A metafrontier analysis approach for assessing the efficiency of freight services providers

Belarmino Adenso-Díaz*[Δ] and Sebastián Lozano**

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*Department of Industrial Engineering, University of Oviedo, Spain, adenso@uniovi.es
** Department of Industrial Management, University of Seville, Spain, slozano@us.es

[Δ] *Corresponding author*

Abstract — This paper presents a DEA approach for a company to assess the efficiency of its shipments and of the haulers that handle them. It is based on the concept of metafrontier, which benchmarks a given shipment, first against all the shipments of the same hauler and then against all the shipments of all the haulers. Thus, the efficiency of each shipment as well as that of the corresponding hauler can be determined. The scale efficiency of the shipments, related to the cost premium paid for shipments whose weight, volume or distance are not large enough, is determined. In addition, the model estimates the functional dependence of the shipment cost on the load weight, volume and the distance. An experimental design to validate the proposed efficiency assessment approach and test the factors that influence its accuracy has been carried out. The application of the proposed approach to a large Spanish food company is presented and used to illustrate its usefulness. The proposed approach is able to determine the minimum cost of a shipment as a function of its weight, volume and distance. This tool proved to be useful to assess the price quotes received by the company and bargain better prices.

Keywords: road freight; shipment efficiency; hauler efficiency; DEA; metafrontier analysis

1. Introduction

Goods transportation is inherent in economic activity. Although for many years this activity was considered as a secondary function in business management, with globalisation it took a more important role and is now imperative to guarantee service and competitiveness. When any unexpected event interrupts the flow of material in the supply chain, social and economic negative impacts affect the life of the whole community. As a paradigmatic example, during the 10 days of a truck drivers' strike in 2018 in Brazil, the lack of fuel, medicines and food provoked the slaughter of millions of chickens and pigs (Lopes *et al.*, 2019).

Road transport is the backbone of distribution activities as it is the only mode able to reach to the last customer. Also, for a medium distance it is the prevalent mode used in most countries, mainly when compared to other modes such as railway. It accounts for one fourth of all the CO_2 emissions deriving from transport, with the trend set to increase in the coming years (Pöllänen *et al*., 2021).

Another important characteristic that defines the road transportation industry is its large degree of outsourcing and fragmentation. According to the European Union (2020), in the EU there are more than 500,000 road haulers, that is, in most cases companies are small or medium sized, which forces them to compete under pressure, given the small margins and price cuts typical of this industry. Therefore, the search for improvement in operational efficiency to provide the delivery service with lower resource consumption is crucial. In this sector, given the high volume of loads moved, small changes in the operational cost has significant impact on profit. (Salhieh *et al*., 2018).

Various authors have studied the "waste" (i.e., everything that does not add value) in road hauler activities that affect efficiency (Sternberg & Harispuru, 2017; Villarreal *et al*., 2016). Arvidsson *et al*. (2013) summarize the various measures to consider to reduce waste at three different levels: internal transport measures, including driving efficiency (eco-driving training or using the correct tyre pressure for instance) or vehicle efficiency; customer collaboration measures (avoiding empty running, consolidating loads, widening time windows for delivery, or packaging efficiency); and regulatory measures imposed by governments (incentives to improve efficiency of haulers).

This paper develops a DEA approach to evaluate the efficiency of the shipments ordered by a company, assessing also the efficiency of the haulers that process them. Real data from a national food company were used, involving more than 90,000 shipments. DEA is a non-parametric methodology that only requires data appertaining to inputs and outputs of each entity to be benchmarked (Molla-Alizadeh-Zavardehi *et al.*, 2021). From the observed data and by making some standard assumptions (e.g., convexity, constant or variable returns to scale, etc.) it infers the Production Possibility Set (PPS), also called DEA technology, that contains all the feasible operating points. The non-dominated subset of the PPS is called the efficient frontier and represents the best practices. Operating points that lie on the efficient frontier are relatively efficient and cannot reduce inputs or increase outputs. Inefficient entities, in contrast, would reduce inputs or increase outputs until reaching the efficient frontier, to improve performance.

Determining the extent of the inefficiency that should be removed and computing target input and output values is one of the useful features of this methodology. Another, is of course, providing a normalized efficiency score. This is achieved by using a DEA optimization model that projects each entity onto the efficient frontier. There are different DEA models, using radial approaches (e.g., Charnes *et al*. 1978, Banker et al. 1978), directional distance function (e.g., Chambers et al. 1996) as well as slack-based approaches (e.g., Tone 2002, Fukuyama and Weber 2009). The reader is referred to existing textbooks and handbooks (e.g., Cooper et al. 2004, 2006) for more information on the DEA methodology.

When the observations of the sample belong to different categories or groups, benchmarking them together is not advisable. It is better to use a metafrontier DEA approach (O'Donnell *et al*. 2008). This consists of benchmarking the entities first only against the entities that fall into the same group. This allows for determining a local frontier that represents the best practices associated with that group or category. In the second phase, all the entities can be pooled and benchmarked together. This determines a global metafrontier that corresponds to the best practices overall. The comparison, i.e. the distance, between the local and the global frontier can be used to determine the efficiency of the corresponding group or category. In this case, the groups correspond to the haulers that have delivered the different shipments.

The proposed metafrontier DEA model is based on the original, convex-metafrontier approach of O'Donnell et al. (2008). Although more complex approaches involving metafrontier Malmquist indexes (e.g., Afsharian et al. 2018), network and dynamic network DEA metafrontiers (e.g., See et al. 2021), non-convex metafrontiers (e.g., Mocholi-Arce et al. 2021) or group-performance metafrontiers (e.g., Gan and Lee 2022) exist, for this application none of those enhancements/variants are needed and a standard metafrontier DEA approach suffices. There are, however, some innovative ideas in the proposed approach. One is considering a NDRS DEA metafrontier, instead of the usual CRS and VRS approaches. The second one is the use of the proposed metafrontier DEA approach to estimate the input as a function of the outputs. The metafrontier approach allows to do this, for each hauler as well as for the whole of them. To the best of our knowledge this inverse function use of metafrontier DEA has not been proposed before.

Therefore, in this paper a novel and simple metafrontier DEA approach is proposed that can be used to analyse the efficiency of the transportation companies working for a large food company. The proposed DEA models allow the manager of the logistics department to gain a better understanding of the costs of the shipments and how they vary with time and with the different haulers. The scale of efficiency of the shipments can also be determined. This represents the cost premium that must be paid for shipments whose weight or distance are not large enough. Finally, the proposed approach includes a DEA model to determine the minimum cost of a shipment as a function of its weight, volume and distance. This tool can prove very useful when contracting the shipments and bargaining with the transport companies.

The structure of the paper is as follows. In section 2 a literature review on DEA studies on the efficiency of logistics services providers is carried out. Section 3 presents and explains the proposed metafrontier analysis approach, which is validated using Monte Carlo simulation in section 4. Section 5 presents a case study of the application of the proposed approach to the shipments of a large Spanish food company. Finally, sections 6 and 7 discusses the findings, summarize and conclude.

