

1 **AN EQUITABLE SIGNALIZED ARTERIAL ORIGIN-DESTINATION FLOW ESTIMA-**
2 **TION BY A FAIRNESS-AWARE ARTIFICIAL INTELLIGENCE**

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ABSTRACT

Precise estimation of Origin-Destination (OD) flow in signalized arterials is essential for efficient operation of coordinated traffic signal systems. While earlier studies have demonstrated sufficient estimation accuracy, it is crucial to consider the variations in accuracy across different OD pairs to avoid potential spatial fairness issues. Especially those based on Connected Vehicle (CV) trajectories may lead to unsatisfactory signal operation in underserved communities. To address this concern, a Fairness-Aware Artificial Intelligence framework is proposed, leveraging partially observed CV trajectories. The proposed model focuses on improving spatial fairness by balancing estimation accuracies across different OD pairs. It achieves this by incorporating a state-of-the-art adaptive weighting technique within a deep-neural-network-based self-supervised learning approach. The performance of the model was evaluated on a simulated real-world arterial corridor. The results were compared with a benchmark model that scales up the CV OD matrix with the global CV market penetration rate and an ordinary self-supervised-learning model without fairness considerations. The findings demonstrated that the proposed model effectively addresses spatial fairness concerns by reducing the disparities in estimation accuracy among OD pairs. Notably, the proposed model achieved comparable overall estimation accuracy to the ordinary self-supervised-learning model while surpassing the benchmark model, which can yield "equally unsatisfactory" estimations. Furthermore, the proposed model showed potential benefits for underserved communities where CV penetration rates might be relatively low. However, it is important to acknowledge the trade-off between overall estimation accuracy and spatial fairness when the base estimation model remains unchanged.

Keywords: Fairness, Origin-Destination Flow Estimation, Signalized Arterial, Artificial Intelligence

1 INTRODUCTION

2 A precise estimation of Origin-Destination (OD) flow in signalized arterials is crucial to ensure
 3 optimal traffic operational efficiency. For instance, coordinated arterial traffic signal control systems(1–3)
 4 designed to alleviate congestion heavily rely on accurate spatial-temporal-dependent OD flow along the
 5 arterial corridor as their input. Studies have been conducted to estimate the OD flow along the arterial
 6 corridor. Traditionally, arterial OD flow estimations are primarily based on traffic counts. Lou and Yin(4)
 7 developed a decomposition framework to estimate dynamic OD flow for signalized arterials from link
 8 counts. Yang and Chang(5) proposed three estimation models based on link counts, intersection turning
 9 movements, and the combination of intersection turning movements and queue lengths, respectively. More
 10 recent studies have leveraged vehicle trajectories to estimate the OD flow(6). Yang et al.(7) developed two
 11 models using GPS locations of probe vehicles, where the first model corrects the scaled probe vehicle OD
 12 flow with link counts, and the second model extends the first one by incorporating observed link probe
 13 ratios. Due to the challenges in acquiring the ground truth historical OD flows, Wang et al.(8) proposed a
 14 self-supervised learning approach to estimate OD flows using the trajectories from connected vehicles (CVs)
 15 without the ground truth, given that the market penetration rate of CVs is low.

16 However, while trajectory-based approaches have shown sufficient estimation accuracy for traffic
 17 signal control systems, they often overlook variations in accuracy across different OD pairs. This lack of
 18 attention to spatial fairness may lead to potential issues. For instance, communities with limited resources
 19 might have lower adoption rates of expensive connectivity technologies in their vehicles due to financial
 20 constraints. Consequently, lower market penetration rates of connected vehicles (CVs) in such areas can
 21 lead to compromised estimation accuracy(8). Unsatisfactory OD flow estimations could then negatively
 22 impact the efficiency of traffic signal systems at intersections within these underserved communities, re-
 23 sulting in less efficient traffic operations.

24 To address these potential fairness concerns, it is crucial to explicitly consider fairness during the
 25 model development process. Fortunately, recent advances in artificial intelligence (AI) research have intro-
 26 duced fairness-aware AI(9), providing a feasible approach to tackle these issues. Therefore, this study pro-
 27 poses a framework based on fairness-aware AI to ensure the spatial fairness of arterial OD estimation. The
 28 OD estimation framework relies on partially observed trajectory data from CVs and employs a fair machine
 29 learning model that explicitly balances overall estimation accuracy and performance distribution across
 30 different OD pairs. By doing so, this framework aims to achieve accurate and spatially equitable OD flow
 31 estimation for signalized arterials, potentially benefiting all communities.

