A Simulation-Based Methodology for Road Freight Network Extraction: Case Study in the Canadian Prairie Region

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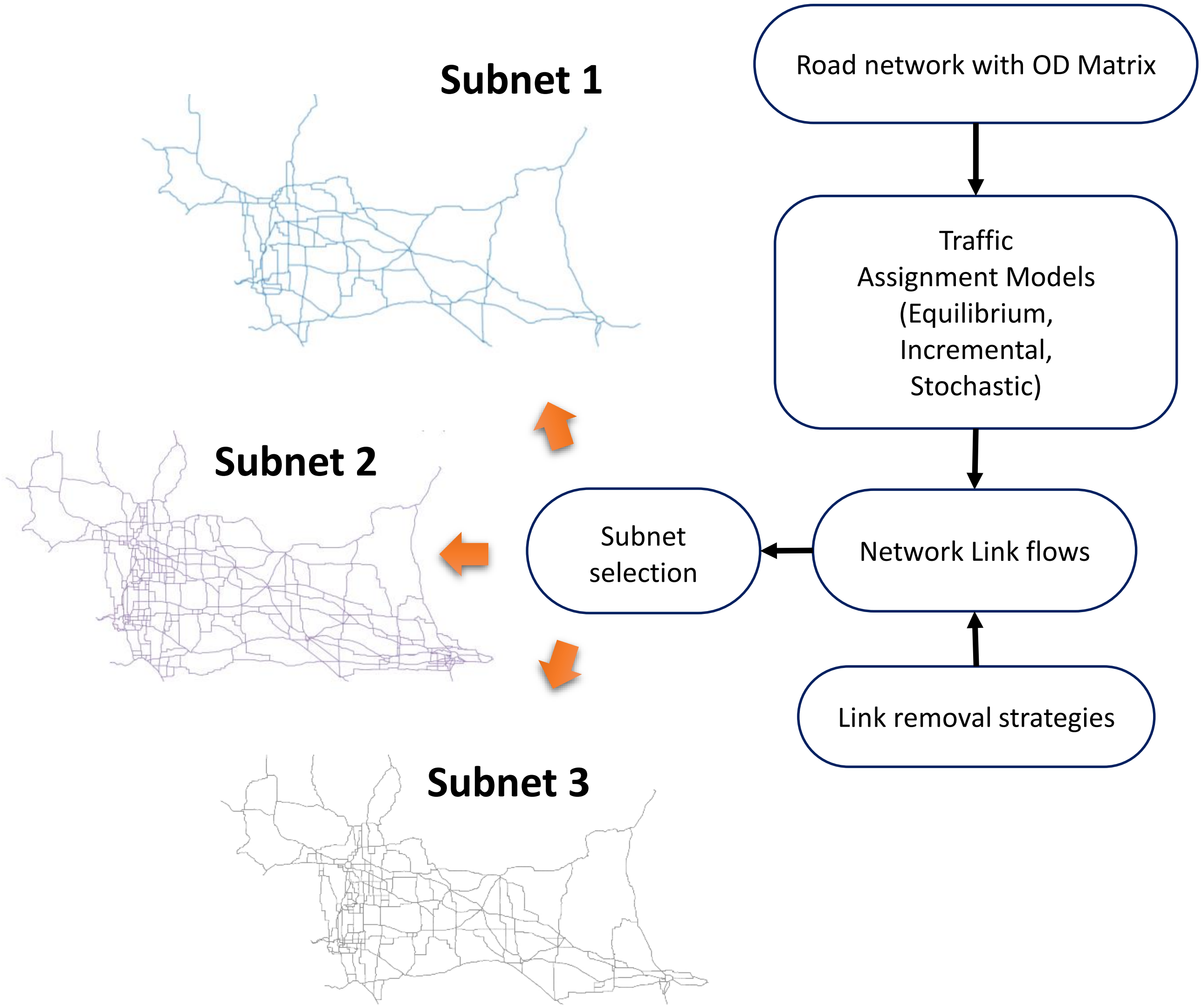
Graphical Abstract



Abstract

Efficient planning and design of road freight networks require an understanding of their spatial characteristics and demand patterns. However, the large scale and dense interconnections of these networks pose challenges in accurately representing and analyzing freight movement while ensuring computational efficiency. Public agencies also face difficulties in traffic monitoring, safety analysis, and asset management on a broader scale. This study focuses on the Prairie region of Canada and leverages data from the Canadian Freight Analysis Framework (CFAF) to propose a methodology for network extraction. Using a multi-model traffic assignment approach, the method extracts a sub-network from the original while preserving essential functional features. Results indicate that the proposed approach significantly simplifies the network without compromising structural integrity, offering a robust foundation for practical applications.

1. Introduction

Developing efficient road freight networks requires a detailed analysis of their spatial and functional attributes. The complexity of road systems presents significant challenges in modeling these dynamics while maintaining computational efficiency. Additionally, public agencies managing such networks face difficulties in large-scale traffic monitoring, safety evaluation, and infrastructure maintenance. These challenges are compounded by the existence of multiple versions of Linear Referencing Systems, e.g., provincially owned systems, national-level datasets available for public use, and data readily available through third parties. Focusing on the Prairie region of Canada, this study proposes a methodology to extract a sub-network using a multi-model traffic assignment approach, aiming to provide a unified network driven by the user data and preserving flow patterns.

