Estimation of Intersection Turning Movement Flows with NETFLOCON: Weight Constraint Calibration

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Abstract

Traffic management strategies grounded on reliable traffic demand information can reduce congestion-related costs. While traffic video images can supply real-time turning movement (TM) information, their cost can be prohibitive, especially to smaller agencies. The NETFLO algorithm utilizes Minimum Cost Flow optimization by generating network flows, from a sparse set of detected link flows. NETFLO construct (NETFLOCON) applies an optimal constraint protocol to the NETFLO algorithm inferring reliable TM estimates from link flows detected in quasi real-time. The research goal is to establish consistently robust weight constraints that enable reliable estimation of urban intersection TM. The optimal weighting scheme consistently outperforms weight sets found in the literature, for estimating 5-min TM flows. The results yield a mean coefficient of determination (R^2) of 93% between observed and modeled TM flows. Mean 5-min Root Mean Square Error (RMSE) is 8.9±0.4 vehicles, while the Pearson correlation coefficient (r) is 0.96±0.01. The repeatable control regime that restrains the NETFLO optimization algorithm is an algorithm construct, NETFLOCON. And this paper shows that NETFLOCON is a reliable urban intersection movement estimator.

Keywords

NETFLO construct, turning movement estimation, weight constraint calibration, intersection management, traffic demand

Introduction

Equilibrium between available infrastructure and user demand is a prerequisite for an economical and efficient transportation system. However, traffic congestion is a growing problem, that diminishes transportation efficiency. Each U.S. driver lost 97 hours in 2018 due to congestion, incurring the cost of $1,348. (Reed, 2019) Traffic annual delay is expected to amount to $2,300 per U.S. commuter- as much as a Boston driver has already paid in 2018. (Centre for Economics and Business Research (CEBR), 2014)

Traffic congestion can be improved through proper management strategies- e.g., adapting traffic signals, speed limits or lane use. Also, information on the available spare capacity helps in rerouting vehicles, e.g., during special events or road closures. But, to identify the efficient management strategy, one needs to have the reliable and timely information on the demand. (Grant, et al., 2011)

The most significant transportation delay component in urban areas arises at intersections since the capacity here is the lowest. (Denney Jr., Curtis, & Olson, 2012) Intersections consist of multiple approach and departure legs, which should accommodate travel demand. For example, a vehicle approaching a 4-legged intersection can take one of the three departure legs by making left turn, right turn, or straight-on maneuver. Twelve known turning movement (TM) flows associated with each possible maneuver identify the intersection demand.

We have traffic detectors on many of our urban traffic networks, but we lack comprehensive state estimation algorithms. While video image detection can supply good estimates, many agencies lack the resources to deploy video to all intersections. So, even in the most instrumented networks, we lack comprehensive real-time flow detectors. The goal of this paper is to present a methodology for the development of a real-time state estimator, that draws on a sparse set of detector data.

The NETFLO algorithm utilizes Minimum Cost Flow (MCF) optimization by generating network flows in one run. (Kennington & Helgason, 1980) NETFLO algorithm was originally written in FORTRAN but was modified for compatibility with Unix Operating System in 1991. (Johnson, 1993) The algorithm sends flow through the network at a minimum total cost, with respect to limitations, allowing infeasibility along the optimization process. (Hillier & Liebeman, 2010) However, NETFLO algorithm is merely an instrument, holding no value in estimating TM, unless properly constrained.

NETFLO construct (NETFLOCON) applies the optimal constraint protocol to the NETFLO algorithm, inferring reliable estimates from sparse detected link flows. (Martin, 1995) NETFLOCON assesses the state of the network travel demand and returns unknown flows. Network flows satisfy the series of linear equations allowing flow continuity, resulting in TM and link flow estimates. All network flows comply with the constraints of detected flows and spatial geometry.

Mid-block detectors continuously collect sparse network flows. Detector coverage of less than 15% is sufficient for reliable NETFLOCON estimation of TM flows. (Martin, 1995) Recurrent detected flows update the algorithm input, producing the quasi real-time (e.g., 5-minute) flow estimates. Ideally, algorithm TM estimates should match the real TM flows acquired from stopline detectors. Available intersection demand could help traffic engineers to monitor intersection performance, implement strategic control and maximize efficiency.

