International Journal of Electrical and Computer Engineering (IJECE)
Vol. 16, No. 2, April 2026, pp. 1010~1019
ISSN: 2088-8708, DOI: 10.11591/ijece.v16i2.pp1010-1019

Impact of electric vehicle demand forecasting on charging station infrastructure development

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Article Info

Article history:

Received Apr 18, 2025
Revised Jan 2, 2026
Accepted Jan 16, 2026

Keywords:

Electric car
Electric vehicle demand
Charging infrastructure
Forecasting
Genetic algorithm
Grey forecasting mode

ABSTRACT

This research addresses the challenge of forecasting electric vehicle (EV) demand in Thailand and its influence on the development of charging infrastructure. To improve predictive capability in environments with restricted historical data, we employed the grey model (GM) and genetic algorithms (GA) both independently and in combination. Using EV registration records from 2019 to 2023 obtained from the Automotive Information Center of Thailand, the optimized GM-GA hybrid model achieved markedly superior accuracy, with a mean absolute error (MAE) of 0.0016 and root mean squared error (RMSE) of 0.0031. These results demonstrate the model's capacity to deliver precise forecasts despite data limitations, making it a valuable decision-making tool for charging station planning and deployment. The outcomes underscore the importance of forward-looking infrastructure strategies to support the growth of Thailand's EV market and its transition toward sustainable mobility.

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1. INTRODUCTION

The global transition toward electric mobility has intensified the need for accurate forecasting models capable of supporting strategic infrastructure planning. As electric vehicle (EV) adoption accelerates in regions such as China, Europe, and the United States, many governments have adopted policies aimed at phasing out internal combustion engine vehicles within the next two decades [1], [2]. These developments highlight a broader shift toward cleaner transportation systems and underscore the importance of aligning infrastructure—particularly charging stations—with projected EV demand. Although extensive research exists in high-adoption markets, emerging economies like Thailand face unique constraints that complicate demand forecasting, including limited historical EV data, non-linear market growth patterns, and uncertainty regarding consumer adoption behavior [3].

In Thailand, the pace of EV adoption has increased steadily, driven by government incentives, technological advancements, and the expansion of privately operated charging networks. However, this growth remains uneven across regions, and the uncertainties inherent in an emerging market introduce significant challenges for long-term planning. Unlike mature EV markets, Thailand lacks robust historical datasets that can be used to train conventional forecasting models such as regression-based time series or deep learning techniques [4]. Traditional models often assume stable or abundant data, making them ineffective in contexts where data scarcity and rapid market evolution occur simultaneously. As a result, there is a growing need for more flexible and adaptive forecasting frameworks that can function effectively with limited observations.

These challenges motivate the use of alternative data-driven approaches tailored to environments with high volatility and limited historical records. The grey model (GM), known for its ability to produce reliable forecasts from small datasets, offers an appealing option. Nevertheless, standard GM models may struggle with rapidly changing market dynamics and non-linear growth curves typically observed in early-stage EV adoption. To address these limitations, optimization algorithms, particularly genetic algorithms (GA), are increasingly being used to refine model parameters and improve predictive performance [5]. By integrating GA with GM, it becomes possible to create an enhanced hybrid model capable of capturing the underlying structure of EV adoption trends more accurately.

This study investigates the application of genetic algorithms, the grey model, and their hybrid (GM-GA) configuration to forecast EV demand in Thailand using vehicle registration data from 2019 to 2023. The research seeks to answer a central question: *How can EV demand be forecasted accurately in a data-limited emerging market environment?* In addition, the study compares the hybrid GM-GA model with neural network–based approaches—specifically artificial neural networks (ANN), recurrent neural networks (RNN), and long short-term memory networks (LSTM)—to evaluate their suitability for Thailand's market conditions.

By addressing the limitations of conventional forecasting techniques and demonstrating a more adaptable modelling approach, the study aims to contribute practical insights for policymakers, energy providers, and industry stakeholders. Accurate demand forecasting is crucial not only for optimizing charging station deployment but also for supporting grid stability, investment planning, and the broader transition toward low-carbon transportation. The findings of this research provide a foundation for informed decision-making as Thailand continues to develop its EV ecosystem.

