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MODELING OF FREIGHT TRANSPORT DISTRIBUTION IN GERMANY — A DISCUSSION OF TRADITIONAL DISTRIBUTION MODELS AND A NEW PROCEDURE FOR PERFORMANCE IMPROVEMENT

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MODELING OF FREIGHT TRANSPORT DISTRIBUTION IN GERMANY

— A DISCUSSION OF TRADITIONAL DISTRIBUTION MODELS AND A NEW PROCEDURE FOR PERFORMANCE IMPROVEMENT

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ABSTRACT

This work aims to discuss modeling issues on solving the transport distribution problem in freight transport. The traditional distribution model – the Gravity Model – is introduced in detail with the focus on its forecasting capability of freight transport distribution. Through analyses on the base of observed and predicted data of freight transport in Germany, it is found that, compared to applying the Gravity Model, directly balancing the observed distribution from the last period using the Furness Method can generate more closer predictions to the official predictions in a planning project of the German Federal Ministry of Transport, Building and Urban Development. However, there is a doubt about whether this Furness Method itself brings about an impact on the deterrence exponent. Based on the proposition that the Furness Method dilutes the deterrence effect of transport costs, a compensating procedure is developed in this work as a supplement to the traditional process, offering a new thinking to improve the prediction performance of distribution models.

Keywords: Transport Distribution Modelling, Freight Transport, the Gravity Model, the Furness Method

1. INTRODUCTION

This article aims to find out a suitable model for transport distribution prediction in the specific area of freight transport.

There is no doubt that transport modeling plays a crucial role for infrastructure planning in a transport system. It provides a plausible prognosis of future transport flows on the existing network; and, thus, increased/decreased requirements on infrastructures in the future can be obtained, which may assist the decisions on new policies, construction planning and system optimizing intentions in a transport system.

According to the classic four stage transport model (trip generation, distribution, mode split and assignment.)[1], transport distribution builds the second step of the whole prediction process. In this step, the trip generation potential has been estimated, while transport modes remain still unconsidered.

A freight transport distribution problem should be understood in a transport system of a certain commodity involving a large number of geographic zones. The amounts of transported goods from zone i to zone j in the time period t is noted as T_{ij}^{t}. The complete set of T_{ij}s for all the zone pairs i-j in period t, $\{T_{ij}^{t}\}$, represents the transport distribution of the studied commodity in period t. In order to predict the transport distribution of a certain commodity in a future period, the transport distribution of the same commodity in a base year, $\{T_{ij}^{o}\}$, must be known prior from existing records or statistics. And the geographical structure of the studied region should also be available, which is usually represented by distances or travel time between every two zones (d_{ij} or t_{ij}). The distance or travel time are understood as transport costs, which induce a barrier effect on trip generation. In this work, distances between every two zones will be used as transport costs. Moreover, production potential (O_i^p) in each zone i in the planning period p and the consuming demand (D_j^p) in each zone j in p should have been already estimated and obtained. Our task is to figure out how and to which extent transport flows will distribute in the region between different zones in the planning period with the production potential and the consuming demand in each zone being satisfied.

In order to predict the transport distribution with the above information, distribution models have been developed, which usually aim at an origin-destination-matrix describing the most probable transport distribution in the studied region. The most popular distribution model is the Gravity Model. It has been intensively discussed and widely applied in the transport distribution area. Thus, the Gravity Model will be explicitly and empirically studied in this article with data from Germany in the specific aspect of freight transport. In previous works, the Gravity Model has been applied for both explanation purpose and prediction purpose. However, merely the prediction performance of it will be measured in this article.

After the analysis of the classic model, flaws of the traditional process will be discussed and an additional procedure will be developed as a remedy.

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[1] See: Ortúzar and Willumsen, “Modelling Transport” 4th edition, 2011

This article is organized as follows: in section 2, the ubiquitous theories of the Gravity Model and a balancing method – the Furness Method – will be reviewed. Then, an analysis and an empirical study of the Gravity Model on its forecasting performance with data from Germany can be found in section 3. And a new developed procedure will be introduced and discussed in section 4. Finally, section 5 will provide conclusions of the article and possible perspectives in this area.

2. LITERATURE REVIEW

2.1 The Gravity Model

The Gravity Model originated from the idea of gravitation that each object in the material world has a force of attraction to pull other objects towards them. The strength of this force is positively correlated with the mass of each involved object while it is negatively correlated with the distance between them. In a freight transport system, geographical zones can be observed as the pulling objects and the production potential and demand of the zones correspond to the mass of the objects, which provide pulling effect of transport flows, while the transport costs, including distances, transport time, etc., are playing the deterrent role. With this intuitive understanding, the Gravity Model is defined as follows:

$$T_{ij} = A_i O_i B_j D_j \, f(c_{ij}) \tag{2.1}$$

with:
O_i = the production of origin i;
D_j = the Attractiveness of destination j;
A_i = balancing factor for O_i;
B_j = balancing factor for D_j;
c_{ij} = transport costs from origin i to destination j;
$f(c_{ij})$ = a deterrence function describing the disincentive strength of c_{ij} on T_{ij}.