33 METHODS

34 Problem Statement

35 Consider an arterial corridor denoted as $C = (N, L)$ (refer to Figure 1), where N represents the
 36 nodes that can be either intersections along the arterials (depicted as red nodes) or points where the vehicles
 37 enter to (origins) and exit from (destinations) the intersections (depicted as blue nodes), and L denotes the
 38 links connect two adjacent nodes in the corridor. A set of OD pairs are defined as $I = \{1, 2, \dots, i\}$. The
 39 analysis period, T , is divided into k uniform intervals, and the set of time intervals is represented as $K =$
 40 $\{1, 2, \dots, k\}$. The traffic pattern of the corridor C during the analysis period T can be represented by an OD
 41 matrix, M , as follows:

$$M = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^k \\ x_2^1 & x_2^2 & \cdots & x_2^k \\ \vdots & \vdots & \ddots & \vdots \\ x_i^1 & x_i^2 & \cdots & x_i^k \end{bmatrix} \quad (1)$$

43 where x_i^k denotes the count of vehicles traveling along the OD pair i during the time interval k .

44 Assume that two types of vehicles, regular vehicles (RVs) and CVs, are traveling along the corridor.
 45 The numbers of the CVs traveling along the OD pairs, represented as the CV OD matrix M_C , can be obtained

as they continuously broadcast their locations in real-time. However, it is worth noting that the market penetration rate of CVs, which indicates the proportion of CVs among all types of vehicles, remains low. On the other hand, the numbers of RVs are unknown, resulting in an unknown RV OD matrix, denoted as M_R .

$$M = M_c + M_r \quad (2)$$

Then the problem can be formulated as estimating the OD matrix, M , using the known CV OD matrix M_c , through a function denoted as f .

$$M = f(M_c) \quad (3)$$

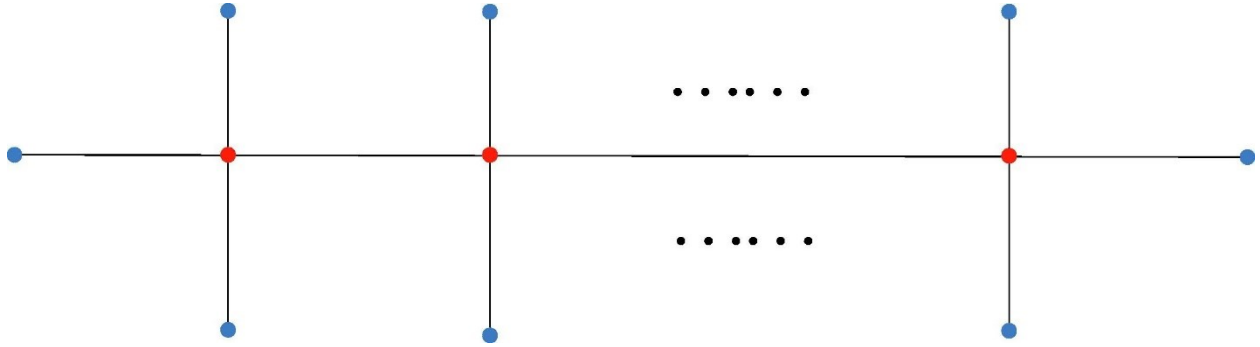


Figure 1 A Simplified Roadway Corridor (Adopted from (8))

Self-Supervised Learning without Ground Truth

In this study, a self-supervised machine learning (SSML) model (8) developed earlier by the authors is utilized to estimate the OD matrix M . The ML model is employed to learn the function f as defined in (3). Conventional supervised ML models learn the function f by minimizing the divergence, represented as the loss $L(M, \hat{M})$, between the ground truth M and the $\hat{M} = f_\theta(M_c)$ estimated by f_θ with a parameter set θ :

$$\min_{\theta} L(M, f_\theta(M_c)) \quad (4)$$

In this specific OD estimation problem, an L2 loss is adopted, which is defined as follows:

$$L = \|f_\theta(M_c) - M\|^2 \quad (5)$$

However, in this problem, the ground truth M is inaccessible due to the unknown number of RVs. Consequently, conventional supervised ML methods cannot be directly applied as the loss cannot be obtained. To address this, a self-supervised ML approach is adopted. Assume that a reasonably accurate estimate of the global market penetration rate of CVs, denoted as β , is known (e.g., 25%). Based on this assumption, a naïve yet flawed estimate, denoted as M_b , of the OD matrix M , and the flaw, denoted as b , in the estimation can be expressed as:

$$M_b = \frac{M_c}{\beta} \quad (6)$$

$$M_b = M + b \quad (7)$$

Given that β is a known and reasonably accurate estimate of the global penetration rate, it is also reasonable to assume that the bias has a zero mean, i.e., $E(b) = 0$. Then,

$$E(M_{b,i}) = M \quad (8)$$

Equation (8) implies that when multiple biased matrices, derived from the same true matrix but with different biases, are obtained, averaging these biased matrices will converge to the true matrix.

