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Adaptable Charging Station Placement: Employing Evolvability

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***Abstract*—This work introduces designing adaptable (mobile) Electric Vehicle charging station infrastructure, employing evolvability and dynamic optimization framework to identify layouts that are not only optimal for current traffic and network conditions but also facilitate easy adaptation to future changes. The framework leverages mechanisms of evolvability, including regulatory change, exploration, and diversity, to enhance the adaptability of the solutions and is tested across 20 cities. A single-objective optimization approach, which implicitly considers the number of reconfigurations is compared with Static placement approach, and a bi-level and bi-objective formulation that explicitly minimizes reconfigurations. Results indicate that although Implicit approach consistently outperforms the Explicit method across all cities, it shows clear advantage relative to Static placement in many cities while remains competitive in others emphasizing the role of network topology in providing robust mobility. Adaptable solutions remain competitive under normal conditions while offering better robustness and flexibility.**

***Index Terms*—Electric charging station placement, optimization, road network, evolvability**

I. Introduction

Road networks are inherently dynamic, undergoing frequent and unpredictable changes influenced by a multitude of factors, including political decisions, economic investments, urban development, and environmental considerations. These fluctuations pose significant challenges for mobility service providers, who must design infrastructure that not only performs effectively under current conditions but also remains resilient and adaptable to future perturbations ideally with minimal reconfiguration efforts. This study addresses the design of evolvable mobility service infrastructure, emphasizing systems that are robust to present-day network states while facilitating seamless adaptation to evolving variants. Our primary focus is on electric vehicle (EV) charging infrastructure, a critical component of sustainable urban mobility amid the global transition towards electrification.

The state-of-the-art approaches generally consider the placement to be static while accounting for the dynamic traffic conditions and spatiotemporal patterns of charging demand [1], as well as integrating charging station sizing to the optimization [2]. Mobile methods employ additional charging stations during temporal peaks in charging demand because of fluctuations in demand [3] or large scale events [4].

In this paper we aim to integrate the concept of evolvability and particularity the three mechanisms regulatory changes, exploration, and diversity within the optimization framework. Moreover, we propose a framework for mobile charging stations capable of responding to key network dynamics, such as shifts in demand distribution, traffic congestion, and road closures, and their combinations. To integrate these mechanisms, we modify the PSO algorithm, which enables the design of charging infrastructures that can dynamically optimize resource allocation and topology in response to real-time network variations, thereby enhancing overall system resilience and sustainability. This approach not only bridges theoretical insights from evolvability research with practical engineering applications but also paves the way for more adaptive urban mobility ecosystems.

In order to evaluate our approach, we test with a real data set of 20 cities. The mechanisms of evolvability will constraint the operational reconfigurations, implicitly optimizing, in addition to the objective, user travel time. Results show that this approach achieves both lower travel times, and better balance between travel time and reconfigurations than when the reconfigurations are explicitly optimized as an objective, and also helps the solutions remain competitive in nominal conditions while offering adaptability when severe disruptions occur when compared with Static placement approach.

II. Evolvability

Evolvability, a concept thoroughly investigated in multiple disciplines, mainly evolutionary biology, is defined as an organism's capacity to generate heritable phenotypic variation. It is believed to have emerged in the course of selection for robust yet flexible processes [5]. However, it may also be selectable trait and is not nearly a byproduct of evolution. Evolvability is an outcome of selection for robustness and flexibility in mildly dynamic or stable environments, but can itself be a selectable trait in highly dynamic environments [6].

Over time, the definition has progressed from simply describing the ability to evolve, to a measurable indicator of evolutionary effectiveness, encompassing not only the potential to evolve but also the quality i.e., efficiency and effectiveness [7]. But quantifying it by a single number still remains challenging, as both the level and speed of adaptation are relevant.

A. Mechanisms of Evolvability

While methods that can directly enhance evolvability remains ambiguous, certain mechanisms are believed to improve

a system's capacity to evolve across disciplines. These mechanisms, spanning biology, network theory, engineering, and AI, collectively enhance evolvability [8] [9]:

- Regulatory Change: frequent change of environments
- Exploration: non-genetic random change (mutation)
- Diversity: variability within individuals

Further mechanisms include, compartmentalization (also known as modularity), weak linkage, canalization, and many other depending on the area of study and the nature of systems.

