# Electric Vehicle Range Estimation using Fuzzy Logic Model

Andrew Myshkevych[1], Chase Hoffman[1], Steve Kang[1], Suk Jin Lee[1]*, and B. Brian Park[2]
*Corresponding Author: lee43sj@jmu.edu

[1] Dept. of Computer Science
James Madison University
Harrisonburg, USA

[2] Depts. of Civil and Environmental Engineering & Systems and Information Engineering
University of Virginia
Charlottesville, USA

***Abstract*—The transition to Electric Vehicles (EVs) is vital for mitigating greenhouse gas emissions, yet the fear of insufficient battery charge, so-called "range anxiety", remains a primary barrier to widespread adoption. This anxiety is often exacerbated by standard manufacturer estimations that fail to account for real-time environmental factors and individual driving habits. This study addresses these limitations by developing an open-source, dynamic range estimation model using a fuzzy logic (FL) system. Unlike traditional static models, the proposed framework integrates critical real-world variables, including ambient temperature, battery State of Charge (SoC), and driver behavior. Utilizing On-Board Diagnostics (OBD-II) data from a 2012 Chevrolet Volt, the methodology processes four key inputs: acceleration aggressiveness, cruise steadiness, temperature, and SoC. These inputs are mapped through physics-aligned membership functions and human-readable rule sets, employing centroid defuzzification to generate a dynamic range multiplier between 0.6 and 1.1. This allows the system to adjust baseline estimates by accounting for up to a 40% reduction in adverse conditions or a 10% gain in optimal scenarios. Experimental results indicate that the FL model provides more realistic estimates than baseline onboard computer readouts. Evaluation metrics demonstrate high predictive accuracy, outperforming the standard $\leq$ 5% benchmark typically observed for more complex architectures. This initiative proves effective at adapting to complex driving scenarios, offering a real-time solution to mitigate range anxiety and validate the operational viability of EVs for prospective consumers.**

***Keywords*—electric vehicle, range estimation, fuzzy logic, on-board diagnostics.**

## I. Introduction

The global transition toward sustainable transportation has established Electric Vehicles (EVs) as a cornerstone technology for reducing greenhouse gas emissions and improving public health by eliminating tailgate pollution. Despite these clear environmental and social benefits, widespread consumer adoption remains significantly hindered by "range anxiety", the persistent fear that a vehicle will lack sufficient energy to reach its destination. This psychological barrier stems largely from the perceived inaccuracy of manufacturer-provided range estimates. Conventional onboard computers often rely on static models that fail to account for dynamic, real-world variables, leading to misleading battery readouts that erode consumer trust [1].

The complexity of accurate range prediction stems from the high sensitivity of EV batteries to external and behavioral factors. Research shows that extreme temperatures are among the biggest contributors to range loss [2] [3]. High-temperature environments can lead to range reductions of over 35% due to increased HVAC loads and reduced battery discharge capacity [2]. Low temperatures hit even harder, with the range dropping by more than 40% due to heater use and increased battery resistance [3]. Additionally, aggressive acceleration and inconsistent cruising add layers of variability that traditional estimates often overlook [4].

Recent academic efforts to mitigate range anxiety have increasingly turned to intelligent, data-driven methods. Machine learning (ML) approaches, including Long Short-Term Memory (LSTM) and Transformer models, have demonstrated high predictive accuracy with error rates often $\leq 5\%$ [5]. For instance, personalized velocity and energy prediction frameworks have successfully integrated road features and time-series driving data to provide reliable pre-trip estimates [6]. However, these Deep Learning (DL) architectures frequently require massive datasets and heavy computational power, which can pose challenges for real-time deployment and limit their interpretability. Other studies have explored Automated ML (AutoML) to simplify model development, yet these remain sensitive to data scarcity and often function as "black box" systems [7]. To address these limitations, this project develops an open-source, dynamic EV range estimation model using an FL framework. Unlike computationally heavy DL models, FL provides a "data-light" and highly explainable approach, translating complex variables into intuitive rule sets. By processing real-time data via OBD-II, the system integrates four key inputs: ambient temperature, battery State of Charge (SoC), driving aggressiveness, and cruise steadiness. These inputs were mapped through physics-aligned membership functions to generate a dynamic multiplier, adjusting the baseline range to reflect current driving conditions.