A J -invariant function (10) can be defined as:

Definition. Let $\mathcal{J}$ be a partition of the dimensions $\{1, 2, \dots, m\}$, where m is the dimension of the matrices $M, M_b \in \mathbb{R}^m$. Let $J \in \mathcal{J}$. A function $f: \mathbb{R}^m \rightarrow \mathbb{R}^m$ is considered J -invariant if $f(M_b)_J$ does not depend on the value of x_J , where $f(M_b)_J$ and x_J denote $f(M_b)$ and x , which is an element of M_b , restricted to J . The function is J -invariant if it is J -invariant for each $J \in \mathcal{J}$.

Then, the self-supervised loss can be proposed over a J -invariant function f as follows:

$$L_b = E\|f(M_b) - M_b\|^2 \quad (9)$$

Proposition. Suppose $E(M_b) = M$, and the flaw in each $J \in \mathcal{J}$ is independent of the flaw in its complement J^c , condition on M . Let f be J -invariant. Then

$$E\|f(M_b) - M_b\|^2 = E\|f(M_b) - M\|^2 + E\|M_b - M\|^2 \quad (10)$$

Equation (10) shows that the self-supervised loss is the summation of the conventional supervised loss and the variance of the flaw. Consequently, when f is J -invariant, minimizing the self-supervised loss indirectly minimizes the supervised loss. The detailed proof of the proposition can be found in the authors' earlier work (8).

According to the **Definition**, if f is J -invariant, it implies that $f(M_b)_J$ does not depend on the value of x_J . Intuitively, J -invariant means that f only uses J^c to estimate x_J . In other words, J -invariant functions can be seen as a set of functions $f: \mathbb{R}^{J^c} \rightarrow \mathbb{R}^J$. Based on this insight, a masking scheme is proposed to create a blind spot, where f is employed to estimate the values of the blind spot. In general, let g_θ be the conventional estimator with a parameter set θ , $h(M_b)$ be the function replacing x_J . Then a J -invariant function f can be defined as follows:

$$f_\theta(M_b) := g_\theta(1_J \cdot h(M_b) + 1_{J^c} \cdot M_b)_J \quad (11)$$

for each $J \in \mathcal{J}$. 1_J and 1_{J^c} are the indicator functions. The element-wise multiplication of 1_J with the $h(M_b)$ will mask the blind spot, and the element-wise multiplication of 1_{J^c} retain the other elements outside the blind spot.

In this study, an interpolation mask was utilized, which estimates the value of an element by computing a local average of its neighboring elements from a $r \times r$ window that does not include the element itself. This approach ensures that no information from the element is leaked, thereby maintaining J -invariant property of the function.

Adaptive Weighting

Conventional ML models solely focus on minimizing the loss, as demonstrated in the equation (4). Since ML models are not flawless, in most cases, the optimal loss is not zero. Consequently, even after training, errors may persist between the estimated OD matrix $\hat{M}$ and the ground truth M . However, conventional ML methods do not account for the distribution of the loss. In other words, in this problem, the ML's performance in terms of estimation accuracy may vary across different OD pairs. This discrepancy in accuracy could potentially lead to fairness issues, as mentioned earlier.

This study adopts a modified and simplified version of the adaptive weighting method originally proposed by Chai and Wang (11). The goal is to balance the estimation accuracy across different OD pairs by adaptively assigning different weights to each x_i^k in the matrix M_f . Essentially, a larger weight $w_i^k \in W$

is assigned to the x_i^k associated with larger loss values. By doing so, the estimator can focus more on the OD pairs with less satisfactory estimations or higher error probabilities.

During the training process, the weight matrix W is continually changing to ensure that it adapts to the changing loss.

The problem of loss-based weighting can be formulated as follows:

$$\max_W \sum_{w_i^k \in W} w_i^k L_b(x_i^k) \quad (12)$$

$$s. t. W^T \mathbf{1} = m, \quad w_i^k \geq 0$$

where $m = ik$.

Intuitively, the solution to problem (12) is assigning a non-zero weight only to the x_i^k the with the largest loss¹, while setting zero weights for all others. However, this approach might exacerbate fairness issues by only correcting the problem for a single x_i^k . To address this issue, a regularization term is introduced, and the optimization is modified as follows:

$$\max_W \sum_{w_i^k \in W} w_i^k L_b(x_i^k) - \alpha \|W\|_2^2 \quad (13)$$

$$s. t. W^T \mathbf{1} = m, \quad w_i^k \geq 0$$

By adjusting the value of α , the number of non-zero weights assigned can be controlled. As α approaches infinity, the significance of the first term diminishes, and all weights become equal to 1.