III. Related Work

Though research on placement of charging stations is extensive, there is little on mobile or adaptable charging station placements and none that employs evolvability in designing adaptable charging station layouts.

A. EV Charging Station Placement

Coverage and flow-capturing models are the most extensively used in solving placement problems. For coverage models the goal is to find placement that offer maximum spatial reach with minimum number of charging stations. Flow models focus on placing charging stations along high-traffic corridors, considering typical travel patterns to meet demand along these routes based on Origin-Destination (OD) data [10].

In most methods, charging stations are deployed in predetermined locations to provide adequate coverage and accessibility, or they add new stations based on predicted variations in traffic. But the fixed charging stations are not yet economically viable with the current EV adaptation rates [11].

B. Employing Evolvability for Adaptability

Opedal et al. [12] proved through their study of vegetative traits of flora that evolvability can predict beyond a few generations, thus enhancing adaptation if environment changes.

Kumawat et al. [13] used digital evolution to investigate how evolvability can follow multiple evolutionary routes in finding alternating phenotypes which can switch from being optimal for one environment to another with minimal changes. They found that cycling environments at intermediate frequencies led to a thousandfold increase in mutations, allowing populations to switch between adaptive traits through two key mechanisms of evolvability i.e., regulatory change and exploration. This occurs as evolving populations localize on phenotypic boundaries in genotype space, where single mutations can toggle between adaptive phenotypes of different environments.

IV. Methodology

Unlike many traditional dynamic optimization methods, which identify distinct solutions for specific conditions, we aim to find a solution that can be easily adapted to a wide range of conditions with minimal reconfigurations. Inspired by the evolution of natural systems, we propose to employ three mechanisms of evolvability to find an optimal solution for charging station layout that is easily adaptable. To facilitate the integration of the mechanisms, we use PSO, a population-based meta-heuristic algorithm, and incorporate the mechanisms as follows:

- Regulatory Change is addressed by the way we calculate the objective values. This is particularly implemented as the cycle of environmental changes.
- Exploration is achieved by introducing a mutation operator and increasing the mutation rates.
- Diversity is maintained by adding new random particles to the population after each change.

We measure the quality of evolvability by how the adaption is reached, i.e., the minimal number of charging stations that need to be relocated to reach the new optimum. More emphasis is placed on the number of reconfigurations rather than cost, as it is assumed that relocating fewer stations over a larger distance is preferable to relocating many stations over shorter distances. And the framework is expected to keep reconfigurations to a minimum by finding adaptive phenotypes.

A. System Dynamics: Variants

In the following, we assume that the traffic data for different cities are static. Since regulatory change is a primary requirement for evolvability, we propose multiple types of system dynamics, also called variants. Several scales of these variants are used to simulate varying magnitudes of system change.

1) Demand Redistribution: It represents the usage dynamics. A proportion of OD demand matrix is shuffled to mimic change in usage pattern. Different proportions of the matrix can be rearranged to create varying scales of demand redistribution, with a proportion of 1.0 corresponding to the matrix being completely rearranged.

2) Traffic Congestion: It represents the network variable dynamics and is simulated to mimic the fluctuations in traffic flow by using edge betweenness centrality as a proxy for likelihood of congestion. Edges with higher betweenness centrality are more critical and more likely to become congested. Travel times of edges are increased proportionally to their centrality.

3) Street Closure: It represents the network structure dynamics and simulates the closure of roads that alters connectivity. Edge betweenness centrality is calculated, and then the top percentile of the streets is carefully removed while ensuring that all the centroids remain connected to the network.

Additionally, we introduce a combination of the above system dynamics, indicated by Combined which integrates all previously described variants of dynamics. More specifically, we consider the demand redistribution to be applied independently to the demand matrix, while congestion and closure are applied to the travel time matrix. Closure is applied first by removing the specified percentile of edges. Edge betweenness centrality is recalculated on the modified network and congestion effects are subsequently applied based on the updated centrality values.

B. Optimization Framework

The problem is framed as a single-objective optimization problem, with the additional goal of minimizing the number of reconfigurations implicitly addressed through the use of mechanisms of evolvability. These mechanisms facilitate adaptable solutions without explicitly quantifying minimizing number

of reconfigurations as an objective. The framework explicitly optimizes user travel times while incorporating operator considerations through adaptive solutions.

