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RESEARCH ARTICLE

A Mathematical Model-Based Integrated Decision-Making Approach for Lithium Battery Manufacturers Evaluation

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ABSTRACT Today, the transportation industry contributes significantly to greenhouse gas emissions-roughly 23% of worldwide emissions. Battery electric vehicles (BEVs) are a viable technical option since they have the ability to drastically cut emissions (e.g., up to 70% compared to gasoline automobiles). Lithium-ion batteries, the fundamental component of BEVs, are essential to the efficiency and performance of the vehicle. Nevertheless, it might be difficult to make the best decision given the wide range of battery producers. In order to close this gap, eleven of the top producers of lithium batteries (e.g., Tesla, Ford and Toyota) were assessed for their 2019-2021 performance. We evaluate battery performance using both the Ordinal Priority Approach (OPA) and Malmquist productivity index (MPI). According to the results, Ford, BMW, and Tesla had the greatest average MPI efficiency. Conversely, Toyota, Hyundai, and Mercedes-Benz secured the highest positions among lithium-battery manufacturers in the OPA rankings. Through the use of these methodologies, we aim to provide comparative rankings that will eventually help promote sustainable mobility by giving decision-makers, investors, consumers and other stakeholders an overview for well-informed battery selections.

INDEX TERMS Ordinal priority approach, lithium battery, decision-making, Malmquist, data envelopment analysis.

I. INTRODUCTION

At the ''Earth summit,'' 172 national governments decided to work together to make eco-efficiency a guiding principle, starting the transition towards a more sustainable world. Specifically, the transportation network was prioritized to minimize automobile emissions, urban traffic jams, and health issues stemming from air pollution and smog [1]. In relation to greenhouse gas emissions, transportation is especially important: The transportation industry was responsible for 14% of global greenhouse gas emissions in 2010, according to the IPCC's Fifth Assessment Report.; concurrently, in 2010 the final energy used for transportation accounted for 28% of all end-use energy. Since 1970, the transportation industry's greenhouse gas (GHG) emissions have more than doubled and are rising faster than those of any other energy end-use sector. Approximately 80% of this rise is attributable to automobiles [3]. Even more concerning is the prediction that, globally, the number of passenger kilometers would more than triple between 2010 and 2100, while the number of freight kilometers may rise by a factor of 3.5 during same time [2]. The battery electric vehicle (BEV) offers the automotive industry a technological solution in this scenario. Energy efficiency may increase fourfold if a car with a combustion engine is converted to an electric one [4]. A prospective solution for significantly lowering emissions from road transportation is the electric car. This is a crucial component in lowering air pollution, noise pollution, and carbon dioxide (CO2) emissions from passenger automobiles and light commercial vehicles [5]. Thus, a broad adoption of electric cars might save most of the total energy consumption in the EU-27's transportation sector by 2050, according to the

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German Advisory Council on Global Change [6]. The trend of shifting to using electric cars to replace fossil fuel vehicles in the future is inevitable.

Electric car batteries are considered as the core technology of the electric vehicle industry. With electric cars, the battery is the ''soul'', the core technology of electric vehicle design, accounting for a large proportion of the selling price of electric cars as well as requiring a high level of science and technology. The choice of battery is an important factor when choosing an electric vehicle. So far, there have been many articles referring to the evaluation of different types of batteries. but there are no comparative reviews of different manufacturers. Therefore, the article selects the topic ''A Mathematical Model-Based Integrated Decision-Making Approach for Lithium Battery Manufacturers Evaluation'' in which the goal of this study is to give customers an open and data-driven platform to evaluate electric vehicles according to the efficiency and longevity of their batteries. This might enable customers to choose the vehicle that best fits their demands and budget with greater knowledge. This research will use a Malmquist productivity index (MPI) methodology to assess the performance of ten lithium battery manufacturers (LBM) with an emphasis on their performance from 2019 to 2021 and the Ordinal Priority Approach (OPA) model, which is predicated on experts' comparative evaluations of the factors involved in choosing batteries for electric cars. To determine opportunities for development for the remaining manufacturers and to highlight efficient manufacturers, MPI is an appropriate tool for comparing the relative efficiency of units with many inputs and outputs. In contrast in OPA, experts would use pairwise comparison to explain the relative relevance of various elements, such as energy density or safety, rather than numerical weights. Wherein MPI's quantitative analysis is supplemented by OPA to include qualitative factors of battery selection. Next, to get the best outcomes, graph the comparison of businesses using the ranking order from the previous two ways. Therefore, the main contribution of this paper is presented as follows:

- The aim of this study is to provide an overview of a combined technique that makes use of both qualitative (Ordinal priority approach) and quantitative (Malmquist productivity index) evaluations. When compared to other approaches that just use quantitative or qualitative assessment, this integration provides a more comprehensive review.
- The research focuses on comparing and ranking lithium battery manufacturers themselves, rather than just evaluating individual batteries. This manufacturer-centric approach provides valuable insights for consumers choosing EVs based on the battery technology behind them.
- The goal of creating an open and data-driven platform for evaluation adds to the novelty. This transparency and accessibility could empower consumers to make informed choices based on real-world data and expert opinions.

The structure of the study is as follows. The study's authors assess relevant research on DEA models and their applications in the manufacturing sector in Section II. An overview of the DEA Malmquist and Ordinal priority approach is included in Section III's analysis of methodology. The authors utilize the case study of lithium battery producers in Section IV to illustrate the efficacy testing of the recommended approach in the aviation industry. We summarize our findings, highlight the study's shortcomings, and make suggestions for more research in Section V, which concludes the article.

II. LITERATURE REVIEW

The first and most evident advantage of electric cars is their environmental friendliness. This car produces no emissions, which lessens pollution and its negative effects on the environment. Driving an electric car will help to ensure that the air is cleaner, there is less pollution, and global warming is decreased [7]. In heavily crowded metropolitan areas, electric cars are also a great mode of transportation [8]. Modern electric vehicle models are suitable for usage in highly populated, heavily used roadway systems, such as those seen in Vietnam. You may drive more simply and conveniently across the city if you own an electric vehicle. Electric cars just require electrical energy to run; they do not require a motor [9]. Electric cars' structural layout includes fewer parts that are connected to the internal combustion engine system, which lowers repair costs in the event of a malfunction [10], [11]. It will not be necessary for users to bother with oil filters, spark plugs, oil changes, or other equipment. The appraisal of electric vehicles has since been brought up by other writers, including Factors of electric car adoption: An expanded theory of planned behavior is used to compare the use of conventional and electric cars. Based on online surveys conducted in Denmark and Sweden, this study analyzes the sociodemographic profiles, attitudinal profiles, and mobility patterns by S Haustein of users of conventional vehicles (CV) and users of battery-electric vehicles (BEVs) [12]. In order to predict the use intention of an electric car, Moons et al. break down the theory of planned behavior through multi-group comparisons and an investigation of how usage intention determinants vary amongst consumer groups with varying levels of environmental consciousness, inventiveness, and personal values [13]. Electric vehicle charging infrastructure (EVCI) can significantly reduce carbon emissions in China by integrating with the circular economy and energy transition, as demonstrated by G Li et al.'s research. This is because EVCI performance can be mitigated by making use of resources and energy structures [14].

The battery is the part that provides power for all electric vehicle operations [15], [16]. Therefore, the battery is also one of the factors that customers often pay attention to when choosing and using green vehicles [17], [18]. To improve the user experience, electric vehicle manufacturers are constantly improving technology, so the battery standards for electric cars are also improved [19], [20]. Also, to improve travel distance, ensure operating safety and optimize costs. There are a lot of people who are considering bringing up the issue of evaluating the performance of lithium battery manufacturers for electric vehicles. For example, Andreas Poullikkas et al In Sustainable Options for Electric Vehicle Technology provides an overview of EV technology and related charging mechanisms [21].