The research establishes consistent and robust NETFLOCON constraints that enable reliable estimation of urban intersection TM flows in quasi real-time. NETFLOCON can be constrained in many ways: through upper and lower bounds, weights and error arc factor. Different constraint structures produce different flow estimates, and consequently- different model reliability. Algorithm objective function integrates weight protocol, so the NETFLOCON estimates' reliability depends on properly chosen weight constraints. (Martin, 1995)

Weight constraints represent costs of traveling through network links. "Expensive" maneuvers discourage TM flows, as cost and demand are associated. Intersection approach volume splits between turning directions according to the weight protocol. Therefore, optimal weight procedure (W*) should depict intersection turning proportions to bind TM estimates to the real flows.

The literature is silent on efforts to thoroughly assess weight constraint formulation and advance performance of NETFLOCON in estimating intersection TM flows. The Theoretical Network is used to systematically calibrate NETFLOCON weight constraint protocol. Established turning proportions produce sets of real and estimated TM flows, generating certain model reliability. Maximum average coefficient of determination (R^2) for all turning ratios points at W*. W* is then validated on a real network during the peak hour.

The methodological objectives that will address the overarching research goal are as follows:

1. Determine how the ratio between left (L) and right (R) TM weights influences R^2 of TM flows and identify the optimal L:R weight proportion.

2. Determine how multiplying weights by a factor influences R^2 and identify the optimal multiplication (m) factor.
3. Determine how manipulating through (T) TM weight influences R^2 and identify the optimal T weight.
4. Determine how manipulating error arc (E) weight influences R^2 and identify the optimal E weight.
5. Identify the optimal weight constraint protocol (W*) by combining L:R weight proportion, m factor, T and E weights. Assess performance of W* on a real network and compare it to the weight sets suggested in the literature.

Decades ago, the time required for algorithm solution was determining factor, dependent on network complexity or the processor power. (Ahuja, Magnanti, & Orlin, 1993) A single execution of NETFLO algorithm lasted for hours. Nowadays, an average computer configuration can produce the estimates instantly, so NETFLOCON can be estimated thoroughly and efficiently. In addition, on-line estimation can now be accomplished practically, rather than just theoretically. So, the lack of NETFLOCON advancement for over 20 years can and needs to change.

The paper is organized as follows: prior studies are synthesized to show that NETFLO algorithm is reliable, repeatable and replicable. The average intersection turning proportions are set to comply with the literature recommendations. Constraint tightening, and validation approach are explained in detail. Findings and conclusions are then reported. Finally, research limitations and proposed and future directions specified.

Literature Review

Direct collection of TM flows is complex, expensive and slow. (Bert, 2009) Static and dynamic models are regularly used for estimation. Static models total the demand over a long period (e.g., peak hour), while dynamic models are continuously fed data and update TM flows in real-time. (Bera & Rao, 2011) Most real-time estimation algorithms, although reliable, assume that intersection inflows and outflows are available. (Chang & Tao, 1998) (Ghanim & Shaaban, 2019) Alternatively, models suffer from insufficient constraints, providing unreliable estimates. (Cremer & Keller, 1987) (Nihan & Davis, 1987) (Bell M. , 1991) (Chang & Wu, 1994) (van der Zijpp, 1996)

Processed images from camera-based vision systems became popular in acquiring traffic data. (Knoop, Hoogendoorn, & van Zuylen, 2009) (Yang & Pun-Cheng, 2018) For example, Miovision software requires collecting recording from scout pole units, uploading it to the website, then accessing the platform to access actual traffic statistics. (Shiravi, 2019) However, this is not suitable for real-time data extraction. Data rich hardware platforms can be engineered to extract real-time high-resolution data and generate Automated Traffic Signal Performance Measures (ATSPM). (Huang, et al., 2018) But, these methods require specific equipment, permits, and technical installation.

The future of TM data could rely on some of the beforementioned algorithms and technologies, paired with information from connected vehicles with Vehicle-to-Infrastructure communication. This way, TM information would be extensive and highly reliable. Yet, most of the agencies currently do not possess resources to equip an entire network. Volume data remain relatively sparse on the majority of the arterial networks, although the need for TM information persists . (Shoup, Remias, Hainen, Grimmer, & Davis, 2013)

The NETFLO algorithm follows the Kirchhoff's Law and flow limitations on the arcs, just as MCF algorithm. The network flow moves from source (supply) nodes to sink (demand) nodes in the most cost-effective manner and produces specific arc flows as an output. The model solves the set of constraints and minimizes the objective function. The network is directed and connected, and vehicles travel through its *i* nodes and *j* arcs. Traffic flow cannot be negative, or above the road capacity.