Using origin-destination freight flow estimates from the Canadian Freight Analysis Framework (CFAF) as input, various traffic assignment models are applied to the study network using PTV Visum, a professional transport demand modeling software, to get the flow footprints in the network. Three distinct link removal policies are then applied to extract the candidate sub-networks. Each candidate network is then evaluated against the original network in terms of criteria-based performance measures. The selection of the most suitable sub-network is guided by ensuring optimal balance between these criteria. Following the selection process, we apply an algorithm to simplify the network by merging roadway segments between intersections, further streamlining the network representation. This additional step enhances the manageability of the network while preserving critical connectivity and traffic flow characteristics. Hence, the primary and broader-level contributions of this study include:

- Developing a methodology to manage the intricacies of road networks by leveraging multi-model traffic assignment, thereby enhancing network optimization strategies.
- Applying real-world transportation planning simulations and data to enable more informed decision-making and enhance policy development.

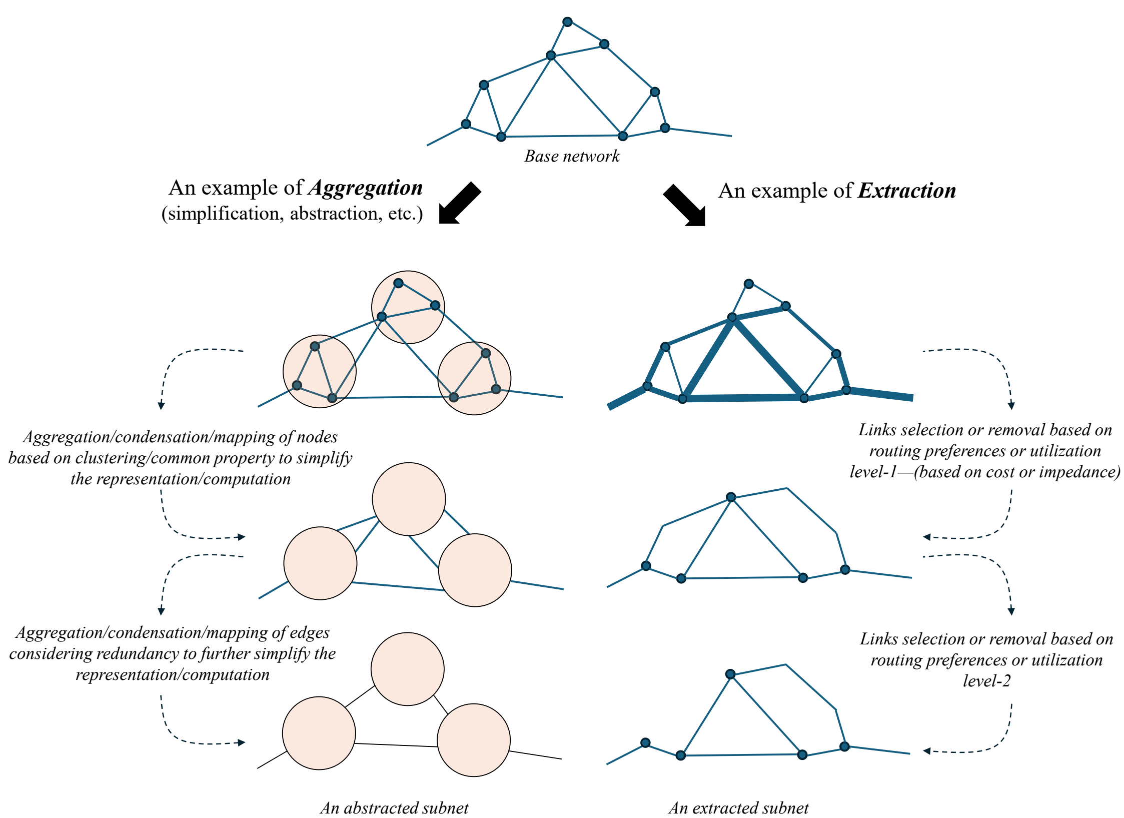
We structure our discussion as follows. The next section presents a literature review. In Section 3, we present the proposed methodology in detail, outlining the steps involved in our network extraction approach. We also elaborate on the application of our proposed methodology to our case study, the highway network of the Canadian Prairie, and describe the dataset used, the Canadian Freight Analysis Framework (CFAF) database. Section 4 analyzes the results with discussion. Finally, the concluding section discusses the implications of our findings, acknowledges the study's limitations, and suggests directions for future research.

2. Background

Reducing a large transportation network to improve the ease of analyses is a long-standing problem that dates back more than half a century. The problem was undertaken as a network aggregation problem in transportation which primarily aims at reducing the number of network elements.[3] It seeks a proxy network for better representation of the detailed one to enhance network analyses. Later, several specifications of the problem emerged including network abstraction, simplification, or condensation, although some literature persistently used the same nomenclature.[28] Some early literature classified network extraction under the umbrella of network aggregation;[14] this study makes a distinction between the two.

