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Accessibility Measures in Modal Choice Models: A Proof of Concept Applied to Freight Transport

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Abstract

Modal choice models applied to interregional or international freight transportation network models are often based on rather coarse origin-destination matrices, containing annual transported tonnages between (sub)regions, for instance. Generally, only basic (sometimes constructed) independent variables (transportation costs or transit times) are used because other variables such as shipment sizes, service frequencies, etc. are not available. Using origin-destination matrices and an assignment model, it is also possible to compute spatial accessibility measures that can further be used as additional explanatory variables. Indeed, several published studies have identified network accessibility as an important element in the mode-choice decision. This paper also shows that the inclusion of an accessibility measure in the utility functions of a logit model substantially improves the performance of a transportation network model, both in the modal choice and the assignment levels of the classical four-step model. Consequently, the assignment of the estimated modal demands results in more accurate estimated traffic on the networks. The model presented in this paper is to be considered as a proof of concept because its workflow should further be streamlined to make it easily useable by modelers.

Keywords

Freight Transport Model, Modal Choice, Accessibility, Assignment

1. Introduction

In the framework of this paper, we are interested in the last two steps of the classical four-stage transport model: modal choice and assignment. Origin-destination (OD) matrices are thus given and used as input for the modal choice model. The specification of the latest, its performance and the measure of its impact on the assignment model are the core topics covered in this paper.

Modal choice models are mostly based on discrete choice theory and, more specifically, on the family of logit models. Stated or revealed preference (SP/RP) data can be used as input for the modal choice model, but not all modal choice models are based on SP/RP data. When applied to interregional or international areas, for example, aggregated demand data, *i.e.*, OD matrices containing annual transported tonnages between the region's centroids for instance, are most often used. Moreover, only basic (and sometimes constructed) independent variables (fares, costs or transit time) are used to explain the modal choice. Information about other variables that might have an impact on the mode choice decision, such as shipment sizes and service frequency, is generally lacking.

The model presented in this paper belongs to this category, in which one also finds [1] [2]. In the first paper, fares and transit time are used as explanatory variables. To avoid multicollinearity (the explanatory variables are highly correlated), the authors applied a Box-Cox transform to the independent variables. In the second paper, the authors use a weighted logit mode-choice model in which "representative agents"[1] are weighted accordingly to their annual transported tonnages. Later, a weighted logit mode-choice model with Box-Cox transformation of the independent variables (transportation costs and transit times) was proposed in [3], combining the approaches of [1] and [2]. This model covers three modes: road, inland waterway (IWW) and rail transport. The model presented in this paper extends this work, including an accessibility measure as an additional variable.

Indeed, in-depth surveys carried out with shippers, carriers and receivers have concluded that network accessibility plays an important role [4] [5] [6] in mode choice. The large ECHO survey conducted in France [7] indicated that more than 30% of shippers consider network accessibility as a criterion for their modal choice. Improved accessibility and connectivity through the establishment of freight corridors are also considered a vector of economic growth [8].

While accessibility is often cited as an important variable in freight mode choice decisions, econometric models that include this variable are rare. An interesting example is the behavioral analysis proposed in [9]. Beside the transportation cost, the trip length, the weight of the commodities and their value, this model integrates the access to road-rail intermodal facilities. However, accessibility is described in this paper as a level of ease to access facilities (easy, neutral or difficult), which is a restrictive definition. Other papers (see the review in [4]) have also defined accessibility relative to the possibility of reaching an intermodal terminal. Finally, accessibility is sometimes defined as the possibility of reaching a destination with a given transportation mode [10]. If the modal choice model is part of a transport network model, which is the case of the work presented in this paper, this type of accessibility is captured by the assignment step, as a modal route cannot always be found between all OD pairs.

[1]A combination of OD pairs and commodity groups.

This is, for example, often the case for IWW transport.

Accessibility can also be defined from a spatial perspective as a measure of the capacity of a location to be reached from different locations [11]. Similarly, it can also be defined from an origin node perspective to measure the capacity to reach different destinations. Therefore, the topology of the transport networks is an important component in the determination of this type of accessibility.

Reference [12] shows that the accessibility of a location by different transportation modes influences manufacturing output and thus the demand for transport. More generally, some authors claim that "despite the importance of factors such as barriers and factor costs, accessibility remains the key linking pin between logistics and the spatial economy" [13]. They considered that the total logistics costs should include an accessibility measure to be able to describe the spatial restructuring effects of logistics trends. Other also conclude that "among the multiple factors that affect the choice of destination, aspects such as accessibility, land use, infrastructure availability and other external features of the surroundings suggest the existence of spatial interactions between the available alternatives to the shipper" [14].

There are thus enough indications that accessibility, in its spatial dimension, could have a significant impact on modal choice and that it is worth testing a model that explicitly includes some spatial accessibility measure, which is the objective of this paper.

Some attempts to incorporate a spatial dimension in a destination choice model can be found in the literature [15] [16]. Spatial metrics are for instance used to compute travel times by car in the area of Antwerp (Belgium) [16]. However, to the best of our knowledge, nothing has been published on the inclusion of such a spatial dimension in the modal choice models for freight transport using multivariate utility functions.

In this paper, the computation of a relevant accessibility measure is presented, and its possible correlation with cost and transit time is examined. Several utility functions including accessibility measures are presented, among which the one giving the best results is retained.

As the modal choice model is intended to be used in a freight transport network model, its output is used as input for an assignment. The performances of the modal choice and assignment models (with and without the accessibility measure) are compared.

The methodological aspects of the model are introduced in Section 2, while Section 3 describes the dataset used for the case study. The results and the model performance are examined in Section 4.

Note that this research was conducted using exclusively publicly available data and open-source software.

2. Methodological Discussion

Logistic modeling is the most used method to predict the choice of a transportation mode. As a reminder, the general logit formula can be written as

$$P_m = \frac{e^{U_m}}{\sum_{k=1}^{M} e^{U_k}} \tag{1}$$

where:

M: Total number of alternative modes

P_m: Probability of choosing mode m

U_m: Utility of mode m

U_k: Utility of mode k within the set of M alternatives

First, a simple model is set up, in which the utility function contains only transportation costs C and transit times T. One could argue that the transport duration is already included in the transportation cost through some time-dependent components (staff salary costs, etc.). However, like [1] [2] we decided to keep C and T as two separated variables to capture the value of the goods during transport, knowing that the value of time is much higher than the opportunity costs [17] [18]. Moreover, the impact of time savings has some importance for policy-makers. Keeping both transportation costs and transit times as separate independent variables makes thus sense. The utility function for this first model can be written as

$$U_m = \alpha C_m + \beta_m T_m + \delta_m \tag{2}$$

where:

C_m = Transportation cost for mode m

T_m = Transit time for mode m

α, β_m, δ_m: Parameters to estimate

In this specification, α is not mode specific, as it does not make sense from an economic theory perspective (it would make welfare analysis difficult). For transit times, β_m is mode specific to obtain mode-specific values of time. It is expected that the α and β_m coefficients have a negative sign because a higher cost or transit time makes a mode less attractive. Finally, δ_m are the modal specific intercepts.