Mathematically, the Gravity Model is derived from the concept of entropy, which aims to identify the distribution that is most probable to occur in a future period with known conditions (the observed data of based year and the predicted potentials and demands in studied zones). This was firstly solved by *A. G. Wilson* in 1967[2]. And his result – adopting the exponential function as the deterrence function – is usually accepted as the classic Gravity Model:

$$T_{ij} = A_i O_i B_j D_j \exp(-\beta c_{ij}) \tag{2.2}$$

With:

$$A_i = \frac{1}{\sum_j B_j D_j \exp(-\beta c_{ij})} \tag{2.3}$$

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[2] See Wilson, A. G. (1969): “The use of Entropy Maximizing Models in the Theory of Trip Distribution, Mode Split and Route Split”. Journal of Transport Economics and Policy, Volume 3, No. 1

$$B_j = \frac{1}{\sum_i A_i O_i \exp(-\beta c_{ij})} \tag{2.4}$$

Discussions on the Gravity Model later in this article will base on this classic Gravity Model as it is found that a Gravity Model with the exponential function matches the data used in empirical studies in this work quite well.

Before applying the Gravity Model for distribution prediction, the model must be calibrated to fit the specific instance. More explicitly, the deterrent exponent β in the specific case, indicating the deterrent strength of distance on transport flows generation, must be estimated. For that, observed distribution in the based period is usually used for calibration and the result of β will be adopted for the planning period.

2.2 Application Methods

2.2.1 Model Calibration

Before applying the model to specific cases, it should be firstly calibrated, because parameters usually alter with characteristics of different studied objects or other properties for a certain instance. In the calibration process of the Gravity Model, the cost deterrence exponent β is to be determined.

In this work, the regression analysis is chosen as the calibration method, since it can generate a unique solution without any set criterion of accuracy. And it can thus ascertain the β value faster. This method aims to find the correlation and its strength between a transport distribution and the distance matrix through a regression analysis.

First of all, the model must be linearized about β. This is usually implemented with the help of a logarithm function. Simultaneously, any impact of the balancing factors A_i and B_j must be precluded. *Sen and Soot (1981) and Gray and Sen (1983)* have proposed a technique to depart the calculation of balancing factors from this calibration procedure, which is called the odds ratio method. Their solution of linearizing is shown as follows:

$$\begin{aligned}\ln T_{ij} - \frac{1}{n}\cdot\sum_j \ln T_{ij} - \frac{1}{m}\cdot\sum_i \ln T_{ij} + \frac{1}{mn}\cdot\sum_i\sum_j \ln T_{ij} \\ = -\beta\cdot\left(\ln c_{ij} - \frac{1}{n}\cdot\sum_j \ln c_{ij} - \frac{1}{m}\cdot\sum_i \ln c_{ij} + \frac{1}{mn}\cdot\sum_i\sum_j \ln c_{ij}\right)\end{aligned} \tag{2.5}$$

with:
m = the number of origins;
n = the number of destinations

By adopting this linear relationship, the logarithm of the matrices of T_{ij}s and of d_{ij}s should firstly be calculated and then each of the logarithm values should minus the corresponding row mean and column mean while add the grand mean of the whole matrix. After that, the resulted matrices could be brought into a regression process. It is preferable to use Weighted Least Squares for the involvement of logarithm transformation. And the suggested weight in this case is $T_{ij}^{0.5}$. In our work, the regression process has been executed through the analysis tool aggregated in MS-Excel.

To be mentioned is that zero cells are troublesome by applying the above method, as the logarithm of zero is not defined. A widely accepted solution of this is to add the number 1 to each zero cells. A merit of this approach is that the modification on the original data is rather subtle and hence rarely affects the accuracy of estimation. Moreover, the logarithm of 1 amounts to 0, which ensures that zone pairs with zero transport flow in the original matrix still remains the smallest in transformed matrix. *Sen and Soot* have tried to use 0.5 instead of 1 in this process, but they have found that this could not provide any improvement to the accuracy of parameter estimates.

2.2.2 Balancing Method

After the calibration process, the estimate of β can be imported as constants into the Gravity Model and the other two parameters associated with trip end constraints could be obtained using balancing methods. In this work, the well known Furness Method has been applied.

The Furness Method is an iterative algorithm. As the first step, each cell in the matrix should be multiplied by the ratio between O_i and the corresponding row-sum, so that the constraints of O_is are satisfied. Then, each cell in the matrix should multiply the ratio between D_j and the corresponding column-sum, so that the D_js are satisfied in this step. After sufficient iterating of the two steps, row-sums and column-sums will converge to satisfy the trip ends constraints.

