MODELING EV ADOPTION AND SUPERCHARGER DEMAND IN WASHINGTON STATE: A STRATEGIC FRAMEWORK FOR TESLA’S ANNUAL INFRASTRUCTURE BUDGET

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PROBLEM STATEMENT

Tesla's long-term sales growth depends heavily on delivering a superior charging experience. *Charging anxiety*—uncertainty about charger availability, distance, and wait times—remains one of the strongest barriers to EV adoption. A strategically planned and well-distributed Supercharger network is therefore essential for both retaining existing Tesla owners and attracting new buyers.

Each year, Tesla dedicates approximately **$500 million** to expand its Supercharger infrastructure across the United States. At the same time, Washington State has implemented aggressive clean-vehicle and decarbonization mandates, creating an urgent need for rapid, equitable, and data-driven charging expansion.

This capstone project aims to develop a blueprint for Tesla's **optimal Supercharger deployment strategy in Washington State** and to determine whether Tesla can realistically reduce charging anxiety, sustain long-term EV adoption, and drive incremental sales within the constraints of a fixed budget.

The project achieves this by constructing a full end-to-end, data-driven analytics pipeline—from raw datasets to actionable insights—summarized in **Figure 1**.

FIGURE 1. PROBLEM-SOLVING APPROACH

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|               1. DATA PREPARATION & BASELINE                   |
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| • Preprocess and clean datasets                                |
|   – Population by county                                       |
|   – EV registrations (VIN counts)                              |
|   – Existing Supercharger network                              |
| • Research state clean-vehicle policy targets                  |
| • Define charging-demand assumptions                           |
|   – Coverage radius (miles)                                    |
|   – Population / density thresholds                            |
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|              2. PROTOTYPE MODEL DEVELOPMENT                    |
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| Build multiple modeling approaches:                            |
|   • Monte Carlo simulations                                    |
|   • Time-series forecasting                                    |
|   • Polynomial + logistic curve fitting                        |
| These represent diverse adoption & charger-demand paths.       |
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|        3. SCALING UP: COUNTY → STATEWIDE MODELING              |
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| • Convert prototype counties into archetypes                   |
| • Apply models to all 39 counties                              |
| • Produce statewide EV adoption + charger requirements         |
| • Generate county-level recommendation engine                  |
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|             4. DECISION INSIGHTS & OUTPUTS                     |
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| Evaluate whether Tesla's $500M/year budget can:                |
|   • Reduce charging anxiety                                    |
|   • Support forecasted EV adoption                             |
|   • Meet state policy-aligned infrastructure targets           |
|   • Drive increased Tesla vehicle sales                        |
| Deliverables: maps, charts, elasticity curves,                 |
| budget feasibility analysis, phased build plan                 |
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DATA AND SOURCE

Defining Policy Target

Washington State law requires deep reductions in greenhouse-gas (GHG) emissions to transition toward a zero-emission transportation system. The legally mandated reductions are:

- 45% reduction by 2030
- 70% reduction by 2040
- 95% reduction by 2050
- 80% Home / Slow Charging Share - National modeling indicates that most EV charging occurs at home or workplace using L1/L2 chargers.

These aggressive decarbonization targets directly drive the need for rapid EV adoption and expanded fast-charging infrastructure statewide.

Source: Washington Department of Ecology – Vehicle Emissions Standards
https://ecology.wa.gov/air-climate/reducing-greenhouse-gas-emissions/vehicle-emissions-standards

Defining Infrastructure Planning

Type	Description	Assumption Recommended	Supporting Source (Link)
Charging Coverage Radius	Dense urban areas require short charging access distance to reduce charging anxiety and support high EV usage.	Urban/Suburb: 2–3 miles coverage radius	Optimal Planning of EV Charging Stations (arXiv): https://arxiv.org/pdf/2404.14452
	Low-density regions can operate effectively with wide charger spacing while maintaining travel-corridor coverage.	Rural: 10–15 miles coverage radius	Multi-Criteria Analysis for EVCS Siting (ScienceDirect): https://www.sciencedirect.com/science/article/pii/S2666691X25000259
Population Served per Charger	Planning ratios vary by density and home-charging access; used to estimate charger demand in each region type.	Urban: 1 per 1,000–2,500	Based on charger-density patterns reported in NREL & ICCT infrastructure demand studies (modeled as assumptions; no fixed national standard).
		Suburban: 1 per 3,000–6,000	
		Rural: 1 per 8,000–15,000	

DATA AND SOURCE

Defining Population

Resident Population (Target Age 25–59)

- Identifies the **core EV adoption demographic** by county.
- Determines **population density classification** (urban / suburban / rural).
- Density directly informs **coverage radius assumptions** and **charger-per-population ratios**.
- Serves as the **demand foundation** of all EV adoption and infrastructure models.
  Source: U.S. Census Bureau (ACS) — https://www.census.gov/programs-surveys/acs

EV Registration Baseline (VIN Counts) (2024)

- Provides the **starting EV population** at the county level (VIN-based).
- Used to compute **historical adoption rate** and distinguish early vs. slow adopter regions.
- Inputs into **Monte Carlo**, **time-series**, and **curve-fitting** models projecting EV growth through 2050.
- Supports modeling of **EV-per-capita**, **EV-per-household**, and **growth potential**.
  Source: Kaggle – U.S. Electric Vehicle Population Dataset — https://www.kaggle.com/datasets

Existing Tesla Supercharger Baseline

- Contains geospatial coordinates and stall counts for Tesla Superchargers in Washington.
- Used in GIS to quantify:
  - ✓ Coverage radius gaps (urban 2–3 miles; rural 10–15 miles)
  - ✓ County-level adequacy vs. population
  - ✓ Chargers per EV and chargers per capita
- Establishes the starting point for gap analysis, budget feasibility, and optimal siting of new chargers.
  Source: Tesla Supercharger Map — https://www.tesla.com/supercharger

PREPROCESSING

Outlines the specific preprocessing steps performed on the core datasets prior to modeling

Population Data (Age 25–59)

- Extract county-level population counts for residents aged 25–59 (the primary EV-adoption demographic).
- Classify each county as urban, suburban, or rural based on population density and geographic characteristics.
- Standardize county names and merged fields to ensure alignment with EV registration and charger datasets.
- Use population totals to determine the denominator for EV adoption rates and to assign density-based modeling assumptions (coverage radius, charger-to-population ratios).

Existing Supercharger Infrastructure

- Filter Tesla Supercharger location data to include only sites within Washington State.
- Aggregate the number of sites and total charging stalls for each county.
- Clean and standardize location fields to ensure compatibility with population and EV datasets.
- Establish the 2024 infrastructure baseline used to evaluate geographic coverage, charger deficits, and required network expansion.

EV Registration Data (Battery Electric Vehicles)

- Filter VIN registration records to include only battery electric vehicles registered in Washington State.
- Map VIN records to counties to derive the 2024 baseline EV count for each region.
- Validate and align county naming conventions across datasets.
- Use these counts as the starting point for EV adoption forecasting and for evaluating county-level EV penetration.

PREPROCESSING- MAPPING

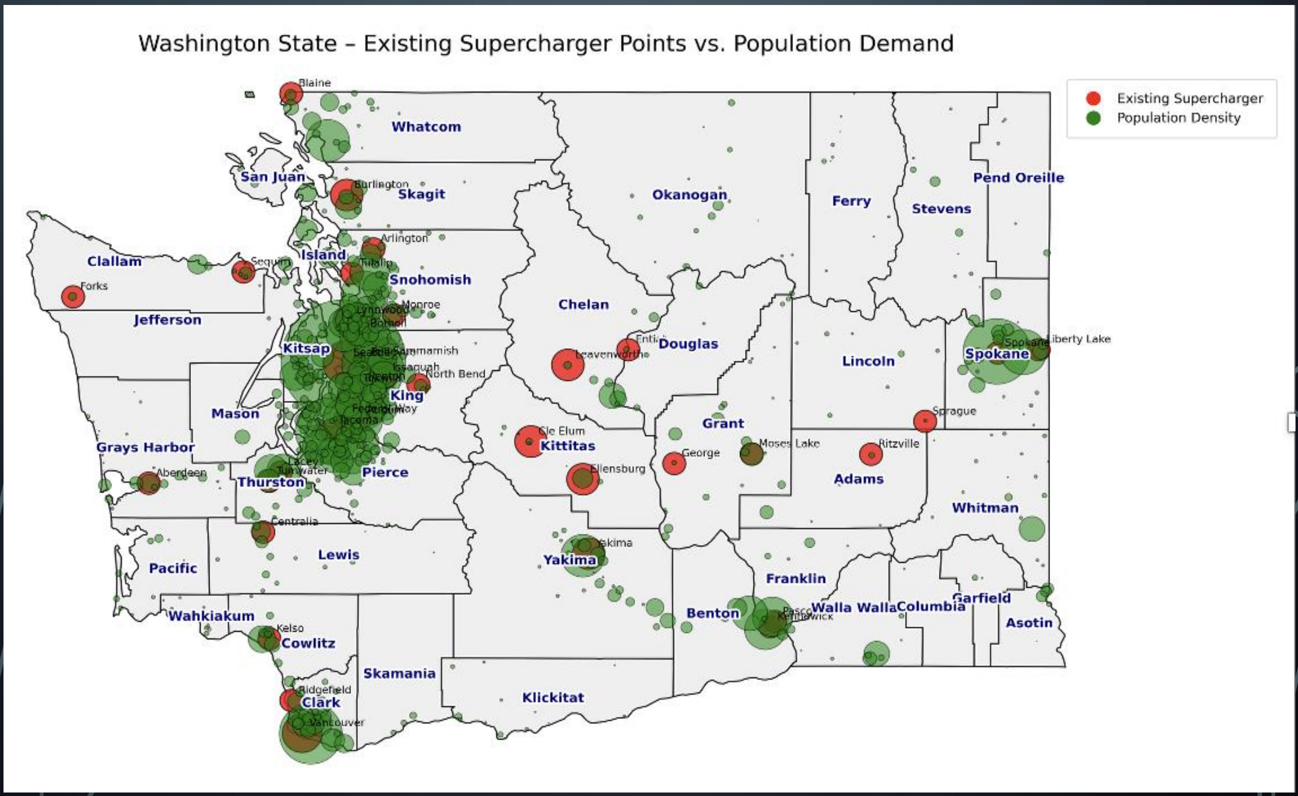
Why This Profiling Matters?