2. LITERATURE REVIEW

The demand estimation for EV uptake has become an essential component of infrastructure planning and long-term system development. A variety of forecasting strategies have been explored to address this need, spanning classic statistical approaches, grey-system models, and modern machine-learning techniques. Among these, neural-network-based architectures such as ANN and RNN have proven effective at identifying complex temporal dependencies. However, these methods typically rely on long-duration, high-resolution datasets, which are difficult to obtain in newer EV markets—including Thailand—where historical records are limited, and adoption patterns are still taking shape. Grey-based forecasting techniques present a contrasting paradigm by maintaining predictive capability even when data availability is minimal or fragmented. The classical GM demonstrates reasonable trend-estimation performance under short-data conditions. Yet, its default formulation tends to lag in responsiveness during periods of rapid market acceleration or abrupt behavioral shifts. To overcome these constraints, the present work applies an enhanced grey–genetic algorithm (GM–GA) structure, in which GA is used to tune and refine internal GM parameters, enabling a more adaptive and resilient forecasting mechanism in volatile and data-scarce settings. The following sections investigate the operational characteristics of these competing forecasting paradigms and explain the motivation for adopting the GM–GA approach for EV demand prediction within Thailand's early-stage EV transition. This analysis provides a basis for selecting strategies that remain reliable despite limited inputs, ultimately supporting more informed infrastructure deployment and investment planning as the EV ecosystem develops.

2.1. Forecasting

Forecasting involves inferring forthcoming developments by examining empirical evidence, behavioral tendencies, and structural relationships present within the data. Within technical and applied disciplines, forecasting methodologies are often categorized into quantitative models—based on measurable inputs and formal mathematical formulations—and qualitative approaches, which depend on domain knowledge, subjective assessment, and contextual interpretation [6], [7], [8]. When large or sufficiently structured datasets are available, quantitative strategies such as time-dependent modelling, statistical regression, and computational predictive schemes are frequently favored, and their predictive performance may be further strengthened through advanced optimization or machine learning augmentation [9], [10].

For the purposes of this study, a quantitative scheme is utilized, supported by accessible numerical indicators such as EV registration records and observable market uptake. Nevertheless, Thailand's electric vehicle market remains transitional, characterized by sparse historical records and evolving adoption behavior, which necessitates forecasting tools capable of functioning effectively under data-limited conditions. To meet this challenge, the proposed framework integrates a grey forecasting architecture refined through genetic algorithm-based parameter tuning (GM–GA), thereby enhancing model responsiveness and predictive resolution. The resulting forecasts are intended to offer reliable guidance for strategic decisions associated with EV infrastructure expansion, including charging-network planning and system capacity management.

2.2. Grey model

The GM provides a forecasting framework suitable for systems with limited or uncertain data. In the GM (n, m) formulation, n represents the order of the differential equation, and m denotes the number of variables, with GM (1,1) being the most commonly applied due to its simple structure and reliable performance on short data sequences. The approach employs an accumulated generating operation (AGO) to smooth the original series into a monotonic form. Afterward, a first-order differential equation is established and analytically solved to derive an exponential forecasting function.

a. Given an original sequence:

$$M^{(0)} = \{M^{(0)}(1), M^{(0)}(2), \ldots, M^{(0)}(n)\}$$

b. Accumulated generating operation (AGO) [11]:

$$M^{(1)}(Y) = \sum_{i=1}^{Y} M^{(0)}(i), \ \text{Y=1, 2, …, n}$$

c. Mean sequences:

$$A^{(1)}(Y) = 0.5 * M^{(1)}(Y) + 0.5 * M^{(1)}(Y-1), \quad \text{Y=2, 3, …, n}$$

d. First-order differential equation:

$$M^{(0)}(Y) + iA^{(1)}(Y) = D$$

where a is the development coefficient and b is the grey input.

e. Parameter estimation (least squares):

$$\hat{\theta} = \begin{bmatrix} e \\ f \end{bmatrix} = (Z^T Z)^{-1} Z^T K$$

where:

$$Z = \begin{bmatrix} -A^{(1)}(2) & 1 \\ -A^{(1)}(3) & 1 \\ \vdots & \vdots \\ -A^{(1)}(n) & 1 \end{bmatrix}, K = \begin{bmatrix} M^{(0)}(2) \\ M^{(0)}(3) \\ \vdots \\ M^{(0)}(n) \end{bmatrix}$$

f. Forecasting function:

$$\widehat{M}^{(1)}(Y) = (M^{(0)}(1) - \frac{f}{e})e^{-i(Y-1)} + \frac{f}{e}$$

g. Inverse AGO (IAGO):

