle ownership model and, then, allocated proportionally to each region based on historical trends and future potential. Future vehicle ownership was computed under two scenarios: high and low growth, alongside business as usual (BAU). In high-growth scenarios, a real GDP growth of 5% was assumed, while in low-growth scenarios, it was assumed to be 3%. Moreover, a 2% inflation rate (aligned with the Bank of Thailand's inflation target range of 2–3%) was factored in for fuel costs. Table 4 presents an elaboration of the scenarios' particulars. This study comprised three processes (as in Figure 1)): (1) developing a macroeconomic-based vehicle ownership model to derive LDV ownership per thousand population and total kingdom vehicles for a specific year; (2) estimating energy demand, fuel composition, and vehicle emissions through a LEAP simulation model that integrates variables and vehicle numbers from the initial process; (3) determining potential peak EV charging demand by considering driving characteristics, vehicle attributes, and predicted ownership model vehicle numbers.

The LEAP software tool is extensively employed in diverse fields, including integrated energy modeling, water resource management, emissions' estimation from various activities, and generation expansion planning. It serves as an optimization framework in regions worldwide, including China, Europe, Canada, and Australia [45–48].

In this work, we utilized the LEAP software Version 2020.1.0.103 (64 bit) on a PC equipped with an Intel(R) Core (TM) i5-1135G7 processor running at 2.40 GHz to implement the methodology outlined in Section 2.1. This methodology was employed to simulate energy demand, GHG emissions, and fuel composition for the scenarios detailed in Table 4.

Furthermore, we utilized MATLAB R2018b to solve the equations outlined in Section 2.3. To demonstrate the impact of charging schemes on peak load, we selected various combinations of charging modes, ranging from exclusive home charging to widespread public fast charging. For simulation purposes, this article references the Nissan Leaf 2019 EV.

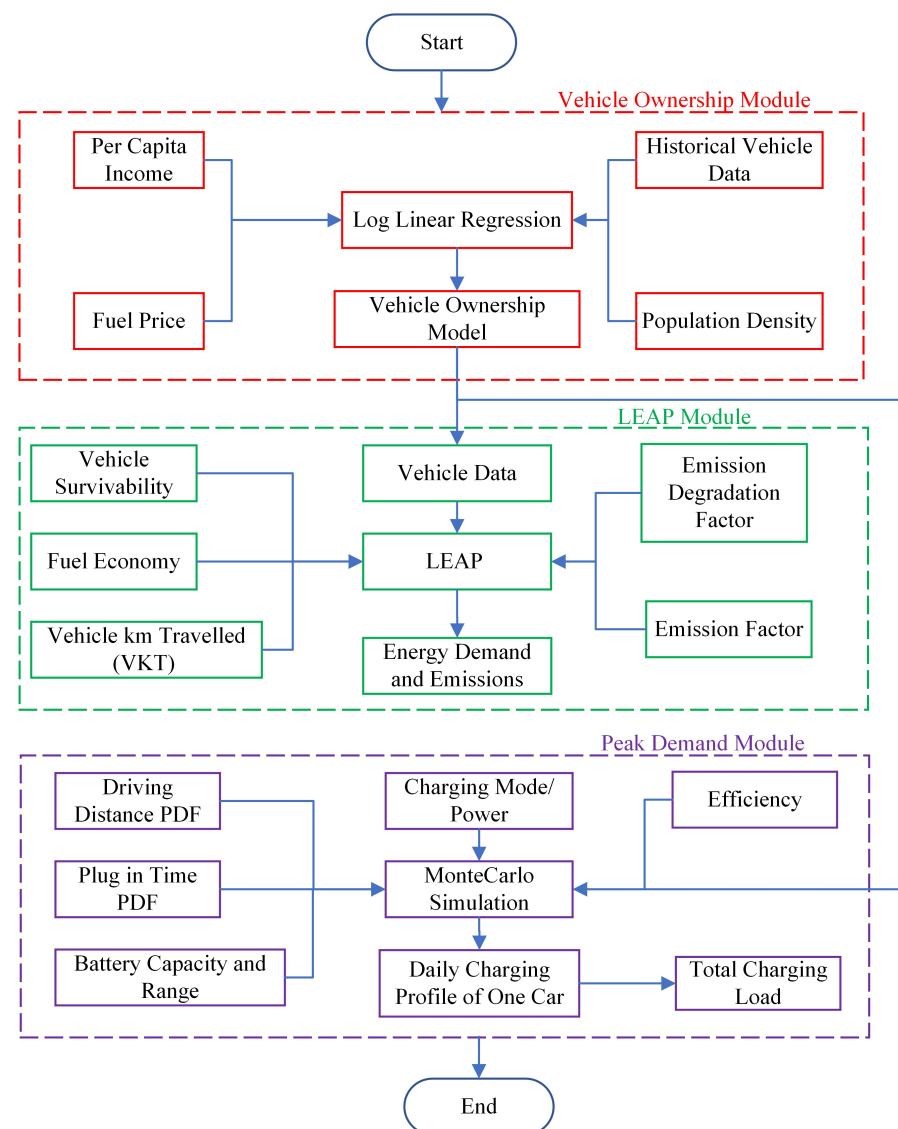


Figure 1. Schematic representation delineating the procedural components explored within this study.

Table 4. Description of the proposed scenarios.

