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Research article

Optimal placement of electric vehicle chargers: A mixed-integer linear programming model

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Abstract: Electric vehicle adoption is growing, but New Hampshire lags in public charging infrastructure, especially in rural areas. This gap increases range anxiety and economic inefficiencies. In this study, we developed a mixed-integer linear programming (MILP) model to optimally locate new electric vehicle chargers statewide, maximizing coverage and equity under budget constraints. The model includes geographic coverage requirements, population-weighted equity, capacity limits, and a $28 million budget. Moreover, the model recommends 855 Level 2 chargers and 149 Direct Current Fast Chargers (DCFCs) across 247 ZIP Codes, nearly doubling public charging capacity and achieving 98.8% coverage within defined service radii. The plan offers a cost-effective strategy that balances urban and rural needs. By integrating coverage, equity, and cost considerations, the model provides an adaptable framework for electric vehicle infrastructure planning and demonstrates how operations research supports sustainable transportation policy.

Keywords: Electric vehicles; charging infrastructure; mixed-integer linear programming; optimization; equity; transportation planning

Abbreviations: EV: Electric Vehicle; BEV: Battery Electric Vehicle (fully electric car with no gasoline engine); MILP: Mixed-Integer Linear Programming; L2: Level 2 EV charger (240 V AC fast charger for home/work, ~7–19 kW); DCFC: Direct Current Fast Charger (high-power public EV fast charger); RUCA: Rural–Urban Commuting Area (classification of areas by rural/urban status); NEVI: National

Electric Vehicle Infrastructure (U.S. federal formula funding program for EV corridors); CFI: Charging and Fueling Infrastructure (U.S. federal grant program for EV charging, especially community/rural)

1. Introduction

EV ownership is rising rapidly across the United States, and New Hampshire is beginning to follow this trajectory. By 2023, the state had over 16,000 plug-in EVs (9,900 battery electric vehicles and 6,600 plug-in hybrid electric vehicles) on the road, compared with just a few hundred in 2016 (see Figure 1) [1].

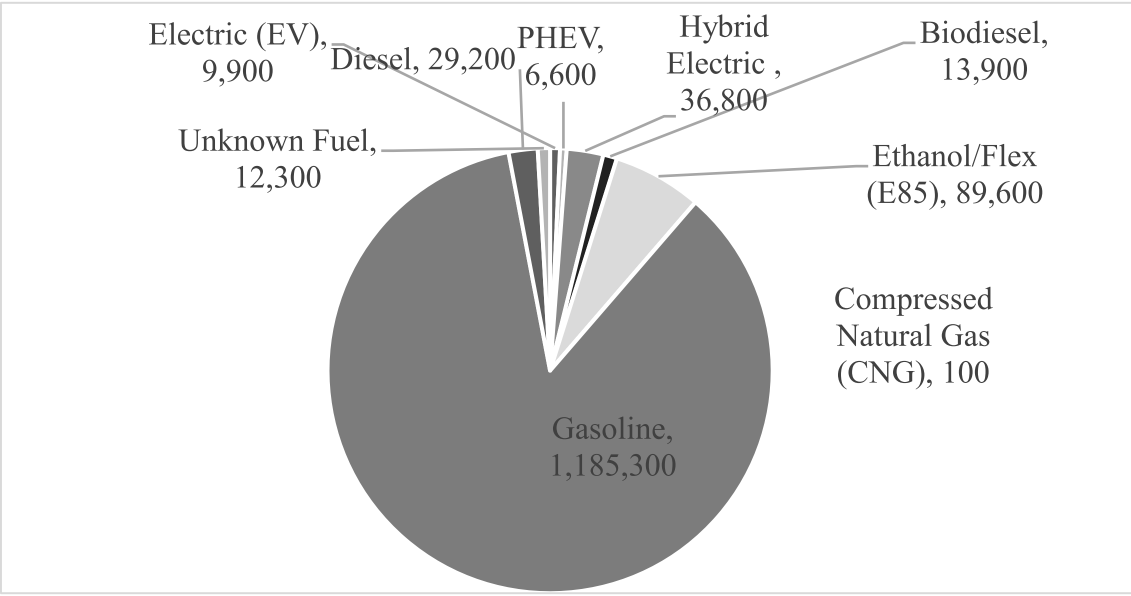

Figure 1. Motor-vehicle registrations in New Hampshire (2023) by fuel type. Note: Data from U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy (2023). [2]

Regional forecasts indicate that this growth will accelerate. By 2033, EVs could comprise roughly 20% of all vehicles in New Hampshire, or approximately 200,000 EVs, up from a negligible share today [3,4]. These projections are consistent with ISO New England's Transportation Electrification Forecast [4], presented in Figure 2. In addition to light-duty vehicles, the state is expected to add hundreds of electric medium-duty trucks and school buses by 2033 (see Figure 3). This anticipated increase in electric mobility will require a significant expansion of charging infrastructure, highlighting the need for rigorous planning tools to guide investment and deployment.

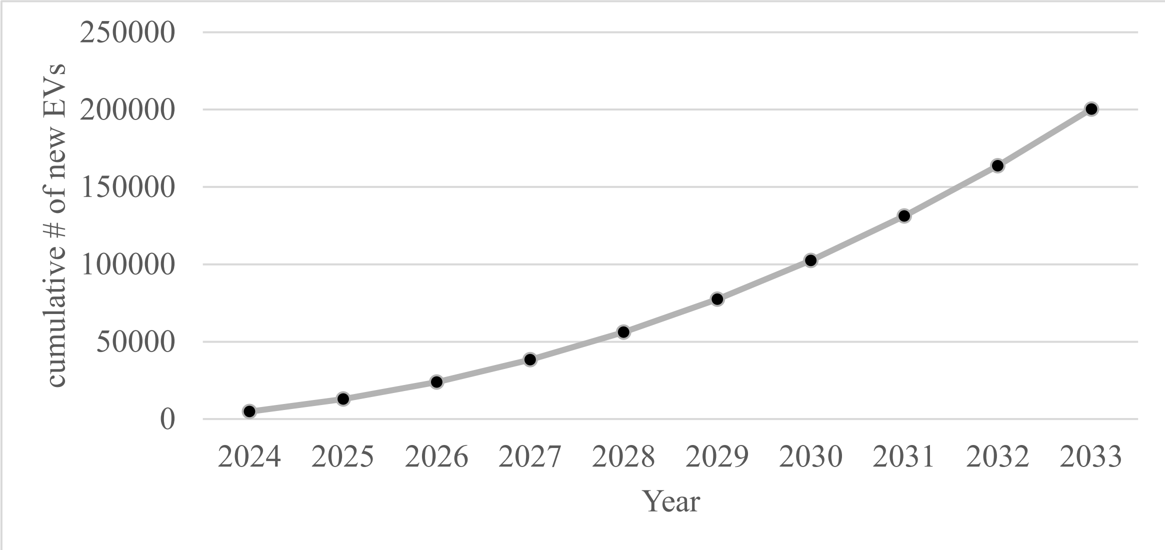

Figure 2. Projected annual increase in cumulative EV stock in New Hampshire, 2024–2033.

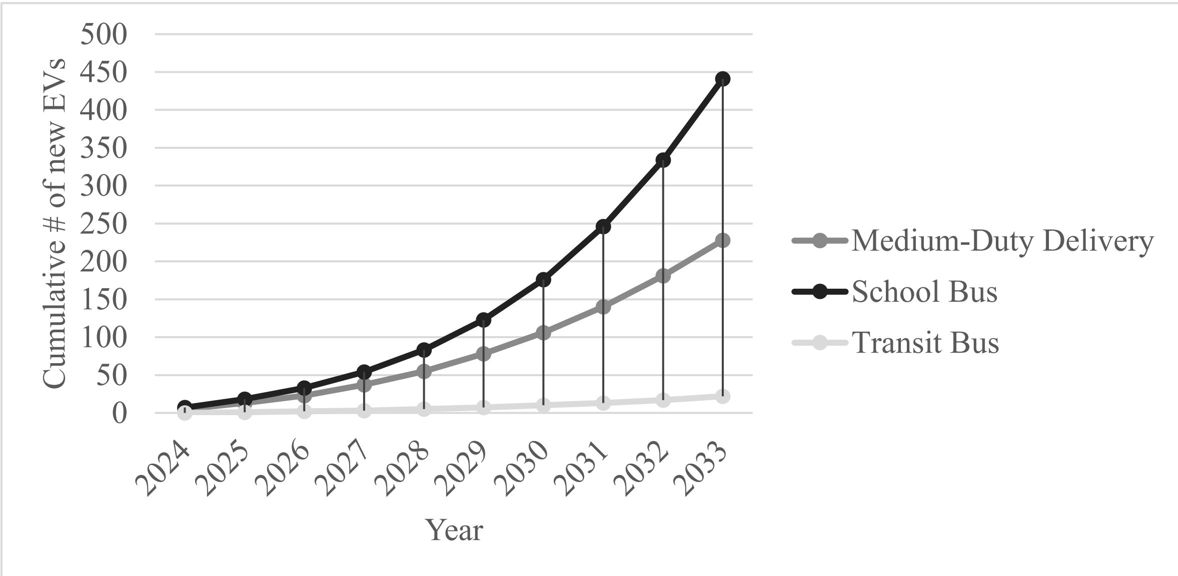

Figure 3. Forecasted Cumulative EV Adoption for Medium-Duty Delivery, School Buses, and Transit Buses in New Hampshire, 2024–2033.

Despite rising EV demand, New Hampshire lags behind neighboring states in charger availability. As of early 2024, the state had approximately 290 public charging station locations (L2 and DCFC), fewer than Vermont and Maine, which had over 470 and 530 stations, respectively, based on AFDC data available at the time of analysis [5].

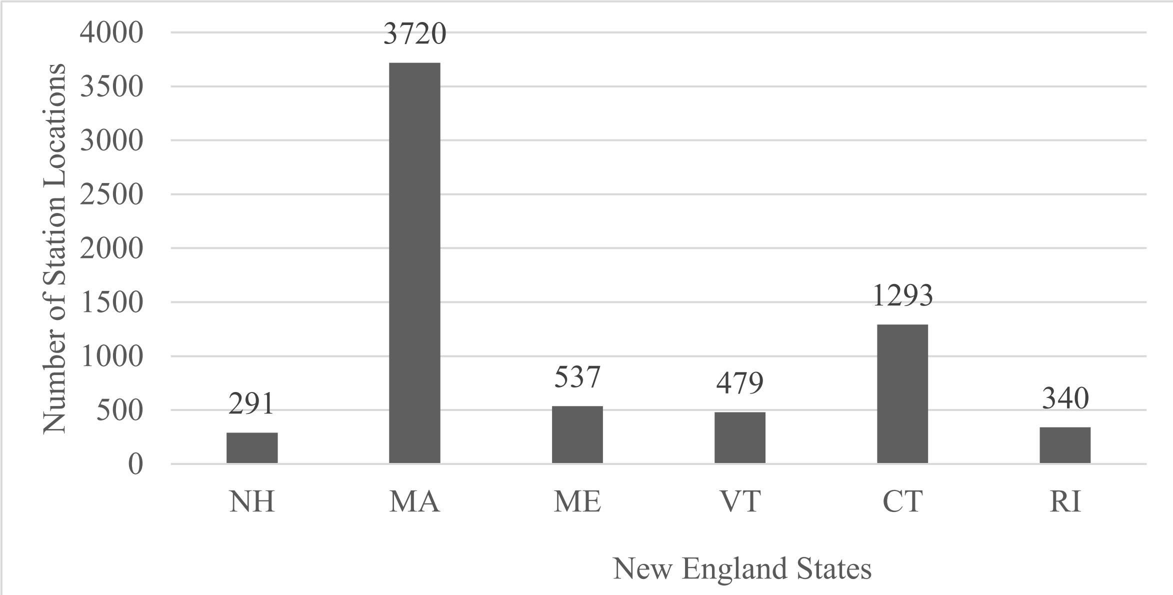

Figure 4. Public EV charging station locations in New England states as of 2024**.** Note: Data from U.S. Department of Energy, Alternative Fueling Station Locator, 2024 [6].

