COMPLEX TECHNOLOGICAL AND ECONOMIC EFFICIENCY ASSESSMENT METHODS IN FREIGHT TRANSPORT AND LOGISTICS WITH SPECIAL EMPHASIS ON DATA ENVELOPMENT ANALYSIS

PhD Thesis

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Declaration

Hereby, I, Rita Markovits-Somogyi declare that I created the present PhD Thesis myself, and I utilized only the sources indicated within. By indicating the relevant source, I have clearly indentified all parts that have been used word by word, or in a reedited way but with the same content from other sources.

..........................................................
Rita Markovits-Somogyi
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<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AHP</td>
<td>Analytic Hierarchy Process</td>
</tr>
<tr>
<td>BCC</td>
<td>DEA variant, named after <em>(Banker, Charnes and Cooper, 1984)</em></td>
</tr>
<tr>
<td>CBA</td>
<td>Cost-Benefit Analysis</td>
</tr>
<tr>
<td>CCR</td>
<td>DEA variant, named after <em>(Charnes, Cooper, Rhodes, 1978)</em></td>
</tr>
<tr>
<td>CEI</td>
<td>Complex Efficiency Index</td>
</tr>
<tr>
<td>COLS</td>
<td>Corrected Ordinary Least Squares method</td>
</tr>
<tr>
<td>CRS</td>
<td>Constant Returns to Scale</td>
</tr>
<tr>
<td>DEA</td>
<td>Data Envelopment Analysis</td>
</tr>
<tr>
<td>DMU</td>
<td>Decision Making Unit</td>
</tr>
<tr>
<td>EW-TFP</td>
<td>Endogenous Weight TFP</td>
</tr>
<tr>
<td>FDH</td>
<td>Free/Flexible Disposal Hull</td>
</tr>
<tr>
<td>GDP</td>
<td>Gross Domestic Product</td>
</tr>
<tr>
<td>LC</td>
<td>Labour Costs</td>
</tr>
<tr>
<td>LP</td>
<td>Linear Programming</td>
</tr>
<tr>
<td>LPI</td>
<td>Logistics Performance Index</td>
</tr>
<tr>
<td>LQC</td>
<td>Logistics quality and competence</td>
</tr>
<tr>
<td>MCA</td>
<td>Multi-criteria Analysis</td>
</tr>
<tr>
<td>MCDA</td>
<td>Multi-Criteria Decision Analysis</td>
</tr>
<tr>
<td>MCMC</td>
<td>Markov Chain Monte Carlo simulation</td>
</tr>
<tr>
<td>MLE</td>
<td>Maximum Likelihood Estimation</td>
</tr>
<tr>
<td>MLPI</td>
<td>Malmquist – Luenberger productivity index</td>
</tr>
<tr>
<td>MPI</td>
<td>Malmquist productivity index</td>
</tr>
<tr>
<td>NVP</td>
<td>Net Value of Production</td>
</tr>
<tr>
<td>OCRA</td>
<td>Operational Competitiveness Rating</td>
</tr>
<tr>
<td>PCA</td>
<td>Principal Component Analysis</td>
</tr>
<tr>
<td>PU</td>
<td>Production Unit</td>
</tr>
<tr>
<td>SFA</td>
<td>Stochastic Frontier Analysis</td>
</tr>
<tr>
<td>TA</td>
<td>Tied-up assets</td>
</tr>
<tr>
<td>TFP</td>
<td>Total Factor Productivity</td>
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<tr>
<td>VRS</td>
<td>Variable Returns to Scale</td>
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1. Introduction

The significance of road freight transport and logistics is gradually increasing in the global economy, thus the optimization of the connecting business and technologic processes might provide a serious monetary advantage. Identification of the efficient stakeholders is a key task requiring integrated technological-economic approach which can contribute to revealing the best practices within the field. Besides, determining the efficiency of the different entities and providing their ranking might also be an incentive which enhances the holistic performance of the industry. Even more so, since “increasing the efficiency of transport and of infrastructure use” and “resource efficiency” are declared goals of the new White Paper setting the long term European objectives of transport development as well (European Commission, 2011).

Efficiency is a keyword in the “Freight Transport Logistics Action Plan” published in 2007 (European Commission, 2007), too. The Freight Transport Thematic Research Summary compiled by the Transport Research Knowledge Centre also assigns a separate chapter to the tools and services developed by research to enhance the quality and efficiency of logistics and supply chain activities (Delle Site, 2009 for a summary on the relevant projects see Markovits-Somogyi et al., 2010). Resource-efficiency is a keyword in the strategic programmes Europe 2020 and Horizon 2020 as well (European Commission 2010 and 2011b).

Regarding the national, Hungarian level it is also essential to make the efficiency of logistics and freight transport quantifiable, since it is the stated goal of the Hungarian Logistics Strategy developed for the period 2007-2013 to “make Hungary the centre of logistics services in the Eastern-European region and intercontinental cargo hub until 2013 (Gecse, 2008).”