The objective function takes the form of:

$$\min \rightarrow \sum w_j x_j$$

subject to:

$$0 \le l_j \le x_j \le u_j, \text{ for each arc } j$$

$$\sum x_j \text{ (outflow)} - \sum x_j \text{ (inflow) } = b_i, \text{ for each node } i$$

where:

w_j - weight (cost) per unit flow through arc j

x_j - flow vector through arc j (decision variable)

l_j - arc lower bound

u_j - arc upper bound

b_i - net flow generated at node i

The necessary condition for a feasible MCF problem is to ensure network is balanced- the sum of flows generated at all nodes equals zero ($\Sigma b_i=0$). However, having the specific arc flow information from detectors ($l_j=x_j=u_j$), inevitably creates an infeasible solution. Introducing flexibility through error arcs can successfully overcome this. (Bell M. C., 1987) Each detector arc has two parallel and opposite error arcs, to allow movement of vehicles in both directions. Figure 1 shows arc types: detector, error, link, and TM arcs.

Error arcs need to be constrained through its lower and upper bound, to inhibit the artificial flows and improve estimation reliability. The capacity of error arcs is defined as a product of error arc factor (φ) and the corresponding detected flow. The experiment on the Leicester, England network has shown that the value of φ should be 0.025. (Martin & Bell, 1992) Upper bound of non-error arcs is defined through Highway Capacity Manual (HCM) capacity guidelines and their lower bound is set to 0.

NETFLOCON can be defined as quasi-dynamic. The period flows are aggregated, but time slices record demand fluctuations. However, analyzed periods should be independent, since queue discharge cannot be modeled. Therefore, periods have to follow two requirements: be as short as possible to approximate real-time flows and be long enough to preserve interval independence. Five-minute periods are viable to satisfy both. (Martin, 1995) (Martin, 1997)

NETFLOCON's performance was tested on the Leicester, England network for 5-min flows during the afternoon peak. (Martin, 1997) This corresponds to the real-time application. Overall mean R^2 was 79-82% between observed and modeled TM flows. However, the flows with lower magnitude were not reliably inferred. The model is shown to be repeatable and relatively reliable.

NETFLOCON is shown to be replicable when tested on San Luis Obispo (SLO), California, U.S.A. network. (Martin, 1995) Detector coverage of 15% confirmed that minimum number of detectors is sufficient for reliable model performance. The model R^2 reached 90% for 5-min intervals. Also, this research shows that weighting constraint is desirable, to differentiate the difficulties of the various maneuvers.

The SLO network experiment enforced weight constraints, which improved estimation reliability. (Martin, 1995) Mean overall R^2 was 84.1-90.6% for non-weighted, and 92.3-94.7% for weighted regimes. However, only four different weight schemes were tested, so systematic assessment of weight protocols is needed. Additionally, relating intersection turning proportions with weight constraints might improve NETFLOCON performance.

Intersection turning ratios are considered as critical input in estimating TM flow estimates and are generally acquired through field or other historical data. (van Zuylen, 1979) The better the information on turning proportions, the more accurate the TM estimation becomes. When unavailable, researchers are inclined to rely on average turning proportions to produce algorithm estimates. (Schaffer, 1988)

Left turn is a cross-flow in most countries, so is generally more demanding and less safe than other intersection maneuvers. Intersection turning proportions can be attributed to different factors, but the most influential are intersection inflow and outflow road type, and location in the urban area. Although these factors might increase the portion of left turns, average turning proportions for the entire network remain relatively predictable. Metropolitan Toronto is used to produce proportion recommendations according to the approach and exit road type (arterial-collector combinations). (Hauer, Pagitsas, & Shin, 1981) Average right turn proportions were larger than or equal to the left turning proportions for all of the cases considered. HCM recommends using 10% for left and 10% for right turn ratios. (Transportation Research Board, 2010)

NETFLOCON has performed well on two networks, showing that the algorithm can reliably estimate intersection demand. Weight constraint protocol improves estimation reliability.

However, weight constraints have not been systematically tested to identify the optimal constraint regime. (Martin, 1997)

Other methods of acquiring TM are image processing, and other detection algorithms. Video detection is expensive. Other detection estimation algorithms need comprehensive link detection to deliver reliable estimates. NETFLOCON can estimate TM flows with no additional investment and from sparse network flows.