Encoding: Each charging station location is represented as a coordinate tuple consisting of latitude and longitude. Formally, an encoding is defined as a set of geographic coordinates $E = \{(\text{lo}_1, \text{la}_1), (\text{lo}_2, \text{la}_2), \ldots, (\text{lo}_n, \text{la}_n)\}$, where $\text{lo}_i, \text{la}_i \in \mathbb{R}$ denote the longitude and latitude of the i'th charging station, respectively, and $n \in \mathbb{N}$ is the total number of charging stations. Charging stations are allowed only at regular nodes, so the nearest regular node to the coordinates is used in objective calculations.

Mutation Operator: We introduce a custom mutation operator to promote exploration during optimization. For a solution encoded as $E = \{(\text{lo}_1, \text{la}_1), \ldots, (\text{lo}_n, \text{la}_n)\}$, each charging station coordinate is selected for mutation according to a mutation probability p_m. When selected, small random perturbations are applied to its longitude and latitude, such that the mutated coordinate is given by $(\text{lo}'_i, \text{la}'_i) = (\text{lo}_i + \delta_i^{\text{lo}}, \text{la}_i + \delta_i^{\text{la}})$, where $\delta_i^{\text{lo}}, \delta_i^{\text{la}} \in \mathbb{R}$ are normally distributed random noise. The mutated values are then clipped if necessary to remain within the geographic bounds of the network.

Objective function: The framework aims to minimize the total travel time via the nearest charging station, normalized by demand. The objective function, which we call travel time per trip, is defined as:

$$F(\mathbf{x}) = \frac{\sum_{(s,d)\in cen}(T_{\text{dev}}(s,d)) * D^*_{s,d}}{\sum_{(s,d)\in cen} D^*_{s,d}}$$

where $T_{\text{dev}}(s,d) = \min_{c\in C}\big(T(s,c) + T(c,d)\big)$.
Here, $T_{\text{dev}}(s,d)$ represents the minimum travel time for a trip starting at a centroid s, going to the nearest charging station c in the set of charging stations C, and ending at a centroid d. $D^*_{s,d}$ denotes the origin–destination (OD) demand between centroids s and d. The total travel time is normalized by the total OD demand. Previously mentioned changes to the system (variants) are reflected in the calculation of the objective through modifications made to the demand (D^*) and travel time (T) matrices.

V. Experiments

We evaluate the method using data from 20 cities. To ensure scalability across cities of varying sizes, the framework adopts a practical density of one charging station per 200 kilometers of road for scaling.

A. Data

Acquiring accurate road network data for transportation analysis remains a significant challenge. Freely available datasets often lack precision or are outdated, while high-quality, reliable data typically comes with a steep cost.

Xu et al. [14] proposed a method to estimate street travel times using the bi-conjugate Frank-Wolfe algorithm, leveraging publicly available network data, and demand data sourced from the U.S. Census Bureau's website. They also made the required data available for 20 cities. However, the dataset



Fig. 1: Example: San Francisco Network

employs a specific network structure with two types of nodes and links. Regular nodes represent actual street intersections within the city's road network and regular links, corresponding to major streets, connect these regular nodes. Since the demand data are at the block level, centroid nodes serve as aggregated points representing those blocks, serving as origins and destinations of travel demand. Connector links join centroids to the regular nodes.

As a result, the limitation of this dataset is that it does not encompass the complete road network of the cities, omitting smaller streets, most of the empty white spaces in between with centroid nodes (red), as shown in Figure 1. And since we will be using flow-capturing model, and the data consists of all the high traffic corridors it is reasonable to assume that travel times of connector links may approximate the travel durations for missing streets. Another concern is that the networks of some cities contain few weakly connected nodes. So, unidirectional links connecting these nodes to the strongly connected component are made bidirectional to make them strongly connected.