The ultimate aim of the present thesis is to investigate the efficiency of already operating entities active in road freight transport and logistics. In order to do that, first the notion of efficiency is to be examined from a theoretical point of view. In everyday life, “efficiency” is often used parallel with “effectiveness” or “cost-efficiency”. It is important to be aware of the differences of these concepts, and also to give a clear definition of efficiency that can be reliably used in the later scientific investigations. “Performance” (Duma, 1999) and “productivity” are also such closely related notions, which are necessary to be included into the examinations, so as to clarify the relationships between these and efficiency. Thus, after the introduction, Section 2. defines and describes efficiency and its peer notions by an academic approach.
Then, the possible efficiency assessment techniques are to be reviewed, in order to be able to choose a method that can further be adapted to the field of road freight transport and logistics. **It has to be emphasized that the efficiency of already operating entities are to be examined.** This means that only those methods are to be included in the scope of investigation, which evaluate the efficiency of already existing firms. Thus, **ex-ante** assessment methods, which help project evaluation before the project is realized [e.g. cost-benefit analysis (CBA) or multi-criteria analysis (MCA) (Kovács and Bóna, 2009), or further complex techniques as in (Simongáti, 2009)], do not belong to the scope of the present work. It is true that ex-ante methods may also be used for a priori efficiency analysis, just as well as **ex-post** methods can be utilized before a project start, but in their essence and by their approach they are not designed for that (see Belton and Stewart, 1999), and they will not to be mixed up in the present research either.

Thus, Section 3. maps the different areas of ex-post efficiency assessment techniques, as based on a literature review. It will be seen that there are basically three main approaches: the indices, the parametric and the non-parametric methods. **Each area in itself could be a topic of a wide-ranging scientific research, so it was vital to choose one direction, in which to move on, in order to enable an in depth analysis of the efficiency of road freight transport and logistics companies.** Keeping in mind practical applicability and the poor availability of results, from this point on research was focused on non-parametric efficiency assessment techniques, as these do not require a priori assumptions about the production function of the units, and their data needs are also significantly lower. Thus, it could be expected that, even by scarce data availability, tests can be carried out in practice, on real-life data. Out of the known non-parametric methods, data envelopment analysis (DEA) was chosen, because this is the technique that is the most widely applied in the transport sector and this has the most reliable and most accepted mathematical background in the field.

The fact declared in the previous statement was established by conscientious literature review, the results of which are the content of Section 4. Here, the detailed mathematical background of data envelopment analysis is provided, focusing on the two main variants of the method, the DEA CCR (named after the initials of the authors Charnes, Cooper, Rhodes, 1978) and the BCC (Banker, Charnes and Cooper, 1984). Then, the application of DEA in the transport and logistics sector is analysed. Reviewing all available sources, the data of 69 transport applications were collected from the literature to investigate the utilized input-output structures. **Data from road freight transport and logistics application were also examined.** However, the number of these was significantly lower. **This confirmed the need for adapting the DEA method to the area of road freight transport and logistics.** This is done in Section 5., where traditional data envelopment
analysis is adapted to the micro- and macroeconomic field in road freight transport and logistics.

First, it is verified using financial data only that DEA can indeed be adapted to the road freight sector. For this reason, a sample of more than 30 firms was collected, and employing a financial indicator, the complex efficiency index, their ranking was established. This was then compared to the rankings provided by DEA. Then the DEA investigation was extended to include technological parameters as well. As a second microeconomic application, DEA was applied to logistics centres too. Finally, the logistics potential of European countries was also tested by a DEA model. All three adaptations were conducted using real-life data.

During literature review and practical adaptation it became clear that there is a disadvantage of DEA that could be circumvented. DEA does not fully rank the different companies [in DEA terminology called decision making units (DMUs)], it creates a subgroup of firms which are all efficient, and these are not ranked, while the inefficient ones are put in an order. Looking at the different solutions to this problem, there was found one which can be further developed. This is the DEA/AHP (analytic hierarchy process) methodology. The modified DEA/AHP methodology is proven to be able to better distinguish between the DMUs. Section 6. introduces this novel methodology and shows how it can be adapted in the field of road freight transport and logistics, by providing examples for assessing the efficiency of road haulage companies and European countries.
2. Definition of efficiency versus effectiveness and cost-efficiency

When characterizing operational entities, efficiency is mentioned frequently, but its meaning is seldom defined explicitly. How can it be distinguished from effectiveness and how does it relate to the performance of the company? In this section an effort is made to try and discern efficiency from performance and effectiveness, keeping in mind the area of application, that is, road freight transport and logistics. Even only using our common sense, we can be aware that efficiency, performance, effectiveness and cost-efficiency are all terms closely interrelated with each other. In order to give the most appropriate definition of efficiency one has to start with looking at performance.

2.1 Performance

Due to its all-encompassing nature and extreme popularity, it is very difficult to find a single definition of performance (Folan et al., 2007), and indeed few authors give an explicit definition for performance but treat it as an axiom (Tibenszkyné, 2008). Webster’s New World College Dictionary defines performance as “1) the act of performing; execution, accomplishment, fulfilment, etc. 2) operation or functioning, usually with regard to effectiveness, as of a machine 3) something done or performed; deed or feat 4) a) a formal exhibition of presentation before an audience, as a play, musical program, etc.; show b) one’s part in this” (Neufeldt, 1996). The Dictionary of the Hungarian Language has a slightly different emphasis. First, there is no reference to the meaning listed in the Webster Dictionary under 4), as in the Hungarian language “performance” as translated to “teljesítmény” lacks this meaning. Then, the definition goes as follows: “the quantifiable, data-like result which can be reached by someone or something in the course of work or other professional activity in a given timeframe” (Bárčzy and Országh, 1959). Very significant part of the definition is the “data-like” nature of the result, which is characterised by different authors in a different way (Markovits-Somogyi et al., 2010).