Finally, as the transport demand is embedded in origin-destination (OD) matrices containing aggregated data (of the total annual transported quantities, for instance), a weighted logit is used [2] [3].

The subsequent models include one or two accessibility measure(s) in the utility function. As explained in the introduction, the accessibility of a node can be defined as the accessibility from this node to all the other nodes or to this node for commodities coming from other places in the network. As it is not immediately clear which measure is the most relevant for freight transport, three specifications are tested:

$$U_m = \alpha C_m + \beta_m T_m + \sigma_m A_m^d + \delta_m \tag{3}$$

$$U_m = \alpha C_m + \beta_m T_m + \tau_m A_m^o + \delta_m \tag{4}$$

$$U_m = \alpha C_m + \beta_m T_m + \sigma_m A_m^d + \delta_m + \tau_m A_m^o \tag{5}$$

where:

A_m^d : Capacity of a location d to be reached from others, using mode m (see 2.2)

A_m^o : Capacity of a location o to reach other locations, using mode m

σ_m, τ_m: Parameters to estimate

The accessibilities A_m^d and A_m^o are specific to each location and each mode. Therefore, the mode-specific σ_m and/or τ_m are estimated.

These models are rather simple and presented here in an Occam's razor spirit. Special attention must, however, be paid to the correlation between C_m and T_m (multicollinearity) and to the definition of the accessibility measure. Both aspects are discussed in the next subsections.

2.1. Handling Multicollinearity

Transportation costs and transit times are most often correlated, which is problematic as the estimators may have a weak statistical power [19] [20]. They may also have unexpected signs. For instance, an estimator with a positive value for the transportation cost by truck would signify that the probability of using trucks increases with their operational costs, which is not what is expected.

Some methods can help to control multicollinearity [19] [21]. In many cases, a simple log transformation of the explanatory variables can solve the problem, but it does not always succeed, which is, for instance, the case with the dataset used in the case study presented in this paper. Therefore, we decided to apply a Box-Cox transformation [22] of the explanatory variables (Equation (6)) as this method is sometimes used to re-establish the presumed signs of the estimators [23] [24].

$$BC(x,\lambda)=\begin{cases}\dfrac{x^{\lambda}-1}{\lambda}, & \text{if } \lambda\neq 0\\ \ln(x), & \text{if } \lambda=0\end{cases} \tag{6}$$

By "bending" the functional form, the used value for λ offers a significant flexibility, providing more degrees of freedom to the modeler: values of $\lambda < 1$ produce convex curves, while $\lambda > 1$ results in a concave inflection. As a result, appropriate "bendings" of the independent variables can reduce multicollinearity. To include the Box-Cox transforms of C and T, the utility functions of the models presented in Equations (2) to (5) can thus be rewritten[2]:

$$U_m=\alpha\left(\frac{C_m^{\lambda_c}-1}{\lambda_c}\right)+\beta_m\left(\frac{T_m^{\lambda_t}-1}{\lambda_t}\right)+\delta_m \tag{7}$$

$$U_m=\alpha\left(\frac{C_m^{\lambda_c}-1}{\lambda_c}\right)+\beta_m\left(\frac{T_m^{\lambda_t}-1}{\lambda_t}\right)+\sigma_m A_m^d+\delta_m \tag{8}$$

$$U_m=\alpha\left(\frac{C_m^{\lambda_c}-1}{\lambda_c}\right)+\beta_m\left(\frac{T_m^{\lambda_t}-1}{\lambda_t}\right)+\tau_m A_m^o+\delta_m \tag{9}$$

[2]Obviously, as specified in Equation (6), ln(Cm) or ln(Tm) is used if λ_c or $\lambda_t = 0$.

$$U_m = \alpha\left(\frac{C_m^{\lambda_c}-1}{\lambda_c}\right)+\beta_m\left(\frac{T_m^{\lambda_t}-1}{\lambda_t}\right)+\sigma_m A_m^d+\tau_m A_m^o+\delta_m \quad (10)$$

where λ_c and λ_t are the Box-Cox parameters to estimate.

2.2. Computing the Accessibility Measure

The computation of an appropriate accessibility index merits some attention. Much has been written about accessibility measures and their ability to evaluate the accessibility impacts of national land-use and transport scenarios, including the related social and economic impacts. It goes beyond the scope of this paper to present an extensive literature review on this topic. The interested reader will find a review in [25] for instance. Most publications deal with passenger transport and are often limited to urban areas. Even if a very simple accessibility measure such as the number of centroids that can be reached by each mode from a given origin can be used [26], the General Accessibility Measure [27] [28] [29] is often applied. It represents the degree of interconnection between a particular reference location and all or a set of other locations in the area [30] [31]. The General Accessibility Measure can be defined from an origin (Equation (11)) or a destination (Equation 12)) perspective:

$$A_m^d = \sum_o w^o f\left(L^{od}\right) \quad (11)$$

$$A_m^o = \sum_d w^d f\left(L^{od}\right) \quad (12)$$

where:

A_m^d : Capacity of a node d to be reached from other nodes by mode m

A_m^o : Capacity a node o to reach other nodes by mode m

w^d: Weight representing the attractiveness of destination d

w^o: Weight representing the attractiveness of origin o

L^{od}: Measure of separation (trip length) between o and d

$f(\ldots)$: Decay function

The value of these accessibility measures directly depends on the weight w^d (transported quantities to destination d) or w^o (transported tonnages coming from o) and on the trip length between the nodes. As a weighted logit is implemented, a relative accessibility index [30] is used to avoid a "double counting" of the weights. The relative accessibility indexes can be written as

$$\Lambda_m^d = \frac{\sum_o w^o f\left(L^{od}\right)}{n\sum_o w^o} \quad (13)$$

$$\Lambda_m^o = \frac{\sum_d w^d f\left(L^{od}\right)}{n\sum_d w^d} \quad (14)$$

where n is the number of centroids in the origin-destination matrix. Therefore, the utility functions presented in Equations (8) to (10) become

$$U_m = \alpha\left(\frac{C_m^{\lambda_c}-1}{\lambda_c}\right)+\beta_m\left(\frac{T_m^{\lambda_t}-1}{\lambda_t}\right)+\sigma_m \Lambda_m^d+\delta_m \quad (15)$$

$$U_m = \alpha\left(\frac{C_m^{\lambda_c}-1}{\lambda_c}\right)+\beta_m\left(\frac{T_m^{\lambda_t}-1}{\lambda_t}\right)+\tau_m\Lambda_m^o+\delta_m \tag{16}$$

$$U_m = \alpha\left(\frac{C_m^{\lambda_c}-1}{\lambda_c}\right)+\beta_m\left(\frac{T_m^{\lambda_t}-1}{\lambda_t}\right)+\sigma_m\Lambda_m^d+\tau_m\Lambda_m^o+\delta_m \tag{17}$$

Most authors use the negative exponential form represented by Equation (19) as a decay function, as it is considered to be closely tied to travel behavior [30], [32]. This choice is, however, seldom challenged or even discussed.