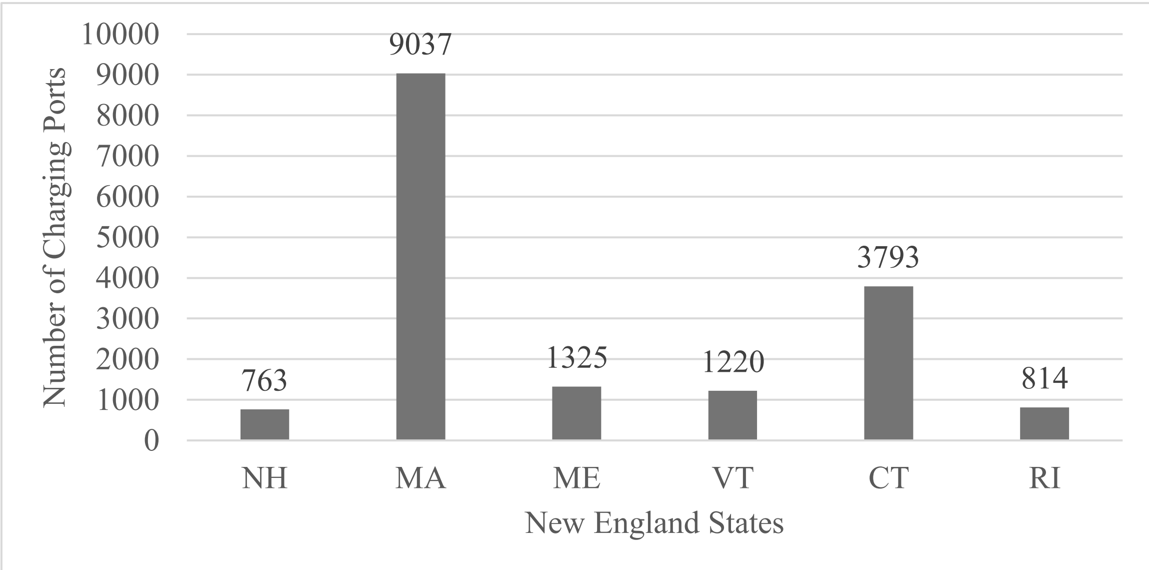

Figure 5. Public EV charging ports in New England states as of 2024**.** Note: Data from U.S. Department of Energy, Alternative Fueling Station Locator, 2024 [6].

An analysis showed that the state has deployed only about 7% of the L2 and 22% of the DCFC capacity estimated to be needed by 2030 [1]. This shortfall is particularly severe in rural and northern areas, where drivers may need to travel over 50 to 60 miles (approximately 80 to 97 kilometers) to find a fast charger, intensifying range anxiety.

This uneven infrastructure distribution not only slows EV adoption but also presents economic risks. One analysis projected that the state could lose up to $1.4 billion in tourism revenue by 2031 if it fails to match neighboring states' investments in charging infrastructure [7]. Because many of these gaps occur in rural and northern regions that are underserved and popular with tourists, ensuring equitable access will be critical not only for advancing clean transportation goals but also for sustaining the state's economic vitality.

Consistent with NEVI minimum standards, DC fast charging stations are required to be spaced no more than 50 miles (approximately 80 kilometers) apart along designated Alternative Fuel Corridors [8]. Public programs are mobilizing to address these gaps. Under the federal NEVI program, New Hampshire was allocated approximately $13.6 million as of early 2025 to install DCFC stations along major corridors such as Interstates 93 and 89, spaced no more than 50 miles (approximately 80 kilometers) apart [9]. In addition, the state received an additional $15 million through the federal CFI grant to deploy nearly 200 public charging ports, with a focus on rural and underserved areas [10]. Together, these funding streams provide approximately $28 million for EV charger expansion, creating a timely opportunity to optimize infrastructure planning statewide.

In response to this transition, we propose an MILP model to identify the optimal locations and types of new EV chargers across New Hampshire. This dual capability makes MILP particularly suitable for infrastructure planning problems that must account for real-world constraints such as budget limits, geographic coverage rules, and equity requirements. Unlike heuristic or simulation-based methods, MILP provides globally optimal solutions with transparent trade-offs, offering reliable guidance for policy and planning decisions. The suitability of MILP for EV charger siting has been demonstrated in other research, and representative examples will be discussed further in Section 2. Building on this foundation, this report applies MILP to balance cost-efficiency, statewide coverage, and equity in New Hampshire's diverse urban–rural landscape. The model's key contributions include incorporating equity-based constraints, implementing ZIP Code-level spatial targeting, and differentiating charger types. It also introduces slack variables to enable limited unmet charging demand in low-density or underserved areas, helping to maintain feasibility while promoting equitable access. Overall, this data-driven framework provides a scalable decision-support tool for policymakers and planners, balancing statewide coverage, cost-efficiency, and social equity, while addressing range anxiety and regional disparities. These contributions are particularly relevant given New Hampshire's existing shortfall in charging infrastructure compared with neighboring states.

2. Literature review

2.1. EV charger placement optimization models

EV charger placement has long been framed as a facility location problem, with early studies emphasizing service coverage, detour minimization, or basic cost constraints. As the demand for electric vehicles has increased, research attention has shifted toward more sophisticated approaches that account for real-world complexity.

Early studies from the past decade illustrate this transition. For example, Gopalakrishnan et al. [11] combined demand forecasting using canonical correlation analysis with a mixed packing-and-covering heuristic framework. Their approach balanced operator objectives (budget and demand maximization) with user needs (coverage and accessibility), achieving notable improvements in demand coverage compared to baseline siting approaches. This integration underscores the importance of jointly considering user behavior and system constraints in charger placement models.

Beyond demand-focused work, other researchers have explored metaheuristics for large-scale planning. Cintrano et al. [12] formulated the Electric Vehicle Charging Station Location problem as a citywide siting challenge constrained by both accessibility and substation capacity. Using a case study in Málaga, Spain, they showed that genetic algorithms and Variable Neighborhood Search (VNS) significantly outperformed existing municipal deployments, reducing average travel distances by more than 50%. Similarly, Lazari and Chassiakos [13] developed a multi-objective Genetic Algorithm (GA)-based framework that minimized both infrastructure costs and travel distances. Their results demonstrate scalability and robustness, illustrating how metaheuristics can generate near-optimal solutions for large-scale combinatorial optimization problems, albeit without the global optimality guarantees of MILP.

In contrast, researchers have emphasized the value of MILP formulations for siting and scheduling. Some have focused on context-specific siting. For example, Bian et al. [14] developed a Geographic Information System (GIS)-based MILP model that identified optimal locations for public fast chargers by combining traffic flow data, land use, and economic feasibility (profit-based investment considerations). Their work highlights the importance of selecting charger types based on local context, favoring fast chargers in high-traffic commercial areas and slower options in residential or workplace settings. Others have examined charger-type heterogeneity. For instance, Parent et al. [15] formulated an MILP model that allocates heterogeneous charging technologies to candidate sites in Montreal under budget constraints, showing how charger-type differentiation and capacity decisions can improve network efficiency. A third group of studies has extended MILP formulations with explicit unmet-demand penalties and joint siting-sizing choices. For instance, Gulbahar et al. present a corridor-focused model in Sustainability [16] that optimizes where to locate stations along highways and how many chargers to install at each, allowing limited unmet demand as a penalty to balance coverage and cost. Case studies on multiple Turkish corridors reveal cost-efficient station counts and charger allocations, demonstrating that penalty terms can guide practical deployment under demand and budget constraints. This approach is conceptually consistent with the present study's use of slack variables and policy-aligned constraints, though applied at the corridor rather than ZIP Code scale. Popa and Sîrbu [17] applied an MILP formulation to Romania's national charging infrastructure, optimizing station siting with objectives including distance coverage, electricity consumption, CO_2 emissions, and EV penetration. Their results highlight MILP's flexibility to integrate environmental and demand factors in large-scale infrastructure planning. Finally, Chen et al. [18] formulated the EV charger siting problem as a mixed-integer linear program but employed an improved Genetic Algorithm heuristic to solve it, demonstrating that this hybrid approach can deliver cost-effectiveness and well-covered urban charging networks.

Building on these MILP foundations, hybrid models illustrate how MILP can be combined with heuristic or real-time control methods. Al Nahid and Qi [19] proposed a two-tier framework integrating MILP-based scheduling with a distributed GA for dynamic charging management. Their results show substantial improvements in fairness, demand balancing, and grid reliability, highlighting how MILP can provide global coordination while heuristics fine-tune local operations. Similarly, Dukpa and Butrylo [20] applied MILP at the station-operation level, optimizing profitability and resource use in PV-based charging stations with battery storage. Although not directly focused on siting, their work reinforces the versatility of MILP for EV charging problems involving mixed discrete–continuous decisions.

Alongside these methodological advances, studies also emphasize equity and scalability considerations. Such considerations are reflected in Kim et al. [21], who modeled charger deployment as a capacitated facility location problem and compared exact, heuristic, and metaheuristic solvers across diverse case studies. By incorporating equity metrics such as the Gini coefficient and combining MILP with machine-learning–based site analysis, their work highlights how advanced methods can complement MILP to balance coverage, cost, and fairness. Separately, complementary approaches outside MILP frameworks have emerged. For instance, Alanazi et al. [22] employed machine-learning models (linear regression and Support Vector Machines [SVM, a supervised machine learning method for classification and regression]) to forecast station needs from socio-economic, grid, and travel indicators, generating demand signals that could subsequently inform MILP-based siting models.