2. Literature review

There are many studies that have addressed the efficiency assessment of Logistics Service Providers (LSP) and Third-Party Logistics companies (3PL) using DEA. Table 1 presents a summary of those studies. As it can be seen, some of them consider basically economic/financial inputs and outputs such as labor costs, other operating expenses, depreciation and amortization expenses associated with property and equipment, net fixed assets, cost of sales, operating income, revenue, etc (Min and Joo 2006; Min and Joo 2009; Park and Lee 2015). By contrast, in other DEA studies 3PL efficiency assessment is based on operational variables such as fleet size, number of employees, labour hours, fuel consumption, warehouse space, total number of shipments handled, tons of transported freight, distance travelled per year, average lead time per delivery, vehicle fleet capacity utilization, etc. (e.g., Hamdan and Rogers 2008). A few of them also include GHG emissions as an undesirable output (Bajec and Tuljak-Suban 2019, Holden *et al*. 2016). There are also researchers who uses both financial and operational variables (e.g., Cavaignac et al. 2021). Other studies have focused on measuring the transport efficiency of distribution centres (e.g., Ross and Droge 2004, Loske and Klumpp 2021), on-road courier routes (Lin *et al*. 2010) and courier delivery areas (Dobrodolac *et al*. 2015). Andrejić *et al*. (2016) distinguished between the tactical level (fleet efficiency) and the operational level (vehicle efficiency) and Loske and Klumpp (2022) used DEA efficiency analysis to evaluate the impact of changing levels of digitalisation of loading process, route planning and truck automation looking for evidence of positive long-term effects of digitalization on transport logistics efficiency.

===== TABLE 1 =====

Also, in order to position our paper in the literature, it is interesting to note that although there exist many applications of DEA to supplier selection in general and sustainable suppliers in particular (see, e.g., Pal et al. 2013, Fotova Čiković et al. 2022), the present paper deals more with vendor (i.e. LSP) assessment than with supplier selection. It allows computing the cost efficiency of the shipments of a company and, as a by-product, of the corresponding carriers. It can also be used to estimate the expected minimum cost of a shipment based on its characteristics.

As can be seen from the above literature review, most DEA applications to LSP and freight transport study the problem from the point of view of the haulers, i.e., the object of the study is to assess the efficiency of the freight company. To the best of the authors' knowledge, there are no studies assessing the efficiency of the freight transport service providers from the point of view of their customers. That is exactly the aim of this paper: measuring the efficiency of the shipments ordered by a company and handled by different haulers. This situation is fairly common in practice. Thus, it has become common place for a company to auction the shipments so that bids are placed and awarded online. Although that auction mechanism is supposed to lead to cost efficiency, the company might be interested in an ex-post assessment of the efficiency of the different shipments and of the haulers that handled them.

3. Proposed DEA model

In order to benchmark the different shipments ordered by the company and carried out by different haulers a single input (namely, Shipment cost) and three outputs (i.e., Shipment weight, volume and distance) will be considered. This is shown in Figure 1. Note that this selection of inputs and outputs is original in the sense that they are so simple and basic that no previous approach has used them. Their relevance is self-evident. Nevertheless, for the case study presented in Section 5 they were validated by the head of logistics of the case study company.

As the three outputs are considered non-discretionary, an input orientation is due. As indicated in the Introduction, a metafrontier DEA approach is used so that all the shipments handled by a given hauler are grouped and benchmarked together to compute their local, i.e. intra-group efficiency. In the second phase, all observations can be pooled and their global metafrontier efficiency determined.

===== FIGURE 1 =====

It is clear that the global efficiency is less than (or at most equal to) the local efficiency. Moreover, the ratio of the global to the local efficiency is a measure of the efficiency of the hauler. There is one such measure for each shipment a hauler has transported. Averaging them provides an estimation of the hauler efficiency.

Before formulating the corresponding DEA models, let us introduce the notation used. Let

Data

C	Number of haulers
c	Index on haulers
j	Index on shipments
$c(j)$	Hauler that handled shipment j
$S(c)=\{j : c(j)=c\}$	Shipments of hauler c
$cost_j$	Cost of shipment j

$weight_j$ Weight of shipment j

$volume_j$ Volume of shipment j

$distance_j$ Distance of shipment j

0 Index of the shipment whose efficiency is assessed

Variables

$(\lambda_1, \lambda_2, ..., \lambda_n)$ Intensity variables used to compute a linear combination of the observed inputs and outputs

θ_0^{local} Local efficiency score of shipment 0

θ_0^{global} Global efficiency score of shipment 0

ξ_c Efficiency score of hauler c

$\theta_0^{local,CRS}$ CRS local efficiency of shipment 0

$\theta_0^{global,CRS}$ CRS global efficiency of shipment 0

σ_0^{local} Local scale efficiency of shipment 0

σ_0^{global} Global scale efficiency score of shipment 0

Input-oriented local efficiency DEA model

$$
\begin{aligned}
&\theta_0^{local} = Min \quad \theta \\
&s.t. \\
&\sum_{j \in S(c(0))} \lambda_j cost_j = \theta \cdot cost_0 \\
&\sum_{j \in S(c(0))} \lambda_j weight_j \geq weight_0 \\
&\sum_{j \in S(c(0))} \lambda_j volume_j \geq volume_0 \\
&\sum_{j \in S(c(0))} \lambda_j distance_j \geq distance_0 \\
&\sum_{j \in S(c(0))} \lambda_j \geq 1 \\
&\lambda_j \geq 0 \;\; \forall j \in S\left(c(0)\right) \qquad \theta \;\; free
\end{aligned}
\tag{1}
$$

Input-oriented global efficiency DEA model

$$
\begin{aligned}
&\theta_0^{global} = Min \quad \theta \\
&s.t. \\
&\sum_{c=1}^{C} \sum_{j \in S(c)} \lambda_j cost_j = \theta \cdot cost_0 \\
&\sum_{c=1}^{C} \sum_{j \in S(c)} \lambda_j weight_j \geq weight_0 \\
&\sum_{c=1}^{C} \sum_{j \in S(c)} \lambda_j volume_j \geq volume_0 \\
&\sum_{c=1}^{C} \sum_{j \in S(c)} \lambda_j distance_j \geq distance_0 \\
&\sum_{c=1}^{C} \sum_{j \in S(c)} \lambda_j \geq 1 \\
&\lambda_j \geq 0 \;\; \forall c \forall j \in S\left(c\right) \qquad \theta \;\; free
\end{aligned}
\tag{2}
$$

The above DEA models are similar and compute, within the corresponding PPS, a virtual operating point that represents a shipment of the same (or larger) weight, volume and distance but with a lower cost. The feasible operating point with the lowest cost is used as reference to determine the cost reduction factor θ_0^{local} or θ_0^{global}, depending on the model. The only difference between the two models is the set of observations that are considered to form the PPS. In the local efficiency case, the PPS is determined using only the observations of the hauler $c(0)$, which is the one that handled shipment 0. By contrast, in the global efficiency case, all the observations of all the haulers are used.