3. AN ANALYSIS OF THE GRAVITY MODEL

Before an empirical study, a large amount of 0-units is observed in the distribution matrix in the based year, which might lead to large deviations in a prediction. These 0-units demonstrate those combinations of i and j in distribution matrices, between which no transport flow has been observed, although neither the corresponding O_i nor the D_j equals 0. This phenomenon is actually ubiquitous in freight transport distributions. However, a Gravity Model never generates 0-units, as long as the product of O_i and D_j does not equal 0. The data acquired for empirical studies in this article can provide us a closer view.

The database of empirical studies in this work has been extracted from the latest version of the project BVWP[3](Bundesverkehrswegeplan: the Federal Transport Infrastructure Plan).

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[3] Detailed information of BVWP can be found by: http://www.bmvbs.de/DE/VerkehrUndMobilitaet/Verkehrspolitik/Infrastrukturplanung/Bundesverkehrswegeplan/bundesverkehrswegeplan_node.html

Its prediction part aims to forecast the transport flows in the year 2025 based on historic data in 2004[4]. We have extracted the data of freight transport in 2004 describing the observed transport distribution including 10 homogeneous commodity groups and altogether 567 zones[5]. Density of transport flows is represented in weight of the studied commodities (in tons) and in the form of an origin-destination-matrix.

Table I – Proportion of 0-Units in the O-D-matrices in 2004

	# nonzero origins	**# nonzero destinations**	**# units in the matrix**	**# zero-units**	**Proportion of zero-units**
0. agriculture and forestry products	563	563	316969	194965	61.51%
1. food and Feed	564	564	318096	190062	59.75%
2. solid mineral fuels	496	520	257920	244917	94.96%
3. petroleum and petroleum products	545	557	303565	275486	90.75%
4. ores and metal wastes	552	552	304704	260879	85.62%
5. iron, steel and nonferrous metals	561	563	315843	221998	70.29%
6. rocks and soils	560	563	315280	197684	62.70%
7. fertilizer	547	545	298115	266900	89.53%
8. chemical products	560	564	315840	200397	63.45%
9. vehicles, machinery, semi-finished and finished goods	567	567	321489	97767	30.41%

The proportion of 0-units in the O-D-matrices for each of the ten groups is shown in table I. It is obvious that 0-units occupy a huge share in the matrices. For some commodity groups, the most units are 0s. Since the Gravity Model is unable to predict their existence, a large deviation between the reality and the estimated results by the Gravity Model can be foreseen.

There is another commonly applied method to overcome this problem: to adopt the observed tranport distribution of the last period as the direct input of the Furness method instead of calibrating the model to obtain β-values. In this way, all the influential factors reflected in the observed data will be well inherited in the forecast, including 0-units.

Moreover, as the model calibration is no longer necessary, possible deviations caused by the calibration process can be also avoided.

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[4] Detailed information of the prediction for 2025 can be found by: http://www.bmvbs.de/SharedDocs/DE/Artikel/UI/verkehrsprognose-2025.html?nn=35978

[5] These zones are coded according to NUTS (Nomenclature of Territorial Units for Statistics). The original data bases on districts on the NUTS-3 level, including 439 cities/small regions in Germany and describing their domestic and international transport activities. Beside the 429 German districts, the other 128 zones in the observed matrix concern with international transport activities. These 128 zones include airports, seaports and foreign regions that exchange commodities with the 439 zones in Germany. The foreign regions are also coded with the NUTS system but on level 0~2.

Therefore, applying the Furness Method on history data is expected to generate a closer distribution forecast with the official prediction than applying the complete Gravity Model in a freight transport system. Several analyses will be carried out in the following subsections to examine this inference.

3.1 Analysis on the NUTS-2 level

In order to mitigate the influence of 0-units, the original data based mainly on the NUTS-3 level is integrated to the NUTS-2 level in this first experiment, which means that cities and small regions as zone units in the original data are integrated to their upper units – the Government Districts in Germany. And merely inland transport is under consideration in this first study. As a result, ten 40×40 O-D-matrices for the ten commodity groups form the database of this analysis.

Both methods introduced above are applied on this database. A distribution prediction from BVU[6] is accepted as a reference of the empirical studies, in order to evaluate estimation accuracy.

In the model calibration process of the Gravity Model, the Weighted Least Square is employed to identify deterrence exponent β for each of the ten groups. Estimates are shown in table II.

Table II – Estimated βs for each commodity group

Commodity Groups	**β-Value**	**R^2**
0. agriculture and forestry products	0.8249***	0.6804
1. food and Feed	0.9493***	0.9012
2. solid mineral fuels	0.8537***	0.7288
3. petroleum and petroleum products	0.8279***	0.8279
4. ores and metal wastes	0.8278***	0.8278
5. iron, steel and nonferrous metals	0.8145***	0.6634
6. rocks and soils	0.9606***	0.9227
7. fertilizer	0.8918***	0.7953
8. chemical products	0.9022***	0.8140
9. vehicles, machinery, semi-finished and finished goods	0.9229***	0.8517

*** indicates the significance on 1% level

R^2 for every group is sufficiently close to 1, demonstrating a good model fitting

The Furness Iteration is used to balance trip ends constraints (O_i and D_j). Two comparison criteria, MAPSE and MAPE, are employed to evaluate estimation accuracy compared to the reference. The former criterion implies fluctuation intensity of deviations in all units, while the latter shows the greatness of deviation of the whole.