Taken together, these strands of research illustrate an evolution from basic facility location models to more sophisticated optimization frameworks that integrate demand prediction, grid constraints, and equity considerations. While heuristic and metaheuristic approaches offer scalability, they often sacrifice global optimality, whereas MILP formulations provide stronger guarantees but may face computational limits at scale. Hybrid methods bridge these trade-offs, and recent studies increasingly emphasize fairness and real-world feasibility. However, gaps remain: Many models assume full demand satisfaction, treat chargers as homogeneous, or overlook policy-driven equity requirements. Addressing these limitations is critical for developing planning tools that are computationally feasible and policy relevant. In response, we adopt a ZIP Code-level MILP framework that distinguishes L2 and DCFC, integrates equity constraints, and introduces slack variables to reflect budget-limited real-world conditions. This formulation provides a more flexible and policy-aligned method for allocating charging infrastructure in geographically diverse and budget-constrained environments.

2.2. Policy-informed constraints in prior models

In addition to methodological advances, policy frameworks are crucial in this study, shaping the optimization model for EV charger deployment. Public-sector EV infrastructure planning in the United States is shaped by federal and state policy objectives that emphasize accessibility, spatial coverage, and equity. Programs such as the NEVI initiative establish minimum regulatory standards, including charger-spacing and performance requirements [8], while analyses from the Electric Power Research Institute provide complementary planning insights, such as fleet-to-infrastructure ratios and utilization-based benchmarks, that inform regional and system-level deployment strategies [23,24].

Several optimization studies have responded by embedding these policy criteria directly into mathematical models. Typical approaches involve applying spatial-coverage constraints, setting minimum charger thresholds by population or geography, and incorporating charger-type differentiation. For example, Mohammed et al. [25] minimized investment costs while satisfying planning standards and engineering guidelines that reflect policy-driven benchmarks. Moreover, Yang et al. [26] incorporated taxi dwell behavior and charging congestion into an integer linear programming framework to inform charger siting and sizing decisions under realistic urban mobility patterns. Together, these studies demonstrate how mathematical programming can serve as a policy-aligned decision-support tool for EV infrastructure planning.

Equity has also emerged as a growing priority, particularly under federal initiatives, such as Justice40, which directs that at least 40% of clean energy investment benefits go toward disadvantaged communities [27]. While few models treat equity as a strict constraint, many adopt flexible strategies such as population weighting or prioritization of underserved zones to reflect Justice40 priorities.

Building on these precedents, we incorporate equity considerations and policy-aligned planning criteria directly into our optimization framework. The implementation of these constraints is described in Section 4.

2.3. Research gap and contribution

Building on the methodological and policy-focused studies reviewed above, several gaps remain that are particularly relevant to rural and underrepresented regions such as New Hampshire. Reports indicate that New Hampshire lacks sufficient charging infrastructure, particularly in northern regions, yet relatively few optimization models have been tailored to this context. Most models focus on urban areas or national-scale strategies, often overlooking the distinct challenges of small-population states with uneven demand, tourism-related traffic, and extensive rural coverage areas.

In terms of methodology, many prior models either assume full coverage or seek to maximize total reach without accounting for the disproportionate cost of serving remote locations. We address this limitation by introducing slack variables into an MILP framework, enabling the model to accept limited unmet demand at a quantifiable penalty. By doing so, the approach provides a cost-conscious way to reflect real-world planning trade-offs between ideal coverage and budget constraints.

Additionally, while some researchers explore charger-type differentiation, most treat charger selection separately from site selection or focus on scenario comparisons. In contrast, this model integrates L2 and DCFC siting decisions within the optimization, enabling location-specific choices based on cost, demand density, and use-case suitability.

Equity is another area where this study builds upon previous work. Rather than treating equity as a post hoc assessment or using coarse-grained geographic categories, the model includes ZIP Code-level constraints that allocate chargers proportionally based on population. Rural-urban classification codes further support prioritization of underserved communities, and a weighted objective term enables additional emphasis on rural ZIP Codes without imposing hard mandates.

Overall, the model's contribution lies in adapting EV infrastructure optimization to the specific challenges of rural coverage, budget-limited deployment, and localized equity targeting. It demonstrates how planners can balance cost-efficiency with broader policy goals through the use of flexible and transparent modeling tools.

3. Dataset construction and sources

To support the optimization model, we compile a spatially and demographically enriched dataset by integrating multiple authoritative sources. Each New Hampshire ZIP Code serves as the basic unit of analysis. The key data components collected and processed include:

Geographic Classification. We use the 2010 ZIP Code-based Rural-Urban Commuting Area (RUCA) codes from the U.S. Department of Agriculture's Economic Research Service. These codes classify areas based on commuting patterns and levels of urbanization [28].

Population and Density. Population counts and density measures are obtained from the U.S. Census Bureau's American Community Survey (ACS) 5-Year Estimates (2017–2021) at the ZIP Code-level [29] and serve as the primary demographic source. To enhance completeness, supplemental demographic attributes (e.g., 2020 population estimates, land area) are retrieved from the SimpleMaps U.S. ZIP Code Database [30]. This integration ensured both consistency and coverage in the demographic dataset.

Existing EV Infrastructure. Data on EV charging stations are retrieved from the U.S. Department of Energy's Alternative Fuels Data Center. The dataset includes publicly accessible charging stations in New Hampshire, with details on charger level (L2 or DCFC), station type, access type, and location [6]. This dataset is filtered to include only public L2 and DCFC chargers within New Hampshire's borders. The resulting records are geospatially joined with the ZIP Code areas, yielding an initial count of chargers per ZIP Code to serve as a baseline for the optimization model.

Distance Matrix. A ZIP-to-ZIP distance matrix is generated using latitude-longitude coordinates for each ZIP Code centroid. This matrix provides pairwise distances between ZIP Codes, enabling the model to determine which areas fall within a given service radius of each other. These calculated distances are subsequently applied to enforce coverage constraints (e.g., whether a ZIP Code has a charger within X miles [X kilometers]).

Together, these components provide a robust empirical foundation for the optimization model described in Section 5.

4. Model inputs and assumptions

In this section, we outline the key assumptions and parameter values used in the charger deployment optimization model. These inputs are calibrated to reflect prevailing federal and state policy requirements, typical industry costs, and infrastructure planning constraints, so that the model outputs are practically feasible and policy compliant.

4.1 Cost assumptions for EV charger deployment

To ensure cost-sensitive optimization, the model uses fixed installation-cost assumptions of $14,000 per L2 charger and $100,000 per DCFC, reflecting realistic expectations for New Hampshire's deployment context. This assumption is supported by several key sources. Borlaug et al. [31] reported a median cost of approximately $6,000 for public L2 equipment and installation, based on billing data from 119 commercial projects. The Alternative Fuels Data Center reports typical installation costs of about $2,500 per L2 connector, excluding hardware [31]. Moreover, the New York State Energy Research and Development Authority Charge Ready NY program identified hardware costs ranging from $1,000 to $4,000 per port and installation costs from $2,000 to $10,000, with complex installations occasionally exceeding $20,000 per port [32].

Given the rural characteristics and limited infrastructure in many parts of New Hampshire, a conservative estimate of $14,000 per L2 charger is adopted to ensure coverage of higher-cost scenarios. Thus, while average installation costs are lower in many urban contexts, the $14,000 assumption reflects rural-specific challenges in New Hampshire, including higher electrical upgrade costs and site preparation complexity. For DCFCs, the assumed cost of $100,000 aligns with typical industry benchmarks for 150 kW stations, which range from $85,000 to over $150,000, depending on electrical upgrades, site preparation, and capacity constraints [33]. This mid-range assumption reflects the higher costs expected in rural deployments and the need for a simplified yet realistic input for statewide modeling.

4.2. Distance-based siting constraints for urban and rural areas

To align with regulatory frameworks and planning practices, this model adopts differentiated siting thresholds for charger placement in urban and rural areas. In urban areas, a 1-mile (approximately 1.6 kilometers) coverage radius is applied, consistent with the Federal Highway Administration's NEVI guidance, which requires DCFCs within 1 mile (approximately 1.6 kilometers) of highway exits on Alternative Fuel Corridors [34]. While this requirement is specific to corridor planning, it provides a practical precedent for close-range charger accessibility in densely populated zones.

In rural contexts, the model applies a more flexible 10-mile (approximately 16 kilometers) coverage radius. Although this specific distance is not mandated by federal or state regulations, it reflects a planning judgment that accounts for New Hampshire's geographic and land use challenges associated with rural deployment. The New Hampshire NEVI Deployment Plan emphasizes the need for adaptable planning approaches in low-density areas, though it does not define any fixed siting distance for rural regions [35]. Similarly, federal guidance encourages rural infrastructure to be responsive to local conditions, mobility patterns, and community needs [36]. The 10-mile (approximately 16 kilometers) threshold represents a middle ground: Short enough to mitigate range anxiety and ensure service continuity, yet long enough to remain feasible in sparsely populated areas. Accordingly, this conservative and practical approximation provides a balanced approach to rural deployment without imposing infeasible density requirements.

4.3. NEVI compliance considerations and rural deployment strategy

The NEVI program sets federal standards for charger placement along Alternative Fuel Corridors (AFCs), including Interstates 93, 89, and Route 101 in New Hampshire. These standards specify a maximum spacing of 50 miles (approximately 80 kilometers) between DCFC stations, installation within 1 mile (approximately 1.6 kilometers) of highway exits, and the provision of at least four 150 kW connectors per site [8]. While these requirements are essential for national planning, we adopt a more flexible ZIP Code-based siting framework to better reflect New Hampshire's geographic and settlement diversity.

Instead of enforcing strict corridor-based deployment, the model introduces a soft constraint requiring that at least 15% of new chargers be DCFC. This adjustment is motivated by three key considerations:

- Geographic overlap: Many rural ZIP Codes in New Hampshire are near highway corridors. Using ZIP Code-level siting can therefore maintain general corridor accessibility without explicitly mapping every charger to the AFC requirements.

- Practical feasibility: Strict NEVI compliance may be unrealistic in low-density rural areas due to limited electrical infrastructure, long distances between exits, or constraints related to site availability.
- Policy alignment: Federal planning documents emphasize adaptive strategies that account for local transportation patterns and community needs [36], supporting flexibility in rural deployment.

By combining rural-weighted population coverage with an emphasis on equitable access, the model enables scalable deployment strategies that remain consistent with NEVI's broader policy objectives while adapting to New Hampshire's unique geographic and demographic conditions.

4.4. Charging station utility weights and scoring

This model applies a dual-weighting approach: DCFC chargers are assigned a utility weight of seven relative to L2 chargers in the optimization objective, while in the coverage and equity constraints each DCFC is treated as functionally equivalent to three L2 chargers. This design captures their superior charging performance in the objective function while ensuring that coverage assumptions remain realistic in both urban and rural contexts.