Methodology

Calibration of NETFLOCON is used to adjust the weight constraints, so model outputs can better portray “real” TM flows for different intersection turning proportions. The Theoretical Network is established, as it allows choosing turning ratios arbitrarily. Each tested intersection proportion produces a set of “real” and estimated TM flows. Paired flow sets yield coefficient of determination (R^2), measuring the strength of the linear relation between estimated and real TM flows. Mean R^2 for all turning ratios is maximized, to identify the optimal weights W*. Calibrated NETFLOCON is then applied to the real network to confirm its predictive power and demonstrate validity.

Calibration

Actual TM flows are subject to intersection approach flow and intersection turning ratio. Similarly, estimated TM flows depend on the estimated approach flow and weight constraint protocol. Approach flow is predictable from network topology, parking data and detected flows. Observed and estimated TM yield R^2, which is used to select W*.

Intersection turning proportions are the percentage of intersection approach flow engaging in certain intersection maneuver. For example, approach volume of 1,000 vehicles and turning ratio

10:70:20 would direct 100 vehicles left, 700 through and 200 right. However, turning proportions often differ over time and for different intersection approaches. As historical data are not a valid algorithm input, W* needs to be robust and applicable to different unknown turning proportion settings. For instance, model should produce reliable estimates for both 5:90:5 and 10:60:30 turning ratios.

All variables are held fixed, while only weights are varied. We monitor changes in decision variable R^2 as it changes unambiguously due to weights changed. Procedure is repeated for different intersection turning proportions, producing a set of R^2 weight-dependent values. Analyzed turning proportions assume either right turn dominant flows, or equally represented right and left flows. Maximum mean R^2 for all turning ratios identifies W*.

R^2 represents the fraction of variation explained by the model and takes values between 0 and 100%. An R^2 value close to 100% means that the model has a strong correlation between observed and modeled TM flows. Perfect fit (R^2=100%) would incline all points to fall on a line of perfect correspondence (1:1), passing through the origin. High R^2 advocates small and unbiased difference between estimates and observations.

We manipulate turning ratios and weight sets on the Theoretical Network based on a real site in Las Cruces, New Mexico, U.S.A. It consists of 15 (7 four-legged and 8 three-legged) intersections. The Theoretical network has 148 nodes and 274 (220 regular and 54 error) arcs. Therefore, two error arcs are added to each of the 27 detector arcs. Detector arcs are fixed, so lower and upper bounds match the detected flows ($l_j=x_j=u_j$). Non-detector arcs have lower bound set to 0. Error arcs have an upper bound of $\varphi*x_j$, where error arc factor φ is optimized. The remaining arcs have capacity of 250 vehicles/period. Topology of the Theoretical Network is presented in Figure 2.

The “real” intersection inflows are uniformly distributed U(5,200) in Microsoft Excel and fixed. Intersection outflows match the inflows, so the Kirchhoff’s law is preserved. Different turning proportions vary sets of TM flows. Only 27 (about 12%) of links are modeled as “detected” flows for NETFLO input. The non-TM flows and external loading are calculated through Kirchhoff’s law. Balancing external loading (BEL) is used to complement flows generated at all nodes, so that feasibility requirement $\Sigma b_i=0$ holds. Methodology flowchart is shown in Figure 3.

The weight constraints follow four hierarchical steps:

1) Left to right weight proportion,
2) Multiplication factor,
3) Through weight, and
4) Error arc weight.

The weight assessment initially sets weights of all arcs to 1. The weights of link and detector arcs remain 1 throughout the process. The error arc weights vary. The hierarchy assumes that step 1 addresses the primary influence, namely left to right split. For each test, within each step, we measure the correlation between observed and modeled flows. The step finishes by selecting the best correlation from all tests. This gives the step weight that is applied throughout the subsequent step. So, with the best weight from the previous step, the current step tests a fresh factor.

Step 1 seeks the optimal proportion of weights between left and right TM, by analyzing 19 different ratios. In step 2, the multiplication factor m brings consistency to the split. In step 3, the manipulation of through movements relies on the improvement of the correlation between the observed and modeled flows. In step 4, error arc weighting deters NETFLOCON from assigning flows. In this way, NETFLOCON strives to diminish error arc flow which represents the corruption of measured detector flows.

