



Electric Vehicle Range Prediction Models: A Systematic Review of Machine Learning, Mathematical, and Simulation Approaches

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Abstract

This review examines 80 research studies on electric vehicle (EV) range prediction published between 2013 and 2024. We categorized all studies into three methodological groups such as machine learning (ML), mathematical modeling (MM), and simulation modeling (SM). The analysis reveals a clear dominance of ML models (48.8% of studies), followed by simulation models (32.5%), mathematical models (12.5%), and hybrid models (6.2%). Among the ML techniques, Neural Networks (25%), Multiple Linear Regression (17.5%), and Decision Trees (16.25%) were the most frequently employed, highlighting the growing emphasis on data-driven and adaptive methods. While simulation techniques are most prevalent within MM studies. Hybrid models, which integrate multiple methods, are gaining popularity for improving prediction accuracy. We also reviewed performance metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) which reflect the diversity of evaluation strategies across the field. We highlight unsolved challenges including robust feature selection, real-time data integration, and battery degradation modeling. Finally, We suggest future research should focus on combining different modeling approaches, using more advanced data-driven methods, and improving reliability through data sharing and collaboration.

Keywords: electric vehicle; driving range; machine learning; simulation; hybrid model



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1. Introduction

The adoption of electric vehicles (EVs) is increasingly recognized as a critical strategy in combating global environmental challenges, particularly climate change and air pollution. Transitioning from internal combustion engine (ICE) vehicles to EVs can significantly reduce greenhouse gas emissions, offering a sustainable alternative for the future of transportation. In response, governments worldwide have implemented policies and incentives to promote the widespread adoption of EVs, acknowledging their potential to mitigate the harmful effects of fossil fuel consumption [1,2]. The growing global trend in EV adoption is supported by technological advancements, decreasing vehicle costs, and heightened consumer awareness regarding environmental issues [2].

Despite the positive trajectory in EV adoption, several challenges remain, particularly regarding the accurate estimation of vehicle range and addressing the psychological barrier known as “range anxiety” [3]. Range anxiety refers to the fear that a vehicle may not have sufficient charge to reach its destination, deterring potential consumers from transitioning

from traditional gasoline-powered vehicles to EVs. This concern is further compounded by the limitations in current battery technologies and the inadequate availability of charging infrastructure, both of which significantly affect consumer confidence in EVs [1,4,5]. Accurate range prediction is essential to addressing these issues, as it directly impacts consumer trust and plays a pivotal role in the success of broader EV adoption strategies [6].

Various approaches, including machine learning, mathematical models, and simulation techniques, have emerged to improve the accuracy of EV range predictions. Each modeling approach has unique strengths, contributing to more reliable and accurate range predictions. Machine learning models leverage vast datasets to uncover complex patterns in vehicle behavior, environmental conditions, and battery performance. By training models on historical data, machine learning can predict range more accurately than traditional methods, and neural networks, in particular, are well-suited for incorporating multiple variables such as battery health, driving cycles, and external conditions [7,8]. These models continuously improve as more data becomes available, making them valuable in dynamic environments where driving conditions are unpredictable.

Mathematical models, on the other hand, offer structured approaches by using equations that represent the physical principles governing energy consumption, vehicle dynamics, and battery performance [9,10]. These models provide valuable insights into the relationships between various factors affecting range and are particularly useful in simulating different driving cycles and optimizing vehicle designs for efficiency [9,11]. Simulation models, particularly those using software like MATLAB/Simulink allow researchers to create virtual environments in which different vehicle configurations and control strategies can be tested [12,13]. Simulations offer flexibility in testing theoretical scenarios before physical prototypes are created, saving time and resources while providing valuable insights into how real-world variables, such as temperature fluctuations and road conditions, impact range [14,15].

This study makes a novel contribution to the field of electric vehicle (EV) range prediction by providing a comprehensive review of 80 studies published between 2013 and 2024, where machine learning, mathematical, simulation, and hybrid models has been used. Unlike previous reviews, our work systematically analyzes not only the methodologies but also the types of data used, the performance metrics, and the applicability of models under real-world driving conditions. We highlight emerging trends such as the increasing adoption of data-sharing practices, the rise of hybrid modeling approaches, and the practical implications for accurate and reliable range prediction. By synthesizing these insights, this review offers guidance for researchers and practitioners, identifies gaps in existing literature, and proposes directions for future work.

We outline the literature review and research motivation in Section 2, detail the research methodology in Section 3, and present analysis and discussions in Section 4. Finally, we discuss future research directions and conclude the paper in Section 5.

2. Literature Review and Motivation

2.1. Overview of Studies on EV Range Prediction

Electric Vehicle (EV) range prediction is a pivotal area of research aimed at reducing range anxiety, a key psychological barrier to EV adoption. Studies in this domain can be categorized into three primary model types: machine learning models, mathematical models, and simulation models. Each of these approaches contributes to more accurate range predictions through distinct methodologies and techniques.

Machine learning (ML) has gained prominence in EV range prediction due to its capacity to analyze large datasets and uncover intricate patterns. Several ML techniques, such as ensemble methods and deep learning frameworks, have been applied to improve prediction

accuracy. For instance, Mishra emphasizes the importance of both model selection and data quality in enhancing user experience and supporting infrastructure planning [16]. Similarly, Airlangga introduces a deep learning approach that combines autoencoders and neural networks, achieving greater prediction accuracy through advanced feature extraction [17]. Ullah et al. have also employed ensemble machine learning algorithms, including random forests and extreme gradient boosting, to predict charging durations, which provides indirect insights into energy consumption patterns [18]. These advancements reflect the growing reliance on ML techniques to enhance EV range predictions.

Mathematical modeling remains a core method for predicting EV range, focusing on relationships among factors such as battery state of charge (SoC), vehicle dynamics, and environmental conditions. Varga et al. provide a detailed review of the challenges associated with range prediction, underscoring the importance of accounting for both internal and external factors affecting vehicle performance [19]. Sarrafan et al. propose an improved SoC and range estimation model that integrates environmental conditions and traction system efficiency [20]. Wang et al.'s work on integrating particle swarm optimization with least squares support vector machines further demonstrates how optimization techniques can be used within mathematical frameworks to increase prediction accuracy [21].

Simulation models are invaluable in testing and validating range prediction methodologies under various driving conditions. Heath et al. critique current range estimation methods, pointing out the limitations of relying exclusively on simulations without considering real-world variability [22]. Simpson et al. develop a model calibrated against real-world data, improving the accuracy of EV range predictions [23]. The work of Mei et al. also explores the evolution of remaining driving range (RDR) research, emphasizing the need for real-time data integration to enhance simulation accuracy [24]. Simulation models provide a versatile platform for exploring a wide range of scenarios and operational limits in EV performance.

Significant breakthroughs in EV range prediction have emerged from integrating real-time data with advanced machine learning models. Techniques like deep learning, ensemble methods, and optimization algorithms are increasingly common in the literature, reflecting the shift toward more sophisticated, data-driven approaches. The development of hybrid models, which combine machine learning and traditional methods, as seen in the work of Eissa and Chen, indicates a movement toward comprehensive solutions that leverage the strengths of multiple methodologies [25].

2.2. Existing Reviews and Their Limitations

Several reviews and meta-analyses have addressed specific aspects of EV range prediction, typically focusing on either machine learning or simulation models. For instance, Gurusamy et al. [26] explore various modeling approaches for estimating energy consumption and driving range, detailing vehicle analytical models, powertrain components, and driver controller models while analyzing the impact of influential parameters on EV performance. Their findings indicate that simulation results align well with chassis dynamometer testing, suggesting that these methods can optimize EV powertrain configurations and identify future research directions for enhancing EV applications in transportation. But their study remained largely theoretical and did not evaluate data-driven prediction accuracy under variable driving environments.