Therefore, the five functional forms presented in [31] and illustrated in **Figure 1** are tested in Section 4.2:

I) Power:

$$f\left(L^{od}\right)=\left(L^{od}\right)^{-\gamma_1} \tag{18}$$

II) Exponential:

$$f\left(L^{od}\right)=\mathrm{e}^{-\gamma_2 L^{od}} \tag{19}$$

III) Log-normal:

$$f\left(L^{od}\right)=\mathrm{e}^{-\gamma_3\left(\log\left(L^{od}\right)\right)^2} \tag{20}$$

IV) Exponential normal:

$$f\left(L^{od}\right)=\mathrm{e}^{-\gamma_4\left(L^{od}\right)^2} \tag{21}$$

VI) Exponential square root:

$$f\left(L^{od}\right)=\mathrm{e}^{-\gamma_5\sqrt{L^{od}}} \tag{22}$$

In these equations, γ_1, γ_2, γ_3, γ_4 and γ_5 are the parameters to estimate.

Finally, if multicollinearity is undoubtedly a problem that must be tackled for C and T, one could argue that the same problem occurs between the relative accessibility measure Λ^o or Λ^d and C and T because these measures are computed using L, which is, by nature, also strongly correlated with C and T. However, the value of L is diluted in the decay function, while w^d or w^o plays a preponderant role. Using the dataset presented in Section 3, the correlation between the computed relative accessibility measures and C or T varies between 0.02 and 0.2, depending on the transportation mode and the type of commodities. The relative accessibility measures are thus not correlated with the two other independent variables.

3. Dataset Description

The dataset used for the case presented in this paper is gathered from the ETIS-Plus European FP7 Research Program [33]. Combining data, analytical modeling with maps and an online interface for accessing the data, it provides an information system useful for assessing European transport policies. Public access to several deliverables and many data is provided, including origin-destination matrices and digitized transportation networks. Unfortunately, contrary to what was initially announced, the data have never been updated.

The OD matrices for 2010 at the NUTS-2 regional level are used. They are available for road, railway, and inland waterway transport, with annual volumes (tonnages) for 10 groups of commodities (NST/R Chapters 0 to 9, Table 1). In this paper, a subset of the OD matrices is used, focused on continental European transport. It includes the countries belonging to the European Union (EU) or to the European Economic Association (EEA), apart from islands and very peripheral zones within some countries. The retained regions, with their centroid, are represented in Figure 2.

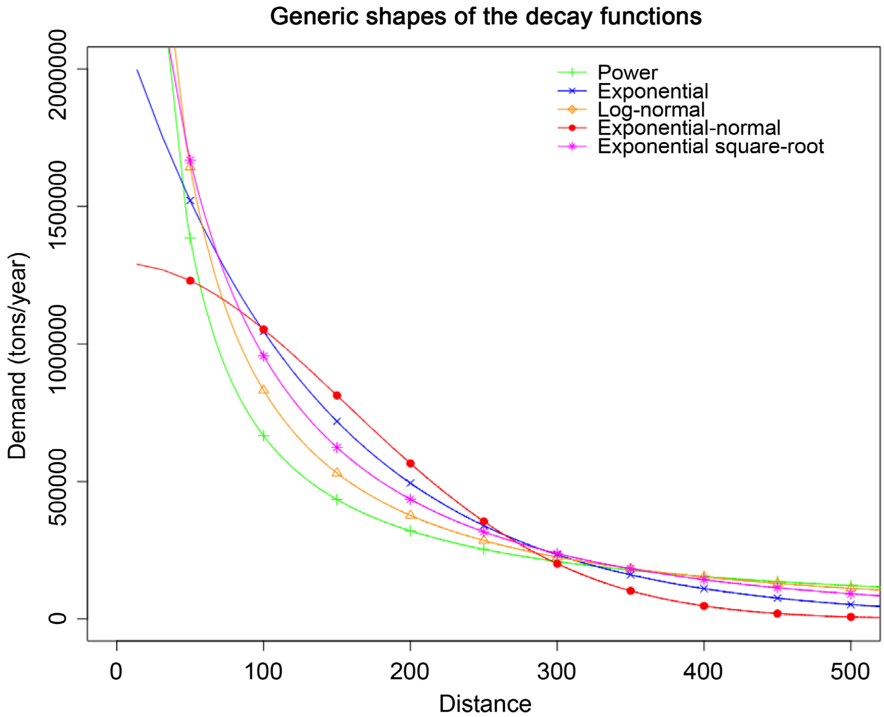

Figure 1. Shapes of the tested decay functions.

Table 1. Description of the NST/R groups of commodities.

NST/R	Description
0	Agricultural products and live animals
1	Foodstuffs and animal fodder
2	Solid mineral fuels
3	Petroleum products
4	Ores and metal waste
5	Metal products
6	Crude and manufactured minerals, building materials
7	Fertilizers
8	Chemicals
9	Machinery, transport equipment, manufactured articles and miscellaneous articles

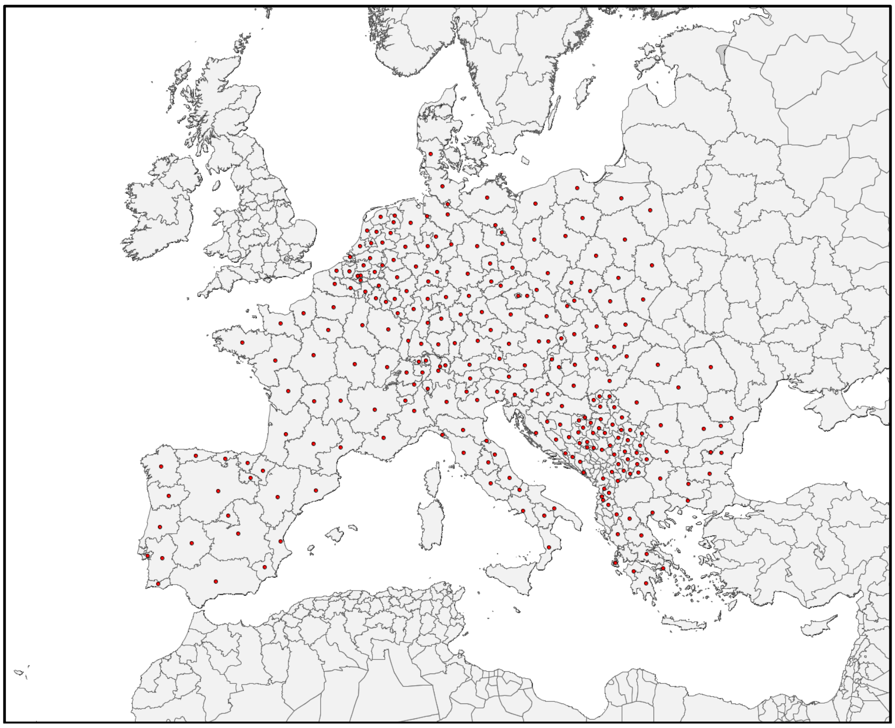

Figure 2. NUTS2 regions and retained centroids for the case study.