In order to create plans, policies, programs, and financial judgements, decision-making is vital. Haseli et al. demonstrated how multi-criteria decision making in green finance may be best distribute resources to the projects that authorities prioritize those that are economically viable, socially acceptable, and environmentally friendly [49]. Also, another notable study for decision-makers with the use of Fuzzy-ZE numbers were able to address in Mexico City invest and improve the condition of the urban transportation system that would result less greenhouse gas emissions and utilizing renewable energy [50]. In their evaluation of the efficiency of lithium-ion batteries in electric vehicles, Barić et al. examined a number of areas that can be assessed using CBA and MCDM methods, including risk assessment, materials supply issues, recycling procedures, optimal technology selection, optimal energy storage systems, efficiency testing, and EV charging location selection [52]. Tang et al. carried out a study comparing the use of EVs and internal combustion engines (ICEVs) in China's various provinces by using a two-stage DEA. In which the study's findings showed that EVs' wheel-to-wheel carbon emissions are generally lower than ICEVs'. That provinces in China with a high hydropower and high degree of power autonomy could modify the amount of thermal power and inter-provincial power transmission to improve environmental sustainability without affecting the environmental efficiency of the provinces [53]. However, most studies do not evaluate the growth of battery companies for electric vehicles year over year, nor do they give consumers a more objective view of the comparison between manufacturers battery output. Various techniques exist for doing performance analysis, including ratio analysis, data packaging analysis (DEA), performance pyramid, analytical hierarchical process (AHP), stochastic frontier analysis (SFA), and variable factor productivity (VFP). In which, the DEA method in calculating and estimating the (technical) efficiency of businesses, banks, schools (collectively referred to as units) Decision Making Unit lithium battery manufacturers (LBM) in the use of input resources to produce outputs [22]. Such efficiency measurement is based on the method of frontier analysis, whereby the most efficient LBMs will establish a production frontier. and the LBMs will be compared with this limit line to determine if they are operating efficiently. For efficient LBMs, since they lie on the limit line, their technical efficiency score (TE) is equal to 1. For less efficient LBMs (within the limit line), their efficiency scores will be smaller [22]. DEA is a linear programming method for measuring the effectiveness of multiple decision-making units (LBMs) as a process. production presents the structure of multiple inputs and outputs [23]. The main advantage of this approach is its ability to accommodate multiple input and output multiples. It is also useful because it considers proportional returns in efficiency calculations, allowing the concept of increasing or decreasing efficiency based on output size and level. One drawback of this technique is the specification of the model and the inclusion/exclusion of variables that could influence the results [24].

However, using the DEA can only provide a quantitative assessment of the annual development specifications of the LBMs. But to be able to evaluate product selection, it is still necessary to pay attention to many external factors of the product. The authors proposed the Ordinal priority approach (OPA) to weighing the selected criteria by experts. OPA is a multi-criteria approach of decision analysis that facilitates collective decision-making on the basis of priority relationships [25], [26]. Rather than utilizing pairwise comparison matrices, the OPA approach has been introduced in recent years to tackle multi-criteria decision-making issues based on ordinal data [26], [27]. Experts might not be sufficiently knowledgeable on a particular approach judgment or set of criteria in real-world scenarios. Since the problem's input data is lacking in this instance, OPA's linear programming should incorporate it. Constraints pertaining to criteria or alternatives that should be eliminated from the OPA linear programming model in order to accommodate deficient input data in the OPA technique. As a result, the paper employed the DEA and OPA approaches concurrently in order to evaluate issues with manufacturer selection in an unbiased manner.

The sections that follow address efficiency measurement techniques that employ the Malmquist and Ordinal priority approach examining the productivity of lithium battery producers. The methodology section presents the procedures and data that were utilized to assess the companies. The outcomes of these investigations and their interpretations were offered in the last part in order to highlight the most efficient and effective manufacturer. For the relevant study, Table 1 shows the inputs, outputs, DMU, and application areas.

III. METHODOLOGY

This section presents the proposed methodology as a parallelly integrated process of DEA Malmquist and OPA models shown in Fig 1. The goal of this study is to assess ten lithium battery producers' efficiency for electric vehicles between 2019 and 2021. Accordingly, the revenue-leading LBMs are considered to perform both qualitative and quantitative efficiency assessments.

In terms of quantitative assessment, firstly, the DEA model's inputs and outputs are determined. Based on the databases, the values of the inputs and outputs are collected. Then Pearson's formula is applied to calculate the correlation among inputs and outputs. Accordingly, the selected inputs and outputs should be isotropic. It implies that the inputs and outputs both increase or decrease together. Otherwise, the input/output selection process is repeated.

TABLE 1. Overview of the methodology and relevant research.

Paper	DMUs	Methodologies	Applied areas
Tang et al. (2023) [53]	30 Provinces in China	Life-Cycle Analysis and Two-Stage DEA	Evaluation of vehicle environmental efficiency
Lee et al. (2023) [51]	6 European Countries	Slack-based model DEA	Energy efficiency evaluation of ICE and EV
He-Boong Kwon 2014 [31]	8 Major Mobile Phone companies	DEA and Back propagation neural networks	Relative effectiveness of the main mobile phone operators
Yang et al. (2016) [32]	35 E-Commerce Firm	CCR and BCC	Operational effectiveness of e-commerce companies
Ko et al. (2017) [33]	32 Domestic retail stores	CCR and Tobit Regression	Comparative effectiveness of South Korea's retail chain
Shah et al. (2019) [34]	33 Sustainable and 247 Non-Sustainable Banks	CCR, BCC and Malmquist	Productivity performance of both sustainable and non-sustainable banks
Wang et al. (2020) [35]	10 US E-Commerce companies	Grey model and Malmquist	Performance Efficiency of USs biggest e-commerce firms
Wang et al. (2021) [36]	18 Commercial banks	Malmquist and Window model	Vietnam's commercial banking system performance
Fang, Chin-Yi, and Pao-Yu Jessie Peng[37]	34 Menu Items	Meta-Frontier DEA and SBM	Teppanyaki restaurant operational effectiveness
This paper, 2023	10 Electric Vehicle Lithium Battery Manufacturers	Malmquist and Ordinal Priority Approach	Evaluation of Lithium Battery Companies

Next, the Malmquist model is applied to determine the efficiency of the LBMs. Their quantitative rank is established based on the Malmquist efficiency of the LBMs.

In terms of qualitative assessment, as a first step, a group of experts, who have expertise in the area under consideration, is identified. Because of the difference in expertise, experts are ranked. Based on expert recommendations as well as references, qualitative efficient evaluation criteria for LBMs are determined. In the next step, ordinal judgments of the criteria are provided by each expert. Simultaneously, each

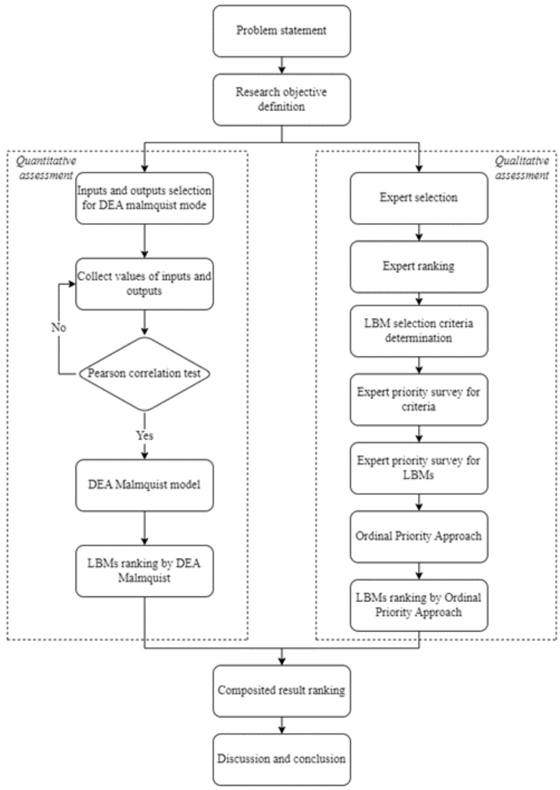

FIGURE 1. Proposed framework.

expert provides ordinal judgments of efficiency among LBMs according to each criterion. Finally, the experts' ranking and their ordinal judgments are applied to the OPA model. The solution of the OPA model provides optimal weights of experts, criteria, and LBMs simultaneously. Their qualitative rank is established based on the optimal weights of the LBMs.