Similarly, Varga et al. [19] investigated physical and behavioral factors influencing EV range but did not assess how modeling frameworks can be systematically compared in terms of prediction performance. Mei et al. [24] review the motivation behind Remaining Driving Range (RDR) prediction, summarize previous work, and identify key influencing factors while analyzing the physical models of EVs. They highlight four main challenges

such as battery state estimation, driving behavior recognition, driving condition prediction, and RDR calculation before proposing a vehicle-cloud collaboration method that leverages cloud computing and machine learning for improved predictions. However, their review focused primarily on methodological categorization rather than on quantitatively comparing model effectiveness across different approaches.

Despite these contributions, a critical gap remains in the literature where no prior review comprehensively compares machine learning (ML), mathematical (MM), and simulation modeling (SM) techniques in terms of their predictive accuracy, data requirements, and applicability to real-world EV operations. Existing reviews often lack an integrated discussion of how these models address the central technical problem of the development of accurate, generalizable, and computationally efficient range prediction systems that can perform reliably across diverse environmental and operational conditions.

To address this gap, this study defines a systematic review that provides a comprehensive comparison of machine learning, mathematical models, and simulation models in EV range prediction. The review systematically analyzes how each modeling approach contributes to solving the challenge of EV range prediction, identifies their strengths and weaknesses, and highlights engineering and algorithmic limitations that hinder their real-world implementation. A sequence of Research Questions (RQs) was formulated and defined based on our target objectives. The research questions are as follows:

RQ 1: What are the different machine learning and other models used for predicting the range of electric vehicles?

RQ 2: How do machine learning models compare with mathematical models in terms of accuracy for EV range prediction?

RQ 3: What types of data are commonly used in EV range prediction studies?

RQ 4: What performance metrics are most commonly used to evaluate EV range prediction models?

RQ 5: Which EV range prediction models demonstrate the highest accuracy and reliability in real-world conditions?

RQ 6: What are the main challenges and limitations identified in existing EV range prediction models?

The motivations behind these research questions are as follows:

1. Identify commonly used machine learning and other model techniques.
2. Identify the accuracy of machine learning models with traditional mathematical models to determine which approach offers better prediction capabilities.
3. Investigate the types of data used in the studies.
4. Identify the performance metrics commonly used for evaluation.
5. Identify the models that perform best in real-world conditions to ensure practical applicability.
6. Investigate the key challenges and limitations faced in range predict.

3. Research Methodology

We employed a systematic literature review (SLR) technique to identify and analyze machine learning, mathematical models, and simulation models approaches used for electric vehicle (EV) range prediction. We adopted the SLR methodology presented in [27], dividing our process into three phases: “Review preparation”, “Performing the Review,” and “Review findings” following the guidelines in [27]. The details of these phases are illustrated in Figure 1.

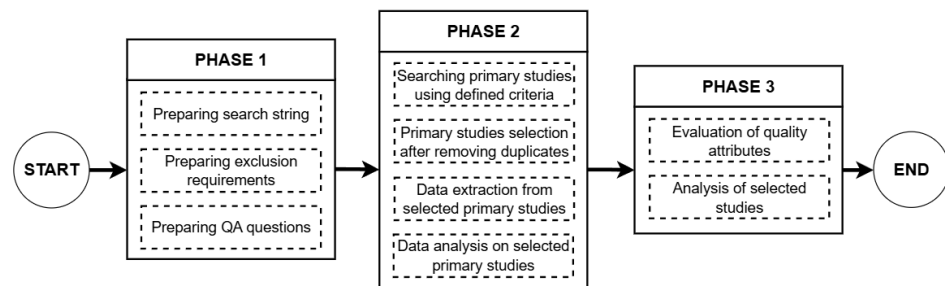


Figure 1. Range prediction systematic review process.

3.1. Phase 1: Review Preparation

The following steps were undertaken while planning this review:

- Choosing research repositories
- Creating search strings for the extraction of articles
- Defining article exclusion requirements
- Defining quality assessment requirements

3.1.1. Primary Study Databases

In selecting digital libraries for our systematic literature review, we focused on coverage, quality, balanced perspective, and ease of accessibility. We began with IEEE Xplore, commonly used for its extensive collection of high-quality, peer-reviewed conference papers and journal articles specifically in electrical engineering and computer science, which are important for recent research on electric vehicle technologies. Similarly, Elsevier's ScienceDirect provides a large collection of scientific and technical research, essential for understanding the engineering and technological aspects of EV range prediction. Springer Link was chosen for its comprehensive coverage of scientific documents, particularly in engineering and applied sciences, offering a reliable source of relevant studies. The Wiley Online Library contributes additional insights with its variety of journals and articles, enhancing our understanding of various methodologies and findings in the field. To ensure comprehensive coverage across many disciplines and sources, we also included Google Scholar, which broadens our search to capture a wide range of research articles and ensure no significant studies are overlooked. Each database was utilized with tailored search queries to optimize relevance and scope of our review.

3.1.2. Search Strings

We adopted a strategic search process, ensuring that our research questions guided every step of the way. To identify the most relevant studies, we carefully selected keywords and their alternatives based on the existing literature in the field of electric vehicle (EV) range estimation and prediction. Our primary search phrase was “Electric vehicle range estimation or prediction,” and we employed this in conjunction with various related terms to capture a comprehensive set of studies.

Utilizing the advanced search options available in the digital libraries, we refined our searches to target the most pertinent research. This involved searching specifically for our keywords in the titles and abstracts of papers, ensuring that the studies retrieved were relevant to our research questions. Additionally, we concentrated on selecting papers from the past decade, ensuring that our review includes the recent and relevant research in the rapidly evolving field of EV range prediction.

3.1.3. Exclusion Requirements

We applied a set of exclusion requirements to filter out papers which is illustrated in Figure 2, which outlines the sequential application of the exclusion criteria (EC1–EC5) and depicts how studies were systematically filtered to obtain the final set of primary studies included in this review. The requirements are:

EC 1: Studies that do not address the research questions defined in Section 2.

EC 2: Studies that do not discuss electric vehicle range prediction using machine learning or mathematical models, or simulation models techniques.

EC 3: Studies that are not written in English.

EC 4: Studies that do not meet the acceptance threshold according to our quality assessment requirements defined in Table 1.

EC 5: Studies that were published before 2013.