## II. Literature Review

Developing reliable EV range models is a multidisciplinary effort involving environmental testing and ML. To reduce "range anxiety," researchers use data-driven methods. This section reviews the environmental, algorithmic, and behavioral models that inform this FL system.

### A. Environmental Impacts on Battery Performance

Recent studies confirm that ambient temperature significantly impacts EV range. Standardized 2024 testing on chassis dynamometers quantified these effects across mainstream EVs. Research conducted in high-temperature environments (35°C) revealed that range reduction can exceed 35%, primarily due to the energy demands of air-conditioning compressors and reduced battery discharge capacity [2]. Conversely, low-temperature testing (-7°C) demonstrated even more drastic penalties, with average range losses of 41.12% and some vehicles losing nearly 48% of their total range [3].

These studies highlighted a significant flaw in current manufacturer estimations. As temperatures reach extremes, the accuracy of built-in range indicators drops sharply, with determination coefficients falling as low as 0.35 in high heat [2] and 0.21 in cold environments [3]. These findings directly informed the inclusion of ambient temperature as a core fuzzy input in this project to correct baseline manufacturer readouts, utilizing membership sets for Cold, Mild, and Hot conditions.

### B. Machine Learning and Predictive Architectures

To address the limitations of static manufacturer models, researchers have explored various ML frameworks. DL models, specifically LSTM and Transformer networks, have set high benchmarks for accuracy. In 2023, studies utilizing Transformer networks for personalized velocity prediction achieved energy estimation errors between 2.35% and 4.92% [5]. These models excel at understanding long-term dependencies in time-series data, such as a driver's historical speed profiles. However, a recurring limitation of these high-performing models is their heavy computational requirement and "black box" nature, which can make real-time deployment and interpretability difficult for the end-user. AutoML frameworks like AutoGluon have been used to simplify model development, though they remain highly dependent on large datasets to avoid inconsistent results [7]. On long-distance trips, errors reached 10.2% due to limited training data [7].

### C. Driver Behavior and Pattern Recognition

Recent studies emphasize that a driver's acceleration and speed maintenance significantly affect energy consumption [5] [6] [8]. One innovative approach involved self-supervised driving pattern clustering, where an autoencoder was used to categorize driving styles into distinct groups without needing human labels [6]. This method allowed for a more flexible range estimation that adapted as the driver's pattern changed during a trip, achieving an average absolute error of just 2.5 km [6]. Furthermore, research into driver behavior profiling using Random Forest models achieved 90% accuracy in identifying risky or aggressive driving [8]. While these behavioral studies are often used for insurance telematics, they provide a framework for quantifying "aggressiveness" and "steadiness". By integrating these behavioral metrics with physical constraints like SoC, models can generate a more realistic multiplier to adjust the expected range.

The synthesis of these preliminary strides reveals a gap between high-accuracy, computationally heavy DL models and the need for a "data-light", interpretable system that can run effectively on real-time vehicle data. While Reinforcement Learning (RL) and complex neural networks offer potential for energy optimization, they face issues with data efficiency and real-time deployment. This project builds upon these findings by utilizing an FL framework that maintains high accuracy, comparable to LSTM models, while ensuring the decision-making process remains human-readable and adaptable to limited datasets. By integrating variables like ambient temperature, SoC, and behavior-based metrics such as aggressiveness and cruise steadiness, the current model generates a dynamic multiplier ranging from 0.6 to 1.1. This approach maintains a physics-aligned methodology while ensuring the decision-making process remains human-readable.

## III. Method

This section describes the end-to-end methodology used to build and evaluate an interpretable EV range estimator from OBD-II telemetry. The approach consists of (i) acquiring and organizing OBD time-series signals, (ii) engineering behavior and context features that correlate with energy consumption [4] [9], (iii) constructing a Mamdani fuzzy inference system (FIS) [10], and (iv) computing the final range estimate and evaluating it quantitatively using standard error metrics and condition-stratified reliability checks.