Kaplan and Norton (2002) regard performance as a merely financial category, and try to capture the “data-like” result referred to above by applying different financial indicators. Another aspect of performance is highlighted by Otley (1999), who defines the notion as the effective realization of the aims of a company. This approach is reflected by Adams et al. (2004) as well, where the above mentioned aim is further defined: “the aim of the organisations is to serve the consumers more effectively and efficiently than its rivals do”. Thus performance is characterised by effectiveness and efficiency. This view is shared by Chikán and Demeter (2003) too, who quantify performance using effectiveness and efficiency.
It has to be noted that the notion of performance may indicate, on the one hand, “business performance” (this can involve financial and non financial elements, e.g. regarding performance on the market or operational issues). Efficiency is one of the dimensions of this performance. On the other hand, in other fields and contexts, performance may also denote a physical value meaning a production or technological performance (often, it is connected to the volume of output or capacity). This double sidedness of performance is present in several industries and in the common language as well.

Kaplan and Atkinson (2003) determine three dimensions of performance: service, quality and cost; and then create key performance indicators according to these dimensions which can help verify whether the performance reaches the expected standards. Whereas Folan et al. (2007) determine the three governing objectives of performance as the following: the action carried out must be 1) standardized, non-random 2) quantifiable and 3) it must retain a relevance to the performer. So again we see that the quantifiable, data-like character of performance emerges. Domonkos (2003) identifies 7 dimensions of performance: effectiveness, efficiency, quality, productivity, labour quality, innovation and profitability. The most widespread view, however, sees performance as a result of only four components: cost-efficiency, effectiveness, productivity and efficiency (Wimmer, 2001). From all the definitions above it seems to be clear that efficiency is one dimension of performance and this is where one can proceed from in the next subsection.

2.2 Efficiency

Having established that efficiency is one dimension of performance one can go further by looking at this notion through the work of different authors. According to Marosi (1978) “that organisation can be regarded as efficient which can achieve its aims successfully with a satisfying, or acceptable ratio of costs and results (or generally speaking, inputs and outputs).” The same idea can be detected in the work of Dobák (2006) who says that “efficiency is the capability of a company to realise its stated objectives, and to use its available resources cost-effectively.” Webster’s Dictionary also defines efficiency in a similar way, according to which efficiency is “1) the ability to produce a desired effect, product, etc. with a minimum of effort, expense or waste; a quality or fact of being efficient 2) the ratio of effective work to the energy expended in producing it, as of a machine; output divided by input” (Neufeldt, 1996). The same view is shared by Borotvás et al. (1980) when they discuss that the essence of economic efficiency is whether certain investments can under the given circumstances provide for the best utilization of the resources (Markovits-Somogyi et al., 2010).

The definitions cited above indicate clearly the two-sidedness of the notion efficiency also highlighted by Wimmer (2010). First, it can be viewed as a ratio, or even just as a
relationship, between the inputs and outputs of a company. In this case efficiency is a quality of performance that can vary in a continuous (i.e. non-discrete) way and the stated objectives of the organisation are not necessarily present in the definition. This approach to efficiency is also mirrored by Drechsler (1981) and Román (1977), and to some extent by Kaplan and Norton (2002) and Győriványi (1992). On the other hand, a company can be viewed as efficient when it can reach its predetermined objectives, when it can create the desired effect. This approach is seldom utilised without the other; nonetheless, the Dictionary of the Hungarian Language defines efficiency by “effectiveness”, i.e. power to produce effects or intended results (Bárczy and Országh, 1959).

Keeping in mind the definitions and usage of the term efficiency in the literature cited above, we will focus on the ratio-like character of efficiency, and will start from the following definition: “The ratio of the products, services and other results produced during a given activity and the resources utilised for their production.” This description has several advantages: with its help efficiency can be objectively measured by mathematical applications and it can easily be adapted to transport logistics (Tíbenszkyné, 2008).

Thus, in the framework of the present thesis, efficiency in road freight transport and logistics shall be defined in the following way: “The ratio of the services and other results produced by the road freight transport or logistics firm and the resources utilised for this production.” It can be stated, that this ratio describes well that non-discrete feature of performance that is generally understood under efficiency.

2.3 Effectiveness, cost-efficiency and productivity

In order to see clearly in the cobweb of notions surrounding performance and to distinguish them from efficiency, three further concepts are dealt with, the other dimensions of performance: effectiveness, cost-efficiency and productivity. It is of utmost importance to define effectiveness, as it seems to be the counterpart of efficiency, and it is also often intertwined with it. In our view effectiveness determines how the given organisation can reach its predefined goals, i.e. this is the “other side” of efficiency. It has nothing to do with inputs, it only shows how the outputs, that is the results, match the predetermined objectives (Tíbenszkyné, 2008). This approach is also backed up by Bauer and Berács (1998) and also by Osborne and Gaebler (1994). As Webster’s Dictionary also states, effective “is applied to that which produces a definite effect or result” (Neufeldt, 1996). Consequently, a company can be called effective in the field of transport logistics if it can reach its predefined goals.
Cost-efficiency, on the other hand, deals with inputs: it shows how economically the available resources have been utilised during the given activity (Tibenszkyné, 2008). According to Webster’s Dictionary cost-effective means “producing good results for the amount of money spent; efficient or economical” (Neufeldt, 1996). As it has been shown, in the common language these notions are often explained with each other, however, it is vital that in the scientific field they are properly distinguished from each other. Thus we can say that a logistics firm is cost-efficient if it utilises its resources economically for the production of its services.