Without any loss of generality, assume that the losses $l_j, l_p \in L_f$ are sorted in descending order such that $l_j \geq l_p, \forall j > p$. The optimal solution W^* to the problem (13) can be derived as follows

$$w_j^* = \max\left(\frac{l_j - \lambda}{2\alpha}, 0\right), j = 1, 2, \dots, m \quad (14)$$

where $\lambda = \frac{\sum_{j=1}^{m'} l_p - 2\alpha m}{m'}$, and m' is determined by $\sum_{j=1}^{m'} l_p - m' l_{m'+1} > 2\alpha m > \sum_{j=1}^{m'} l_p - m' l_{m'}$. When $\sum_{j=1}^{m'} l_p - 2\alpha m \leq 0, \forall m', m' = m$ and $\lambda \leq 0$. The solution (14) is obtained using the method of Lagrange multipliers, and the detailed proof is omitted for simplicity.

Deep Neural Network

A deep neural network is employed as the base ML model for the self-supervised learning framework with adaptive reweighing. The neural network model comprises a Long Short-Term Memory (LSTM) component(12) and the attention mechanism(13). LSTM is commonly used in time-dependent traffic studies(14–16). It is used to capture the temporal features of OD flows at a higher level. Moreover, the attention mechanism is widely utilized in traffic studies (17, 18) to enhance estimation performance by dynamically exploring the most relevant temporal and spatial correlations. In this study, a multi-head attention mechanism is implemented to capture both spatial and temporal correlations in the OD matrix. The structure of the customized deep neural network used in this study is illustrated in Figure 2. Additionally, the dropout technique is applied to the dense layers to further improve the performance.

¹ Non-zero-equal weights are assigned in case of ties. However, such situations are rare.

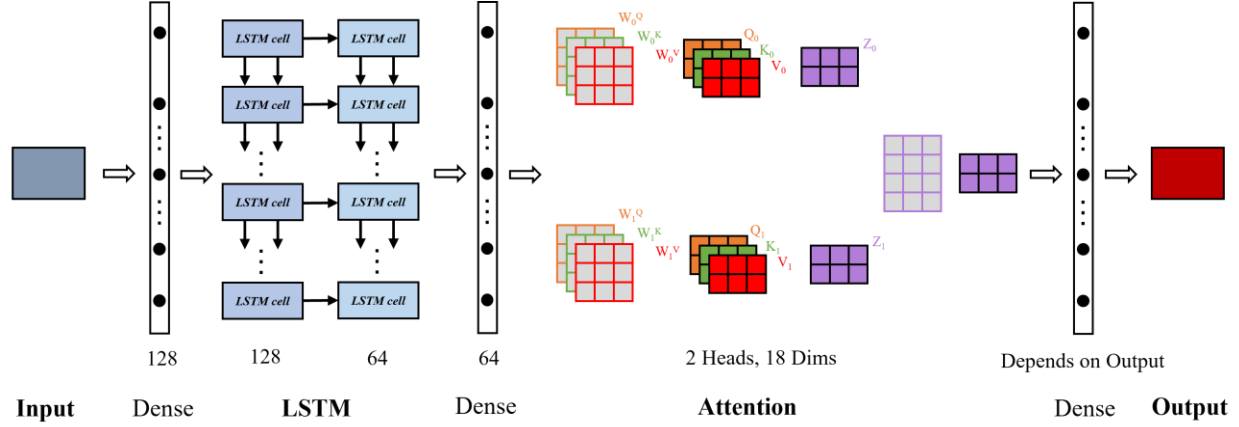


Figure 2 The Structure of the Customized Deep Neural Network

The Fair Self-Supervised Learning

The pseudocode below summarizes the proposed fair self-supervised learning algorithm:

Algorithm Fair Self-Supervised Learning

Input: weight regulation rate α , learning rate λ , number of training epochs N

Initialization: set $w_i^k := 1, \forall j$

for epoch = 1 to N **do**

1. Obtain the self-supervised loss L_b by applying estimator $f_\theta(M_b)$

2. Update W by solving (13):

$$\begin{aligned} \max_W \quad & \sum_{w_i^k \in W} w_i^k L_b(x_i^k) - \alpha \|W\|_2^2 \\ \text{s.t.} \quad & W^T \mathbf{1} = m, \quad w_i^k \geq 0 \end{aligned}$$

3. Updated θ by the weighted self-supervised loss WL_b using Adam (19)

end for

return f_θ

EXPERIMENT

Design and Implementation

Due to the challenges in obtaining ground truth OD flows from real-world field data, we conducted evaluations using a simulated arterial corridor that represents a segment of Redwood Road in Salt Lake City, Utah. The layout of this corridor is depicted in Figure 3. The simulations were performed using the PTV VISSIM platform. To calibrate the simulation scenarios, we utilized field turning movement count data collected from the Automated Traffic Signal Performance Measures (ATSPM) system. Specifically, the ATSPM system collects turning movement counts at the stop-bar using Wavetronix SmarterSensor Matrix detectors.