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[6] The company BVU has been engaged in the project BVWP for many years and their results for earlier planning periods have been accepted by the government and have played a role in the construction investment decisions in Germany. Thus, their results can be considered as an authority and are accepted in this work as the reference of empirical studies.

$$\mathrm{MAPSE} = \frac{1}{\mathrm{m \cdot n}} \cdot \sum_i \sum_j \frac{|\mathrm{T_{ij}} - \mathrm{T_{ij}^{BVWP}}|}{\mathrm{T_{ij}^{BVWP}}} \tag{3.1}$$

$$\mathrm{MAPE} = \frac{\sum_i \sum_j \left|\mathrm{T_{ij}} - \mathrm{T_{ij}^{BVWP}}\right|}{\sum_i \sum_j \mathrm{T_{ij}^{BVWP}}} \tag{3.2}$$

m = the total number of origins;
n = the total number of destinations;
T_{ij} = the estimated results;
T_{ij}^{BVWP} = the reference results from the project BVWP.

Table III demonstrates the accuracy of results from both methods. It is obvious that applying the Furness Method directly on the history data of the observed distribution performs much better than applying the whole Gravity Model both on the fluctuation intensity and on the deviation. In most commodity groups, results from the whole Gravity model deviate about once the transport amount, so that this prediction cannot be accepted.

Table III – Accuracy evaluation of the Gravity Model and the Furness Model on NUTZ-2 level

Commodity Groups	**Proportion of 0-units**	**Gravity Model**		**Furness Method**	
		MAPSE	**MAPE**	**MAPSE**	**MAPE**
0. agriculture and forestry products	8.875%	92.16%	104.92%	9.53%	4.48%
1. food and feed	2.81%	99.25%	110.95%	10.00%	5.03%
2. solid mineral fuels	71.06%	115.49%	80.51%	2.95%	2.26%
3. petroleum and petroleum products	42.69%	74.87%	90.45%	6.27%	4.21%
4. ores and metal wastes	43.88%	67.16%	78.99%	5.64%	4.41%
5. iron, steel and nonferrous metals	12.31%	102.52%	111.30%	8.71%	7.16%
6. rocks and soils	7.19%	91.16%	44.92%	14.97%	3.27%
7. fertilizer	56.12%	96.77%	80.02%	5.58%	6.98%
8. chemical products	7.75%	91.85%	81.12%	10.16%	5.15%
9. vehicles, machinery, semi-finished and finished goods	0.38%	101.26%	114.20%	8.54%	4.86%

Moreover, it is found in the estimated distribution matrices from the Gravity Model that there is a large amount of units, which amount to extremely small values. In order to acquire a more orderly view of the distributions, all the values smaller than 0.0001 (ton) in the matrices were ignored by substituting them with the number 0. It is then interesting to notice that nearly all the transport flows converge to the diagonal from the upper left to the lower right in the matrices after transformation – that is, local transport is strongly preferred to inter-district transport. It is actually reasonable for the Gravity Model to generate such matrices. Each of these districts does produce all the studied commodities and they consume them as well; meanwhile, local transport indicates a much smaller distance (much smaller transport costs) than inter-district transport. According to a Model considering merely the trip ends attractiveness and distances, local transport activities may surely enjoy a priority. Unfortunately, this phenomenon is invisible either in the observed data from 2004 or in the reference data.

Thus, the Gravity Model is strongly restricted on its prediction capability. We can conclude with the result of this analysis that applying the Furness Method on the observed data can provide more plausible distribution forecasts in a freight transport system according to the official transport predictions.

3.2 Analysis on the NUTS-3 level

Another analysis based on the origin database (on the NUTS-3 level, including 567 zones) will be carried out in this section, in order to confirm the conclusion above in a more complicated situation, including domestic transport and international interchanges of Germany. For this instance, the business factors should be more comprehensive, including e.g. international trade protocols, import and export policies, which are not considered in the Gravity Model, either. Thus, the prediction accuracy is expected to reduce in some extent.

The same working process and methods are applied and results are shown in table IV.