As shown in Table 2, the datasets corresponding to the different groups of commodities are quite different in size (number of non-null OD cells), volume (million tons/year) and modal split (market shares). The modal choice models presented in Section 2 are solved for each group of commodities separately, as different coefficients can be expected for different commodities. This is also useful to test the robustness of the model on different datasets.

In addition to the OD matrices, digitized networks are available in the ESRI shapefile format. Even if the downloaded files can be visualized directly in GIS software, the ETISPlus networks cannot be used for assignments. They are indeed not conceived for this, and some important manipulations are needed to make them "assignment compatible" [34]. The resulting networks contain more than 58,000 road links, 1600 inland waterway (IWW) links and 10,000 railroad links.

4. Application and Model Performance

The methodology outlined in Section 2 is applied to the dataset described in Section 3, following the workflow illustrated in Figure 3. The digitized networks, the modal OD matrices and the transportation cost functions (Section 4.1) are used as input for a first assignment using the Nodus [35] open-source transportation network modeling software especially designed for multimodal and intermodal freight transport. This allows retrieving, for each OD cell and each mode, the transportation cost, the transit time and the length of the trip. The latest is further used as input to compute the accessibility measures. Furthermore, for

Table 2. Content of the OD matrices.

	OD cells			Volumes (10^6 t)			Market shares (% of tons)		
NST-R	Road	IWW	Rail	Road	IWW	Rail	Road	IWW	Rail
0	40,619	1137	3771	361.6	24.2	34.2	86.1%	5.8%	8.1%
1	40,042	1151	1532	478.1	25.7	9.3	93.2%	5.0%	1.8%
2	19,761	559	4115	47.5	37.2	158.4	19.5%	15.3%	65.2%
3	27,137	664	4199	190.1	67.0	26.5	67.0%	23.6%	9.3%
4	27,596	977	5816	569.0	31.7	72.9	84.5%	4.7%	10.8%
5	36,317	677	5377	189.4	11.7	43.5	77.4%	4.8%	17.8%
6	36,771	1356	5714	1059.5	111.3	179.3	78.5%	8.2%	13.3%
7	27,136	738	5392	43.0	5.8	76.8	34.2%	4.6%	61.2%
8	39,834	1072	5493	302.0	37.0	38.8	79.9%	9.8%	10.3%
9	44,408	1075	5846	1030.5	66.7	93.5	86.5%	5.6%	7.8%

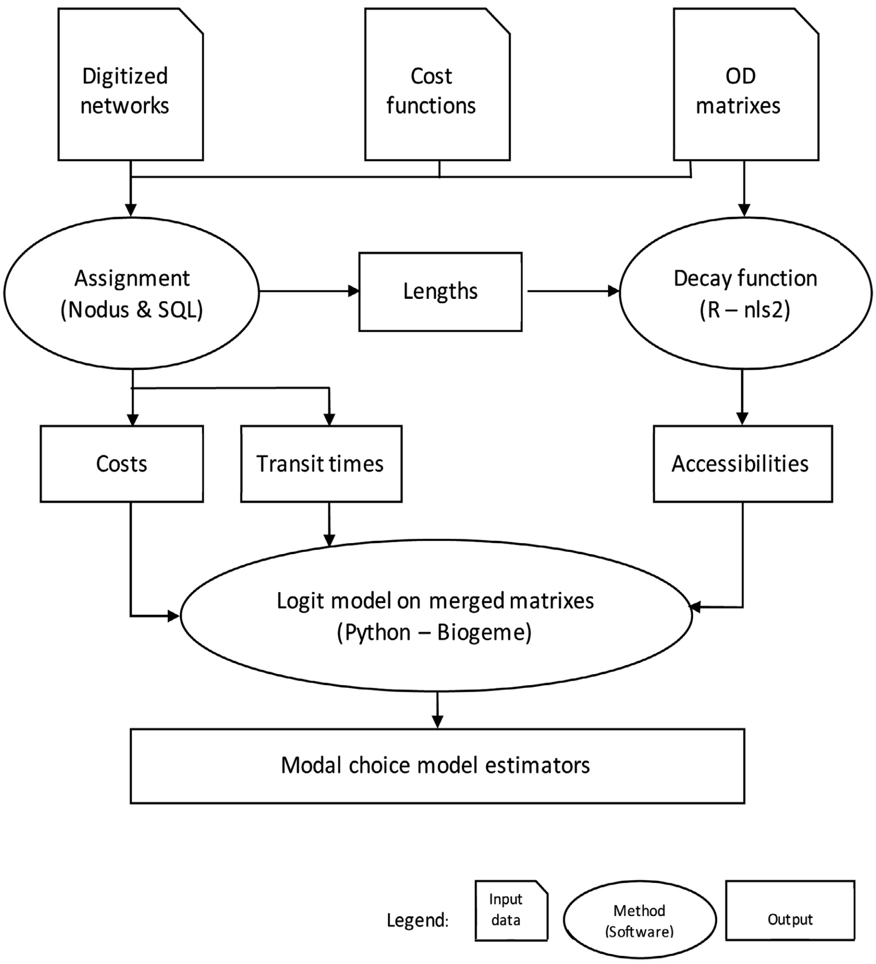

Figure 3. Model workflow.

each group of commodities, the modal matrices are combined, and the modal choice models are applied to the merged matrices.

Note that some nodes do not have rail or IWW access and that no modal route can therefore be found. Those cases correspond to a nonexistent cell in the modal OD matrix and can be properly handled by the Biogeme software package [36] used to estimate the logit models (Section 4.3). This also has an impact on the accessibility measures Λ_m^o and Λ_m^d (Equations (13) and (14)). Indeed, the numerator is computed using only the OD relations for which a route exists, and the denominator uses a fixed number of nodes *n* (the number of centroids in the area). As a result, the accessibility of a node decreases with the difference between *n* and the number of nodes taken into account in the numerator, which is an expected result.

The workflow presented in **Figure 3** is rather complex and relies on several tools and programing languages. Therefore, the model must still be considered as a proof of concept that must further be streamlined. Ideally, only one tool should be used, and the model should be able to estimate the parameters of the decay function along with the other estimators. This work must still be done.