No.	Scenarios	Description	Notation
1	Business as usual	Continuation of the current trend without any policy intervention.	BAU
2	High growth and aggressive transition	The objective entails attaining a 5% GDP growth, along with achieving new EV registrations of 50% by 2030 and 100% by 2035.	GDP5A
3	High growth and moderate transition	Aiming for a 5% GDP growth, the target for new EV registrations includes 30% by 2030, 50% by 2035, and 100% by 2040.	GDP5M
4	Low growth and aggressive transition	Envisioning a 3% GDP growth, the aspiration is for new EV registrations to attain 50% by 2030 and 100% by 2035.	GDP3A
5	Low growth and moderate transition	With a projected 3% GDP growth, the objective is to achieve new EV registrations of 30% by 2030, 50% by 2035, and 100% by 2040.	GDP3M

4. Results and Discussion

4.1. Simulation Results

In the GDP5 scenario, vehicle ownership in 2040 is projected at approximately 382 per thousand population, while in the GDP3 scenario, it is estimated to be around 338 per thousand population. These figures represent substantial growth of approximately 80% and 59%, respectively, compared to the base year value of 213. Among the three variables, population density exhibits the highest elasticity; however, the Thai population has already peaked and remained relatively stable throughout the study period, resulting in a less-pronounced impact on determining vehicle ownership. Both per capita income and fuel inflation display comparable elasticity values, but with contrasting effects. This implies that a scenario characterized by higher and sustained growth with limited inflationary constraints would be more favorable. Under the BAU scenario, total energy consumption is projected to be 271 TWh in 2040, reflecting a 27% increase compared to the base year energy consumption of 213 TWh (depicted in Figure 2). Notably, the GDP3A scenario is associated with a minimal energy demand of 184 TWh due to fewer vehicles overall, albeit with a relatively higher proportion of EVs. Across all scenarios, energy demand is expected to rise until reaching a peak and, subsequently, decrease in all scenarios except for the BAU scenario. Initially, the proportion of IC vehicles is notably high; over time, the share of EVs in the vehicle fleet increases, contributing to the moderation of energy demand.

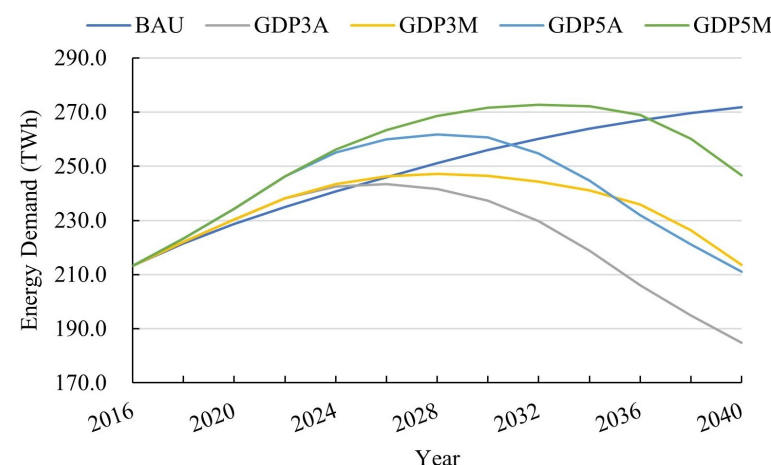


Figure 2. Annual energy demand.

Fuel composition is a pivotal consideration within this simulation. Figures 3–7 illustrate the proportionate distribution of each fuel type within the final energy demand. Despite the surge in newly registered EVs, ICVs are projected to maintain dominance over a substantial period. Even in the most-ambitious EV transition scenario (GDP5A) for 2040, fossil fuels are anticipated to contribute to more than 70% of the overall demand. In the BAU scenario, electricity is predicted to account for less than 3% of the demand in 2040. Across scenarios GDP3M, GDP5M, GDP3A, and GDP5A, the share of electricity in the total energy mix is projected to be 16.4%, 17.6%, 27.1%, and 29.4%, respectively. The utilization of diesel sees a notable decline in later years due to the considerably superior fuel efficiency of electric vehicles compared to diesel engines. On the other hand, scenarios show a slight upward trajectory for LPG and CNG consumption.

Table 5 provides a comprehensive depiction of the yearly electricity demand across various scenarios, representing the central parameter of concern in this study. Demand begins to rise after 2022 in all scenarios except for the BAU scenario. The highest projected demand of 62 TWh for 2040 is observed in the GDP5A scenario, closely followed by 50 TWh in GDP3A. This dataset holds pivotal importance for power system expansion planning. Beyond the actual energy demand figures, the annual growth rate is of paramount significance. In the initial stages of the fuel transition, the annual growth consistently exhibits higher rates. However, this aspect may not pose a significant challenge for the power

system, as the growth emanates from a low baseline and the actual demand increment is modest at best. Concerns arise when the previous year's demand is relatively high while the growth rate remains notably elevated. After the year 2028, demand across all scenarios, except BAU, embarks on a steep ascent. The growth rate in GDP3M and GDP5M scenarios for the year 2028 hovers around 26% and 27%, subsequently tapering to approximately 14% by 2040. Similarly, the annual growth rates for electricity demand in the years 2028 and 2040 are calculated at 32.6%, 33.6% and 6.9%, 7.1% for GDP3A and GDP5A, respectively. In view of these trends, meticulous planning for power generation and transmission infrastructure becomes imperative to accommodate the mounting additional demand.

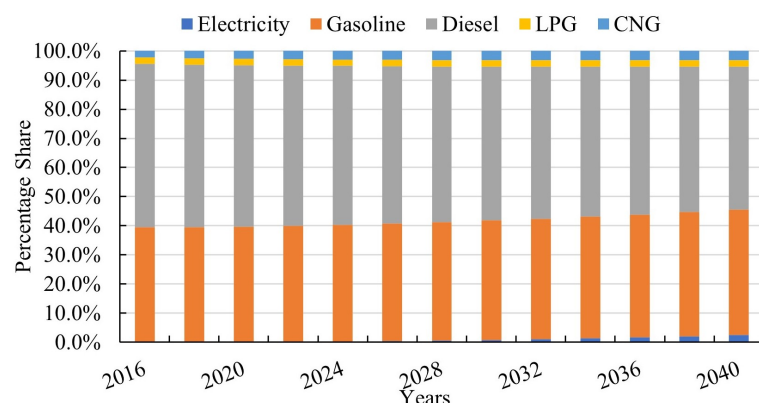


Figure 3. Fuel composition in BAU scenario.

