Data-driven left-turn restriction decision framework for urban networks: A case study of Downtown Pittsburgh

Tanveer Ahmed*
PhD. Candidate
Department of Civil and Environmental Engineering
The Pennsylvania State University
406 B Sackett Building
University Park, PA, 16802
tpa5285@psu.edu

Vikash V. Gayah
Department of Civil and Environmental Engineering
The Pennsylvania State University
231L Sackett Building
University Park, PA, 16802
gayah@engr.psu.edu

*Corresponding author

Word Count: 6553 words + 2 tables (500 words) = 7053 words

July 2024

Abstract

Left-turn movements pose significant safety hazards and reduce the operational efficiency of signalized intersections. One effective strategy to mitigate these issues is to restrict conflicting left-turns at strategic locations. However, determining the optimal locations for such restrictions in large urban networks is challenging due to the complexity of traffic dynamics and the large solution space. This paper presents a two-stage methodology to optimize left-turn restriction decisions in urban networks, utilizing a bi-level optimization framework combined with a binary logit model. The bi-level framework employs the Population Based Incremental Learning (PBIL) algorithm at the upper level and AIMSUN micro-simulation platform at the lower level to determine near-optimal left-turn restriction locations. The best solutions from PBIL serve as the dependent variable in a binary logit model that explains the traffic parameters influencing these decisions and predicts the propensity of intersections likely to benefit from left-turn restrictions in unknown scenarios. When applied to the Pittsburgh traffic network, the PBIL algorithm demonstrated up to a 15% reduction in travel time under peak demand without significantly increasing trip lengths. The logit model, trained on known demand scenarios, indicates that intersections with higher values of left-turning green-ratio, flow-ratio, and protected green-ratio are less likely to benefit from left-turn restrictions. Furthermore, the model's predictions for unknown demand levels can identify locations of left-turn restriction that are comparable to the PBIL in terms of travel time improvements. This framework provides a data-driven approach for transportation agencies to determine optimal left-turn restriction locations, balancing operational efficiency and network performance.

Keywords: Left-turn restriction, optimal location, optimization, heuristics, population based incremental learning, binary logit model

INTRODUCTION

Left-turning movements at intersections conflict with the through and right-turning movements from the opposite direction, creating significant challenges for signal operations and intersection safety. At signalized intersections, conflicting left-turn movements are typically accommodated either via permitted or protected left-turn signal phases. When served using permitted phasing, left-turning vehicles must wait for gaps in oncoming traffic, which contributes to increased delay and increases the risk of angle crashes (*1*). Furthermore, the storage of queued vehicles on dedicated left-turn lanes has the potential to spill-back and impede the flow of other movements (*2*). By contrast, the use of protected left-turn phases eliminates conflicts but reduces the green time available for other movements, lowering the overall throughput of the intersection (*3*, *4*). Researchers have also proposed numerous alternative intersection designs to more safely and efficiently accommodate left-turning traffic (*5–12*). However, these treatments are expensive and cannot always be accommodated in dense urban networks due to the large spatial footprints required.

An alternative strategy to mitigate issues arising from conflicting left-turns is to restrict their movements at signalized intersections, specifically in dense urban street networks. Studies have shown that prohibiting left-turns in this setting can not only improve the capacity and safety of signalized intersections, but also increase the trip completion rates in a transportation network (*13–16*). Despite the operational and safety benefits of restricting left-turns, decision-making at the microscopic level has its challenges. Drivers may be required to travel additional distances, such as making three right turns to achieve the equivalent of one left-turn, which can increase travel time and inconvenience. Additionally, banning left-turns can divert traffic to other routes, potentially leading to increased congestion in areas that were previously less affected. Therefore, identifying the most optimal locations to restrict left-turns in a network is critical.

Determining the optimal locations for treatments in a transportation network (i.e., at which locations to restrict left-turn movements) is classified as an NP-hard optimization problem (*17*). Additionally, restricting left-turn movements at one intersection alters the traffic flows at its neighboring intersections, hence, these treatment decisions are interdependent. Some studies have used simple analytical traffic models to analyze the effect of implementing left-turn restrictions; however, these are unable to capture traffic dynamics such as re-routing and queue spillback (*18–22*). To overcome this issue, researchers have also proposed using agent-based simulation techniques that enable dynamic traffic assignment to capture the true effect of these treatments (*12*, *23*). However, the complexity of optimal location problems escalates significantly with the increase in the number of treatments or potential locations; e.g., for each traffic pattern and level of demand, the decision to either restrict left-turns or not in a network with N number of intersections has 2^N possible combinations that need to be analyzed to determine the globally optimal solution. To address this challenge, heuristics such as evolutionary algorithms provide a computationally efficient means of determining near-optimal solutions of problems with extremely large solution spaces (*24–26*). However, the drawback of these black-box algorithms is the lack of interpretability; they provide solutions without insights into the underlying reasons behind those solutions. This opacity makes it challenging for transportation agencies to understand which specific factors are driving the decision to restrict left-turns at particular intersections.

In light of the gaps in existing literature, this study proposes a two-stage methodology to optimize left-turn restriction decision in urban networks using a bi-level optimization framework, and a binary logit regression model to identify the traffic parameters that influence these decisions. The bi-level optimization framework uses the population based incremental learning (PBIL) algorithm at the upper level and AIMSUN micro-simulation platform at the lower-level to identify near-optimal locations in a network where implementing left-turn movement restrictions result in improved travel times. The identified solutions are then used to train a binary logit regression model, which seeks to relate these decisions (i.e., if left-turns are banned at a particular location in the optimal solution) to traffic flow and signal timing information. The results provide greater transparency and should allow decision-makers to determine the key factors influencing left-turn restriction decisions and predict optimal locations for unknown scenarios. The proposed method was applied on a real network of downtown Pittsburgh, PA. The results reveal that left-turn restriction configurations generated by PBIL can achieve up to nearly 15% improvement in travel time under peak conditions without significantly increasing individual trip lengths. Moreover, the logit model, trained using the best PBIL configurations of known demand scenarios suggests that intersections with a higher average left-turning green-ratio, sum of left-turning flow-ratio and sum of left-turning protected green-ratio are less likely to benefit from restricting left-turns. The trained model was applied on two different test-demand settings to generate propensity scores that indicate each intersection's potential at reducing travel time if left-turns are banned. Selecting intersections with higher propensity scores for left-turn restrictions results in significant travel time improvements, whereas restricting left-turns at intersections with lower scores increases travel time. Overall, the framework provides a data-driven guideline to identify critical features transportation engineers and planners should consider when deciding whether or not to ban left-turns at a given intersection.

The remainder of this paper is as follows. The following section introduces the proposed two-stage optimization methodology. This is followed by the simulation setup used to test the proposed methodology. Next, the results of the bi-level optimization as well as the binary logit model are compared. The final section highlights the findings and suggests directions for future work.

METHOD

This section describes the two-stage methodology that is proposed in this paper. This includes the bi-level optimization framework that generates near-optimal configurations as a starting point for known demand scenarios and the binary logit model that is applied to predict and justify the optimal location of implementing left-turn restrictions for unknown scenarios in a signalized urban traffic network. The outline of the methodology is shown in Figure 1.