Note that, as in transportation the returns to scale can be increasing, the above models consider Non-Decreasing Returns to Scale (NDRS). Therefore, as the feasible region of (2) includes that of (1), it follows that $\theta_0^{global} \le \theta_0^{local}$ and, hence, $\frac{\theta_0^{global}}{\theta_0^{local}} \le 1$. Actually, the ratio represents the difference between considering only the shipments of hauler $c(0)$ and considering also those of the other haulers. That ratio, therefore, represents the distance between the local frontier corresponding to the best practices of hauler $c(0)$ and the global metafrontier that corresponds to the overall best practices. Averaging those ratios provides an estimation of the efficiency of the different hauler, i.e.

$$\xi_c = \frac{1}{|S(c)|} \cdot \sum_{j \in S(c)} \frac{\theta_j^{global}}{\theta_j^{local}} \tag{3}$$

The scale of efficiency of the shipments in relation to the local or the global frontier can also be determined, comparing θ_0^{local} and θ_0^{global} with the corresponding Constant Returns to Scale (CRS) efficiency scores computed removing the constraints on the sum of the intensity variables λ_j from the respective models and leaving just the non-negativity of the intensity variables $\lambda_j \ge 0$ as the only constraints on those variables. Mathematically,

$$\sigma_0^{local} = \frac{\theta_0^{local,CRS}}{\theta_0^{local}} \tag{4}$$

$$\sigma_0^{global} = \frac{\theta_0^{global,CRS}}{\theta_0^{global}} \tag{5}$$

Finally, the proposed approach can also be used to determine the lowest cost of a given hauler c and the overall lowest cost that can be expected for a shipment given its weight, volume and distance. To that end, the following two models can be considered.

Hauler c cost estimation DEA model

$$
\begin{aligned}
& cost_c(weight, volume, distance) = Min \quad cost \\
& s.t. \\
& \sum_{j \in S(c)} \lambda_j cost_j = cost \\
& \sum_{j \in S(c)} \lambda_j weight_j \geq weight \\
& \sum_{j \in S(c)} \lambda_j volume_j \geq volume \\
& \sum_{j \in S(c)} \lambda_j distance_j \geq distance \\
& \sum_{j \in S(c)} \lambda_j \geq 1 \\
& \lambda_j \geq 0 \quad \forall j \in S(c)
\end{aligned}
\tag{6}
$$

Minimum cost estimation DEA model

$$
\begin{aligned}
& cost(weight, volume, distance) = Min \quad cost \\
& s.t. \\
& \sum_{c=1}^{C} \sum_{j \in S(c)} \lambda_j cost_j = cost \\
& \sum_{c=1}^{C} \sum_{j \in S(c)} \lambda_j weight_j \geq weight \\
& \sum_{c=1}^{C} \sum_{j \in S(c)} \lambda_j volume_j \geq volume \\
& \sum_{c=1}^{C} \sum_{j \in S(c)} \lambda_j distance_j \geq distance \\
& \sum_{c=1}^{C} \sum_{j \in S(c)} \lambda_j \geq 1 \\
& \lambda_j \geq 0 \quad \forall c \forall j \in S(c)
\end{aligned}
\tag{7}
$$

4. Model validation

In order to test whether the defined model is able to correctly identify the efficiency of the haulers, a Monte Carlo simulation was designed. With that purpose, a group of hauler companies, each with a predefined efficiency that allows their ranking, was considered, and the validation process consists of testing if the DEA model ranks the companies according to those predefined implicit efficiencies.

Each company is delivering a certain number of hauls (100 services in each instance), with their corresponding weight (i.e., kg), volume (i.e. m^3) and distance (e.g. km), with the cost calculated following a single-output Cobb-Douglas function (see for instance Chen and Delmas, 2012):

$$X = K \cdot Y_{km}^{\alpha_1} \cdot Y_{m3}^{\alpha_2} \cdot Y_{km}^{\alpha_3} \cdot F \cdot R \qquad (8)$$

where in this case Y_{kg}~Unif(10,000;25,000), Y_{m3}~Unif(40;80) and Y_{km}~Unif(100;1,000) are the weight, volume and distance of the service respectively; F(={1;1.1;1.2;…}) corrects the base cost by including the efficiency of the hauler (unity for the most efficient, and therefore the less efficient hauler the larger value F); and R a random noise that includes many other secondary variables that makes the price of the haul non deterministic. All these values are randomly generated for each haul according to the parameters defined in Table 2. Constant K is estimated in each instance in such a way that the cost obtained is in the range of cost of real services, according to current prices in Spain.

===== TABLE 2 =====

As can be seen, three factors (at two levels) were considered when generating the instances in order to test if they have influence in the accuracy of the model. The first factor F1, the number of transportation companies, takes the values 5 and 10; the second F2 the noise level, following a uniform distribution with a range ±10% or ±30%; finally the third factor will take into account if the process exhibits a constant return of scale or not.

Regarding replications, for each of the 2^3 factor level treatments 20 instances were generated, which makes a total of 160 problem instances, each having 100×F1 transportation services.

To assess the level of success of the model guessing the original efficiencies of the haulers, the ranking of the efficiencies given by the model was compared with the real ranking used when generating the instances, and the Spearman's rank correlation coefficient r_s was considered to measure the accuracy level. The resulting average value of r_s was 0.992 with an exact estimation of the efficiency rank for 127 out of 160 instances

(79,4%). For some additional 32 instances the wrong ranking would be amended just by exchanging the position of 2 haulers. These results confirm the validity of the model.

Regarding the influence of the 3 factors considered, Figure 2 shows a boxplot of the r_s coefficients depending on their levels. As observed, even for the higher noise level the accuracy level of the model is quite high ($\overline{r_s}$ =0.985), with accuracy decreasing, as expected, as the number of haulers increases, and for the NDRS case, although always maintaining very high levels of success.

===== FIGURE 2 =====

5. Application case

To show how the model can be implemented in a real company, data from a large food company with different processing plants in Spain have been gathered. All the daily transportation contracts made during 51 weeks in year 2018 (hence prior to the pandemics) were collected, including origin and destination (km), the weight transported and the cost of such logistics service. This represents a total of 90,357 transport services, grouped by weeks, involving 83 haulers. Given the nature of the model that only compares the transport services with those in the same week, it was not necessary to consider the average price of fuel as an explicit (non-discretionary) variable. Note that, since in this application there is basically only one type of product (i.e., packaged milk) and weight and volume are highly correlated, only one of these two variables (plus, of course, shipment distance) has been considered as output.

An initial filtering of the data was performed for the sake of homogeneity, deleting non continental shipping, small loads (less than 10 tons), and occasional haulers (with less than 90 loads per month). This reduces the number of transports to 41,597 and only 7 recurrent haulers that will be analysed.

Regarding the 7 haulers that provide most of the logistics services for this company, Figure 3 shows the details of the distance and weight of each service. It can be observed that 3 out of the 7 are restricted to very short hauls (50 km at most), acting #1 as “jack of all trades” for short distance shipments. Haulers #3 and #6 provide mostly a medium haul service, while #7 works medium and long hauls. As seems natural, each LSP appears to center its activity in the niche that better suits its logistics capacity.