A total of 1,000 simulation replications were conducted, each with different random seeds. Out of these replications, 900 were used for training purposes, while the remaining 100 were reserved for testing. Each replication had a duration of 3 hours² to ensure that at least one connected vehicle (CV) traveled through each OD pair. The trajectories of all simulated vehicles were collected to calculate the ten-minute traffic flow for each OD pair. During the self-training process, the CV flow served as the input, and the CV OD matrix was directly scaled up by the global market penetration rate, serving as the "ground truth" for

² Without warm-up.

the estimation. However, during the testing stage, the total CV flow was utilized as the ground truth for performance evaluation. The penetration rate of CV is set to be 25%.

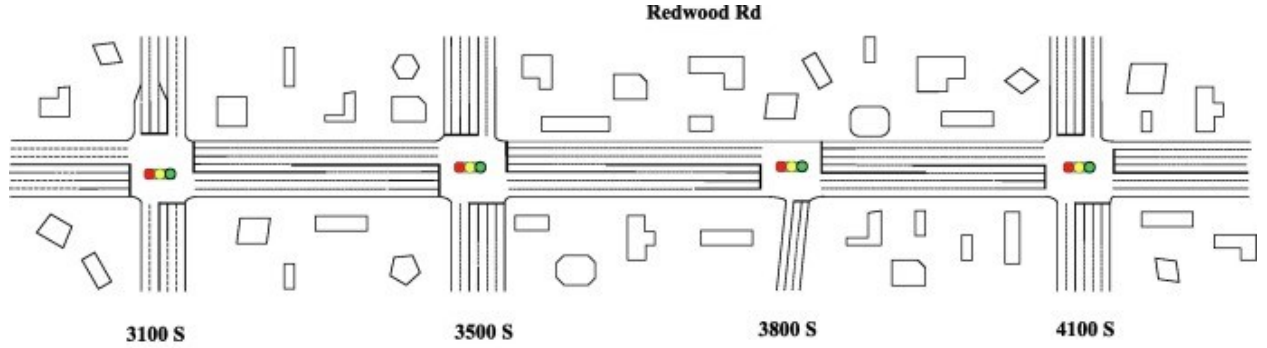


Figure 3 The Layout of the Study Site

The comparison involves three different models: 1) the benchmark model, which estimates the OD matrix by simply scaling up the CV OD matrix with the global CV market penetration rate; 2) the ordinary self-supervised learning model (SSL) that does not consider fairness; 3) and the proposed fair self-supervised learning model (FSSL). It's worth noting that the structures of the base deep neural network are the same between SSL and FSSL (refer to Figure 2). The remaining hyperparameters related to the training process can be found in Table 1. The only differing hyperparameter is the learning rate, as the introduction of adaptive weighting significantly alters the learning process.

TABLE 1 List of Training Hyperparameters

Name	SSL	FSSL
Number of Training Epochs	3,000	
Dropout Rate	0.5	
Batch Size	10	
Learning Rate	0.001	0.005
Weight Regulation Rate	N/A	0.5

Two metrics, namely mean absolute percentage error (MAPE) and Gini Index (G), are employed to evaluate the performance of the aforementioned three models in terms of estimation accuracy and fairness, respectively. The MAPE measures the relative error and can be defined as follows:

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{x_i - \hat{x}_i}{x_i} \right| \quad (14)$$

where x_i and $\hat{x}_i$ represent the ground-truth and the estimated OD flow, respectively; and N is the total number of OD pairs.

The Gini Index (20) is a measure of statistical dispersion used to represent inequality. Originally, it was designed to measure income inequality or wealth inequality within a nation. The GI can be defined as follows:

$$G = \frac{\sum_{i=1}^N \sum_{j=1}^N |y_i - y_j|}{2N^2 \bar{y}} \quad (15)$$

where y_i and y_j are observed values, $\bar{y}$ is the mean, and N is number of values. A lower G indicates higher equality, meaning that values are more evenly distributed. A G of 0 represents perfect equality, where all values are identical. On the other hand, a G of 1 reflects maximal inequality among values, where one value dominates all others. In this study, since the aim is to ensure fair estimation among the OD pairs, y denotes the average estimation accuracy represented by the MAPE of a specific OD pair across different time intervals.