$$\widehat{M}^{(0)}(Y) = \widehat{M}^{(1)}(Y) - \widehat{M}^{(1)}(Y-1)$$

h. Modelling procedure

- Data preparation: Collect the original time series $M^{(0)}$ with $n \geq 4$ observations.
- AGO transformation: Apply the accumulated generating operation to reduce randomness in the series.
- Mean sequence construction: Generate $A^{(1)}$ as the adjacent mean of the AGO sequence [11].
- Model parameter estimation: Estimate e and f using the least squares method.
- Model solution: Derive the forecasting function $\widehat{M}^{(1)}(Y)$ and apply IAGO to obtain the predicted original series $\widehat{M}^{(0)}(Y)$.

2.3. Genetic algorithm

The genetic algorithm (GA), proposed by Holland in 1975 [12], is an evolutionary optimization method that relies on population-based search to handle problems that are difficult for conventional analytical techniques, especially those exhibiting non-linear characteristics, multiple optima, or high-dimensional structures. GA enhances a pool of candidate solutions through iterative evolutionary operators—selection, crossover, and mutation—which collectively guide the search toward improved solutions [13], [14].

- The selection in genetic algorithms, the selection process determines which individuals from the current population will be used to produce the next generation. Individuals with higher fitness scores are more likely to be selected, ensuring that better-performing solutions have a greater chance of continuing.
- Crossover in genetic algorithms, crossover is the process of merging genetic material from two parent solutions to create new offspring. This operation helps the algorithm explore areas of the solution space that have not been examined before.
- Mutation in genetic algorithms, mutation introduces small random changes to offspring, which helps keep the population diverse and prevents the algorithm from converging too soon. The main steps of the genetic algorithm are as follows:
- Initializations: A generates an initial population of candidate solutions randomly or based on prior knowledge.
- Fitness evaluation: Calculate the fitness value of each individual according to a predefined objective function.
- Selection: Select parent individuals based on fitness, commonly using methods such as roulette wheel selection or tournament selection.
- Crossover: Apply crossover operations to generate new offspring from selected parents.
- Mutation: Apply mutation to offspring to maintain diversity in the population. Replacement: Form the new generation by selecting individuals from parents and offspring.
- Termination: Repeat steps 2–6 until a stopping criterion is met, such as reaching a maximum number of generations or achieving a satisfactory fitness level [15].

GA is advantageous for its flexibility, robustness, and ability to escape local optima [16]. However, its performance heavily depends on parameter settings such as population size, crossover rate, and mutation rate, which need careful tuning [12].

2.4. Artificial neural networks

Artificial neural networks (ANN) are computational models inspired by the biological neural networks of the human brain. They are composed of interconnected processing elements, known as neurons, which work collectively to solve complex problems. ANNs are widely used in various domains such as forecasting, classification, and pattern recognition due to their capability to learn non-linear relationships from data without requiring explicit model assumptions [17], [18]. A typical ANN consists of three main layers:

- Input layer: Receives the input features of the dataset.
- Hidden layer(s): Perform non-linear transformations through weighted connections and activation functions.
- Output layer: Produces the final predictions or classifications.

The learning process in ANN involves adjusting connection weights through optimization algorithms such as gradient descent to minimize an error function (*e.g.*, mean squared error). This process is known as training. Once trained, the network can generalize patterns from the training data to predict unseen data [19], [20]. The main advantages of ANNs include their ability to approximate complex non-linear functions, adaptability to different types of data, and robustness to noise. However, they often require a relatively large dataset for effective training and may be prone to overfitting if not properly regularized [15], [17].

2.5. Recurrent neural network

Recurrent neural networks (RNNs) are a class of artificial neural networks designed to model sequential data by maintaining a hidden state that captures information from previous time steps. Unlike traditional feedforward networks, RNNs utilize recurrent connections, allowing past inputs to influence current outputs [21]. This makes them particularly effective for tasks such as time series forecasting, speech recognition, and natural language processing [20]. Mathematically, the hidden state h_t and output y_t at time step t are expressed as:

$$h_t = f(W_{xh}x_t + W_{hh}h_{t-1} + b_h), y_t = g(W_{hy}h_t + b_y)$$

where W_{xh}, W_{hh}, W_{hy} are weight matrices, b_h, b_y are bias terms, and $f(\,), g(\,)$ are activation functions. Despite their strengths, standard RNNs encounter challenges such as the vanishing gradient problem, which limits their ability to capture long-term dependencies. To overcome this, advanced variants such as long short-term memory (LSTM) and gated recurrent unit (GRU) have been introduced, enabling more effective modelling of long-range temporal patterns [22].