![Figure 2.1. The place of “efficiency” within the different dimensions of performance (Source: own edition as based on (Tibenszkyné, 2008) and own research)](image)

Productivity shall also be connected to the input side of the production process, as it emphasizes how much input is needed for the production of one unity of output. Its most popular form is labour productivity, which expresses the amount of labour required for the production of output (Borotvás et al., 1980). Figure 2.1. illustrates the difference between the different dimensions of performance.

### 2.4 Conclusion

Having mapped its surrounding notions, efficiency can be characterized as one of the dimensions of performance. Its ratio-like nature is to be emphasized, which is also reflected by the definition set up to be used in the present thesis further on: “The ratio of the services and other results produced by the road freight transport or logistics firm and the resources utilised for this production.” It is not to be confused with “effectiveness”, which shows whether the predetermined objectives of a decision making unit have been achieved.
3. Review and mathematical background of various ex-post efficiency measurement techniques

The aim of the present thesis is to analyse efficiency in the road freight transport and logistics field and to investigate the methods available for this purpose. As it has been stated before, the scope of the present work does not extend to ex-ante efficiency measurement techniques. The scope of the thesis covers only to ex-post investigations, where the efficiency of already operational entities is examined. Although sometimes similar in their mathematical formulation, the primary aim and field of utilization of these two clusters are rather distinct, and they should not be mixed when being discussed.

Cost-efficiency analysis and multi-criteria decision analysis (MCDA) are typically ex-ante efficiency measurement techniques. They attempt to give advice related to the future by estimating the future – or sometimes present – value of certain factors and a certain level of well-managed subjectivity is accepted in case of these methods. Whereas ex-post investigations, which include e.g. the use of indices, data envelopment analysis or stochastic frontier analysis, do not deal with the question of what option to choose from several possibilities, but they endeavour to monitor the efficiency of already operational entities by using measured data and trying to minimize subjectivity. There are some examples of MCDA techniques being used for monitoring, and vice versa DEA has also been observed as being applied for decision making but principally they are meant to operate in different environments. For detailed analysis on this subject the reader is referred to (Belton and Stewart, 1999).

As stated before, the goal of the present research is to monitor the efficiency of already functioning entities. Keeping this in mind and by reviewing the literature, the systematization of ex-post efficiency measurement techniques was carried out and a flow diagram (see Figure 3.1.) was created to outline the inner structure of the practical choices lying before the researcher when selecting an efficiency measurement method.

The flow diagram follows the traditional approach in that it distinguishes the techniques as the ones using an index, the ones using a production function (parametric approach) and the ones not using a production function (non-parametric approach). The rectangles indicate the decisions to be met, while the shaded forms present the techniques and versions selected.
It has to be emphasized that the flow diagram indicates the methods most frequently employed for efficiency measurement in the transport sector\(^1\). It is possible that there are further measures in the literature of other fields but those were not in the scope of the research. Furthermore, it shall be noted that other, completely different methodological approaches may also applicable when analysing or enhancing efficiency in transport and logistics. For example, improving the cost calculation procedures and the performance management regimes in transport can contribute to increasing the accuracy of resource allocations (Bokor, 2009). However, these are not in the scope of the present thesis either.

\[\text{Figure 3.1. The flow diagram outlining the choice between efficiency measurement techniques} \]
\[\text{(Source: own research)}\]

The basic observation is that although all of the discussed methods can be utilised individually for the efficiency measurement of systems in the transport sector,\(^1\) as it will be shown later on, there are rather few practical applications of ex-post efficiency measurement techniques, and within that, of data envelopment analysis in the logistics sector, and that is why it is reasonable to investigate this field together with the entirety of the transport sector which is intertwined with the logistics sector itself.
methodologically they show overlapping elements. In the following the efficiency measurement techniques are to be presented as based on Figure 3.1., summarizing the main characteristics of each and giving examples of their utilization in the transport sector.

3.1 Use of indices

First it has to be decided whether an index and within that a “single” (non-decomposed) or a decomposed index is to be used. The choice of a non-decomposed index is justified when the data available are scarce and/or very general and solely of a financial nature. A multitude of such kind of indices exist, examples (also indicated in Figure 3.1.) include Total Factor Productivity (TFP) (Oum and Yu, 1995), the TFP Törnquist index, and the Complex Efficiency Index (CEI) (Tibenszkyné, 2008; Pap, 2009).

\[
TFP = \frac{Y}{K^\alpha L^\beta} \quad (3.1)
\]

where
- \( TFP \) total factor productivity
- \( Y \) added value (or output)
- \( K \) capital
- \( L \) labour costs
- \( \alpha, \beta \) weights (in (Tibenszkyné, 2008): \( \alpha = s, \beta = s-1 \), indicating a weighing which expresses what part of \( Y \) is due to labour (and the rest is assumed to be due to the capital).

\[
TFPTörnquist_{priceindex,t,s} = \prod_{m=1}^{M} \left( \frac{p_{mt}}{p_{ms}} \right)^{-\omega_{ms} + \omega_{mt}} \quad m = 1, 2, ..., M \quad (3.2)
\]

where
- \( p_{mt}, p_{ms} \) the price of the \( m \)th good (or service) in period \( t \) and period \( s \), respectively,
- \( M \) the number of goods or services,
- \( \omega_{ms} = \frac{p_{ms}q_{ms}}{\sum_{m=1}^{M} p_{ms}q_{ms}}, \quad \omega_{mt} = \frac{p_{mt}q_{mt}}{\sum_{m=1}^{M} p_{mt}q_{mt}} \)
- \( q_{ms}, q_{mt} \) the quality of the good (or service) in period \( t \) and period \( s \), respectively.

\[
CEI = \frac{NVP}{\alpha TA + \beta LC} \quad (3.3)
\]

where
- \( CEI \) complex efficiency index,
- \( NVP \) net value of production,
- \( TA \) tied-up assets,
These simple indices provide only a broad judgement of the efficiency of the firms and that is why the decomposed indices have gained much place recently. Nevertheless it is important to be aware of their existence as they provide the basis for the decomposed indices and can give an estimation of efficiency if only few data are available.

