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Article

DATA-DRIVEN AND LEARNING-BASED MULTI-OBJECTIVE EV ROUTING: A SURVEY OF PREDICTIVE MODELS AND OPTIMIZATION FRAMEWORKS

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Abstract: The growing adoption of electric vehicles (EVs) has resulted in the surge in the use of intelligent routing systems to optimally balance the time of travel, energy consumption, and the need for charging. EV routing is complex by nature, because of limited battery capacity, non-linear energy consumption, dynamic traffic situation and the uncertain availability of charging stations. Traditional deterministic approach has difficulty in accommodating these multiple constraint sides, which is the reason for the appearance of data driven methodologies. Leveraging open datasets - including Open Street Map (OSM), Open Mobility, NREL and TomTom - researchers are able to capture spatial, temporal, and energy-related information that is very detailed to help inform predictive models. Machine learning (ML), including graph neural network (GNN) for representing the road net, LSTMs / GNNs for time-series forecasting of traffic, and regression or K-Neighbours (KN) for estimating energy consumption help to predict some important routing parameters accurately. Complementing these predictions, multi-objective optimization frameworks ranging from evolutionary algorithms, to swarm intelligence, to hybrid metaheuristics, allow to analyse systematically the trade-off between travel time, energy cost, state-of-charge and charging delays. This review compiles existing research into a well-established taxonomy, compares datasets, ML models and optimization strategies, identifies existing research gaps in issues of scalability, handling uncertainty and generalization, as well as propose future research directions

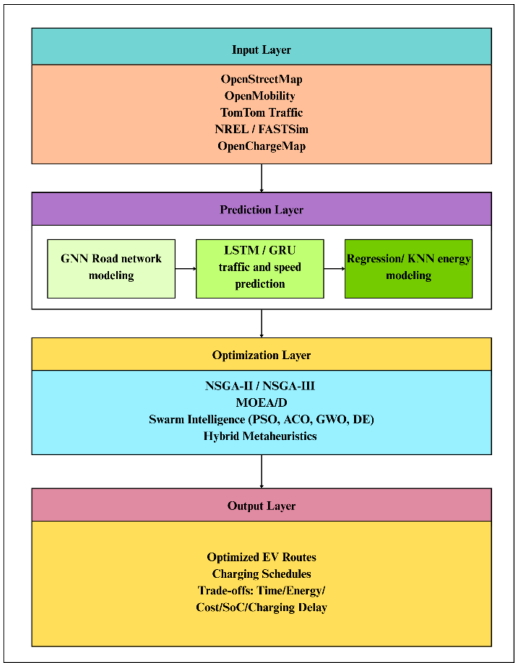
Keywords: EV Routing, Optimization techniques, LSTM, Neural network.

1. INTRODUCTION

The move towards electric mobility has become integrated which has led to the need for some smart route planning systems that can fit in the special operational constraints of Electric Vehicles (EVs) [1]. Unlike the conventional vehicles, the routing of the EVs have to consider the limited battery capacity, non-linear energy consumption pattern, heterogeneous traffic condition and dynamic availability of the charging infrastructure [2]. These factors bring several conflicting objectives (e.g. minimizing travel time, energy usage, charging cost, and waiting delays) into the picture which causes the overall problem of EV routing to be multi-objective and computationally challenging in nature. Traditional deterministic routing methods struggle to cope with this complexity, so much more so when considering real-world variability in traffic and charging behaviour [3].

Recent advances in open mobility data and machine learning (ML) have made it possible to model the EV routing scenarios in a more accurate and realistic manner [4]. Public datasets such as Open Street Map, Open Mobility traffic feeds, NREL energy modelling data and global charging station repositories are now a rich source of spatial-temporal information which is essential for decision-making on the basis of data [1]. ML models like LSTM / GRU networks for traffic prediction, regression based energy estimators and graph neural networks (GNNs) for learning road topology boosts prediction of essential parameters which affects the choice of routes [5].