2.6. Long short-term memory networks

Long short-term memory (LSTM) networks, proposed by Hochreiter and Schmidhuber in 1997 [23], are an advanced variant of recurrent neural networks designed to overcome the vanishing and exploding gradient problems of standard RNNs. LSTMs introduce a memory cell and three gating mechanisms—input gate, forget gate, and output gate—which regulate the flow of information and enable the network to retain relevant information over long sequences while discarding irrelevant data [24]. At each time step *t*, the cell state C_t and hidden state h_t are updated as follows:

$$f_t = \sigma(M_f[a_{t-1}, b_t] + c_f), i_t = \sigma(M_i[a_{t-1}, b_t] + c_i), \widetilde{D}_t = tanh(M_C[a_{t-1}, b_t] + c_C)$$
$$Q_t = i_t \odot d_{t-1} + s_t \odot \widetilde{D}_t, o_t = \sigma(M_o[a_{t-1}, b_t] + c_o), a_t = o_t \odot tanh(Q_t)$$

where: σ is the sigmoid activation function, tanh is the hyperbolic tangent function, and $\odot$ denotes element-wise multiplication. LSTMs are widely applied in the time series a forecasting, the natural language a processing, and speech recognition due to their ability to capture both the short-term patterns and a long-term dependency in the sequential data. Their robustness makes them particularly effective in domains where relationships between inputs and outputs span long time intervals [23].

2.7. Errors analysis in neural networks

Assessing neural network performance, including RNNs and LSTMs, is crucial for obtaining accurate and reliable predictions. Common error metrics are mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) [22]. These metrics quantify prediction errors and guide adjustments to model parameters to enhance accuracy.

a. MAE: The average absolute difference between predicted and actual values; MAE is less affected by outliers than RMSE.

$$e_i = F_i - A_i$$

b. RMSE: Calculates the size of prediction errors by squaring the deviations from actual values before averaging, making it highly responsive to large errors.

$$MAE = \frac{1}{a}\sum_{i-1}^{a}|e_j|$$

c. MAPE: Calculates the average prediction error as a percentage, making it straightforward to interpret and communicate.

$$MAPE = \frac{1}{n}\sum_{i-1}^{n}\left|\frac{e_j}{A_j}\right| = \frac{1}{n}\sum_{i-1}^{n}\left|\frac{F_j - A_j}{A_j}\right|$$

This research applies MAE, MAPE, and RMSE to evaluate the LSTM-based forecasting models developed for predicting EV demand in Thailand. Using these metrics allows comprehensive testing and verification of the models, assuring the dependability of the forecasts produced [24], [25].

3. METHODOLOGY

This study employs a combination of advanced forecasting techniques, specifically the GA and the GM, to predict EV demand in Thailand. The GM-GA hybrid model was chosen due to its suitability for handling the unique challenges posed by the limited and non-linear data typical of emerging markets. The methodology is structured as follows to ensure clarity and logical flow.

3.1. Data collection

Data was sourced from the Automotive Information Center of Thailand, covering new vehicle registrations from January 2019 to December 2023, and updated information on EV charging stations as of April 2024. This comprehensive dataset provides a foundation for understanding the trends in EV adoption and the corresponding infrastructure needs. The decision to focus on this timeframe is justified by the significant growth in EV adoption during these years, making it critical for accurate forecasting.

3.2. Data cleaning

Data cleaning was performed to retain only information relevant to the forecasting models. This process involved discarding unnecessary records and selecting features associated with EV demand. The goal of cleaning is to minimize noise while highlighting factors that strongly influence the model's predictions. Maintaining clean and reliable input data is critical, as the accuracy of the forecasting models depends heavily on it.

3.3. Model generating

This study applied five forecasting models—ANN, RNN, LSTM, GM, and GM-GA—to predict EV demand in Thailand's data-limited and rapidly changing market. ANN modelled complex non-linear patterns as a baseline. RNN captured sequential trends, while LSTM improved long-term dependency modelling. GM generated forecasts from sparse data using differential equations. GM-GA optimized GM parameters with Genetic Algorithms, enhancing adaptability and accuracy. Together, these models provide a balanced approach that combines robustness, flexibility, and precision in challenging forecasting conditions.