Table IV - Accuracy evaluation of the Gravity Model and the Furness Method on NUTZ-3 level

Commodity Groups	**Proportion of 0-units**	**Gravity Model**		**Furness Method**	
		MAPSE	**MAPE**	**MAPSE**	**MAPE**
0. agriculture and forestry products	61.51%	71 548.32%	196.93%	12.82%	7.73%
1. food and feed	59.75%	133 589.04%	193.21%	18.61%	16.67%
2. solid mineral fuels	94.96%	23 439.00%	187.24%	330.52%	16.58%
3. petroleum and petroleum products	90.75%	44 402.20%	190.23%	2.16%	8.05%
4. ores and metal wastes	85.62%	25 434.40%	187.61%	4.92%	7.22%
5. iron, steel and nonferrous metals	70.29%	46 660.60%	187.15%	6.43%	9.35%
6. rocks and soils	62.70%	409 169.00%	189.07%	27.51%	4.08%
7. fertilizer	89.53%	14 768.50%	197.94%	2.97%	9.40%
8. chemical products	63.45%	102 092.00%	188.16%	14.66%	9.63%
9. vehicles, machinery, semi-finished and finished goods	30.41%	412 151.00%	194.32%	15.70%	15.03%

It is apparent that the Furness Method still performs much better than applying the whole Gravity Model in this experiment, since all characteristics of the transport system can be much better inherited through the Furness Method, while the Gravity Model generates even larger deviations and stronger fluctuations. It can be learned from the results that applying only the Furness Method has provided distribution forecasts with acceptably small deviations compared to the reference. And for most groups, the fluctuation of deviation in each unit is also acceptable, except in group 2, which has the highest 0-unit proportion (94.96%). However, it has been observed in the matrix that several extreme units have mainly contributed to the large MAPSE. Thus, the performance of the Furness Method is still evaluated as satisfying.

All in all, the conclusion in the last section remains true with the results from the second analysis: adopting the observed distribution directly into the Furness Method can generate closer distribution prediction with the official prediction than applying the Gravity Model completely.

4. A NEW COMPENSATING PROCEDURE

After the empirical analyses, another interesting phenomenon has been noticed: the deterrence effect of distances on the distribution, which is reflected by the value of β, reduces in the predictions for all ten commodity groups. The β values of each group are estimated for the observed distribution in 2004 and for both predictions of 2025 and the results are shown in table V. It can be seen that the deterrent exponents in 2025 both in our prediction and in the prediction from BVU reduce slightly compared to those in the observed distribution from 2004.

Table V – Estimated βs from different matrices

Commodity Groups	β of 2004	β of 2025 (Furness Method)	β of 2025 (estimated by BVU)
0. agriculture and forestry products	0.6139^{***}	0.5110^{***}	0.5418^{***}
1. food and feed	0.6300^{***}	0.5893^{***}	0.5526^{***}
2. solid mineral fuels	0.7338^{***}	0.7148^{***}	0.5636^{***}
3. petroleum and petroleum products	0.8059^{***}	0.7972^{***}	0.7904^{***}
4. ores and metal wastes	0.6439^{***}	0.5801^{***}	0.5888^{***}
5. iron, steel and nonferrous metals	0.6229^{***}	0.5171^{***}	0.5163^{***}
6. rocks and soils	0.8721^{***}	0.8083^{***}	0.8583^{***}
7. fertilizer	0.6273^{***}	0.5943^{***}	0.6277^{***}
8. chemical products	0.7054^{***}	0.6356^{***}	0.6203^{***}
9. vehicles, machinery, semi-finished and finished goods	0.4577^{***}	0.3567^{***}	0.3437^{***}

*** indicates the significance on 1 percent level

There could be multiple reasons for this dilution of deterrence effect of distances. And there is no evidence to exclude possible impact from the Furness Algorithm.

Assuming that the Furness Method itself does influence the deterrent exponent to some extent, a compensating remedy is acquired since an algorithm is not allowed to affect any parameter of the system. And because the transport flow prognosis is an important information resource supporting a government to make future investment plans of construction, unexpected changes of the deterrence effect of distances can be misleading for planning and the resulting transport system may end up problematic. The misjudging in the construction planning may not only lead to a transport system that is inexpedient for future transport requirements but may also generate unnecessary total cost increase. To understand the latter consequence, it is to be taken into account that any new construction or improvement on infrastructure between a zone pair can make the section more attractive owing to e.g. shorter transport time, less fuel consumption and/or slighter abrasion of vehicles, and may thus encourage transport flows on the improved links. Imagine that if a construction investment plan is made between a costly (distant) origin-destination zone pair due to overestimated future transport flows on it, transport activities between them will be encouraged rather than between some closer districts without improvement in the next period and this may induce a larger total transport cost (tons*kilometers) in the system than necessary.

In order to compensate the inadequate deterrent power of distance, it is reasonable to expect an additional procedure working as a supplement to the traditional Furness process, which should also not add much complexity in practice. With this attempt, a regulating method is developed in this work.

According to the Furness Method, the observed distribution, say T_{ij}^{o}, will be iteratively adjusted under constraints of total supplies of origins (O_i) and total demands of destinations (D_j). The result is a trip matrix, say T_{ij}^{*}. Suppose that there is a function, $\mu(d_{ij})$, whose value sways slightly around 1 according to the greatness of d_{ij} – more explicitly, if d_{ij} is bigger than a given standard value, then $\mu(d_{ij})$ is slightly smaller than 1; while on the contrast, if d_{ij} is smaller than the standard value, $\mu(d_{ij})$ is slightly larger than 1 – we may then adjust the observed transport distribution matrix T_{ij}^{o} as:

$$T_{ij}^{o}{}' = T_{ij}^{o} * \mu(d_{ij}) \tag{4.1}$$

In this new matrix $T_{ij}^{o}{}'$, transport flow between faraway districts shrinks moderately, while that between close districts is slightly enlarged. The changing extent depends on how strong the distance deviates from the given value of d_{ij}. After this regulating procedure the Furness Process will then be executed.