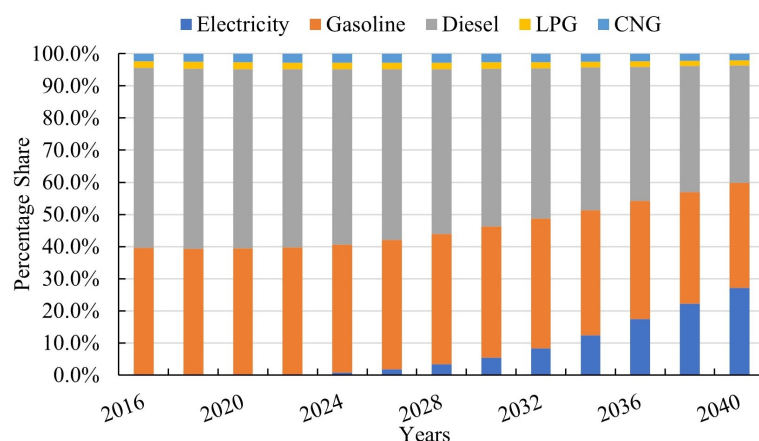


Figure 4. Fuel composition in GDP3A scenario.

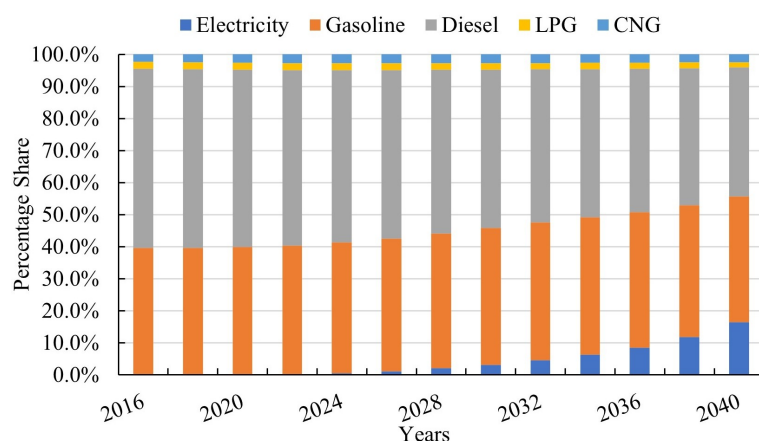


Figure 5. Fuel composition in GDP3M scenario.

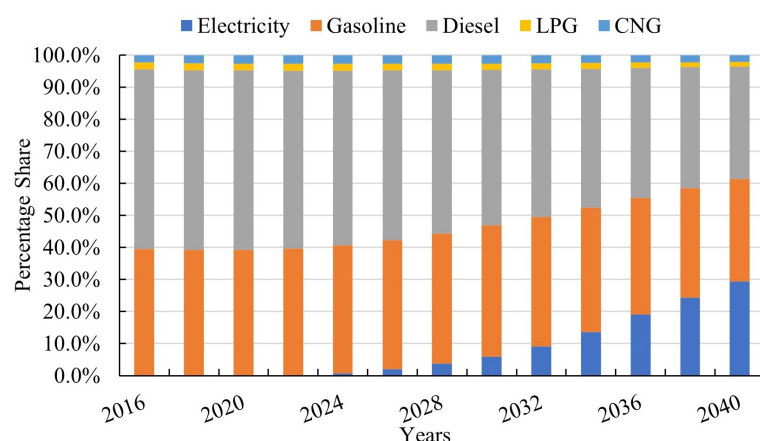


Figure 6. Fuel composition in GDP5A scenario.

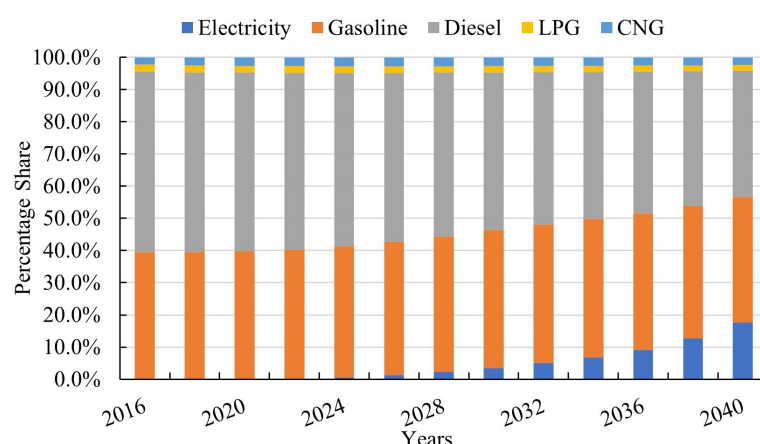


Figure 7. Fuel composition in GDP5M scenario.

Table 5. Electricity demand by year (TWh).

Scenarios	2018	2019	2020	2022	2024	2026	2028	2030	2032	2034	2036	2038	2040
BAU	0.0	0.1	0.2	0.3	0.6	1.0	1.4	2.0	2.7	3.5	4.5	5.5	6.7
GDP3A	0.0	0.1	0.2	0.3	1.7	4.4	8.1	12.8	19.1	27.2	35.9	43.3	50.0
GDP3M	0.0	0.1	0.2	0.3	1.2	2.8	5.1	7.9	11.3	15.2	20.0	26.8	35.0
GDP5A	0.0	0.1	0.2	0.4	2.0	5.2	9.7	15.6	23.4	33.4	44.3	53.7	62.1
GDP5M	0.0	0.1	0.2	0.4	1.4	3.3	6.1	9.6	13.8	18.7	24.7	33.2	43.5

Regarding emission estimation, the focus lied on four primary pollutants: carbon dioxide (CO₂), carbon monoxide (CO), nitrogen oxides (NO_x), and particulate matter (PM₁₀). Figures 8–11 provide an overview of the estimations for CO₂, CO, NO_x, and PM₁₀ emissions. In the base year, CO₂ emissions are approximately 45-billion kg and are projected to exhibit significant declines in all scenarios except for BAU, where a marginal increase of 1-billion kg is anticipated. It is worth noting that both the GDP5A and GDP5M scenarios initially witness higher emissions compared to BAU due to the prevalence of IC vehicles. Nevertheless, as the share of EVs becomes more substantial over time, emissions start to sharply decrease. These estimations were based on the assumption of no further policy interventions related to emission standards. The implementation of more-robust emission standards could result in further emission reductions. Notably, a notable drop is evident in CO, NO_x, and PM₁₀ emissions during specific years. This anomaly arises from the retirement of all remaining vehicles adhering to previous emission standards. Such reductions occur precisely 20 years after the introduction of new emission standards to replace the existing ones.