3.4. Implementation of forecasting models

Five forecasting models—ANN, RNN, LSTM, GM, and GM-GA—were applied to predict EV demand in Thailand. ANN used a multilayer perceptron (MLP) with ReLU, trained via backpropagation and gradient descent. RNN modeled temporal dependencies through recurrent connections. LSTM improved long-term pattern capture using gated memory cells. GM forecasted from sparse data via a first-order differential equation. GM-GA optimized GM parameters with genetic algorithm operations, minimizing MAE. Together, these models offered complementary strengths for accurate forecasting in a data-limited emerging market.

3.5. Model evaluation

MAE, RMSE, and MAPE were used to evaluate LSTM-based models predicting EV demand in Thailand. MAE measures the average absolute difference between predicted and actual values, offering a simple accuracy indicator that is less sensitive to outliers. RMSE emphasizes larger errors, helping identify models with substantial deviations, which is important for EV infrastructure planning. MAPE represents errors as percentages, enabling comparison across different demand levels; lower values indicate more consistent predictions. These metrics provide a clear assessment of model performance, supporting reliable EV demand forecasting and guiding infrastructure decisions.

4. RESULTS

This section presents a summary of the forecasting results obtained from the models applied in this study, including ANN, RNN, LSTM, the conventional GM, and the grey model improved using a genetic algorithm (GM-GA). The predictive accuracy of these models for EV demand in Thailand was evaluated using three metrics: MAE, RMSE, and MAPE.

4.1. Optimizing a residual revised grey model using genetic algorithm (GM-GA)

A GM-GA hybrid model was developed to forecast EV registrations in Thailand by optimizing GM residuals with GA, combining GM's strength in limited data handling with GA's optimization capability. The convergence of this optimization process is illustrated in Figure 1, which demonstrates how the genetic algorithm minimizes the objective function over iterations. The performance metrics were: MAPE=∞, MAE=0.000000136, and RMSE=0.000000489, the lowest among all models. This demonstrates that GA significantly enhanced GM's accuracy, making GM-GA highly effective for the data-scarce and dynamic Thai EV market, and far outperforming machine learning models.

4.2. Comparative analysis of models

As shown in Table 1, the findings reveal that the GM-GA model provides the most accurate predictions of EV demand in Thailand among the evaluated methods. The integration of a genetic algorithm was crucial for tailoring the grey model to the market's specific characteristics. In contrast, the ANN, RNN, and LSTM models, while performing well with large datasets, produced higher error values and were therefore less suited for this particular forecasting scenario.

From Table 1, the GM-GA model achieved the highest accuracy among all models, with MAE=0.000000136 and RMSE=0.0000004890965, far outperforming GA, LSTM, RNN, and ANN. Its superior performance is due to GA's optimization of GM parameters, effectively minimizing forecasting errors. This is especially valuable for Thailand's EV market, where data is limited and conditions change rapidly. The GM-GA model not only met but exceeded the study's objective of accurate EV demand forecasting, providing precise results crucial for infrastructure planning and policy-making. The findings underscore the benefits of integrating optimization techniques, including GA, with traditional models to improve adaptability and predictive accuracy in developing markets.

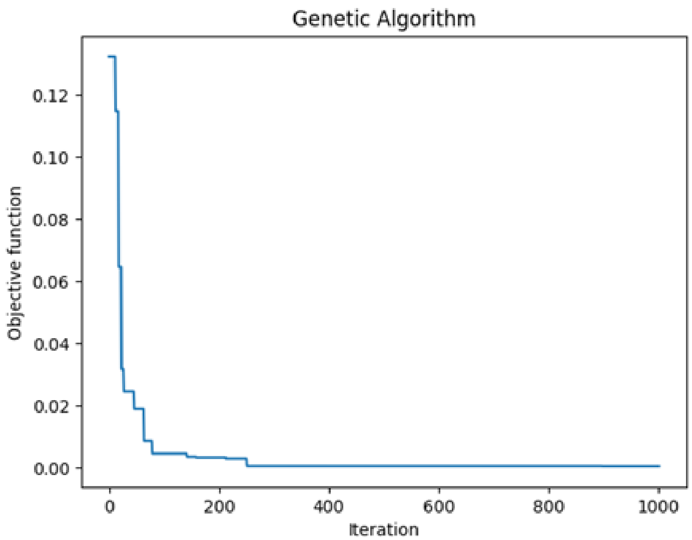

Figure 1. The convergence curve of the genetic algorithm optimization showing the minimization of the objective function