The regulating function, $\mu(d_{ij})$, plays a crucial part in this regulating process. It is expect to possess the following three characteristics:

1. This $\mu(d_{ij})$ should be continuous in the domain of d_{ij};
2. It should decrease monotonically with d_{ij};
3. When d_{ij} tends to infinity, say $d_{ij} \rightarrow +\infty$, the value of $\mu(d_{ij})$ should tend to a certain value (moderately smaller than 1) as its under limit, and vice versa, because the regulating factor is supposed to be restricted in a narrow area, in order to prevent an overkill.

All these considerations are suggestive of an arctangent function. A variant of it is supposed to provide us an apt solution:

$$\mu(d_{ij}) = -a * \arctan\left[b * \left(d_{ij} - c\right)\right] + 1 \tag{4.2}$$

By setting appropriate values for parameters *a*, *b* and *c*, a fitting regulating function can be generated. In order to test the effectiveness of this new procedure, the database from

BVWP will be referred to again with the new process and its results will be compared to those estimated in empirical studies above.

Firstly, a fixed regulating function should be defined. For that, some important statistic values of the geographical structure are obtained. The mean value of d_{ij} (401km) is accepted as the origin point of this function, that is $c = 401$, and thus $\mu(401) = 1$. Since the arctangent function is more sensitive in the range $x \in [-1,1]$ than in other ranges of its domain, we would rather spread this range as wide as the maximal value of d_{ij} (3261km), so that the difference between regulating values of different d_{ij}s can be better recognizable. That gives the $b = 2/3261$. Finally, as the value of $\mu(d_{ij})$ is supposed to sway moderately in a narrow range around 1, we set this range as [0.9 , 1.1]. Thus $a = 0.2/\pi$.

$$\mu(d_{ij}) = -\left(\frac{0.2}{\pi}\right) \cdot \arctan\left[\frac{2}{3261} \cdot (d_{ij} - 401)\right] + 1 \qquad (4.3)$$

The curve of this function is depicted in Figure 1.

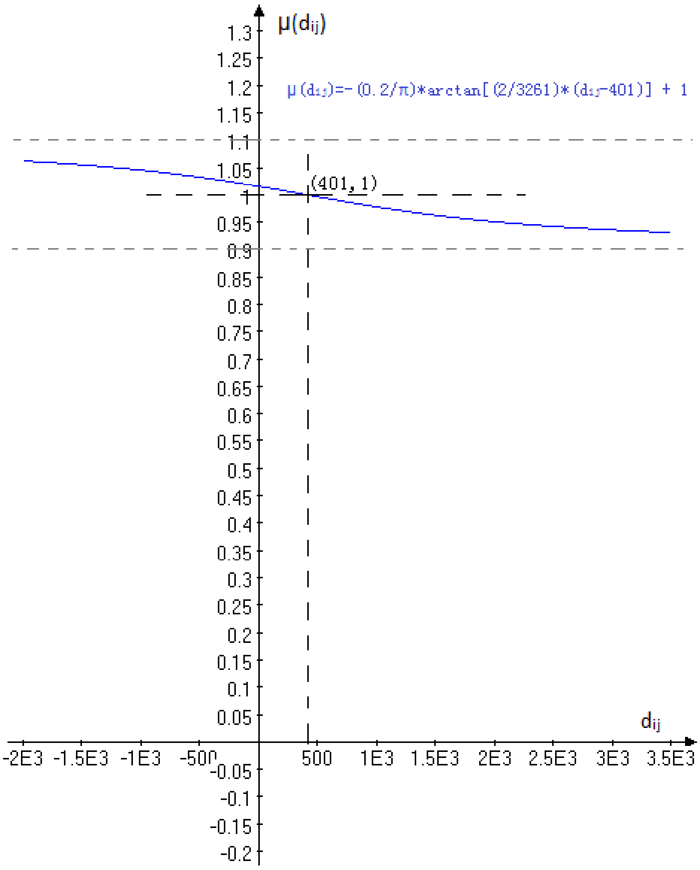

Figure 1 – The curve of the regulating function

To be mentioned is that the value settings of these parameters are rather subjective, since this is only an attempt to strengthen the deterrent effect of distance. And it is hard to assess whether the regulating strength is too strong or is still insufficient. An objective and accurate evaluation could only be possible in the future by comparing the prediction estimated with the regulating function to the real data, which is observed in the future period. And the construction investment has based itself on the prediction with the new method, because the transport distribution in the future period is supposed to react to the infrastructure constructions.