The 7:1 weighting in the objective reflects the substantial difference in charging throughput and time efficiency between the two charger types. According to the U.S. Department of Transportation, L2 chargers typically deliver between 10-20 miles (approximately 16-32 kilometers) of electric range per hour, whereas DCFCs can supply approximately 180-240 miles (approximately 290-386 kilometers) in the same time frame [37]. Similarly, Plug In America reports that while L2 chargers take approximately 4-10 hours to charge a BEV to 80%, a DCFC can achieve the same charge level within 20-30 minutes [38]. Taken together, these observations suggest a throughput advantage of approximately 7:1 to 12:1 in favor of DCFCs. To maintain conservative yet realistic assumptions, this study adopts the lower bound of 7:1 to account for variability in site conditions, battery-tapering effects, and user behavior.

On the other hand, the 3:1 ratio applied in equity and coverage constraints reflects practical deployment realities. While DCFCs deliver substantially faster charging, they are typically installed along highway corridors and other high-traffic public locations, where their utility is maximized. In contrast, L2 chargers are more commonly deployed in residential, workplace, and mixed-use settings, where vehicles remain parked for longer periods and slower charging is sufficient and cost-effective [39]. Treating each DCFC as equivalent to three L2 chargers ensures that these high-capacity stations meaningfully contribute to coverage calculations without overstating their role in settings where L2 chargers remain more practical.

Together, this dual-weighting structure (7:1 in the objective function and 3:1 in the constraints) creates a balanced deployment framework. It supports targeted investment in fast-charging infrastructure where justified by demand and travel patterns, while preserving equitable geographic access across ZIP Codes of varying density. In doing so, the model aligns with federal guidance encouraging flexibility in EV infrastructure planning across both rural and urban contexts [36].

4.5. Land-use and density constraints

We incorporate practical land-use constraints using population density as a proxy for site feasibility rather than modeling full zoning or grid-capacity limitations. ZIP Codes with a population density exceeding 1,000 people per square mile (approximately 386 people per square kilometer) are assumed to face greater spatial and permitting challenges, consistent with the U.S. Census Bureau's classification of urban areas [40]. To operationalize this assumption, the model caps the total number of new chargers (L2 and DCFC combined) at a maximum of four per high-density ZIP Code. The 1,000-person benchmark aligns with federal definitions used in the delineation of urban cores, where similar thresholds have historically guided classifications based on housing density and population per unit area.

Conversely, for ZIP Codes with population densities below this threshold, no artificial upper bound is imposed, enabling more flexible allocation of charging infrastructure in rural and semi-rural regions. Although simplified, this density-based constraint serves as a scalable and policy-relevant proxy for urban development pressures, enabling the model to incorporate land-use considerations into charger deployment strategies in a consistent manner.

4.6. Rural–urban classification using RUCA codes

To more accurately distinguish urban and rural contexts, we employ the Rural-Urban Commuting Area (RUCA) classification system, developed by the U.S. Department of Agriculture. RUCA codes offer a nuanced approach that incorporates not only population density and urbanization but also commuting patterns, thereby enabling a more functionally grounded classification than population thresholds alone [28].

In the present model, ZIP Codes with RUCA primary codes ranging from 1.0 to 3.0 are classified as urban. These RUCA values correspond to metropolitan cores, micropolitan areas, and their associated high-commuting zones. ZIP Codes with RUCA values of 4.0 or higher are categorized as rural, encompassing smaller towns, low-commuting regions, and isolated areas. This binary classification enables the application of distinct planning parameters, such as charger spacing thresholds or deployment priorities, that reflect the differing mobility patterns and infrastructure needs of both rural and urban communities.

Integrating RUCA codes ensures that the model captures not only demographic and geographic characteristics but also regional economic integration. For instance, a small town where many residents commute to a nearby city may be classified as urban under this framework, reflecting its functional connection to the larger metropolitan area rather than its population size alone.

4.7. Funding context for EV charger deployment in New Hampshire

The model adopts a consolidated public funding budget of $28 million for EV charger deployment in New Hampshire, combining the most reliable federal resources available as of mid-2025. This includes a $15 million grant awarded under the CFI program by the U.S. Department of Transportation and the obligated portion of the state's $17.27 million allocation from the NEVI formula program that was approved before its suspension [36,9].

The model incorporates only the obligated NEVI funding that is officially approved and available prior to the suspension, excluding any future allocations that were planned but not confirmed. New

Hampshire was initially slated to receive NEVI funds from 2022 to 2026, but only the first round (Phase 1) was approved before the program was paused in early 2025 due to federal review [9]. This conservative approach avoids modeling uncertainty associated with unconfirmed funding streams.

Other potential funding sources were excluded. For example, New Hampshire received approximately $30.9 million from the Volkswagen (VW) Environmental Mitigation Trust, with up to 15% (around $4.6 million) allocated for light-duty EV charging infrastructure. However, these funds were fully awarded by 2022 through a competitive fast-charging request-for-proposals (RFP) process [41,42]. Although newer RFPs have been issued for other types of mitigation projects, none have been dedicated to EV charger deployment. Likewise, utility-sponsored rebates (typically capped at $5,000 per site) were considered too limited in scale to meaningfully affect statewide siting plans [41].

By anchoring the model to a conservative $28 million funding envelope, this study ensures that deployment recommendations are not only technically sound but also consistent with current fiscal and policy conditions. This approach enables actionable and context-appropriate planning for EV infrastructure development in New Hampshire.

4.8. Equity-based coverage constraint justification

Various countries and organizations have adopted ratio-based targets or equity-focused policies to ensure the fair deployment of EV chargers. Such strategies provide statistical and regulatory support for setting a population-based benchmark for charger deployment in New Hampshire.

In the European Union, the 2023 Alternative Fuels Infrastructure Regulation (AFIR) mandates that each Member State must provide a minimum of 1 kW of publicly accessible charging power per BEV, increasing to 3 kW by 2030 [43]. In parallel, and prior to AFIR, the Alternative Fuels Infrastructure Directive (AFID) set a recommended benchmark of roughly one public charging point per ten EVs; AFIR has since shifted emphasis from "points" to installed power capacity, linking targets to fleet composition (e.g., 1.3 kW per BEV and 0.8 kW per PHEV), as documented by the European Environment Agency (EEA) [44]. These targets are fleet-based and scale proportionally with EV adoption, encouraging decentralized deployment across regions to ensure geographic equity [45]. Member States are also encouraged to create national policy frameworks with financial mechanisms to support deployment in rural and underserved areas, thereby promoting a more balanced rollout of public infrastructure [46,47].

In the United States, while there is no formal federal population-based ratio, equity is promoted through the Justice40 initiative, which requires that at least 40% of the benefits of certain federal programs flow to disadvantaged communities (DACs) [48,49]. Some state-level plans, such as Arkansas's NEVI Plan, have implemented scoring systems that prioritize charger proximity to DACs and emphasize reduced travel time, accessibility, and job creation [50].

According to comparative studies, Vermont leads in EV charger availability with 156 chargers per 100,000 people, followed by California (130) and Massachusetts (105) [51,43]. These levels correspond to approximately a 1:640–1:950 charger-to-population ratio, providing realistic and high-performing domestic benchmarks. Vermont and Massachusetts thus serve as instructive examples of effective deployment practices.

Building on these global and national precedents, this study establishes a 1-charger-per-500-

residents ratio in New Hampshire as an ambitious yet evidence-based equity constraint. This benchmark ensures basic coverage even in low-demand or rural ZIP Codes, aligning with best practices from Europe and leading U.S. states, while upholding principles of energy justice and accessibility.

4.9. Adoption heterogeneity across geographic areas

Future electric vehicle adoption is expected to vary substantially across communities due to differences in demographic composition, economic conditions, and spatial development patterns. National assessments by NREL [52] indicate large variability not only in total fleet growth but also in its regional distribution. Mid-range projections for 2030 estimate approximately 33 million plug-in electric vehicles (PEVs) on U.S. roads, with low and high scenarios spanning 30–42 million. Beyond total fleet size, NREL projects pronounced regional differences in adoption, with electric vehicles potentially comprising as much as 35% of light-duty vehicles in some urban areas but only about 3% in rural regions. Such disparities imply that if adoption accelerates in urban ZIP Codes but lags in rural areas, a deployment optimized under uniform adoption assumptions may overbuild in rural regions or underinvest in cities. Introducing a scenario-weighted parameter (m_i), therefore, enables the model to test the robustness of siting recommendations under divergent adoption trajectories.

To represent this heterogeneity in a tractable manner, the optimization introduces a scenario-weighted parameter (m_i), applied to population-linked terms for each ZIP Code i. In the baseline specification, $m_i = 1.0$ statewide, corresponding to a uniform adoption trajectory analogous to NREL's "Alternate PEV Adoption" case used for sensitivity analysis. Alternative pathways are represented by assigning differentiated values of m_i according to contextual factors. For example, the model can simulate a rural-growth scenario (higher weights for ZIP Codes with RUCA ≥ 4), an urban-acceleration scenario (higher weights for ZIP Codes with RUCA < 4), or a density-tiered scenario (higher weights for ZIP Codes with population density ≥ 1,000 persons/m_i^2). This scenario-weighted specification enables structured robustness checks of deployment outcomes under plausible community-specific adoption trajectories, aligning with the scenario and sensitivity framework emphasized in NREL [52].

5. Optimization model formulation

In this study, we employ an MILP model to determine the optimal siting and sizing of EV chargers across ZIP Code-level regions in New Hampshire. The model simultaneously considers five complementary objectives: maximizing total population coverage, prioritizing rural equity, maximizing charger utility, minimizing unmet demand, and ensuring a minimum required share of DCFCs.

5.1. Sets and indices

- I: Set of all ZIP Codes in New Hampshire considered as candidate charger sites (indexed by i or j).
- N_i: Set of ZIP Codes within coverage radius R_i of ZIP Code i (defined as approximately 1.6 kilometers (1 mile) in urban areas and 16 kilometers (10 miles) in rural areas).

5.2. Parameters and constants

- p_i : Population of ZIP Code *i*.
- $RUCA_i \in [0, 10]$: Rural-Urban Commuting Area score for ZIP Code *i*.
- d_i : population density in ZIP Code *i*.
- I_i : Existing charger capacity in ZIP Code *i*.
- m_i : (dimensionless): scenario-weighted adoption factor for ZIP Code *i*, applied to population-linked terms to reflect heterogeneous adoption trajectories; baseline $m_i = 1.0 \ \forall \ i \in I$ domain: $m_i \in \mathbb{R}_{\geq 0}$.
- R_i : Radius of coverage for ZIP Code *i* (approximately 1.6 kilometers (1 mile) in urban areas and 16 kilometers (10 miles) in rural areas).
- B : Total budget available for new charger installations.
- c^{L2} : Cost to install one L2 charger.
- c^{DC} : Cost to install one DCFC.
- $D_i : \begin{cases} 1, & if \quad d_i \geq 1000 \ (high - density \ ZIP) \\ 0, & if \quad d_i < 1000 \ (Low - density \ ZIP) \end{cases}$
- *M*: A large constant, representing an effectively unconstrained upper bound for low-density ZIP Codes.