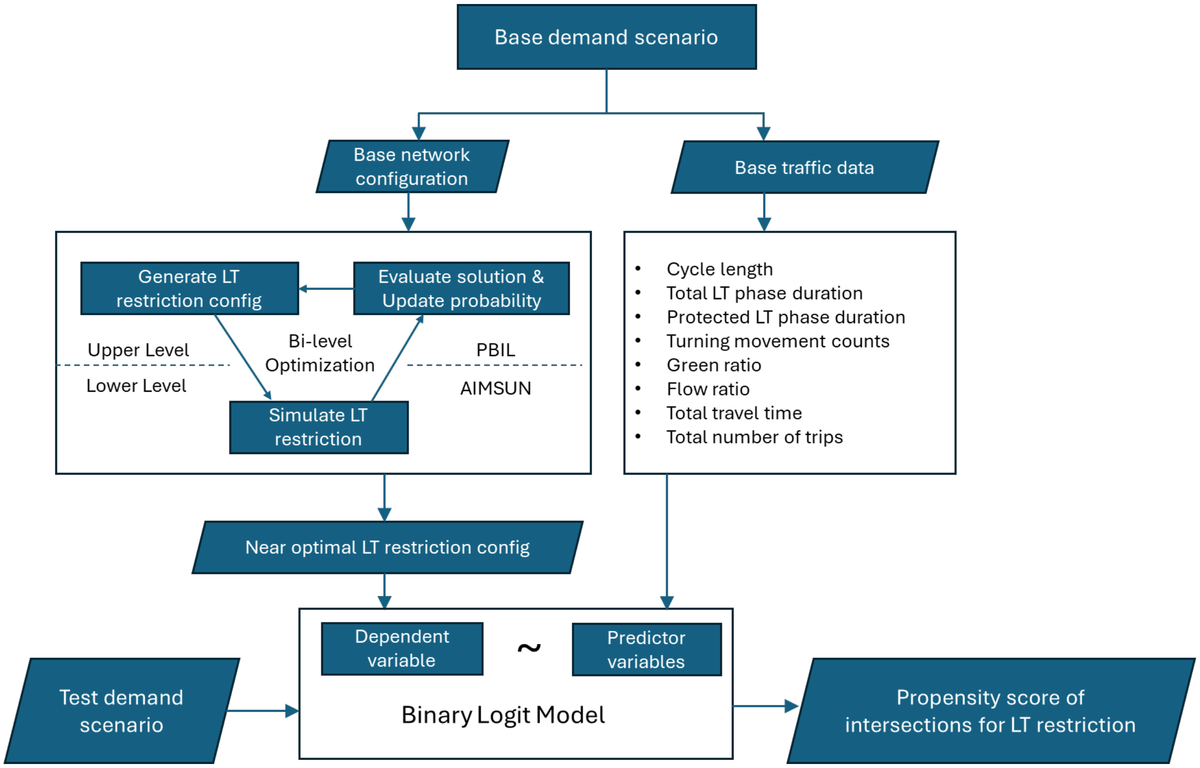


Figure 1. Methodology of left-turn restriction prediction model

Bi-Level optimization framework

A bi-level optimization framework operates by dividing the optimization problem into two hierarchical levels: the upper level identifies decision variables, such as the configuration of traffic treatments to optimize overall network performance; and, the lower level evaluates the effectiveness of these configurations using detailed simulations or analytical models. This iterative process continues, with the upper level refining its decisions based on feedback from the lower level, until an optimal or near-optimal solution is reached.

Lower level: AIMSUN to evaluate effectiveness of specific left-turn restriction configuration

Since the optimization problem of identifying the optimal locations to restrict left-turns does not have an exact solution, each configuration generated by the upper level is evaluated at the lower level. While existing studies have used static models to simulate the effect of transportation treatments on a network such as Stochastic User Equilibrium (SUE) functions, they do not capture traffic dynamics when implementing transportation treatment solutions (*19*, *21*, *22*). Other studies have employed dynamic models such as the Link Transmission Model or micro-simulation software such as AIMSUN, VISSIM or SUMO (*27–31*) to better models traffic dynamics and provide a detailed and realistic assessment of the impact of different treatment strategies. For this study, AIMSUN was selected in the lower level for its ability to capture queue formation, spillback, re-routing and ease of programming. For each generated configuration, the conflicting left-turn movements of selected intersection were identified and removed. Note, left-turn movements on one-way streets that do not conflict with through or right-turn movements from the opposite direction were not removed. Next, any dedicated left-turn lanes were modified to serve the through movements. Finally, the signal timing was adjusted without altering the cycle length by re-allocating green time for protected left-turn phases toward the through-right movement in the same direction. Therefore, the total duration of green time allocated to serving the movements in either the north-south or east-west direction remained unchanged.

Upper level: PBIL to identify potential left-turn restriction configurations

The upper level of a bi-level optimization framework employs heuristic methods (e.g., an evolutionary algorithm) to generate random configurations of a treatment and continues to update until it converges toward an optimal solution. However, most genetic algorithms do not capture the interdependency between solutions that exist in case of transportation network treatment problems. To address this, the Population Based Incremental Learning (PBIL) algorithm is employed which is an evolutionary algorithm that combines elements of genetic algorithms with learning processes and considers solution dependencies (*32*). PBIL has been successfully applied in network level transportation treatment problems (*24–26*, *33–35*). Key parameter definitions of the PBIL algorithm and values used in this study are summarized in Table 1.

Table 1. Key parameters of the PBIL algorithm

Parameter	Symbol	Description	Value
Generation Size	$\mathcal{G}$	Number of times the algorithm will iterate and generate a new set of configurations	20
Population Size	$\mathcal{P}$	Number of generated LT restriction configurations in each generation	20
Candidate Size	$\mathcal{C}$	Number of intersections that are candidates for LT restriction	39
Probability Vector	$\wp = (\mathcal{G}, \mathcal{C})$	Two-dimensional vector where each element $\wp_{g,i}$ denotes the probability of implementing LT restriction at intersection i in generation g	
Population Vector	$P = (\mathcal{G}, \mathcal{P}, \mathcal{C})$	Three-dimensional vector where each element $P_{g,p,i}$ is [0,1] that indicates whether LT is restricted at intersection i in configuration p of generation g	
Result Vector	$R = (\mathcal{G}, \mathcal{P})$	Two-dimensional vector where each element $r_{g,p}$ contains the fitness of the objective function after evaluating the LT restriction configuration p in generation g	
Positive Learning Rate	LR^+	Rate at which probabilities of intersections present in the best configuration, B_g of generation g are increased	0.1
Negative Learning Rate	LR^-	Rate at which probabilities of intersections in the worst configuration, W_g of generation g are decreased	0.075
Mutation Rate	Δ_m	Rate at which probabilities are randomly mutated	0.05
Mutation Probability	m	Probability that a given intersection will undergo mutation	0.02

The PBIL algorithm is initialized by generating a population of configurations containing locations to implement left-turn restriction using an initial probability vector, $\wp_0$. Each candidate intersection was assigned an initial probability $\wp_{0,i}$ of 0.5 to allow unbiased selection of any intersection in the first generation. This allows exploration of the entire solution space in the initial stage of the algorithm.

Each configuration is passed into the lower level where its performance is simulated in AIMSUN, and the fitness of each configuration is determined based on the total travel time resulting from the implementation of the left-turn restriction at the selected intersections. Using the fitness score, the best and the worst configuration of generation g is identified and the probability vector of generation $g + 1$ is updated through positive learning, negative learning, and a mutation operation. Essentially, the PBIL algorithm learns from and exploits superior solutions while moving away from the inferior ones. The objective of the positive learning operations is to increase the probabilities of selecting the intersections present in the best solutions:

$$\mathscr{p}_{g+1,i} = \mathscr{p}_{g,i} \times (1 - LR^{+}) + LR^{+} \times B_g; \quad \forall i. \tag{1}$$

On the other hand, the negative learning operation decreases the probabilities of the intersections present only in the worst solution, so they have a lower likelihood of being selected in the next generation:

$$\mathscr{p}_{g+1,i} = \mathscr{p}_{g,i} \times (1 - LR^{-}) + LR^{-} \times B_g; \quad \forall i \tag{2}$$

Note, however, that probabilities of intersections present in both the best and worst solutions are not altered.

The mutation operation mutates the probabilities of randomly selected intersections by the mutation rate using the formula given in (3) to increase the exploration within the solution space:

$$\mathscr{p}_{g+1,i} = \mathscr{p}_{g,i} \times (1 - \Delta_m) + \Delta_m; \quad \forall i \ s.t. M_{g,i} = 1 \tag{3}$$

The algorithm finally terminates if the algorithm converges according to a predefined threshold (e.g., the fitness of the generated solutions no longer improves) or if the maximum number of generations has been reached; the speed of convergence can be changed by adjusting the learning rates. Since the objective of the bi-level optimization step of this study is to approximate a near-optimal solution, the latter termination criterion was selected. The output of the algorithm is the left-turn restricted network configuration that corresponds to the lowest observed travel time.