Fig. 1. : Data-to-Optimization Pipeline for EV Routing



Complementing these predictive models, multi-objective optimization frameworks, such as evolutionary algorithms, Pareto-based search and hybrid metaheuristics, enable the systematic exploration of trade-offs between conflicting routing objectives [6]. The combination of open data, ML based prediction and sophisticated optimization form an emerging paradigm of intelligent and adaptive EV routing [7] as shown in fig 1. This review is an attempt to synthesize the existing research across these pillars to form a structured understanding of data-driven multi-objective EV routing and future opportunities for integrated, scalable and real-time mobility solutions.

Open Traffic, Energy, and Charging Datasets for EV Routing

Open datasets are at the heart of Electric Vehicle (EV) data-driven routing in which critical data relating to the road network, traffic flows, energy consumption, and the charging infrastructure are available. Accurate and complete datasets enable realistic modelling of EV behaviour and predictive and optimization frameworks.

Road Network and Traffic Datasets

Open Street Map (OSM) is a crowd sourced geospatial information database worldwide like road geometry, road connectivity, speed limit, etc. making it a good base to use for a real-time routing and map matching application [8]. To achieve a better temporal granularity, Open Mobility Data and Open Traffic extend OSM with attributes associated to the traffic flow and the feed on real-time congestion, which allows fine-grained representation of the travel conditions for EVs [9]. Complementary sources such as TomTom Traffic Index and partial open extracts from Google and Apple Mobility Reports provide high-resolution speed and congestion data yet have low temporal coverage and low update cycles often being proprietary [10]. Together these datasets support static as well as dynamic route evaluation.

Energy and Consumption Datasets

Energy modelling is quite important for a multi-objective EV routing. The Transportation Secure Data Centre (TSDC) and FASTSim datasets from NREL provide detailed powertrain and consumption parameters under a variety of driving cycles for the proper prediction of the energy use of the battery [11]. In addition, open datasets of EV telemetry and simulations can also supply empirical state-of-charge (SoC) profiles in different urban scenarios, playing an important role in the realistic evaluation of the feasibility of a route and energy constraints.

Charging Infrastructure and dataset Preprocessing

Charging station dataset like OpenChargeMap, U.S. Department of Energy's AFDC Station Dataset that has geolocation, plug type, rated power and pricing information are important for route planning and charging scheduling [12]. A complement to the global coverage is achieved by regional repositories in Europe, India and China, that allow to measure the accessibility to charging and detour costs, in multi-objective optimization studies [13]. Integration of traffic, energy and charging data sets needs a well-structured preprocessing pipeline. Key steps include map matching to match GPS traces with the road networks, noise removal, feature extraction and spatial-temporal alignment to match heterogeneous datasets, and this ensures the data consistency for the predictive and optimization models [14].

Dataset Comparison and Evaluation

Table 1 provides an overview of some of the prominent open data sets that are used in EV routing research. As illustrated, OSM and OpenMobility are better in terms of spatial coverage and road-level resolution, on the other hand, NREL and FASTSim are better for an accurate energy modelling. Charging datasets such as OpenChargeMap provide very important operational characteristics but are plagued by temporal incompleteness as well as regional disparity. Researchers often combine multiple data sets to leverage multiple data sets for complementary purposes in order to form an integrated data pipeline for robust EV route optimization.

Table 1. Comparative Overview of Open Datasets for EV Routing

Dataset	**Type**	**Coverage**	**Key Attributes**	**Strengths**	**Limitations**
OSM[8]	Road network	Global	Geometry, topology, speed limits	High coverage, free access	Lacks temporal traffic
OpenMobility / OpenTraffic[9]	Traffic & network	City/ region	Traffic flows, congestion	Temporal traffic data	Limited global coverage
TomTom Traffic Index[10]	Traffic	Regional	Speed, congestion	High-resolution data	Proprietary, limited update
NREL TSDC / FASTSim[11]	Energy	US, simulations	Consumption, powertrain	Accurate energy modelling	Limited real-world diversity
OpenChargeMap / DOE AFDC[12]	Charging	Global	Location, plug type, power, price	Essential for routing	Temporal gaps, regional disparity

Machine Learning Models for EV Routing Components

Machine learning (ML) has become a backbone for electric vehicle (EV) routing for the purpose of dynamic optimization of interdependent sub-systems (traffic, energy, and charging networks, etc.). By allowing intelligent forecasts, ML helps in increasing operational efficiency and sustainability by bringing foresight into the decision-making processes [15]. Modern EV routing implements a pipeline based on predictive optimization, that is, passing through a series of steps that predict traffic, energy and charging in turn before choosing the route. Each stage influences the next stages and prediction errors may be propagated, and have a negative impact on Pareto efficiency in multi-objective optimization [16]. Studies have shown positively that when prediction accuracy is higher, trade-offs between travel time, energy cost and battery longevity is improved [17]. The combination of probabilistic models and reinforcement learning frameworks has also enabled safer and real-time adaptability in stochastic traffic and demand conditions [18], [19].