===== FIGURE 3 =====

After calculating the weekly activity of each hauler regarding the global and local scale efficiency of their shipments and averaging their ratio as per (3), the efficiency ξ_c of each courier *c* in each week is shown in Figure 4. As can be seen, there are clearly two clusters of haulers: those with most efficiencies between 0.8 and 1.0 (haulers #1, #4, and the long-distance hauler #7), and the rest, with efficiencies between 0.3 and 0.65.

===== FIGURE 4 =====

Figure 5 shows the Global scale efficiency of each service depending on weight or distance. This scale efficiency represents a measure of the cost premium paid for the shipment due to its size (in terms of both weight and distance). It can be seen that as the weight or the distance of the shipment increases, the global efficiency increases. Thus, large and distant shipments have a scale efficiency of unity, while the scale efficiency decreases (i.e. the cost premium increases) as the load weight or the distance transported decreases.

===== FIGURE 5 =====

Using model (7) and the observed data, the proposed approach allows the client company to estimate, for a fixed distance (e.g. 500 km) or for a fixed weight (e.g. 20 ton) the minimum costs that could be obtained among the various haulers. As these minimum costs are computed for each week (because the fuel prices and hence the shipping costs vary from one week to the next), they are shown in Figure 6 using boxplots to reflect the variability of the minimum costs among the 51 weeks considered.

6.Discussion and managerial considerations

Observing the previous results, it can be seen that the minimum cost increases with both weight and distance although it increases faster with the distance than with the load weight: Note also the increase in the variability of the minimum cost among the various time periods as the distance increases. This means that, for large distance shipments, significant differences in the cost of shipments throughout the year can be expected. Apart from seasonality factors and the varying fuel prices along the year, this variability may also be due to the dynamic character of the market conditions in general and of the specific situation of each hauler in terms of order backlog and resources availability.

===== FIGURE 6 ====

It should be remarked the usefulness of model (7) by studying the functional dependence of the cost of a shipment with weights and distance. As there are two independent variables, this function can be plotted as 3D surface or, as in Figure 7, plotting the cost as a function of one variable (e.g. distance) for a fixed value of the other variable (weight). Again, the minimum cost varies depending on the week considered. Hence, as representatives, Figure 7 plots the corresponding curves for weeks 1 and 51, i.e. the first and the last week of the time period considered. Although the two weeks are not identical, their behavior is very similar. Thus, in both cases, there is an almost linear relationship between cost and distance with the cost rate increasing as the load weight increases. Note that this behavior is surprising. What should be emphasised is the ability of the proposed approach to quantify this functional dependency and to do it in a non-parametric way using just the observed data.

===== FIGURE 7 ====

Regarding the managerial relevance of the scale efficiencies computed for each shipment, they allow estimating the cost premium paid for shipments whose load weight or distance are not large enough. The proposed approach can also be used to determine the minimum cost that can be expected from a specific hauler and the minimum cost overall for a shipment of given weight, volume and distance. This information allows the company to assess the price quotes received and bargain better prices. The dependence of shipment costs on each of the independent variables considered can also be studied with the proposed models.

Although the proposed metafrontier DEA approach refers to transport activities, it can in principle be extended to other inbound and outbound logistics activities. Thus, the basic idea is to adopt a company-centric approach for assessing the cost efficiency of the services provided by the different LSPs it works with. The output variables however need to be tailored to the activity being considered and may include other dimensions such as safety, on-time pickup, on-time delivery, duration of the storage service, etc.

7. Conclusions

This paper has presented a metafrontier analysis approach that allows a company to assess the cost efficiency of its shipments and of the haulers that handle them. It is based on a simple DEA model that assumes that the cost of a shipment basically depends on its weight, volume and distance. These three variables are considered non-discretionary and hence the efficiency assessment involves computing the cost reduction that could have been obtained for each shipment. Similarly, the hauler efficiency scores gauge their relative cost index. Also, the scale efficiency of each shipment can be computed and the existence of increasing returns to scale can be determined. In this regard, the proposed approach is innovative as it makes use of a NDRS metafrontier (instead of the conventional CRS or VRS). Morover, the proposed approch allows computing an estimation of the inputs as a function of the outputs, for each hauler and for the whole of them. All this information is helpful for the manager of the logistics department, who can thus better assess the price competitiveness of the haulers and bargain price quotes with an increased knowledge.

With regard to the limitations of the proposed approach, it does not allow the efficiency of the haulers to be assessed (and of the shipments) from an environmental point of view. This is because companies do not usually have information on the carbon dioxide emissions associated with the shipment. One possibility is to request the haulers to quote that too when bidding for a shipment. Another would be to request the hauler to report ex post the actual carbon dioxide emissions (or at least the fuel consumption) due to the shipment. In any case, the reliability of the data provided would depend on the hauler and the validity of its estimation/allocation method.

Another limitation of the proposed approach is that it does not take into account directly, i.e. as an explicit factor, the fuel price or the level of competition in the transport market. However, both factors are taken into account implicitly by considering only data on the most recent shipments made by the company (e.g., using a weekly time window). Actually, comparing the current global efficiency scores with the global efficiency scores computed using historical data can be used as a freight cost index. Such dynamic application of the proposed approach is left as a topic for further research as it is also the influence of centralized versus decentralized procurement of freight services. Also, as suggested by one of the referees, the possibility of including fleet or vehicle utilization ratios of haulers in the analysis could also be considered. Finally, it would be very interesting to include the environmental impact dimension (e.g., CO_2 emissions) in the analysis, in line with the growing concern of LSPs about the sustainability of their operations. This can be done using a metafrontier DEA approach that considers undesirable outputs (e.g., Beltrán-Esteve et al. 2014).

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Short biographies.-

Prof. Belarmino Adenso-Díaz is a professor of Operations Management at the Industrial Engineering School of the University of Oviedo in Spain. He worked for the Spanish National Steel Company for seven years, and has been a visiting professor at the Universities of Colorado and Michigan. He has authored four books, and published articles in scientific journals such as the Operations Research, Journal of Operations Management, Production and Operations Management, European Journal of Operational Research, International Journal of Production Research, Omega, IIE Transactions, etc. He is associate editor of Omega and the Journal of Heuristics.

Prof. Sebastian Lozano is Professor of Quantitative Methods in Management in the Department of Management at the University of Seville. He holds a Ph.D. from the University of Seville and a Master of Engineering in Industrial Management from the Katholieke Universiteit Leuven. He has published in different journal in the Management Science and Operations Research field such as the International Journal of Production Research, Robotics and Computer Integrated Manufacturing, Computers and Industrial Engineering, the Journal of the Operational Research Society, the European Journal of Operational Research, Journal of Productivity Analysis, etc. His main research interests are reverse logistics, closed-loop supply chains and performance/efficiency assessment including environmental impacts.