Binary Logit prediction model

While the bi-level optimization framework effectively generates optimal configurations for left-turn restriction locations in a traffic network, a significant drawback is its lack of interpretability. The framework achieves optimal solutions by simulating numerous random configurations until a near-optimal configuration is identified. However, this process does not provide insights into the underlying factors that drive the selection of specific intersections for left-turn restrictions. As a result, decision-makers are left with optimal solutions that lack the necessary explanatory context, making it difficult to justify and understand the decisions made. To address this limitation, the optimal configuration generated by the bi-level optimization framework is utilized as an input to a binary logit model where it is treated as the dependent variable, and various traffic data and parameters related to left-turn movements at intersections serve as the independent variables. By training the model with the correct parameters, it learns which factors are most significant in explaining the selection of left-turn restrictions at intersections.

Model inputs

The dependent variable in the binary logit model is the selection of left-turn restrictions at a particular intersection. This binary variable encoded as 1 or 0 represents the presence or absence of a left-turn restriction at each intersection of the network as determined by the best configuration output from the bi-level optimization framework. To understand why a particular intersection benefits from left-turn restriction, a variety of traffic flow and signal timing parameters from training demand scenarios are extracted and used as predictor variables to train the binary logit model. This includes intersection level data such as the cycle length and the total intersection throughput from turning movement counts. Additionally, for each conflicting left-turn movement at an intersection, the following parameters were extracted:

- Duration of left-turn phase
- Green ratio of left-turn phase
- Duration of protected left-turn phase
- Green ratio of protected left-turn phase
- Left-turn volume
- Left-turn flow ratio

Since an intersection may accommodate multiple conflicting left-turn movements, the parameters were aggregated for each intersection by taking the sum, mean, minimum and the maximum of the parameters from all conflicting left-turn movements. The final variables included in the model were the total number of trips generated, and the total travel time of each simulated demand to allow the model to differentiate between different demand scenarios.

Model formulation

The probability function under the binary logit formulation for predicting the propensity of an intersection receiving a left-turn restriction can be expressed as:

$$P(LT_i|X_i) = E(y_i) = \frac{e^{\beta X_i}}{1+e^{\beta X_i}}, \quad (4)$$

where LT_i denotes the presence of a left-turn restriction at intersection i; X_i is the vector of predictor variables for intersection i; and, β is the vector of corresponding coefficients to be estimated. The coefficients are estimated by maximizing the log-likelihood function:

$$\log L(LT) = \sum_{i=1}^{N} \log P(LT_i|X_i). \quad (5)$$

The estimated coefficients β describe the relationship between each traffic parameter and the likelihood of a left-turn restriction being applied to an intersection. Positive coefficients indicate that higher values of the parameter increase the likelihood of a left-turn restriction, while negative coefficients suggest the opposite.

SIMULATION SETUP

The proposed methodology was tested on the traffic network of Downtown Pittsburgh, PA that consists of peripheral collectors (e.g., Fort Duquesne Blvd, Liberty Ave, Blvd of the Allies, Fort Pitt Blvd running in the east-west direction and Grant St. in the north-south direction) and local streets in the central region forming a triangular grid. The turning movement counts at each intersection from Synchro were used to calibrate an Origin-Destination (OD) matrix with 58 origin and destination nodes that accurately represents the distribution of trips throughout the network in an evening peak scenario. The total number of trips in the calibrated peak demand scenario (referred to here as "D-100") averaged 21,150 across multiple random seeds. Additionally, three lower demand scenarios, (referred to in this study as "D-94", "D-87" and, "D-80") were simulated with an average of 19,800, 18,400 and, 17,000 trips generated across multiple random seeds. The binary logit model was trained two times to predict the propensity of restricting left-turns for D-94 and D-87 respectively. In each case, one demand level was reserved as the testing dataset and the model was trained using the outcomes of the other three training demands. This allowed the testing of the binary logit on unseen demand patterns within the network. Note that D-100 and D-80 were not used for testing as they represent the upper/lower bound of the demand levels considered.

The signal timing plan was imported from an optimized PM Peak Synchro plan, which includes cycle lengths, phase splits, and offsets of each signalized intersection. The simulated network consists of a total of 76 signalized intersections of which 39 intersections were selected as candidates to implement left-turn restrictions on due to their centrality in the network and the potential impact of the restriction decisions on overall congestion reduction (Figure 2). Of the intersections not selected, 7 had no conflicting left-turn movements with the through or right-turn movements from the opposite direction and 30 intersections were located at the periphery of the network or connected to major O-D nodes. Restricting left-turning movements at these peripheral intersections may significantly increase the traveled distance and so were also excluded from left-turn restriction considerations.

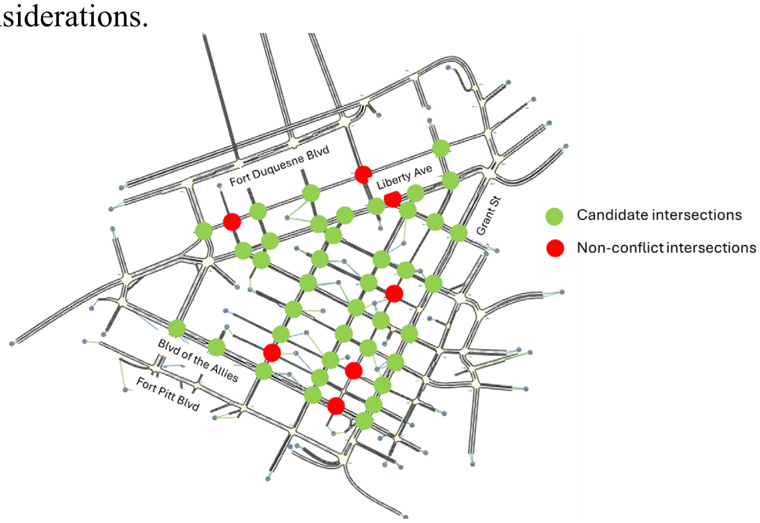


Figure 2. Map of simulated Downtown Pittsburgh

RESULTS

This section describes the outcome of implementing left-turn restriction in the network based on the solutions generated from the PBIL algorithm as well as the training of the binary logit model that is later used to determine the parameters influencing the decision of restricting left-turns. Finally, the predictive performance of the model is investigated on unknown scenarios.

Impact of left-turn restriction at individual intersections

To demonstrate the variability in performance of restricting left-turns at individual intersections, Figure 3 illustrates the percent change in the total travel time when left-turns were restricted at each intersection for all four demand levels. First, it is evident that the peak demand scenario experiences a larger variability in travel times with a maximum improvement (reduction) of nearly 9% to an increase in travel time of approximately 20% over the base scenario. As demand decreases (D-94, D-87, D-80), this variability in travel time diminishes suggesting that the impact of left-turn restrictions is influenced significantly by traffic volume.

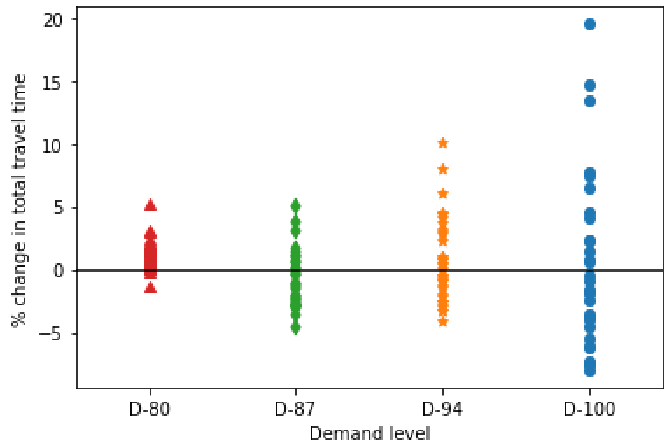


Figure 3. Percent change in total travel time over base demand due to the implementation of left-turn restriction at individual intersections

Optimal left-turn restriction solutions using PBIL

PBIL convergence

As a heuristic method, the PBIL cannot guarantee an optimal solution. Instead, the goal is to provide a configuration that significantly improves performance (i.e., travel time) without having to test all possible configurations. Note that there are $2^{39} = 549{,}755{,}813{,}888$ possible configurations to be tested in the Pittsburgh network. However, the PBIL simulates only 400 configurations (20 configurations in each of the 20 generations of the algorithm) to obtain well-performing solutions that will serve as input for the binary logit model.