The use of decomposed indices enables a much more sophisticated evaluation as it shows the effects of the different components. These can be, for instance, the decomposed TFP index, the Malmquist productivity index (MPI) and the Malmquist – Luenberger productivity index (MLPI). The decomposed TFP method relies on the TFP index given in Eq. 3.1., but they try to pinpoint the reasons behind the efficiency values. Obeng and Sakano (2002) for instance decompose TFP in such a way that input demand effect, pure scale effect, indirect output effect and pure technical change can all be investigated separately and the influence of subsidies can also be followed. A further example of TFP decomposition can be found by Graham (2008) who employs it to analyse the efficiency of 89 urban railway companies. The authors of different papers are not decomposing TFP in a unanimous way, different researchers create their own approaches.

The Malmquist productivity index (MPI) and the Malmquist-Luenberger productivity index (MLPI) (sometimes also referred to solely as TFP indices) can also be decomposed to provide us with two (or more) aspects of efficiency. The basic form of the index is given by Eq. 3.4. (Barros and Weber, 2009).

\[
MPI_{t,t+1} = \left( \frac{\theta_{t+1}(y_{t,1}, x_{t,1})}{\theta_{t}(y_{t,1}, x_{t,1})} \right) \left( \frac{\theta_{t+1}(y_{t,2}, x_{t,2})}{\theta_{t}(y_{t,2}, x_{t,2})} \right) \cdots \left( \frac{\theta_{t+1}(y_{t,M}, x_{t,M})}{\theta_{t}(y_{t,M}, x_{t,M})} \right)
\]

(3.4)

where

\(MPI\) the Malmquist productivity index,
\(\theta_{t,i}\) efficiency score for a given firm in period \(t\), by an input-oriented approach (i),
\(x_t = (x_{1,t}, x_{2,t}, \ldots, x_{N,t})\) a vector of \(N\) non-negative inputs in period \(t\),
\(y_t = (y_{1,t}, y_{2,t}, \ldots, y_{M,t})\) a vector of \(M\) non-negative outputs in period \(t\).

There are two major features of MPI – also visible from Eq. 3.4. – that have to be kept in mind. First, it is the time dynamics inherent in MPI: this index investigates the change in efficiency over time, thus it can be utilized in slightly different situations than the majority of the rest of the methods. Second, in order to achieve this dynamics, a priori information is necessary regarding the efficiency ranking of the firms in the different time periods.
This information can be made available with other methods to be outlined later on, like the SFA or the DEA method. However, it is exactly this latter feature that enables the evaluation of efficiency change without the need to make behavioural assumption made during its construction. As Yu et al. (2008) point out, it is also popular because it rests on the quantity of information and no price information is necessary for its use.

\[
MPI_{t,t+1} = \frac{\theta_{t,t+1}(y_{t+1},x_{t+1})}{\theta_{t,t}(y_{t},x_{t})} \sqrt{\frac{\theta_{t,t}(y_{t},x_{t})}{\theta_{t+1,t}(y_{t},x_{t})}} \frac{\theta_{t,t+1}(y_{t+1},x_{t+1})}{\theta_{t+1,t+1}(y_{t+1},x_{t+1})}
\]  \hspace{1cm} (3.5)

where

\[
\frac{\theta_{t,t+1}(y_{t+1},x_{t+1})}{\theta_{t,t}(y_{t},x_{t})} = EFFCH
\]  \hspace{1cm} (3.6)

is the efficiency change component, and

\[
\sqrt{\frac{\theta_{t,t}(y_{t},x_{t})}{\theta_{t+1,t}(y_{t},x_{t})}} \frac{\theta_{t,t+1}(y_{t+1},x_{t+1})}{\theta_{t+1,t+1}(y_{t+1},x_{t+1})} = TECH
\]  \hspace{1cm} (3.7)

is the technology change component.

Using the notations of Eq. 3.4., Eq. 3.5. presents the decomposed index (Barros and Weber, 2009). The two basic components of the decomposed Malmquist index are efficiency change (also called the “catching up” index), and the technology change (also referred to as “frontier shift” index). Despite their names both indicate a sort of efficiency change: the former shows how the individual companies have improved in catching up with others on the frontier (i.e. the frontier created by the best performers), while the latter measures the change of frontier between the two time periods selected (Odeck, 2008).