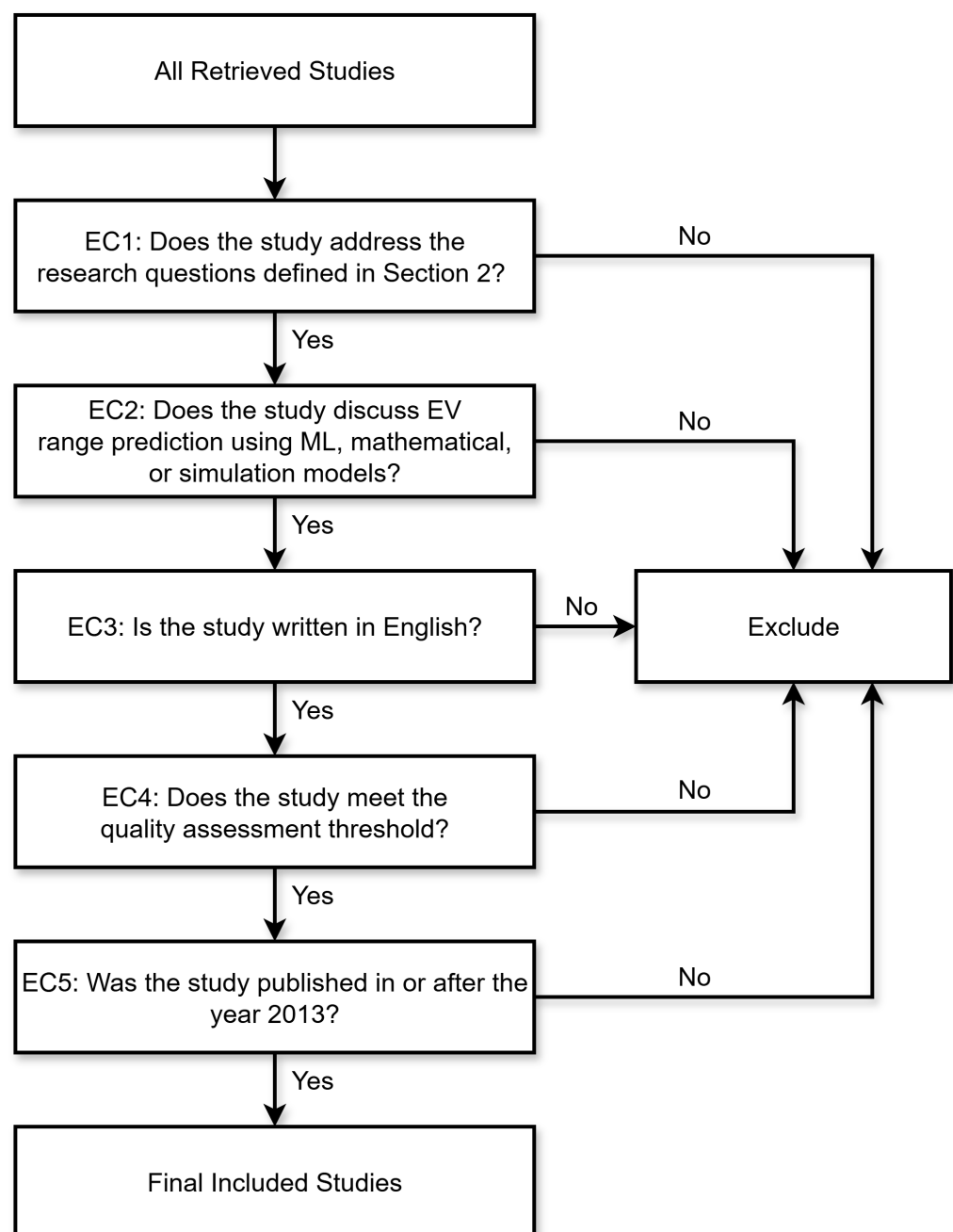


Figure 2. Exclusion process for primary studies based on defined criteria (EC1–EC5). The quality assessment steps listed in Table 1.

Table 1. Quality Assessment Questions.

Q No.	Quality Question	Yes	No
1	Are the research objectives and questions clearly stated?	1	0
2	Is the scope of the study relevant to the research question of the SLR?	1	0
3	Is the study design appropriate for answering the research questions?	1	0
4	Are the methodologies for data collection and analysis clearly described?	1	0
5	Does the study use an appropriate model (e.g., machine learning, mathematical, simulation) for EV range prediction?	1	0
6	Is the dataset used in the study adequately described?	1	0
7	Are the performance metrics for model evaluation clearly defined and justified?	1	0
8	Are the results of the model evaluation presented in a clear and comprehensive manner?	1	0
9	Does the study include a comparative analysis of different models or approaches?	1	0
10	Are potential biases and limitations of the study identified and discussed?	1	0
11	Are the study's findings supported by the data and analysis?	1	0
12	Are the theoretical and practical implications of the study clearly discussed?	1	0

3.1.4. Quality Assessment of Primary Selected Studies

We determined the quality of chosen studies considering our exclusion requirements mentioned Section 3.1.3. Once we independently evaluate the selected studies, we award scores using the following scoring method:

A score of '1' is awarded to papers that present the correct answer to the checklist question.

A score of '0' is awarded to papers that do not answer the checklist questions at all.

Each selected study is given a quality score, with a maximum possible score of 12 points. A score of 1 point is awarded if the paper fully satisfies our quality assessment requirements. Our quality assessment questions cover several categories:

- The first three questions relate to the overall quality of the article.
- The fourth question aligns the methodology section, specifically focusing on the details of how data was collected and analyzed.
- The fifth question relates to the methodology and model implementation sections, discussing the types of models used for EV range prediction.
- The sixth question relates to the data section, where the datasets used for training and testing the models should be described in detail.
- The seventh, eight, and ninth questions address the quality of the results, the use of performance measures, and the threats to the validity of the results.
- The last three questions relates to the discussion and limitations.

Our questions and the possible marks for each are shown in Table 1, with scores of 1, or 0 awarded.

3.2. Phase 2: Performing the Review

We selected papers following our search process and shortlisted studies based on exclusion requirements. Finally, we processed the initially selected studies through our quality assessment procedure, resulting in a list of shortlisted studies. The details of our process and the associated activities in the selection process are discussed in the following sections.

3.2.1. Selection of Primary Study

We identified a significant number of reports during the selection process and used the Tollgate approach by [28] to optimize the selection process. The Tollgate approach involves multiple phases, as depicted in Figure 3 and detailed in Table 2. In the first phase, we removed duplicates, resulting in the selection of 354 articles based on title and abstract exclusion criteria from all databases. In the next phase, this selection was further refined to 80 articles based on full-text exclusion criteria, as shown in Figure 3. Among the selected

studies, 47.5% were from IEEE, 26.25% from Google Scholar, 15% from Elsevier, 3.75% from Springer Link, and 7.5% from Wiley Online Library databases (see Table 2).

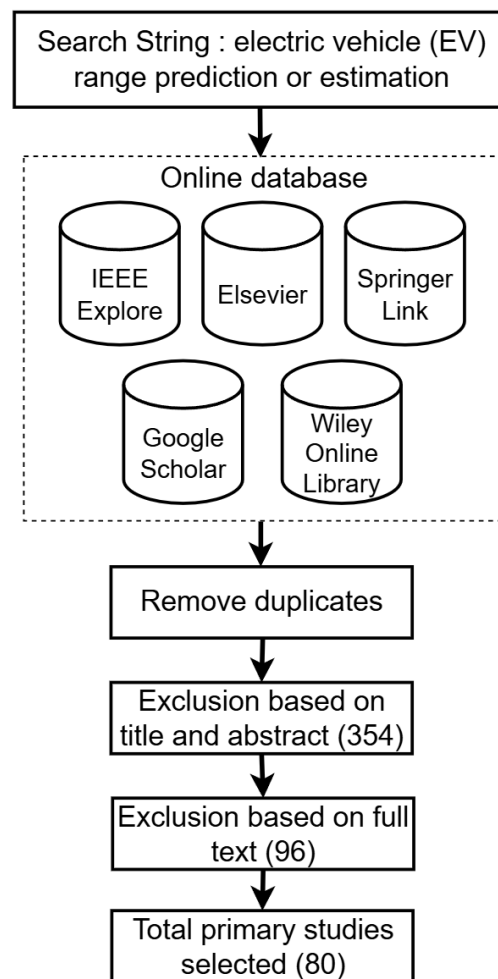


Figure 3. Selection process of primary studies.

Table 2. Selected studies.