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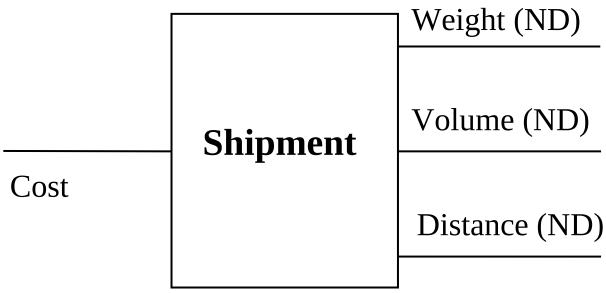

Figure 1. Inputs and outputs considered (ND: Non-discretionary)

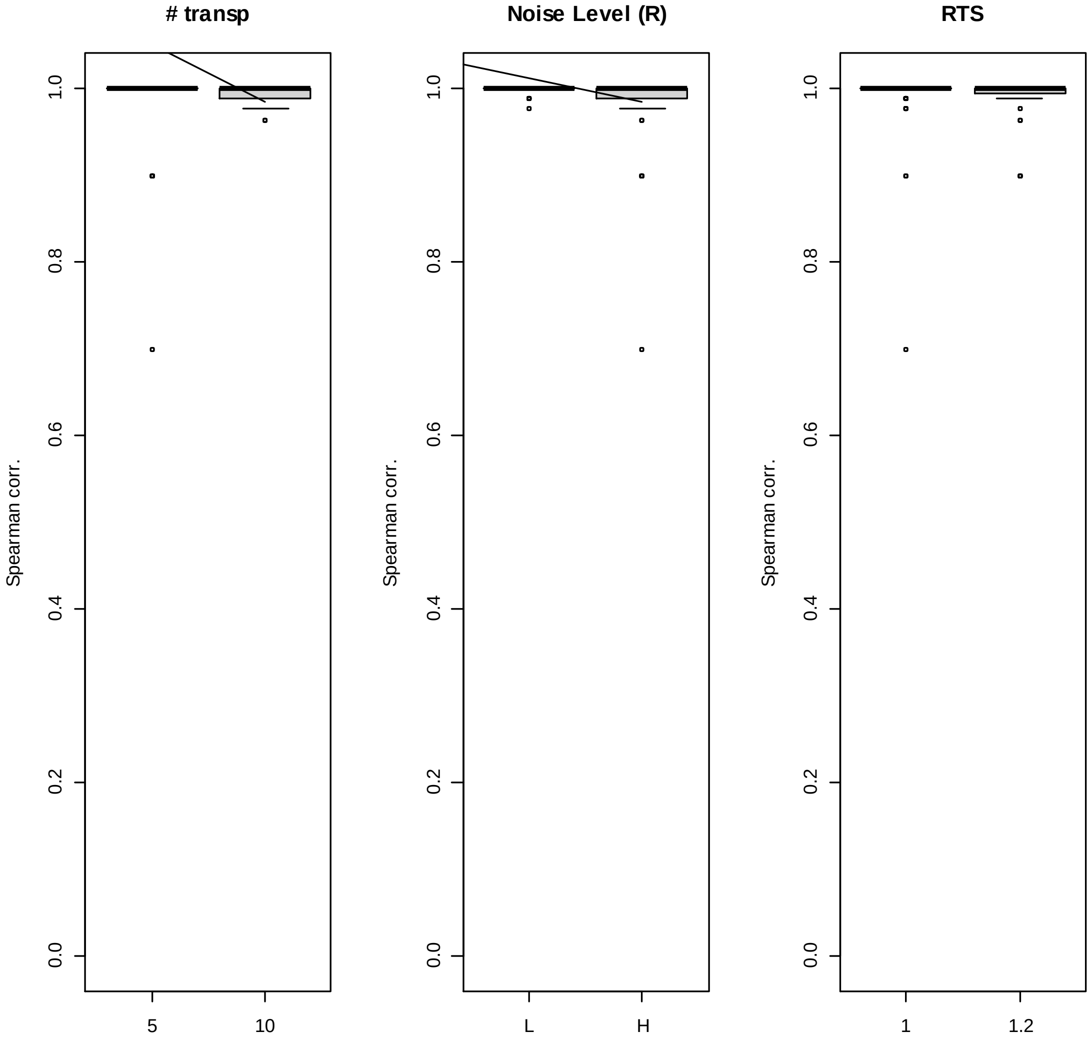

Figure 2. Box plot of the Spearman regression coefficients for the 3 factors considered in the experimentation for validation