5.3. Decision variables

- $x_i^{L2} \in \mathbb{Z}_{>0}$: Number of new L2 chargers in ZIP Code *i*.
- $x_i^{DC} \in \mathbb{Z}_{>0}$: Number of new DCFC in ZIP Code *i*.
- $Cov_i : \begin{cases} 1, & if \ ZIP \ Code \ i \ is \ covered \ by \ at \ least \ one \ charger \ within \ its \ radius \\ 0, & otherwise \end{cases}$
- $\delta_i \geq 0$: Slack variable for unmet charger demand in ZIP Code *i*.

5.4. Objective function

$$\max\left(\beta_1 \sum_i m_i . p_i . Cov_i + \beta_2 \sum_i m_i . \left(\frac{RUCA_i}{10}\right) . p_i . Cov_i + \beta_3 \sum_i \left(1 . x_i^{L2} + 7 . x_i^{DC}\right) - \beta_4 \sum_i \delta_i \right.$$
$$\left. - \beta_5 . \max\left(0, \quad 0.15 . \sum_i (x_i^{L2} + x_i^{DC}\right) - \sum_i x_i^{DC}\right),$$

Component Explanation:

- Population Coverage Reward ($\beta_1 = 1.0$): Rewards coverage of residents across ZIP Codes, addressing the widespread lack of charging access.
- Rural Equity Reward ($\beta_2 = 1.5$): Prioritizes rural areas by scaling coverage with RUCA weights, thereby strengthening equitable deployment.
- Charger Utility Reward ($\beta_3 = 2.0$): Rewards installation of chargers, with DCFCs weighted seven times (7×) more than L2 chargers to reflect higher throughput.

- Unmet Demand Penalty ($\beta_4 = 1.0$): Penalizes shortfalls relative to the equity threshold of one charger per 500 residents.
- DCFC Share Penalty ($\beta_5 = 4.0$): Penalizes deviations from the 15% minimum DCFC share, supporting corridor coverage without imposing hard constraints.

The selected β-values reflect practical priorities and observed conditions in New Hampshire. β_1 addresses general statewide access, β_2 emphasizes rural equity, β_3 captures the higher performance of DCFCs, β_4 discourages unmet demand unless justified by cost, and β_5 encourages corridor alignment. These values are calibrated through iterative sensitivity analysis to balance performance, equity, and budget efficiency.

Importantly, the five objectives are integrated into a single weighted-sum formulation, where each component is multiplied by its respective weight ($\beta_1 - \beta_5$) and combined into one maximization objective. This design ensures that trade-offs among coverage, equity, utility, unmet demand, and DCFC share are evaluated simultaneously.

Accordingly, the weighted-sum approach is selected because it is computationally efficient, well-suited to linear formulations, and capable of producing an optimal solution to the combined MILP problem under the specified weights. It also provides a transparent mechanism for communicating trade-offs to policymakers. Furthermore, compared with lexicographic or ε-constraint methods, the weighted-sum formulation offers greater flexibility and clarity, while the calibrated β-values ensure alignment with real-world policy and planning priorities.

5.5 Constraints

Consistent with the assumptions outlined in Section 4, the following constraints formalize how the model integrates equity, geographic accessibility, financial feasibility, and land-use considerations, thereby ensuring that the optimization results remain technically sound and operationally implementable.

5.5.1. Population-based minimum infrastructure constraint

To ensure equitable access to charging infrastructure, the model imposes a population-based minimum requirement across ZIP Codes. Specifically, each ZIP Code i must maintain at least one charger (existing or planned) per 500 residents, aggregated over its neighborhood N_i. This includes new L2 and DCFC installations, as well as existing charger capacity I_j, with DCFCs assigned a weight factor of 3 to reflect higher throughput. Formally, for each ZIP i:

$$\sum_{j \in N_i} (x_j^{L2} + 3\, x_j^{DC} + I_j) + \delta_i \geq \left\lceil \frac{m_i . p_i}{500} \right\rceil \; \forall\, i,$$

Here, $\delta_i \geq 0$ represents a non-negative slack variable that enables limited violation of the equity threshold, which is penalized in the objective function. This relaxed constraint ensures that all communities meet a baseline service level while maintaining model feasibility in low-density or high-cost areas.

5.5.2. Coverage definition

To operationalize geographic accessibility, the model defines a ZIP Code i as "covered" when the total effective charger capacity (accounting for existing and new infrastructure) in any neighboring ZIP Codes $j \in N_i$ meets or exceeds at least one full unit. Coverage is determined by the following constraint:

$$Cov_i \leq \sum_{j \in N_i} \min\left(1, I_j + x_j^{L2} + 3x_j^{DC}\right) \forall i,$$

The coverage neighborhood N_i is defined based on RUCA classification:

$$R_i = \begin{cases} 10 & if\ RUCA_i \geq 4\ (rural) \\ 1 & if\ RUCA_i < 4\ (urban) \end{cases}$$

This structure ensures spatial equity by requiring that at least one unit of charger capacity is accessible within R_i. Although coverage is implemented via this formula and incorporated into the objective function, it is conceptually aligned with a binary interpretation: A ZIP Code is considered "covered" when sufficient charger capacity exists within its defined neighborhood. This framework encourages balanced infrastructure deployment across both urban and rural areas.

Coverage is evaluated strictly on a per–ZIP Code basis. Once a ZIP Code i is deemed covered by any charger within its neighborhood set N_i, its contribution to the objective is fixed at one ($Cov_i = 1$). Even if multiple neighboring ZIP Codes provide overlapping coverage, the population of ZIP Code i is counted only once in the objective function. This approach ensures that overlapping service areas enhance redundancy and reliability without inflating measured coverage benefits. Additional chargers in nearby ZIP Codes contribute utility through the charger-count term of the objective function but not through repeated population counts. Together, these provisions prevent double-counting and maintain consistency between geographic accessibility and utility assessment.

5.5.3. Budget constraint

To ensure financial feasibility, the model imposes a budget constraint that limits total installation costs:

$$\sum_i \left(c^{L2} x_i^{L2} + c^{DC} x_i^{DC}\right) \leq B,$$

c^{L2} *=\$14,000*: Cost of installing one L2 charger
c^{DC} *=\$100,000*: Cost of installing one DCFC
B=\$28,000,000: The total available budget based on confirmed and active public funding

5.5.4. Density constraints

To reflect physical and regulatory limitations in high-density areas, the model applies the following condition:

$$x_i^{L2} + x_i^{DC} \leq M\,(1 - D_i) + 4D_i \;\forall i$$

This formulation limits the total number of chargers to a maximum of four in dense urban ZIP Codes, where land availability and permitting are constrained, while enabling more flexible deployment in rural or low-density areas. Accordingly, this constraint aligns infrastructure planning with local feasibility and actual siting conditions.

5.5.5. Domain constraints

$$x_i^{L2}, x_i^{DC} \in \mathbb{Z}_{\geq 0}, Cov_i \in \{0, 1\}, \delta_i > 0,$$

All decision variables are subject to appropriate domain restrictions: Charger counts must be non-negative integers, coverage indicators must be binary, and slack variables must be constrained to be non-negative. These constraints maintain mathematical consistency and ensure that all model outputs are interpretable and implementable.

6. Methodology and model implementation

The methodological workflow applied in this study is summarized in Figure 6 and integrates data preparation, scenario design, model formulation, and computational execution into a coherent pipeline for optimizing EV charger deployment in New Hampshire.

Data from demographic, infrastructure, and spatial sources are standardized at the ZIP Code-level and merged into a single analytical dataset. Neighborhood sets are constructed from the centroid-to-centroid distance matrix (Section 3) and use different coverage radii based on RUCA classification (Sections 4.2 and 4.6) to distinguish urban and rural coverage. Scenario variation enters via the adoption weights m_i (Section 4.9), which rescale population-linked terms under alternative trajectories.

The optimization is formulated as a mixed-integer linear program, using the decision variables defined in Section 5.3 (x_i^{L2}, x_i^{DC}, Cov_i,δ_i). The objective function (Section 5.4) balances population coverage, rural equity, charger utility, unmet-demand penalties, and a minimum DCFC share, while feasibility is enforced by the constraints in Section 5.5, which capture population-based requirements, coverage definition, budget and density limits, and variable domains.

Implementation is carried out in Python 3.10 using the CVXPY optimization library [53], with ECOS_BB employed to handle the integer structure of the model. The optimization code written in Python iterates over all ZIP Codes, dynamically constructing neighborhood-level constraints. Data preprocessing and aggregation are conducted in Microsoft Excel and Power BI to standardize inputs prior to model development. Outputs, including charger allocations, coverage indicators, budget utilization, and slack measures, are exported to structured CSV files for analysis. When infeasibility occurs, key assumptions are adjusted and the model re-run to restore feasibility.

To ensure transparency and reproducibility, the complete implementation (including preprocessing, model formulation, and output generation) is publicly available via GitHub [54].

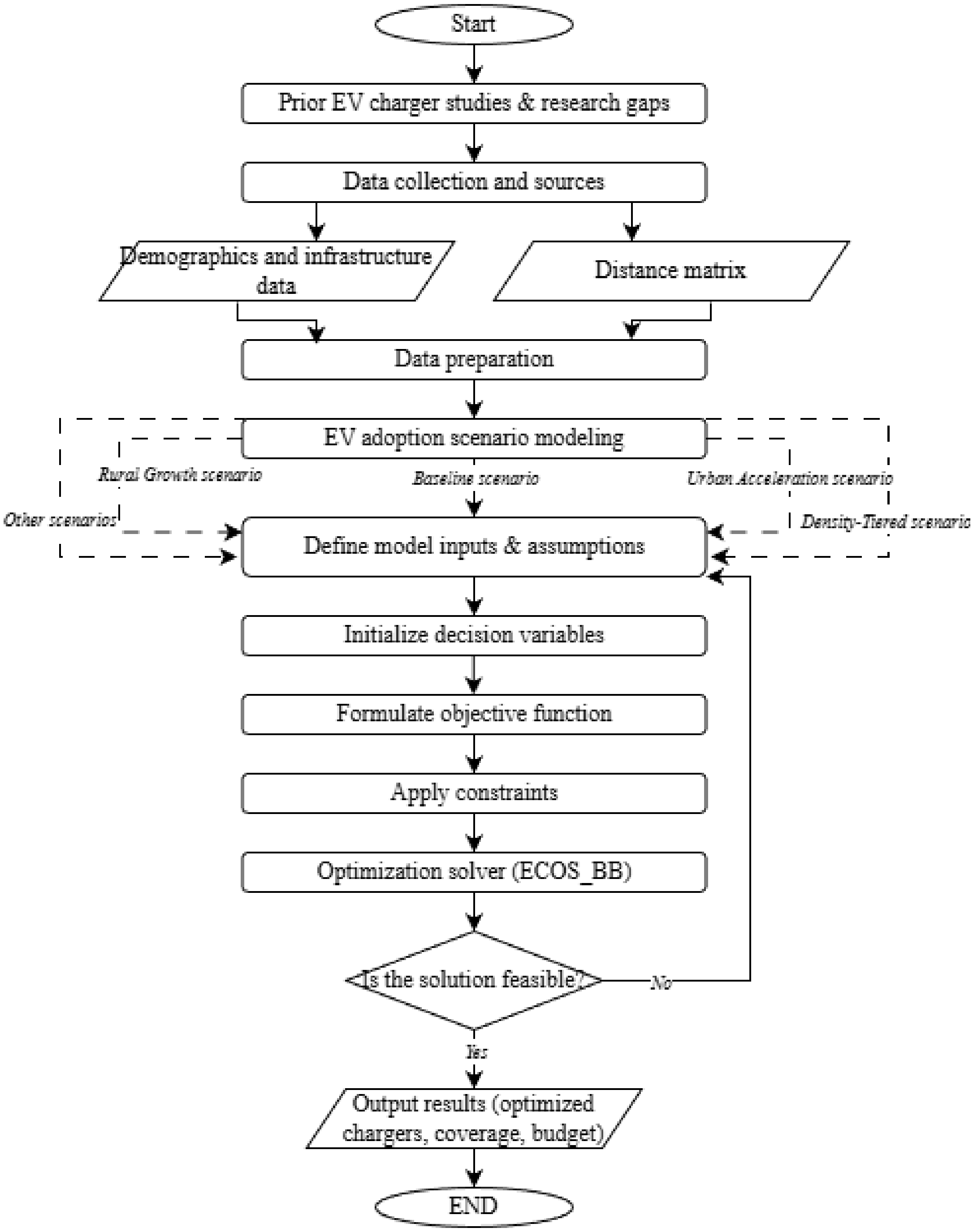

Figure 6. Methodological Workflow for the EV Charger Optimization Model.