### A. Data Source and Acquisition

We used OBD-II logging to stream time-stamped vehicle telemetry during real-world driving. In total, 3.3 hours of data were collected by a driver. The minimum required signals for the proposed estimator were:

- **Time:** monotonically increased timestamp $t$.
- **Vehicle speed:** $v_t$ in mph (or converted to mph).
- **State of charge (SoC):** $\mathrm{SoC}_t$ in percent (%).
- **Ambient temperature:** $T_t$ in degrees Fahrenheit (°F).

These signals were selected because they are commonly accessible through consumer OBD-II scanners and are sufficient to (a) compute a baseline range with SoC, (b) estimate driving behavior through the speed trajectory, and (c) incorporate environmental context with temperature. When certain auxiliary OBD fields were present (e.g., engine load proxies on hybrids, battery voltage), they were retained for exploratory analysis but not required by the final fuzzy-only estimator.

### B. Time Alignment and Handling of Variable Sampling

OBD logs may be sampled at non-uniform intervals due to Bluetooth latency or app-side buffering. Therefore, all computations that depend on rates were explicitly based on the elapsed time between consecutive samples:

$$\Delta t_t = t_t - t_{t-1}. \tag{1}$$

Any records with non-positive $\Delta t_t$ were treated as invalid for derivative calculations and were excluded from rate-based feature computation for that step. This ensures that acceleration and other derivative-like terms are physically consistent and comparable across drives even when sampling is not perfectly uniform.

### *C. Baseline Range Model*

A baseline remaining range estimate was computed using SoC and a rated-range constant:

$$R_{\text{base},t} = \left(\frac{\text{SoC}_t}{100}\right) \times R_{\text{rated}}. \tag{2}$$

$R_{\text{rated}}$ is the vehicle's rated range (e.g., EPA/WLTP manufacturer value) and provides a simple linear reference that approximates "percent battery remaining $\times$ nominal total distance." This baseline intentionally excludes context factors (temperature, traffic, and driving style) so that performance gains can be attributed to the fuzzy correction rather than to changes in the base model.

*1) Baseline Comparison:* The baseline used for comparison was derived from the OBD parameter `DISTANCE_SINCE_DTC_CLEAR`, which accumulates the distance traveled since diagnostic trouble codes were last cleared. While this field is not a direct remaining-range estimate, it provides a monotonic distance reference that can be used to compute distance increments $\Delta d_t$ for analysis and to verify consistency of the SoC-to-distance relationship during testing.

For each timestamp $t$, we computed the distance increment:

$$\Delta d_t = d_t - d_{t-1}, \tag{3}$$

where $d_t$ is `DISTANCE_SINCE_DTC_CLEAR` in miles. The remaining-range baseline used for error comparison is the SoC-proportional estimate in (2), using an effective rated-range constant $\hat{R}_{\text{rated}}$ defined in Section III-F1. This baseline provides a consistent reference against which the fuzzy multiplier correction is evaluated.

### *D. Feature Engineering*

The fuzzy system uses both *state* inputs (SoC, temperature) and *behavior* inputs derived from the speed trajectory, with features defined in native physical units for interpretability.

*1) Aggressiveness (Absolute Acceleration):* Aggressiveness quantifies the intensity of acceleration and braking events, which are strongly associated with increased energy use due to traction power peaks and frequent speed transients [4]. We estimate longitudinal acceleration from the speed stream using a finite difference:

$$a_t = \frac{v_t - v_{t-1}}{\Delta t_t} \quad \text{(mph/s)}. \tag{4}$$

We define aggressiveness as the magnitude of acceleration:

$$A_t = |a_t|. \tag{5}$$

In practice, $v_t$ is the OBD speed in mph and $\Delta t_t$ is the elapsed time between samples. Larger $A_t$ values correspond to rapid acceleration or braking events and indicate energy-inefficient driving behavior. Using $|a_t|$ collapses acceleration and deceleration into a single "intensity" measure; this is appropriate for range estimation because both rapid acceleration and hard braking generally increase energy consumption compared to smoother driving [4].