Other authors break up the index even further, like Barros and Weber (2009), who examine within technology change the bias in the production of outputs, the bias in using inputs and the magnitude in the shift of the production frontier. A further interesting decomposition of MPI is presented by Yu et al. (2008), who use MLPI to examine the effects of undesirable outputs. This allows for the possibility of crediting firms for the reduction in disagreeable effects. In this case the undesirable effect is aircraft noise, this factor is included in the efficiency evaluation of four Taiwanese airports over a five years time period using panel data. Further practical employment of the decomposed MPI index includes the efficiency measurement of 18 road toll companies in the period between 2002-2004 (Odeck, 2008), of 25 regional airports of China between 1995-2004 (Fung et al., 2008), of 25 UK airports between 2000-2005 (Barros and Weber, 2009), and 26 Spanish airports between 1993-1999 (Tovar, B. and Martín-Cejas, 2010).
3.2 Use of production functions

Another way of estimating efficiency is the application of production (or cost) functions; that is the econometric approach. The advantages and disadvantages of this approach lie at the same point: namely the need for a priori assumptions about the relationship between the inputs used and outputs generated. It might prove difficult to construct the production function, but then the effects of the different components can be easier measured than with non-parametric approaches and noise in the data is also possible to be dealt with. Production functions can be deterministic (algebraic) and stochastic, the most frequently applied function forms being: the linear, the Cobb-Douglas, the quadratic, the normalised quadratic, the translog, the generalised Leontief, and the constant elasticity of substitution (Coelli et al., 2005). Due to the nature of the fields examined, the use of stochastic functions is much more present in the literature relating to transport and the technique employing this approach is generally called stochastic frontier analysis (SFA). SFA was created simultaneously by Aigner et al. (1977) and Meeusen and van den Broeck (1977), and is applied to measure the deviation of a firm’s efficiency as compared to the best achievable target. In order to do this, first it creates the production function leaving room for random shocks and measurement error; and then evaluates the performance of the individual firms as compared to this frontier.

After Diana (Diana, 2010) the basic idea of SFA is as follows:

\[ Y_i = f(x_i, \beta) \cdot TE \]  \hspace{1cm} (3.8)

where

- \( Y_i \) vector of \( i = 1, ..., M \) numbers of producer outputs,
- \( f(x_i, \beta) \) the production frontier, and within that:
  - \( x_i \) vector of \( N \) inputs used by the producer,
  - \( \beta \) vector of (technology) parameters, and
  - \( TE \) technical efficiency.

Eq. 3.8. can for example be rewritten in the following log-linear Cobb-Douglas function form:

\[ \ln y_i = \beta_0 + \sum_n \beta_n \ln x_i + v_i - u_i , \text{ and} \]  \hspace{1cm} (3.9)

\[ TE_i = \exp \{- u_i\}, \text{ while } u_i \geq 0. \]  \hspace{1cm} (3.10)

- \( v_i \) is the noise component with a two-sided normal distribution, and accounts for measurement errors, while
- \( u_i \) is the non-negative technical inefficiency with either a half normal, a truncated normal, an exponential, or gamma distribution,

\( (v_i-u_i) \) can also be viewed as the compound error term, whereas

- \( \beta \) is the vector of (technology) parameters, as defined earlier, and
- \( n \) is the number of technology parameters.
In the transport sector Eq. 3.8. can and is frequently estimated with the translog function form as well. Its general form is the following (Coelli et al., 2005):

\[
y = \exp(\beta_0 + \sum_{n=1}^{N} \beta_n \ln x_n + \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} \beta_{mn} \ln x_n \ln x_m)
\]  

(3.11)

s.t. \( \beta_{mn} = \beta_{nm} \) for all \( m \) and \( n \), and where

- \( y \) the dependent variable,
- \( x_n \quad (n = 1, 2, \ldots, N) \): the explanatory variables,
- \( \beta_n, \beta_{mn} \) unknown parameters to be estimated.

Whichever production function is chosen, the parameters have to be estimated, which can be done with different methods. In case of a deterministic function, the corrected ordinary least squares method (COLS) or linear programming (LP) can be used. If the SFA method is selected, these two can still be applied [see (Coelli and Perelman, 1999)], or the maximum likelihood estimation (MLE) [see (Cullinane et al., 2006)] or the Markov Chain Monte Carlo simulation (MCMC) [see (Oum et al., 2008)] can also be employed.

Oum et al. (2008) use SFA with a translog function to evaluate the efficiency of 109 worldwide airports, Diana (2010) utilizes SFA with a log-linear Cobb-Douglas form for the examination of airport performance, Tsionas (2003) combines SFA with a non-parametric method to investigate the efficiency of 10 US airlines over a 14 year long period, Cullinane et al. (2006) look into the efficiency of 28 internationally very important container ports with an SFA method using a log-linear Cobb-Douglas production function, Coelli and Perelman (1999) estimate the efficiency of 17 European railway companies with this method, employing a translog function and applying the LP and the COLS technique and Tovar and Martín-Cejas (2010) use SFA as the basic method to calculate the efficiency rankings to be used in Malmquist productivity indexes in order to evaluate the efficiency of Spanish airports.

Finally, the endogenous weight TFP (EW-TFP) method has to be mentioned which is a unique technique in as much as it utilizes both an index and a production function, i.e. it creates an index from two functions: one that characterizes the input consumption, and the other which describes the production. Yoshida and Fujimoto (2004) examine the efficiency of 67 airports with the method, and further examples of its employment can also be found in the literature.