B. Parameter Settings

The system dynamics variants are defined using demand, congestion, and closure and a combination of all these network-disruption parameters, resulting in 25 variants. One base variant, and four demand-redistribution variants with proportions $\{0.25, 0.5, 0.75, 1.0\}$. Congestion is modeled by scaling edge travel times such that $T_e^{\text{cong}} = \alpha_e T_e$, where edges are ranked by centrality and $\alpha_e \in \{2.5, 2.0, 1.5, 1.25, 1.0\}$ is assigned to the top 5%, next 15%, next 20%, next 30%, and remaining edges, respectively. Additionally, a global scaling $\beta \in \{1.0, 1.5, \ldots, 4.5\}$ is applied to central edges, yielding $T_e^{\text{final}} = \beta T_e^{\text{cong}}$. Street closures are modeled by removing

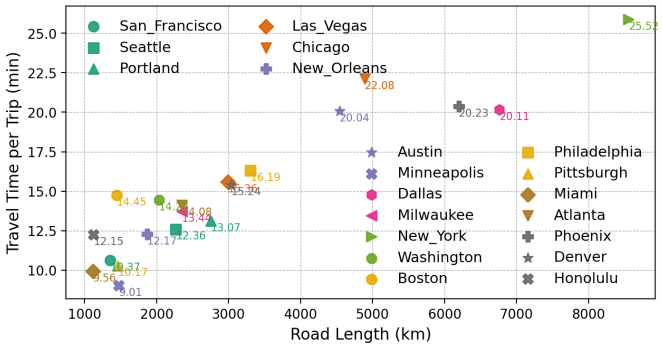


Fig. 2: All Cities Optimal Travel Times: Normal Traffic

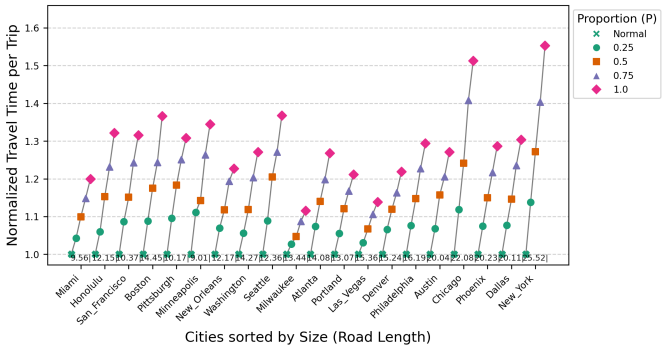


Fig. 3: Different Proportions of Demand Redistribution

a subset of edges with proportions $\{0.025, 0.05, \ldots, 0.20\}$. Throughout the remainder of the paper, *proportion* (P) refers to the level of demand redistribution, *scale* (S) denotes the congestion scaling factor, *percentile* (C) indicates the fraction of edges removed due to street closures, and *combined* refers to the joint application of these three mechanisms. The four combined variants of different levels are: $(\mathrm{P}, \mathrm{S}, \mathrm{C}) = (0.3, 1.0, 3\%), (0.6, 2.0, 6\%), (1.0, 2.5, 10\%), (0.9, 3.0, 9\%)$. Closure is applied first and then congestion with remaining streets on travel time matrix. Demand is applied independently on demand matrix.

A modified PSO to accommodate coordinates for encoding, and clear calculated velocities and global best at every change is employed to solve the problem. The optimization begins with normal conditions (base variant) with a population size of 100 particles (individuals). After 25 generations, the variant is cyclically changed. After 625 generations, the environment returns to the normal variant. This cycle is repeated 12 times, resulting in a total of 7,500 generations. To maintain diversity and reduce the risk of being stuck in local minima, 10% of the population is replaced with new particles at each variant change, and all previously saved best solutions are cleared. The results presented for evaluation are aggregated from 20 independent runs per city.

C. Results

Figure 2 shows the optimal travel time per trip for all cities as a function of their total road length. A linear scaling is assumed for number of charging stations and if this were sufficient, all cities would be expected to exhibit similar travel times. However, this is not the case. Larger cities consistently show longer travel times, indicating that the relationship is not linear, and it overlooks the longer and more complex trips characteristic of larger urban areas. A nonlinear, adaptive scaling approach that not only accounts for the size but also the inherent travel patterns of cities of different could improve the scalability of the framework.