Because the moment you put the data on a map… the story jumps out! **Population Demand vs Existing Chargers.**

- **Huge green population clusters** with **no red Superchargers** anywhere nearby
- **Overloaded corridors** where chargers exist but don't match demand
- **Massive rural gaps** where EV drivers would panic before their battery does

Why Expansion in infrastructure is needed?

- **Untapped sales opportunities** hiding in counties Tesla barely touches today
- **Washington has far more EV demand than Supercharger supply**—meaning huge room for growth and revenue! **50 supercharger points vs 3.5M target population!**



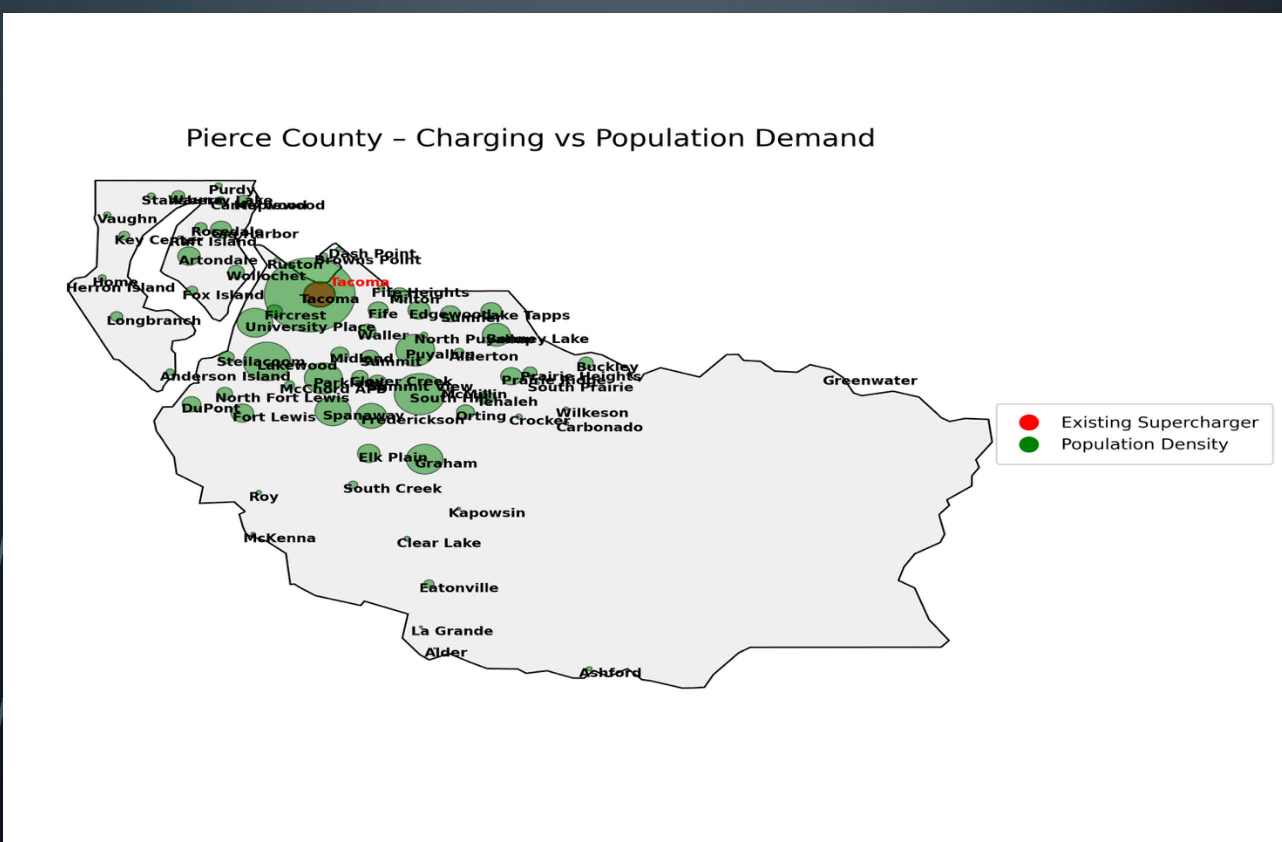
PREPROCESSING- MAPPING

Closer look at a County-Level. For example.

How should Tesla plan the build out/setting blue-print?

- Should Tesla expand based on population density?
- But it is more likely that customer prefer EV because of cost saving due to home charger instead of supercharger?
- Then, should Tesla expand based on distance radius? Does this lead to slower adoption?
- If Tesla goes with more aggressive expansion, is it still within budget?

← Our forecast model will answer all these questions!



PREPROCESSING- MAPPING

What Is Performed in Python?

A full GIS-based spatial analysis **is conducted** to visually profile Washington State's EV charging landscape and **identify** gaps between population demand and existing Tesla Supercharger infrastructure.

County Boundary Extraction

- **Pull** Washington State county polygons from the ArcGIS REST API.
- **Convert** raw ArcGIS geometry into GeoJSON format for compatibility with GeoPandas.
- **Filter** to FIPS 53 to isolate Washington counties only.

Supercharger Location Processing

- **Clean** the Tesla Supercharger dataset to include only sites listed under "Washington State"—not "WA" or surrounding states.
- **Extract** city names from address fields and **standardize** county names.
- **Generate** a city-level summary including Supercharger counts and coordinates.
- **Map** cities to latitude/longitude using a custom coordinate dictionary.

Population Demand Layer

- **Import** Washington population data at the city level (2025 dataset).
- **Convert** each city into geographic points with lat/lon coordinates.
- **Scale** population dots proportionally to "Proportion (%)" to reflect relative demand.

Combined Spatial Mapping

- **Produce** both statewide and county-level maps showing:
    - **Red circles** = Existing Tesla Superchargers
    - **Green circles** = Population density ("demand hotspots")
- **Scale** markers to make infrastructure–demand imbalances visually explicit.
- **Create** individual maps for all 39 counties and **export** them as PNG files.
- This dataset profiling **enables** a clean, interpretable, and spatially accurate visualization of infrastructure gaps.

MODELING APPROACH - DEFINE PROTOTYPE

Defining/Setting 4 Prototype

- Four representative counties were selected—each aligned to a distinct demographic and geographic archetype—to ensure the model generalizes across urban, suburban, and rural environments.

Why do we need to select different prototypes?

- These archetypes illustrate how EV adoption and charging demand vary across population segments and provide scalable patterns for forecasting outcomes in the remaining counties/statewide.
- This modeling framework combines county-level archetypes, EV baseline registration counts, existing supercharger points, population characteristics, and charger-coverage formulas to forecast EV growth and charging-infrastructure needs through 2050.

County	Archetype	Population Profile
King County	Urban	High density, strong EV demand
Pierce County	Urban/Suburban	Mixed density with rising adoption
Kitsap County	Suburban	Commuter-driven population, moderate adoption
Chelan County	Rural/Forest	Low density, limited charging access

MODELING APPROACH – APPLYING ASSUMPTION

Applying Assumption

Policy Target
Washington’s statewide EV adoption goals define the long-term adoption curve:

- Required adoption: **45% by 2030**
- Required adoption: **70% by 2040**
- Required adoption: **95% by 2050**

All county-level adoption forecasts are forced to converge toward these mandatory trajectory points.

Three Adoption Phases
EV adoption from 2025–2050 is modeled in three macro phases:

Phase 1 — 2025–2030: Rapid Expansion

- Tesla accelerates Supercharger deployment
- Drivers show strong interest in EVs due to cost savings + rising popularity
- Competition increases pressure to expand infrastructure
- Adoption rises quickly in response to improving accessibility

Phase 2 — 2030–2040: Shift to 80% Home Charging

- Modeled based on national NREL projections showing **L1/L2 handling ~80% of total charging by 2030**
- Public Supercharger growth slows as home charging becomes dominant
- Market rebalances between public and residential charging
- Adoption continues but at a moderated pace

Phase 3 — 2040–2050: Saturation and Slowdown

- Most households have transitioned to EVs
- Remaining adopters enter gradually
- Public charging growth stabilizes, focused on replacement + rural coverage

MODELING APPROACH – SETTING UPPER AND LOWER BOUND SCENARIOS

Lower Bound Scenario — Geographic Coverage Minimum

Purpose

- Estimates the **minimum number of chargers needed** to ensure basic accessibility across each county, regardless of EV adoption levels.
- This forms the *infrastructure floor*, reflecting the chargers required simply to eliminate coverage gaps and reduce charging anxiety.

Key Logic

Each county's land area is divided by a density-appropriate service radius:

- **King - Urban:** ~2 miles
- **Pierce - Urban/Suburban:** ~3 miles
- **Kitsap - Suburban:** ~5 miles
- **Chelan - Rural:** ~15 miles

Formula

- $\text{Chargers}_{\text{min}} = \left\lceil \frac{\textit{County Area}}{\pi r^2} \right\rceil$

Characteristics

- Annual build rate remains constant across years
- Independent of EV population, income, or adoption rate
- Ensures basic geographic accessibility rather than demand matching
- Adoption phases have minimal practical effect

Interpretation

This scenario answers:

"What is the minimum number of chargers required so drivers never travel too far without charging?"

MODELING APPROACH – SETTING UPPER AND LOWER BOUND SCENARIOS

Upper Bound Scenario — Population-Driven Charger Demand

Purpose

- Models the **maximum charger capacity needed** to support statewide EV adoption aligned with Washington's policy targets
  (45% by 2030 → 95% by 2050).
- This represents the *infrastructure ceiling*—the build-out necessary if public charging must scale with rising EV usage.