7. Deployment results and model performance

The proposed MILP model yields the installation of 855 new Level 2 (L2) chargers and 149 direct current fast chargers (DCFCs), bringing New Hampshire's total public charging infrastructure to 1,767 chargers, based on existing public charging ports as of early 2024. The solution achieves coverage in 244 out of 247 ZIP Codes (98.8%), consistent with coverage definition in Section 5.5.2 and the urban–rural radii in Sections 4.2 and 4.6. Importantly, the model operates within the fiscal envelope set in Section 4.7, utilizing approximately $26.87 million of the available $28 million, indicating a cost-effective and resource-conscious deployment. The resulting DCFC share of new installations is approximately 15%, aligning with the soft share target embedded in the objective (Section 5.4).

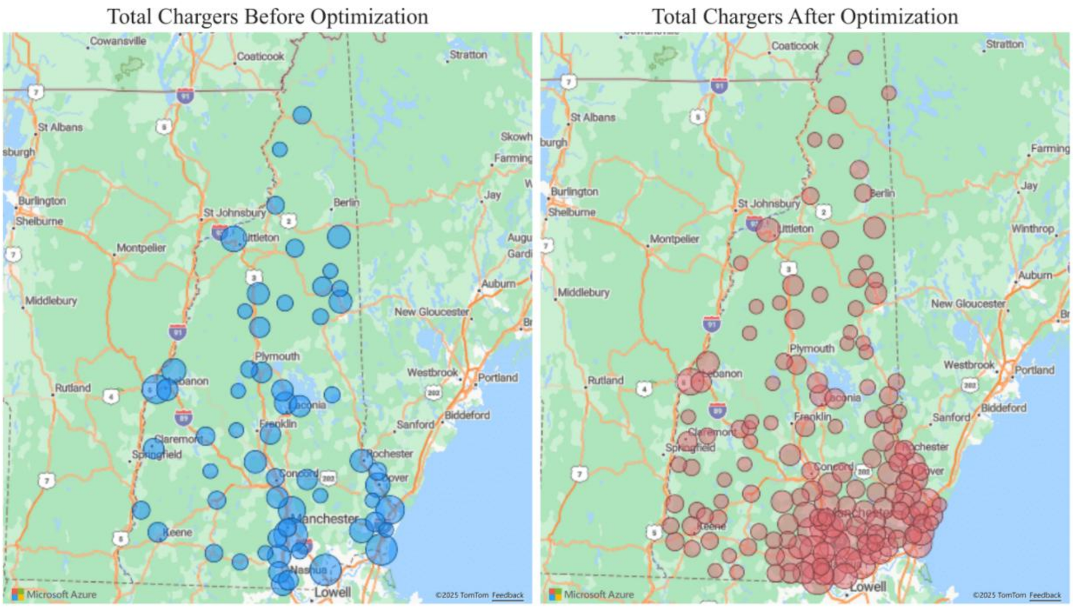

Figure 7. Total Public EV Chargers in New Hampshire Before and After Optimization. Note: Bubble position represents ZIP Code location, while bubble size represents charger quantity.

In the above figure, the bubble size represents the total number of public chargers associated with each ZIP Code. In the “Before Optimization” map (left, blue), bubble size corresponds to the number of chargers. In the “After Optimization” map (right, red), bubble size corresponds to the total chargers following optimization, which includes existing and newly allocated chargers.

Following optimization, the charger network becomes more geographically balanced, extending into central and northern regions while reinforcing dense southern clusters where utilization potential is highest. This reflects the model’s integrated priorities: Maximizing population-linked coverage and charger utility in higher-demand areas (Sections 5.4 and 4.4), while ensuring minimum statewide access through the equity-based population requirement (Section 5.5.1) and RUCA-informed coverage radii (Sections 4.2 and 4.6).

At a broader geographic scale, Figure 8 reports the net increase in public EV chargers by county (L2 + DCFC) after optimization. The largest gains occur in Rockingham (386 units), Hillsborough (372), and Strafford (147), consistent with higher population levels, more urban RUCA classifications, and siting opportunities under the density cap (Section 5.5.4). By contrast, rural counties such as Cheshire (31), Merrimack (27), Carroll (13), Coös (13), Sullivan (10), Grafton (3), Belknap (1), and Oxford (1) record modest additions that nonetheless improve baseline accessibility within the 10-miles (approximately16 kilometers) rural radius (Sections 4.2 and 4.6). In aggregate, these adjustments reconcile equity and feasibility: Rural ZIP Codes meet population-based minimums without overbuilding, while urban ZIP Codes receive capacity where demand density and dwell-time patterns support efficient utilization (Sections 4.4–4.6).

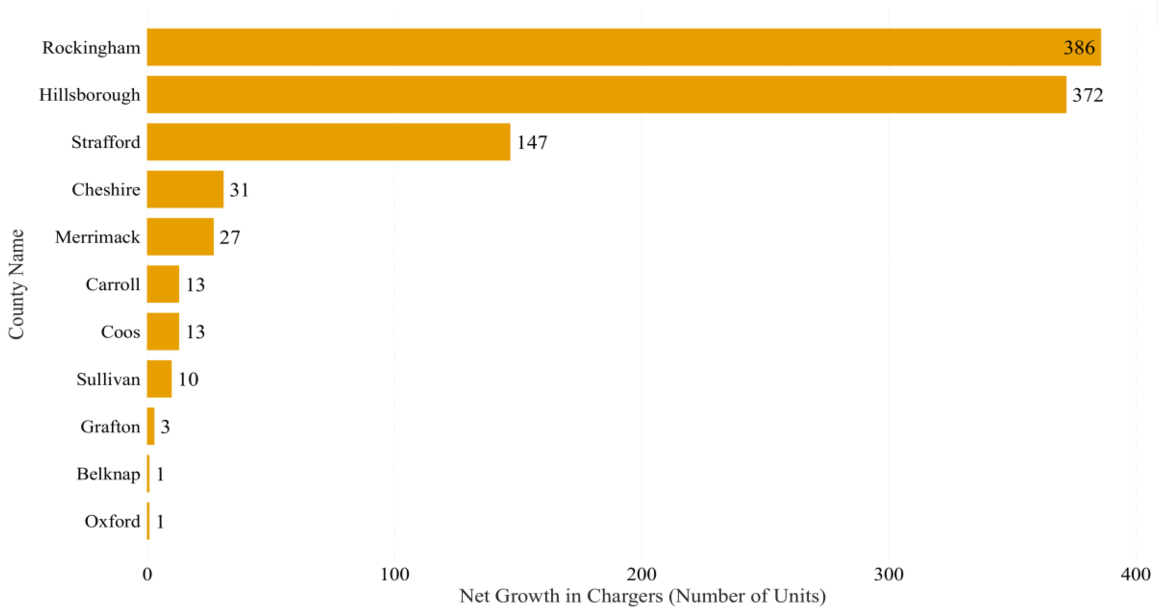

Figure 8. Net Growth in Public EV Chargers (L2+DCFC) by County.

Overall, the optimized deployment demonstrates that a policy-aligned, budget-constrained MILP can expand coverage statewide, rebalance spatial access, and respect practical siting limits. The results are consistent with the model's weighted objective (Section 5.4), which trades off population coverage, rural emphasis, charger utility, unmet-demand penalties, and an approximate DCFC share target, producing a deployment plan that remains both implementable and equitable under current funding conditions. The subsequent analyses (Figures 9–13 and Table 1) examine corridor alignment, city-level growth, cost distribution, and potential grid impacts.

Building on the statewide and county-level results in Figures 7 and 8, we examine corridor alignment and ZIP Code-level spatial patterns.

In contrast to Figure 7, where bubble size reflects total chargers, Figure 9 uses bubble size to represent charger growth, defined as the number of newly added chargers in each ZIP Code after optimization.

Although the model does not impose an explicit corridor-siting constraint, the results nevertheless align with major transportation routes. As defined earlier (Sections 4.2 and 4.6), urban and rural ZIP Codes use distinct coverage radii, and the objective incorporates a soft DCFC-share term (Section 5.4). Together, these elements produce deployment patterns that cluster along the state's highways (depicted in orange on the map), as illustrated in Figure 9.

Geographically, charger growth concentrates along Interstate 93 (particularly its southern segment between Concord and the Massachusetts border) and along Interstate 95 in the Seacoast region. Interstate 89 exhibits moderate expansion extending north from Concord toward Lebanon, while Interstate 91 shows only partial coverage, especially in the southern and central portions near Keene and Claremont. Additional routes, such as U.S. Route 3 in Hillsborough County and segments of NH

Route 16 (the Spaulding Turnpike from Portsmouth through Dover and Rochester), also display noticeable growth. In Figure 9, these alignments appear as clusters of bubbles tracing the state's principal road network.