Network aggregation is undertaken to transform a network to a more simplified space to facilitate analyses or representation. Network extraction, on the other hand, is undertaken to take out the core yet more meaningful portion of the network based on an intended purpose.[5] The absence of certain nodes or links is more obvious in the extracted network than in the abstracted or simplified network, as they are more likely considered as hidden or better represented in the latter case and unimportant or residual in the former case. Figure 1 illustrates the distinction between network aggregation and extraction. This difference between network extraction and aggregation has also been noted in the literature.[4]

Figure 1. Difference between network aggregation and extraction



Recent research in network extraction stems from the fact that some node pairs in the network could be sporadic and might not possess a meaningful connection, hence introducing unwanted biases in the link weights estimations,[20] obfuscating the interpretation of the intricacies of the network topologies,[5] or obscuring the underlying phenomenon of interest[7], such as redundancy, reliability or efficiency of the network. Hence, extracting a network which retains only those links which are considered significant and encapsulates most of information from the original network, drastically reduces the complexity and enhances the interpretation of the network, with other computational benefits. Another benefit of network extraction is its flexibility to incorporate homogenous performance criteria to define the importance of the network. For example, in cases where multiple underlying networks have different methods of linear referencing systems, a unified network can still be extracted based on probabilistic estimates of flow between the origin and destination points.

Network extraction can be classified into three main categories:[32] 1) Structural-based extraction, 2) Statistical-based extraction, 3) Hybrid extraction. Structural-based extraction exploits the topological properties of the network elements such as maximum spanning tree, shortest-path distance,[12 25] node degree,[9] edge betweenness,[11] network planarity,[29] and modularity,[21] among other composite properties.[17 23] Statistical-based extraction exploits the statistical significance of network edges and filtering them based on their p-values. These methods include, but are not limited to, filtering edges based on the spread of node connections across their neighbors,[24] filtering edges based on high correlation coefficient between the observed edge weight distribution and the hypothetical one,[31] filtering edges based on the probability of choosing an edge randomly with a weight equal to an observed weight,[8] or filtering edges based on the strength of the connected nodes forming the edges.[6] Hybrid extraction uses both structural and statistical techniques by first calculating the structural properties of network elements and then applying a statistical test on these properties to filter the elements.[33] The reader is referred to comprehensive works on the evaluation of such extracted networks.[5 32]
Although these methods can be interpreted in some special cases of road networks where resilience, connectivity, or vulnerability is sought, they fail to cater to some classical aspects of functional characteristics of a transportation network, such as traffic flow between origin-destination (OD) pairs, temporal travel patterns, user-choices on route and mode of travel, and stochasticity of link travel times and other routing attributes such as risk, safety, or security. These functional characteristics play a key role in transportation applications. In addition, the challenge of evaluating such extracted networks is still open for research. Some closely related works on improving traffic assignments in networks relied on network aggregation techniques. For instance, by transforming the regional network into a reduced form while incorporating virtual links to represent paths, efficient cost estimation methods can attain traffic assignment accuracy while achieving faster computation of equilibrium compared to the original network.[2] Similarly, preserving the functional relationship between traffic demand and the level of service during network transformation could bypass the re-evaluation of the equilibrium model.[4] Prominent examples of network extraction from satellite imageries are available in the literature.[1 10 15 16 18 30] These working examples serve a slightly different purpose of extraction, i.e., network retrieval rather than extraction of important subnetwork.

The present work demonstrates a methodology to extract a backbone of a road network based on potential flows given origin-destination (OD) flow matrix. The work is novel in its application to road freight transport.

3. Methodology and Application

The approach used to conduct this study includes two phases: methodology and its application.

3.1 Methodology

In a network with N nodes, the OD trip matrix is represented as an $N \times N$ matrix, where each element corresponds to the number of trips between a specific origin and destination pair. Modelling these trip counts is essential for analyzing travel demand patterns. Within a static assignment framework, assuming n freight OD matrices and m traffic assignment methods are available, where multiple OD matrices are used to better capture the variability and uncertainty in real-world freight flows. In practice, the true OD demand is often not precisely known and can vary due to factors such as daily fluctuations, seasonal patterns, or data collection limitations. Using multiple OD matrices allows for a more robust evaluation of traffic flow patterns and ensures that the analysis is not biased by relying on a single representation of demand. The following steps outline our proposed network extraction approach:

OD matrix assignment on original network

In this step, n available freight OD matrices are assigned to the network using m different assignment methods. This process yields $n \times m$ distinct sets of traffic volumes. In this study, the assignments are performed using PTV Visum to obtain the resulting flow patterns within the network.

Link removal

In this step, we extract a sub-network by removing links based on three predefined policies, applied to the $n \times m$ traffic volume sets obtained in the previous step. These policies determine whether a link is removed based on its usage across all assignment scenarios.

- Policy 1: A link is removed if any of the $n \times m$ truck traffic volume values is zero in either direction. In other words, if a link is unused in even one scenario, regardless of assignment method or OD matrix, it is excluded from the resulting network.
- Policy 2: A link is removed if all $n \times m$ truck traffic volume values are zero in both directions. This rule filters out links that are never used in all scenarios.
- Policy 3: A link is removed if all $n \times m$ truck traffic volume values are zero in either direction. This captures links that may be used in one direction but are unused in the opposite direction in all scenarios.

Each of these policies are applied individually, results in a distinct network configuration, yielding three possible sub-networks in total.

OD matrix assignment on extracted sub-networks

In this step, the same OD matrices used in the previous assignment phase are reassigned to each of the extracted networks. The resulting traffic volumes are then compared to those obtained from the original network. Each candidate network is assessed against the original network based on the performance metrics outlined in the results section.

Segment merging

After selecting the optimal network configuration, we apply an algorithm to merge roadway segments between intersections, further refining the network representation. This step improves manageability while ensuring that essential connectivity and traffic flow characteristics remain intact.