The blue, orange, green and red line plots in Figure 4 illustrate the convergence trends of the PBIL algorithm for each of the demands in terms of the percent improvement in total travel time over the base network. It is evident that better solutions are discovered as the algorithm progresses as all demand levels show a decline in travel time. Moreover, most scenarios demonstrate significant improvements early in the iterations and stabilize quickly. Despite the significant improvement in travel time, the models do not appear to have fully converged. Nonetheless, the best-performing solutions comprising the locations of intersections to restrict left-turns obtained from the PBIL are identified and used to train the logit model.

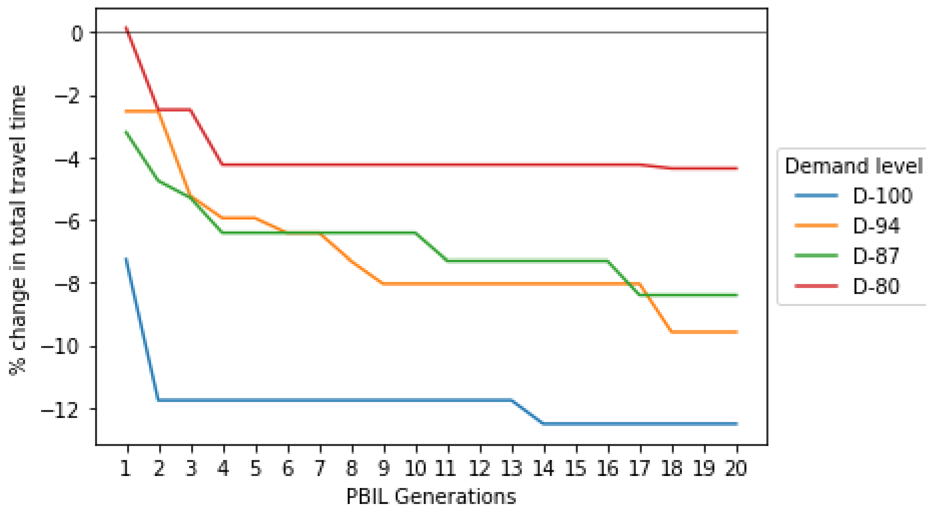


Figure 4. Convergence of PBIL for each demand level

Locations of left-turn restrictions

The locations left-turn restrictions present in the top five configurations generated by the PBIL are shown in Figure 5 for each of the demand levels. The intensity of the markers at each intersection indicates how many times that intersection appears in the best configurations for that demand. Due to the inherent randomness of the PBIL and the interdependence of the solutions, the best configurations do not always contain the same set of intersections. However, significant overlap can be seen across all demands, with some intersections selected multiple times at all demand levels to receive a left-turn restriction. At D-100 (Figure 5a), there is lower variability, with a few intersections repeatedly selected, most of these are concentrated in the central grid region. In contrast, the best solutions for lower demand levels (Figure 5b-d) have more intersections where left-turns are restricted. These intersections are not limited to the central region, rather intersections on arterials like Liberty Avenue and Grant Street benefit more from prohibiting left-turns.

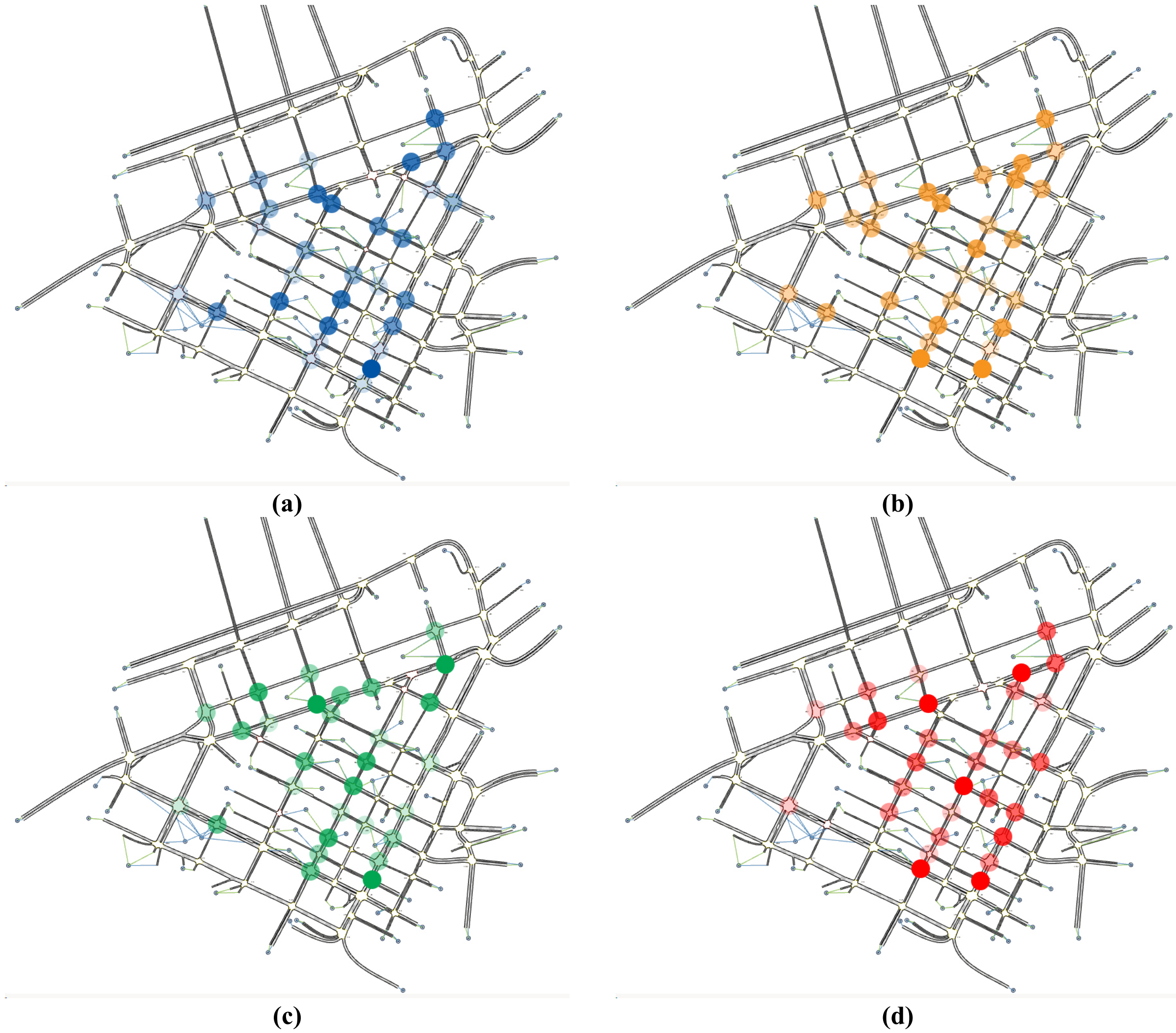


Figure 5. Locations of left-turn restriction decisions from top 5 configurations generated using PBIL: (a) D-100; (b) D-94; (c) D-87; (d) D-80.

Impact on travel time distributions

The objective function of the PBIL algorithm was to determine the set of intersections where restricting left-turns would minimize the total travel time in the network. Figure 6 shows the distribution of the probability density function of the travel time of individual trips for the base scenario (in black) and the best configuration of the PBIL for all four demand levels. The results reveal that the PBIL algorithm significantly improves not only the total travel times but also the individual trip durations. For each scenario, the distribution of travel times in the base simulation is skewed to the right whereas the PBIL best configurations have taller peaks and more uniformly distributed. Hence, a higher percentage of vehicles experience shorter trip durations as a result of the left-turn restrictions.