Key Logic

Charger demand is estimated using population-based ratios:

- **King - Urban:** ~1 charger per 1,500 residents
- **Pierce/Kitsap- Suburban:** ~1 per 2,500
- **Chelan – Rural/Forest:** ~1 per 5,000

Formula

- $\text{Chargers}_{demand} = \left\lceil \dfrac{Population_{25-59}}{Residents\ per\ Charger} \right\rceil$

Characteristics

Why the Upper Bound Is Highly Sensitive to Phasing

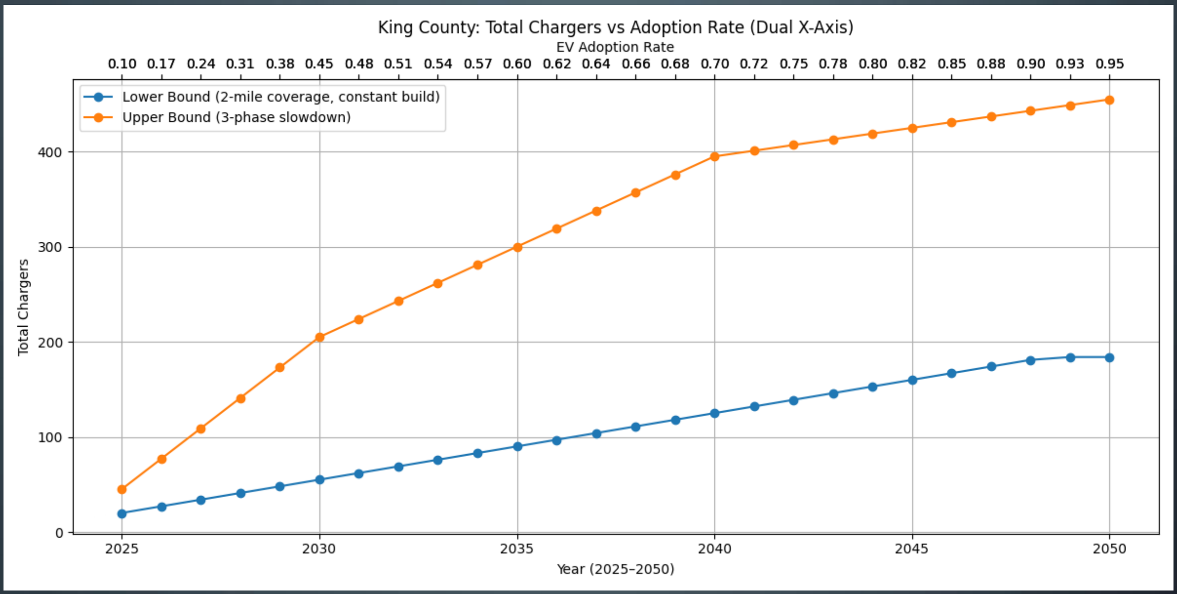
- Phase 1's rapid adoption because of EV trending and popularity in 2020s. Sensitive to supercharger rapid infrastructure expansion
- Phase 2's home-charging shift significantly lowers public charger growth
- Phase 3's saturation flattens additional charger requirements
- In contrast, the geographic lower bound barely changes with adoption phases.

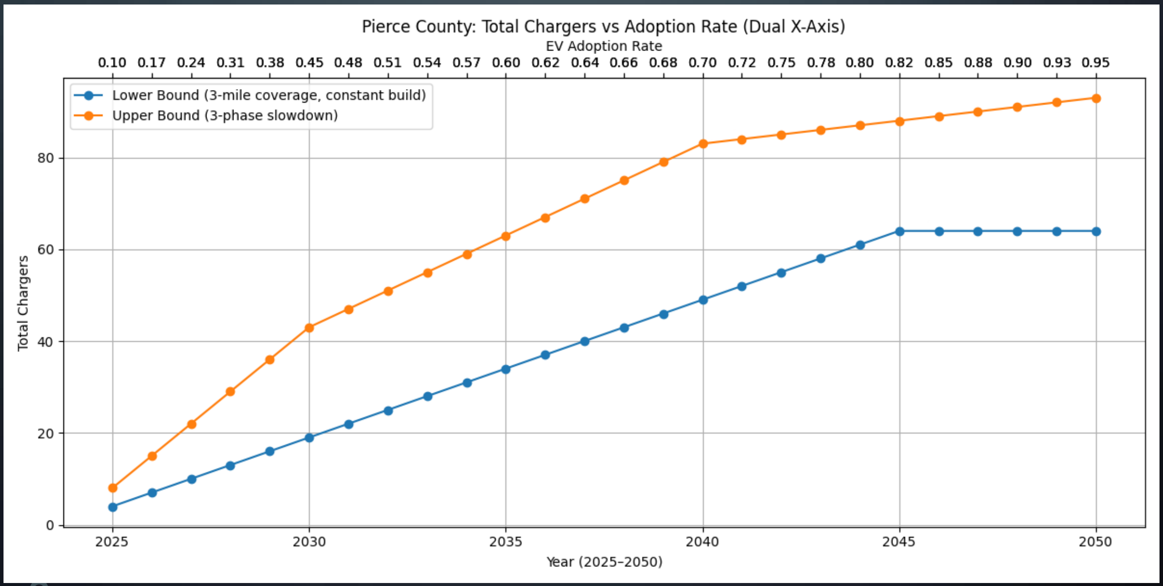
Interpretation

- This scenario answers:
  "If chargers must grow to fully support policy-aligned EV demand, how many would Washington require?"

VISUALIZE THE LOWER AND UPPER BOUND ADOPTION AND CHARGER BUILD-OUT OF THE 4 PROTOTYPE – KING AND PIERCE

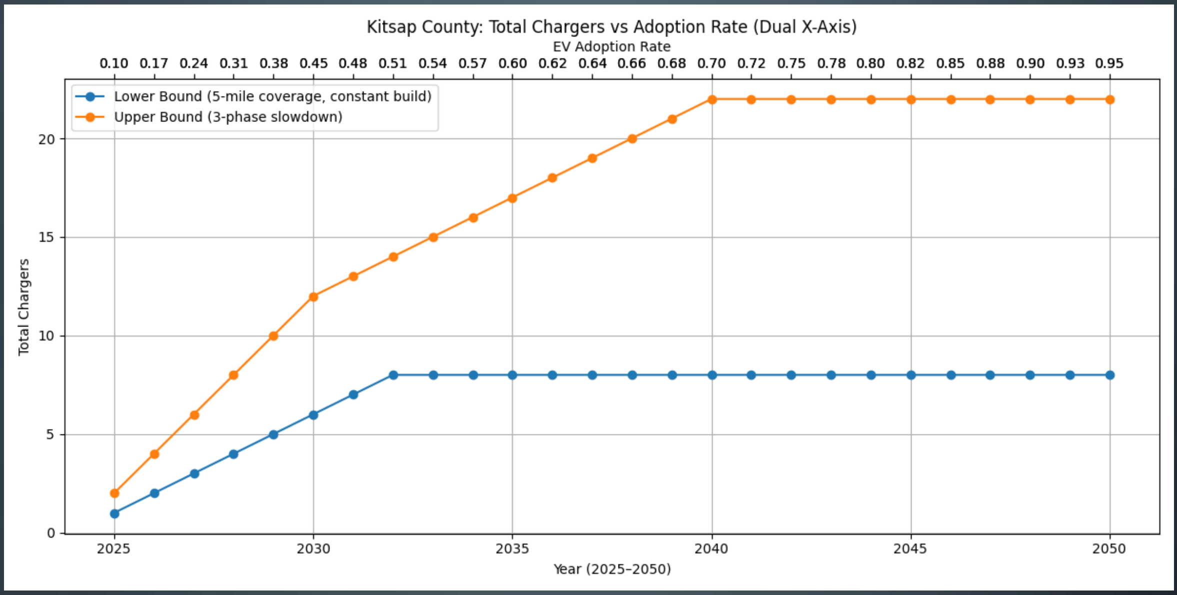
Lower-bound use a dampened adoption slope, while upper-bound use a steeper, policy-aligned slope, ensuring trajectory families reflect optimistic vs conservative adoption behavior



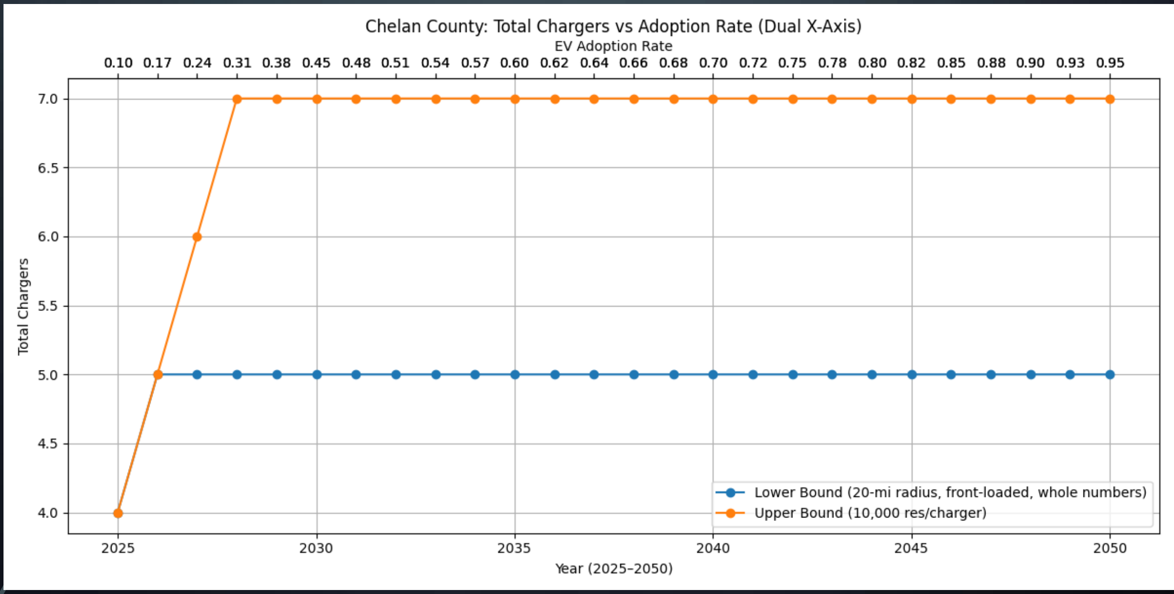


VISUALIZE THE LOWER AND UPPER BOUND ADOPTION AND CHARGER BUILD-OUT OF THE 4 PROTOTYPE – KITSAP AND CHELAN

Lower-bound use a dampened adoption slope, while upper-bound use a steeper, policy-aligned slope, ensuring trajectory families reflect optimistic vs conservative adoption behavior



For counties with extremely low infrastructure needs (e.g., Chelan), the model uses a front-loaded deployment. Likely to met coverage in early years because very few deployment needed for geographic (distance radius) coverage.