Databases	Exclusion Based on Title and Abstract	Exclusion Based on Full Text	Total Selected Articles for Primary Study	Percentage of the Final Selected Articles
Google Scholar	36	28	21	26.25%
IEEE Xplore	63	44	38	47.5%
Elsevier	89	12	12	15%
Springer Link	31	6	3	3.75%
Wiley Online Library	135	6	6	7.5%
Total	354	96	80	100%

3.2.2. Data Extraction and Analysis

To ensure consistency, accuracy, and completeness, a standardized data extraction protocol was developed and applied to all 80 selected studies. Data extraction was conducted independently by four reviewers to minimize bias. Each reviewer extracted relevant information from the included studies using the standardized form. The extracted data were then cross-verified, and any discrepancies were resolved through discussion. The final data extraction form captured the following key elements from each study:

- **Quality Indicators:** Compliance with the predefined quality assessment criteria (Section 3.1.4), including study design clarity, methodological transparency, and validation strategy.
- **Study Characteristics:** Title, authors, publication year, journal/conference, and study objectives.
- **Methodology:** Type of model or algorithm used (e.g., Machine Learning, Simulation, or Hybrid), and model details.
- **Data Details:** Source and type of data used (experimental, simulated, or public dataset), key features (e.g., vehicle dynamics, battery data, environmental factors), and availability of datasets.
- **Results:** Including reported evaluation metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or R^2 , as well as model accuracy or error ranges.
- **Challenges and limitations:** Reported challenges in data handling, feature selection, model generalization, or validation, along with limitations acknowledged by the authors.

We organized the information gathered from the primary studies and conducted a filtering process considering both our exclusion criteria and research questions. The data collection process involved four individuals who contributed to evaluating the selected studies. All scores in the quality assessment are averages of the evaluations from four individuals. This approach ensures that any differences in judgment are balanced, and the final score reflects a consensus between both evaluators. The results of our quality assessment are presented in Table 3 and 4.

Table 3. Quality Assessment Results (PS01–PS40).

PS	Ref.	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Score
PS01	[29]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS02	[30]	1	1	1	1	0	0.75	1	1	1	0	1	0.25	9
PS03	[31]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS04	[32]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS05	[33]	1	1	1	1	1	0	1	1	0	1	1	0.5	9.5
PS06	[34]	1	1	1	1	1	0.75	1	1	0	1	1	1	10.75
PS07	[35]	1	1	1	1	1	0	1	1	0	1	1	0.5	9.5
PS08	[36]	1	1	1	1	1	0.5	1	0	0	1	1	1	9.5
PS09	[37]	1	1	1	1	1	1	1	1	0.75	1	1	1	11.75
PS10	[38]	1	1	1	1	1	1	0.5	1	0.75	1	1	1	11.25
PS11	[39]	1	1	1	0	1	1	1	0.25	0.25	0.75	1	0.5	8.75
PS12	[40]	1	1	1	0.5	1	1	1	1	1	1	1	1	11.5
PS13	[41]	1	1	1	1	1	0.5	1	1	1	1	1	1	11.5
PS14	[20]	1	1	1	1	1	0.25	1	1	1	1	1	0.5	10.75
PS15	[42]	1	1	1	1	1	1	1	1	0.5	1	1	1	11.5
PS16	[43]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS17	[44]	1	1	1	1	1	0.75	1	1	1	1	1	0.75	11.5
PS18	[25]	1	1	1	1	1	1	1	1	0.5	1	1	1	11.5
PS19	[45]	1	1	1	1	1	0.25	1	1	1	1	1	1	11.25
PS20	[46]	1	1	1	1	1	0	1	1	1	1	1	1	11
PS21	[47]	1	1	1	1	0	0	0	0.5	0.75	1	0.75	1	8
PS22	[48]	1	1	1	1	1	0.25	0	0.5	0.5	0	1	0.25	7.5
PS23	[49]	1	1	1	1	1	0	1	1	0	1	1	0.75	9.75
PS24	[50]	1	1	1	1	1	1	0.5	1	0.25	0.5	1	0.5	9.75
PS25	[51]	1	1	1	1	1	1	0	1	0	1	1	0.5	9.5
PS26	[52]	1	1	1	1	1	1	1	1	0	0.25	1	1	10.25
PS27	[53]	1	1	1	1	1	1	1	1	0	0	1	0.5	9.5
PS28	[54]	1	1	1	1	1	1	1	1	0.25	0	1	0.25	9.5
PS29	[55]	1	1	1	1	1	1	1	1	0	0.75	1	1	10.75
PS30	[56]	1	1	1	1	1	0	1	1	0	0.5	1	1	9.75
PS31	[57]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS32	[58]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS33	[59]	1	1	1	1	1	0.5	1	1	0	1	1	1	10.5
PS34	[60]	1	1	1	1	0.25	0	0.5	1	0.25	1	1	1	9
PS35	[61]	1	1	1	0.5	1	0	0	0	0	1	0.5	0.5	6.5
PS36	[62]	1	1	1	1	1	1	1	1	0.75	1	1	1	11.75
PS37	[63]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS38	[64]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS39	[65]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS40	[66]	1	1	1	1	1	1	1	1	0.25	1	1	1	11.25

Table 4. Quality Assessment Results (PS41–PS80).

PS	Ref.	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Score
PS41	[67]	1	1	1	1	1	1	1	1	0.25	1	1	1	11.25
PS42	[68]	1	1	1	0.25	1	0	1	1	0	1	1	1	9.25
PS43	[69]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS44	[70]	1	1	1	0	1	0	1	1	0.25	1	1	1	9.25
PS45	[71]	1	1	1	1	1	0.5	1	1	0.25	1	1	1	10.75
PS46	[72]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS47	[73]	1	1	1	1	1	0.75	1	1	1	1	1	1	11.75
PS48	[74]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS49	[75]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS50	[76]	1	1	1	1	1	1	1	1	0	0.75	1	1	10.75
PS51	[77]	1	1	1	1	1	1	1	1	1	0.75	1	1	11.75
PS52	[78]	1	1	1	1	1	0.5	1	1	0	1	1	1	10.5
PS53	[79]	1	1	1	1	1	0.5	0.25	1	0.75	1	1	1	10.5
PS54	[80]	1	1	1	0	1	0.5	1	1	0	1	1	1	9.5
PS55	[81]	1	1	1	1	1	1	1	1	0	0.5	1	1	10.5
PS56	[82]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS57	[83]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS58	[84]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS59	[85]	1	1	1	1	1	1	1	1	0.25	1	1	1	11.25
PS60	[86]	1	1	1	1	1	1	1	1	0.5	0.75	1	1	11.25
PS61	[87]	1	1	1	1	1	0.5	1	1	0.25	0.25	1	0.5	9.5
PS62	[88]	1	1	1	1	1	1	1	1	0	0.5	1	1	10.5
PS63	[89]	1	1	1	1	1	1	1	1	0.25	1	1	1	11.25
PS64	[90]	1	1	1	1	1	1	1	1	1	1	1	1	12
PS65	[91]	1	1	1	1	1	0	1	1	1	0.75	1	1	10.75
PS66	[92]	1	1	1	0.5	1	0.75	0	1	0	1	1	1	9.25
PS67	[93]	1	1	1	1	1	0.5	1	1	0	0.5	1	1	10
PS68	[94]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS69	[95]	1	1	1	1	1	0.5	0.5	1	0	1	1	1	10
PS70	[96]	1	1	1	1	1	1	0.5	1	1	0.5	1	1	11
PS71	[97]	1	1	1	0.5	0	0	0	1	1	0	1	1	7.5
PS72	[98]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS73	[99]	1	1	1	1	1	0.5	0.5	1	0.5	1	1	1	10.5
PS74	[100]	1	1	1	1	1	1	1	1	0.5	1	1	1	11.5
PS75	[101]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS76	[21]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS77	[102]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS78	[103]	1	1	1	1	1	1	1	1	0	1	1	1	11
PS79	[104]	1	1	1	1	1	1	0	1	1	1	1	1	11
PS80	[105]	1	1	1	1	1	1	1	1	0.25	1	1	1	11.25

3.3. Phase 3: Review Findings

In the reporting phase, we consolidate our findings from the systematic literature review, providing a clear and detailed presentation of the selected studies and their analyses. This phase encompasses several steps to ensure the robustness and clarity of our final report.