Validation

The optimal weight constraints are validated on a real network in Orem, Utah, U.S.A. Orem is the fifth-largest city in Utah, located about 45 miles South of Salt Lake City, populated by about 98,000 people in 2017. (U.S. Census Bureau, 2018) This network is chosen as it encompasses principal arterials, minor arterials and urban collectors. The analyzed area is bounded by 800W Street in the West and 800E Street in the East, 400N in the North, and 800S Street to the South. The study area is shown in Figure 4.

Automated Traffic Signal Performance Measures (ATSPM) website contains high-resolution data from each signalized intersection, collected from controllers and traffic probes. (Utah Department of Transportation (UDOT), 2019) (Federal Highway Administration (FHWA), 2019) Information from the website is used as the algorithm input: sparse traffic flows, signal settings, external network loading and TM counts to correlate real and estimated flows. Number of lanes and turning options are detected in Google Maps.

The Orem network consists of 12 signalized intersections, with 128 nodes and 208 arcs, as shown in Figure 5. Flow detectors are placed on 12.3% of the network, which is 26 arcs. Therefore, NETFLOCON implements additional 52 error arcs, 260 in total. We analyze 5-min traffic demand on Wednesday, May 3rd, 2017 during the afternoon peak hour (4:50-5:50). Each of the 12 modeling periods produce different R^2 for analyzed weight sets.

The 5-minute sparse traffic flows and network supply and demand information are used to produce complete network flow estimates through NETFLOCON. Error arc factor is established as one fortieth of the corresponding detector arc (φ=0.025). Lower bound is set to 0 (v=0) for all arcs, and the upper bounds (u) are identified through HCM 2010 equations.

Weight constraints are the only ones varied. Five different weight sets are assessed: four proposed in the literature on the SLO network (Martin, 1995), and the fifth- optimal weight set (W*) extracted from the Theoretical Network calibration. The model is validated through three parameters: Coefficient of determination (R^2), Pearson correlation coefficient (r) and Root Mean Square Error (RMSE).

R^2 is a commonly used quantitative model assessment parameter and United States Department of Transportation recommends values of at least 88% for travel model validations. (Cambridge Systematics, Inc., 2010) Overall flows represent 144 pairs of observed-modeled TM flows, containing 48 pairs of each TM direction (left, through and right). R^2 is reported for overall TM flows and each TM separately, for twelve 5-min periods. Treating validation tests as rigorously as calibration tests is adequate, so reporting only R^2 for both calibration and validation is sufficient. (Hollander & Liu, 2008) Coefficient of determination is used as a decision parameter in the calibration, but additional estimation quality indicators can further support conclusions, so are used in the validation.

Pearson correlation coefficient (r) is reported as it supplements R^2 in measuring linear correlation between variables. Extreme values ±1 of r correspond to data points lying exactly on a line, while value of 0 represents no linear correlation. Pearson correlation is a popular measure of goodness-of-fit, but it provides no additional information on the nature of the error. (Hourdakis, Michalopoulos, & Kottommannil, 2003) It can equally penalize small and large errors, even though minor variations around the mean are in the nature of traffic phenomena.

On the other hand, RMSE depends on the squared difference between observed and estimated TM flows, and hence places a higher penalty on large errors. RMSE denotes a deviation of unexplained variance. It is convenient as it quantifies estimation error within the same scale (units) as a variable. (Chen, Chootinan, Ryu, Lee, & Recker, 2012) (Lu, Rao, Wu, Guo, & Xia, 2015) However, following specific RMSE target values would not be applicable here, as we are using short intervals and very low and unstable traffic flows.

The process time of employing the algorithm is expressed through actual Central Processing Unit (CPU) time in milliseconds (ms). This value consists of two components: time used in executing the specific process and amount of CPU time spent in the kernel within the process. The actual CPU time is extracted directly from the Linux command line window, while running NETFLO on a desktop computer.

Results

Calibration

Arc weights are calibrated through four steps: left to right turning movement proportion, multiplication factor (m), through turning movement and error arc factor. The optimal weights from each step are transferred to the next. The output from step 4 represents the optimal weight set W*. The mean R^2 values for all turning proportions are presented in Figure 6.