*2) Cruise Steadiness (Speed Variability):* Cruise steadiness captures whether the vehicle is moving at approximately constant speed (typical of efficient highway cruising) or experiencing stop-and-go or highly variable speed (typical of urban congestion). We represent steadiness by the rolling standard deviation of speed:

$$C_t = \sigma\big(v_{t-w:t}\big) \quad \text{(mph)}, \tag{6}$$

We compute $C_t$ over a short rolling window (e.g., 3–10 seconds depending on sampling rate). Lower $C_t$ indicates near-constant speed (high steadiness), while higher $C_t$ indicates stop-and-go or variable driving (low steadiness). $w$ is the window length in samples (or in seconds, mapped to the nearest sample window). Low $C_t$ indicates steady cruise; high $C_t$ indicates unsteady driving. Variable-speed operation and stop-and-go conditions are commonly associated with increased EV energy consumption [4] [9]. In the fuzzy rule base, "low cruise steadiness" is interpreted as high variability (i.e., a penalty condition), while "high cruise steadiness" indicates low variability (a favorable condition).

*3) Temperature and SoC:* Temperature $T_t$ was used directly in °F and mapped into fuzzy sets representing *cold*, *mild*, and *hot* conditions. These categories reflect the observation that EV efficiency degrades at thermal extremes due to battery chemistry effects and HVAC loads [11] [12]. SoC was used directly in percent and mapped into *low*, *medium*, and *high* states; a dedicated low-SoC rule (failsafe) was included to avoid optimistic estimates near depletion.

### *E. Fuzzy Inference System (Mamdani FIS)*

We implemented a Mamdani-style FIS to compute a scalar multiplier $m_t$ that adjusts the baseline range [10]. The final range estimate is:

$$R_{\text{est},t} = R_{\text{base},t} \times m_t = \left(\frac{\text{SoC}_t}{100}\right) \times R_{\text{rated}} \times m_t. \tag{7}$$

The multiplier output was bounded to:

$$m_t \in [0.60, 1.10], \tag{8}$$

which encodes two design principles: (i) adverse conditions can produce substantial range penalties (down to a 40% reduction), and (ii) favorable conditions should not produce unrealistic optimism (capped at a 10% increase). This design choice aligns with documented impacts of thermal extremes and driving conditions on EV efficiency [4] [9] [11] [12].

The bounds $m \in [0.60, 1.10]$ were selected to reflect realistic efficiency variation: adverse conditions such as extreme cold and aggressive stop-and-go driving can reduce usable range by roughly 30–45%, while ideal mild temperatures and steady cruising typically yield only modest improvements. Although extreme scenarios (e.g., sustained highway speed with heavy HVAC usage) could produce larger penalties, bounding $m$ prevents unstable or overly optimistic estimates and improves reliability for real-time use.

*1) Linguistic Variables:* The FIS uses four antecedents and one consequent:

- **SoC:** $\{low, med, high\}$ on 0–100%.
- **Temperature:** $\{cold, mild, hot\}$ on a practical °F range.
- **Aggressiveness:** $\{low, med, high\}$ on mph/s.
- **Cruise steadiness:** $\{low, med, high\}$ on $C_t$ (mph).
- **Multiplier (output):** $\{very\_low, low, med, high\}$ on $[0.60, 1.10]$.

These sets were chosen to balance expressiveness with interpretability [10].

*2) Membership Functions:* Membership functions map crisp inputs to degrees of membership in $[0, 1]$. For interpretability and ease of tuning, we used triangular and trapezoidal shapes [10]:

- **Triangular:** $\mu(x; a, b, c)$ peaks at $b$ and tapers linearly to 0 at $a$ and $c$.
- **Trapezoidal:** $\mu(x; a, b, c, d)$ rises linearly from $a$ to $b$, stays at 1 between $b$ and $c$, then falls linearly to 0 at $d$.

Temperature sets were defined such that *mild* covers the typical comfort/efficiency band (broad support), while *cold* and *hot* activate primarily at thermal extremes [11] [12]. Aggressiveness and cruise sets were defined to separate gentle, moderate, and intense dynamics in the collected data [4] [9]. SoC sets were defined so that the *low* region activates early enough to enforce conservative estimates as the battery approaches depletion.