3.2 Application of the Methodology

Network Preparation

This study focuses on the primary and secondary class of highways in the rural highway network of the Prairie region. These corridors are critical to Canada's transportation infrastructure for facilitating the movement of goods and providing reliable connections to major border crossings and transport hubs. Figure 2 illustrates the highway network within the Prairie provinces, along with the centroid of Traffic Analysis Zones (TAZs) selected for analysis. The selection of TAZs is based on the available origin-destination datasets and underlying traffic conditions. The map was created using QGIS Version 3.28 and integrates three separate GIS files, which were merged to form a cohesive network. Although the GIS files used to create the map were pre-existing,[13] significant improvements were made to ensure network continuity and accuracy.

Figure 2. Highway network in the Prairie and TAZ centroids

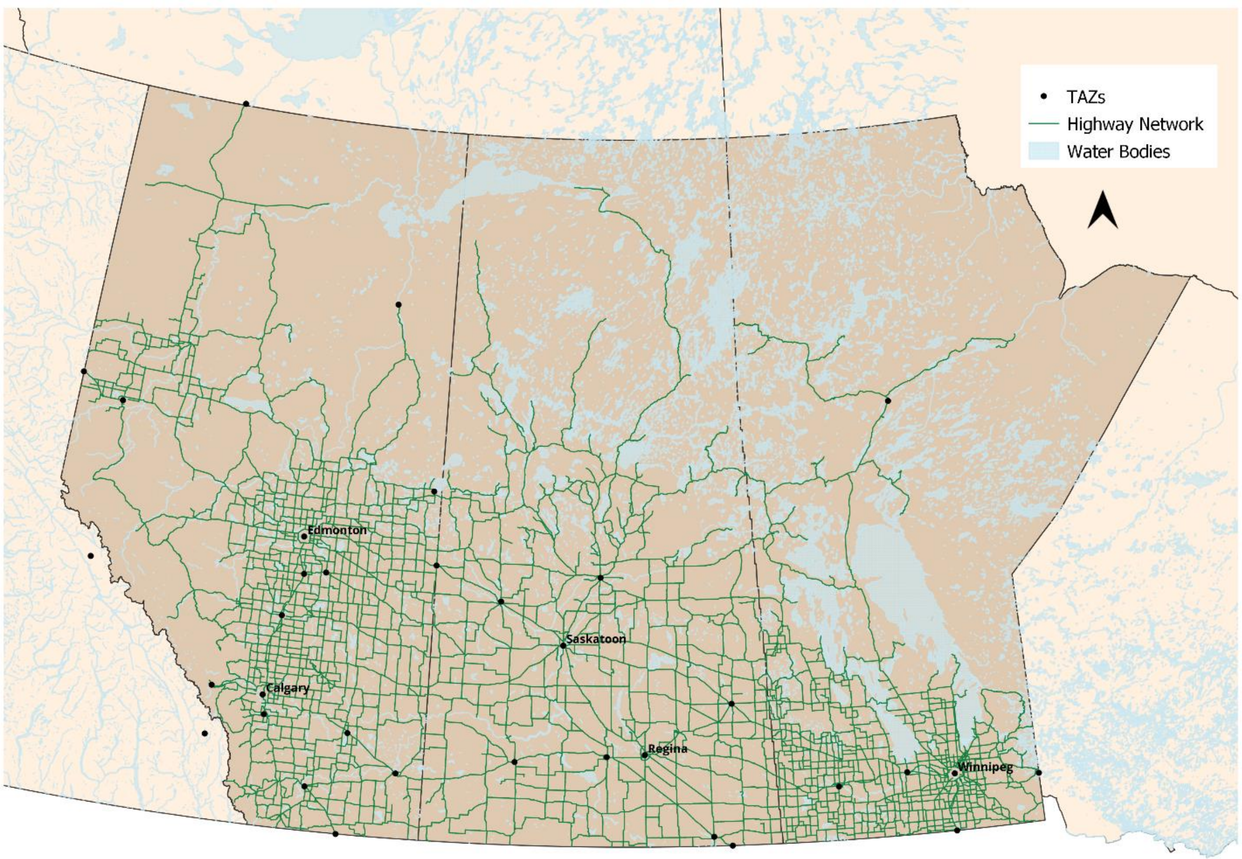


Table 1. Highway Segment Classifications

Type	Division	Number of Lanes	NHS	Speed(km/h)	Capacity(veh/h/lane)	Total Capacity(veh/h)
1	Undivided	1	No	90	1700	1700
2	Divided	2	No	90	2100	4200
3	Undivided	1	Yes	100	2300	2300
4	Divided	2	Yes	100	2300	4600

These GIS files lacked critical attributes such as the number of lanes, speed limits, and capacity, which are essential for network modeling in transport planning software. To address this limitation, we utilized the available division information, which indicates whether a road segment is divided or undivided. Based on empirical observations of multiple segments, we assumed that divided road segments have two lanes per direction, while undivided segments have one lane per direction. Speed limits were assigned based on whether a segment is part of the National Highway System (NHS), serving as the backbone for intraprovincial, interprovincial, and international trade and travel. NHS roads were assumed to have an average speed limit of 100 km/h, while non-NHS roads were assigned a speed limit of 90 km/h. Using these attributes, roadway capacities were estimated in accordance with the guidelines outlined in the Highway Capacity Manual.[22] As a result, the highway segments were classified into four distinct types, as summarized in Table 1. The GIS file is imported into PTV Visum, a professional transport planning software.[19] The network includes 6,350 unique links without considering direction, and 12,700 when direction is accounted for. Each TAZ centroid is subsequently connected to the nearest network link(s) based on its location, using one or more connectors. In total, the network includes 31 TAZ centroids and 108 connectors.