After the definition of $\mu(d_{ij})$, the new process is applied on the database from BVWP on the NUTS-3 level. Observed distribution must be regulated by $\mu(d_{ij})$ and the result should be then input into the Furness Iteration until trip end constraints are satisfied.

Finally, results of the new process are juxtaposed with the old results from the traditional Furness Method in table VI.

In the table VI, the newly estimated results deviate slightly larger. Consider that the results of our reference are also estimated on the base of the Furness Method, it is understandable that an additional procedure brings about extra deviations. As the distribution prediction estimated by BVU has included multiple parameters and influential factors in a more complex model with rich experience, it is still supposed to be a very accurate forecast. Nevertheless, although our new results may not achieve a higher accuracy, the additional procedure might be able to provide an improvement if it is considered in the prediction process of BVU.

Table VI – Evaluation of the new process

Commodity Groups	**New Process**		**Furness Method**	
	MAPSE	**MAPE**	**MAPSE**	**MAPE**
0. agriculture and forestry products	12.96%	7.89%	12.82%	7.73%
1. food and feed	18.68%	16.83%	18.61%	16.67%
2. solid mineral fuels	330.18%	16.64%	330.52%	16.58%
3. petroleum and petroleum products	2.17%	8.13%	2.16%	8.05%
4. ores and metal wastes	4.93%	7.20%	4.92%	7.22%
5. iron, steel and nonferrous metals	6.51%	9.58%	6.43%	9.35%
6. rocks and soils	27.78%	4.19%	27.51%	4.08%
7. fertilizer	2.98%	9.52%	2.97%	9.40%
8. chemical products	14.77%	9.78%	14.66%	9.63%
9. vehicles, machinery, semi-finished and finished goods	15.86%	15.15%	15.70%	15.03%

To examine whether the deterrence effect of distance has been strengthened through the new process, values of the deterrent exponent β of the new set of results have been calculated and are shown in table VII.

The last column of table VII lists the β values of the new results. And βs of the other two result sets are also juxtaposed in the table. When compared to the Furness Method, it is obvious that the deterrent power in the new process is slightly strengthened in every commodity group, which confirms the effectiveness of the regulating function $\mu(d_{ij})$. However, the parameter settings of $\mu(d_{ij})$ seem still insufficiently powerful enough to completely compensate the diluted deterrence effect of distance completely, since the β values of new results are still smaller than those estimated from the observed distribution matrix in 2004. An appropriate setting of the parameters in $\mu(d_{ij})$ may generate closer values of β to the observed ones. But whether the prediction accuracy increases with the similarity of β values still needs deeper specific investigation.

Table VII – Estimated βs from results of the new process

Commodity Groups	**β of 2004**	**β of 2025 (Furness Method)**	**β of 2025 (estimated by BVU)**	**βof 2025 (new process)**
0. agriculture and forestry products	0.6139***	0.5110***	0.5418***	0.5136***
1. food and feed	0.6300***	0.5893***	0.5526***	0.5941***
2. solid mineral fuels	0.7338***	0.7148***	0.5636***	0.7154***
3. petroleum and petroleum products	0.8059***	0.7972***	0.7904***	0.7981***
4. ores and metal wastes	0.6439***	0.5801***	0.5888***	0.5815***
5. iron, steel and nonferrous metals	0.6229***	0.5171***	0.5163***	0.5199***
6. rocks and soils	0.8721***	0.8083***	0.8583***	0.8087***
7. fertilizer	0.6273***	0.5943***	0.6277***	0.5958***
8. chemical products	0.7054***	0.6356***	0.6203***	0.6386***
9. vehicles, machinery, semi-finished and finished goods	0.4577***	0.3567***	0.3437***	0.3624***

5. CONCLUSIONS AND PERSPECTIVES

Aiming to solve a freight transport distribution problem, two popular distribution models have been explicitly introduced with the focus on their capabilities of forecasting in a freight transport system. On the basis of different analyses, we can conclude that applying the Furness Method on the observed transport distribution in the last period performes much better than applying the whole Gravity Model in generating forecast of freight transport distribution. However, there is a doubt about whether applying the Furness Method causes a dilution of deterrence effect of transport costs/distances.

Based on the assumption that the Furness Algorithm itself dilutes the deterrence effect of transport distances to some extent, an innovative procedure has been developed as a supplement, aiming to strengthen the deterrence effect. The core mechanism of this procedure is to incorporate an additional regulating function $\mu(d_{ij})$ before the Furness Iteration to revise the observe distribution matrix according to transport costs/distance. In the results from this new process, transport flows of those i-j zone pairs with large distance will reduce moderately compared to the results from the traditional Furness Method, while the transportation activities between nearby zones will be encouraged.