Membership parameters were selected using a hybrid approach: temperature breakpoints were chosen to reflect known efficiency penalties at thermal extremes, while aggressiveness and cruise steadiness breakpoints were empirically tuned using observed distributions in the collected OBD data (e.g., selecting cut-points near low/median/high percentiles). Tuning was performed manually to reduce MAE/MAPE while preserving interpretability and avoiding overfitting to a single trip.

*3) Rule Base Construction:* Rules are human-readable IF–THEN statements that map antecedent conditions to an output category. Our rule base was designed around common EV efficiency principles supported by prior studies [4] [9] [11] [12].

1) **Thermal extremes reduce range.** Cold and hot temperatures increase energy per mile; thus, rules involving *cold* or *hot* tend to reduce the multiplier [11] [12].
2) **Aggressive driving reduces range.** High $A_t$ reduces range; thus, *high aggressiveness* maps to lower multiplier consequents [4].
3) **Stop-and-go reduces range.** High variability maps to lower multiplier consequents [4] [9].
4) **Ideal conditions allow modest improvements.** Mild temperature plus steady cruise plus low aggressiveness maps to higher multiplier consequents, but bounded by 1.10.
5) **Low-SoC failsafe.** Low SoC triggers conservative behavior regardless of other factors.

Representative rules (not exhaustive) include:

- IF Temperature is *cold* AND Cruise steadiness is *low* THEN Multiplier is *very_low*.
- IF Aggressiveness is *high* AND Cruise steadiness is *low* THEN Multiplier is *very_low*.
- IF Temperature is *cold* OR Temperature is *hot* OR Aggressiveness is *high* THEN Multiplier is *low*.
- IF Temperature is *mild* AND Aggressiveness is *low* AND Cruise steadiness is *high* THEN Multiplier is *high*.
- IF SoC is *low* THEN Multiplier is *low* (failsafe).

Logical OR and AND operations were implemented using standard fuzzy operators (typically max for OR and min for AND), which produce a continuous rule firing strength rather than a binary decision [10].

*4) Aggregation and Centroid Defuzzification:* Each fired rule produces a clipped (or scaled) version of its consequent membership function. These consequents are then aggregated into a single output membership function $\mu_M(z)$. A crisp multiplier is obtained using centroid (center-of-gravity) defuzzification [10]:

$$m_t = \frac{\int z\, \mu_M(z)\, dz}{\int \mu_M(z)\, dz}, \tag{9}$$

where $z$ is the multiplier universe. In practice, this integral is computed numerically over a discretized grid on $[0.60, 1.10]$.

### *F. Experimental Setup and Evaluation Criteria*

*1) Ground Truth Definition:* To compute error metrics, we required a reference "true" remaining range $R_{\text{true},t}$. Because consumer OBD logs do not always include an explicit distance-to-empty signal, we defined ground truth using an empirical full-charge range estimate derived from the vehicle's observed SoC-to-distance relationship.

We measured the average distance traveled per 10% SoC interval during representative drives. Let $\bar{d}_{10}$ denote the mean miles per 10% SoC drop. The effective full-charge range was:

$$\hat{R}_{\text{rated}} = 10 \cdot \bar{d}_{10}. \tag{10}$$

The ground truth remaining range at time $t$ was:

$$R_{\text{true},t} = \left(\frac{\text{SoC}_t}{100}\right)\hat{R}_{\text{rated}}. \tag{11}$$

This provides a vehicle-specific reference that accounts for battery degradation and enables consistent error computation across the dataset.

Performance was evaluated by comparing predicted remaining range $R_{\text{est},t}$ to a ground-truth range proxy $R_{\text{true},t}$ available in the dataset (or trip-based reference values when direct range-to-empty is not logged). We report standard regression error metrics: Mean Absolute Error (MAE), Root Mean

Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), where a small constant $\epsilon$ prevents division by zero when $R_{\text{true}}$ is near zero.

*2) Reliability Checks with Stratified Analysis:* To test reliability beyond a single aggregate score, we stratified evaluation by operating condition:

- **Temperature band:** cold / mild / hot [11] [12].
- **Cruise steadiness:** tertiles of $C_t$ (low/medium/high steadiness) [4] [9].
- **Aggressiveness:** tertiles of $A_t$ (low/medium/high) [4].
- **SoC band:** low / medium / high.