Data Preparation

The database used in our analysis is derived from the Canadian Freight Analysis Framework (CFAF), provided by Statistics Canada.[26] A key component of CFAF is the Trucking Commodity Origin and Destination Survey (TCOD), which Statistics Canada conducts to monitor commodity movements within the Canadian trucking industry.[27] By integrating TCOD data with other sources, CFAF offers a comprehensive overview of freight flows across the country. The dataset is disaggregated by geography, commodity, and mode of transport, including key metrics such as tonnage, value, tonne-kilometers, and shipment counts. The publicly available dataset covers annual freight flow data from 2011 to 2017 and primarily includes Census Metropolitan Areas (CMAs) across Canada. To support more accurate modeling of freight flows, Statistics Canada provided an updated, non-public dataset spanning 2011 to 2018 and featuring more detailed geographic coverage of the Canadian Prairie region. In addition to CMAs across Canada, this dataset includes information on freight movements for Census Agglomerations (CAs) within the Prairies. Given the focus of this study on the Prairie highway network, we specifically utilize data for Manitoba, Saskatchewan, and Alberta, along with relevant connections to neighboring provinces, Eastern Canada, and the United States.

We used the number of shipments as the metric for selected OD pairs and normalized the annual shipment counts by dividing them by 365 to obtain the average daily shipments for each calendar year. Given that the dataset spans eight years, we generated eight OD matrices, one for each year of available data. Since the number of shipments does not directly correspond to the number of truck trips, we refined these matrices using the TFlowFuzzy method in PTV Visum. By integrating actual link counts from the highway network in 2019,[13] we converted the shipment-based OD matrices into truck-based OD matrices, offering a more realistic representation of truck movements. It is worth noting that, as we rely on average annual demand aggregated over an 8-year period (2011–2018), no distinction is made between peak and off-peak periods, nor are seasonal variations explicitly modeled. This is primarily due to the lack of temporally disaggregated freight data in the Canadian context, especially for rural freight movements.

Implementation

In this step, we assign both the original and refined OD data from the previous step to the network simulated in Visum. The demand used for assignment is based on the average OD data over an 8-year period for both datasets. This results in two distinct average OD matrices: one representing the average of original data and the other reflecting the average of refined data. The assignment is performed using three methods: user equilibrium, incremental, and stochastic.

Incremental assignment was selected since these networks rarely experience heavy congestion, and the computational efficiency of this method remains reasonable for most scenarios. The User Equilibrium method was selected because it adheres to Wardrop's first principle, where drivers minimize their own travel times. This approach is widely adopted in transportation planning due to its realistic representation of driver behavior. However, to account for potential variations in driver behavior, such as differing perceptions of travel time or route preferences, Stochastic assignment was also applied. Together, these methods allow for a comprehensive evaluation of traffic distribution, addressing both idealized and imperfect decision-making scenarios. All tuning parameters are set to Visum's default values. Although the study incorporates demand-side calibration by refining shipment-based OD matrices and multiple assignment models to capture behavioral variability, the lack of explicit calibration of assignment parameters due to data limitations is acknowledged as a limitation and identified as a direction for future work.

We obtain six sets of traffic volume due to the combination of two different OD matrices and three distinct assignment methods. We then apply link removal policies 1, 2, and 3 separately to the six traffic volume sets, resulting in three distinct sub-networks. To identify the preferred sub-network, we assign the same two matrices to each sub-network and compare their performance against the original network.

4. Result

In this section, we analyze the results of the proposed approach and compare the three abstracted networks generated after link removal, as shown in Figure 3. The results indicate that policy 1 led to the highest number of links removed, policy 2 to the lowest, and policy 3 to an intermediate level. After link removal, the network under policy 1 has 2,189, policy 2 has 4,112, and policy 3 has 3,193 unique links out of the original 6,350.

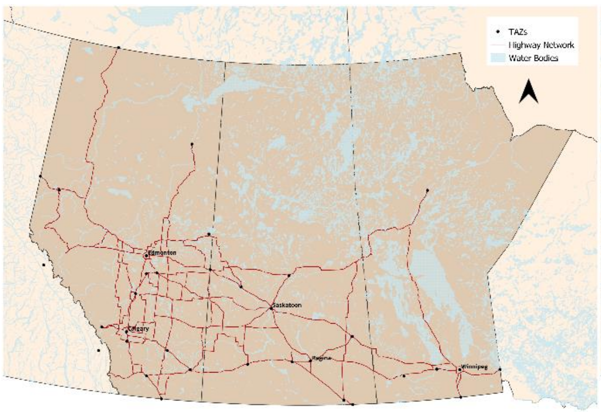
As outlined in section 3, the link volumes resulting from the matrix assignments are compared against those of the original network. Figure 4 compares the link volumes from the equilibrium assignment of the average refined OD matrix under policies 1, 2, and 3 against those of the original network. Similarly, Figures 5 and 6 present the corresponding results for the incremental and stochastic assignments, respectively. Table 2 summarizes and compares the link volume results using the following metrics:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE),
- MAE divided by the number of links in each abstracted network (MAE per link), and
- RMSE divided by the number of links in each abstracted network (RMSE per link)