3.3.1. Evaluation of Quality Attributes

We rigorously evaluate the quality of all selected studies based on predetermined quality requirements which are listed in Table 1. This process is conducted in consensus meeting. We hold a series of meetings to discuss each study in detail, addressing any discrepancies in scores. This collaborative discussion ensures a balanced and unbiased final quality score. The quality scores for each primary study are compiled and presented in Table 3 and 4.

3.3.2. Distribution over Time and Trends

To understand the evolution of research in electric vehicle range prediction, we analyze the distribution over time of the selected studies. This analysis helps identify trends over time and highlights periods of increased research activity. We categorize the studies into three distinct periods: 2013–2016, 2017–2020, and 2021–2024 and visualize in Figure 4.

During the years between 2013 to 2016, research was limited, reflecting the early stages of EV range prediction methods. Most works concentrated on fundamental concepts like mathematical modeling and basic simulation methodologies, providing the platform for future research. In the 2017–2020 period, a notable increase in publications corresponds to the growing integration of machine learning techniques into EV range prediction. Researchers began exploring neural networks, decision trees, and support vector machines, signaling a

shift towards data-driven approaches that leverage the increasing availability of vehicle and sensor data. Simulation studies also expanded during this period, highlighting the importance of scenario testing and virtual experimentation.

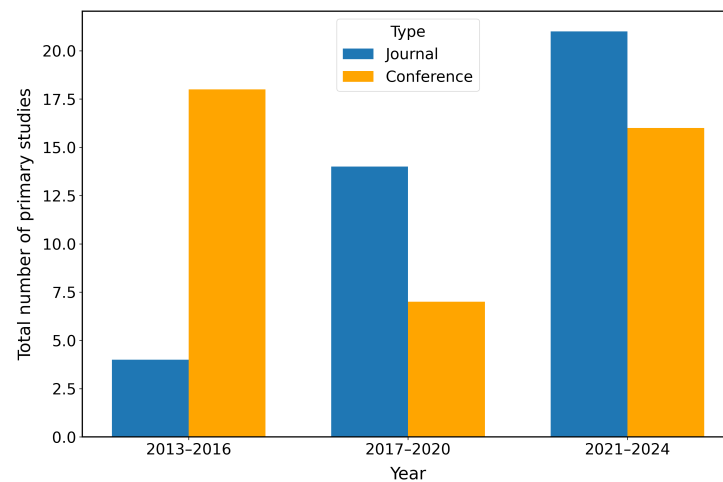


Figure 4. Total number of primary studies over years.

The most recent period, 2021–2024, has seen a large increase in publication volume, reflecting the field’s diversity. This period is dominated by machine learning models, although hybrid approaches that combine simulation and ML have also emerged, with a focus on balancing real-world application with model accuracy. This increase in papers is in accordance with the global increase in EV use, indicating the research community’s response to practical difficulties such as battery management, driving behavior variability, and route-specific energy consumption.

3.3.3. Publication Type

As shown in Figure 5, the distribution of the retrieved studies between journal articles and conference papers is nearly balanced. Journal articles constitute 49% of the total studies, while conference papers account for 51%. This distribution highlights the equal interest in disseminating research findings in both journals and conferences, underscoring the importance of the subject matter in both academic and professional communities. Journal articles tend to focus on more comprehensive analyses, including rigorous evaluation of models, extended datasets, and detailed methodological explanations. In contrast, conference papers frequently present novel methods, preliminary results, or innovative applications, allowing rapid dissemination of emerging techniques.

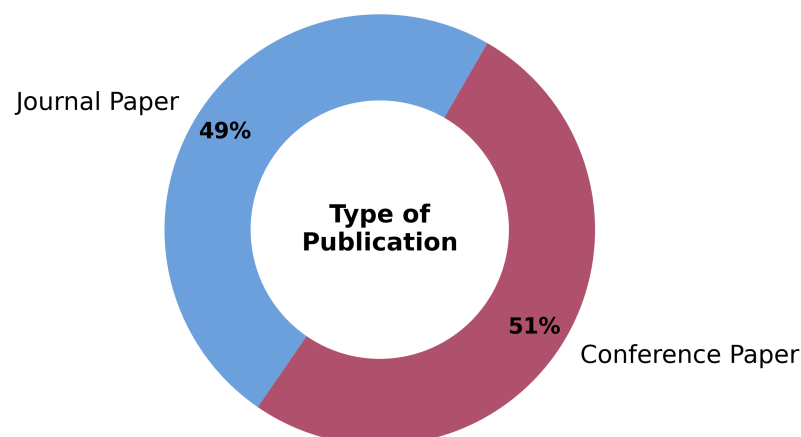


Figure 5. Types of publications.

4. Analysis and Discussion

In this section, we present and discuss the findings from the review of 80 papers published between 2013 and 2024 on electric vehicle (EV) range prediction.

4.1. Overview of Models Used in EV Range Prediction

We observed that several machine learning models are employed in the primary studies we reviewed. To provide a detailed overview, we compiled and summarized these studies, and highlighting the specific machine learning models used. The detailed summary of these findings is presented in Figure 6.

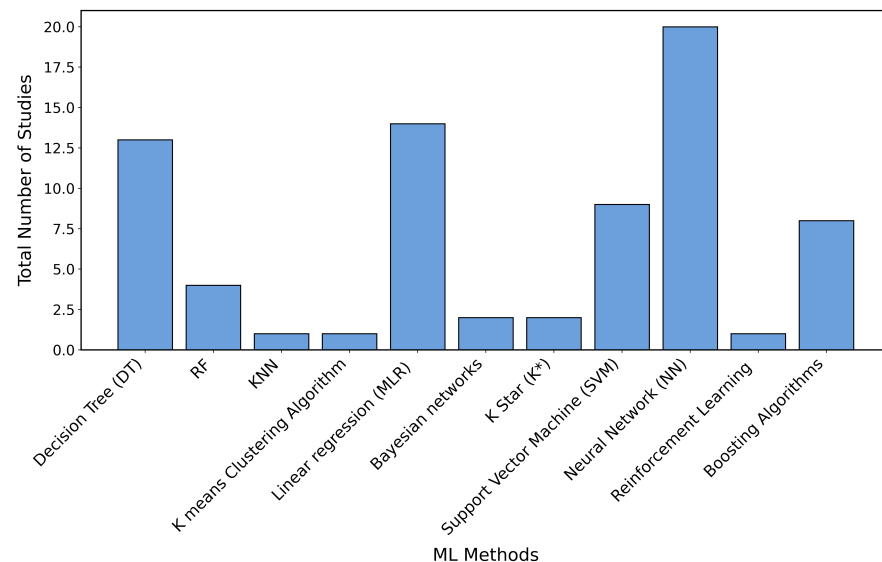


Figure 6. ML methods used in primary studies.

Figure 6 displays the studies and corresponding percentages associated with various machine learning methods among all primary studies. Neural Networks (NN) are the most researched method, with 20 studies, accounting for 25% of the total, indicating high interest and widespread application. Linear Regression (MLR) also shows substantial popularity, with 14 studies (17.5%). Similarly, Decision Trees (DT) have a significant presence, with 13 studies (16.25%). Support Vector Machines (SVM), Boosting Algorithms, Random Forest (RF), Bayesian Networks and K Star (K)* have a moderate presence, while K-Nearest Neighbors (KNN), K Means Clustering Algorithm, and Reinforcement Learning are the least researched, with each accounting for only 1 study (1.25%).

This distribution reflects a trend where neural networks dominate contemporary research, but simpler and interpretable models like linear regression and decision trees continue to play a role. In addition to ML methods, various mathematical and simulation-based models are utilized in the studies, which are critical for modeling vehicle physics and evaluating EV range under controlled or theoretical conditions. Figure 7 summarizes the prevalence of these alternative methods.