Initial R^2 for non-weighted regime is 52.9%. The first calibration step suggests that weight proportion between left and right TM weights should be 5:4, resulting in 85.8% reliability. The mean R^2 slightly grows as multiplication factor increases in step 2, reaching stability for m=12. So, step 2 advocates that left TM weight should be 60, while right TM weight should be 48. Step 3 evaluates if through TM arc weight should be changed. However, through weight should remain 1, as there is no estimation quality improvement when it increases. Similar conclusion is reached in step 4 for error arc weight. Therefore, optimal weights are 60 for left TM, 48 for right TM, and 1 for all the other arcs.

Validation

Validation utilizes the real network in Orem, Utah, U.S.A. applying four initial weights (W0, W1, W2 and W3) used on SLO network and optimal weight W*. (Martin, 1995) The W0 is the base, non-weighted hierarchy. The logic applied to the weighted regimes was that the order of driving difficulty is: driving through a link was the simplest, intersection through movement, left-protected, right-unprotected, followed by left-permitted maneuver, which is the most complex. Error arcs were the most weighted, being approximately 3 times the value of the next most expensive arc.

The optimal weights (W*) extracted from the Theoretical Network calibration also inferred R^2. The optimal weight set uses 60 for left TM and does not differ if turn is permitted or protected. Right TM weight is 48, while error, link and through weights are 1. Table 1 summarizes coefficient of determination for twelve 5-min periods and 5 weight sets presented in Table 2.

Estimation reliability when using optimal weight set (W*) outperforms use of all the other analyzed weight protocols (W0, W1, W2, W3). Mean R^2 value for optimal weights is 92.7±1.0% ranging from 90.4-94.1%. The second-best estimation is for W2 weight set, inducing 90.2±1.4% reliability and ranging from 87.4-92.8%. Weight protocols W1 and W3 achieved mean R^2 of

87.1±2.4% and 88.4±2.0%, respectively. Non-weighted regime W0 was the least reliable with R^2 of 78.8±2.8%.

The estimation reliability for twelve 5-min periods is shown in Table 3. Three parameters are calculated for optimal weights (W*) and combined TM: coefficient of determination (R^2), Root Mean Square Error (RMSE) and Pearson correlation coefficient (r). Also, R^2 is presented for each of the TM.

Mean 5-min R^2 for all TM during P.M. peak hour is 92.7±1.0%, reaching 94.1%. Almost all through movement (dominant) flows are correctly predicted (R^2=96.7±1.0%). However, left and right intersection turn estimations were not as reliable. Mean R^2 for right TM is 41.7±13.6% and for left TM 28.5±15.5%. Overall RMSE is 8.9±0.4 vehicles, while r is 0.96±0.01. Mean actual CPU time needed for the NETFLOCON execution is 6±1ms, ranging between 4ms and 9ms.

Discussion

NETFLOCON can quickly produce reliable intersection TM estimates. Differently constrained algorithm yields different TM flow estimations. Consequently, different reliability is incurred when comparing modeled and actual (unknown) TM flows. Identifying the optimal constraint structure is crucial to produce consistent TM flow approximations.

The Theoretical Network is used to calibrate weight constraints. The optimal weight protocol must allow reasonable reliability under diverse traffic conditions, since NETFLOCON does not use information from previous periods. Different intersection turning proportions are examined, since they can fluctuate from one period to another. Ten intersection turning proportions are analyzed, and through movement was always prevailing. Right/left turns were either equally represented, or right turn dominated over left.

The four-step calibration produced optimal weight (W*) regime: 60 for left TM, 48 for right TM, 1 for all other weights. Optimal weights return the highest mean R^2 for all intersection turning proportions of 86.7%. W* applied to commonly encountered turning flow distributions can reliably predict TM flows. Unlike found in the literature, error arc weight should be 1, advocating that error arcs do not need to be constrained through weight for reliable results.

The Orem, Utah Network validates optimal weight regime attained from calibration. The simulated and actual flows are compared for twelve 5-min intervals during the P.M. peak hour. Straight-on flows are reliably predicted. Almost 50% of right and 30% of left maneuvers are successfully estimated. Figure 7 shows how NETFLO estimates and real flows compare for different TM during one observation period (5:00 P.M.-5:05 P.M.).

Left and Right TM flows are not reliably inferred, due to their low values. Even small differences in estimated and observed values produce high errors. Neither Left nor Right turns exceed 40 vehicles/5 min, keeping most flows at half of that. So, NETFLOCON cannot be used for precise operations, such as determining the optimal signal timing plan.