This stratification verifies that improvements are concentrated in the intended regimes (e.g., cold and stop-and-go) and that the model remains conservative at low SoC.

*3) Implementation Notes for Reproducibility:* For each trip, the pipeline was executed sequentially: compute $R_{\text{base}}$, compute features ($A_t$, $C_t$), compute $m_t$ by the FIS, then compute $R_{\text{est}}$. The same membership functions and rule base were used across runs, enabling direct comparison across conditions. Reported results include overall metrics and stratified metrics to support reliability claims.

### G. Generalizability and Vehicle-Specific Tuning

The fuzzy inference structure (inputs, rule logic, and defuzzification) is intended to be transferable across EVs because it encodes general efficiency mechanisms: thermal extremes, aggressive transients, and stop-and-go variability. However, membership cut-points and the effective rated range $\hat{R}_{\text{rated}}$ may require vehicle-specific tuning due to differences in battery capacity, thermal management, drivetrain efficiency, and regenerative braking performance. Future work will evaluate the same rule base on additional EV models and calibrate membership parameters using small amounts of vehicle-specific data.

## IV. Results

The evaluation of the proposed fuzzy logic range estimator demonstrated significant improvements in predictive accuracy when compared to standard manufacturer baselines. By integrating real-time environmental and behavioral data, the model effectively mitigated the "range anxiety" often caused by misleading static readouts.

*1) Model Performance and Accuracy Metrics:* The transition from the first model to the current iteration resulted in a marked reduction across all error metrics. The sharpened, physics-based membership functions and expanded rule set allowed the system to more accurately reflect the non-linear energy consumption of the test vehicle. Table I summarizes the evaluation metrics for both model iterations.

TABLE I
Evaluation Metrics: First Model vs. Latest Model

| Metrics | First Model | Latest Model |
|---|---|---|
| MAE | 0.91 miles | 0.66 miles |
| MSE | 2.61 | 1.94 |
| RMSE | 1.62 miles | 1.39 miles |
| MAPE | 3.87% | 2.80% |

The final MAPE of 2.80% indicates a high level of precision, outperforming some DL approaches which, while accurate ($\leq 5\%$ error), require higher computational overhead.

*2) Comparative Analysis of Range Estimates:* A primary focus of the results was the comparison between the Kalman Filter (KF) estimate, the OBD-actual values, and the manufacturer-rated range. The manufacturer-rated range for a 2012 Chevrolet Volt, the official EPA-rate range is 37 miles. Due to battery degradation, the aging test vehicle was unable to reach a 100% SoC. An empirical analysis of 10% SoC intervals revealed an average distance of 3.83 miles per interval. Correcting for the missing top-end capacity, the true maximum range was established at 34.5 miles. The KF-based estimation yielded a range of 33.32 miles, which closely aligns with the observed OBD-actual distance of 34.64 miles. This demonstrates that the model successfully corrected the overly optimistic manufacturer rating to reflect the actual health and performance of the specific vehicle.

*3) Influence of Fuzzy Inputs:* The model's responsiveness was driven by four key fuzzy inputs: Aggressiveness, Cruise Steadiness, Air Temperature, and SoC. High aggressiveness scores (near 1.0), characterized by rapid acceleration and braking, triggered very low multipliers, reflecting the increased energy expenditure of such maneuvers. Conversely, high cruise steadiness (near 1.0) rewarded stable highway driving with higher range multipliers. The inclusion of temperature as a sharp fuzzy set effectively captured the 35-47% range loss observed in extreme climates. Results confirmed that "Cold" ($\leq 45F$) and "Hot"($\geq 85F$) conditions served as significant range penalties. As the SoC dropped below 30%, the model applied more conservative multipliers to account for increased internal resistance and reduced regeneration efficiency near the bottom of the battery's capacity.