This plot presents only the optimal travel time for each city under normal conditions and does not capture variations across different variants. The next four figures correspond to different types of system dynamics: demand redistribution, congestion, closure, and combined variants. The separate plots are to facilitate ease of interpretation and to allow examination of

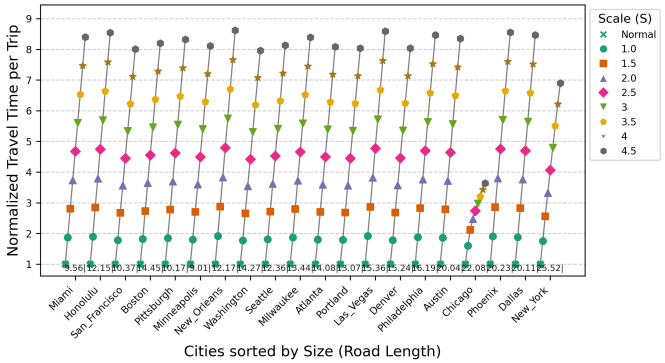


Fig. 4: Different Scales of Congestion

how different cities respond to each type of dynamic change. In these figures, the normalized optimal travel times are shown for the various variant levels. Normalization is performed by dividing the travel time of each variant by the corresponding base (normal) travel time, enabling a scale-free comparison across cities. In this representation, the points indicate the proportional increase in travel time resulting from the applied dynamics, with the base variant always at 1. Each point represents a different level of respective system dynamics.

Figure 3 illustrates the proportional increase in travel time resulting from demand redistribution across 4 different proportions. Most cities have an increase of 20 to 30% in travel time when the demand is completely redistributed. But Milwaukee exhibits an increase of approximately 10%, while Chicago and New York experience increases of about 50%. However, the demand redistribution is a stochastic process and the travel times can vary. Similarly, Figure 4 presents 8 scales of congestion. Most cities exhibit a comparable escalation in travel time under congestion, except Chicago, which has the most ordered road network in the U.S. [15].

Figure 5 shows 8 levels of closure as percentiles. No consistent pattern is observed across cities, as each exhibits distinct behavior. However, Chicago once again demonstrates the best overall performance which could be a benefit from its grid like structure. Figure 6 presents the normalized times for 4 previously described combinations of variants. Among the cities, Miami, Denver, and Chicago exhibit the best overall performance under combined dynamics, exhibiting smaller proportional increases in travel time compared to others.

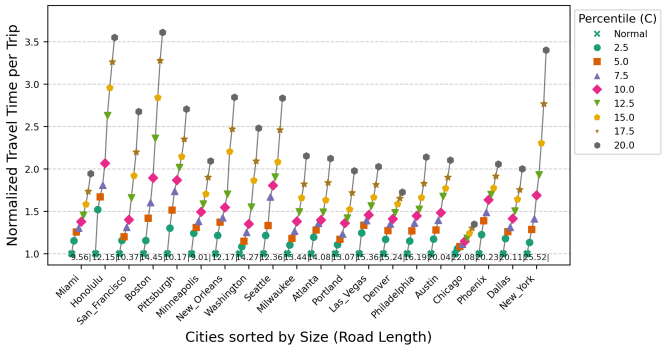


Fig. 5: Different Percentiles of Closure

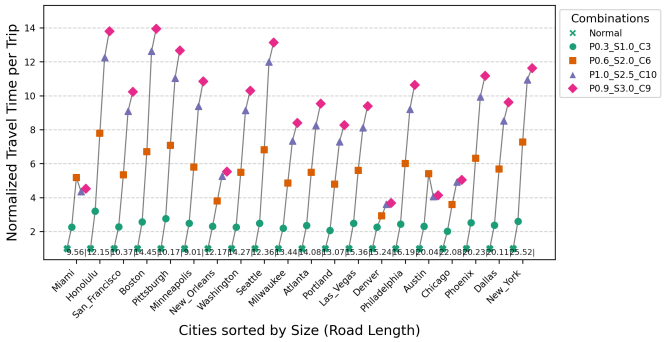


Fig. 6: Different levels of Combinations

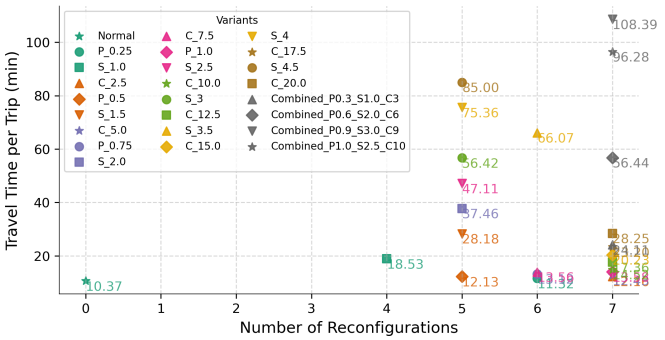


Fig. 7: Travel Times of all variants and Required Reconfigurations for San Francisco