The experiments were implemented using the Python programming language. Specifically, the deep learning model was developed using TensorFlow(21) and the optimization problem of adaptive weights was solved using CVXPY(22).

Results

Table 2 presents the performance of the models in terms of MAPE and Gini Index. In regard to overall estimation accuracy, both the SSL and FSSL models exhibit improvements compared to the benchmark model. The SSL model shows a MAPE improvement of 21.41%, while the FSSL model shows a slightly lower improvement of 18.65%. Nevertheless, the overall estimation accuracy of the FSSL model remains comparable to other trajectory-based OD estimation methods(3, 6, 7). Regarding spatial fairness, the benchmark model demonstrates a satisfactory distribution of estimation accuracy across different OD pairs, as indicated by its Gini Index. However, the SSL model raises some potential spatial fairness concerns, with its Gini Index being 52.56% higher than that of the benchmark model. The FSSL model addresses fairness concerns to some extent, showing a 15.13% improvement in Gini Index over the SSL model. Nevertheless, the Gini Index of the FSSL model still remains higher than that of the benchmark model.

TABLE 2 Summary of the Performance

Model	MAPE	Gini Index
Benchmark	40.718	0.078
SSL	32.001 (21.41%)	0.119 (-52.56%)
FSSL	33.123 (18.65%)	0.101 (-29.49%)
FSSL Improvement Over SSL	MAPE	-3.51%
	Gini Index	15.13%

To gain a comprehensive understanding of the spatial fairness of the three models, the distribution of estimation accuracy across the OD pairs is illustrated in the violin plot depicted in Figure 4. The benchmark model exhibits a significantly smaller range of estimation errors compared to both ML models. However, this seemingly promising spatial fairness comes at the cost of systematically larger errors, as evidenced by its maximum, minimum, and median MAPEs. In other words, the benchmark model generates estimations that are "equally unsatisfactory" across all OD pairs. Conversely, the SSL model achieves more satisfactory estimations for certain OD pairs, as indicated by its minimum and median MAPEs. However, the wide upper tile suggests that it can also lead to some extremely unsatisfactory estimations, even when compared with the benchmark model. One of the major contributions of the FSSL model is narrowing this upper tile, thereby reducing the number of extremely unsatisfactory estimations. Furthermore, although the medians of MAPEs for the SSL and FSSL models are nearly the same, the FSSL model exhibits a wider central region, indicating a more balanced and equally accurate estimation across the OD pairs. Nevertheless, it is important to note that the minimum MAPE for the FSSL model is higher compared to the SSL model, indicating a trade-off between overall estimation accuracy and fairness when using the exact base estimation model.