4.1. Computation of Costs and Transit Times

The OD matrices and the transportation networks are imported in Nodus [35] to compute the values of the explanatory variables needed for the modal choice models. The software allows retrieving, for each OD pair, each mode *m* and each group of commodities *g*, the total cost of transport C_m^g, the total transit time T_m^g and the trip length L_m^g. The explanatory variables are thus constructed variables retrieved from the results of an assignment of each modal OD matrix on its corresponding digitized transportation network.

The total cost C_m^g of a route between an origin and a destination for a vehicle of mode *m* transporting commodities of type *g* is equal to

$$C_m^g = ld\_cost_m^g + ul\_cost_m^g + \sum_l^R mv\_cost_{l,m}^g \tag{23}$$

where:

ld_cost: loading cost

ul_cost: unloading cost

mv_cost: moving cost

R: the set of successive links representing the route

The loading and unloading costs are fixed costs, although they vary with the mode and the transported goods. The transshipment costs associated with intermodal transport chains are not explicitly modeled in this paper. The loading factors of the vehicles are taken from the ECCONET research project [37]. They are exogenous but specific for each group of commodities and type of vehicle (trucks, trains or barges) included in the model. The traveling unit cost, or moving cost, *mv_cost*, depends on the length and on the average commercial speed for the considered mode. It considers all the carrier's costs during transport: labor, capital invested in vehicles, fuel, maintenance, insurance, services directly linked to a transport, plus all residual indirect costs such as those of administrative services. A given link *l* belonging to a network of mode *m* is computed as

$$mv\_cost_{l,m}^{g} = \frac{Average\ speed_m}{Speed_{l,m}} * length_l * unitmv\_cost_m^g \tag{24}$$

As the unit *mv_cost* also contains time-related costs, the *average speed/speed* ratio allows for considering higher/lower costs than average costs on slower/faster segments of the network. $Average\ Speed_m$ represents the average speed for mode *m* on the transportation network, and $Speed_{l,m}$ is the average speed on link *l*.

Similarly, the total transit time T_m^g has fixed elements (the loading and unloading durations (*ld_duration* and *ul_duration*)) and a variable part (the travel duration that depends on length and speed on the successive links along the route). Thus,

$$T_m^g = ld\_duration_m^g + ul\_duration_m^g + \sum_{l}^{R} mv\_duration_{l,m} \tag{25}$$

With

$$mv\_duration_{l,m} = length_l / speed_{l,m} \tag{26}$$

4.2. Choice of a Decay Function

The γ_x parameters of Equations (18) to (22) are estimated using the R "nls2" package [38], which determines the nonlinear least square estimates of the parameters of a nonlinear model. The five decay functions are estimated for the three transportation modes and the ten groups of commodities listed in **Table 1**. As shown in **Figure 1**, and unlike the other formulations, the exponential normal decay function has an S-shape. This is probably why it was considered the less efficient decay function in [31]. The conclusion drawn by the authors could be explained by the fact that they used the R^2 values of the models to compare the performances of the different functional forms. However, R^2 is known not to be an appropriate performance measure for nonlinear functions [39] [40]. Indeed, the following problems occur:

- R^2 is consistently high for both excellent and appalling models.
- R^2 will not always increase for better models.
- If R^2 is used to pick the best model, it leads to the proper model only 28% - 43% of the time [40].

Therefore, another measure, such as the residual standard error, must be used instead. **Table 3** compares the relative residual standard error ($RSE_{model}/RSE_{best\ model}$) of each specification (I-V, as given by Equations (18) to (22)). It appears that the differences between the specifications are limited but that the exponential normal decay function (IV, Equation (21)) always performs best for road transport. For the other two modes, no decay function clearly outperforms the others.

Table 3. Relative residual standard error for the 5 decay functions (per mode and NST/R).

	Road					IWW					Rail				
NST/R	I	II	III	IV	V	I	II	III	IV	V	I	II	III	IV	V
0	1.04	1.01	1.03	1.00	1.01	1.00	1.00	1.00	1.01	1.00	1.00	1.01	1.00	1.01	1.00
1	1.05	1.01	1.03	1.00	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	1.02	1.01	1.02	1.00	1.01	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00
3	1.03	1.00	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4	1.04	1.01	1.03	1.00	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
5	1.02	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.01	1.00
6	1.04	1.01	1.03	1.00	1.02	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
7	1.02	1.01	1.02	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00
8	1.05	1.01	1.03	1.00	1.02	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00
9	1.04	1.01	1.03	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00

Altogether, the exponential normal formulation will be used in this paper to compute the relative accessibility measures Λ_m^d and Λ_m^o.

4.3. Logit Model Estimation

Now that all the explanatory variables can be computed, the modal choice models can be estimated. Among the three utility functions (Equations (15) to (17)), the one that includes both accessibility measures performs best, indicating that accessibility to the customers from a location and accessibility to the suppliers (sourcing choice) appear to be relevant for the modal choice. Therefore, only the model with both accessibilities is further used and discussed.

Table 4 presents the estimators for the model without accessibility (Equation (7)), while Table 5 contains those of the model with both accessibility measures (Equation (17)). The parameters are estimated using Biogeme [35], an open-source Python package designed for the maximum likelihood estimation of parametric models in general, with a special emphasis on discrete choice models. The following constraints are imposed on the models:

- α and β_m must be negative (see Section 2).
- Λ_m^d and Λ_m^o must be positive, as better modal accessibility is also supposed to make a mode more attractive.

With a confidence level of 0.05, all the estimators are significant except τ_{road} for NST/R 0 (agricultural products and live animals) and α for NSTR/5 (metal products) in the model with accessibility measures (Table 5).

The Box-Cox parameters λ_c and λ_t for both models are lower than 1 for all groups of commodities, meaning that the negative effect of a cost increase or a longer transit time is marginally decreasing.

In most cases, σ_{mode} is lower than τ_{mode}, indicating that the capacity of a node

Table 4. Estimated parameters for the model without accessibility measure.