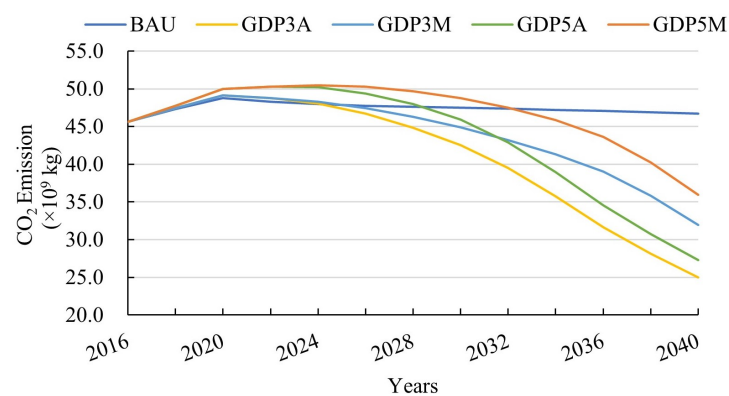


Figure 8. CO₂ emission projection.

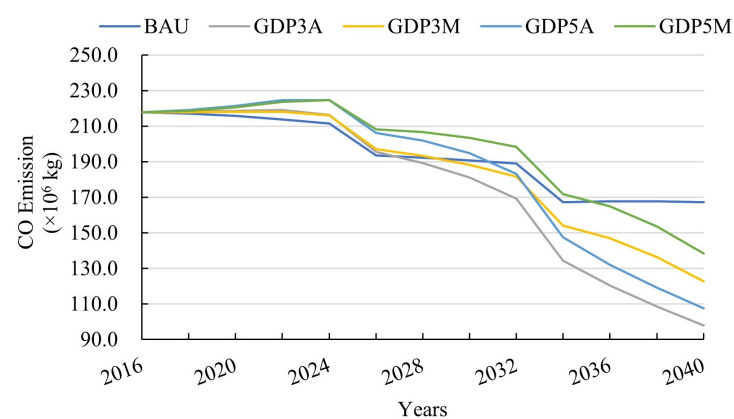


Figure 9. CO emission projection.

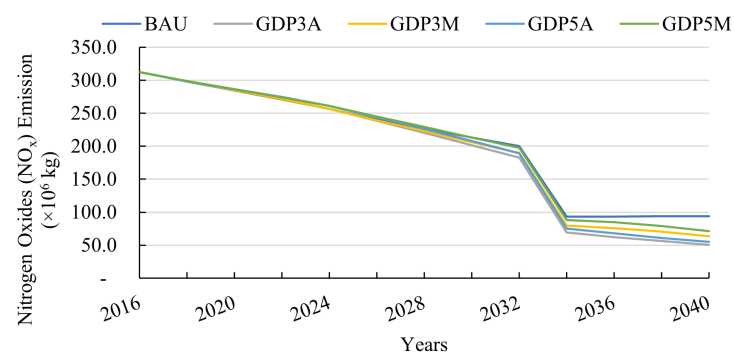


Figure 10. NO_x emission estimation.

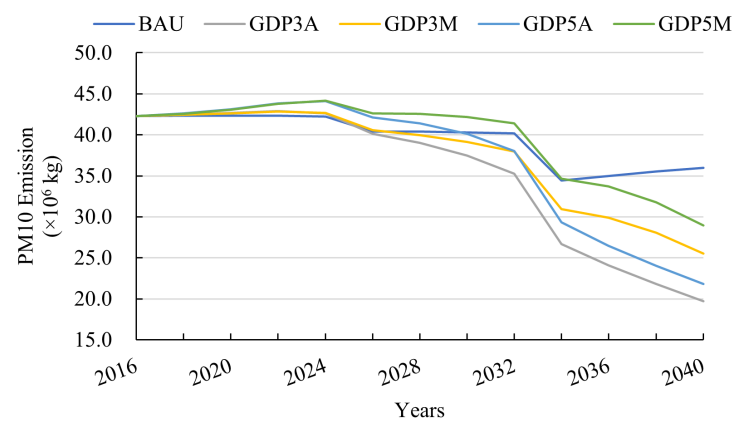


Figure 11. PM₁₀ emission projection.

Charging load is contingent on three key variables: charging rates, charging time, and battery SoC. This study considered three charging modes: home charging, office charging, and public charging. The assessment employed the 2019 Nissan Leaf EV battery as a reference and assumed double-speed charging with a Type II charger for both home and office charging. For public charging, it was presumed that the battery will reach up to 80% charge within 30 min. Given the substantial variations in charging rates across each mode, peak demand correspondingly fluctuates. Figure 12 illustrates such variations, displaying the charging load for 10,000 vehicles on a typical day across different combinations of charging modes. It is posited that 5% of vehicles will charge at the office, with the remaining distributed between home and public charging.