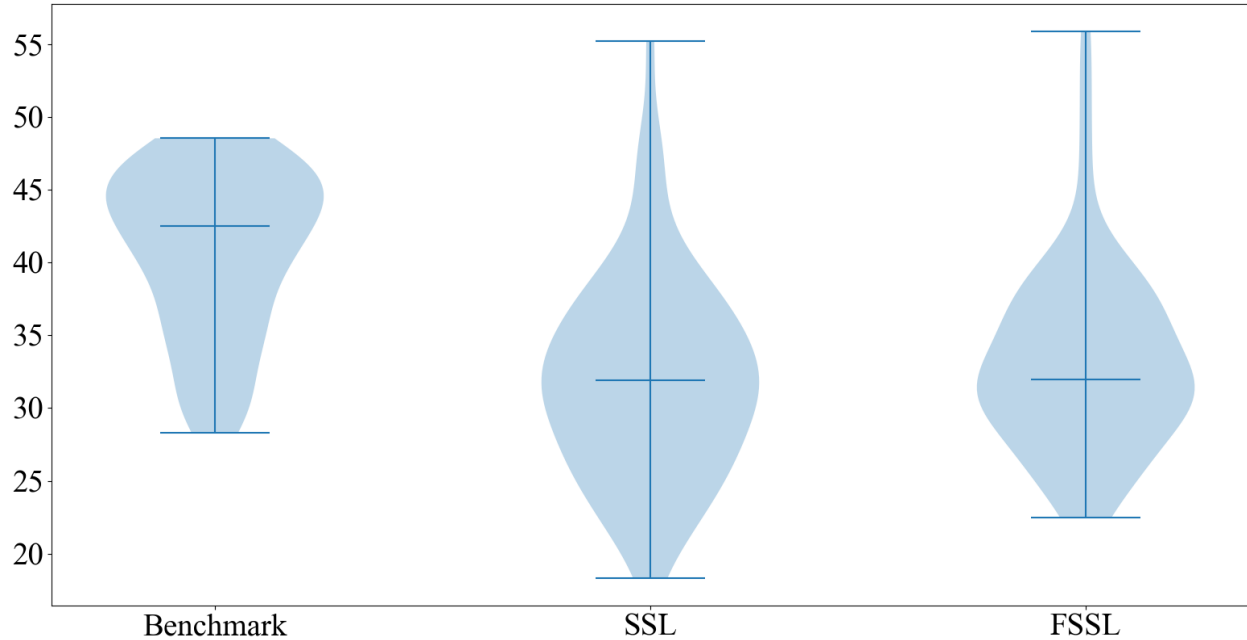


Figure 4 The Distribution of MAPE of the Three Models

To provide further insight into the performances of the models under different circumstances, snapshots of the model estimations were obtained. Figure 4 displays the flow estimations of all 72 OD pairs at specific ten-minute intervals from the first testing replication. The top plot illustrates the estimated OD flows when the machine learning models' performance is satisfactory ($k = 6$), while the bottom plot shows the less satisfactory scenario ($k = 0$). In general, both models are capable of capturing the variations of flows across different OD pairs to some degree. However, the estimation of the FSSL model appears to be more conservative and less adaptive to variations across the OD pairs. This leads to an interesting observation that the estimations of FSSL are less likely to be impacted by the CV penetration rates. On one hand, when the CV penetration rates are sufficiently high for specific OD pairs (e.g., OD pairs 1 to 6 and OD pairs 65 to 72), meaning that the total OD flow can be well estimated or even overestimated by input CV flows, the performance of FSSL may be less satisfactory due to its conservative nature. On the other hand, when the CV penetration rates are too low to accurately reflect the total OD flows (e.g., OD pairs 28 to 32 and OD pairs 42 to 46), a conservative estimator is less likely to be dominated by flawed input CV OD flows. In other words, the conservative nature of the FSSL model has potentials to benefit underserved communities, where the CV penetration rate is relatively low.

In summary, the proposed FSSL method effectively improves spatial fairness by balancing estimation accuracies across different OD pairs. It achieves similar overall estimation accuracy compared to the ordinary SSL model without fairness considerations, while avoiding the "equally unsatisfactory" outcomes observed in the benchmark model. Furthermore, the FSSL model demonstrates potential benefits for underserved communities with relatively low CV penetration rates. However, it is important to acknowledge that there might be a trade-off between estimation accuracy and fairness when the base estimation model remains unchanged. Overall, the FSSL method represents a valuable step towards more equitable and efficient traffic flow estimation in signalized arterials.