TIME-SERIES & MONTE CARLO

What This Model Is Forecasting

The project uses a combined **Monte Carlo simulation** and **time-series adoption model** to forecast EV adoption in each Washington county from **2025 to 2050**. The forecasting system captures how EV adoption evolves as a function of:

- charging infrastructure expansion
- population characteristics
- state policy milestones (2030–2050 targets)
- expected shift toward 80% home charging
- regional urban–suburban–rural differences
- behavioral uncertainty at different stages of market maturity
- Instead of predicting one definitive adoption curve, the model produces a **range of plausible futures**, showing how adoption may accelerate or slow under different infrastructure and policy environments.

Relationship Between Monte Carlo Outputs and the Lower/Upper Bound Scenarios

The Monte Carlo system does not operate independently—it is “bounded” by two deterministic infrastructure scenarios defined earlier:

Lower Bound (Geographic Coverage Floor)

- Minimum chargers needed to eliminate physical gaps
- Based on 2–15 mile coverage radius
- Not tied to population growth

Upper Bound (Population-Driven Ceiling)

- Maximum chargers needed to fully meet modeled EV demand
- Based on residents-per-charger ratios (1:1500 to 1:10,000)
- Sensitive to population density and adoption speed

How these bounds interact with Monte Carlo:

- The **lower bound** sets the *minimum* charger path the simulation must respect.
- The **upper bound** defines the *maximum plausible charger demand*.
- All stochastic adoption trajectories evolve **between these two constraints**, ensuring realistic future paths that never drift outside physically feasible infrastructure levels.
- High-growth Monte Carlo paths align more closely with the **upper bound**, while low-growth paths behave closer to the **lower bound**.
- The bounds act as structural “rails” that give the stochastic model shape, realism, and policy alignment.

TIME-SERIES & MONTE CARLO

Stochastic Monte Carlo Simulation (1,000 trajectories per county)

The simulation generates **1,000 plausible adoption paths** from 2025–2050 for each county. Each trajectory represents a different "future" shaped by controlled randomness, reflecting:

- year-to-year behavioral noise
- variation in responsiveness to charger growth
- uncertainty introduced by the home-charging transition
- variable sensitivity to each policy phase
- socioeconomic influences on adoption rates
- Although all trajectories follow the same structural rules, they diverge through random draws in the noise terms (σ), reversion behavior (κ), and charger-response multipliers.

Additional Modeling Mechanics Implemented

The following technical elements were implemented in code and are essential to how the forecasting engine behaves.

(1)Charger-Momentum Effect (Trailing 3-Year Growth)

the model looks back at **how fast chargers increased over the last 3 years** and uses that trend to influence adoption. If chargers have been consistently growing, the momentum is strong → EV adoption accelerates. If charger growth slows, the momentum weakens → adoption slows.

(2) Phase-Specific Volatility (σ) and Mean Reversion (κ)

Each policy phase has distinct uncertainty characteristics:

- **Phase 1 (2025–2030)** → high volatility, fast market growth
- **Phase 2 (2030–2040)** → reduced volatility due to home-charging stabilization
- **Phase 3 (2040–2050)** → rising uncertainty as adoption nears saturation

σ introduces randomness each year; κ pulls trajectories back toward expected phase-level targets, ensuring realism. For example, when drifting **too high** or **too low** compared to what is expected for that phase (Phase 1 fast growth, Phase 2 slower growth, Phase 3 saturation), κ gently **pulls it back toward the expected path**.

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Additional Modeling Mechanics Implemented

(3) Monotonicity Enforcement (Adoption/Charger Built Never Declines)

- EV adoption cannot fall year-to-year. The model applies:

$$A[t] = \max(A[t-1] + \Delta A , A[t-1])$$

preventing downward dips caused by stochastic variation.

(4) Saturation Limit (≤ 95% Adoption)

The model caps maximum adoption at **95%** to reflect realistic market saturation:

- not all households convert
- late adopters transition slowly
- policy targets imply an asymptotic limit
- After monotonicity enforcement, the model applies:
- $A[t] = \min(A[t], 0.95)$

ensuring trajectories never exceed plausible real-world EV saturation.

(5) Charger Growth Cap (≤ 50% per year)

The model does **not allow charger installations to grow faster than 50% in any single year**. Why?

Because without this limit, the simulation might create unrealistic scenarios such as:

- charger counts doubling in a single year
- counties building 100 chargers when they only have 50 today
- explosive jumps that no utility, contractor, or permitting system can actually support

The 50% cap maintains realistic, steady charger growth consistent with real-world infrastructure deployment. In low-density counties, the model typically forecasts only one charger per year; therefore, early front-loading is necessary so that geographic coverage can be completed in the initial phase.

(6) Monte Carlo Initialization (35% Lower, 65% Upper)

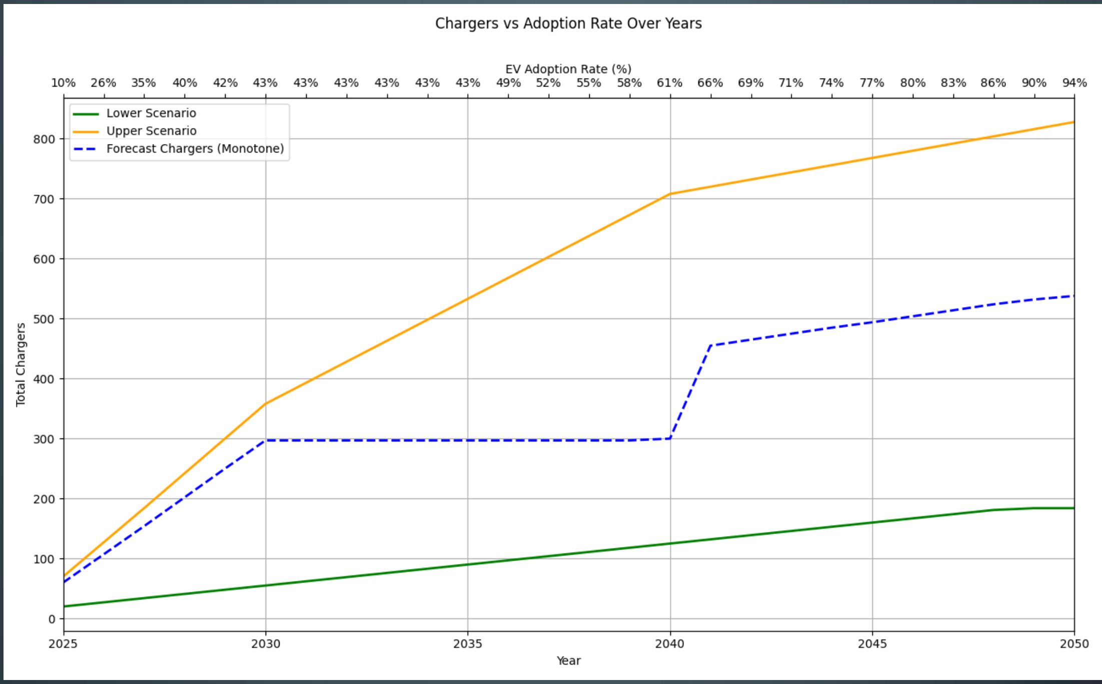
For each county, the model begins forecasting in **2025**, and it must choose a reasonable *starting adoption value* for the Monte Carlo simulations.35% weight from the lower bound and 65% weight from the upper bound. Since Washington State has **high EV maturity**—large EV fleet, strong charging network—the "true" starting point is expected to be **closer to the upper-bound** than the lower.

$$\textbf{Initial Adoption}_{2025} = \mathbf{0.35} \times \textbf{LowerBound}_{2025} + \mathbf{0.65} \times \textbf{UpperBound}_{2025}$$