It must be noted that the definition of the regulating function $\mu(d_{ij})$, namely the parameter setting of the arctangent function, is rather subjective. To determine the best parameter setting, which may achieve the highest accuracy, still requires further investigation with the help of observed distribution in a future period, in which the predicted distribution through the distribution models incorporating this regulating procedure has been used as a reference of construction investment planning, because the reaction of transport flows to the new constructed and improved infrastructures must be considered. However, there is a paradox that if the accuracy of incorporating the regulating procedure to the distribution prediction process is not verified, the new procedure may not be allowed to affect construction planning and thus corresponding distribution in the practice cannot be observed. Therefore, a simulation process may be needed for further investigation, which simulates reactions of the whole transport system on predictions and the resulting constructions along several time periods.

Moreover, the negative arctangent function has been chosen arbitrarily to be the base of the regulating function in this work. According to the three requirements, another function, $y = -\sqrt[3]{x}$, can also provide a satisfying curve. Setting appropriate parameters to the cube root function may also provide a regulating function with similar effectiveness on strengthen the deterrence effect of distance. Thus, the performance of applying the cube root function as the base of the regulating function also deserves further investigation. And a comparison of the capabilities of the two alternatives on generating accurate distribution forecast is also valuable.

REFERENCES

Allan, John (2007). “PTRC Manchester Lecture Series – 4-stage modelling”.

Black, William R. (1973). “An Analysis of Gravity Model Distance Exponents”. Transportation, Volume 2, p. 299 – 312 .

BVU (2007). “Prognose der deutschlandweiten Verkehrsverflechtungen 2025”.

Chow, Joseph Y. J.; Yang, Choon Heon and Regan, Amelia C. (2010). “State-of-the art of freight forecast modelling: lessons learned and the road ahead”. Transportation, Volume 37, Number 6, p.1011 – 1030.

Duanmu, Jun; Foytik, Peter; Khattak, Asad and Robinson, R. Michael (2012). “Distribution Analysis of Freight Transportation using Gravity Model and Genetic Algorithm”.

Duffus, Leonnie N.; Alfa, Attahiru Sule and Soliman, Afifi H. (1987). “The Reliability of using the Gravity Model for forecasting trip distribution”. Transportation, Volume 14, p. 175 – 192.

Erlander, Sven (1980). “Optimal Spatial Interaction and the Gravity Model”. Lecture Notes in Economics and Mathematical Systems, No. 174.

Fidrmuc, Jarko. “Gravity models in integrated panels”. Empirical economics, Volume 37, No.2, p.435 – 446.

Friedrich, Hanno (2010). “Simulation of logistics in food retailing for freight transportation analysis”.

Fotheringham, A. S. and O'Kelly, M. E. (1989). "Spatial Interaction Models: Formulations and Applications". Kluwer Academic Publishers, Dordrecht and Boston

Gallo, Mariano; Marzano, Vittorio and Simonelli, Fulvio (2012). "An Empirical Comparison of Pparametric and Non-Parametric Trade Gravity Models".

Gray, Robert M. (2009). "Entropy and Information Theory".

Kimura, Fukunari and Lee, Hyun-Hoon (2006). "The Gravity Equation in International Trade in Services". Review of world economics, Volumn 142, No. 1, p. 92 – 121.

Lohse, Dieter; Teichert, Heidrun; Dugge, Birgit and Bachner, Gerald (1997). "Ermittlung von Verkehrsströmen mit n-linearen Gleichungssystemen – Verkehrsnachfragemodellierung".

Martinez-Zarzoso, Inmaculada (2003). "Gravity Model: An Application to Trade Between Regional Blocs". Atlantic Economic Journal, Volume 31, p. 174 – 187.

Morphet, Robin (1975). "A Note on the Calculation and Calibration of Doubly Constrained Trip Distribution Models". Transportation, Volume 4, p. 43 – 53.

Ortúzar, Juan de Dios and Willumsen, Luis G. (2004). "Transport Modelling", the third edition. John Wiley & Sons Ltd, UK.

Pel, Adam J.; Bliemer, Michiel C. J. and Hoogendoorn, Serge P. (2011). "A review on travel behaviour modelling in dynamic traffic simulation models for evacuations". Transportation, Online First(TM), 28 January 2011.

Sargento, Ana Lúcia Marto (2007). "Empirical Examination of the Gravity Model in two Different Contexts: Estimation and Explanation". Jahrbuch für Regionalwissenschaft, Volume 27, p. 103 – 127.

Shannon, Claude E. and Weaver, Warren (1959). "The Mathematical Theory of Communication". University of Illinois Press, Urbana.

Veenstra, S. A.; Thomas, T. and Tutert, S. I. A. (2010). "Trip distribution for limited destinations: a case study for grocery shopping trips in the Netherlands". Transportation, Volume 37, Number 4, p. 663 – 676.

Willumsen, L. G. (1981). "Simplified transport models based on traffic counts ". Transportation, Volume 10, Number 3, p. 257 – 278.

Wilson, A. G. (1969). "The use of Entropy Maximizing Models in the Theory of Trip Distribution, Mode Split and Route Split". Journal of Transport Economics and Policy, Volume 3, No. 1,

Wilson, A. G. (1970). "Entropy in urban and regional modelling (Pion Monographs in Spatial and Environmental Systems Analysis)".