However, prominent, in this case Through, TM flows can be estimated with high certainty, identifying potentially congested routes. Available spare capacity on the network could guide vehicle rerouting operational decision. NETFLOCON can be used to bridge the gap until automation of data collection becomes feasible everywhere.

Left TM flows are low for all arcs and are underestimated by NETFLO. On the other hand, through TM are dominant and are often overestimated. Right TM flows, although low, do not show obvious or consistent irregularity when compared to real flows. While dominant flows can be predicted with high accuracy, estimation discrepancy persists through overestimation and underestimation. Therefore, model might be improved to better capture underlying structure of the data.

Value of actual CPU time is very short (less than a second) and encompasses only the startup run-time overhead, caused by simply invoking the algorithm. Therefore, NETFLOCON can produce the output instantaneously, needing negligible computation time. However, computation time should be verified for larger than Orem, Utah Network. This way, the upper asymptotic mathematical notation (the Big O) could be extracted to describe the algorithm's running time as a function of its input complexity.

Limitations

Although reliable, the NETFLO algorithm is limited in three ways. First, it is pseudo-dynamic, so independence between intervals needs to be preserved. Vehicles that remain in the network from the previous period are not accounted for, and queue discharge is not considered. Therefore, modeling intervals cannot be too short. Second, internal source/supply nodes account for parking activity in the network, often estimated from parking capacity and limitations. Finally, the NETFLO algorithm is integer based. Error arc upper bounds need to be rounded up. For example, $\varphi=0.005$ and $\varphi=0.025$ might produce the same capacity constraint for low flows detected. Error arc factor cannot be defined precisely.

The main limitation of the Theoretical Network calibration is the use of random uniformly distributed flow values for different TM. "Actual" flows are assigned arbitrary in Microsoft Excel, without considering network topology. Therefore, external node loading for the Theoretical network was much greater than in reality, as flows lacked consistency from node to node.

Consequently, error arc factor had to be much larger (φ=0.2) than if used under real conditions. Capacity of error arcs was relatively high, and the model reliability suffered.

Additionally, the Theoretical Network has the same upper bound for all non-error arcs. The Theoretical Network was used only as a setting to infer optimal weight structure, not to suggest use of particular error arc factor or expected TM flow reliability. R^2 values on the Theoretical Network pose no empirical importance relevant to validation. It is merely the best summary of optimal weight set, that needs to be tested on an actual network. Moreover, "real" flows are assigned to the Theoretical Network, so each intersection had the average turning proportion. However, this is not realistic- even consecutive intersections might have completely different turn proportions. This is another reason why real network validation is necessary.

Conclusion

The NETFLOCON estimates intersection TM flows by minimizing the weighted objective function. Both objective function and estimation quality hinge on weight constraints. The Theoretical Network is used to systematically identify the optimal weight constraint formulation. The chosen weights produce the highest mean R^2 for ten average intersection turning proportions. This way, actual turning proportions become irrelevant to NETFLOCON performance, as optimal reliability is reached. The Orem, Utah Network validates the findings by estimating twelve 5-min flows in the afternoon peak hour. The main research findings are as follows:

1. As higher cost discourages movement through the arc, the cost of left turns should be higher than of right turns. Specifically, optimal proportion between left and right TM (w(L):w(R)) should be 5:4.

2. Estimation quality is maximized after the multiplication factor (m) reaches the value of 5. However, this value should be at least 12 to stabilize R^2. This means that higher multiplication factors would produce the same results for all turning proportions. The minimum value m=12 is chosen as optimal.
3. Manipulating the weight of through turning movement arcs shows no estimation quality improvement, so optimal through TM weight (w(T)) should be 1. This finding supports the premise that the through movement maneuver is the easiest and therefore, the cheapest.
4. Manipulating the weight of error arcs does not improve estimation estimates. The optimal error arc weight (w(E)) should be 1, since weighted error arcs do not enhance algorithm reliability. This suggests that the error arc factor and upper bound limit can sufficiently constrain error arcs and deter error arc flows.
5. The optimal weight set consistently outperforms previous weighted regimes in the literature for each of the 5-min periods. Optimal weights yield mean R^2 of 92.7±1.0%, while the best performing weight set in the literature reaches 90.2±1.4%. The optimal weights' performance is confirmed as superior, producing higher R^2, thereby deviating less.