In the last stage, quantitative and qualitative ranking results are integrated to classify LBMs. Based on the classification results, discussions, and recommendations for groups of LBMs are provided.

A. VALIDATION OF THE DATA

Ensuring that every input and output utilized for analysis has a good correlation is essential before utilizing the DEA Malmquist. In order to confirm that this requirement is satisfied, the Pearson correlation test was initially employed. The link between the input and output variables is said to be closer when the correlation coefficient is higher, and less so when it is lower [36]. where n denotes the sample size, x_I, $y_I$are the individual points indexed i, lastly the $\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_I$ is the sample mean and analogous for $\overline{y}$.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \quad (1)$$

B. MALMQUIST MODEL

The Malmquist productivity index (MPI) assesses a DMU's performance across two set periods of time. Equations (2) through (4) show that the efficiencies of the DMUs is assessed from t to period t+1 and is composed of three components: technical efficiency change (catch-up index, $(CP)^{t\rightarrow t+1}$), technological change (frontier-shift, FS_t^{t+1}), and Malmquist productivity index ($(MP)^{t\rightarrow t+1}$), [36], [46]. where $MP_t^{t+1} > 1$ indicates that operational efficiency increased, $MP_t^{t+1} < 1$indicates that operational efficiency decreased, and $MP_t^{t+1} = 1$ indicates that there has been no change in operational efficiency.

$$CP^{t\rightarrow t+1} = \frac{\frac{OZ_{t+1}^{t+1}}{OZ^{t+1}}}{\frac{OZ_t^t}{OZ^t}} = \frac{TSE^{t+1}}{TSE^t} \tag{2}$$

$$\begin{aligned} FS_t^{t+1} &= \left[\frac{\frac{OZ_t^t}{OZ^t} \times \frac{OZ_t^{t+1}}{OZ^{t+1}}}{\frac{OZ_{t+1}^t}{OZ^t} \times \frac{OZ_{t+1}^{t+1}}{OZ^{t+1}}}\right]^{0.5} \\ &= \left[\frac{TSE^t}{TSE^{t+1}} \times \frac{IEI^{t+1\rightarrow t}}{IEI^{t\rightarrow t+1}}\right]^{0.5} \end{aligned} \tag{3}$$

$$\begin{aligned} MP_t^{t+1} &= C^{t\rightarrow t+1} \times F_t^{t+1} \\ &= \frac{TSE^{t+1}}{TSE^t} \times \left[\frac{TSE^t}{TSE^{t+1}} \times \frac{IEI^{t+1\rightarrow t}}{IEI^{t\rightarrow t+1}}\right]^{0.5} \\ &= \left[\frac{TSE^{t+1}}{TSE^t} \times \frac{IEI^{t+1\rightarrow t}}{IEI^{t\rightarrow t+1}}\right]^{0.5} \end{aligned} \tag{4}$$

C. ORDINAL PRIORITY APPROACH

Ataei et al. presented the OPA, a newly developed MCDM technique, in 2020. This approach to MCDM problem solving is based on ordinal relations and linear programming. The OPA is recognized by researchers as an effective, objective, and flexible method. The distinct advantages of this method are that it does not require the normalization procedure, pairwise comparisons, and data completeness. Shown in Table 2 displays the set, parameters, and decision variables of the OPA mathematical model used in this investigation.

TABLE 2. The OPA method's sets, parameters, and variables.

Sets	
I	Set of experts $\forall i \in I$
J	Set of criteria $\forall j \in J$
Indexes	
p	Index of the experts $(1, \ldots, k)$
j	Index of the criteria $(1, \ldots, m)$
Variables	
Z	Objective function
w_{pj}^r	Weight (importance) of jth criterion by pth expert at rth rank

The procedure for weighting the criteria using OPA in this study includes the following steps:

Step 1: Identify a group of experts or decision-makers. Because their expertise is different, experts are ranked by ordinal numbers based on level of education and years of experience.

Step 2: The criteria are prioritized by each expert.

Step 3: Based on the ordinal judgments in steps 1 and 2, the mathematical model (5) is developed and solved.

Where Z: Unrestricted in sign

$$\begin{aligned} &\text{Maximize } Z \\ &s.t.:\ Z \leq p\left(j\left(w_{pj}^r - w_{pj}^{r+1}\right)\right) \quad \forall p, j, r \\ &\quad Z \leq pjw_{pj}^j \quad \forall p,\ j \\ &\quad \sum_{p=1}^{k}\sum_{j=1}^{m} w_{pj} = 1 \\ &\quad w_{pj} \geq 0 \quad \forall p, j \end{aligned} \tag{5}$$

After solving Model (5), the criteria and expert's weights are determined using following Equations (6)-(7):

$$w_j = \sum_{p=1}^{k} w_{pj} \forall j \tag{6}$$

$$w_p = \sum_{j=1}^{m} w_{pj} \forall p \tag{7}$$

IV. CASE STUDY

A. DATA ENVELOPMENT ANALYSIS (DECISION-MAKING UNITS SELECTION)

This study evaluates the effectiveness and productivity of the top ten producers of lithium batteries for electric vehicles between 2019 and 2021 as shown in Table 3. The study's dataset was gathered from the global stock market [38].

TABLE 3. List of decision-making units.

DMU	MANUFACTURERS
LBM-01	Toyota
LBM -02	Mercedes-Benz
LBM -03	Tesla
LBM -04	Volkswagen
LBM -05	BMW
LBM -06	Honda
LBM -07	Ford
LBM -08	Nissan
LBM -09	Volvo
LBM -10	Hyundai

The DEA Malmquist model relies heavily on inputs and outputs to assess the effectiveness of LBM. To justify the choice of the financial variables in the paper's model, the authors looked at a large number of pertinent papers published over the last several decades. After a thorough study, the authors consider four inputs, namely cost of revenue, operating expense, Total Current Assets, and Total Non-Current Assets, while gross profit and total revenue are

TABLE 4. Statistical description of inputs in billion USD.

Period	Statistics	I1	I2	I3	I4
2019	Max.	203.490	33.124	187.463	300.608
	Min.	20.509	3.989	11.838	4.256
	Ave.	90.761	14.870	75.401	114.296
	St. Dev	59.848	8.888	56.234	92.810
2020	Max.	183.937	28.890	194.944	302.170
	Min.	24.117	4.636	12.222	21.456
	Ave.	85.022	13.383	75.013	121.415
	St. Dev	55.694	7.516	54.620	88.044
2021	Max.	202.959	31.288	200.347	328.261
	Min.	26.269	4.430	12.795	7.061
	Ave.	83.913	12.829	77.643	124.442
	St. Dev	54.376	7.371	58.562	102.548

TABLE 5. Statistical description of outputs in billion USD.

Period	Statistics	TNCA	GP	TR
2019	Max.		49.143	252.633
	Min.		4.069	24.578
	Ave.		20.409	111.171
	St. Dev		13.818	73.518
2020	Max.		38.947	222.884
	Min.		6.630	31.475
	Ave.		18.151	103.173
	St. Dev		11.744	67.247
2021	Max.		47.240	250.199
	Min.		7.356	34.616
	Ave.		20.608	104.521
	St. Dev		12.423	66.531

considered as output variables. As shown in Table 4 and Table 5, the statistical description of the input and output data.

Input factors:

- Cost of Revenue (I1): The total cost associated with producing and offering a good product or service to customers.
- Operating expenses (I2): expenses incurred by a firm in the course of its regular operations. Rent, equipment, inventory rates, marketing, wages, insurance, handling charges, and funds for research and development are all considered forms of operating expenditures.
- Total Current Assets (I3): The physical manifestation of components directly involved in production business activities (these components are also known as labor objects).
- Total Non-Current Assets (I4): The value of assets that are not reflected in the short-term assets. Long-term assets are assets with a maturity of more than 12 months at the reporting time.