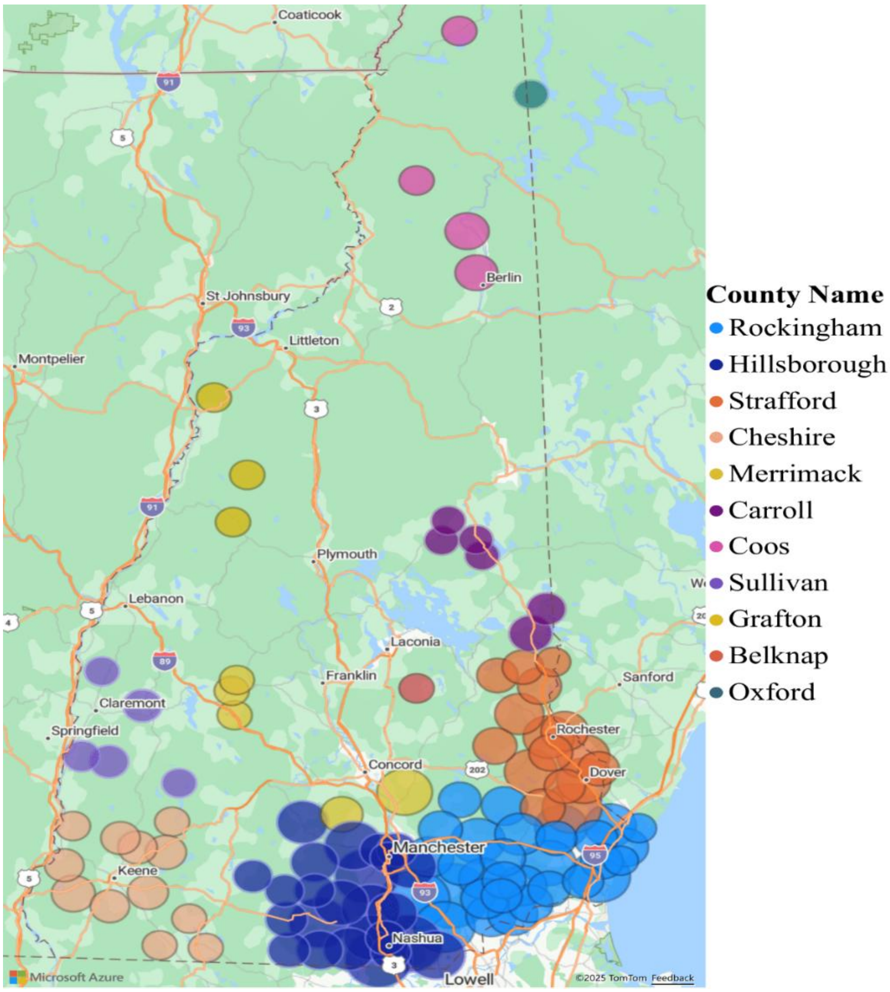

Figure 9. Geographic Distribution of EV Charger Growth by ZIP Code.

Additionally, Figure 9 highlights ZIP Code-level variation in deployment growth. Bubble area is proportional to the number of added chargers (L2 + DCFC combined), and bubble color denotes the county (categorical). Growth is concentrated in the southern urban corridor, with Nashua (67), Derry (62), and Hudson (45) showing the largest increases (see Figure 10), while many rural ZIP Codes record only single-digit additions (e.g., Coös 03592: 1; Rockingham 03854: 1; Grafton 03780: 1; for more details, see Table 1). Locations with zero growth are not displayed because bubble size is proportional to the number of added chargers.

This ZIP Code-level distribution is consistent with the county totals presented in Figure 8 while also revealing localized disparities. The observed spatial pattern reflects the model's design features, including caps on chargers in high-density ZIP Codes (>1,000 persons/mi^2, Section 4.5), distance-based service constraints that differentiate urban and rural radii (Sections 4.2 and 4.6), and the population-based minimum requirement (Section 5.5.1). Together, these provisions ensure statewide coverage while concentrating larger deployments in the high-demand southern ZIP Codes.

Consistent with the southern-corridor clusters observed in Figure 9, Figure 10 ranks the top 15 municipalities by newly installed chargers. Nashua (67), Derry (62), and Hudson (45) lead the list, reflecting their status as high-demand, high-density urban centers. These cities are in the southern part of the state (Nashua and Hudson in Hillsborough County, and Derry in Rockingham County), aligning with the model's emphasis on prioritizing areas with higher population concentration and greater siting feasibility.

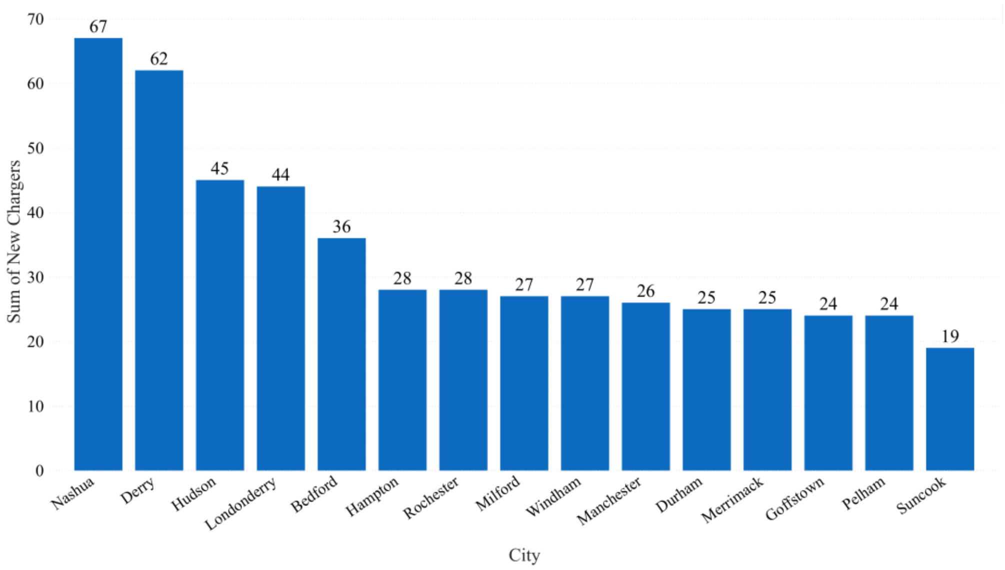

Figure 10. Top 15 Cities by New Charger Installations.

In summary, the model effectively balances efficiency and equity. While dense and urbanized areas receive the highest number of chargers, consistent with the population-based minimum requirement (Section 5.5.1), the density cap (Section 5.5.4), and the budget constraint (Section 5.5.3), nearly all ZIP Codes attain at least a basic service. These deployment outcomes reflect a deliberate, data-driven strategy that aligns with infrastructure readiness and regional mobility needs, avoiding over-concentration of investment and the exclusion of rural communities.

Figure 11 illustrates the distribution of Level 2 and DCFC installation costs by county across New Hampshire. Most infrastructure spending is concentrated in Hillsborough and Rockingham counties, which together account for nearly $20 million of total investment. These high-density counties prioritize both charger types (especially DCFCs) reflecting stronger demand and greater siting feasibility.

By contrast, rural counties such as Grafton, Belknap, and Coös primarily receive L2 chargers, directing limited funds toward meeting minimum accessibility thresholds. This pattern is consistent with the model's design: High-cost DCFCs are deployed strategically in high-demand corridors (where throughput and reduced travel time benefits justify the investment), while cost-effective L2 units provide broad geographic access.

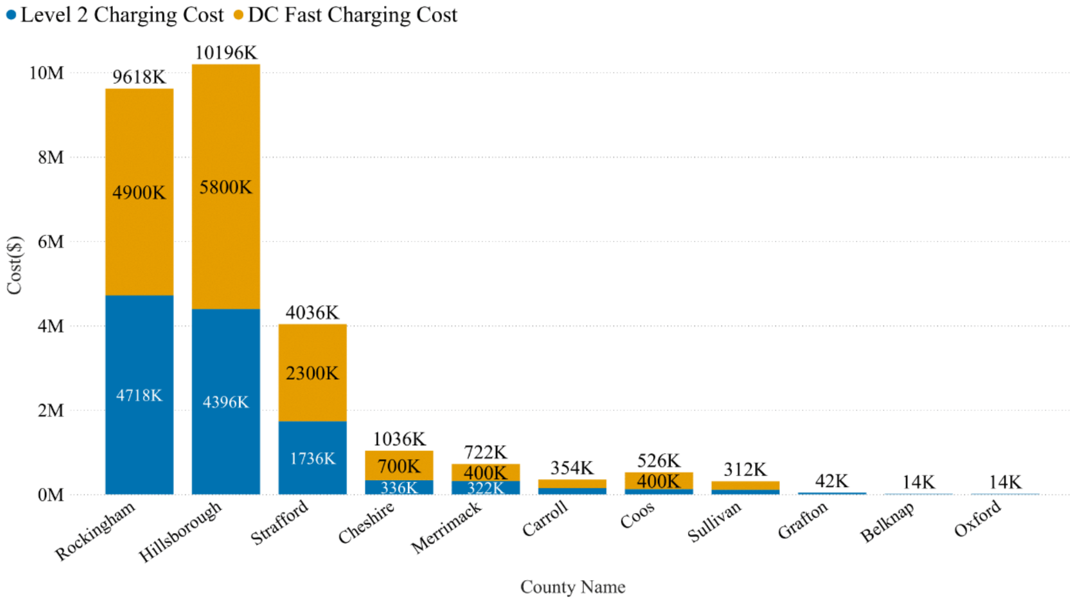

Figure 11. Distribution of Level 2 and DCFC Installation Costs by County.

Statewide, approximately 55% of the budget is allocated to L2 chargers and 45% to DCFCs, consistent with the budget constraint (Section 5.5.3) and the assumed cost structure (Section 4.1). Although DCFCs represent about 15% of newly installed units, their higher per-unit cost warrants a significant share of spending, supporting regional mobility and reliability goals.

Figure 12 examines how the deployment results translate into spatial outcomes by illustrating the relationship between ZIP Code population and the total number of public EV chargers after optimization. Although the relationship is not perfectly proportional, the figure indicates a clear positive association: ZIP Codes with larger populations generally host more chargers. Urban ZIP Codes (blue diamonds with a blue dashed trend line) align more closely with this population-based pattern, especially at higher population levels, consistent with the minimum-population requirement (Section 5.5.1) and the 1-mile urban service radius (Sections 4.2 and 4.6). In contrast, rural ZIP Codes (orange open circles with an orange dotted trend line and mostly below 10,000 residents) display greater dispersion, reflecting lower population density, the wider 10-mile (approximately 16 kilometers) rural coverage radius, and equity-oriented siting rules.

Because the optimization model incorporates a minimum-accessibility requirement for all ZIP Codes, a subset of sparsely populated rural areas receives chargers even when their census-recorded populations are very small. This explains the non-zero charger values appearing near the origin of Figure 12 and reflects the model's coverage and equity constraints (Sections 5.5.1 and 5.5.2), rather than a data inconsistency. This pattern indicates that the model provides a baseline level of accessibility in underserved rural regions, even when population alone would not justify additional installations.