Table 1. Summary of model performance metrics

Algorithm	MAPE	MAE	RMSE
LSTM	inf	286.97	1183.24
RNN	inf	277.832	1208.928
ANN	inf	221.34965	1222.528
GM	Inf	176.69596	186.53869
GA	Inf	0.0016025	0.003126
GM-GA	inf	0.000000136	0.0000004890965

5. DISCUSSION

The research developed and evaluated a forecasting model for EV demand in Thailand, a market with limited historical data and rapidly evolving conditions. The grey model enhanced with a genetic algorithm (GM-GA) was applied to address these challenges, and its performance was compared with other commonly used forecasting approaches. Results demonstrated that the GM-GA model achieved higher predictive accuracy, providing a reliable tool for EV demand estimation. The discussion highlights implications for the automotive and energy sectors, potential applications beyond the EV market, and study limitations, while suggesting directions for future research.

5.1. Broader implications for the industry

The findings have major implications for Thailand's automotive and energy sectors. The GM-GA model provides highly accurate EV demand forecasts, guiding infrastructure planning, including charging station placement, to match the pace of EV adoption. For manufacturers, it supports production planning and prevents over- or under-supply. Energy companies can prepare the grid for rising demand, while policymakers can craft regulations and incentives that drive strategic growth in EV infrastructure, contributing to national and global sustainability goals.

5.2. Potential applications of the research

Beyond EVs, the GM-GA model can be applied in industries that require accurate forecasts with limited data, such as renewable energy (solar and wind), healthcare technology adoption, and consumer electronics. In urban planning, it can project demand for smart city innovations like electric buses or autonomous vehicles, enabling infrastructure investments that align with future needs and technological advancements.

5.3. Limitation

While the GM-GA model showed superior accuracy, it faces limitations. Its performance depends on data quality and availability, which can be a challenge in markets like Thailand with limited EV adoption history. The integration of GA increases computational complexity, posing issues for real-time use in resource-constrained settings. Its adaptability to other forecasting tasks remains untested, and integrating GA with other models could further improve accuracy. Future research should address these limitations by testing in diverse markets, optimizing computation, and refining long-term forecasting capabilities.

6. CONCLUSION

This study developed an optimized grey model with genetic algorithm (GM-GA) to forecast EV demand in Thailand. The GM-GA outperformed ANN, RNN, LSTM, and standard GM, achieving the lowest MAE and RMSE, making it the most reliable for data-limited markets. Its accuracy supports infrastructure planning, policy development, and energy grid management. Beyond EVs, GM-GA shows potential for other industries in data-scarce environments. Refining this model can further enhance its applicability, contributing to sustainable transportation and broader demand forecasting advancements.

While the GM-GA model showed exceptional accuracy in forecasting EV demand in Thailand, future research should test its applicability in diverse markets—both developed and emerging (*e.g.*, India, Brazil, and South Africa)—to assess adaptability under varying adoption rates, infrastructure levels, and policy support. Extending the forecasting horizon to 10–20 years and incorporating scenario analysis on factors like technology, policy, and energy prices could enhance strategic planning. Integrating user behavior data from surveys and social media may further refine predictions. These directions would strengthen the GM-GA model's robustness, ensuring its relevance for dynamic and diverse forecasting environments.

ACKNOWLEDGMENT

Thank you to the Automotive Information Center website and the Office of Vehicle Registration and Tax Standards (OBEC) for supporting this research by providing access to data and information on the history of electric cars, as well as details about electric vehicles and charging stations. Special thanks to the Pea Volta, Evolt, EA Anywhere, Elexa, Mea EV, and PTT EV Station apps for assisting in locating and providing information on electric car charging stations throughout Thailand.

FUNDING INFORMATION

Authors state no funding involved.

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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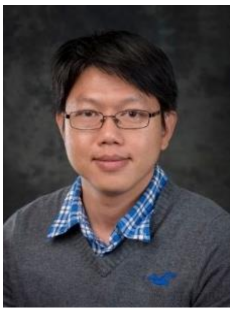

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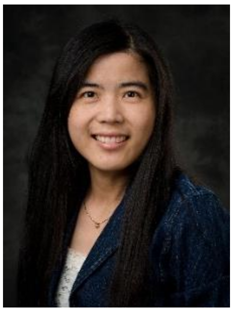

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