Output factors:

- Gross profit (O1): Revenue less the cost of products sold is what is known as gross profit. It should be noted that other fixed and variable expenditures like rent, utilities, and payroll are not subtracted from gross profit.
- Total revenue (O2): The complete sales of goods and services multiplied by the pricing of goods and services results in the total sales of products and services.

B. ORDINAL PRIORITY APPROACH (CRITERIA SELECTION)

This selection of criteria plays an important role in the application of the OPA model. By referring to the relevant literature reviews on the quality evaluation criteria of lithium batteries for electric vehicles as shown in Table 6.

TABLE 6. List of previous studies on battery evaluation.

No.	Author (s)	Criteria	Topic
1	Junye Wang[39]	price, durability, and reliability	Barriers of scaling-up fuel cells: Cost, durability, and reliability
2	Maxwell Woody et al.[40]	new battery materials, longevity	Strategies to limit degradation and maximize Li-ion battery service lifetime - Critical review and guidance for stakeholders
3	Xuebing Han[41]	longevity	A review on the key issues of the lithium-ion battery degradation among the whole life cycle
4	Brian C. H. Steele[42]	price and durability	Materials for fuel-cell technologies
5	Jonathan W. Kimball[43]	price, size, reliability, and longevity	A System Design Approach for Unattended Solar Energy Harvesting Supply
6	Divya, K. C., and Jacob[44]	wattage, reliability	Battery energy storage technology for power systems—An overview
7	Xu, Lin, et al.[45]	Price, wattage, reliability	An Improved Optimal Sizing Method for Wind-Solar-Battery Hybrid Power System

From Table 6, checking the appropriate correlation between the criteria, the decision was made to choose four criteria including price, longevity, wattage, reliability. The definition of the criteria is clearly shown in Table 7.

V. RESULT ANALYSIS

A. FRONTIER-SHIFT ANALYSIS (TECHNOLOGICAL CHANGE)

The efficiency frontiers (technological change) of the LBMs between two time periods are expressed by frontier-shift indices, which also represent the LBMs' performance in light of numerous external factors including innovations, competition, technical development, and the regulatory and political environment.

According to Fig. 2, for the period of 2019-2021, all LBMs have a growing average Frontier-shift index. Volvo, Ford, and Honda have the highest average Frontier-shift index.

TABLE 7. Definition of each criterion.

Criteria	Definition
Price (C1)	The amount that must be paid for an item, or the monetary representation of that thing's value. In general, it refers to the sum of money that must be paid for a property, a service, or a thing. Commodity prices are often based on a value-centered variable.
Longevity (C2)	The stage shown throughout the process from product birth to disposal.
Wattage (C3)	A parameter displayed to the user to know exactly how much electricity the device consumes or how much electricity it will consume in a period of 1 month as a basis for calculating the amount of electricity to spend pay.
Reliability (C4)	A product that is likely to fail or fail within an instrument's time possible.

Meanwhile, Nissan and Volkswagen also have a growing average Frontier-shift index. But they have the lowest growth.

As shown in Fig. 2, all LBMs are developed in the period of 2019-2021. Of these Ford has the most stable technology performance in the period of 2019-2021. Ford achieved the highest Frontier-shift index in the period 2020-2021. Next, in the period of 2019-2021, Nissan is the LBM with the lowest Frontier-shift index. But by 2020-2021, Nissan has thrived, becoming the LBM with the fourth Frontier-shift index out of ten LBMs. Although BMW and Volkswagen are also developing, they are growing more slowly than other LBMs. In the period of 2019-2020 BMW and Volkswagen are the two LBMs with the highest growth among the ten LBMs. By the period of 2020-2021, BMW and Volkswagen are the two LBMs with the lowest Frontier-shift index among the ten LBMs. As a result, shown in Fig. 2 Ford and Volvo were the top performers, regularly showing high frontier-shift indices, while Nissan significantly improved its score from the lowest to the fourth highest, indicating potential for progress. Conversely, slower growth was seen by BMW and VW, which had a strong growth at first, followed by a fall in growth over the research period.

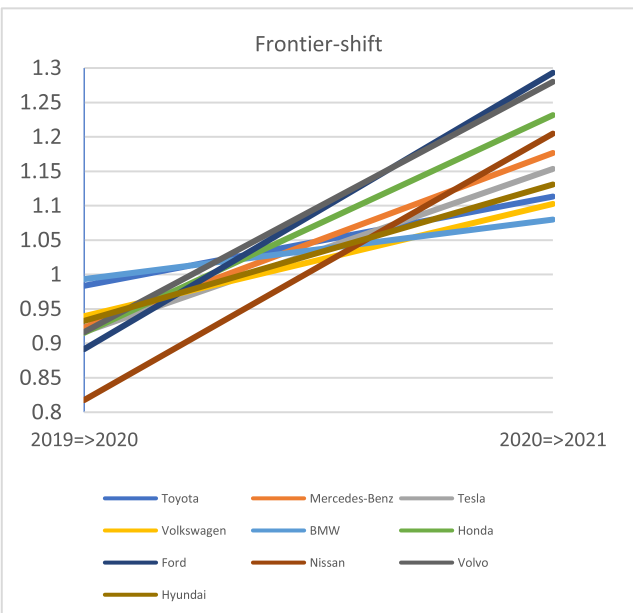

FIGURE 2. Technological change for the period 2019 to 2021.

B. CATCH-UP ANALYSIS (TECHNICAL EFFICIENCY)

As shown in Fig 3, which track the development indicators of lithium battery manufacturers over time, illustrates how the technological efficiency of LBMs has changed over time. If the catch-up index is greater than 1 (>1), then it corresponds to progress. Conversely, the catch-up index is less than 1 (<1), which corresponds to the regression of the technical efficiency of the LBMs.

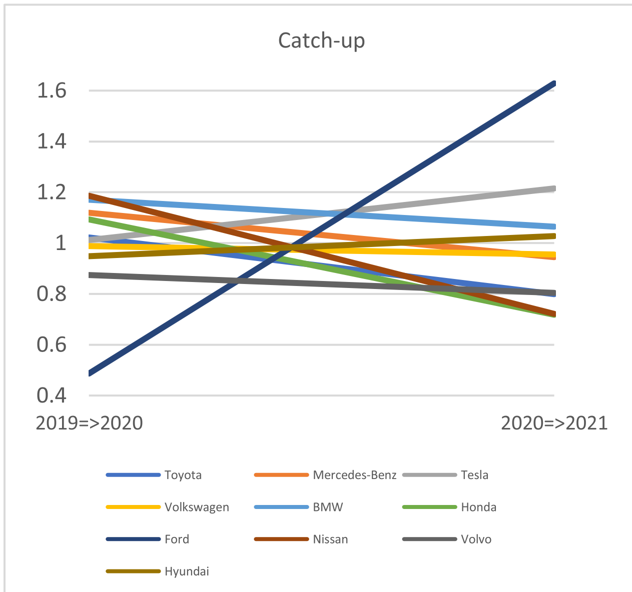

FIGURE 3. Technological change (catch-up).

The average catch-up index of LBMs for the 2019–2021 period is less than 1. The three LBMs that have improved their average technical efficiency the most between 2019 and 2021 are Ford, Tesla, and BMW. In contrast, Volvo, Honda, and Toyota were the LBMs with the least effective means of technical improvement.

From Fig. 3, we can see that in the period of 2019-2021, Ford and Tesla have the strongest growth fluctuations in the research period. Specifically, in the period of 2019-2020, Ford has the lowest catch-up index. But by the period 2020-2021, Ford has thrived, becoming the LBM with the highest catch-up index. Next, Tesla does the same, in the period of 2019- 2020, Tesla has an average catch-up index compared to the remaining LBMs. By the period 2020-2021, Tesla has risen to second place. In contrast, Honda and Nissan dropped the most. In the period of 2019-2020, Honda and Nissan have grown strongly. But in the period 2020-2021 Honda and Nissan fell sharply, with the lowest catch-up index compared to the remaining LBMs. As a result, shown in Fig. 3 Ford, Tesla, and BMW were the top improvers and show promising catch-up tendencies. In contrast, Ford and Tesla's swings indicate possible instability in their methods even if they reached high peaks, making them the volatile performers. Conversely, Honda and Nissan had rapid declines after their first rise.