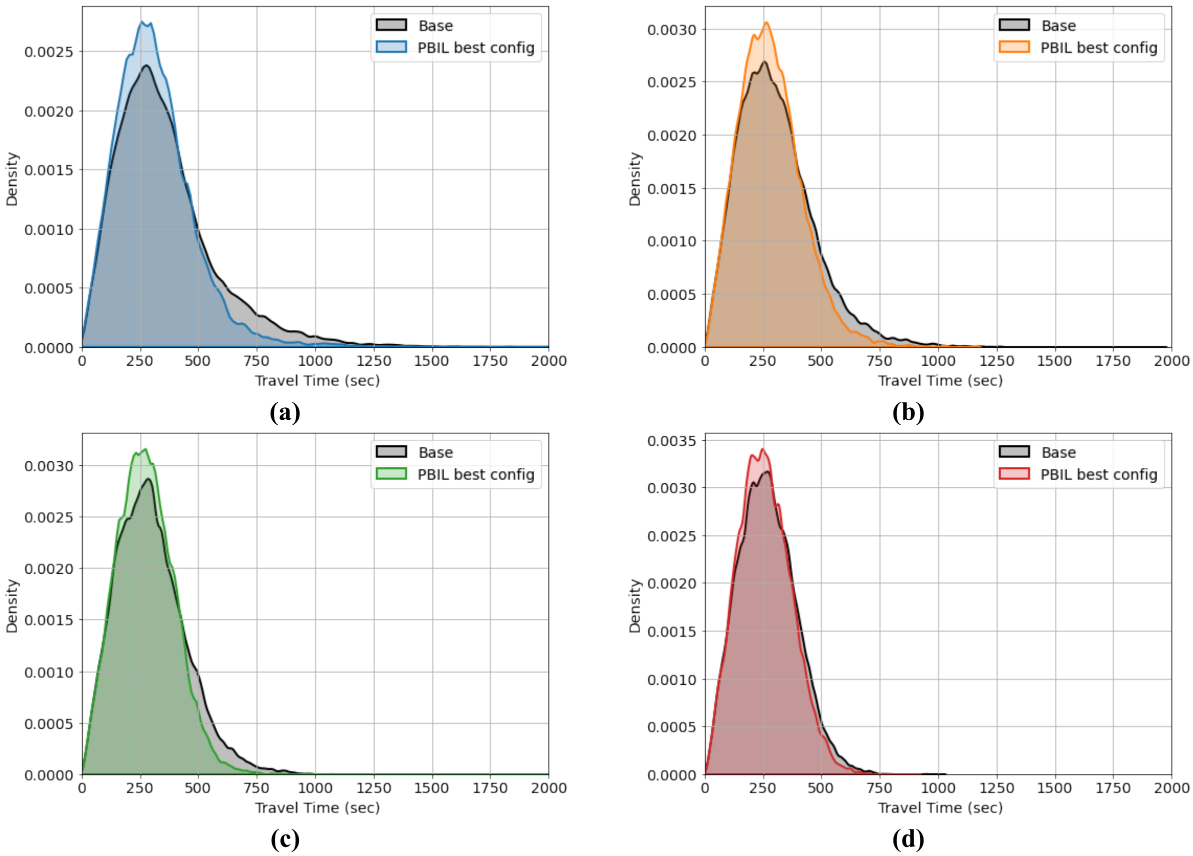


Figure 6. Probability density function of trip durations: (a) D-100; (b) D-94; (c) D-87; (d) D-80.

<u>Impact on traveled distance distribution</u>

Intuitively, the restriction of left-turns in a traffic network is expected to result in increased travel distances as vehicles may need to make additional turns to reach their destinations. However, the best solutions generated by the PBIL algorithm demonstrates a negligible increase in the total traveled distances over the base simulation which is evident from the distribution of individual trip lengths (Figure 7). Considerable overlap can be seen between the base scenario and the PBIL best configurations as the increase in the total distance traveled ranges between only 0.4% to 0.8% across the different demand levels. This is due to driver behavior and the tendency to reroute under congested environments either using navigation information or from personal experiences. AIMSUN's dynamic traffic assignment settings mimic this rerouting behavior of drivers and vehicles adjust their paths based on real-time traffic conditions. Under the base scenario when the network is more congested, the shortest available paths may not be the most optimal; hence, vehicles re-route and travel additional distances to reach their destination. However, restricting left-turns and allocating green time to serve the through-right movement phases reduce the lost time and increase the intersection throughput. As a result, more efficient paths may be available that are not significantly higher than that of the base scenario.

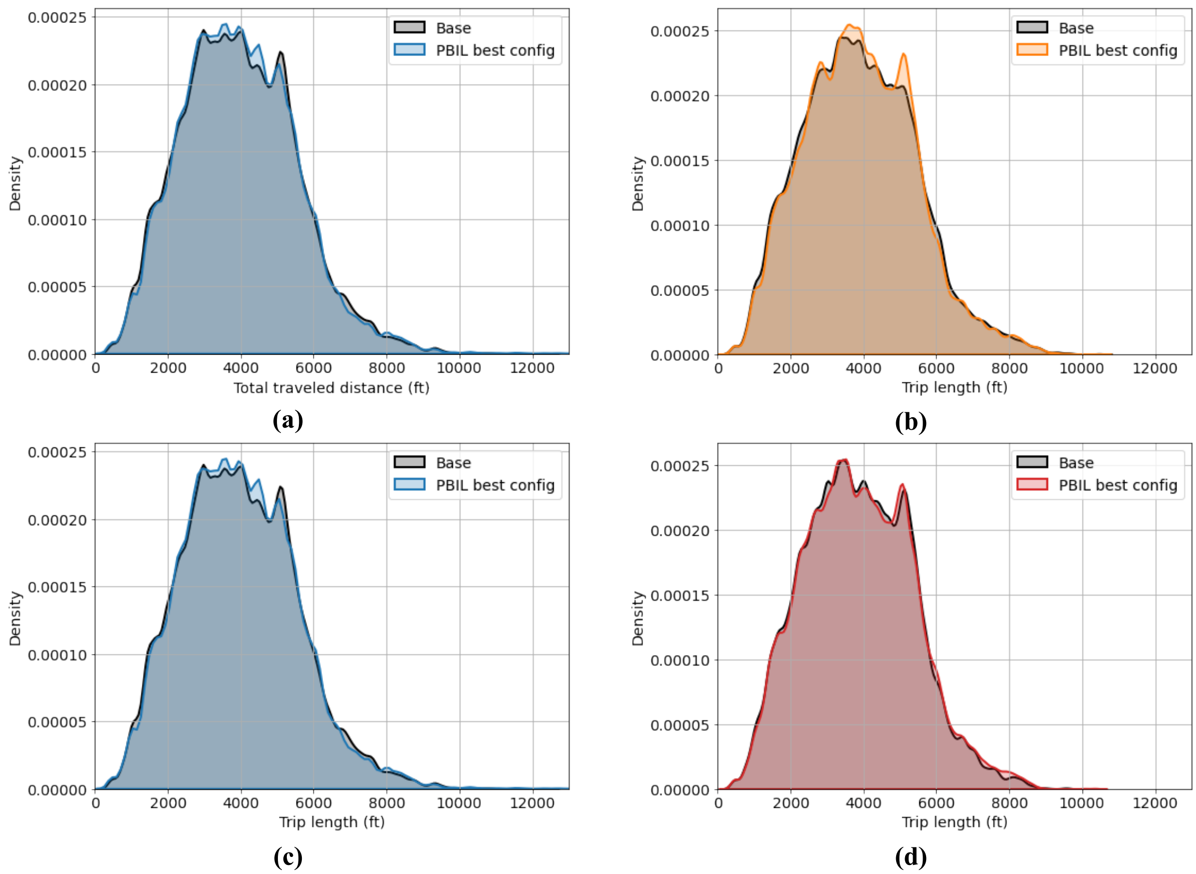


Figure 7. Probability density function of trip lengths: (a) D-100; (b) D-94; (c) D-87; (d) D-80.