Table 2. Summary of Machine Learning Models for EV Routing Components

ML Model	Application Domain	Key Features	Performance / Impact
LSTM / GRU [19]	Traffic & Speed Prediction	Temporal sequence learning	High accuracy, captures congestion dynamics
GNN [20]	Road Network Modelling	Graph representation, network dependencies	Improved spatial prediction
Regression / KNN [20]	Energy Consumption	Simple, interpretable, physics-informed	Moderate accuracy, low computational cost
Bayesian / Probabilistic NN [21], [29]	Energy & Uncertainty	Probabilistic outputs	Robust to speed/load variability
XGBoost / Gradient Boosting [23], [24]	Charging Station Forecast	Ensemble learning, feature-rich	>94% accuracy
Neuro-Fuzzy Models [16]	Charging Optimization	Rule-based adaptation	Improved station selection

Traffic and speed prediction has gone through two phases from classical models such as ARIMA and linear regression that give baselines estimates to deep learning architectures that could be used to model complex spatiotemporal congestion dynamics. Recurrent network like LSTMs and GRUs in combination with a graph neural network (GNN) have proved useful in capturing the network wide dependencies and predicting the dynamic speeds [20], [21]. Federated implementations, like fleet, use ML in conjunction with computer vision in order to better estimate congestion by 12%, while still preserving data privacy [21].

Energy consumption prediction has also developed into the hybrid physics informed deep learning. A framework based on LSTMs has been applied to lessen the error in route energy estimation by more than 10% [22]and online-adaptive quantile regression networks have achieved a mean error of 5.04% which improves the reliability of uncertainty intervals [20]. Bayesian and probabilistic neural networks are further improvements to increase robustness under variable loads and also speed profiles and ambientes [21].

Accurate prediction of availability and waiting time of charging stations is a major component of successful route optimization. Ensemble methods such as XGBoost and Gradient Boosting are gaining over 94% of accuracy in occupancy prediction study [23], [24]. Spatiotemporal features integration identifies urban-rural disparity in demand [25] Neuro-fuzzy models are optimized for station selection for routing [16] Uncertainty-aware routing methods. Uncertainty-aware routing methods like probabilistic deep learning and safe reinforcement learning could improve the reliability in dynamic traffic and charging environments. [18], [21], [26] Federated learning allows to preserve the reliability of the prediction without losing privacy.

Despite these advances there are still a number of challenges. Generalization across cities; incomplete/ noisy telemetry and computational limitations for real-time on board inference remain factors to limit practical deployment [27]. Moreover, finding the balance between the accuracy of the predictions and their model-ness is an open issue, especially as the deep architectures become more and more opaque. The future work will have to focus on explainable AI and multi-modality learning, by combining the traffic vision, power-grid data and user behaviour to boost the end-to-end EV routing performance [19], [28].

Table 2 gives a comparative summary on prominent ML models used in the field of EV routing, which includes domain, main features, and performance characteristics. As it can be seen, LSTM and GRU are suitable to be used for temporal prediction, GNN will understand the dependence of the network, regression/KNN is still good for energy estimation, and ensemble is the winner for charging station forecasting.

Multi-Objective Optimization Techniques for EV Route Planning

As the character of electric vehicle or EV routing has shifted from deterministic to predictive data-driven systems, the concepts of multi-objective optimization (MOO) are taking centre stage as the analytical backbone linking the predictive power of forecasting systems, which are machine learning (ML)-driven, to the practical route planning process. As opposed to single objective methods, MOO frameworks are able to balance the competing objectives (travel time, distance, energy consumption, monetary cost, waiting time at the charging station, battery health, etc.) simultaneously, keeping in mind the operational constraints (battery state of charge [SoC], availability of the charger, dynamic vehicle conditions, etc.).