C. MALMQUIST PRODUCTIVITY INDEX

The Malmquist Productivity Index (MPI) is presented in Fig 4 shows the firms' MPIs as they progressed through each phase. When MPI = 1 indicates the state of efficient production, MPI > 1 indicates highly efficient production, and MPI < 1 corresponds to loss of efficiency.

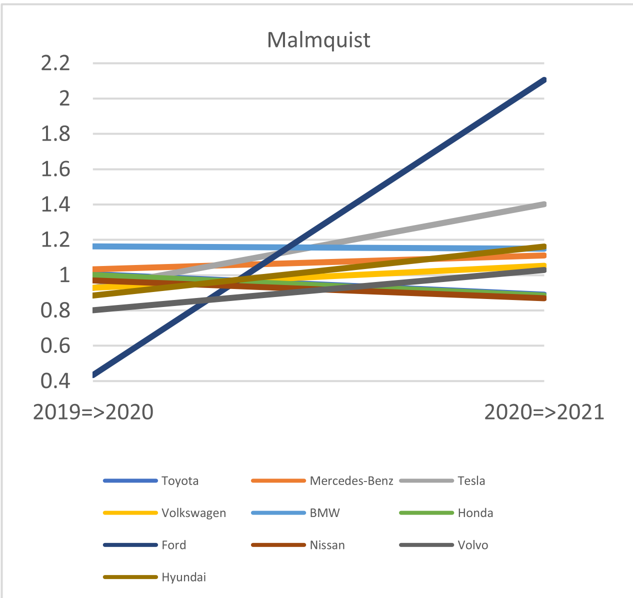

FIGURE 4. Total productivity change (Malmquist).

The results reveal that all LBMs have an average MPI greater than 1, which suggests that over the research period, the firms' production increased. The three firms with the highest average MPI are Tesla, BMW, and Ford. That these LBMs have demonstrated strong performance in terms of technological and technical efficiency. In contrast, Nissan and Volvo are the two companies with the smallest MPI compared to the remaining LBMs.

According to Fig 4, it seems that the development performance of companies is different. Specifically, in the period of 2019-2020, Ford is the company with an MPI of less than 1, the company with the smallest MPI of the ten LBMs. But by the period 2020-2021, Ford is the company with strong growth, with the largest MPI. Next is Tesla. In the period of 2019-2020, tesla is the company with MPI lower than 1. but in the period of 2020-2021, Tesla thrives to rise to the 2nd position compared to other LBMs. In contrast, Nissa is the LBM with the strongest downtrend. In the period of 2019-2020, Nissan has an MPI of less than 1. By the period of 2020-2021, Nissan continues to decrease, becoming the LBM with the lowest MPI. As a result, shown in Fig. 4 Tesla, BMW, and Ford are the best performers with continuously high average MPIs that lead to notable efficiency benefits. Nissan's ongoing downward trajectory, however, points to a lack of long-term viability.

D. ORDINAL PRIORITY APPROACH RESULT

In this application, the article presents a multi-criteria decision-making problem for consideration. We determine that price, longevity, wattage, reliability influence the choice of lithium battery manufacturing company. By constructing 10 different manufacturers (LBMs) and four criteria, experts from academia and related business fields were contacted and reviewed the literature for evaluation selection. Five experts were interviewed for a comparative assessment of the four criteria shown in Table 8.

TABLE 8. Experts' evaluation criteria ranking.

Expert	C1	C2	C3	C4
E1	1	2	3	4
E2	3	2	4	1
E3	1	4	3	2
E4	4	3	1	1
E5	4	2	3	1

As seen in Fig. 5, five experts have evaluated and compared the LBMs according to four criteria: price, longevity, wattage, and reliability. Their evaluations are based on impartial assessments and professional credentials. After the evaluator compares the criteria, and compares the LBMs based on four different criteria, this study uses the Ordinal Priority Approach model (5) to evaluate. Based on Fig. 6, price (31%) and reliability (29%), are the two factors that experts evaluate the highest. Next, two criteria longevity and wattage are compared equally at a 20% ratio.

As shown in Fig 7, the highest rated LBM is Toyota with a ratio of 0.131. Next, Hyundai (0.118) and Mercedes-Benz (0.115) are the highest ranked companies after Toyota. The lowest rated LBM is Nissan (0.06). The two nearly equally underrated LBMs on only Nissan are Ford (0.086) and Volvo (0.084). Based on the obtained results, we arrange the order of LBM. According to the study, choosing the finest LBM for the needs may be aided by taking into account factors like pricing, reliability, longevity and wattage. Based on expert judgment within this paradigm, Toyota comes out on top.

VI. DISCUSSION

According to Fig 8, we can see the ranking of the LBMs through two different evaluations. We use the results of that ranking from 1st to 10th to draw a diagram. The horizontal column is the ranking results of the LBMs based on the

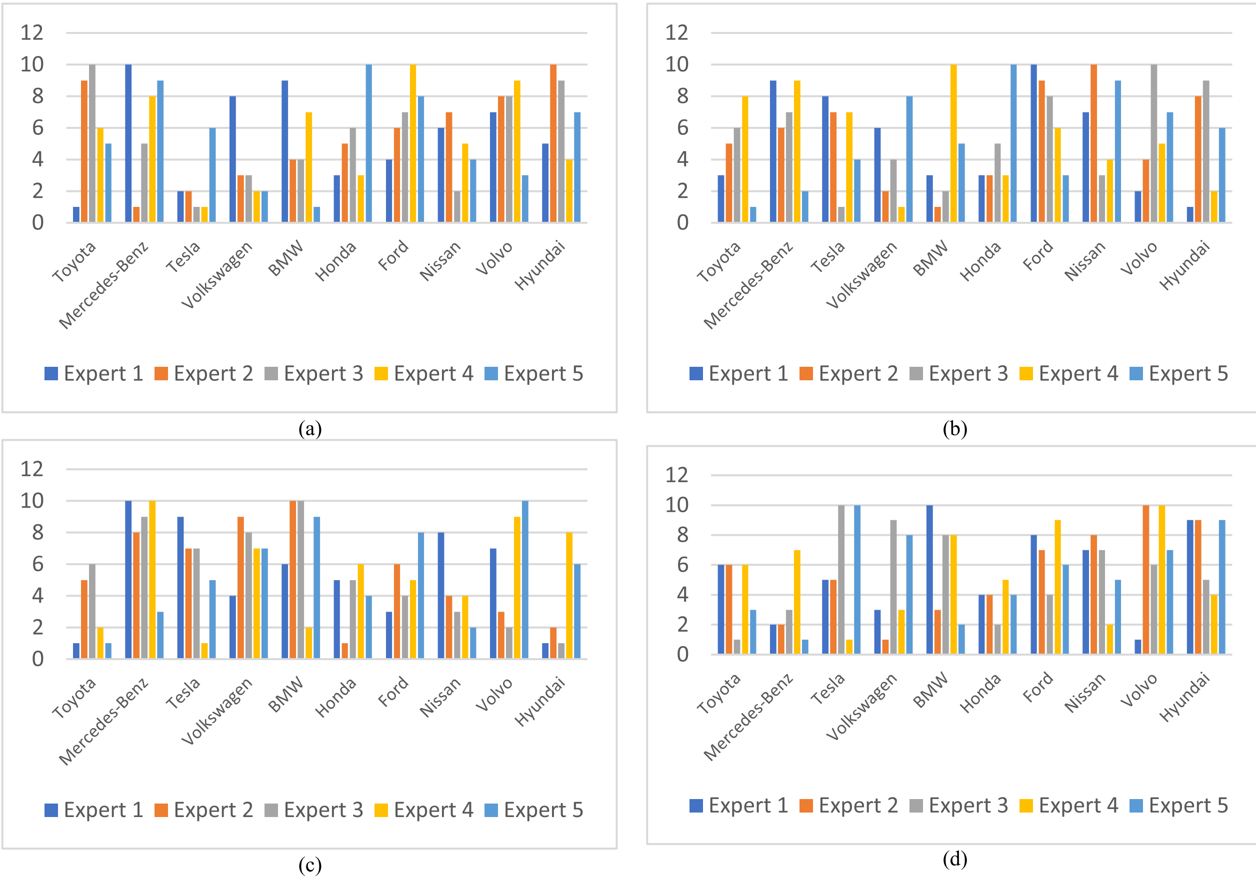

FIGURE 5. Expert survey for DMUs ranking according to criteria: (a) Wattage; (b) Longevity; (c) Price; (d) Reliability.