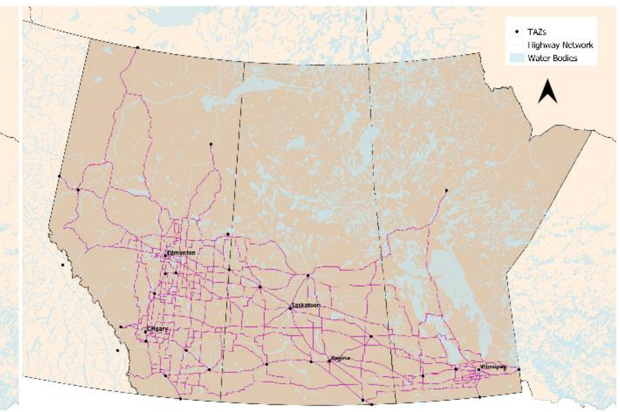
The results show that policy 1 achieved the highest error values, while policy 2 yielded the lowest. policy 3 produced intermediate results between the two. Although Policy 3 yields slightly higher error values than Policy 2, it operates on a smaller network (fewer total links), potentially making it more suitable for applications requiring network-wide assessment. The strategy for selecting the sub-network is based on multiple criteria, and additional factors can be incorporated depending on specific needs, potentially influencing the final outcome.

Figure 7 presents the graph (nodes and links) of the sub-network extracted using Policy 3, overlaid on the original network map. The nodes in this sub-network are associated with the GIS file and the segmentation system. These nodes are partly linked to lower hierarchical roads that are missing from the original file and partly consist of nodes that remained after the link removal step in the proposed methodology. Since no roads cross these nodes, the links connecting them can be merged to further simplify the network. This simplification enhances the manageability of the network, particularly during simulation. Figure 8 illustrates the sub-network before and after the link merging process.

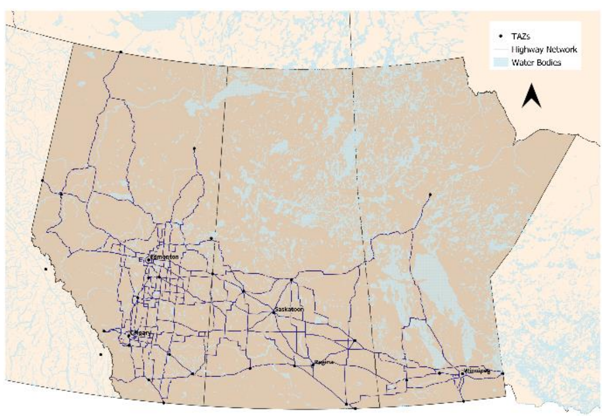
Figure 3. Extracted networks after different link removal policies



a) Abstracted network under policy 1

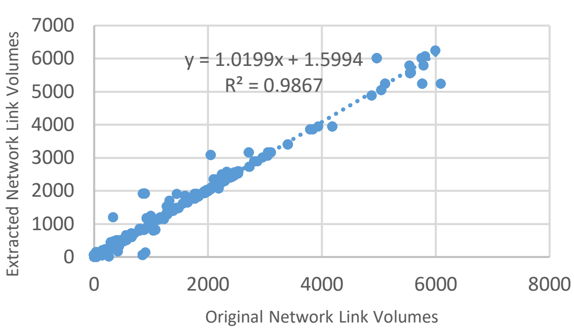


b) Abstracted network under policy 2

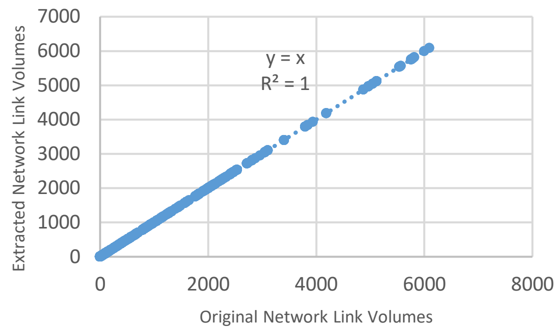


c) Abstracted network under policy 3

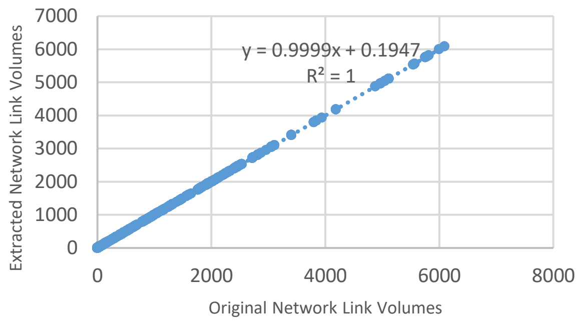
Figure 4. Link volumes from incremental assignment under the proposed policies vs. the original network