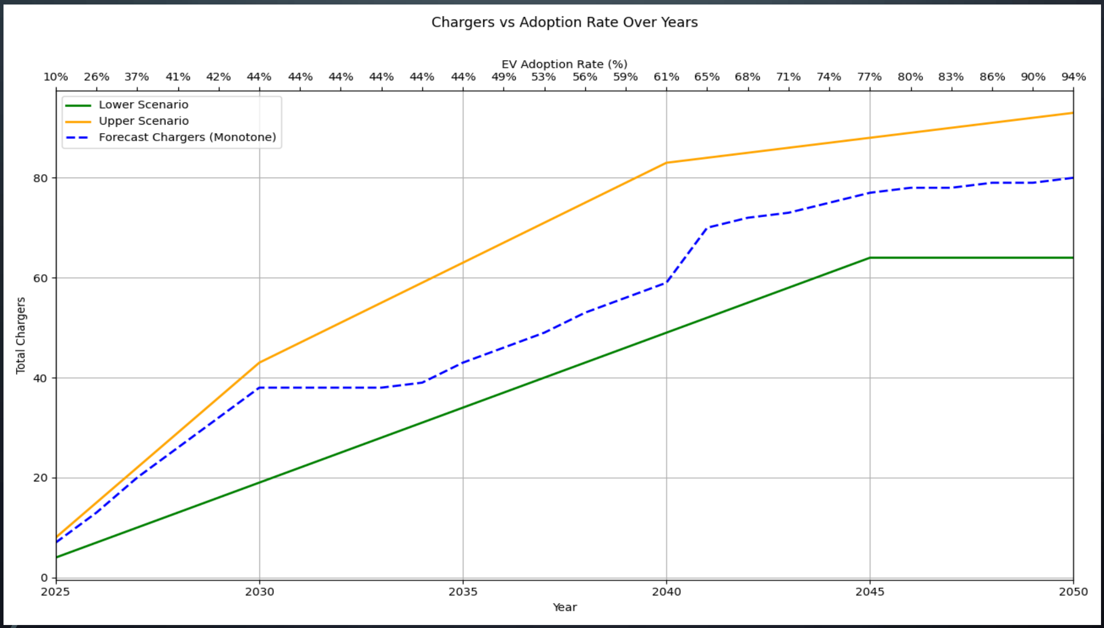
TIME-SERIES & MONTE CARLO

Visualize the forecast

- King



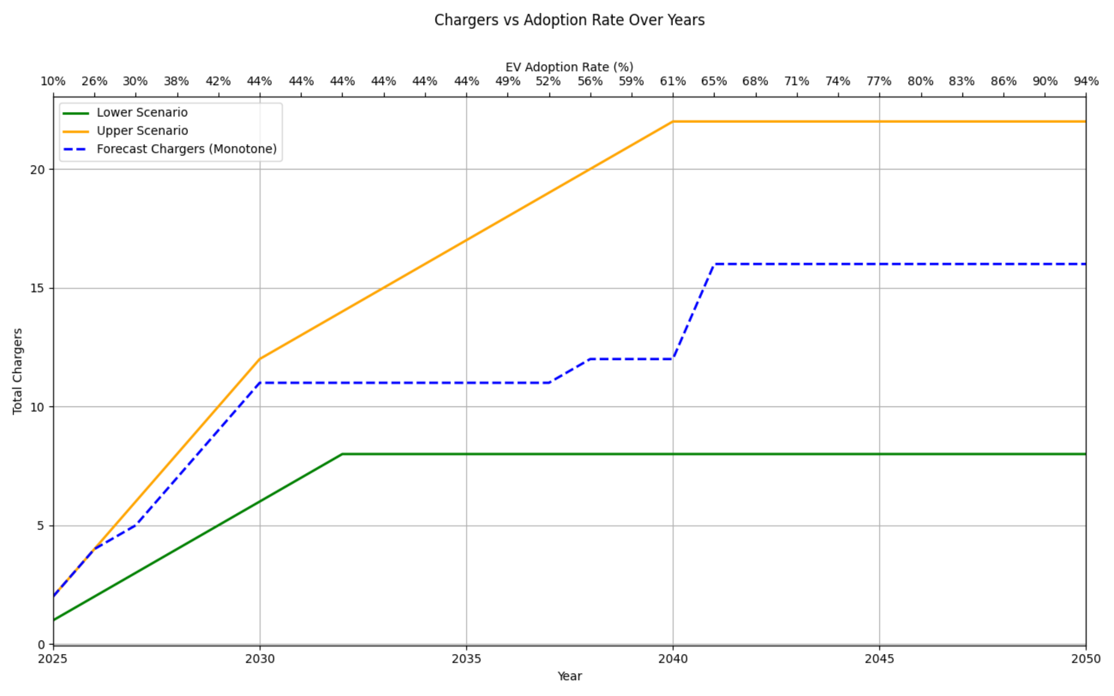
- Pierce



TIME-SERIES & MONTE CARLO

Visualize the forecast

- Kitsap



Insight Summary

Urban and suburban counties (King, Pierce, Kitsap) show **very similar EV-adoption patterns**. Their higher density and relatively short charger-coverage radii (2–5 miles) make adoption grow smoothly through each policy phase:

- Strong early growth (Phase 1)
- Moderate expansion as home-charging rises (Phase 2)
- Near-saturation by 2040–2050 (Phase 3)

Because chargers serve many residents within a small radius, adoption is predictable and tightly clustered across all Monte Carlo trajectories.

TIME-SERIES & MONTE CARLO

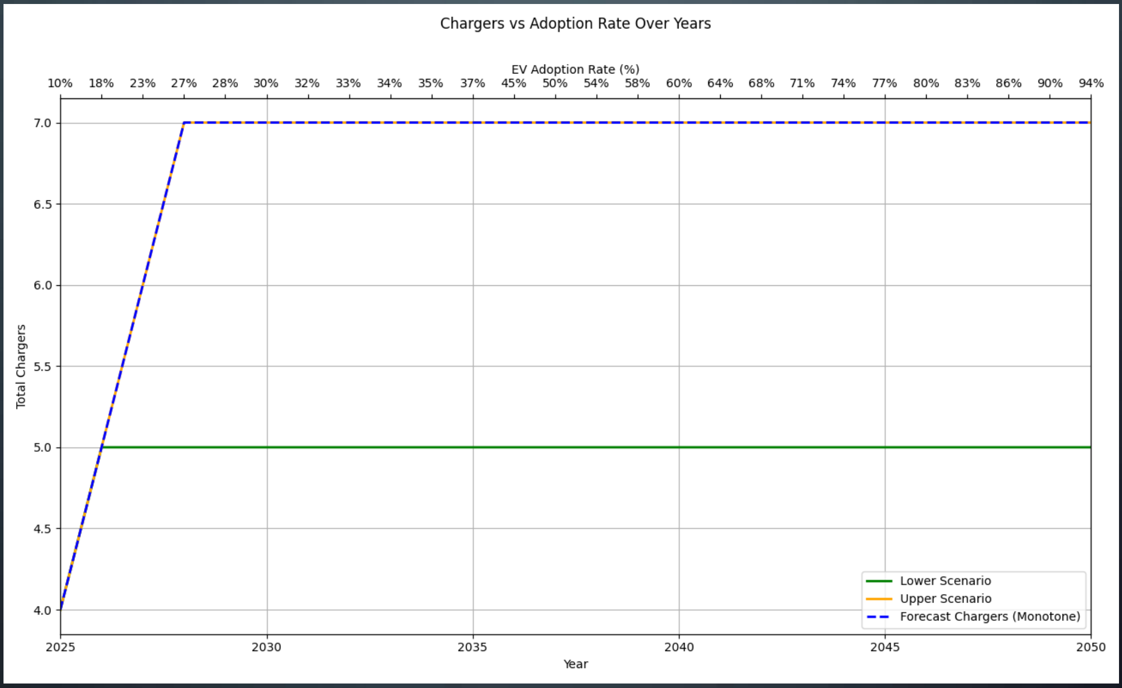
Insight Summary

Rural/Forest) - Chelan County is different - With **very low population density** and a **15-mile coverage radius** required to serve long-distance rural travel, EV adoption becomes **infrastructure-dependent**:

- Early adoption remains limited until minimum public coverage is built
- Once coverage is established, adoption accelerates sharply
- Uncertainty is higher because a single charger covers a large geographic area

Overall, dense counties grow based on population demand, while rural counties grow based on the availability and geographic reach of public chargers—exactly matching the model’s phase-based expectations.

- Chelan



CURVE FITTING · COUNTY ARCHETYPE SCALING (4 → 39 COUNTIES)

County Archetype Scaling (4 Templates → 39 Counties)

- The model begins with four representative counties — King, Pierce, Kitsap, and Chelan — each representing a different **population and infrastructure archetype**:

Population Range	Assigned Template	County Characteristics
> 1,000,000	King	Dense urban core
130k–1M	Pierce	Commuter + suburban mix
34k–130k	Kitsap	Suburban / mid-density
< 34k	Chelan	Rural / forest, long-distance

- Assign each county to a template based on population size. Run each county through its template to generate yearly data:
  - Forecast_Adoption
  - Forecast_Chargers
  - EVs(year) = Adoption(year) × Pop_2024

    Population is held constant to simplify computation and isolate the EV adoption curve behavior.
- This produces a full 2024–2050 forecast data for all 39 counties.

Why county-level forecast is important?

- **Prevents one-size-fits-all modeling:** Avoids applying a single statewide growth curve that would obscure meaningful differences in adoption patterns, infrastructure needs, and growth timing across counties.
- **Aligns curve behavior with real-world density constraints:** Ensures growth dynamics reflect actual urban, suburban, and rural conditions, including realistic saturation and expansion limits.
- **Provides context for interpreting 2050 outcomes:** Enables clearer interpretation of long-term results by identifying where adoption scale, saturation, or infrastructure constraints drive county-level differences.

CURVE FITTING · COUNTY ARCHETYPE SCALING (4 → 39 COUNTIES)

Time-Based Forecasting Models

Why time-based forecasting models are required?

- **Budgeting & Dollar Impact:** Enable year-by-year capital planning, comparison of front-loaded versus phased investments, and better control of total infrastructure spending as deployment approaches saturation.
- **Geographic Planning:** Support year-over-year GIS analysis to identify charger density gaps, prioritize cost-effective locations, and avoid overbuilding in low-demand areas.
- **Annual Targets:** Translate long-term forecasts into clear yearly deployment goals aligned with policy milestones (2030, 2040, 2050).
- **Adaptive Deployment:** Provide a time-sequenced roadmap that allows Washington State—and private operators such as Tesla—to reallocate investment from saturated counties to underserved regions or other states as marginal returns decline.

Polynomial & Logistic Curve Fitting

- Scatter plots were generated for each county using 2024–2050 forecast data to visualize EV adoption and charge-point growth over time.
- Multiple candidate curve type were fitted, and the model with the highest R^2 was selected as the best fit:
  - ➢ Linear,
  - ➢ Quadratic,
  - ➢ Cubic,
  - ➢ Logistic
- The coefficient of determination (R^2 (measures the proportion of variation in the observed data that is explained by the fitted curve; higher R^2 values indicate that the model more accurately captures the underlying growth pattern.

Year-Based Forecasting Functions – County-Level

- For each county, **two time-based equations** were generated:

Function	Purpose
Number Charge Points vs Time	Charger deployment planning
EV Adoption Rate vs Time	Demand forecasting

STATEWIDE AGGREGATION

Scaling to Statewide Level

- Statewide results are generated by aggregating county-level forecasts rather than modeling Washington State as a single homogeneous unit.
- This approach preserves local growth dynamics while providing a coherent statewide view for planning and policy analysis.

Aggregation of Forecast Data

- **Population (2024 baseline):**
  - $\text{Pop}\_2024^{Statewide} = \sum_{i=1}^{N} Pop\_2024_i$
- **Electric Vehicles (2024–2050):**
  - $\text{EVs}_y^{Statewide} = \sum_{i=1}^{N} EVs_{i,y}$
- **Charging Infrastructure (2024–2050):**
  - $\text{Superchargers}_y^{Statewide} = \sum_{i=1}^{N} Superchargers_{i,y}$
  - where i indexes counties and y denotes the forecast year.
- **EV Adoption Rate (2024–2050):**
  - $\text{Adoption}_y^{Statewide} = \frac{\sum_{i=1}^{N} (Adoption_{i,y} \times Pop\_2024_i)}{\sum_{i=1}^{N} Pop\_2024_i}$
  - **EV adoption rates** are aggregated using a **population-weighted average** to ensure proportional county representation and prevent small counties from distorting statewide results.

Year-Based Forecasting Functions – Statewide

- **Consistent with the county-level methodology**, statewide analysis begins with a scatter plot of aggregated annual data (2024–2050), representing the combined county outputs for each year.
- **Multiple candidate curve models (linear, quadratic, cubic, and logistic)** are fitted to the statewide scatter, using the same functional forms applied at the county level.
- **The best-fitting model is selected based on highest** R^2 to ensure comparability and statistical consistency with county results.