Training and predictive performance of Binary Logit model

<u>*Model training*</u>

While a total of four different demand scenarios were simulated in this study, the binary logit models were trained using signal timing information, traffic flow data and the locations of the intersections to implement left-turn restriction from any three of the known demands, while the remaining demand was held out to test the logit model's performance. Of the 28 parameters available for inclusion in the logit model, three were identified that best influence the likelihood of restricting left-turns: average green ratio for left-turn phases, sum of flow ratio for left-turn movements, and sum of green ratio for protected left-turn phases. These key parameters were selected through a combination of recursive feature selection method and applying engineering judgement. Table 2 shows the two models that were developed for D-94 and, D-87 respectively using known data from their complementary set of demands. Note that the coefficients of all three parameters are negative, which suggests that intersection with higher values of these parameters were less likely to have left-turns restricted in the best-performing configuration. All three are associated with higher left-turn volumes, which reasonably suggests that intersections with the highest left-turn activity are most likely to experience negative impacts of left-turn restrictions. Intersections with protected left-turn phases are particularly less likely to have left-turns restricted. The correlation matrix in Figure 8 shows that neither of the selected variables are highly correlated.

Table 2. Binary logit model parameters for left-turn restriction estimations

Training demands	D-100, D-87, D-80		D-100, D-94, D-80	
Test Demand	D-94		D-87	
Predictor Variables	β	σ	β	σ
Constant	2.59	0.69	2.78	0.71
Average green ratio of left-turn phases	- 3.61	1.31	- 3.88	1.34
Sum of flow ratio of left-turn movements	-8.23	1.55	-8.80	1.57
Sum of green ratio of protected left-turn phase	-1.82	1.00	-1.79	1.00
Goodness of fit				
Number of observations	390	390	390	390
Log-likelihood value	-240.21	-237.73	-235.96	-239.33
Pseudo R-squared	0.087	0.091	0.099	0.085

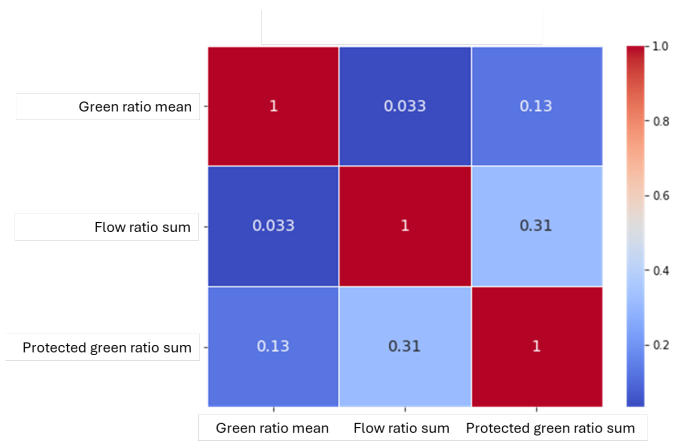


Figure 8. Correlation matrix of selected predictor variables

Performance evaluation of prediction model

To assess the effectiveness of the trained binary logit model, a propensity score indicating the likelihood of having a left-turn restriction was computed for each intersection using the average green ratio of left-turn phases, the sum of the flow ratio of left-turn movements, and the sum of the green ratio of protected left-turn phases from their respective base simulations into the model. These propensity scores were then used to rank each intersection's eligibility for implementing left-turn restrictions; i.e., to identify those intersections for which it may be more beneficial to restrict left-turns to reduce travel times. For each of the D-87 and D-94 demand scenarios, intersections were sequentially selected for left-turn restrictions in a descending order of propensity scores (i.e., starting with the highest propensity score and adding the next highest) and the total travel time was computed using AIMSUN. The orange and green solid line plots in Figure 9 illustrates the performance of these configurations for a given number of intersections with left-turns restricted. The best solution obtained from the PBIL algorithm are also shown using dashed horizontal lines for each demand scenario.

The results shown in Figure 9 reveal that selecting intersections for left-turn restrictions using the trained logit model provides remarkably good results that are comparable to—and sometimes surpass—that obtained from the PBIL algorithm applied directly to those demand scenarios. For example, the PBIL algorithm applied to scenario D-87 was able to find a solution that restricts left-turns at 17 intersections and results in an improvement in travel time by 8.4%. However, an improvement of 8.47% was achieved when left-turns were restricted at the 11 intersections with the highest propensity scores, and despite fluctuations, a maximum improvement of 9.98% was achieved when left-turns were prohibited at the top 18 intersections. Similarly, the best configuration generated using the logit model for scenario D-94 comprises 17 intersections and results in similar improvements as the best solution from PBIL. Beyond this configuration, however, the total travel time in the network begins to increase as more intersections are added.

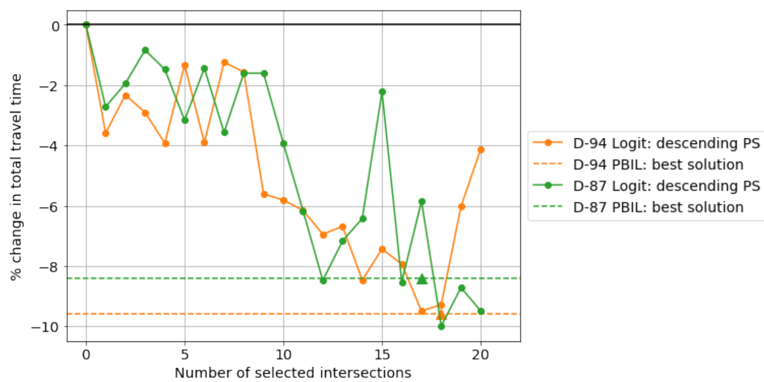


Figure 9. Effect of sequentially implementing left-turn restrictions at intersections by descending order of propensity scores

The proposed logit model can also help identify which intersections to <u>not</u> implement left-turn restrictions. Figure 10 presents the results of sequentially restricting left-turns in ascending order of propensity scores (i.e., starting by restricting left-turns at the worst potential location corresponding to the lowest propensity score and sequentially adding additional intersections). The intersections being added are those with a higher average green-ratio, sum of flow-ratio and sum of protected green-ratio of conflicting left-turning traffic. As left-turns are restricted at more of these suboptimal intersections, there is a noticeable increase in travel time. Beyond 12 intersections, scenario D-94 experiences such heavy congestion that the simulated network gridlocks. This highlights the model's ability to accurately rank intersections based on their suitability for left-turn restrictions

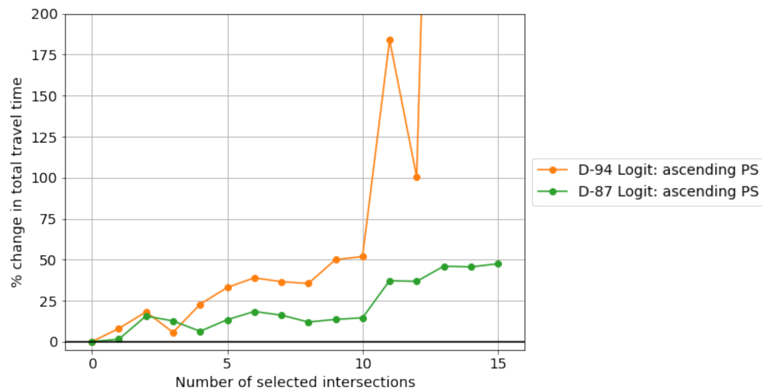
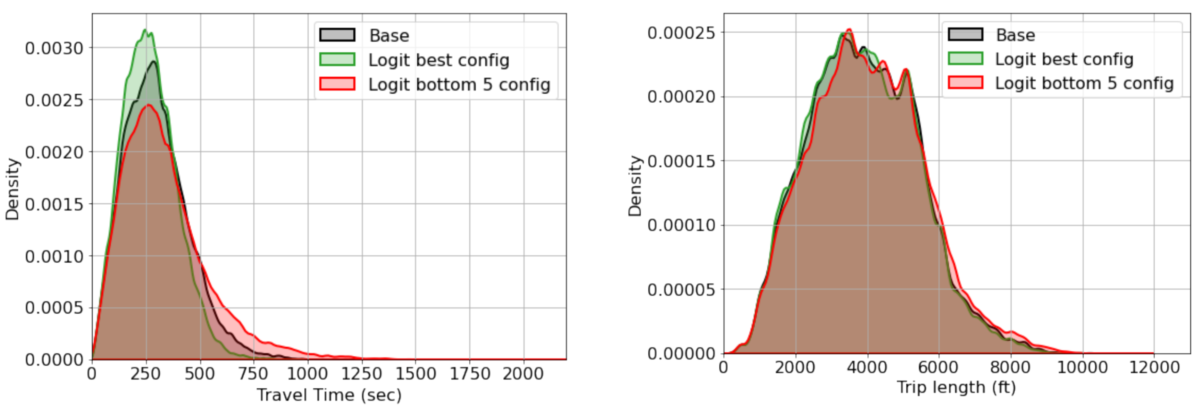