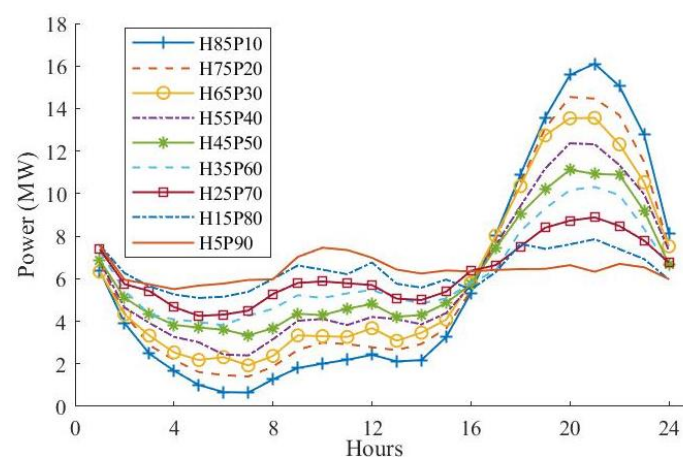


Figure 12. Charging demand variation due to the selection of various combinations of charging modes.

Figure 12 displays a substantial range of peak power demand variations. Should 90% of vehicles opt for public charging stations, the peak power demand would be approximately 7.4 MW. In contrast, the adoption of public fast charging by only 10% would result in a peak power demand of approximately 16.1 MW. Optimizing this configuration over an extensive time frame poses considerable challenge due to the evolving nature of EV technology, making accurate future predictions challenging. Nonetheless, the proliferation of public charging stations is poised for exponential growth in the forthcoming decade. To address this, the analysis focused on two extreme conditions: the worst-case scenario (85% home charging) and the best-case scenario (90% public charging station). Tables 6 and 7 outline the projected additional peak demand attributed to the transition to electric vehicles for the worst-case and best-case scenarios, respectively.

In 2020, demand across all scenarios remains relatively consistent due to the comparable total vehicle counts. However, peak demand is anticipated to experience substantial growth across the board, as outlined in Tables 6 and 7. By 2040, the GDP5A scenario could introduce over 21,000 MW of additional load if home charging predominates. Conversely, with an extensive adoption of public fast charging stations, this demand could be confined to around 9348 MW.

Table 6. Additional peak demand estimation based on the selection of the charging scheme: worst case additional peak demand (MW).

Scenarios	2020	2025	2030	2035	2040
BAU	57	266	721	1468	2533
GDP3A	59	768	3742	9967	17,258
GDP3M	59	535	2329	5560	11,613
GDP5A	62	897	4537	12,265	21,368
GDP5M	62	621	2817	6831	14,387

Table 7. Additional peak demand estimation based on the selection of the charging scheme: best case additional peak demand (MW).

Scenarios	2020	2025	2030	2035	2040
BAU	25	116	315	642	1108
GDP3A	25	336	1637	4360	7550
GDP3M	25	234	1018	2432	5081
GDP5A	27	392	1985	5365	9348
GDP5M	27	271	1232	2988	6294

4.2. Discussion

In the high-growth scenario, the projected number of vehicles in 2040 is approximately 27-million, whereas it is expected to be limited to around 23-million in a slower economy scenario. However, a previous study [35] projected a higher value for the same year, approximately 14% higher than the estimate in this paper. This difference could be attributed to the consideration of a 20-year retirement period in this study. Conversely, the estimate of 19-million vehicles for 2030 in another study [32] aligns closely with the current projection of 20-million. The Energy Efficiency Plan (EEP) 2015 has set an energy-saving target of 351 TWh for the entire transportation sector by 2036 [27]. The most-aggressive EV promotion scheme can contribute to saving approximately 36 TWh (around 10%) from the LDV segment alone, highlighting the significant potential of EVs in energy efficiency programs.

It is important to note that electrical power demand represents less than one-third of total energy consumption, with demand expected to continue rising beyond 2040. The widespread use of home charging poses challenges for system operators and utilities, highlighting the need for robust fast charging infrastructure. Strategies such as improved charging technology, battery swapping, V2G technology, time-of-use pricing, and real-time tariffs can help address excessive home charging.

PDP2018's official 2037 projections are 367.4 TWh for electrical energy demand, 77.2 TW for installed capacity, and 54 TW for peak load. These projections are based on 1.2-million EVs by 2030, but do not consider a ban on IC vehicles by 2035. The highest EV projection for 2030 is 2.83-million in the GDP5A scenario, requiring 15.6 TWh annually and 4537 MW of extra peak demand in the worst charging configuration. These demands seem manageable within PDP2018's limits until 2030. However, the LDV numbers surge after 2030, leading to significant demand growth in both annual demand and peak load. PDP2018 may not accommodate this growth, suggesting a need for future revisions.

In comparison, unlike [35], this article estimated around 26-million LDVs in 2037, 14% lower, possibly due to varying survival probability profiles. This study assumed a 20-year vehicle lifespan, removing any remaining vehicles after this period. However, Reference [32] projected 19-million LDVs for 2030, closely aligning with our current estimate of 20-million.

The study highlighted TIEB's ability to meet the additional energy and power demand from the EV transition in the medium term. It also emphasized the impact of uncoordinated charging on peak load and suggested that widespread use of public fast charging could help manage peak demand. This information may prompt authorities to accelerate public charging infrastructure development. While the reduction in overall power demand aligns with energy efficiency goals, electricity's share in total energy demand remains below one-third even in the most-favorable scenario.

5. Conclusions

In this paper, we presented a scenario-based LEAP model that integrated EV growth potential and penetration rates to forecast future energy demand, fuel composition, and GHG emissions. Thailand served as the case study, and the key findings were as follows:

- Vehicle ownership has steadily increased, albeit subject to the country's future economic performance.

- In almost all scenarios, the overall energy demand will be significantly lower than in the BAU scenario, aligning with energy efficiency policy goals. However, even in the most-favorable scenario, the share of electricity in total energy demand remains below one-third.
- This article also highlighted potential challenges associated with EV introduction into the electrical generation system. Uncoordinated home charging could pose significant issues for the system operator by causing a considerable rise in peak demand. However, widespread use of public fast charging could help mitigate peak demand.
- Despite TIEB only considering a 30% EV penetration rate in 2030, the proposed generation infrastructure could potentially support even the most-aggressive EV transition scenario described in the article in the medium term, especially if fast charging becomes widespread.
- In all scenarios, vehicle exhaust emissions are significantly lower compared to both the BAU scenario and the base-year emission levels.