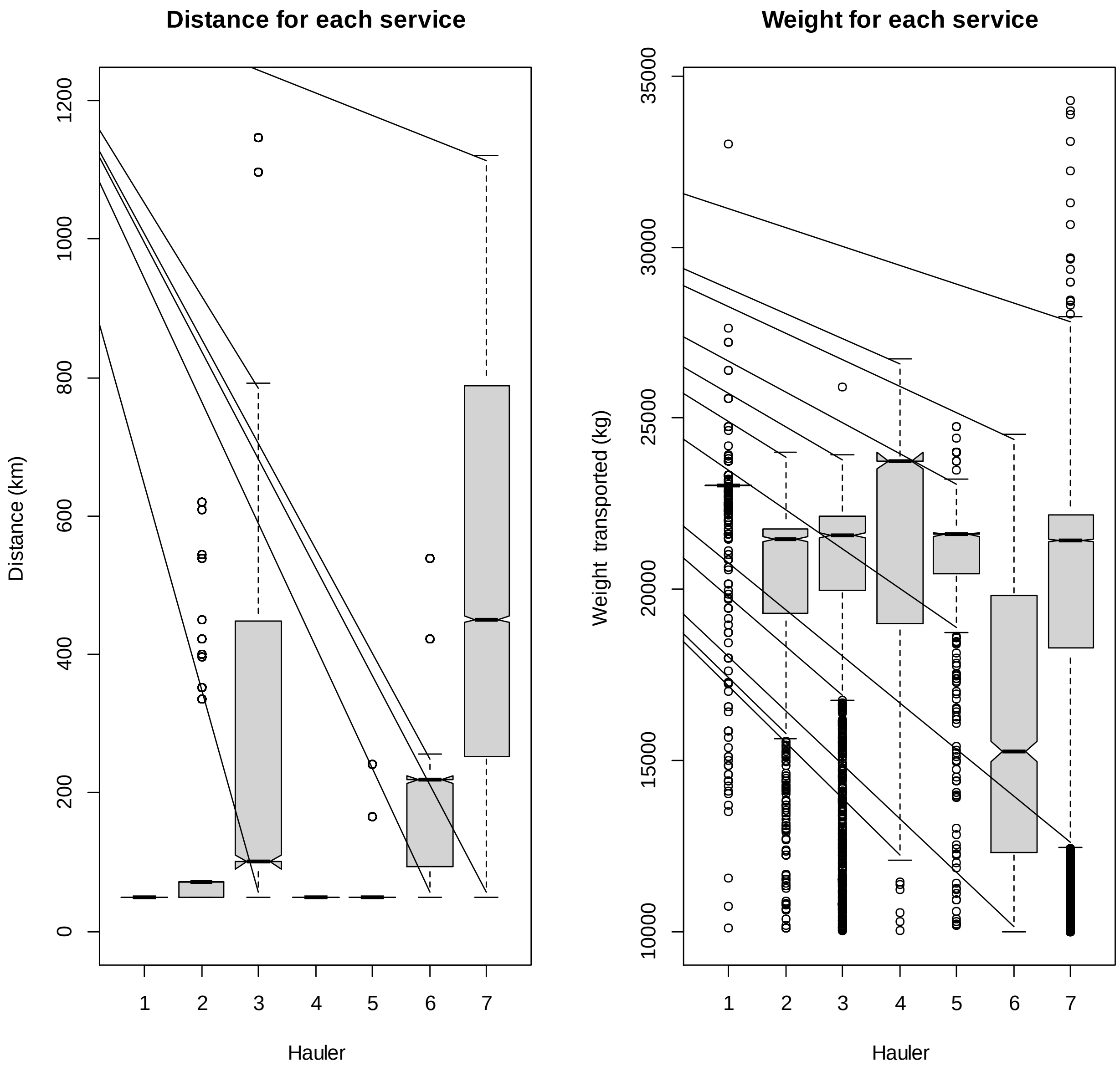

Figure 3. Characteristics of the logistics services provided by the seven main haulers, regarding distance and weight of the shipments

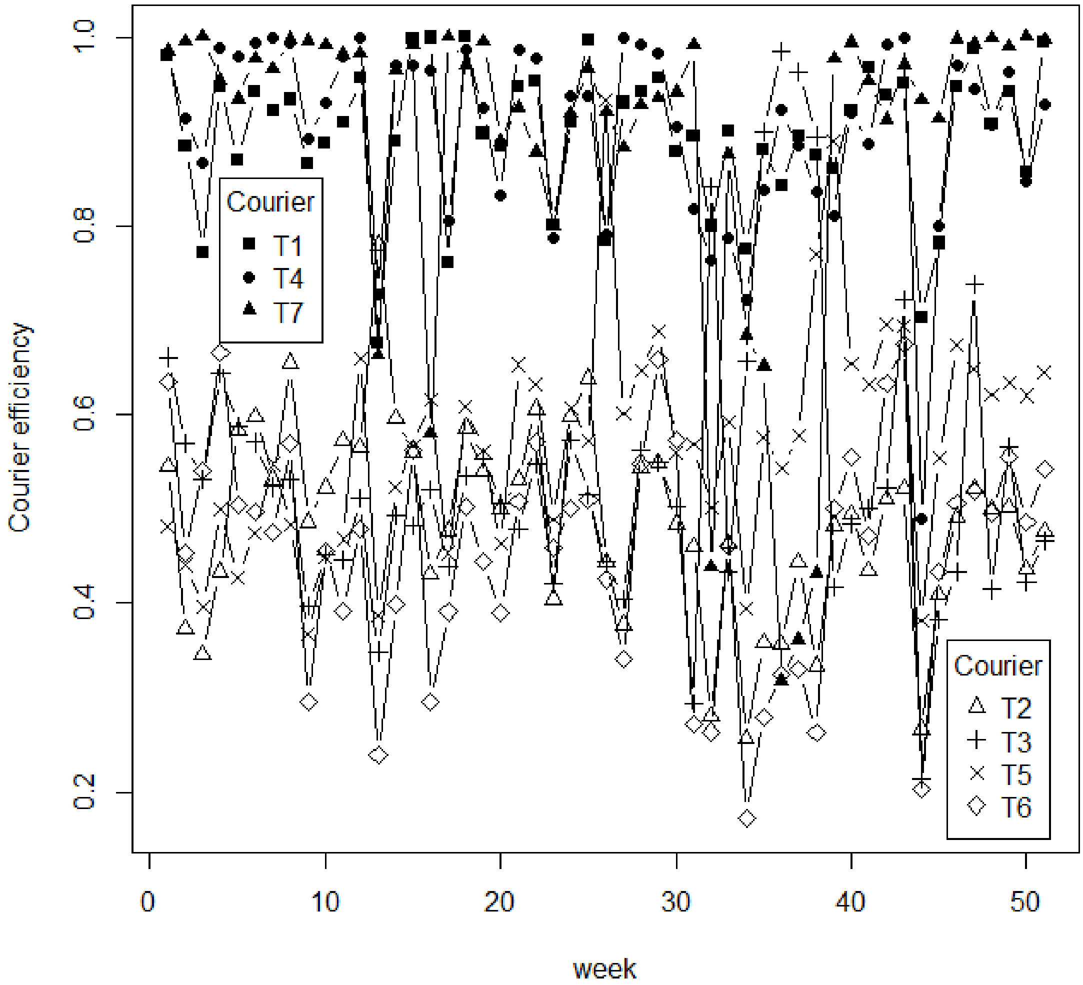

Figure 4. Evolution of the hauler efficiency ξ_c for each the seven haulers

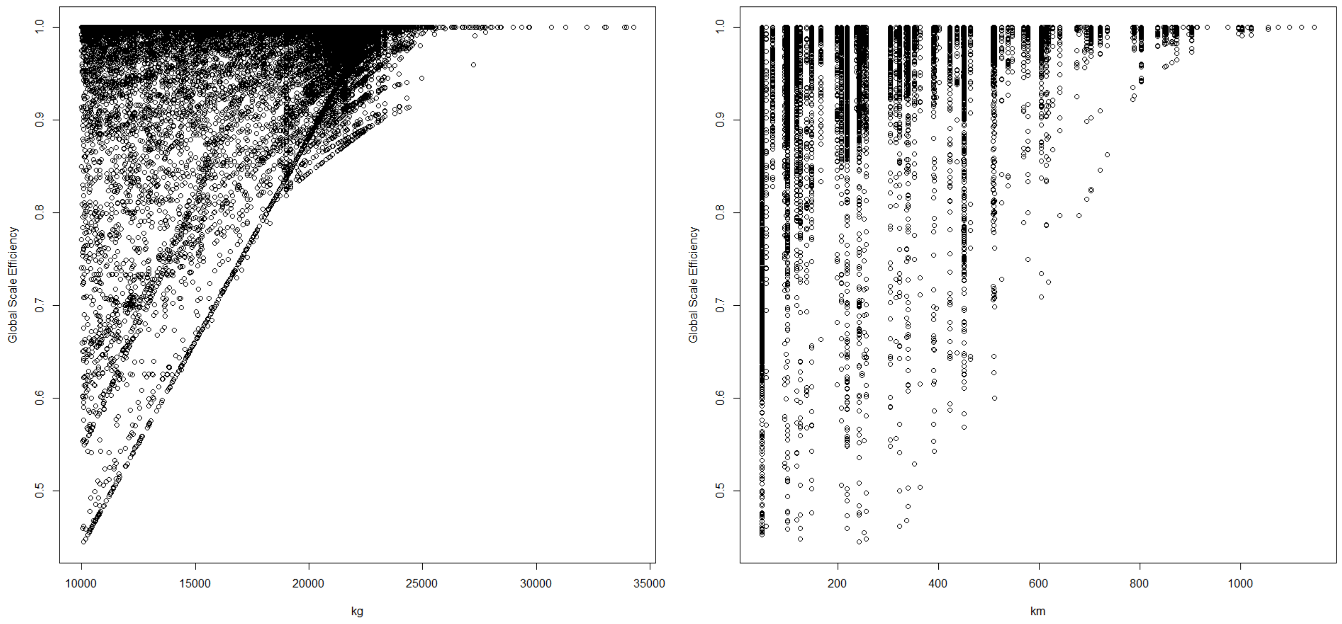

Figure 5. Global scale efficiency as a function of the distance and the weigh, for each of the shipments