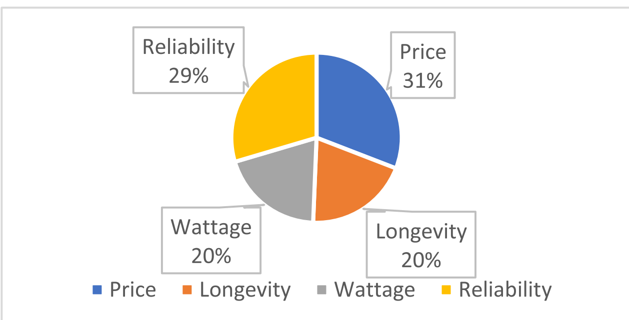

FIGURE 6. Criteria weights by OPA model.

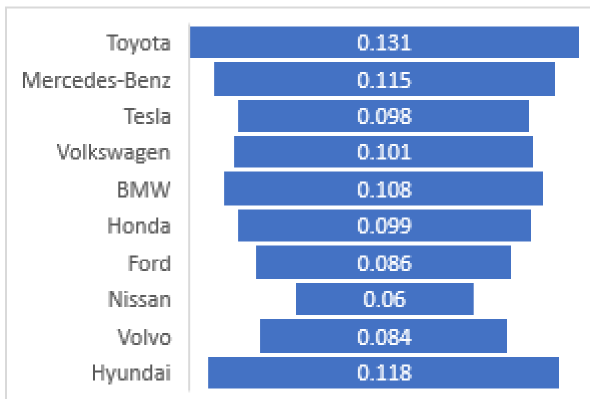

FIGURE 7. Evaluation of Lithium battery manufacturers.

Malmquist DEA method. Vertical columns are the result of ratings of the OPA model through expert judgment of experts. We have 10 LBMs in each vertical and horizontal column. Vertical column divided into 2 parts (reviewed by experts and not appreciated by experts). The horizontal column is divided into 2 parts (high performance and low efficiency).

As shown in Fig 8, we can see that BMW, Mercedes-Benz, and Hyundai are the options that are highly appreciated for their economic production efficiency and highly appreciated by experts (positive group). In contrast, Nisan, Volvo, and Honda are three options that are not appreciated in both aspects (expectation group).

In the remaining, Ford and Tesla are economic production companies with high efficiency but not highly appreciated by experts (new technical group). Volkswagen and Toyota are two companies that are highly appreciated by experts, but the eco-nomic and technical production results vary from year to year (high confidence group).

- Positive group: This group is highly appreciated in economic development, technical and expert assessment. But for partner companies and investors, it will be a challenge. because there are many competitors.

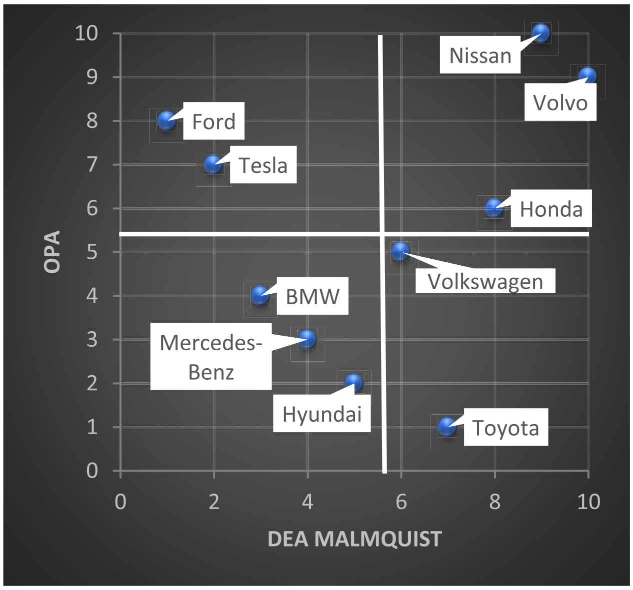

FIGURE 8. Evaluation of Lithium battery manufacturers.

- Expectation group: This is a group that is not appreciated in both aspects compared to other companies in the ten evaluated companies. but these are still three of the top ten companies by revenue in the field of battery production for electric vehicles. So, this is still a group with high expectations, and can still be considered when collaborating.
- Economic development group: This is a group highly appreciated in economic and technical development. investors, partner companies can pay attention to invest in these companies. but these companies are not appreciated by experts in the field of battery manufacturing for electric vehicles. Therefore, the company needs to consider more product development.
- High confidence group: This is the group that is highly rated by experts. but in the assessment of economic development, technology is not high. This is a challenge for companies in this group. They need to consider more development to have the appropriate direction. Customers may consider choosing this group more.

VII. CONCLUSION

In order to establish an adequate and feasible framework for the performance evaluation process of lithium battery manufacturers for electric cars, the main objective of the current study was to examine the performance of companies that create lithium batteries for electric vehicles. This was done by concentrating on two aspects that correspond to the two images in the study. In terms of methodology, the combined method used the above-mentioned advantages of DEA Malmquist and OPA models over classical models. Applying the suggested approach to a sample of ten corresponding lithium battery manufacturing companies in 2019–2021 is done using financial indicator data from the stock market: operating expenses, total current assets, total non-current assets, cost of revenue, gross profit, and total revenue (output variables). Using Malmquist indices, the productivity growth rate of operators over the 2019–2021 period is provided, and the results are used to rank companies according to their technological advancements during this time. This allows the Malmquist DEA model to investigate the pattern of efficiency changes over time. Conversely, the OPA model relies on the views and references of experts in the field. Next, each expert, ranked according to expertise, evaluates the impact's size using an ordinal scale. The OPA approach is then used to compute the weights of the effects. Consequently, this integrated strategy provides a more effective framework for managing and evaluating the operations and expansion of the business.

The study that is being presented provides information and useful applications to the field of performance monitoring in the lithium battery manufacturing sector. The results are significant because they help manufacturers comprehend and recognize key indications in the operations and expansion of their businesses. As a result, businesses may improve their technological and technical performance.

In conclusion, the primary contributions of this research may be summed up as follows: (1) By integrating the OPA model with DEA Malmquist, the study carried out a novel comparative evaluation of lithium battery manufacturers for electric cars. This method can calculate the rating index of LBM based on the objective assessments of various experts, which means that both internal and external aspects are analyzed and evaluated in a general way to get an overview. It can also measure the total relative productivity of LBMs in many stages—multiple input and output variables through technology assessment.; (2) findings from a case study that offers thorough and accurate information on the top ten lithium battery manufacturers for electric cars in recent years; (3) Based on the performance of a few profitable companies, the paper anticipates that the model findings will accurately depict the current state of lithium battery companies for electric vehicles. In order to help decision-makers, investors, and customers—as well as any business worldwide—improve their performance in the direction of sustainable development, this article might serve as a helpful guide.

However, the current studies has some limitations, the DEA is well recognized for assessing manufacturers' efficiency, in certain earlier instances, by using the bootstrapping technique can also employ to measure the inaccuracy in the estimations for future studies. By applying bootstrapping provides for sensitive analyses if scaling indicators and efficiency score sensitivities by sampling the original data many times [47]. On the other hand, the main issue with practically every MCDM technique is the standardization of incommensurable criteria, which is why the OPA method has so much flexibility in handling uncertainty in decision-making situations [48]. Future research should take into account more factors connected to numerous other factors in order to broaden the quantitative and qualitative criteria.