Therefore, NETFLOCON can reliably estimate urban intersection TM flows in quasi real-time when constrained by the weight protocol reported. Weight constraint formulation is robust and consistent, when applied to the Theoretical network under different turning proportions. Optimality is first achieved when left turns cost 60 and right turns cost 48 units. But, dominant (through) turning flows are overestimated, while left turns are underestimated. Overestimation of congestion can negatively impact decision making (e.g., needless road construction).

Orem, Utah Network has a turning proportion of 15%-70%-15% with up to 4% deviation for each direction. Different turning ratios should be examined to check if overestimation of dominant flows preserves. Also, other networks should be tested to confirm weight protocol repeatability and replicability. Large networks are of particular interest when identifying the computing complexity of the algorithm.

Moreover, research should identify how to further constrain NETFLO. This paper confirms that the reliability of TM flows can be improved through deeper weight constraint examination. Nevertheless, there is room for further constraint study. For example, lower and upper bound calibration may diminish left turn underestimation and in turn, decrease the overestimation of intersection through movements.

The initial network setup requires identifying network topology and entering predefined constraints. NETFLOCON could then be fed the available detected flows, yielding TM estimates instantly. The new period would supply the new detected values and update the TM flows. Traffic management strategies based on reliable and timely information tend to be successful. NETFLOCON can provide intersection demand information, crucial for alleviating urban congestion. This way, reliable TM estimates can be produced as soon as bottlenecks occur. Consequently, traffic would maximize its efficiency, cost-effectiveness, safety and driver comfort.

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Tables

Table 1. Calculated R^2 for different weight sets (Orem, Utah Network)

	R^2 (%)				
Period	W0	W1	W2	W3	W*
1	75.0	85.2	89.9	87.5	92.2
2	77.3	85.2	89.9	86.9	92.8
3	75.8	89.4	90.6	91.2	94.1
4	79.5	85.5	88.6	87.7	91.9
5	80.2	87.6	87.4	88.0	93.0
6	76.3	81.3	89.9	84.1	91.7
7	79.5	87.9	89.8	89.3	92.4
8	78.9	88.0	90.3	88.5	92.9
9	75.5	86.4	89.5	86.4	90.4
10	84.3	89.9	91.6	90.4	93.5
11	82.2	88.6	92.8	90.6	93.7
12	81.1	90.1	92.3	90.7	93.1
Mean	78.8	87.1	90.2	88.4	92.7
Std. Dev.	2.8	2.4	1.4	2.0	1.0
Min	75.0	81.3	87.4	84.1	90.4
Max	84.3	90.1	92.8	91.2	94.1

Note: W0, W1, W2, W3- Martin, P.T. (1995)- SLO Weights
W*- Optimal Weights

Table 2. Weight sets used in the validation

Arc	Weight Sets				
	W0	W1	W2	W3	W*
Left Protected	1	3	6	3	60
Right	1	3	6	4	48
Through	1	2	3	2	1
Error	3	15	30	20	1
Link	1	1	1	1	1
Left Permitted	1	5	9	7	60

Note: W0, W1, W2, W3- Martin, P.T. (1995)- SLO Weights
W*- Optimal Weights

Table 3. Calculated estimation reliability parameters for optimal weights (W*) and actual CPU time (Orem, Utah Network)

Period	R^2 (%)				Overall RMSE (# veh.)	Overall r	Actual CPU Time (ms)
	L	T	R	Overall			
1	0.7	95.7	39.5	92.2	9.0	0.96	9
2	35.0	96.9	50.1	92.8	8.8	0.96	7
3	37.8	97.6	69.5	94.1	8.2	0.97	6
4	29.8	96.5	37.6	91.9	9.2	0.96	4
5	21.6	96.6	42.3	93.0	9.6	0.96	6
6	8.0	95.7	39.5	91.7	8.7	0.96	7
7	36.1	97.7	13.6	92.4	8.8	0.96	6
8	37.9	97.4	49.8	92.9	8.7	0.96	7
9	7.0	94.1	23.4	90.4	9.7	0.95	5
10	55.4	96.9	43.1	93.5	9.1	0.97	7
11	41.7	98.0	56.8	93.7	8.6	0.97	6
12	31.6	97.1	35.7	93.1	9.0	0.96	6
Mean	28.5	96.7	41.7	92.7	8.9	0.96	6
Std. Dev.	15.5	1.0	13.9	1.0	0.4	0.01	1
Min	0.7	94.1	13.6	90.4	8.2	0.95	4
Max	55.4	98.0	69.5	94.1	9.7	0.97	9