Estimators		α	β_{road}	β_{iww}	β_{rail}	δ_{iww}	δ_{rail}	λ_c	λ_t
NST/R									
0	Value	−9.71	−1.42	−0.28	−2.99	−1.02	32.77	−6.32	0.51
	t test	−86.03	−38.31	−16.49	−20.34	−13.23	46.83		
1	Value	−0.29	−2.46	−2.93	−19.15	5.59	69.43	0.54	0.01
	t test	−8.22	−15.19	−5.12	−5.84	5.06	11.56		
2	Value	−2.01	−0.74	−0.06	−0.76	−1.18	32.37	0.00	0.96
	t test	−21.86	−16.35	−7.60	−8.91	−6.19	22.63		
3	Value	−0.30	−1.72	−1.82	−3.91	3.15	10.46	0.59	0.00
	t test	−13.25	−18.33	−29.39	−7.86	16.66	5.55		
4	Value	−60.03	−4.01	−1.65	−9.84	−0.94	40.95	−1.75	0.12
	t test	−11.23	−25.89	−9.43	−10.89	−1.58	15.52		
5	Value	−0.36	−2.58	−2.96	−17.03	6.27	62.65	0.00	0.00
	t test	−3.28	−25.97	−25.38	−40.50	13.79	41.26		
6	Value	−0.11	−1.77	−3.59	−13.54	9.90	48.97	0.87	0.00
	t test	−13.50	−25.54	−53.52	−32.91	42.37	30.94		
7	Value	−0.84	−2.33	−2.43	−19.54	4.42	74.27	0.00	0.00
	t test	−8.60	−28.18	−24.79	−36.34	10.71	35.75		
8	Value	−1.23	−1.75	−1.59	−10.10	0.99	35.72	0.00	0.00
	t test	−12.34	−20.08	−18.66	−27.27	3.12	26.43		
9	Value	−0.24	−0.86	−0.58	−2.82	2.87	31.32	0.59	0.49
	t test	−6.78	−15.01	−7.91	−9.45	9.34	26.69		

to be reached from other locations plays a less important role in the mode choice decision than the capacity of a location to reach the other locations in the area of interest. This is not true for road transport of NSTR/0 commodities (agricultural products and live animals), for which τ_{road} is equal to zero. The choices of road transport for NSTR/4 (ores and metal waste) and IWW transport for NSTR/2 (solid mineral fuels) are also clearly more influenced by the accessibility of the destination from the different origin nodes. To a lesser extent, this is also true for road transport for NSTR/7 (fertilizers). The case of IWW for NSTR/2 could be explained by the fact that most of the tonnage comes from a reduced number of origins, mainly Belgian and Dutch ports. The topology of the inland waterway networks is such that relatively few European destinations are accessible by barge from these ports. We confess that we did not find an explanation for the other "outliers".

Altogether, except for those cases, no τ_{mode} clearly outperforms σ_{mode}, indicating

Table 5. Estimated parameters for the model with accessibility measures.

Estimator		α	β_{road}	β_{iww}	β_{rail}	δ_{iww}	δ_{rail}	λ_c	λ_t
NST/R									
0	Value	−0.89	−1.20	−0.28	−8.98	−4.66	31.74	0.21	0.00
	t test	−9.45	−12.99	−2.66	−23.14	−10.89	22.19		
1	Value	−1.61	−2.44	−1.82	−22.13	−2.71	48.16	0.00	−0.24
	t test	−19.81	−15.01	−5.58	−6.31	−3.87	10.70		
2	Value	−0.33	−1.32	−1.88	−16.53	3.77	63.37	0.64	0.00
	t test	−9.42	−10.92	−17.52	−21.90	9.38	21.79		
3	Value	−0.82	−1.89	−0.72	−5.24	−1.78	22.87	0.31	0.16
	t test	−8.35	−18.06	−11.52	−12.21	−6.54	12.02		
4	Value	−61.51	−2.51	−0.60	−1.49	−3.00	1.85	−2.04	0.17
	t test	−7.70	−17.66	−5.67	−3.06	−5.82	0.71		
5	Value	−0.13	−2.42	−2.25	−11.70	3.26	41.03	0.00	0.00
	t test	−1.41	−28.60	−23.16	−30.35	8.75	29.01		
6	Value	−0.39	−1.23	−0.38	−1.97	−1.27	12.22	0.24	0.35
	t test	−7.51	−18.85	−11.15	−10.71	−6.63	10.25		
7	Value	−2.34	−1.30	−0.28	−5.92	−4.70	20.46	−0.18	0.00
	t test	−12.72	−17.54	−2.57	−10.48	−9.82	9.34		
8	Value	−0.18	−2.88	−2.46	−13.32	3.10	46.12	0.17	0.00
	t test	−3.00	−32.42	−30.97	−34.74	11.38	32.80		
9	Value	−0.55	−2.02	−2.63	−13.41	4.62	47.79	−0.01	0.00
	t test	−4.41	−22.16	−24.01	−28.66	10.93	27.35		

Estimator		σ_{road}	σ_{iww}	σ_{rail}	τ_{road}	τ_{iww}	τ_{rail}
NST/R							
0	Value	6.14	1.33	2.55	0.00	1.75	2.05
	t test	28.23	33.24	56.05	0.00	50.72	40.75
1	Value	2.29	0.57	1.40	3.35	1.40	1.52
	t test	10.76	55.53	43.53	11.89	34.74	35.82
2	Value	2.67	1.45	1.04	2.81	0.51	1.68
	t test	21.38	40.72	27.84	25.02	21.14	33.61
3	Value	1.27	0.59	1.42	2.18	1.63	1.80
	t test	15.35	47.12	41.50	15.22	31.90	20.92
4	Value	4.10	0.20	2.07	1.82	0.25	3.35
	t test	20.91	39.13	44.19	11.64	38.60	46.30
5	Value	1.97	0.78	2.18	1.97	0.89	3.99
	t test	34.99	51.72	61.93	22.16	50.22	66.79
6	Value	1.96	1.91	1.93	2.33	1.18	1.53
	t test	15.58	44.80	53.43	15.38	36.38	34.12
7	Value	2.05	1.24	2.33	1.29	1.84	2.64
	t test	30.09	47.37	34.84	19.24	29.26	37.99
8	Value	1.47	1.38	1.95	2.04	1.28	2.55
	t test	18.59	70.14	56.35	20.49	61.20	57.30
9	Value	3.06	0.61	2.49	2.92	0.67	4.43
	t test	17.17	69.57	63.34	16.20	73.41	74.02

that both accessibilities are important in the mode choice decision. Thus, not only are the characteristics of the possible modal itineraries between an origin and a destination (cost and transit time) taken into account, but the level of accessibility from/to the whole network at both locations is also important. As the spatial accessibility measures used in this paper are closely related to the concept of connectivity (the density of connections in path or road networks and the directness of links), one can conclude that the qualities of the network connections to the surrounding areas of the origins and destinations are important. In an interregional or international context, this means, for instance, that the will of the European Commission to finalize the TEN (Trans-European Network) makes sense, as this improves the accessibility to some regions. However, the TEN is mainly concentrated in the most important industrial areas. This undoubtedly raises the question of the accessibility of more peripheral areas, which is more the responsibility of local (national or regional) authorities.

4.4. Comparative Performances

The log-likelihood and the Akaike information criterion of the model with accessibility are better for all groups of commodities. As these performance measures do not give a comprehensive idea of the added value of the accessibility measure in the model, an analysis of the mean absolute percentage error (MAPE) between the observed and computed tonnages is presented in **Table 6**. This metric is commonly used in forecasting. More precisely, the weighted variant of the MAPE is used, because a prediction error for an OD relation with an important tonnage is more damageable than for a less significant OD. Such a MAPE (sometimes referred to as WMAPE in the literature) can be computed as

Table 6. MAPE between observed and estimated quantities at the OD level.