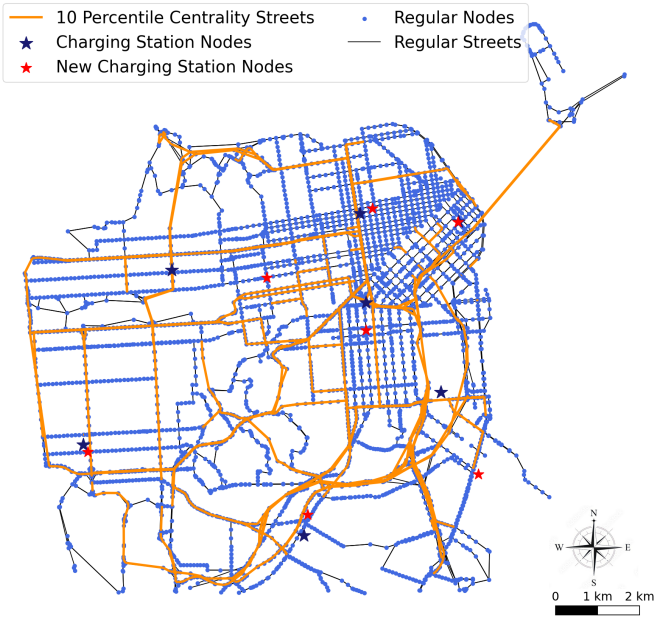


Fig. 8: Effects of Closure and Congestion

D. Discussion

The primary benefit of the proposed framework lies in its implicit optimization capacity, i.e., minimizing the number of charging station relocations required to maintain optimal performance under varying traffic dynamics. Figure 7 shows, for the city San Francisco, the number of reconfigurations needed across all tested variants to transition from the optimal placement in the normal variant (0 reconfigurations) to achieve their respective optimal travel times. Each point represents the travel time of the optimal solution found for each variant and the number of reconfigurations required to achieve this optimal placement for that variant from the base variant i.e., the count of charging stations that need to be relocated. For San Francisco, the total number of possible reconfigurations, corresponding to the total number of charging stations is seven.

At first glance, it may appear that the reconfiguration constraint by regulator change may be insufficient, as in most variants, at least five charging stations need to be relocated and no optimal placement could be achieved with reconfigurations less than four. However, this outcome is not unexpected given the design of the test variants. The variants are deliberately constructed to represent extreme disruption: for congestion, travel times are sharply increased on the most central and heavily used streets; for closures, these same critical links are entirely removed. Consequently, the original station placements become highly suboptimal under these extreme conditions, necessitating substantial reconfiguration.

Figure 8 illustrates this disruptive nature of variants. In this plot, we display only the regular nodes, as charging stations are permitted solely at these locations. The blue points represent the optimal charging station placements under normal conditions, without any disruptions. Streets highlighted in yellow correspond to those with centrality values in the top 10 percentile. It is intuitive that the optimal placements in the normal variant are located near these streets, since the flow-capturing methodology prioritizes high-traffic corridors for station placement. In the closure variant, the high-centrality streets that belong to the 10 percentile are removed. Consequently, the new placement for 10 percentile closure, shown as red points, shifts as the yellow streets are removed.