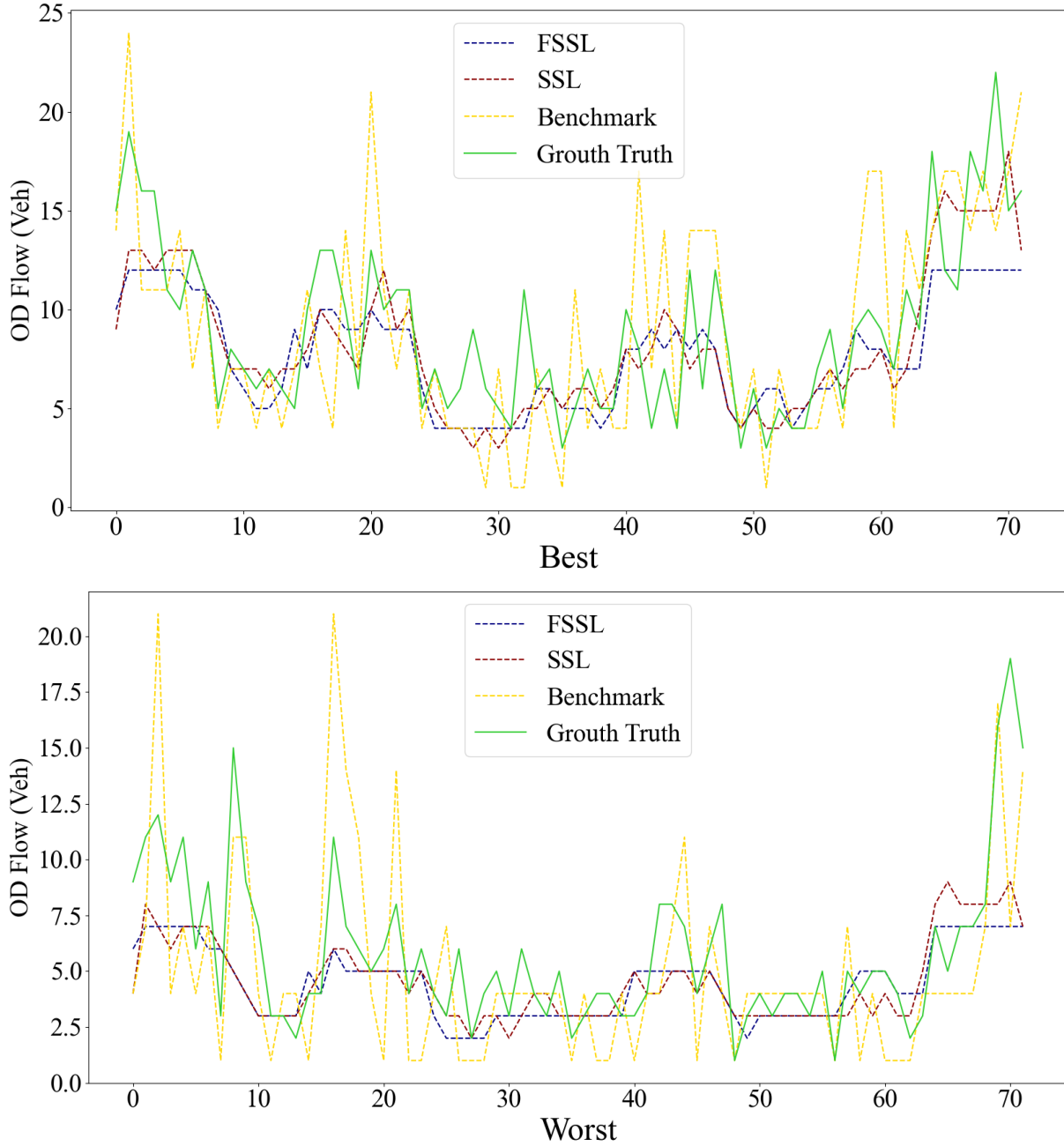


Figure 5 Flow Estimations of All OD Pairs During a Specific Time Interval (Top: Best Performed, Bottom: Worst Performed)

CONCLUSIONS

Precise estimation of OD flow in signalized arterials is essential for optimizing traffic operational efficiency. While trajectory-based approaches have demonstrated sufficient accuracy for traffic signal control systems, it is crucial to consider the variations in accuracy across different OD pairs to avoid potential fairness issues. Especially those based on CV trajectories may leads to unsatisfactory results in underserved communities.

To address this concern, a novel Fair Self-Supervised Learning (FSSL) framework for estimating OD flows in signalized arterials is proposed, leveraging partially observed CV trajectories. The FSSL model focuses on improving spatial fairness by balancing estimation accuracies across different OD pairs. It

achieves this by incorporating a state-of-the-art adaptive weighting technique within a deep-neural-network-based self-supervised learning approach.

The performance of the FSSL model was evaluated on a simulated real-world arterial corridor, considering overall estimation accuracy measured by MAPE and spatial fairness measured by the Gini Index. The results were compared with a benchmark model that scales up the CV OD matrix with the global CV market penetration rate and an ordinary SSL model without fairness considerations. The findings demonstrated that the FSSL model effectively addresses spatial fairness concerns by reducing the disparities in estimation accuracy among OD pairs. Notably, the FSSL model achieved comparable overall estimation accuracy to the ordinary SSL model while surpassing the benchmark model, which can yield "equally unsatisfactory" estimations. Furthermore, the FSSL model showed potential benefits for underserved communities where CV penetration rates might be relatively low. However, it is important to acknowledge the trade-off between estimation accuracy and fairness when the base estimation model remains unchanged.

Overall, the FSSL framework represents a promising solution that enhances spatial fairness without significantly compromising overall estimation accuracy. Nevertheless, some limitations should be considered. The training of the FSSL model is computationally expensive due to the added optimization process of the adaptive weighting. Future research may explore more efficient approaches to ensure fairness. Additionally, while the model was evaluated in a corridor, conducting larger-scale experiments could assess its scalability. Finally, the effectiveness of the proposed model in a traffic signal control system has not been validated yet. Future studies may integrate the proposed model into a traffic signal control system and examine its performance.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Y. Gong, Q. Wang, X. Yang; simulation and data collection: Q. Wang; analysis and interpretation of results: Y. Gong; draft manuscript preparation: Y. Gong, Q. Wang, X. Yang. All authors reviewed the results and approved the final version of the manuscript.

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