a) Policy 1

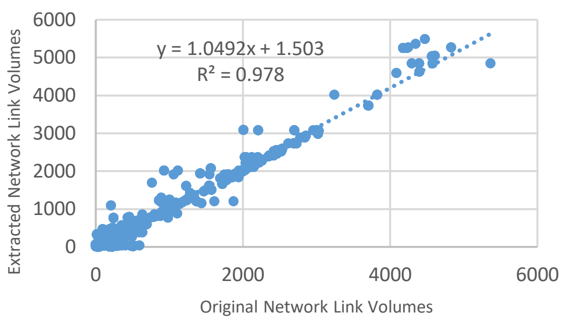


b) Policy 2

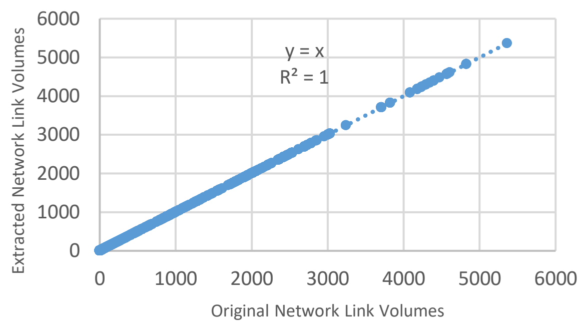


c) Policy 3

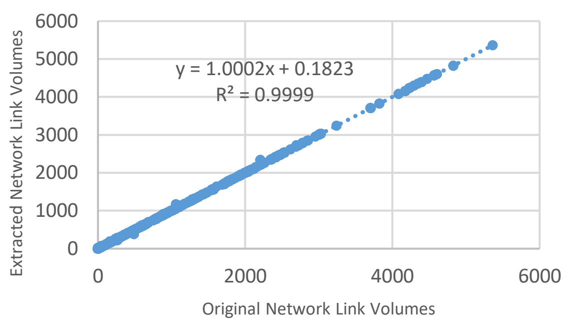
Figure 5. Link volumes from equilibrium assignment under the proposed policies vs. the original network



a) Policy 1

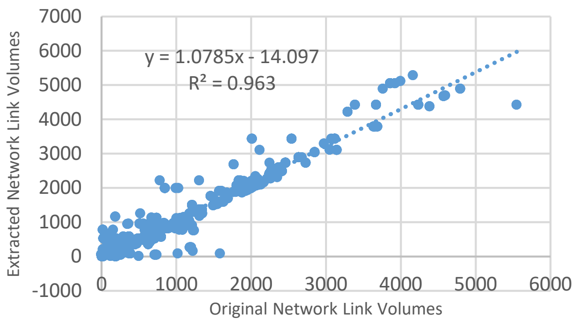


b) Policy 2

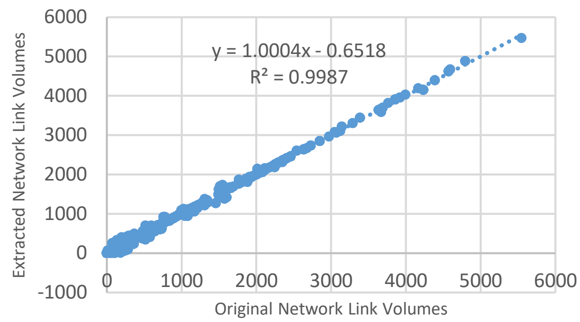


c) Policy 3

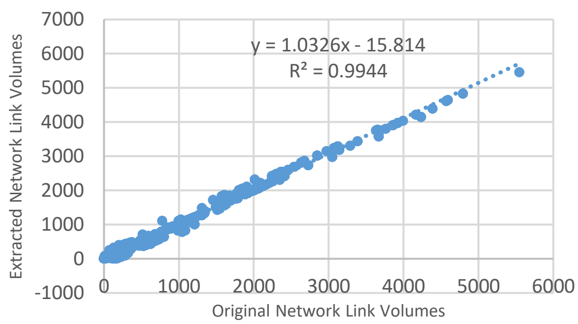
Figure 6. Link volumes from stochastic assignment under the proposed policies vs. the original network



a) Policy 1



b) Policy 2



c) Policy 3

Table 2. Link volume error between the original network and sub-networks across different traffic assignment methods

Assignment method	Approach	MAE	RMSE	MAE / No. links	RMSE / No. links
Incremental	Policy 1	43.4449	129.7677	0.0198	0.0593
	Policy 2	0.0000	0.0000	0.0000	0.0000
	Policy 3	0.3414	1.5188	0.0001	0.0005
Equilibrium	Policy 1	70.5304	167.9868	0.0322	0.0767
	Policy 2	0.0000	0.0000	0.0000	0.0000
	Policy 3	1.4579	6.8521	0.0004	0.0021
Stochastic	Policy 1	104.1868	217.2713	0.0476	0.0992
	Policy 2	7.8183	28.1871	0.0019	0.0068
	Policy 3	36.7717	72.3287	0.0115	0.0226

Figure 7. Sub-network extracted using Policy 3, visualized on top of the original network map