Function	Purpose
Number Charge Points vs Time	Charger deployment planning
EV Adoption Rate vs Time	Demand forecasting

CONVERTING 39 COUNTY CURVES INTO A UNIFIED WASHINGTON FORECAST

Year-Based Forecasting Functions – Statewide

- **Number Charge Points vs Time** - Cubic time-based model selected as best fit:
  - $y = 0.1428\left(x - 2024\right)^3 - 6.8790(x - 2024)^2 + 132.5427(x - 2024) + 50$
  - y = Charge Points, x = Year
  - Goodness of fit: $R^2 = 0.9382$,
  - Captures rapid early expansion followed by gradual tapering as deployment matures

- **EV Adoption Rate vs Time** - Quadratic time-based model selected as best fit
  - $y = -5.9998 \times 10^{-4}\left(x - 2024\right)^2 + 0.04741(x - 2024) + 0.05271$
  - y = Adoption Rate, x = Year
  - Goodness of fit: $R^2 = 0.9165$,
  - Reflects strong early adoption growth with slowing acceleration over time

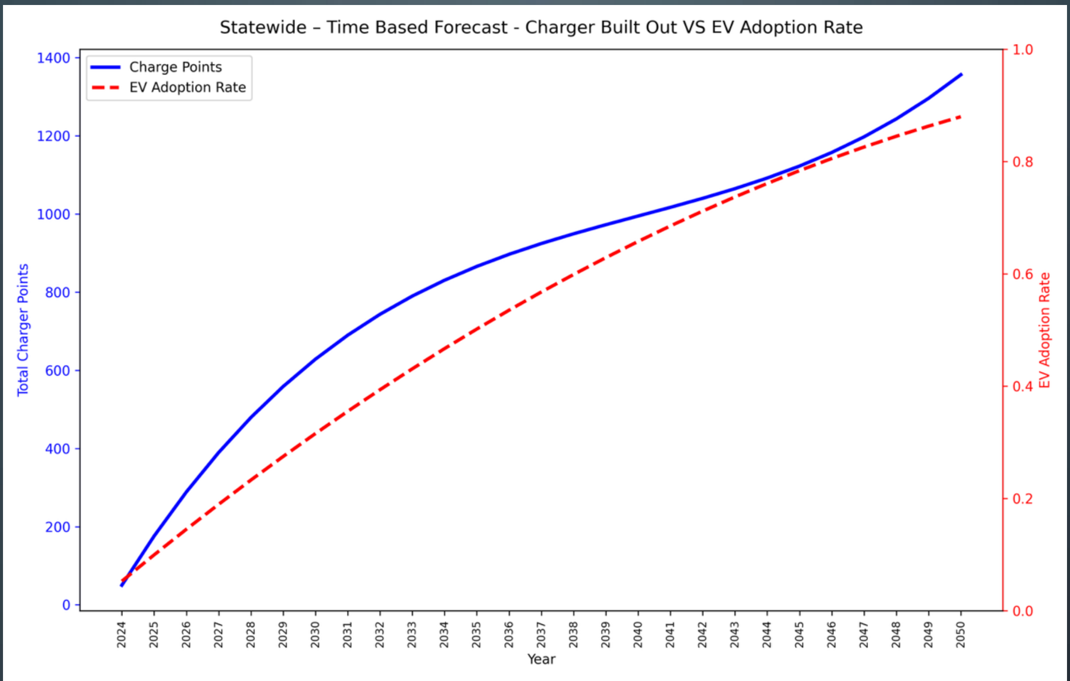
Modeling Implications

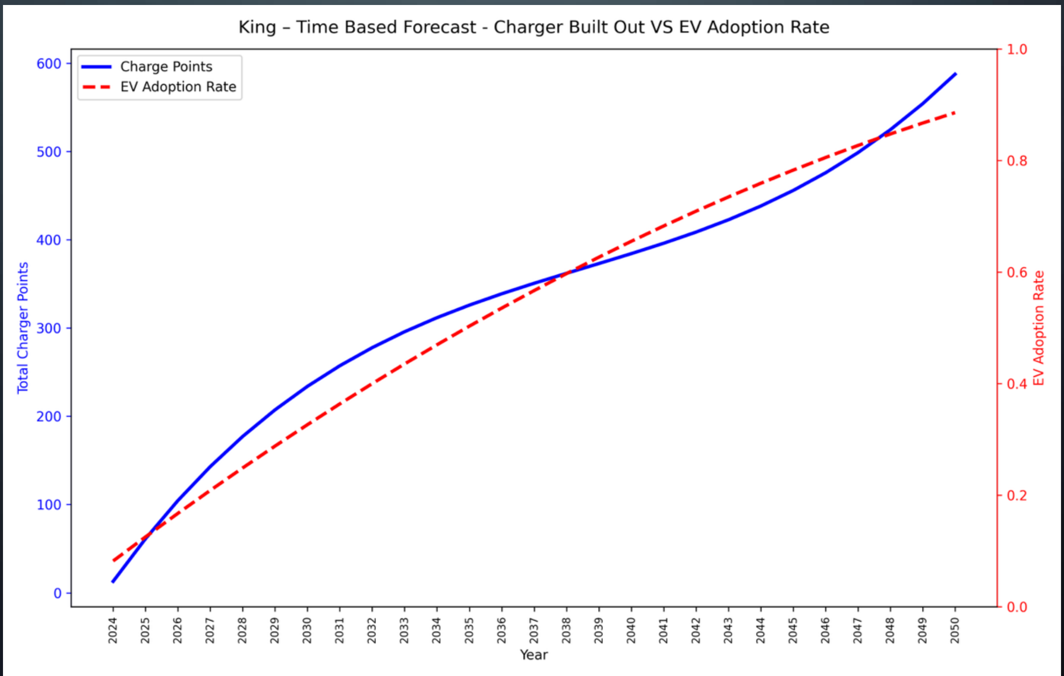
- **Strong positive** R^2 demonstrate high explanatory power and a strong fit to observed trends
- Time-indexed functions enable statistically robust, year-by-year forecasts that support statewide planning, budgeting, and long-term infrastructure strategy.

Why a Statewide View Is Important

- **Consolidates county insights:** Brings together diverse county-level forecasts into a single statewide view while preserving local growth patterns.
- **Supports state-level planning:** Enables alignment of EV adoption, charging infrastructure, and budget decisions with statewide policy targets (2030, 2040, 2050).
- **Guides strategic investment:** Highlights where funding should expand, shift, or taper as counties progress toward saturation at different rates.
- **Provides a common benchmark:** Establishes a consistent statewide reference for tracking progress, comparing county outcomes, and communicating results to decision-makers.

LET'S VISUALIZE THE FORECAST!





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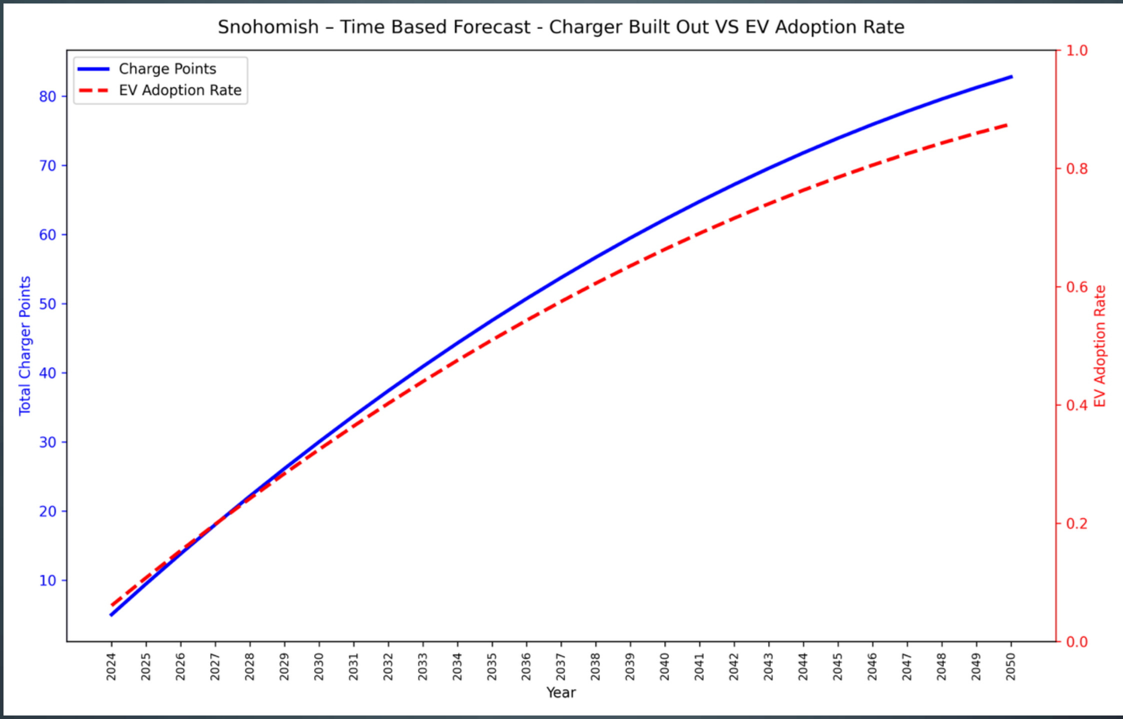
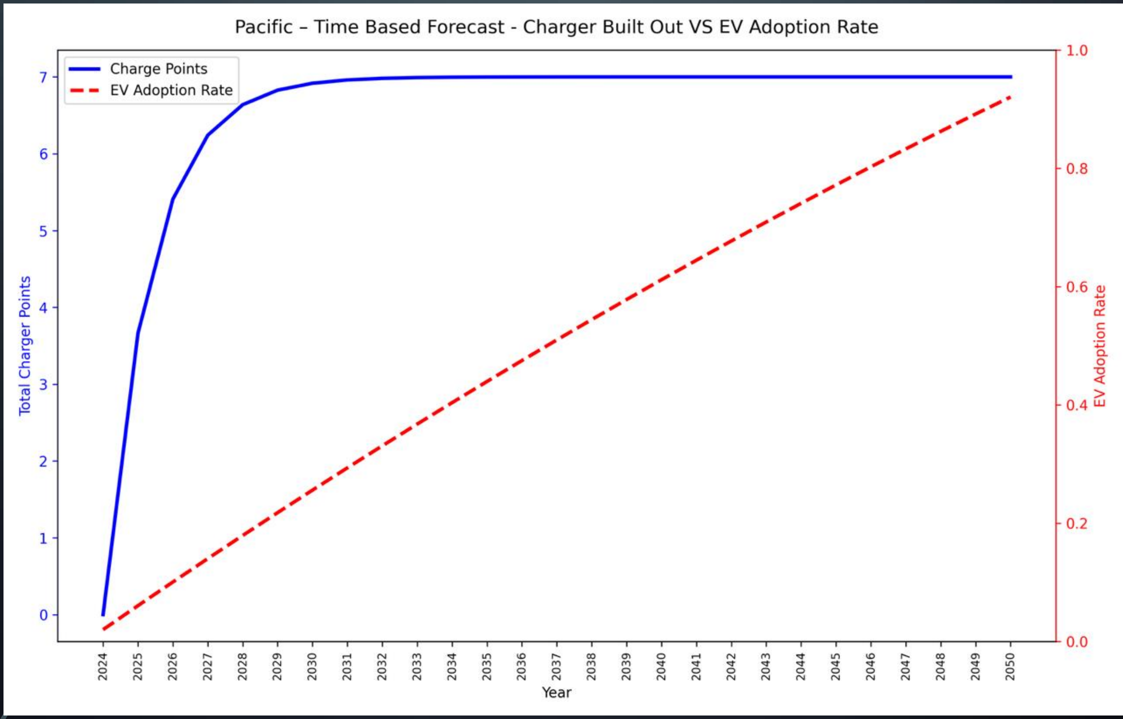