Figure 7 indicates that simulation models are the most frequently applied, appearing in 30 studies (37.5%). The Physics-Based Mathematical Model is also widely used, appearing in 24 studies (30%). Markov Chains and the Kalman Filter (KF) show moderate popularity, with 6 studies (7.5%) and 3 studies (3.75%), respectively. Other methods, such as the Coulomb Counting (ECC) method, Radial Basis Function (RBF), Fuzzy Logic Classifiers, Monte Carlo Method, and the FASTSim Simulation Model, each appear in fewer studies. This distribution underscores the substantial focus on simulation techniques, while other methods like Markov Chains and Kalman Filter have a modest presence. Less common

methods, such as ECC, RBF, and Fuzzy Logic Classifiers, are emerging or less favored in the current research landscape.

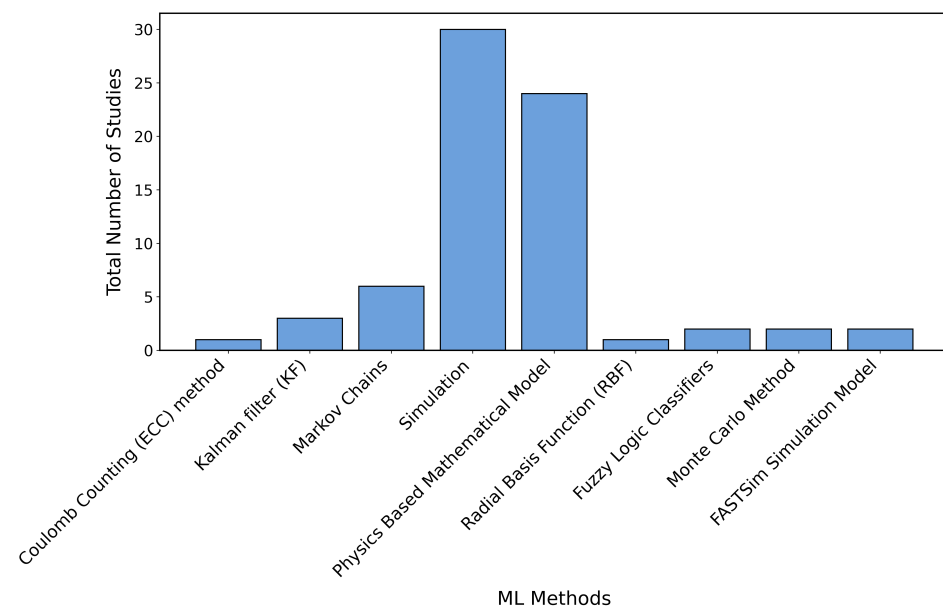


Figure 7. Other methods used in primary studies.

4.2. Comparison Between Different Types of Models

We categorized the selected studies based on their methodological approaches: machine learning, mathematical, simulation, and hybrid models. Figure 8 shows the distribution of these approaches across the primary studies.

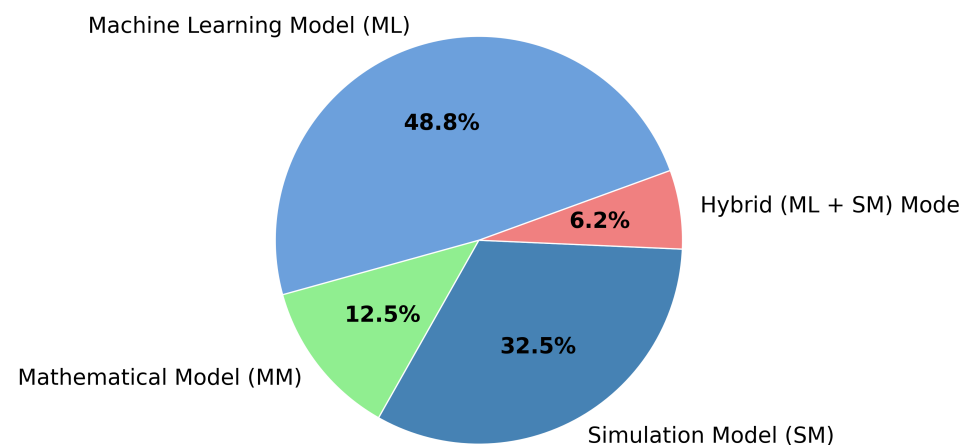


Figure 8. Classifications of methods across the primary studies.

Machine learning models dominate with 48.8%, reflecting the increasing reliance on data-driven methods. These models, including neural networks, SVMs, and decision trees, leverage large datasets to capture complex relationships between variables like driving behavior, road conditions, and vehicle characteristics, making them suitable for real-time predictions. Mathematical models account for 12.5% and rely on established physical equations to describe EV range factors such as battery capacity, energy consumption, and vehicle dynamics. They are reliable under idealized conditions but may not fully capture real-world variability. Simulation models represent 32.5% of the studies and replicate real-world scenarios in a controlled virtual environment. They allow testing of factors like weather, road types, and driver behavior without costly on-road experiments and can integrate ML or mathematical models to improve predictions. Hybrid models (6.2%)

combine ML and simulation techniques to enhance prediction accuracy and robustness, leveraging both data-driven adaptability and scenario-specific insights. These approaches are emerging as a promising solution for handling complex real-world driving conditions.

Figure 9 displays a bar chart illustrating the yearly distribution of four types of approaches: machine learning, mathematical, simulation, and hybrid, grouped across three publication periods: 2013–2016, 2017–2020, and 2021–2024. The x-axis represents the publication periods, while the y-axis indicates the number of publications. During 2013–2016, mathematical modeling and simulation approaches were moderately represented, while ML publications were fewer but gradually emerging. Hybrid approaches occasionally appeared. In the 2017–2020 period, ML and simulation studies gained popularity, with ML publications showing a clear upward trend, while mathematical modeling remained limited. Hybrid models continued to appear occasionally. In the most recent period, 2021–2024, ML publications surged significantly, becoming the dominant approach. Simulation and hybrid studies maintained a moderate presence, while mathematical modeling remained lower. Overall, the data highlight a clear shift toward machine learning over the past decade, with hybrid and simulation methods retaining consistent but smaller shares.

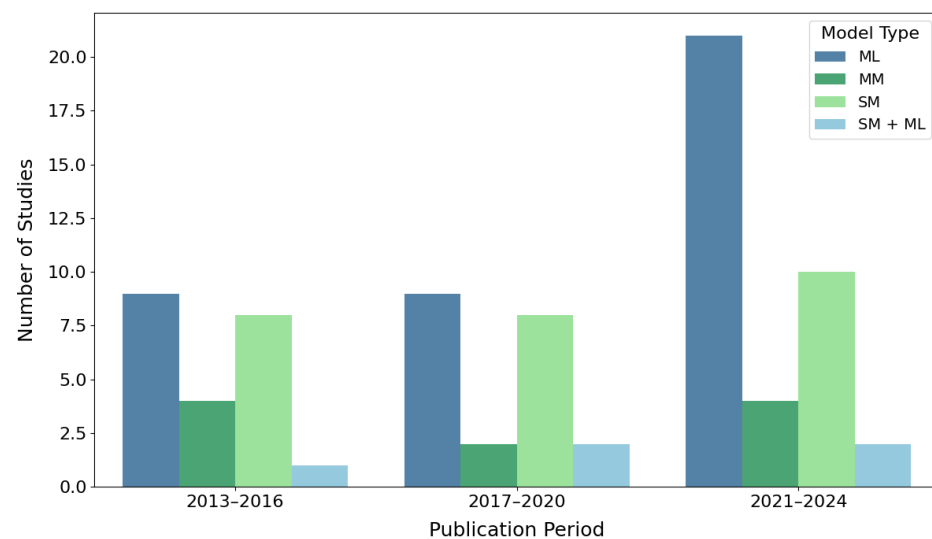


Figure 9. Trends in model popularity over the years.