This article underscored the significance of rapid public charging infrastructure in shaping peak charging demand, emphasizing the need for its prioritized development. Despite various transition scenarios, the share of electricity in the fuel mix remained below one-third due to the presence of older IC vehicles. Future policies aimed at phasing out these IC vehicles before their useful life ends are recommended to enhance emission reduction efforts. It is worth noting that this article did not consider the implementation of stricter emission standards, solely demonstrating the impact of EV adoption on emission reduction. Even without such standards, emissions decreased notably, but introducing new standards could further limit emissions.

Future research will prioritize the development of an optimal coordinated charging scheme and a new power development plan, aligned with the outcomes of the optimized charging scheme featuring increased renewable energy integration. This analysis will yield insights into the net emission reduction resulting from EV promotion, serving as a crucial test of the program's effectiveness in fulfilling climate commitments.

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Abbreviations

The following abbreviations are used in this manuscript:

IC	Internal combustion
LDV	Light-duty vehicle
LEAP	Low Emission Analysis Platform
SoC	State-of-charge
ZEV	Zero-emission vehicle
TIEB	Thailand Integrated Energy Blueprint

PDP	Power Development Plan
AEDP	Alternative Energy Development Plan
EEP	Energy Efficiency Plan
V2G	Vehicle-to-grid
ED	Energy demand
FE	Fuel economy
HEV	Hybrid electric vehicle
BEV	Battery electric vehicle
VO	Vehicle ownership
PCI	Per capita income
FP	Fuel price

References

1. International Energy Agency, Global EV Outlook 2020 Entering the Decade of Electric Drive? Available online: <https://www.iea.org/reports/global-ev-outlook-2020> (accessed on 22 October 2022).
2. Clean Energy Ministerial, EV30@30 CAMPAIGN. Available online: <https://www.cleanenergyministerial.org/initiatives-campaigns/ev3030-campaign/> (accessed on 13 August 2023).
3. Bibra, E.M.; Connelly, E.; Dhir, S.; Drtil, M.; Henriot, P.; Hwang, I.; Le Marois, J.B.; McBain, S.; Paoli, L.; Teter, J. Global EV Outlook 2022: Securing Supplies for an Electric Future. Available online: <https://www.iea.org/reports/global-ev-outlook-2022> (accessed on 3 August 2023).
4. Ministry of Heavy Industries Government of India, FAME-INDIA II Scheme. Available online: <https://heavyindustries.gov.in/UserView/index?mid=1378> (accessed on 23 August 2023).
5. Australian Government Department of Climate Change Energy the Environment and Water, New Funding for Zero Emission Fleet Vehicles. Available online: <https://www.dcccew.gov.au/about/news/new-funding-for-zero-emission-fleet-vehicles> (accessed on 23 August 2023).
6. New Zealand Transport Agency, Clean Car Discount Overview. Available online: <https://www.nzta.govt.nz/vehicles/clean-car-programme/clean-car-discount/overview/> (accessed on 23 August 2023).
7. European Alternative Fuels Observatory, France Incentives and Legislation. Available online: <https://alternative-fuels-observatory.ec.europa.eu/transport-mode/road/france/incentives-legislations> (accessed on 23 August 2023).
8. European Alternative Fuels Observatory, Germany Incentives and Legislations. Available online: <https://alternative-fuels-observatory.ec.europa.eu/transport-mode/road/germany/incentives-legislations> (accessed on 23 August 2023).
9. Government of the United Kingdom, Transitioning to Zero Emission Cars and Vans: 2035 Delivery Plan. Available online: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1005301/transitioning-to-zero-emission-cars-vans-2035-delivery-plan.pdf (accessed on 23 August 2023).
10. Government of Canada, Zero-Emission Vehicles. Available online: <https://tc.canada.ca/en/road-transportation/innovative-technologies/zero-emission-vehicles> (accessed on 23 August 2023).
11. Joint Office of Energy and Transportation, State Plans for Electric Vehicle Charging. Available online: <https://driveelectric.gov/state-plans/> (accessed on 23 August 2023).
12. Internal Revenue Service United States Government, Credits for New Clean Vehicles Purchased in 2023 or After. Available online: <https://www.irs.gov/credits-deductions/credits-for-new-clean-vehicles-purchased-in-2023-or-after> (accessed on 23 August 2023).
13. Cabinet Secretariat of the Republic of Indonesia, Gov't Launches Incentives for Electric Cars and Bus. Available online: <https://setkab.go.id/en/govt-launches-incentive-for-purchasing-electric-car-and-bus/> (accessed on 23 August 2023).
14. Ministry of Energy Green Technology and Water Malaysia, Green-Technology-Master-Plan-Malaysia-2017-2030. Available online: <https://www.pmo.gov.my/wp-content/uploads/2019/07/Green-Technology-Master-Plan-Malaysia-2017-2030.pdf> (accessed on 24 August 2023).
15. Global EV Outlook. *Catching Up with Climate Ambitions*; IEA: Paris, France, 2023.
16. Kohn, E.; Huang, C.; Kong, N.; Hardman, S. *Electric Vehicle Incentives in 15 Leading Electric Vehicle Markets*; Institute of Transportation Studies: Davis, CA, USA, 2022.
17. Li, S.; Zhu, X.; Ma, Y.; Zhang, F.; Zhou, H. The role of government in the market for electric vehicles: Evidence from China. *J. Policy Anal. Manag.* **2022**, *41*, 450–485. [CrossRef]
18. Department of Land Transport, Statistics. Available online: <https://web.dlt.go.th/statistics/> (accessed on 13 December 2022).
19. Thananusak, T.; Punnakitikashem, P.; Tanthasith, S.; Kongarchapata, B. The development of electric vehicle charging stations in Thailand: Policies, players, and key issues (2015–2020). *World Electr. Veh. J.* **2020**, *12*, 2. [CrossRef]
20. Energy Policy and Planning Office, “Guidelines for Promoting Electric Vehicles. Available online: <https://www.eppo.go.th/index.php/en/component/k2/item/17415-ev-charging-221064-04> (accessed on 13 December 2022).
21. Thailand Board of Investment, Investment Promotion Guide 2023. Available online: https://www.boi.go.th/upload/content/BOI_A_Guide_EN.pdf (accessed on 13 August 2023).