	Model 1 (cost & transit time)			Model 2 (cost, transit time & accessibilities)		
NST/R	Road	IWW	Rail	Road	IWW	Rail
0	0.19	0.75	0.98	0.13	0.58	0.70
1	0.09	0.90	1.02	0.06	0.58	0.91
2	1.05	0.71	0.32	0.78	0.21	0.20
3	0.39	0.60	0.82	0.23	0.29	0.63
4	0.20	0.92	0.88	0.13	0.58	0.62
5	0.31	1.01	0.87	0.23	0.71	0.65
6	0.26	0.83	0.91	0.20	0.58	0.76
7	0.95	1.02	0.43	0.60	0.50	0.25
8	0.26	0.88	0.93	0.19	0.54	0.79
9	0.20	1.03	1.01	0.12	0.49	0.77

$$\text{MAPE} = \sum_{z=1}^{Z} \left| A_z - F_z \right| \Big/ \sum_{z=1}^{Z} A_z \tag{27}$$

where:

Z: number of fitted points

A_t: actual value

F_t: forecast value

The MAPE values are obtained following the workflow presented in Figure 4. The ETISPlus "observed" modal OD matrices for a given group of commodities are merged, so the resulting matrix contains the sum of the transported quantities by each mode. The modal choice model is then applied to this matrix to obtain the computed (estimated) matrices for each mode. The MAPE can then be computed for each mode and group of commodities, comparing the values of the "observed" OD cells Q_{xy} and their corresponding estimated values $\bar{Q}_{xy}$.

Table 6 shows that the mean absolute percentage error is systematically lower for all modes and groups of commodities for the model with accessibility measures. One could argue that the overall performance of the model remains rather poor, as the average errors are high and even sometimes larger than 100% for the first model. This is obviously because the model does not integrate more relevant explanatory variables (that are not available). The important conclusion is, however, that the integration of the accessibility measures in the utility function substantially improves the predictive power of the modal choice model.

The values presented in Table 6 do not take the impact of the improved modal choice model on the estimated traffic on the networks into account. This can be captured using the workflow presented in Figure 5.

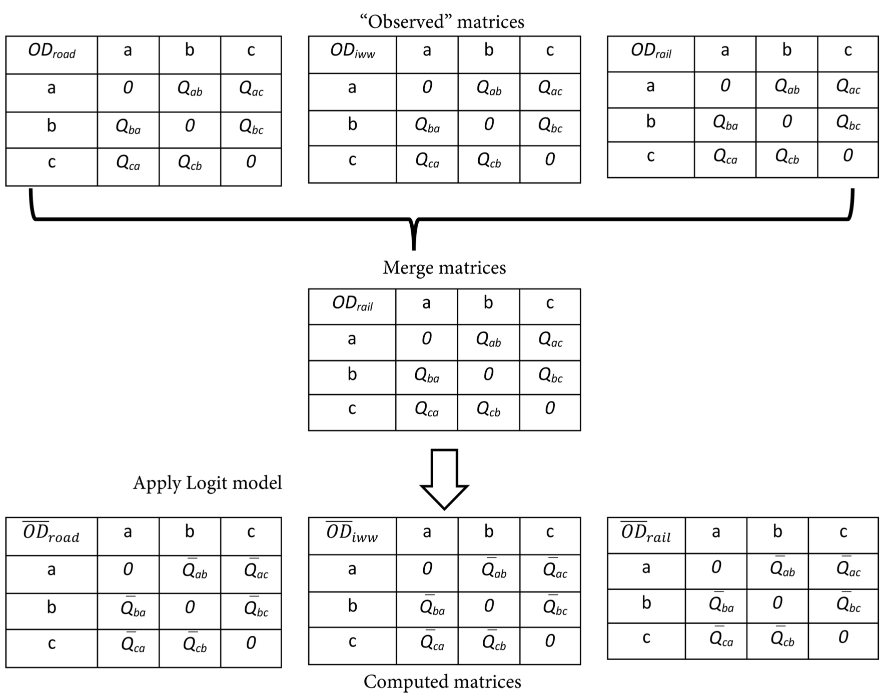

Figure 4. Validation process at the OD level for one group of commodities.

As no observed count data are available along the segments of the networks, the traffic computed by separate assignments of each mode (the "observed" OD matrix of a mode assigned to its own network) is used as a proxy of the actual transported tonnage on each link T_{link}. These reference tonnages are then compared to the computed $\overline{T}_{link}$ values obtained by an assignment of the estimated modal OD matrices.

Table 7 gives the resulting MAPE values[3] between the T_{link} and $\overline{T}_{link}$ series. The values show that the model with accessibility always performs better, especially for IWW transport. The "Aggregate" line gives the values computed using the total tonnages, including all commodities. These totals represent the traffic on the networks (at least for nonempty vehicles), which is usually of interest to policy-makers. The scatter plots of Figure 6 (in this case for IWW transport of solid mineral fuels) provide further insight into how the model with accessibility improves the predictive power of the assignment model.

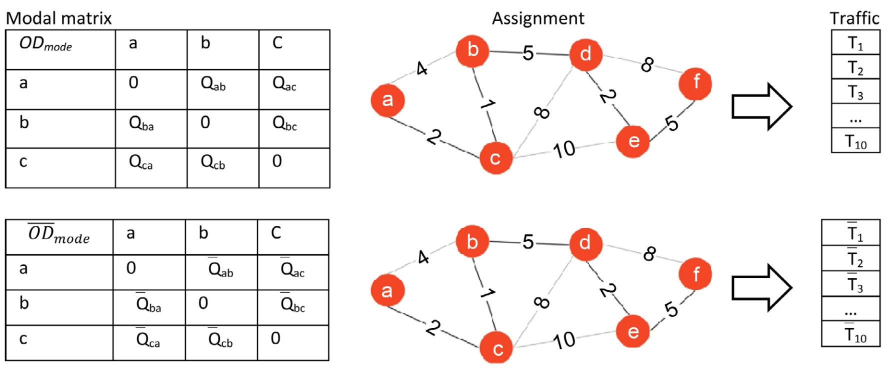

Figure 5. Validation process at the network (traffic) level for one mode.

Table 7. MAPE between "observed" and computed traffic on the networks.