Enhancing the effectiveness towards sustainable development will greatly benefit from more study in this area. In the context of the future study, input and output factors requiring further evaluation include physical production and environmental variables. In addition, the ability to rank business units and compare the results using several multicriteria decision-making processes such as TOPSIS, AHP, VIKOR, and Fuzzy including other areas like efficiency testing, selection of EV charging location, in order to provide more precise and understandable results.

ABBREVIATION

DEA	Data Envelopment Analysis.
MPI	Malmquist Productivity index.
DMU	Decision making units.
OPA	Ordinal Priority Approach.
MCDM	Multi-criteria decision making.
LBM	Lithium Battery Manufacturers.
BEV	Battery Electric Vehicles.
EV	Electric Vehicle.
ICEV	Internal combustion engine vehicle.

REFERENCES

[1] C. Emelie, "United Nations conference on the environment after the Rio de Janeiro of 1992: It's implications for environmental protection," *Chukwuemeka Odumegwu Ojukwu Univ. J. Private Public Law*, vol. 2, no. 1, 2020.

[2] (2014). *Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change: Mitigation of Climate Change*. [Online]. Available: https://repository.uneca.org/handle/10855/22514

[3] O. Edenhofer, "Reforming emissions trading," *Nature Climate Change*, vol. 4, no. 8, pp. 663–664, Jul. 2014, doi: 10.1038/nclimate2327.

[4] K. Okajima, S. Shigaki, T. Suko, D.-N. Luong, C. H. Reyes, Y. Hattori, K. Sanada, and D. Kurabayashi, "A novel framework based on a data-driven approach for modelling the behaviour of organisms in chemical plume tracing," *J. Roy. Soc. Interface*, vol. 18, no. 181, Aug. 2021, Art. no. 20210171, doi: 10.1098/rsif.2021.0171.

[5] S. Brown, D. Pyke, and P. Steenhof, "Electric vehicles: The role and importance of standards in an emerging market," *Energy Policy*, vol. 38, no. 7, pp. 3797–3806, Jul. 2010, doi: 10.1016/j.enpol.2010.02.059.

[6] K. Brown, *Resilience, Development and Global Change*. Evanston, IL, USA: Routledge, 2015.

[7] C. Barbarossa, S. C. Beckmann, P. De Pelsmacker, I. Moons, and W. Gwozdz, "A self-identity based model of electric car adoption intention: A cross-cultural comparative study," *J. Environ. Psychol.*, vol. 42, pp. 149–160, Jun. 2015, doi: 10.1016/j.jenvp.2015.04.001.

[8] V. Viswanathan, D. Zehe, J. Ivanchev, D. Pelzer, A. Knoll, and H. Aydt, "Simulation-assisted exploration of charging infrastructure requirements for electric vehicles in urban environments," *J. Comput. Sci.*, vol. 12, pp. 1–10, Jan. 2016, doi: 10.1016/j.jocs.2015.10.012.

[9] K. T. Chau and Y. S. Wong, "Overview of power management in hybrid electric vehicles," *Energy Convers. Manage.*, vol. 43, no. 15, pp. 1953–1968, Oct. 2002, doi: 10.1016/s0196-8904(01)00148-0.

[10] F. Kley, C. Lerch, and D. Dallinger, "New business models for electric cars—A holistic approach," *Energy Policy*, vol. 39, no. 6, pp. 3392–3403, Jun. 2011, doi: 10.1016/j.enpol.2011.03.036.

[11] K. V. Singh, H. O. Bansal, and D. Singh, "A comprehensive review on hybrid electric vehicles: Architectures and components," *J. Mod. Transp.*, vol. 27, no. 2, pp. 77–107, Mar. 2019, doi: 10.1007/s40534-019-0184-3.

[12] S. Haustein and A. F. Jensen, "Factors of electric vehicle adoption: A comparison of conventional and electric car users based on an extended theory of planned behavior," *Int. J. Sustain. Transp.*, vol. 12, no. 7, pp. 484–496, Jan. 2018, doi: 10.1080/15568318.2017.1398790.

[13] I. Moons and P. De Pelsmacker, "An extended decomposed theory of planned behaviour to predict the usage intention of the electric car: A multi-group comparison," *Sustainability*, vol. 7, no. 5, pp. 6212–6245, May 2015, doi: 10.3390/su7056212.

[14] G. Li, T. Luo, and Y. Song, "Climate change mitigation efficiency of electric vehicle charging infrastructure in China: From the perspective of energy transition and circular economy," *Resour., Conservation Recycling*, vol. 179, Apr. 2022, Art. no. 106048, doi: 10.1016/j.resconrec.2021.106048.

[15] W. Kempton and S. E. Letendre, "Electric vehicles as a new power source for electric utilities," *Transp. Res. D, Transp. Environ.*, vol. 2, no. 3, pp. 157–175, Sep. 1997, doi: 10.1016/s1361-9209(97)00001-1.

[16] Y. J. Jang, "Survey of the operation and system study on wireless charging electric vehicle systems," *Transp. Res. C, Emerg. Technol.*, vol. 95, pp. 844–866, Oct. 2018, doi: 10.1016/j.trc.2018.04.006.

[17] W. Li, R. Long, H. Chen, and J. Geng, "A review of factors influencing consumer intentions to adopt battery electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 78, pp. 318–328, Oct. 2017, doi: 10.1016/j.rser.2017.04.076.

[18] F. Liao, E. Molin, and B. van Wee, "Consumer preferences for electric vehicles: A literature review," *Transp. Rev.*, vol. 37, no. 3, pp. 252–275, Sep. 2016, doi: 10.1080/01441647.2016.1230794.

[19] B. G. Pollet, I. Staffell, and J. L. Shang, "Current status of hybrid, battery and fuel cell electric vehicles: From electrochemistry to market prospects," *Electrochimica Acta*, vol. 84, pp. 235–249, Dec. 2012, doi: 10.1016/j.electacta.2012.03.172.

[20] E. Karden, S. Ploumen, B. Fricke, T. Miller, and K. Snyder, "Energy storage devices for future hybrid electric vehicles," *J. Power Sources*, vol. 168, no. 1, pp. 2–11, May 2007, doi: 10.1016/j.jpowsour.2006.10.090.

[21] A. Poullikkas, "Sustainable options for electric vehicle technologies," *Renew. Sustain. Energy Rev.*, vol. 41, pp. 1277–1287, Jan. 2015, doi: 10.1016/j.rser.2014.09.016.

[22] N. Dang-Thanh, "Huong Dan Su Dung Phuong Phap Phan Tich Bao Du Lieu Trong Excel (Vietnamese DEA add-in for Excel)," *SSRN Electron. J.*, Jan. 2015, doi: 10.2139/ssrn.2577136.

[23] G. Quang. (Jan. 1, 2006). *Evaluating Technical Efficiency Using the Data Envelopment Analyis Approach in Litchi Production in Bac Giang Province, Vietnam*. [Online]. Available: https://www.researchgate.net/publication/255711311_Evaluating_technical_efficiency_using_the_data_envelopment_analyis_approach_in_litchi_production_in_Bac_Giang_province_Vietnam

[24] S. C. Hui and M. C. Wan, "Study of hotel energy performance using data envelopment analysis," in *Proc. SET*. Hong Kong: Special Adminstrative Region of the People's Republic of China, 2013, pp. 26–29.

[25] Y. Ataei, A. Mahmoudi, M. R. Feylizadeh, and D.-F. Li, "Ordinal priority approach (OPA) in multiple attribute decision-making," *Appl. Soft Comput.*, vol. 86, Jan. 2020, Art. no. 105893, doi: 10.1016/j.asoc.2019.105893.

[26] M.-T. Le and N.-L. Nhieu, "A novel multi-criteria assessment approach for post-COVID-19 production strategies in Vietnam manufacturing industry: OPA-Fuzzy EDAS model," *Sustainability*, vol. 14, no. 8, p. 4732, Apr. 2022, doi: 10.3390/su14084732.