Recent ML-based models are transforming the way range predictions are conducted in electric vehicles. A notable trend is the deployment of deep learning techniques. For instance, a machine learning method developed by Sun et al. [32] specifically utilizes feature-based linear regression to model route preferences and provide probabilistic attainability maps for EV drivers. The use of neural networks has also proven effective in real-time energy consumption estimation by considering a variety of factors including speed, temperature, road conditions, and battery state-of-charge (SOC) [25,31,39,44,51,53,54]. Such models can process and interpret large datasets to improve prediction accuracy, showcasing a distinct advantage over classical modeling techniques which may not account for the same breadth of influencing factors.

4.3. Data Types in EV Range Prediction Studies

Most studies collected their own data, often without public sharing. A few used online datasets such as [PS02], [PS17], [PS37], [PS64], and [PS71], while others shared their data on platforms like GitHub, Kaggle, or other websites, e.g., [PS06], [PS26], [PS32], [PS33], and [PS38], mostly from 2022–2023. This indicates a growing trend towards data sharing and collaboration, enhancing reproducibility and scalability of EV range prediction models.

We categorized the data types used in these studies into eight groups: vehicle data, road information, environmental information, timestamp data, battery data, GPS data, user data, and additional sensor data. Figure 10 summarizes the usage of these data types across the studies.

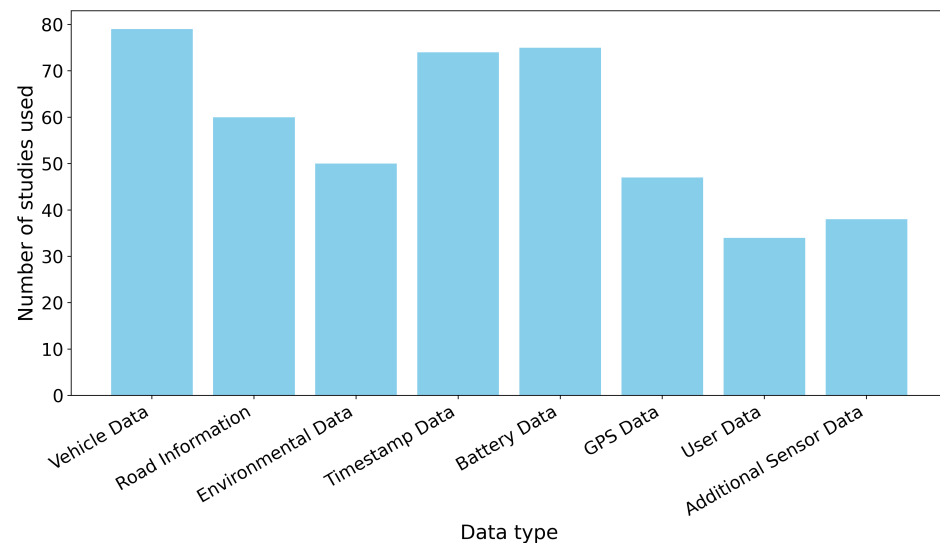


Figure 10. Data used in primary studies.

Figure 10 illustrates that vehicle data, such as vehicle dynamics, speed, and acceleration, is the most frequently used, appearing in 79 studies. These features are essential for capturing real-time driving behavior, which directly affects energy consumption. Battery-related data, such as state of charge (SOC), battery health, and temperature, follows closely, used in 75 studies, as it reflects the remaining energy and efficiency of the vehicle's power system. Timestamp data, including date, time, and timeseries information, appears in 74 studies and is important for tracking temporal patterns in driving and energy use. Road information (e.g., elevation, traffic information, road segments), used in 60 studies, impacts energy consumption by determining the load on the vehicle in different driving conditions. For instance, driving uphill consumes more energy, while traffic congestion may result in stop-and-go driving, which influences range predictions.

Environmental data (e.g., weather conditions, temperature, wind direction) is employed in 50 studies, which can significantly impact battery performance and vehicle efficiency, making these features vital for model accuracy. GPS data, providing location and route information, appears in 47 studies. While user data (e.g., driver behavior, age, driving habits, acceleration, stop, and deceleration patterns) was used in 34 studies, its inclusion remains less frequent. However, studies that consider user behavior have shown that aggressive driving can drastically reduce range, making it a potentially valuable feature for improving model performance.

The model performance is heavily influenced by the specific features selected from these data types. Studies that use a broader range of features, especially those integrating vehicle dynamics, battery health, road conditions, and environmental factors, tend to produce more accurate predictions. On the other hand, models relying on limited data types may lack the necessary context to account for real-world variability, leading to less reliable predictions.

4.4. Performance Metrics

We observed various performance metrics utilized to evaluate mathematical models, simulation models, and machine learning models. To provide a clear understanding,

we have summarized the performance evaluations of these models. Figure 11 offers a graphical representation of the evaluation techniques across all models, providing a visual comparison and highlighting key trends.

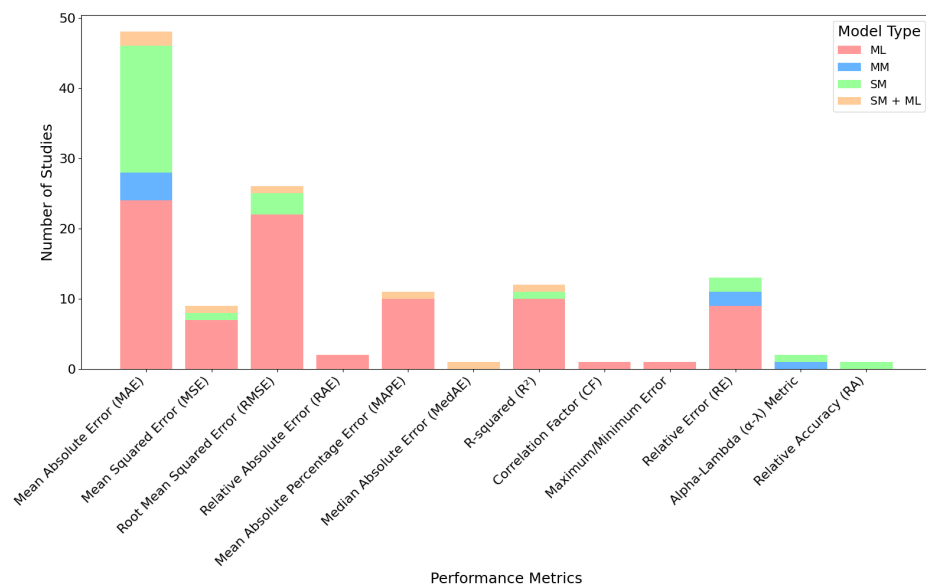


Figure 11. Evaluation techniques in primary studies.

Figure 11 provides an overview of various performance metrics used in studies for evaluating models, along with the frequency of their usage. The most commonly used metric is Mean Absolute Error (MAE), which appears in 48 studies, indicating its widespread acceptance for assessing model accuracy. Root Mean Squared Error (RMSE) is also frequently used, appearing in 26 studies, followed by Relative Error (RE), which is utilized in 13 studies. Other notable metrics include Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE), each used in 9 and 12 studies, respectively. Relative Absolute Error (RAE) and Alpha-Lambda ($\alpha - \lambda$) Metric are used in 2 studies each. Less commonly used metrics include Median Absolute Error (MEDAE), R-squared (R^2), Correlation Factor (CF), Maximum/Minimum Error, and Relative Accuracy (RA), each appearing in 1 or 2 studies.

This distribution highlights the preference for certain metrics like MAE, RMSE, and RE in model evaluation, while others are less frequently employed. The inclusion of different performance metrics such as ML (machine learning-based), MM (mathematical models), SM (simulation models), and combinations of SM + ML highlights the diversity of methodologies researchers use to evaluate the performance and accuracy of their models. However, despite the variety of metrics used, it was not possible to conduct a direct, head-to-head comparison of model performance across identical datasets. This limitation arises because the primary studies employed diverse datasets, driving conditions, and vehicle types, preventing a standardized quantitative comparison.