	Model 1 (cost & transit time)			Model 2 (cost, transit time & accessibility)		
NST/R	Road	IWW	Rail	Road	IWW	Rail
0	0.17	0.67	0.98	0.13	0.47	0.71
1	0.08	0.72	1.32	0.06	0.27	1.11
2	0.82	0.7	0.34	0.61	0.16	0.21
3	0.38	0.56	0.71	0.26	0.19	0.61
4	0.24	1.07	0.75	0.15	0.43	0.5
5	0.24	0.89	0.69	0.18	0.39	0.5
6	0.23	0.84	0.71	0.19	0.33	0.61
7	0.71	1.25	0.41	0.49	0.27	0.19
8	0.2	0.77	0.73	0.16	0.28	0.56
9	0.13	1.25	0.85	0.08	0.31	0.53
Aggregate	0.19	0.76	0.68	0.16	0.43	0.64

[3]In order not to bias the calculation, the links connected to only two other links of the same mode and from which it is not possible to change direction are removed from the process. Indeed, the flow on these links is always equal to the flow on their preceding and following links.

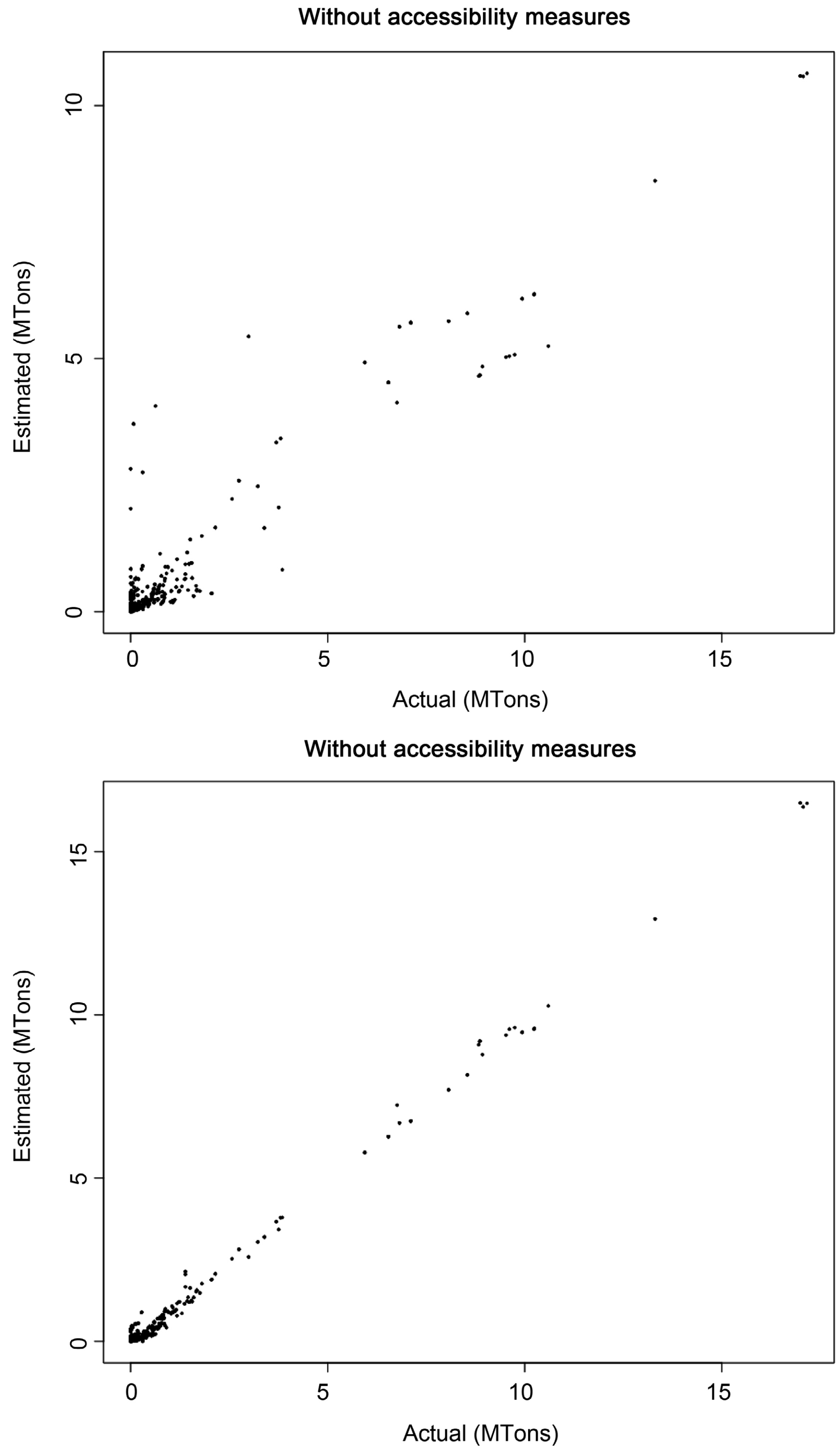

Figure 6. Scatter plots of actual vs. estimated tonnages (IWW, NSTR/2).

5. Conclusions and Perspectives

In this paper, a modal choice model is presented in which network accessibility is used as an additional explanatory variable, in addition to transport cost and transit time.

The concept of accessibility is defined in this paper from a spatial perspective as a measure of the capacity of a location to be reached from different locations or from an origin node perspective to measure the capacity to reach different destinations.

The model is designed to be used in a transportation network model. Therefore, its performance is measured at the modal-choice and assignment steps.

Special attention is given to two specific aspects of the model. First, multicollinearity between transport costs and transit times must be addressed. For this purpose, a Box-Cox transform is applied to both independent variables. Second, several possible functional forms of the decay function used to compute the accessibility measures are tested. If the negative exponential form is often considered as appropriate for transport over medium and long distances, as generally cited in the literature, we conclude that the exponential-normal curve fits better. It also appears that the chosen accessibility measures are not correlated with transport costs and transit times.

In most cases, the capacity of a node to be reached from other locations plays a less important role in the mode choice decision than the capacity of a location to reach the other locations in the area of interest. Both accessibility measures are, however, important and taken into account in the mode choice decision.

To assess the added value of the introduction of the (relative) accessibility measures in the modal choice model, two performance indicators are presented for a case study based on the ETISPlus European OD matrices containing annual transported tonnages for 10 groups of commodities. The first compares the mean absolute percentage errors (MAPEs) of the observed transported tonnages and those estimated by the modal choice models. The MAPE values of the model with the accessibility measures are substantially lower. A similar exercise is performed with the "observed" and computed tonnages along the roads, inland waterways, and railroads of the digitized transportation networks. Here also, the MAPE values are also systematically better for the model with accessibility measures.

While keeping the econometric model simple, the inclusion of an accessibility measure in the modal choice model module improves the predictive power of the transportation network model, which is an advantage for modelers because it increases the accuracy of cost-benefit or socioeconomic analysis, for instance. However, the workflow of the model remains rather complex as it relies on several software tools and programing languages. An additional research effort toward a simultaneous estimation of mode choice and decay function is needed to make the model more easily useable by modelers.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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