### 3.3 Use of non-parametric methods

Non-parametric methods differ significantly from the rest of the efficiency measurement techniques. The idea behind these is that they create a benchmark from the data of the
sample available and compare all of the companies (or more generally, decision making units, DMUs) to the best performing frontier. This is the biggest advantage to this method: there is no need to create previous assumptions about the characteristics of the production or service. Of course, this approach makes it more difficult to estimate the influence of different factors and outliers may influence the results (except in OCRA); but various techniques exist which help overcome these problems. Thus non-parametric methods are used extensively for the estimation of efficiency in the transport sector.

Beyond doubt, data envelopment analysis (DEA) is the most widely used non-parametric efficiency evaluation method. Its basic idea is presented below to show its place among the different efficiency measurement techniques, it is, however, discussed in more detail in Section 4. Eq. 3.12. shows the weighted ratio of the outputs and inputs which is to be maximized for all the decision making units (Cooper et al., 2004).

\[
\max h(u, v) = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}
\]  

(3.12)

subject to

\[
\sum_{j=1}^{n} u_r y_{rj} \leq 1 \quad j = 1, 2, ..., n,
\]

and \(u_r, v_i \geq 0\).

where

- \(h\) the function to be maximized,
- \(x_{ij}\) the amount of input \(i\) consumed by DMU \(j\) where \(i = 1, 2, ..., m\),
- \(y_{rj}\) the amount of output \(r\) produced by DMU \(j\) where \(r = 1, 2, ..., s\),
- \(m\) the number of inputs consumed,
- \(s\) the number of outputs generated,
- \(j\) number of DMUs,
- \(\theta\) index of DMU being examined,
- \(u, v\) weights to be calculated,

and subject to \(x_{ij} \geq 0, y_{rj} \geq 0\) and assuming that for each DMU there is at least one positive input and one positive output.

Applying the Charnes-Cooper transformation, the duality theory of linear programming and including non-zero slacks, Eq. 3.12. can be rewritten to yield the following envelopment model (input oriented approach):
\[
\min \theta - \varepsilon (\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+) \\
\text{s. t.} \\
\sum_{j=1}^{n} x_{ij} \lambda_j + s_i^- = \theta x_{i0} \quad i = 1, 2, ..., m \\
\sum_{j=1}^{n} y_{rj} \lambda_j - s_r^+ = y_{r0} \quad r = 1, 2, ..., s \\
\lambda_j, s_i^-, s_r^+ \geq 0 \quad \forall i, j, r \\
\text{where} \\
\theta \quad \text{efficiency value,} \\
s_i^-, s_r^+ \quad \text{input and output slacks,} \\
\lambda_j \quad \text{weights (developed as a result of the Charnes-Cooper transformation and the use of the duality theory),} \\
\varepsilon \quad \text{a non-Archimedean element, defined to be smaller than any positive real number.}
\]

The model described in Eq. 3.13 is the traditional DEA CCR method [named after the initials of its authors, Charnes, Cooper, Rhodes (Charnes et al., 1978)], and can investigate the DMUs on a constant returns to scale basis. If the constraint of Eq. 3.14 is added to it, the result is the DEA BCC model [named after Banker, Charnes and Cooper (Banker et al., 1984)], which enables the examination of variable returns to scale situations, i.e. when the change in inputs does not lead to a linearly proportional change in outputs.

\[
\sum_{j=1}^{m} \lambda_j = 1 \\
\text{(3.14)}
\]

Although DEA is not constructed in a way to facilitate the investigation of the effect of different components, if price information is available, above technical efficiency, allocative efficiency, overall efficiency, and even profit efficiency can be evaluated (Cooper et al., 2004). Moreover various techniques have been developed to permit the analysis of the influence of different factors contributing to the efficiency ranking, e.g. the Tobit model, or its special case, the recently created Simar-Wilson procedure with a truncated bootstrap regression (Barros and Dieke, 2008; Hirschhausen and Cullmann, 2010; Hung et al., 2010).

The literature on the application is immense indeed: airlines, railways, public transport companies, ports and airports are evaluated with the DEA method. Some of the most interesting examples include: Adler and Berechman (2001) investigate airports from the airlines’ view, carrying out a poll of the companies and then correlating this with a DEA VRS; Barros (2008) examines 32 Argentinean airports with DEA and the Simar-Wilson methodology, Yu (2008) performs a two-level DEA, focusing first on technical efficiency (i.e. the capacity provided by the transport company), then on service effectiveness (i.e.
the number of seats sold) of railways. Tongzon (2001) was the first to apply DEA to ports, and examined the efficiency of 16 international container ports, Sharma and Yu (Sharma and Yu, 2010) did the same for 70 container ports using decision tree based, context dependent DEA model. Sampaio et al. (2008) evaluated 19 public transport companies in Brazil and Europe, Hirschhausen and Cullmann (2010) investigated the efficiency of 179 German bus companies.

Naturally, the present thesis covers only transport and logistics utilizations, but it needs to be mentioned, that DEA is also widely applied in very different fields as well, for the efficiency analysis of banks (Charnes et al., 1990), schools (Kirjavainen and Loikkanen, 1998), universities (Tibenszkyné, 2007) and hospitals (Sherman, 1984) too². For a detailed discussion on the utilization of DEA in the transport and logistics sector, see Section 4.2.