22. Cabinet Approves 2.9 bn Baht EV Sale Subsidy, National News Bureau of Thailand. Available online: <https://thainews.prd.go.th/en/news/detail/TCATG220823221824371> (accessed on 13 August 2023).
23. Kongklaew, C.; Phoungthong, K.; Prabpayak, C.; Chowdhury, M.S.; Khan, I.; Yuangyai, N.; Yuangyai, C.; Techato, K. Barriers to electric vehicle adoption in Thailand. *Sustainability* **2021**, *13*, 12839. [\[CrossRef\]](#)
24. Manutworakit, P.; Choocharukul, K. Factors influencing battery electric vehicle adoption in Thailand—Expanding the unified theory of acceptance and use of technology’s variables. *Sustainability* **2022**, *14*, 8482. [\[CrossRef\]](#)
25. Mohamad, M.; Songthaveephol, V. Clash of titans: The challenges of socio-technical transitions in the electrical vehicle technologies—the case study of Thai automotive industry. *Technol. Forecast. Soc. Chang.* **2020**, *153*, 119772. [\[CrossRef\]](#)
26. Wangsupphaphol, A.; Chaitusaney, S. A simple leveled cost of electricity for EV charging with PV and battery energy storage system: Thailand case study. *Int. J. Power Electron. Drive Syst.* **2020**, *11*, 2223–2230. [\[CrossRef\]](#)
27. Uthathip, N.; Bhasaputra, P.; Pattaraprakorn, W. Stochastic Modelling to Analyze the Impact of Electric Vehicle Penetration in Thailand. *Energies* **2021**, *14*, 5037. [\[CrossRef\]](#)
28. Sangswang, A.; Konghirun, M. Optimal Strategies in Home Energy Management System Integrating Solar Power, Energy Storage, and Vehicle-to-Grid for Grid Support and Energy Efficiency. *IEEE Trans. Ind. Appl.* **2020**, *56*, 5716–5728. [\[CrossRef\]](#)
29. Sritong, N.; Promjiraprawat, K.; Limmeechokchai, B. CO₂ mitigation in the road transport sector in Thailand: Analysis of energy efficiency and bio-energy. *Energy Procedia* **2014**, *52*, 131–141. [\[CrossRef\]](#)
30. Wangjiraniran, W.; Pongthanasawan, J.; Junlakarn, S.; Phadungsri, D. Scenario analysis of disruptive technology penetration on the energy system in Thailand. *Energy Procedia* **2017**, *142*, 2661–2668. [\[CrossRef\]](#)
31. Winyuchakrit, P.; Sukamongkol, Y.; Limmeechokchai, B. Do electric vehicles really reduce GHG emissions in Thailand? *Energy Procedia* **2017**, *138*, 348–353. [\[CrossRef\]](#)
32. Saisirirat, P.; Chollacoop, N.; Tongroon, M.; Laoonual, Y.; Pongthanasawan, J. Scenario analysis of electric vehicle technology penetration in Thailand: Comparisons of required electricity with power development plan and projections of fossil fuel and greenhouse gas reduction. *Energy Procedia* **2013**, *34*, 459–470. [\[CrossRef\]](#)
33. Phdungsilp, A. Integrated energy and carbon modeling with a decision support system: Policy scenarios for low-carbon city development in Bangkok. *Energy Policy* **2010**, *38*, 4808–4817. [\[CrossRef\]](#)
34. Traivivatana, S.; Wangjiraniran, W. Thailand Integrated Energy Blueprint (TIEB): One step towards sustainable energy sector. *Energy Procedia* **2019**, *157*, 492–497. [\[CrossRef\]](#)
35. Wattana, B.; Wattana, S. Implications of electric vehicle promotion policy on the road transport and electricity sectors for Thailand. *Energy Strategy Rev.* **2022**, *42*, 100901. [\[CrossRef\]](#)
36. Selvakkumaran, S.; Ahlgren, E.O.; Winyuchakrit, P.; Limmeechokchai, B. Electric Vehicle (EV) Transition in Thailand: Is it Beneficial? In Proceedings of the 2018 International Conference and Utility Exhibition on Green Energy for Sustainable Development (ICUE), Phuket, Thailand, 24–26 October 2018; pp. 1–7.
37. Chantharaphaha, K. Future Directions of Electric Vehicles and the Thai Automobile Industry. *Asian Adm. Manag. Rev.* **2020**, *3*, 15–21.
38. Almansour, M. Electric vehicles (EV) and sustainability: Consumer response to twin transition, the role of e-businesses and digital marketing. *Technol. Soc.* **2022**, *71*, 102135. [\[CrossRef\]](#)
39. Farid, A.M.; Viswanath, A.; Al-Junaibi, R.; Allan, D.; Van der Wardt, T.J. Electric vehicle integration into road transportation, intelligent transportation, and electric power systems: An Abu Dhabi case study. *Smart Cities* **2021**, *4*, 1039–1057. [\[CrossRef\]](#)
40. Lampropoulos, I.; Alsaif, T.; Schram, W.; Bontekoe, E.; Coccato, S.; Van Sark, W. Review of energy in the built environment. *Smart Cities* **2020**, *3*, 15. [\[CrossRef\]](#)
41. Bokolo, A.J. Examining the Adoption of Sustainable eMobility-Sharing in Smart Communities: Diffusion of Innovation Theory Perspective. *Smart Cities* **2023**, *6*, 2057–2080. [\[CrossRef\]](#)
42. Ringkjøb, H.K.; Haugan, P.M.; Solbrekke, I.M. A review of modelling tools for energy and electricity systems with large shares of variable renewables. *Renew. Sustain. Energy Rev.* **2018**, *96*, 440–459. [\[CrossRef\]](#)
43. Heaps, C.; Veysey, J.; Ulloa, S.; Binnington, T. The Low Emissions Analysis Platform. Stockholm Environment Institute. 2022. Available online: <https://www.sei.org/projects-and-tools/tools/leap-long-range-energy-alternatives-planning-system> (accessed on 13 August 2023).
44. Pulugurtha, S.S.; Duddu, V.R.; Venigalla, M. Evaluating spatial and temporal effects of planned special events on travel time performance measures. *Transp. Res. Interdiscip. Perspect.* **2020**, *6*, 100168. [\[CrossRef\]](#)
45. Agrawal, N.; Ahiduzzaman, M.; Kumar, A. The development of an integrated model for the assessment of water and GHG footprints for the power generation sector. *Appl. Energy* **2018**, *216*, 558–575. [\[CrossRef\]](#)
46. Zhang, D.; Liu, G.; Chen, C.; Zhang, Y.; Hao, Y.; Casazza, M. Medium-to-long-term coupled strategies for energy efficiency and greenhouse gas emissions reduction in Beijing (China). *Energy Policy* **2019**, *127*, 350–360. [\[CrossRef\]](#)
47. Perissi, I.; Martelloni, G.; Bardì, U.; Natalini, D.; Jones, A.; Nikolaev, A.; Eggler, L.; Baumann, M.; Samsó, R.; Solé, J. Cross-validation of the MEDEAS energy-economy-environment model with the Integrated MARKAL-EFOM System (TIMES) and the Long-range Energy Alternatives Planning system (LEAP). *Sustainability* **2021**, *13*, 1967. [\[CrossRef\]](#)
48. Emodi, N.V.; Chaiechi, T.; Beg, A.R.A. Are emission reduction policies effective under climate change conditions? A backcasting and exploratory scenario approach using the LEAP-OSeMOSYS Model. *Appl. Energy* **2019**, *236*, 1183–1217. [\[CrossRef\]](#)