[27] A. Mahmoudi, S. A. Javed, and A. Mardani, "Gresilient supplier selection through fuzzy ordinal priority approach: Decision-making in post-COVID era," *Oper. Manage. Res.*, vol. 15, nos. 1–2, pp. 208–232, Mar. 2021, doi: 10.1007/s12063-021-00178-z.

[28] *Automotive Industry 2022 Ranking*. Accessed: Nov. 9, 2022. [Online]. Available: https://brandirectory.com/rankings/auto/table?fbclid=IwAR2XnRn1NYCfgtc-AGkG3jQLy_rMn8T88-efpfwUKSB37HPwrH9j21wB21k

[29] H.-H. Yang and C.-Y. Chang, "Using DEA window analysis to measure efficiencies of Taiwan's integrated telecommunication firms," *Telecommun. Policy*, vol. 33, nos. 1–2, pp. 98–108, Feb. 2009, doi: 10.1016/j.telpol.2008.11.001.

[30] W.-M. Lu and S.-W. Hung, "Exploring the efficiency and effectiveness in global e-retailing companies," *Comput. Oper. Res.*, vol. 38, no. 9, pp. 1351–1360, Sep. 2011, doi: 10.1016/j.cor.2010.12.009.

[31] H.-B. Kwon, "Performance modeling of mobile phone providers: A DEA-ANN combined approach," *Benchmarking, Int. J.*, vol. 21, no. 6, pp. 1120–1144, Sep. 2014, doi: 10.1108/bij-01-2013-0016.

[32] Z. Yang, Y. Shi, and H. Yan, "Scale, congestion, efficiency and effectiveness in e-commerce firms," *Electron. Commerce Res. Appl.*, vol. 20, pp. 171–182, Nov. 2016, doi: 10.1016/j.elerap.2016.07.003.

[33] K. Ko, M. Chang, E.-S. Bae, and D. Kim, "Efficiency analysis of retail chain stores in Korea," *Sustainability*, vol. 9, no. 9, p. 1629, Sep. 2017, doi: 10.3390/su9091629.

[34] A. A. Shah, D. Wu, and V. Korotkov, "Are sustainable banks efficient and productive? A data envelopment analysis and the Malmquist productivity index analysis," *Sustainability*, vol. 11, no. 8, p. 2398, Apr. 2019, doi: 10.3390/su11082398.

[35] C.-N. Wang, T.-T. Dang, N.-A.-T. Nguyen, and T.-T.-H. Le, "Supporting better decision-making: A combined grey model and data envelopment analysis for efficiency evaluation in e-commerce marketplaces," *Sustainability*, vol. 12, no. 24, p. 10385, Dec. 2020, doi: 10.3390/su122410385.

[36] C.-N. Wang, N.-A.-T. Nguyen, T.-T. Dang, and T.-T.-Q. Trinh, "A decision support model for measuring technological progress and productivity growth: The case of commercial banks in Vietnam," *Axioms*, vol. 10, no. 3, p. 131, Jun. 2021, doi: 10.3390/axioms10030131.

[37] C. Fang, P. J. Peng, and W. W. Pan, "Does using an à la carte or combo set menu affect the performance of a teppanyaki-style restaurant?" *Int. J. Contemp. Hospitality Manage.*, vol. 25, no. 4, pp. 491–509, May 2013, doi: 10.1108/09596111311322899.

[38] Morningstar. (2022). *Morningstar Database*. Accessed: Nov. 9, 2022. [Online]. Available: https://www.morningstar.com

[39] J. Wang, "Barriers of scaling-up fuel cells: Cost, durability and reliability," *Energy*, vol. 80, pp. 509–521, Feb. 2015, doi: 10.1016/j.energy.2014.12.007.

[40] M. Woody, M. Arbabzadeh, G. M. Lewis, G. A. Keoleian, and A. Stefanopoulou, "Strategies to limit degradation and maximize Li-ion battery service lifetime—Critical review and guidance for stakeholders," *J. Energy Storage*, vol. 28, Apr. 2020, Art. no. 101231, doi: 10.1016/j.est.2020.101231.

[41] X. Han, L. Lu, Y. Zheng, X. Feng, Z. Li, J. Li, and M. Ouyang, "A review on the key issues of the lithium ion battery degradation among the whole life cycle," *eTransportation*, vol. 1, Aug. 2019, Art. no. 100005, doi: 10.1016/j.etran.2019.100005.

[42] B. C. H. Steele and A. Heinzel, "Materials for fuel-cell technologies," *Nature*, vol. 414, no. 6861, pp. 345–352, Nov. 2001, doi: 10.1038/35104620.

[43] J. W. Kimball, B. T. Kuhn, and R. S. Balog, "A system design approach for unattended solar energy harvesting supply," *IEEE Trans. Power Electron.*, vol. 24, no. 4, pp. 952–962, Apr. 2009, doi: 10.1109/TPEL.2008.2009056.

[44] K. C. Divya and J. Østergaard, "Battery energy storage technology for power systems—An overview," *Electr. Power Syst. Res.*, vol. 79, no. 4, pp. 511–520, Apr. 2009, doi: 10.1016/j.epsr.2008.09.017.

[45] L. Xu, X. Ruan, C. Mao, B. Zhang, and Y. Luo, "An improved optimal sizing method for wind-solar-battery hybrid power system," *IEEE Trans. Sustain. Energy*, vol. 4, no. 3, pp. 774–785, Jul. 2013, doi: 10.1109/TSTE.2012.2228509.

[46] K. Tone, "Malmquist productivity index," in *Handbook on Data Envelopment Analysis* (International Series in Operations Research & Management Science). Boston, MA, USA: Springer, 2004, pp. 203–227, doi: 10.1007/1-4020-7798-x_8.

[47] S. Chaabouni, "China's regional tourism efficiency: A two-stage double bootstrap data envelopment analysis," *J. Destination Marketing Manage.*, vol. 11, pp. 183–191, Mar. 2019, doi: 10.1016/j.jdmm.2017.09.002.

[48] T. K. Quartey-Papafio, S. Islam, and A. R. Dehaghani, "Evaluating suppliers for healthcare centre using ordinal priority approach," *Manage. Sci. Bus. Decisions*, vol. 1, no. 1, pp. 5–11, Jul. 2021, doi: 10.52812/msbd.12.

[49] G. Haseli, M. Deveci, M. Isik, I. Gokasar, D. Pamucar, and M. Hajiaghaei-Keshteli, "Providing climate change resilient land-use transport projects with green finance using Z extended numbers based decision-making model," *Expert Syst. Appl.*, vol. 243, Jun. 2024, Art. no. 122858, doi: 10.1016/j.eswa.2023.122858.

[50] G. Haseli, S. R. Bonab, M. Hajiaghaei-Keshteli, S. J. Ghoushchi, and M. Deveci, "Fuzzy ZE-numbers framework in group decision-making using the BCM and CoCoSo to address sustainable urban transportation," *Inf. Sci.*, vol. 653, Jan. 2024, Art. no. 119809, doi: 10.1016/j.ins.2023.119809.

[51] J. Lee and J. Kim, "Are electric vehicles more efficient? A slacks-based data envelopment analysis for European road passenger transportation," *Energy*, vol. 279, Sep. 2023, Art. no. 128117, doi: 10.1016/j.energy.2023.128117.

[52] D. Barić, S. Grabušić, M. Jakara, and M. Emanović, "Reviewing the cost–benefit analysis and multi-criteria decision-making methods for evaluating the effectiveness of lithium-ion batteries in electric vehicles," *Sustainability*, vol. 16, no. 1, p. 233, Dec. 2023, doi: 10.3390/su16010233.

[53] G. Tang, M. Zhang, and F. Bu, "Vehicle environmental efficiency evaluation in different regions in China: A combination of the life cycle analysis (LCA) and two-stage data envelopment analysis (DEA) methods," *Sustainability*, vol. 15, no. 15, p. 11984, Aug. 2023, doi: 10.3390/su151511984.

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