Figure 10. Effect of sequentially implementing left-turn restrictions at intersections by ascending order of propensity scores

To further understand the impact of restricting left-turns based on propensity scores, Figure 11 shows the distribution of individual trip durations and trip lengths for scenario D-87. The result of the base simulation without left-turn restrictions is shown in black, while the performance of best configuration predicted by the logit model with the top 18 intersections is denoted in green, and the configuration comprising 5 intersections with the least propensity scores is shown in red. The results indicate that the logit model's best configuration significantly reduces the individual travel times compared to the base scenario. The distribution for the best configuration is narrower, meaning a higher percentage of vehicles experience shorter trip durations. In contrast, the bottom 5 configuration results in a distribution similar to the base scenario but more skewed to the right. However, the trip lengths do not differ significantly from the base scenario for any of the configurations, indicating that re-routing is minimal despite the left-turn restrictions. This suggests that drivers can seek out efficient travel paths even with restricted left-turns.



(a) **(b)**

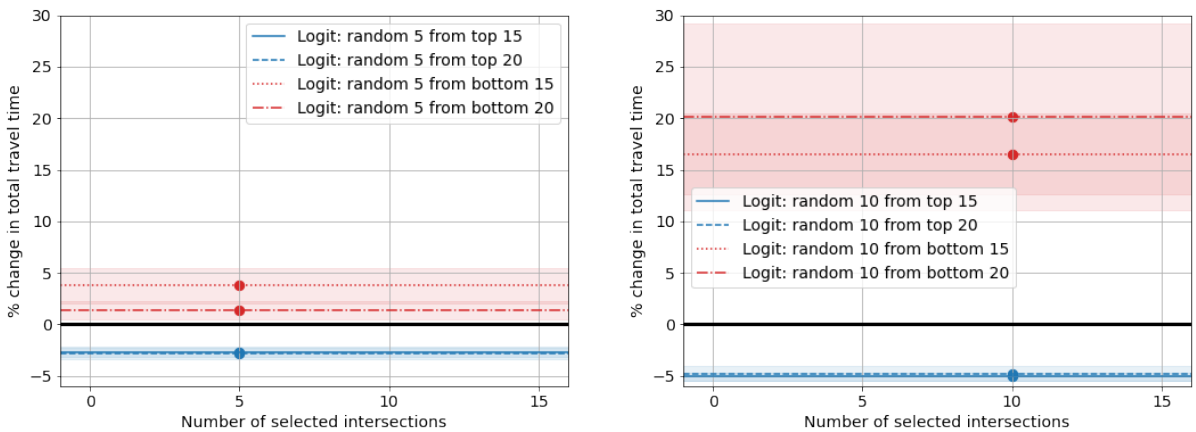
Figure 11. Probability density function of (a) trip durations; (b) trip lengths

The locations of the top 18 selected intersections and the bottom 5 intersections of the logit model for D-87 are shown on a map in Figure 12 using green and red markers respectively where the intensity of the markers indicate their propensity scores, i.e., a darker color indicates a higher propensity to receive left-turn restriction and vice versa. Compared to Figure 5c that demonstrated the top locations to implement left-turn restrictions using PBIL, the binary-logit model selects fewer intersections along Liberty Avenue. However, both figures show a concentration of intersections in the central grid region and typically comprise a series of 2-3 adjacent intersections in the north-south or east-west direction. This is likely because these intersections experience similar levels of left-turning demand and are programmed with similar signal-timing parameters.

Figure 12. Locations of left-turn restrictions in best configuration of binary logit model, and the configuration comprising bottom 5 intersections of the binary logit model for D-87.

<u>Robustness of prediction model for practical implementation</u>

Although the propensity scores of intersections present a guide for agencies in selecting intersections to restrict left-turns on, some intersections may have unobserved characteristics that are not reflected in the model, for which turn restrictions may not be applicable to those intersections. Further, agencies might have other priorities for determining where to restrict left-turn movements. Thus, this section demonstrates the performance of restricting left-turns at a random number of intersections selected from those with the highest (lowest) propensity scores obtained from the logit model using D-87 as an example. Specifically, random subsets of intersections picked multiple times from the top 15, top 20, bottom 15 and bottom 20 propensity scores. The percent change in travel time over the base scenario for configurations comprising left-turn restrictions at 5 and 10 intersections are shown in Figure 13a-b, respectively, where the blue and red lines show configurations picked from the top and the lower end, respectively. The shaded area around each line indicates the variability of one standard error across 10 random configurations. The findings suggest that configurations generated from the top 15 and top 20 yield consistent improvements with low variability and higher improvements are possible by restricting left-turns at 10 intersections as opposed to 5. As expected, random configurations generated from intersections with the least propensity scores generally lead to congestion in parts of the network and result in an increase in total travel time and have a higher variability. Therefore, the prediction model remains robust for practical implementation by agencies, ensuring significant improvements while accounting for the potential exclusion of certain intersections due to practical considerations.



(a) **(b)**

Figure 13. Effect of randomly implementing left-turn restrictions at intersections from top and bottom subsets by propensity scores

CONCLUSION

This paper presents a data-driven methodology to identify the contributing factors behind restricting left-turns in an urban network to improve traffic flow and mitigate congestion in real urban settings. The two-stage methodology consists of a bi-level optimization framework that is used to randomly sample the solution space and identify near-optimal locations to prohibit left-turns with the objective of reducing total travel time. These near-optimal locations are then used to train a binary logit model where traffic flow and signal timing variables pertaining to left-turning movements at each intersection are used to determine which parameters influence left-turn restriction decisions.

The results show that the implementation of left-turn restrictions at individual intersections has mixed effects, as some intersections experience improved mobility while prohibiting left-turns indiscriminately may result in increased congestion. However, the PBIL efficiently identifies left-turn restriction configurations that significantly reduce travel time across all demand levels without increasing trip distances. Moreover, when these solutions were used to train a binary logit model, it was found that intersections with longer left-turn phases or higher left-turning flows have a lower likelihood of being selected for restriction. The trained model was then used to make predictions on unknown scenarios, where travel time in the network significantly improved as left-turns were sequentially restricted at intersections based on the propensity scores from the binary logit model. The best configuration generated from the data-driven model performed at a similar level or better than the best solution obtained using the PBIL.

The model was further validated by simulating intersections with the lowest propensity scores, which resulted in an increase in travel time. Therefore, the model's interpretability and predictive accuracy ensure it can be readily used by agencies to make informed and practical decisions for transportation improvement treatments in large urban networks.

ACKNOWLEDGEMENTS

This research was supported by NSF Grant CMMI-1749200.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: TA, VG; analysis and interpretation of results: TA, VG; draft manuscript preparation: TA, VG. All authors reviewed the results and approved the final version of the manuscript.