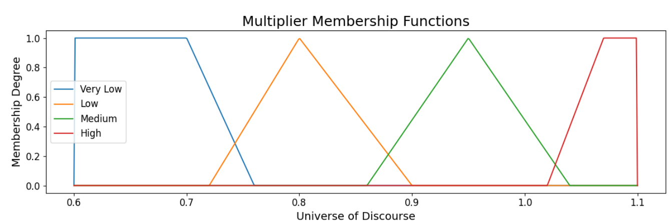


Fig. 1. Multiplier Membership Functions Graph

Figure 1 displays the multiplier membership functions of the current model, which dynamically adjust the baseline EV range in response to environmental and operational conditions. Moving beyond linear calculations (SoC × rated range), this multiplier acts as a dynamic factor, accounting for efficiency variations or energy waste within specific scenarios.

*4) Visualization of Refinement:* Figure 2 shows a scatter plot of the latest model with a significant reduction in outliers. The current model exhibits a more compact, linear relationship between SoC and the estimated range, confirming that the additional rules and refined setpoints created a smoother, more realistic adjustment curve.

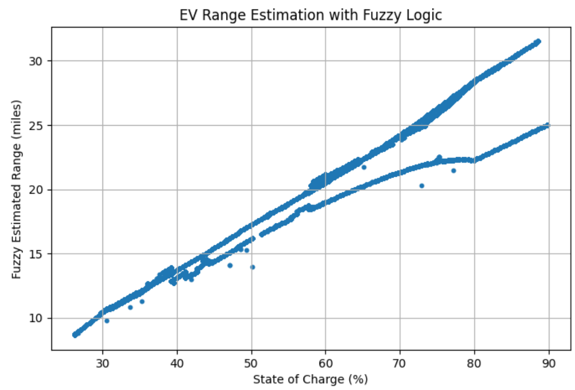


Fig. 2. Range estimation scatter plot for the latest model

## V. Discussion

The findings of this study demonstrate that a fuzzy-logic-based multiplier can improve EV range estimation by addressing real-world variabilities typically ignored by standard manufacturer baselines. The system produces a scalar multiplier bounded between 0.6 and 1.1, represented by four output membership functions (Very Low, Low, Medium, and High), where each shape encodes conditions ranging from worst-case (40% range reduction) to ideal (10% range gain); once all relevant IF-THEN rules fire, centroid defuzzification collapses the aggregated shape into a single crisp multiplier that scales the vehicle's baseline range estimate. By shifting from simplistic linear calculations to physics-based membership functions, the system achieved an MAPE of 2.80%. This performance is particularly noteworthy as it rivals complex architectures like LSTM or Transformer networks while requiring substantially less training data and computational power. Unlike "black-box" DL models, this system utilizes transparent IF-THEN rules, making range adjustments easily traceable to specific driving conditions.

However, several challenges were identified during development. The primary limitation was a lack of data diversity, which restricted the model's performance across varied terrains and conditions. Additionally, time constraints prevented the exploration of alternative KF configurations, and gathering high-fidelity data proved difficult. While the current iteration shows a much tighter estimation curve, minor outliers persist.

## VI. Conclusions and Future Works

This open-source EV range estimator mitigates "range anxiety" by providing a data-driven alternative to standard manufacturer readouts. Using a data-light FL model, this study achieved a high precision by integrating four real-time variables: driving aggressiveness, cruise steadiness, ambient temperature, and State of Charge (SoC). Tested on a 2012 Chevrolet Volt, the model proves that interpretable ML can rival the accuracy of complex systems while remaining computationally efficient. By bridging the gap between lab analysis and real-time application, this research contributes a viable tool to increase consumer confidence and accelerate electric mobility adoption. This project demonstrates how context-aware estimation can effectively overcome technical and psychological barriers to EV transition.

Future iterations of the model will focus on expanding the system's versatility and technical depth to ensure long-term success. A primary objective is to integrate a larger, more varied dataset that includes additional environmental and mechanical variables such as road slope percentage and battery temperature. Another objective is to collect the data using a different vehicle other than the Chevrolet Volt in order to test the model even more. Integrating KF directly with the FL model will unify the architecture, enabling seamless, real-time range estimation. These advancements will move the project closer to a production-ready tool capable of providing dynamic, reliable feedback to drivers in all conditions.

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