Multi-Objective Formulation

Recent studies are based on the conceptualization of EV routing as a nonlinear MOO problem with energy and temporal dependencies [22]. Each objective brings along trade-offs, by minimizing energy the travelling time increases and vice versa when taking aggressive optimization from the time perspective, charging cost increases and SoC degrades faster. Contemporary frameworks such as NSGA-III, MOEA/D enable Pareto front generation to be adaptive to capture these interdependencies [30]. Using ML predicted inputs, such as traffic and waiting time at the charger, also enables the further potential adjustment of constraints to further improve routing efficiency up to 20% [31].

Classical Multi-Objective Optimization

Foundational techniques--weighted-sum, e-constraint, and Pareto dominance--still are useful for baseline comparisons. While their analytical simplicity enables fast convergence, they are sensitive to the assignment of weights, and often cannot capture non-convex Pareto fronts [32]. In the field of EV applications, such methods are mainly used for the cost-time optimization with dual objectives. Hybrid adaptations with the use of adaptive weights have shown a decrease of 8-10% of total cost with respect to static formulations [33].

Evolutionary Multi-Objective Algorithms (EMOAs)

Evolutionary algorithms have gained a lot of development especially NSGA-II, NSGA-III, SPEA2 and MOEA/D to revolutionize the optimization of EV routing problem. These algorithms maintain diversity in high dimensional objective spaces and they are scalable in terms of convergence. NSGA-II is a benchmark in nature for its balanced performance, whereas NSGA-III and MOEA/D decompose objectives into scalar sub-problems in order to properly trade off [34]. Comparative analyses suggest NSGA-III is 15% better in terms of variance reduction of travel costs, and is faster in terms of Pareto convergence [30]. MOEA/D's decomposition takes optimal account of the restrictions of battery health and charging, which increases the strength of the solution by up to 25% [35], [36].

Swarm Intelligence-Based MOO

Swarm intelligence algorithms -- PSO, ACO, Firefly, DE and GWO -- are extensions of MOO in the case of continuous and nonlinear EV scenarios. PSO variants for traffic-energy co-optimization have up to 30% energy losses incurred due to congestion [37]. ACO based models make use of updates in the pheromone inspired routes to excel deterministic routing in the face of real-time uncertainty with a reduction of 12% in the total travel time [20]. Adaptive inertia weighting and chaos-enhanced PSO formulations are another way to overcome the premature convergence phenomenon and ensure Pareto diversity in dynamic networks [32], [38].

Hybrid Optimization Frameworks

The popularity of hybrid frameworks employing metaheuristics and mathematical and surrogate models is due to the multi-scale complexity in EV routing. Surrogate assisted NSGA variants based on ML models such as Gaussian Process regression or deep neural networks were added with the computational cost of nearly 40% and 95% Pareto accuracy [39], [40], [41]. Multi-constraint fuzzy NSGA models allow additional levels of interpretability in the case of uncertain SoC or charging data.

Route + Charging Co-Optimization

Emerging research is based on the optimization of the route and the charging schedules. By combining the predictive charging availability [16] and ML based energy forecasting [20], NSGA-II frameworks are 15% shorter and 20% more cost effective in terms of cost of the charging. MOEA/D and NSGA-III with the introduction of dynamic pricing limits obtain an additional optimization on multi-station detours, between the convenience of the user and the stability of the grid. Future work is focusing on distributed MOO for Federated Learning for EV fleets [42]. Table 3 summarizes the main techniques of MOO used in EV routing, their advantages, the most common applications and what they tell us about their performance. As we can see, for high dimensional and constrained routing optimization, evolutionary and hybrid algorithms is the best choice, while swarm intelligence is good for nonlinear and dynamic environment.