Effectiveness of Framework: To further assess the effectiveness of the Implicit optimization approach, an Explicit optimization framework is also formulated as a bi-level, bi-objective optimization problem, where the second objective explicitly minimizes the number of reconfigurations. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) [16] is used to solve this problem. The approach follows a bi-level structure: at the first level, placement is optimized as a single objective under normal conditions to determine the

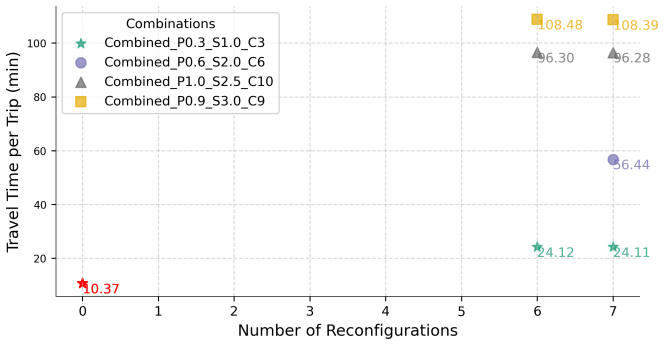


Fig. 9: Implicit Objective: Pareto Fronts for different scales of combined

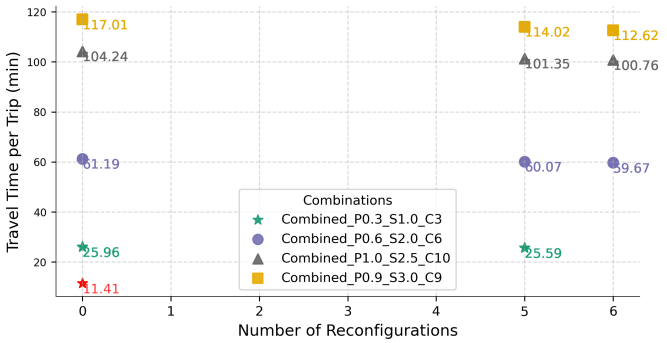


Fig. 10: Explicit Objective: Pareto Fronts for different scales of combined

base layout, and at the second level, this layout is used to evaluate and minimize the number of reconfigurations. The optimization parameters are identical to those used in the single-objective case, with the addition of a two-point crossover operator, modified to accommodate the encoding. Of the 625 generations per cycle, 25 optimize in the first level (base variant) and the rest 600 (25 each for the remaining variants) optimize in the second level. After the completion of the cycle it repeats with the next 25 generations after 625 again optimizing for the normal conditions in the first level.

The effectiveness of the proposed framework is evaluated at different levels: variant, type of dynamics and city. First we examine the trade-off between travel time and the number of reconfigurations required under dynamic conditions. Instead of selecting a single optimal solution for each variant, multiple non dominated solutions are chosen, considering both travel time and reconfigurations, for each variant.

Figure 9 illustrates one such example for the city of San Francisco under combined variants and Implicit single objective optimization approach and Figure 10 presents the Pareto Front of the Explicit bi-objective optimization approach. The legend in both the figures is identical to that explained for Figure 6. As discussed earlier, due to the strong distortions introduced by variant dynamics, achieving the best travel times often requires relocating all charging stations. However, with a slight compromise in travel time, the number of required reconfigurations can be reduced. The results indicate only a marginal improvement in the number of reconfigurations when it is treated explicitly as an optimization objective. Due to elitism in NSGA-II, the base solution is always preserved in

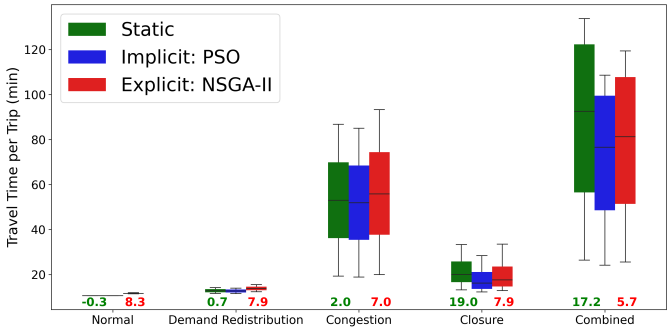


Fig. 11: System Dynamics Level Effectiveness: San Francisco

the population, which results in solutions with zero reconfigurations for all variants. However, because of the bi-level structure of the optimization, the travel time does not reach the same level of optimality. For instance, under the base variant, the optimal travel time when reconfigurations are treated as an implicit objective is about 10 minutes, compared with 11 minutes when optimized explicitly. Moreover, for cases with the same number of reconfigurations, the Implicit single objective optimization approach consistently achieves better travel times than the Explicit bi-objective optimization approach. This trend is consistent across all variants, demonstrating that incorporating evolvability mechanisms effectively balances adaptability and performance without explicitly optimizing for reconfigurations.