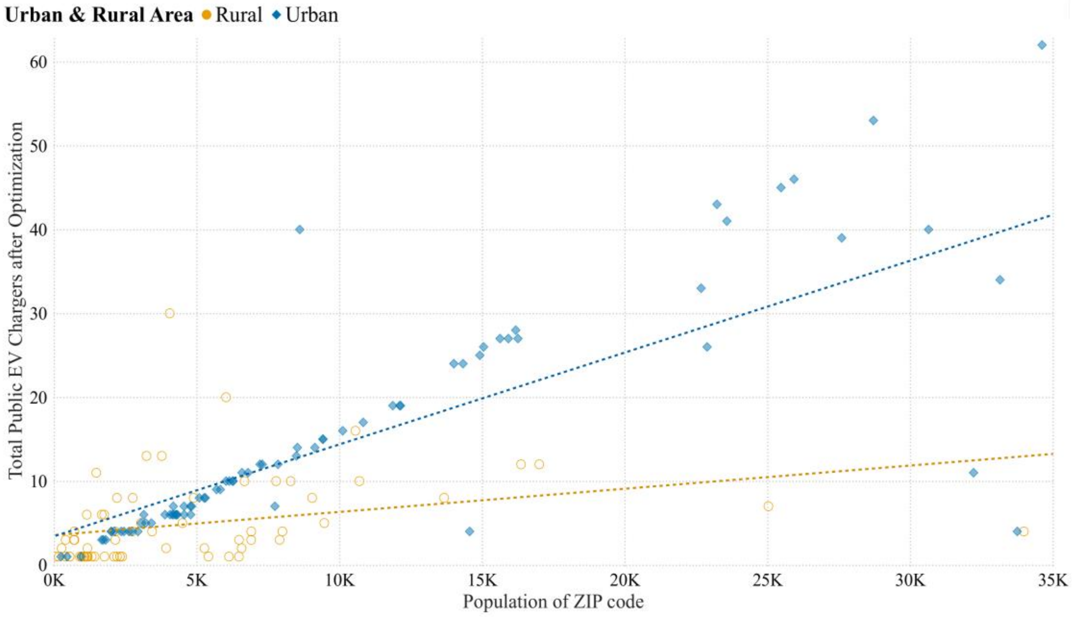

Figure 12. Relationship Between Population and Total EV Chargers by Urban–Rural Classification.

Table 1. Top ZIP Codes by Slack Population and Newly Added Chargers.

County Name	ZIP Code	Population	Slack Population	Total New Charger
Hillsborough	3104	35274	59	4
Hillsborough	3102	33755	56	4
Hillsborough	3060	32223	34	4
Hillsborough	3064	14565	18	4
Grafton	3740	1049	2	1
Grafton	3240	1248	2	0
Grafton	3777	1289	2	0
Grafton	3774	1606	2	0
Grafton	3785	2141	2	0
Grafton	3574	2545	2	0
Merrimack	3257	4503	2	0
Cheshire	3461	6482	2	1
Hillsborough	3244	8005	2	0
Grafton	3780	599	1	0
Grafton	3765	667	1	0
Grafton	3771	807	1	0
Rockingham	3854	948	1	1
Coos	3592	972	1	1
Grafton	3282	1075	1	1

Moreover, Table 1 identifies ZIP Codes with the largest slack populations, that is, residents not covered by the 1:500 population minimum formalized in Section 5.5.1 and captured by the slack variable δ_i. In several dense urban ZIP Codes (e.g., 03104 and 03102 in Manchester), the density-based cap of four chargers (Section 5.5.4) constrain deployment, leaving these areas slightly underserved despite high demand.

In contrast, most rural ZIP Codes meet their coverage targets with fewer installations, aided by lower populations and the larger 10-mile (approximately 16 kilometers) service radius (Sections 4.2 and 4.6). Although not shown here, the average number of chargers per 1,000 residents is 1.58 in urban areas and 1.00 in rural areas, implying a rural-to-urban parity ratio of approximately 0.63. Notably, 174 of the 218 total slack residents are in Hillsborough County, confirming that residual service gaps are concentrated in dense urban zones. These modest shortfalls suggest targeted urban reinvestment or policy refinement as pragmatic next steps.

As a final analysis, we evaluate whether the modeled number of chargers could impose a significant burden on New Hampshire's and New England's electricity systems. Consistent with the modeling conventions used elsewhere in this report, ex-post coincident peak nameplate demand is estimated using 7.2 kW per Level 2 (L2) port (240 V, 30 A; SAE J1772; DOE AFDC) and 150 kW per DC fast-charging (DCFC) port, aligned with FHWA NEVI standards [39,55]. These values represent instantaneous power capacity rather than annual energy use and therefore capture the maximum potential grid requirement under a hypothetical simultaneous-operation condition.

Under these assumptions, the optimized deployment of 855 new L2 ports and 149 new DCFC ports corresponds to approximately 28.5 MW of additional statewide load. Of this increment, L2 contributes about 6.2 MW and DCFC contributes about 22.4 MW, underscoring the greater intensity of fast charging. When combined with the approximately 43.0 MW of public electric vehicle supply equipment (Section 3; AFDC, early 2024: 297 L2 and 272 DCFC ports), the post-deployment electric vehicle supply equipment (EVSE) nameplate capacity totals approximately 71.4 MW, representing about a 66% increase over baseline levels.

To contextualize system impacts, ISO New England (ISO-NE), the regional transmission organization for the six New England states, forecasts summer peak demand of approximately 24.8 GW under typical weather and approximately 25.9 GW under extreme conditions [56]. Against this backdrop, the incremental 28.5 MW constitutes only about 0.1 to 0.3 %of the ISO-NE peak, which is a negligible addition at the bulk-system level. At the state level, New Hampshire accounts for approximately 9% of New England's electricity consumption [57], implying a summer peak of approximately 2.2 GW. Relative to this benchmark, the modeled EVSE load equals approximately 1.3% of state peak demand, confirming that statewide impacts remain modest.

The county-level distribution of added demand is reported in Figure 13. Hillsborough (about 11.0 MW) and Rockingham (about 9.8 MW) dominate the incremental load, followed by Strafford (about 4.3 MW). All other counties register less than 2 MW, while rural areas such as Belknap, Grafton, and Oxford add only marginal capacity. Across nearly all counties, DC fast chargers drive most of the increment and often contribute three to four times the load of L2 ports. This pattern is consistent with the charger-utility weighting in Section 4.4 and the DCFC share term in the objective (Section 5.4).

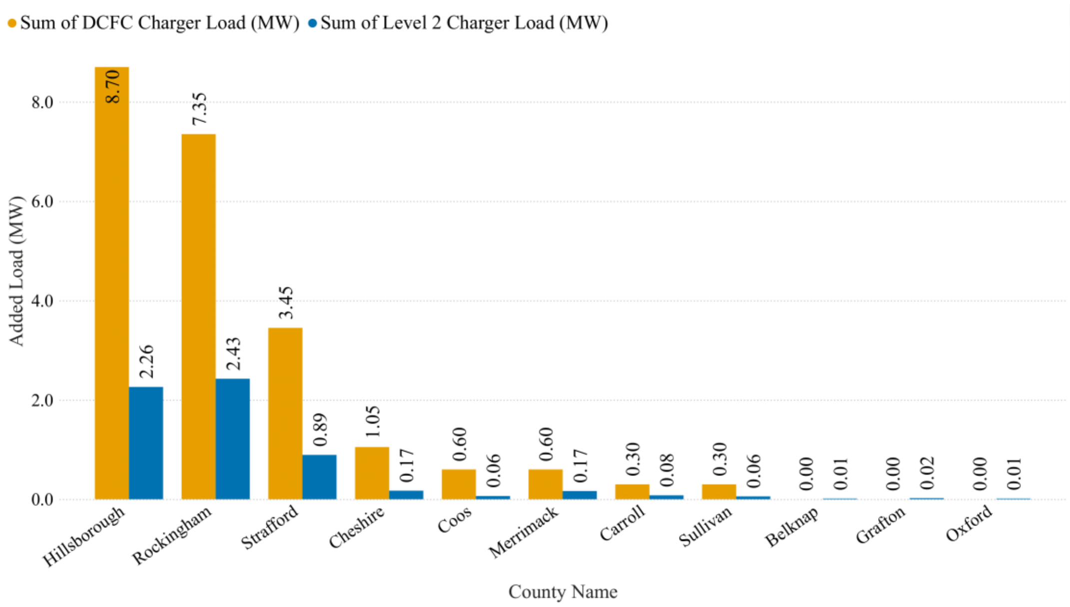

Figure 13. Added charger load by county and type (MW).

Taken together, these results indicate that while regional grid impacts are minimal, localized distribution-system constraints, particularly in rural areas with weaker substations or feeders, they can influence siting and phasing. Because DCFCs account for most of the incremental load (Figure 13) and their deployment is encouraged through the objective's soft share term (Section 5.4) and supported by the RUCA-informed coverage radii (Sections 4.2 and 4.6), corridor clusters in high-demand counties (Figures 8–10) may necessitate targeted distribution upgrades or load-management strategies (e.g., managed charging, demand response, and power-sharing cabinets). A focused assessment of substation and feeder headroom at priority sites is therefore an important direction for future work.

8. Conclusion

In this study, we present a MILP-based optimization model for deploying EV charging infrastructure across New Hampshire, addressing coverage, equity, and cost efficiency within a $28 million budget. The optimized solution allocates 855 L2 and 149 DCFC chargers across 247 ZIP Codes, achieving 98.8% statewide coverage while utilizing $26.87 million. The plan increases nameplate EVSE capacity by approximately 66% relative to the baseline and delivers a geographically balanced rollout that improves rural accessibility.

The deployment strategy supports key policy objectives, including bridging urban–rural disparities and ensuring the prudent use of public funds. By extending access into underserved communities and aligning charger types with local context, the model illustrates how optimization can guide practical, policy-aligned planning. The integration of equity constraints and RUCA-informed siting radii ensures that high-demand urban areas and low-density rural zones receive adequate service.

Although effective, the model embodies several simplifying assumptions. It relies on static demand data and ZIP Code-level aggregation, which may mask localized variations in charging needs.

While the analysis indicates modest impacts at the regional grid scale, distribution-level constraints are not explicitly represented. Rural substations and feeders with limited capacity may face challenges in accommodating clusters of DC fast chargers, suggesting that localized bottlenecks could alter siting outcomes. In addition, because the model caps new chargers in high-density urban ZIP Codes (a maximum of four per ZIP Code) and does not explicitly model distribution network constraints (for example, feeder headroom, voltage limits, and transformer loading), the results are best interpreted as strategic planning guidance rather than detailed engineering design. Accordingly, the findings offer high-level strategic guidance rather than site-specific prescriptions.

In future research, researchers should extend the model by incorporating dynamic EV adoption trends, finer spatial resolution, explicit grid feasibility constraints (for example, hosting capacity and interconnection costs), and temporal demand variation to enhance deployment realism. The scenario-weighted adoption specification (Section 4.9) provides a pathway for reflecting differentiated adoption trajectories across communities; future applications can employ alternative adoption scenarios or ZIP Code-level forecasts to test the robustness of siting strategies as adoption patterns evolve. Applying and validating the framework in other regions would test its generalizability and support broader efforts in equitable and cost-effective EV infrastructure development.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflicts of interest in this paper.

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