REFERENCES

1. Wang, X., and M. Abdel-Aty. Modeling Left-Turn Crash Occurrence at Signalized Intersections by Conflicting Patterns. *Accident Analysis and Prevention*, Vol. 40, No. 1, 2008. https://doi.org/10.1016/j.aap.2007.04.006.
2. Haddad, J., and N. Geroliminis. The Effect of Left-Turns in Arterial Capacity with Queue Spillbacks. *Transportation Research Board, 92nd Annual Meeting*, No. 13, 2013.
3. Messer, C. J., and D. B. Fambro. EFFECTS OF SIGNAL PHASING AND LENGTH OF LEFT-TURN BAY ON CAPACITY. *Transportation Research Record*, No. 644, 1977.
4. Newell, G. F. The Effect of Left Turns on the Capacity of a Traffic Intersection. *Quarterly of Applied Mathematics*, Vol. 17, No. 1, 1959. https://doi.org/10.1090/qam/103121.
5. Zhao, J., and Y. Liu. Safety Evaluation of Intersections with Dynamic Use of Exit-Lanes for Left-Turn Using Field Data. *Accident Analysis and Prevention*, Vol. 102, 2017. https://doi.org/10.1016/j.aap.2017.02.023.
6. Zhao, J., W. Ma, H. M. Zhang, and X. Yang. Increasing the Capacity of Signalized Intersections with Dynamic Use of Exit Lanes for Left-Turn Traffic. *Transportation Research Record*, No. 2355, 2013. https://doi.org/10.3141/2355-06.
7. Xuan, Y., C. F. Daganzo, and M. J. Cassidy. Increasing the Capacity of Signalized Intersections with Separate Left Turn Phases. *Transportation Research Part B: Methodological*, Vol. 45, No. 5, 2011. https://doi.org/10.1016/j.trb.2011.02.009.
8. Xuan, Y., V. Gayah, M. Cassidy, and C. Daganzo. Presignal Used to Increase Bus-and Car-Carrying Capacity at Intersections. *Transportation Research Record*, No. 2315, 2012. https://doi.org/10.3141/2315-20.
9. Reid, J. D., and J. E. Hummer. Travel Time Comparisons between Seven Unconventional Arterial Intersection Designs. 2001.
10. Berkowitz, C., C. Bragdon, and F. Mier. Continuous Flow Intersection: A Public Private Partnership. 1996.
11. Hummer, J. E. Unconventional Left-Turn Alternatives for Urban and Suburban Arterials - Part One. *ITE Journal (Institute of Transportation Engineers)*, Vol. 68, No. 9, 1998.
12. Chowdhury, M. S. An Evaluation of New Jersey Jug-Handle Intersection (NJJI) with and without Pre-Signals. 2011.
13. Deprator, A. J., O. Hitchcock, and V. V. Gayah. Improving Urban Street Network Efficiency by Prohibiting Conflicting Left Turns at Signalized Intersections. *Transportation Research Record*, Vol. 2622, No. 1, 2017. https://doi.org/10.3141/2622-06.

14. Gayah, V. V., and C. F. Daganzo. Clockwise Hysteresis Loops in the Macroscopic Fundamental Diagram: An Effect of Network Instability. *Transportation Research Part B: Methodological*, Vol. 45, No. 4, 2011. https://doi.org/10.1016/j.trb.2010.11.006.

15. Daganzo, C. F. Urban Gridlock: Macroscopic Modeling and Mitigation Approaches. *Transportation Research Part B: Methodological*, Vol. 41, No. 1, 2007, pp. 49–62. https://doi.org/10.1016/j.trb.2006.03.001.

16. Daganzo, C. F., and N. Geroliminis. An Analytical Approximation for the Macroscopic Fundamental Diagram of Urban Traffic. *Transportation Research Part B: Methodological*, Vol. 42, No. 9, 2008, pp. 771–781. https://doi.org/10.1016/j.trb.2008.06.008.

17. Drira, A., H. Pierreval, and S. Hajri-Gabouj. Facility Layout Problems: A Survey. *Annual Reviews in Control*, Vol. 31, No. 2, 2007, pp. 255–267. https://doi.org/10.1016/j.arcontrol.2007.04.001.

18. Tang, Q., and B. Friedrich. Minimization of Travel Time in Signalized Networks by Prohibiting Left Turns. No. 14, 2016.

19. Tang, Q., H. Liu, and B. Friedrich. Lane-Based Signal Optimization with Left Turn Prohibition in Urban Road Networks. *Canadian Journal of Civil Engineering*, Vol. 46, No. 2, 2019. https://doi.org/10.1139/cjce-2018-0079.

20. Tang, Q., and B. Friedrich. Design of Signal Timing Plan for Urban Signalized Networks Including Left Turn Prohibition. *Journal of Advanced Transportation*, Vol. 2018, 2018. https://doi.org/10.1155/2018/1645475.

21. Liu, Y., and Z. Luo. A Bi-Level Model for Planning Signalized and Uninterrupted Flow Intersections in an Evacuation Network. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 27, No. 10, 2012. https://doi.org/10.1111/j.1467-8667.2012.00778.x.

22. Long, J., W. Y. Szeto, and H. J. Huang. A Bi-Objective Turning Restriction Design Problem in Urban Road Networks. *European Journal of Operational Research*, Vol. 237, No. 2, 2014. https://doi.org/10.1016/j.ejor.2014.01.053.

23. Hajbabaie, A., J. C. Medina, and R. F. Benekohal. Effects of ITS-Based Left Turn Policies on Network Performance. 2010.

24. Bayrak, M., and V. V. Gayah. Identification of Optimal Left-Turn Restriction Locations Using Heuristic Methods. In *Transportation Research Record*, SAGE Publications Ltd, pp. 452–467.

25. Bayrak, M., Z. Yu, and V. V. Gayah. A Population-Based Incremental Learning Algorithm to Identify Optimal Location of Left-Turn Restrictions in Urban Grid Networks. *Transportmetrica B: Transport Dynamics*, Vol. 11, No. 1, 2023, pp. 528–547. https://doi.org/10.1080/21680566.2022.2102553.

26. Ahmed, T., H. Liu, and V. V. Gayah. Identification of Optimal Locations of Adaptive Traffic Signal Control Using Heuristic Methods. *International Journal of Transportation Science and Technology*, Vol. 13, 2024, pp. 122–136. https://doi.org/10.1016/j.ijtst.2023.12.003.

27. Barceló, J., and J. Casas. Dynamic Network Simulation with AIMSUN. In *Simulation Approaches in Transportation Analysis*, Springer, Boston, pp. 57–98.

28. Fellendorf, M., and P. Vortisch. Microscopic Traffic Flow Simulator VISSIM. In *International Series in Operations Research and Management Science*.

29. Abdeen, M. A. R., S. Farrag, M. Benaida, T. Sheltami, and Y. El-Hansali. VISSIM Calibration and Validation of Urban Traffic: A Case Study Al-Madinah City. *Personal and Ubiquitous Computing*, 2023. https://doi.org/10.1007/s00779-023-01738-9.

30. Yperman, I., S. Logghe, and B. Immers. The Link Transmission Model: An Efficient Implementation of the Kinematic Wave Theory in Traffic Networks. *Proceedings of the 10th EWGT Meeting and 16th Mini-Euro Conference*, 2005.

31. Prajapati, A. K., A. Sengupta, and S. I. Guler. Accounting for Traffic Dynamics in Pavement Maintenance Scheduling. *Transportation Research Record: Journal of the Transportation Research Board*, 2023. https://doi.org/10.1177/03611981231206176.

32. Baluja, S. Population-Based Incremental Learning: A Method for Integrating Genetic Search Based Function Optimization and Competitive Learning. *Tech. Rep. CMU-CS94-163, School Comput. Sci., Carnegie Mellon Univ., Pittsburgh, PA*, 1994.

33. Bayrak, M., and S. I. Guler. Linkage Problem in Location Optimization of Dedicated Bus Lanes on a Network. *Transportation Research Record: Journal of the Transportation Research Board*, 2023, p. 036119812211484. https://doi.org/10.1177/03611981221148490.

34. Bayrak, M., S. I. Guler, and P. Schonfeld. Implementation Sequence Optimization for Dedicated Bus Lane Projects. In *Transportation Research Record*, SAGE Publications Ltd, pp. 1184–1195.

35. Chowdhury, L. F. Multi-Objective Optimization of Maintenance, Repair and Rehabilitation Schedule Considering Greenhouse Gas Emissions. Accessed Aug. 29, 2023.