For a more comprehensive comparison, we select the best solutions from both the Implicit and Explicit approaches and evaluate their performance by calculating their travel times across all variant conditions using the travel. For reference, we also include the Static placement baseline, i.e., the solution optimized exclusively for the base variant.

Figure 11 shows the distribution of travel times of the optimal adaptable layout from each variant for the city of San Francisco (solutions shown in Figures 7) under other variant's system dynamics. Each box plot aggregates travel times for a type of dynamics, illustrating the effectiveness of the adaptable solutions obtained by each approach and how each city responds to different dynamic conditions. The improvement in median travel time achieved by the Implicit approach over the other two for each dynamics type is shown as text beneath the corresponding box plot. The Implicit approach consistently outperforms the Explicit approach with significant improvement in normal and demand variants, likely due to the limitations of the bi-level formulation. In bi-level, the optimization of variants in second-level is limited because it relies on a single first-level base solution, which is used to evaluate reconfiguration objective thus restricting the exploration of variant specific solutions. Conversely, the Static approach beats the Implicit approach slightly across base variant as expected, since it is optimized exclusively for the base. However, under other disruptive conditions, the Implicit approach performs substantially better than the Static approach clearly demonstrating that the adaptable solutions remain competitive in nominal conditions while offering robustness

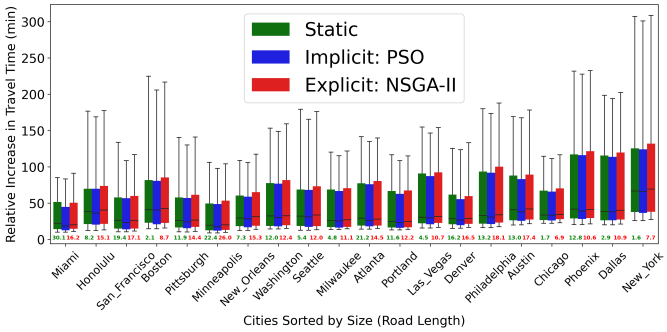


Fig. 12: City Level Effectiveness

when severe disruptions occur.

Figure 12 displays for all cities, the distribution of relative increases in travel time for all variants of each optimization approach, relative to the normal travel time of implicit approach. The relative percent increase compared to the Implicit approach is annotated below each approach's box plot. Across all cities, the Implicit approach consistently yields a lower median travel time than Explicit and Static approaches, although the magnitude of improvement varies. In some cities – including Chicago, New York, Boston, and Dallas – Static approach remains competitive with the Implicit approach.

VI. Conclusion

This study proposes a framework for designing adaptable placements of electric vehicle (EV) charging stations by enhancing evolvability. Three mechanisms of evolvability, regulatory change, exploration, and diversity are employed to improve the evolvability at both individual and population level. The framework is tested across 20 U.S. cities using multiple types and scale of system dynamics as environments for regulatory change. The problem is formulated as a single-objective optimization, with the objective of minimizing the average travel time per trip while implicitly minimizing the number of reconfigurations as a measure of the quality of evolvability. PSO is used to solve this formulation and is compared against a bi-objective optimization approach, in which minimizing reconfigurations is treated as an Explicit second objective and solved using NSGA-II. Although the Explicit formulation reduces the number of reconfigurations, the Implicit approach performs better overall, achieving both lower travel times and a more efficient balance between adaptability and operational performance. Compared to Static approach, the framework offers clear advantages in several cities, yet Static remains competitive in some.

Future work could explore the impact of distinct mutation operators, varying mutation probabilities, different representation methods (binary, graph). In the current framework, all variants are treated with equal importance, which may not be ideal. Assigning greater weight to the most probable variants could reveal whether such weighting influences outcomes. Another promising direction involves benchmarking the proposed approach against algorithms tailored to the problem domain and with matched computational budgets. Investigating which road network features and topological properties contribute most to the adaptable infrastructure use, and a detailed analysis would provide deeper insights and clarity on why different city networks respond differently to similar strategies. A non-linear scaling strategy that encompasses both size and travel patterns of a city could be developed to determine the number of charging stations. Furthermore, diversity integration could be enhanced, for example, by the use of haplodiploid systems, and its effects should be investigated.

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