49. Lu, S. *Vehicle Survivability and Travel Mileage Schedules*; Technical Report; The National Academies of Sciences, Engineering, and Medicine: Washington, DC, USA, 2006.
50. Rith, M.; Fillone, A.M.; Biona, J.B.M. Development and application of the Weibull distribution-based vehicle survivorship models for a metropolis of a developing country. *Songklanakarin J. Sci. Technol.* **2020**, *42*, 1233.
51. Limanond, T.; Pongthanasawan, J.; Watthanaklang, D.; Sangphong, O. *An Analysis of Vehicle Kilometers of Travel of Major Cities in Thailand*; ATRANS Final Report 2009; Asian Transportation Research Society (ATrans): Bangkok, Thailand, 2009.
52. Pongthanasawan, J.; Sorapipatana, C.; Limmeechokchai, B. Road transport energy demand analysis and energy saving potentials in Thailand. *Asian J. Energy Environ.* **2007**, *8*, 49–72.
53. Bloyd, C. *Thailand Alternative Fuels Update 2017*; United State Department of Energy: Washington, DC, USA, 2017.
54. Thailand: Making Transport More Energy Efficient. Available online: <https://documents1.worldbank.org/curated/en/470771468173950665/pdf/500340WP0p10951y0Updater01310812009.pdf> (accessed on 20 August 2023).
55. Secretariat, A. *ASEAN Fuel Economy Roadmap for the Transport Sector 2018–2025: With Focus on Light-Duty Vehicles*; ASEAN Secretariat: Jakarta, Indonesia, 2019.
56. Shakti, S.P.; Hassan, M.K.; Zhenning, Y.; Caytiles, R.D.; Iyenger, N. Annual automobile sales prediction using ARIMA model. *Int. J. Hybrid Inf. Technol.* **2017**, *10*, 13–22. [CrossRef]
57. Irhami, E.A.; Farizal, F. Forecasting the Number of Vehicles in Indonesia Using Auto Regressive Integrative Moving Average (ARIMA) Method. *J. Phys. Conf. Ser.* **2021**, *1845*, 012024. [CrossRef]
58. Leenawong, C.; Chaikajonwat, T. Event Forecasting for Thailand's Car Sales during the COVID-19 Pandemic. *Data* **2022**, *7*, 86. [CrossRef]
59. Button, K.; Ngoe, N.; Hine, J. Modelling vehicle ownership and use in low income countries. *J. Transp. Econ. Policy* **1993**, *27*, 51–67.
60. Sillaparcharn, P. Vehicle ownership and trip generation modelling: A case study of Thailand. *IATSS Res.* **2007**, *31*, 17–26. [CrossRef]
61. The World Bank, Data Thailand. Available online: <https://data.worldbank.org/country/thailand> (accessed on 5 October 2022).
62. Bank of Thailand, Price of Certain Manufactured Goods. Available online: https://app.bot.or.th/BTWS_STAT/statistics/BOTWEBSTAT.aspx?reportID=90&language=ENG (accessed on 9 October 2022).
63. Adianto, Y.; Baguley, C.; Madawala, U.; Hariyanto, N.; Suwarno, S.; Kurniawan, T. The coordinated operation of vertically structured power systems for electric vehicle charge scheduling. *Energies* **2021**, *15*, 27. [CrossRef]
64. Zhou, K.; Cheng, L.; Wen, L.; Lu, X.; Ding, T. A coordinated charging scheduling method for electric vehicles considering different charging demands. *Energy* **2020**, *213*, 118882. [CrossRef]

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