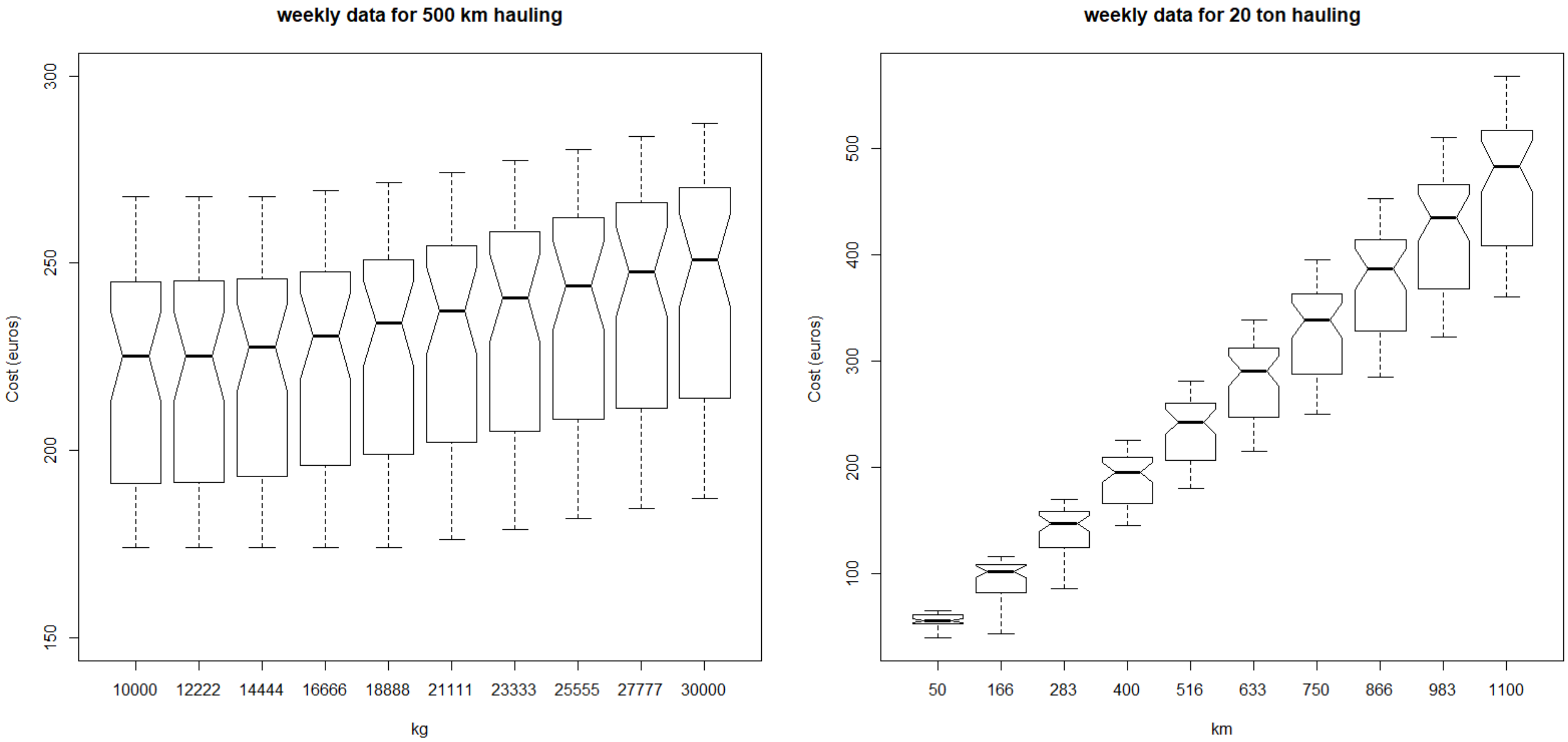

Figure 6. Boxplot of the minimum expected cost of the logistics services for a fixed distance (resp. for a fixed weight) depending on the weight (resp. distance) of the shipment