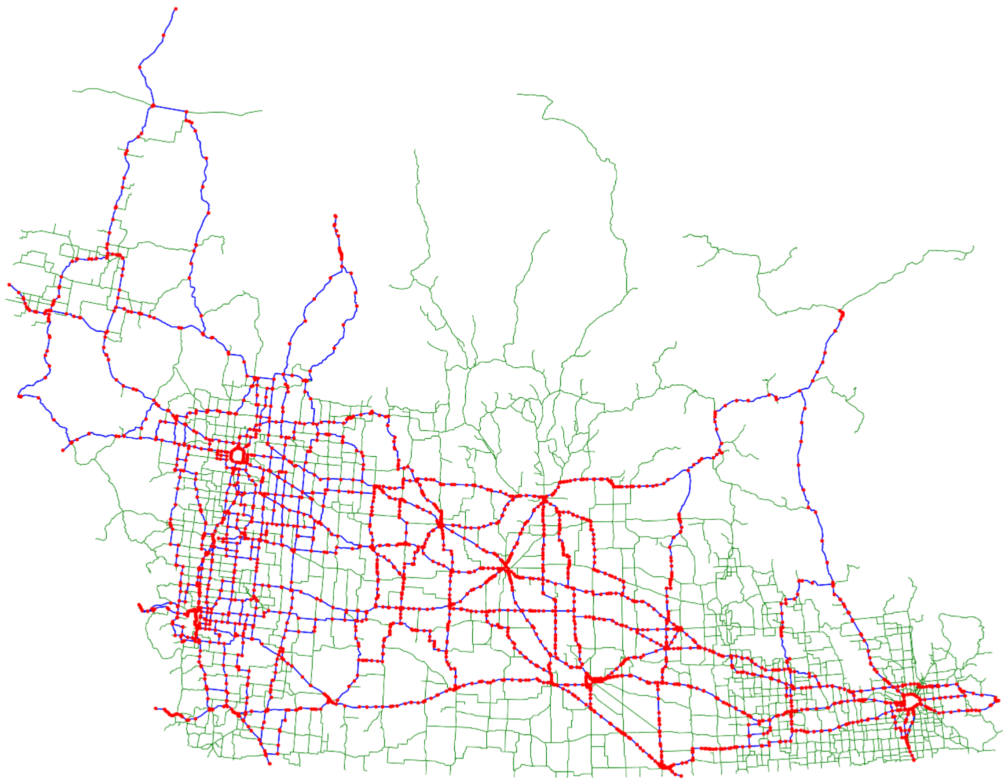
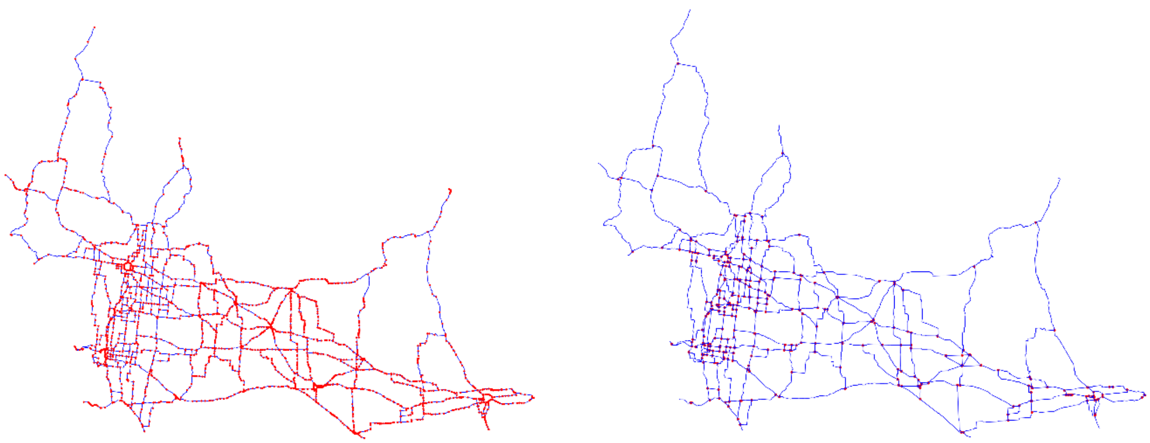


Figure 8. Sub-network visualized before and after merging the links



a) Sub-network before link merging

b) Sub-network after link merging

5. Conclusion

This study presents a practical and scalable methodology for extracting and simplifying freight road networks using multi-model traffic assignment and data-driven decision rules. Applied to the Prairie region of Canada, the proposed approach demonstrates its ability to significantly reduce network complexity while preserving essential structural and functional characteristics. A key strength of the method is its potential for full automation, allowing it to be efficiently deployed across broader regions and applications. By leveraging real-world freight flow data from the Canadian Freight Analysis Framework (CFAF), the method provides a unified and manageable network representation well-suited for simulation and strategic planning.

The resulting sub-network offers a robust foundation for diverse applications, including asset management, safety analysis, investment prioritization, and policy development. It could also be used to consider where upgrades to current highways might be worthwhile. Moreover, the flexibility of the methodology allows for adaptation to other transportation systems, such as passenger vehicle networks, and enables for future integration with emerging technologies, including AI-driven models for dynamic traffic prediction and infrastructure optimization.

Several limitations can be acknowledged. The use of existing TAZ data introduces biases in network selection, leading to discrepancies between the extracted network and established strategic network designations (e.g., RTAC, A1, B1). Specifically, some links are omitted despite their strategic importance, while others are included even though they are not part of the designated strategic networks. Although incorporating a greater number of TAZs may produce results more closely aligned with these strategic designations, the algorithmic method used here offers an alternative perspective—highlighting links that may warrant investment or upgrades from a resilience standpoint, as it relies on shortest path algorithms for assignment. Overall, the use of more refined TAZs, combined with validation against established strategic network designations using complementary metrics, is recommended. The results could also be refined by incorporating more accurate speed limit representations, road hierarchy, and integration of load classification.

The current methodology is designed as a one-time simplification process, but its automation and modular design make it well-suited for iterative use. Future research could formalize an iterative workflow where extracted networks are refined and validated using complementary inputs, such as expert judgment, policy feedback, real-time data, or comparison against established strategic networks. This iterative framework would enhance the method's applicability in dynamic planning environments and support ongoing certification or updating of freight corridor priorities. In addition, a promising direction for future research is the integration of freight value into the modeling framework. While the current study is trip-based (focusing on shipments and truck volumes), incorporating commodity value from CFAF could enhance the model's utility for agencies aiming to prioritize corridors not just by traffic volume but also by economic significance.

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