INSIGHT OF FORECAST CURVE

Population Density Archetype	Typical Best-Fit Models	R^2	Charging Infrastructure Deployment Trend	EV Adoption Behavior	2050 Adoption Outlook
High-Density Counties(e.g., King, Snohomish, Pierce, Spokane)	Adoption: Quadratic Chargers: Cubic	Adoption: ~0.88–0.92 Chargers: ~0.92–0.97	Rapid early expansion with strong non-linear growth; deployment tapers as networks mature	Fast early adoption followed by gradual deceleration as markets approach saturation	~85–90%
Medium-Density Counties(e.g., Clark, Thurston, Kitsap, Skagit)	Adoption: Quadratic Chargers: Logistic / Cubic	Adoption: ~0.89–0.92 Chargers: ~0.93–0.97	Consistent charger growth transitioning toward stabilization in later years	Steady adoption growth with moderate curvature	~87–90%
Low-Density Counties(e.g., Chelan, Kittitas, Jefferson, San Juan)	Adoption: Quadratic Chargers: Logistic	Adoption: ~0.92–0.99 Chargers: ~0.99	Early leveling of charger deployment driven by geographic coverage requirements	Gradual but persistent adoption growth without sharp saturation	~92–95%
Rural Counties(e.g., Adams, Ferry, Garfield, Wahkiakum)	Adoption: Quadratic Chargers: Logistic	Adoption: ~0.97–0.99 Chargers: ~0.99	Limited deployment with early saturation once minimum coverage is achieved	Slow initial adoption followed by steady incremental growth	~90–93%
Statewide (Aggregated)	Adoption: Quadratic Chargers: Cubic	Adoption: 0.9165 Chargers: 0.9382	Non-linear expansion reflecting combined urban acceleration and rural saturation	Smooth aggregated adoption pattern summarizing county-level behavior	~88%

Summary:

- **County-level patterns shape the statewide outcome:** Counties representing approximately **91.5% of Washington's population** fall into high- and medium-density groups and display consistent adoption and infrastructure trends, supported by strong model fit (adoption R^2 ,**0.92–0.88**chargers $R^2$0.92–0.97)
- **Adoption converges by 2050:** EV adoption in these counties converges to **~85–90% by 2050** and, given their dominant share of population and charging infrastructure, **drives the statewide adoption projection of ~88%**.
- **Rural dynamics differ:** Rural and forest counties reach **minimum charger coverage earlier** due to lower demand, with higher variability influenced by longer travel distances, climate conditions, and economic constraints.

INSIGHT OF FORECAST CURVE STATEWIDE

Why 94 to 95%% Adoption Is Not Expected by 2050?

Even with strong charger growth, Washington will not realistically reach 94–100% EV adoption. Several structural and behavioral factors create a natural ceiling around **~88%. Reasons why 12% of driver would not adopt EV**:

🚚 **1. Light-Duty Truck & Utility Vehicle Users Adopt Later**

•Towing, hauling, and long-distance rural travel make many truck owners slower to convert.

•Cold-weather range loss further delays adoption in mountain and forest regions.

🏎️ **2. Ultra-Luxury & Specialty Vehicle Segments Don’t Fully Electrify**

•Exotic and collector car buyers prefer sound, performance, heritage, or brand identity over efficiency.

•This small but persistent group remains outside mainstream EV demand.

🌲 **3. Rural Geography Creates Built-In Barriers**

•Long travel distances and limited chargers reduce readiness; sparse regions electrify slower.

•Even after hitting minimum charger requirements, rural adoption grows unevenly and less predictably.

🚐 **4. Fleet Replacement Cycles Are Long**

•Government, construction, and small-business fleets replace vehicles every 10–20 years, slowing full transition.

MODEL LIFECYCLE: 5-YEAR UPDATE & RECALIBRATION CYCLE

What the 5-Year Cycle Means

- The EV forecasting framework operates on a **fixed 5-year lifecycle**, preserving the long-term **2024–2050 strategic blueprint** while remaining responsive to real-world adoption, infrastructure, and policy changes.

Years 1–4: Observation Phase

- Monitor EV adoption relative to forecast bands
- Track new Supercharger installations and utilization
- Incorporate population and demographic updates
- Assess progress toward climate and policy targets
- Adjust annual charger deployment **within the existing forecast envelope** if adoption deviates, without full model re-estimation

Year 5: Recalibration Phase

- Refresh core inputs:
  - Population baselines
  - Charger inventory
  - EV VIN registrations
  - Policy targets and incentives
  - Observed charging behavior parameters
- Re-estimate model outputs:
  - Updated lower / median / upper curves
  - Refreshed Monte Carlo forecasts

Why a 5-Year Recalibration Cycle Works

- **Balances stability and flexibility:** Maintains long-term planning continuity while adapting to structural changes
- **Absorbs short-term noise:** Year-to-year volatility is managed within forecast bands rather than triggering frequent re-modeling
- **Aligns with infrastructure budgeting:** Capital planning and permitting typically follow multi-year cycles
- **Improves signal quality:** Five years of observed data provides stronger behavioral and adoption signals for recalibration

🚀 BUDGET PLANNING & DEPLOYMENT STRATEGY

- **Key Question:** Do we have sufficient funding to meet policy targets while maximizing sales revenue?
- **Answer:** Yes. The targets are **feasible and financially manageable**, especially with a clear, phased proposal plan.

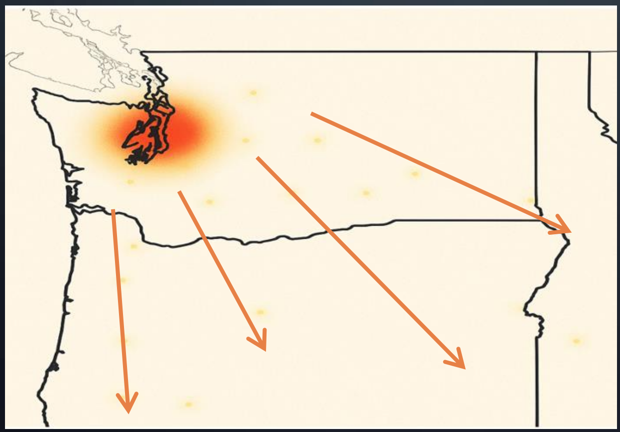
Deep-Dive into the Plan!

Why Tesla Should Focus First on EV-Popular States

- **Momentum builds confidence:** Early wins in EV-leading states deliver immediate utilization, faster learning, and visible proof-of-concept—accelerating growth while building public and regulatory trust.
- **Revenue arrives faster:** Dense EV ownership boosts charger utilization, shortening payback periods and improving capital efficiency.
- **Anxiety drops where it matters:** Solving charging in high-adoption regions removes the main barrier for the next wave of EV buyers.
- **The halo effect spreads:** Once major EV hubs are "solved," expansion into lower-adoption states becomes easier, lower-risk, and more scalable.

🧭 Top 6 States Do NOT Dominate the Budget Forever

- **Phase 1 (2025–2030):** Top EV states need more funding due to high demand, strong ROI, and early corridor buildout.
- **Phase 2 and 3 (2030–2050):** Growth flattens as home charging takes over, reducing their stall requirements and budget use.
- **Result:** Funding naturally shifts toward low-EV states, rural regions, long-distance corridors, and apartment-dense areas.
- **Insight:** Invest early where EVs thrive; redirect later where EV readiness still lags.



🚀 BUDGET PLANNING & DEPLOYMENT STRATEGY

💰Tesla's $500M Expansion Budget — Washington's Share

- Tesla allocates **80% of its $500M** expansion budget to the **top 6 EV-popular states** (population-based EV count):

State	EV Count
California	1,256,646
Florida	254,878
Texas	230,125
Washington	152,101
New Jersey	134,753
New York	131,250

- **Total EVs (Top 6):** 2,159,753
  - ➢📌 **Washington's share = (152,101 ÷ 2,159,753) × (80% of 500M)**
  - ➢80% of $500M = **$400M pool**
  - ➢Washington's proportion = **7.04%**
- 👉 **Washington receives ≈ $28.2M**
  Source: https://afdc.energy.gov/data/10962

Year-Based Forecasting Confirms Washington Will Meet Expected Adoption

- Thanks to the **Year → Chargers and Adoption rate** formulas, Washington's EV future is no longer a mystery—it's a predictable, math-driven storyline.
- The statewide charger deployment planning year-based model:
  - ➢$y = 0.1428\left(x - 2024\right)^3 - 6.8790(x - 2024)^2 + 132.5427(x - 2024) + 50$
  - ➢y = Charge Points, x = Year
- Produces a **smooth, monotonic charger curve**, meaning:
- No unexpected jumps
- No infrastructure "cliffs"
- Extremely high chance Washington hits its EV adoption targets on schedule

🚀 BUDGET PLANNING & DEPLOYMENT STRATEGY

Translating the Formula Into Annual Charger Build Needs (2025–2050)

Charger counts and year-over-year increases are calculated using the statewide cubic model:

- $y=0.1428(x-2024)^3-6.8790(x-2024)^2+132.5427(x-2024)+50$
  Where y = Charge Points, x = Year

Phased deployment trend:

- Phase 1 front-loads public charger construction to reduce range anxiety and accelerate early adoption;
- Phase 2 shifts emphasis toward home charging as adoption stabilizes;
- Phase 3 focuses on targeted catch-up and reinforcement, informed by observed customer charging behavior and long-term Supercharger demand.