4.5. EV Range Prediction Models' Performance in Real-World Conditions

The compilation of various studies on the prediction accuracy of electric vehicle (EV) range presents a diverse array of methodologies and outcomes. Many studies reported impressive accuracy metrics, indicating significant progress in predictive modeling for EVs. For instance, some models achieved a Mean Absolute Error (MAE) as low as 0.695 km [30] and Root Mean Square Error (RMSE) values under 2 km, reflecting precise estimations of remaining driving range (RDR). A notable study achieved an MAE of 1.20 km and a Mean

Absolute Percentage Error (MAPE) of 1.31% when validated against real-world driving data, showcasing robust model performance in practical applications [29].

The accuracy of range predictions varied across different driving conditions, such as city, rural, and highway scenarios, with Relative Accuracy (RA) values ranging from 85.47% to 99.70% [35]. Some models reported a maximum relative difference in final SoC values of only 1.1%, underscoring their reliability [34]. Another significant finding was the low average prediction error, approximately 0.7 km, demonstrating the models' efficacy in minimizing deviations from actual driving data [32]. Several studies highlighted the importance of hybrid methods and neural network models in enhancing prediction accuracy. For example, the hybrid method achieved an accuracy higher than 99% when tested over an intercity route, closely aligning with measured data [38]. Similarly, the Neural Network State of Charge Estimation Model (NN-SOC-EM) achieved a remarkable accuracy of 97.6%, coupled with an adaptability score of 89.2% [91].

Furthermore, the Root Mean Square Percentage Error (RMSPE) in some models was as low as 0.091, indicating minimal percentage-based errors [39]. Another study reported an average relative error of approximately 9.76% across various tests, illustrating the high level of precision attained by contemporary predictive models [37]. Some models demonstrated an accuracy of 93.25% for predicting the range of Battery Electric Vehicles (BEVs) using mathematical models of the battery's Depth-of-Discharge (DOD) [92]. In specific cases, the prediction accuracy for remaining driving range (RDR) was highly commendable, with errors less than 4 km and a significant reduction in error (52.1%) compared to standard SoC-based methods [101]. One of the studies achieved an R-squared score of 0.9961 and an RMSE of 6.6%, further emphasizing the robustness of modern predictive algorithms [99].

We found that 41 studies included a comparative analysis of their results with other studies, providing valuable insight into how different methodologies perform in various contexts. However, most of the studies did not compare their models with other approaches in detail, focusing primarily on presenting their own performance metrics, often in real-world conditions, but without cross-study benchmarks. This lack of comparative analysis limits the ability to assess the relative strengths and weaknesses of the models across different datasets and methodologies. Additionally, most studies evaluated their models using a single dataset, which raises concerns about the validity of their findings to other datasets or driving conditions.

4.6. Challenges and Limitations

The challenges and limitations in predicting the electric vehicle (EV) range are multifaceted, encompassing various technical and practical aspects. A significant challenge is balancing predictive accuracy with computational efficiency, as extensive data cleaning and preprocessing are required to handle duplicated sampling, outliers, and irrelevant data segments [29]. Feature selection also poses difficulties; while increasing input features might seem beneficial, it can introduce noise due to sensor errors or incorrect measurements, negatively impacting model performance [31]. The impact of external factors such as driving habits, traffic conditions, and environmental variables adds non-linearities and complexities, making the model sensitive to the quality and comprehensiveness of the input data [31]. Moreover, computational resources and battery degradation significantly influence the accuracy of range predictions [32]. Battery aging and the dependency on the number of evaluated driving cycles further complicate the estimation process [34,35].

Powertrain limitations are another critical factor affecting EV range prediction. Battery degradation and state-of-health (SOH) estimation make accurate remaining-range prediction challenging [77]. The performance of powertrains is also influenced by vehicle dynamics, including speed, acceleration, and road gradient, which add variability that

existing models may struggle to capture. From an industrial perspective, the high cost and limited availability of high-performance batteries constrain manufacturers' research priorities and impact market adoption. Standardizing data collection for model training and validation is essential, as inconsistencies can result in skewed predictions and reduce consumer trust in EV technology [31].

Ensuring model robustness across different driving conditions and vehicle types remains a key challenge, requiring further optimization and validation [53]. The dynamic nature of data, such as fluctuating traffic conditions, necessitates frequent queries to services like Google Directions, which can impact system responsiveness [54]. Additionally, prediction accuracy is affected by the lengths of road segments provided by mapping services; longer segments reduce accuracy, whereas dividing them into shorter ones increases computational complexity [55].

Real-world driving conditions often differ from the standardized drive cycles used in simulations, further complicating range estimation. Factors like battery aging and temperature fluctuations exacerbate this challenge [92]. Moreover, assumptions about Gaussian distributions for underlying data or consistent drive cycle patterns may not hold true in real-world scenarios, potentially reducing the model's effectiveness [99]. Accurate traffic phase classification and driver behavior modeling are critical yet difficult to achieve, as they may not always reflect real-time variations [101]. Lastly, the need for extensive historical data for model training may be impractical for all fleet operations, and using a specific vehicle model in simulations may limit the relevance of the findings to other vehicle types [104].

Despite the potential that artificial intelligence and machine learning hold for addressing these challenges, the ongoing development and refinement of algorithms must also be balanced with practical implementation considerations. Consequently, while research continues to evolve, there remains a pressing need for collaboration between researchers and industry to ensure that solutions are effectively designed to meet real-world demands.

5. Conclusions

In conclusion, significant advancements have been made in EV range prediction models, demonstrating impressive accuracy under real-world conditions. However, challenges remain, including the need for robust feature selection, handling dynamic real-time data, and accounting for battery degradation. By addressing these challenges and exploring future research directions, the accuracy, reliability, and applicability of EV range prediction models can be further enhanced. These advancements are crucial for the continued development and optimization of electric vehicles, ultimately contributing to their broader adoption and success.

Our review of 80 studies from 2013 to 2024 reveals that Neural Networks (NN), Linear Regression (MLR), and Decision Trees (DT) are the most researched machine learning methods for predicting the range of electric vehicles. ML models are highly suitable for real-time range prediction and data-rich environments, where large-scale driving and environmental data are available. Mathematical models are recommended for early stage vehicle design, optimization of control parameters, and battery modeling when the physical equations and measurable parameters are well defined. However, simulation techniques are prevalent among mathematical models, indicating a strong preference for these methods. It is most effective for scenario testing, calibration, and route-level evaluation, especially when real-world data collection is limited or controlled experimentation is required. The emerging category of hybrid models, which combine data-driven and physics-based approaches, shows strong potential for bridging the gap between real-world adaptability and theoretical accuracy. These are recommended for integrated vehicle platforms or fleet-level applica-

tions, where both precision and generalization are required. Furthermore, hybridization can reduce model bias and improve transferability across driving conditions and vehicle types.

Future research should focus on developing standardized evaluation metrics and improving cross-dataset validation to ensure consistency and comparability among different approaches. The development of hybrid models that combine machine learning, mathematical, and simulation approaches could harness the strengths of each method, leading to more reliable and robust predictions. Additionally, the implementation of advanced feature selection techniques is critical to minimize noise and enhance model performance. Incorporating real-time data, such as traffic conditions, road elevation, and weather updates, can further improve the precision of range predictions. Addressing battery degradation through more sophisticated modeling techniques and developing personalized prediction models that account for individual driving habits will be crucial in refining the accuracy and dependability of range estimates across various real-world scenarios. Furthermore, expanding the evaluation of models across multiple datasets and ensuring comparative analysis with other approaches will help establish the applicability and relative strengths of the models.

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