Table 3. Summary of Multi-Objective Optimization Techniques for EV Routing

Technique	Key Features	Typical Applications	Performance
Weighted-Sum / ε-Constraint [32], [33]	Simplicity, fast convergence	Baseline dual-objective routing	Limited for non-convex fronts
NSGA-II / NSGA-III [30]	Pareto diversity, scalable	Multi-objective routing	15% cost variance reduction, faster convergence
SPEA2 / MOEA/D [35], [36]	Decomposition, diversity maintenance	Battery & charging-aware routing	25% improvement in solution robustness
PSO / ACO / DE / GWO [37]	Swarm-based, adaptive	Traffic-energy co-optimization	Up to 30% energy savings
Hybrid NSGA + Surrogates [39], [41]	ML-assisted Pareto evaluation	High-dimensional constrained routing	40% reduced computation, 95% Pareto accuracy

Research Gaps and Challenges

Despite tremendous advance into data-driven multi-objective EV routing, there are still several gaps in the research and practical difficulties. First of all, generalization of predictive models for varying urban contexts, for example, traffic patterns, road topologies and charging infrastructure vary considerably from city to city, implying that the transferability of ML-based forecasts [27]. Second, data quality issues, such as incomplete telemetry and noisy GPS trace data, as well as sparse charging station logs, reduces the reliability of the predictions and makes it more difficult to make real-time decisions. While preprocessing pipelines minimize the effects of these issues, fully automated and scalable ways of cleaning and aligning are understudied [14]. Third is that combining ML predictions with multi objective optimization frameworks are computationally bottlenecked, particularly for on-board EV systems, fleet operations at large. Surrogate assisted and hybrid MOO methods do behave slightly in addressing this and add to the approximation errors and require careful tuning of hyperparameters [39], [41]. Fourth, uncertainty modelling is a crucial challenge, existing probabilistic and reinforcement learning methods model the stochasticity of traffic and charging conditions, but do not scale with respect to their interpretability and multi-modal fusing of data [18], [26]. Finally, the absence of standardized criteria for benchmarking the evaluation makes comparison of two studies difficult, particularly when aggregating heterogeneous datasets, ML architectures and optimization strategies. It is important to fill these gaps in order to develop personable, real-time and extension and scalable EV routing solutions that are energy-efficient and user-centric.

Future Research Directions

Future research in data-driven multi-objective EV routing will be aimed at improving the integration of predictive modelling, optimization and real-time decision-making addressing practical challenges for deployment. One promising way is to create transferable and adaptive ML models that can be generalized across heterogeneous urban networks, can take into account multi-modal traffic data, and can learn from federated or distributed data while preserving privacy while improving prediction accuracy [28], [42]. Complementary to this, advanced uncertainty-aware models that combine probabilistic deep learning and safe reinforcement learning models can help to make them more robust in the face of dynamic traffic, stochastic energy consumption, and variable charging stations availability.

Another important direction is development of hybrid multi-objective optimization techniques involving the use of surrogate models, fuzzy logic and adaptive metaheuristics for scalable and real-time route and charging co-optimization. Incorporation of dynamic pricing, grid constraint and battery health metrics within these frameworks can ensure both cost efficiency and sustainability. Additionally, open benchmarking data sets and evaluation metrics standardization is important in order to evaluate and compare algorithms consistently. Finally, taking advantage of explainable AI and optimization approaches that are interpretable can help build trust with users and move forward with deployment in commercial EV fleets to support intelligent, energy-efficient, and user-centric routing solutions in a wide variety of urban settings across the globe.

2. CONCLUSION

This review presented a systematic overview of the landscape of data-driven, multi-objective electric vehicle (EV) routing and focused on the collaboration of the open traffic and energy datasets, machine learning (ML) predictive models and advanced optimization techniques. We discussed the importance of ML (e.g. LSTM/GRU, GNN, ensemble methods) in predicting traffic dynamics, energy usage, and the charging station availability and how prediction are incorporated into multi-objective optimization approaches (e.g. NSGA-II/III, MOEA/D and hybrid metaheuristics). Comparative evaluation of datasets, models, and optimization strategies identified existing strengths and limitations and gaps in scalability, generalization, and uncertainty handling. The review makes a constructive contribution to synthesis of predictive and optimization methods, identifies urgent research questions, and outlines the future directions towards real-time interpretable and energy-efficient routing in EVs which can provide a basic roadmap for future academic research and practical implementation in the context of intelligent electric mobility systems.

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