Year	Chargers	Increase Per Year
2024	50	–
2025	175.8	125.8
2026	288.7	112.9
2027	389.6	100.9
2028	479.2	89.7
2029	558.6	79.3
2030	628.5	69.9
2031	689.7	61.3
2032	743.2	53.5
2033	789.8	46.6
2034	830.3	40.5
2035	865.7	35.4
2036	896.7	31
2037	924.3	27.6
2038	949.2	24.9
2039	972.4	23.2
2040	994.7	22.3
2041	1016.9	22.2
2042	1039.9	23
2043	1064.6	24.7
2044	1091.8	27.2
2045	1122.5	30.6
2046	1157.3	34.8
2047	1197.2	39.9
2048	1243.1	45.9
2049	1295.8	52.7
2050	1356.2	60.4

🚀 BUDGET PLANNING & DEPLOYMENT STRATEGY

Does Washington State receive enough funding?

Converting Budget → Stalls → Sites

- Washington receives **$28.2M** from Tesla's expansion budget.
- At **$42,500 per stall**, this funds:
- $\frac{28.2M}{42{,}500} \approx 663\ \textit{stalls}$
- Using **6 stalls per site**—the recommended deployment to focus on distance coverage rather than density—Washington can build:
- $663 \div 6 \approx \mathbf{110}\ \textit{statewide charging sites}$

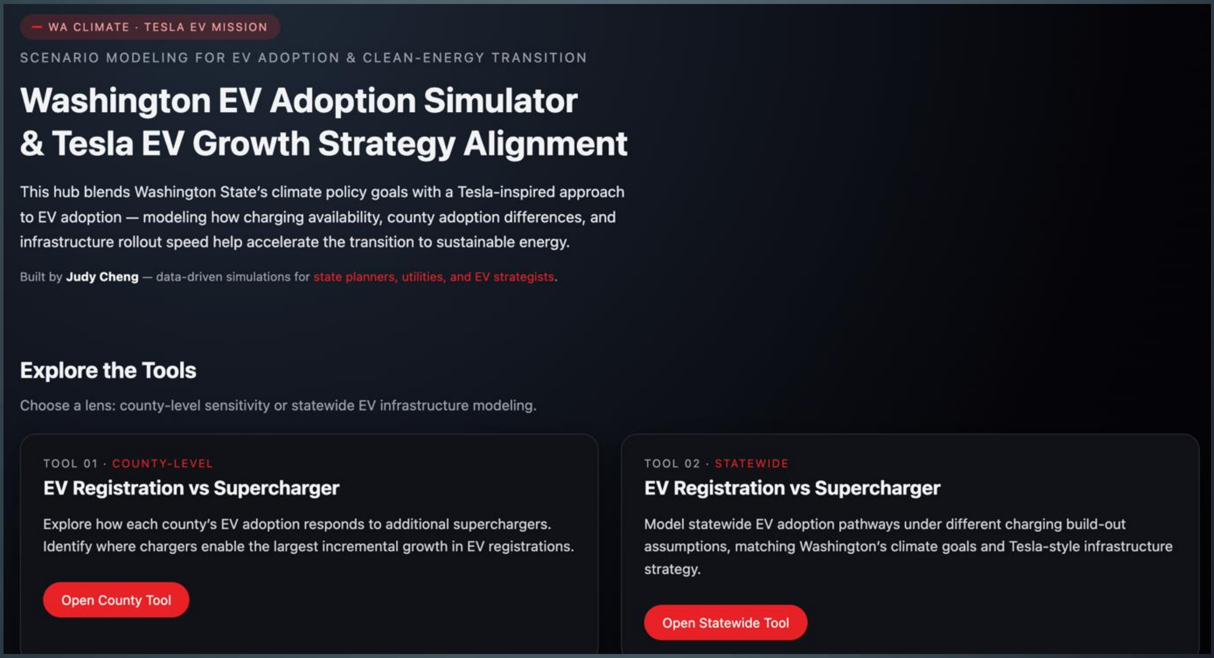
- **NO in 2025 and 2026** - **Early front-loading:** Deployment exceeds budget in **2025–2026** to accelerate adoption and reduce range anxiety.
- **YES overall from 2024 to 2050** - **Long-run affordability:**
  - ➢ Average demand is approximately **102 sites per year over the first five years** and **78 sites per year over the first ten years**.
  - ➢ While deployment temporarily exceeds annual capacity in **2025–2026**, the excess sites can be deferred to **2027 or later years** without affecting long-term targets, as later deployment needs remain well within available funding
  - ➢ **Why it works:** Slower growth later offsets early investment, showing the plan is affordable over the full horizon and why **long-term forecasting matters**.

🗺 Why Prioritize Wide Distance Coverage Over Urban Clustering

- **Coverage reduces anxiety:** Drivers value reaching the next charger more than having many chargers in one location.
- **More sites > bigger sites:** Distributing **6-stall sites** across more locations provides broader coverage than clustering 12-stall hubs.
- **Urban demand shifts:** As adoption grows, cities rely more on home charging, lowering the need for new mega-sites.
- **Corridor coverage matters:** Evenly spaced rural and intercity sites enable reliable statewide travel.
- **Capital efficiency:** Smaller, distributed sites stretch budgets further and improve equitable access.

DEPLOYMENT - WASHINGTON EV ADOPTION SIMULATOR

- https://home-page-ev.onrender.com/
- Navigate to County or Statewide Tool



DEPLOYMENT - WASHINGTON EV ADOPTION SIMULATOR - STATEWIDE

- User to input Year (2024 to 2050). Forecast information will appear in result

Washington Statewide EV Forecast

Enter Forecast Year (2024–2050):

Calculate

Statewide Forecast for 2040

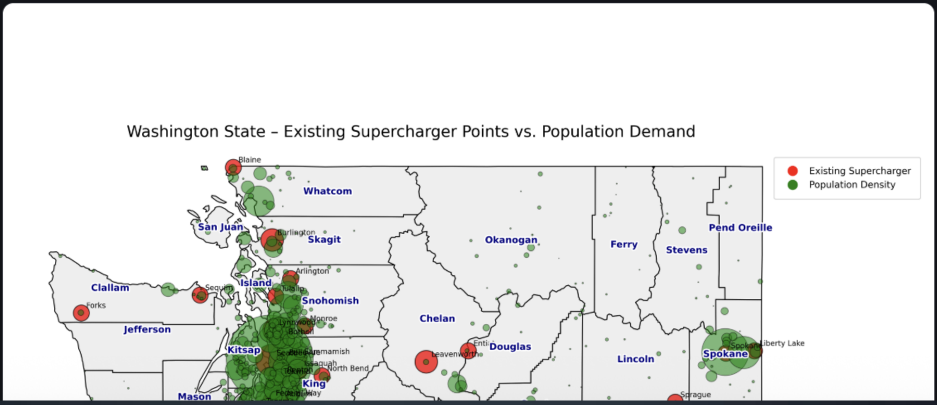
Projected Supercharger Points: 995

Adoption Rate: 65.77%

EV Registrations: 2,484,357

Statewide Supercharger & Population Map

Existing Supercharger Points Statewide (Baseline): 50



DEPLOYMENT - WASHINGTON EV ADOPTION SIMULATOR – COUNTY-LEVEL

- User to input County Name and Year. Forecast result will appear.

Washington County-Level EV Forecast

County Name

Clark

Forecast Year (2024–2050)

2044

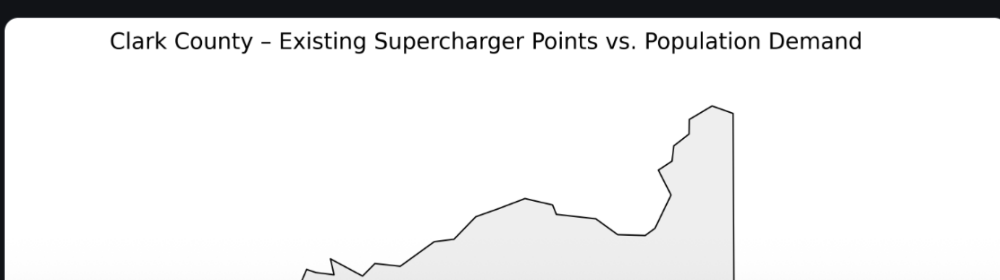
Calculate

Clark

- **Forecasted Supercharger Points:** 72
- **Adoption Rate:** 76.48%
- **EV Registrations:** 188,374

Existing Supercharger Infrastructure

Existing Supercharger Points: 4



CONCLUSION

- **From uncertainty to clarity:** This capstone demonstrates that charging anxiety can be systematically reduced through county-level, time-based forecasting that turns EV adoption and infrastructure growth into a predictable planning problem.
- **Targets are achievable and affordable:** Washington can reach ~89% EV adoption by 2050 with a Supercharger deployment path that remains financially viable when evaluated over a multi-decade horizon.
- **Phased investment works:** Front-loaded charging deployment accelerates early adoption and confidence, while slower expansion later balances long-term budget constraints.
- **Coverage drives adoption:** Broad, evenly spaced charging coverage delivers more value than urban clustering, improving statewide mobility and capital efficiency.
- **Designed for the real world:** The built-in 5-year recalibration cycle ensures the strategy adapts to evolving adoption patterns, policy shifts, and customer behavior.
- **Strategic implication:** With disciplined, data-driven planning, Tesla can expand charging infrastructure in Washington in a way that sustains EV sales growth, maximizes return on capital, and supports long-term decarbonization goals.