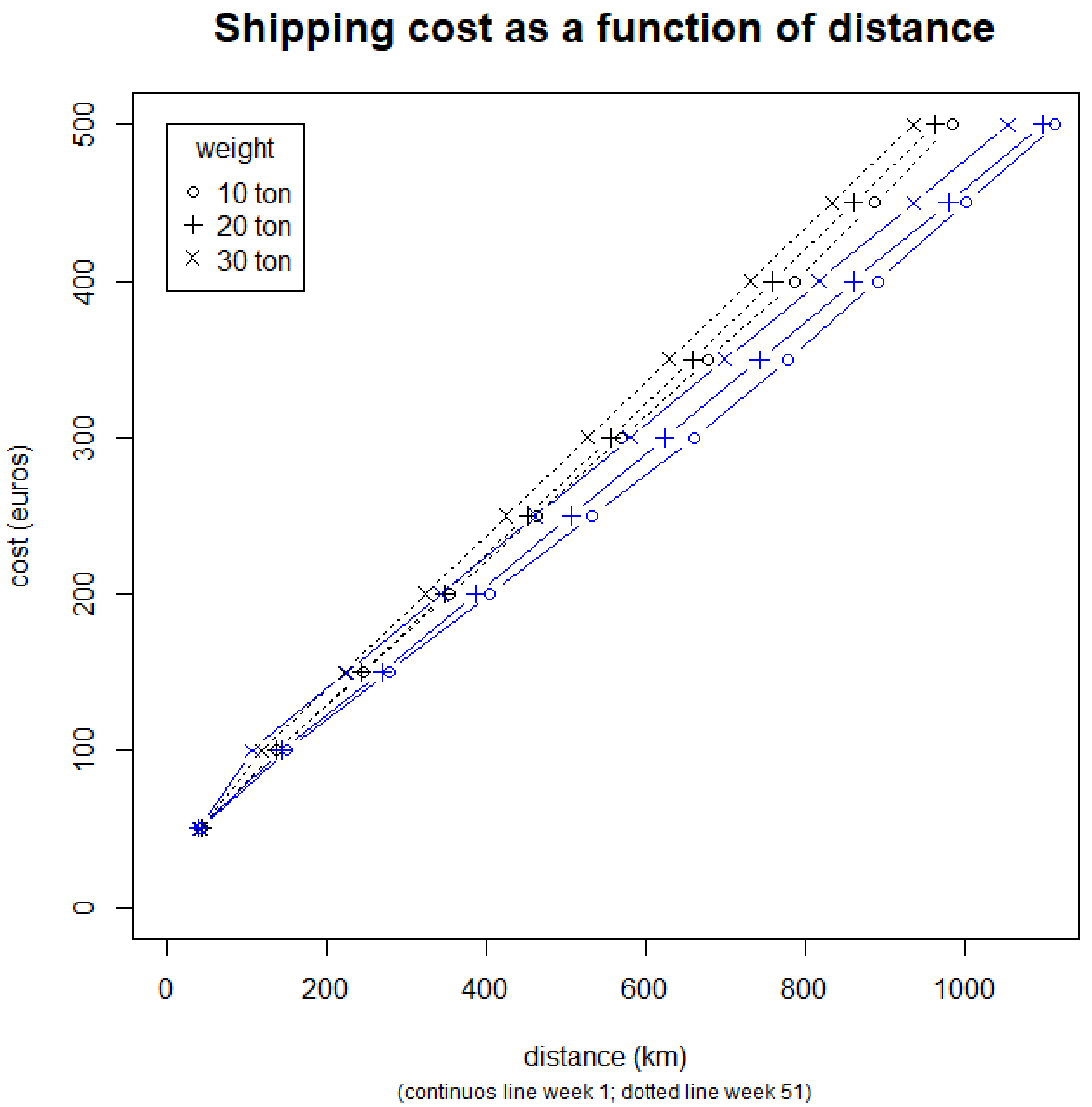

Figure 7. Minimum cost of a shipment as a function of distance for different load weights

Table 1. Literature review summary

Reference	DMUs	Inputs	Outputs	DEA approach	Remarks
Min and Joo (2006)	24 DMUs (3PL); USA	Accounts receivable; Salaries and wages of employees; Other operating expenses; Property & equipment	Operating income	CRS; input orientation; radial model	-
Min and Joo (2009)	36 DMUs (3PL); USA	DEA expense model: Cost of sales; Selling, general & administrative expense DEA asset model: Current assets; Fixed assets; Other assets	DEA expense model: Revenue DEA asset model: Revenue	VRS; input orientation; radial model; SBM model	Technical efficiency decomposition
Park and Lee (2015)	14 DMUs (LSP); Korea	Assets; Capital; No. of employees	Total revenue	VRS; input orientation; radial model; scale efficiency; super-efficiency	Five-year panel data; Window analysis; Malmquist index
Hamdan and Rogers (2008)	19 DMUs (3PL warehouses); USA	Labour hours; Warehouse space; Technology investment; Material handling equipment	Throughput; No. of orders filled; Space utilization	CRS; input orientation; radial model	Weight restrictions (Assurance region)
Bajec and Tuljak-Suban (2019)	18 DMUs (LSP); Slovenia	Total no. of employees; Total no of trucks; Average years of education per employee	Undesirable outputs: Average lead time per delivery; GHG emissions Desirable outputs: Profit per delivery; Turnover per km; Capacity utilization of vehicle fleet; Total number of orders	CRS; output orientation; SBM model; super-efficiency	AHP for selection of output variables
Cavaignac et al. (2021)	130 (117) DMUs (3PL); France	No. of warehouses; Mean area of warehouses; No. of employees; No. vehicles	Turnover	VRS; output orientation; radial model; returns to scale	PCA for outlier detection; Second-stage regression (several specifications)
Ross and Droge (2004)	207 DMUs (DC); USA	Vehicle fleet size; Drivers' experience; Regional index (non-discretionary)	No. of deliveries; Product delivery volume; Distance travelled by vehicles	VRS; input orientation; radial model; scale efficiency	Metafrontier analysis (3 regions)
Loske and Klumpp (2021)	1296 DMUs (depot-distribution channel); Germany	Total SKUs to transport; Available working time of truck drivers; No. of stores to deliver	On-time delivered stores; Total operational costs; Total no. of routes; Total waiting time at stores	CRS; output orientation; fuzzy DEA; radial model; weighted SBM model	AHP for output weights; Depots with different AI support levels
Andrejić et al. (2016)	13 DMUs (DC); Serbia	No. of vehicles, Fuel costs; Total trucks time	Distance driven; Shipped tons; Vehicle utilization	CRS; PCA-DEA model	Factors that affect efficiency: Transport management; Catchment area

Andrejić et al. (2016)	170 DMUs (vehicles); Serbia	Fuel consumption	No. of stops; Distance driven; Shipped pallets	CRS; radial model	Factors that affect efficiency: Vehicle age; Vehicle manufacturer; Vehicle capacity
Lin et al. (2010)	248 DMUs (on-road routes); Taiwan	Labour hours per month; Distance travelled per month; Vehicle capacity	No. of documents and boxes picked up and delivered per month	VRS	Exogenous fixed inputs: Stop density, Average travel speed in the area Categorial variable: Industrial-zone dummy variable
Dobrodolac et al. (2015)	6 DMUs (CDA); Serbia	Distance travelled; Time spent at served addresses; Time spent driving	No. of addresses served	CRS; input orientation; radial model; super-efficiency	-
Loske and Klumpp (2022)	60 DMUs (truck drivers); Germany	Time needed to load the truck; Relevant transportation costs	Income from the rendered logistics services; No. of loaded units; Inverse of the value of goods damaged	CRS; input orientation; radial model; DEA bootstrapping	Cross-sectional study; One-time digitalisation of truck loading; Factors affecting efficiency: Seniority; Level of vocational training
Loske and Klumpp (2022)	50 DMUs (truck drivers); Germany	Time needed to load the truck; Relevant transportation costs; Total truck capacity; Operating costs of trucks; Personnel costs; Fuel costs	Income from rendered logistics services; Fully-delivered units; Truck capacity utilization; Tons transported; No. of customers served	VRS; input orientation; radial model; Malmquist index	Longitudinal study; Continuously-increasing levels of digitalisation of truck loading, route planning and truck automation
Holden et al. (2016)	Simulated data (on-road freight transport companies)	Fleet-wise weight and volume capacities; Distance travelled by the fleet	Greenhouse gases emissions (transformed undesirable output)	VRS; output orientation; radial model	Context-dependent DEA (stepwise efficiency improvement path)

Notes: 3PL: Third-Party Logistics company; DC: Distribution Centre; LSP: Logistics Services Provider; SKU: Stock Keeping Unit; CDA: Courier Delivery Area
DMU: Decision Making Unit; CRS: Constant Returns to Scale; VRS: Variable Returns to Scale; SBM: Slacks-Based Measure (of efficiency)
AHP: Analytic Hierarchy Process; PCA: Principal Components Analysis; AI: Artificial Intelligence

Table 2. Parameters used for the generation of the instance in the Monte Carlo validation

	(F1) **No. of companies**	**(F2)** **R**	**(F3)** **RTS**
Low level	5	Uniform (0.9;1.1)	α_1=Uniform (0.3;0.4) α_2=Uniform (0.3;0.4) $\Sigma\alpha$=1 (CRS)
High level	10	Uniform (0.7;1.3)	α_1=Uniform (0.35;0.45) α_2=Uniform (0.35;0.45) $\Sigma\alpha$=1.2 (NDRS)