**Operational competitiveness rating** (OCRA) is also a non-parametric efficiency measurement technique but it is applied considerably fewer times than DEA. There was only one example of its usage in the transport sector: Parkan (2002) applied it to the evaluation of a public transport company. Nonetheless, as it has a very similar approach of the one used in the DEA method, OCRA is worth mentioning and discussing, even more so, since it claims to overcome some problems inherent in the DEA method. OCRA is a distance function based approach just as DEA. It measures the closeness of a DMU’s (or in the OCRA terminology, the PU’s – production unit’s) performance from the ideal PU on a category by category basis, focusing on inefficiency in the following way (Parkan and Wu, 1999):

\[
E_k = \sum_{m=1}^{M} \left[ \frac{C_{k,m} - \min_n \{C_{nm}\} a_m}{\min_n \{C_{nm}\}} \right] \text{ s.t. } \sum_{m=1}^{M} a_m = 1 \quad (3.15)
\]

where
- \(E_k\) resource consumption inefficiency rating of the \(k^{th}\) PU (in DEA terminology it would be called rather something like “input inefficiency”),
- \(C_{k,m}\) cost of the \(m^{th}\) resource category for the \(k^{th}\) PU,
- \(M\) the number of cost categories,
- \(C_{nm}\) the \(n^{th}\) cost in cost category \(m\),
- \(a_m\) calibration constant.

\[
F_k = \sum_{h=1}^{H} \left[ \frac{\max_n \{R_{nh}\} - R_{k,h} b_h}{\min_n \{R_{nh}\}} \right] \text{ s.t. } \sum_{h=1}^{H} b_h = 1 \quad (3.16)
\]

where

² The references given in brackets provide only some examples, the relevant literature is much more extensive.
Complex technological and economic efficiency assessment methods in road freight transport and logistics with special emphasis on data envelopment analysis

- $F_k$ value generation inefficiency rating of the $k^{th}$ PU (“output inefficiency”),
- $R_{k,h}$ the revenue generated from the $h^{th}$ category of outputs,
- $H$ the number of revenue categories,
- $R_{n,h}$ the $n^{th}$ revenue in revenue category $h$,
- $b_h$ calibration constant, and

\[
G_k = w_c E_k + w_r F_k \tag{3.17}
\]

subject to $w_c + w_r = 1$, for $k = 1,...,K$

where

- $G_k$ combined inefficiency rating of the $k^{th}$ PU,
- $w_c, w_r$ relative importance of a production unit’s cost and revenue,
- $K$ the number of production units.

It is worth noting that the method outlined in Eq.3.15-3.17 can only be followed if the measurement problem justifies the assumption of identical calibration constant distribution for all PUs, if that is not the case, a more complex method is to be applied. The developer of OCRA, Parkan and Wu provide a method for the determination of the calibration constants, while it is mentioned that they could be settled with the use of other methods, like AHP as well (Parkan and Wu, 1999).

The merits of OCRA are claimed to be that the cost/revenue categories need not to be the same for all PUs, so the comparison of dissimilar entities becomes possible, and the possibly small number of PUs or many cost and/or revenue categories, or even outliers in the data do not present a problem (Parkan, 2003). The main difference between OCRA and DEA is that in the former the weights are determined manually, while in the latter the LP itself quantifies them. This can be construed as an advantage to OCRA, in as much as the decision makers can make priorities with respect to different cost/revenue variations. However at the same time, these calibration constants seem to be the biggest stumble block of the method, they have even triggered a debate about the validity of OCRA.

Wang in a note (Wang, 2006) pointed out several problems with the method, the two most significant of them being that 1) OCRA measures efficiency on the basis of monetary value, but doing so the subjective judgement regarding the “importance” of the categories are superfluous (there are simpler solutions to do the same, e.g. ANOVA) 2) Concerning the calibration recommended by Parkan, he finds that the use of average cost/revenue shares as calibration constant values might ensure that $1 less (or more) spent on a cost category would have the same effect on ratings as $1 less (or more) spent in another category, i.e. the category with the higher cost is more important than the one with the lower cost. He says that this assumption is frequently incorrect, and so the ratings of OCRA do not reflect performance. He supported his arguments with an example.
of application. Parkan in his reply (Parkan, 2006) showed that the results of Wang were based on an incorrect application of OCRA, and he also pointed out that in previous studies he had already applied OCRA to non-monetary inputs/outputs.

Looking at the numbers, we can say that indeed there were some mistakes in the calculation of Wang in as much as in his Scenario 1. he rounded certain calibration values which lead to the ranking criticized later on, but at the same time his theoretical viewpoint is correct. It is true that for an evaluation based on monetary values only, OCRA is not only too complex, but unnecessarily so. As for the calibration values: Parkan himself gets into contradiction when with his Scenario 1A. and 1B. proves contradictory statements. He creates the calibration values strictly on the basis of cost share and then claims that the cost category with larger cost/revenue ratio is not more important. The next section will analyse the correlation and reliability of the techniques outlined in Section 2, here OCRA is scrutinized again to see how it correlates with other efficiency evaluation techniques and it will be shown whether or not it is advisable to use this method.

Lastly the free/flexible disposal hull (FDH) technique has to be cited, as a non-parametric method used for efficiency evaluation. It is mentioned by Coelli and Perelman (1999) and Odeck (2008). The latter refers to two examples of its utilization, but both authors agree that it is a method rarely used. The reason might be its shortcomings: in FDH a DMU will be declared efficient by default if there are not enough number of observations on it and thus the method is discriminatory (Odeck, 2008).

3.4 Discussion on the correlation and links between the methods

Having reviewed numerous efficiency evaluation methods, the question arises naturally whether all of these techniques yield the same results and in how much the individual methods can be expected to be robust enough. The authors of the various papers have conducted correlation analyses the results of which are revealing: Cullinane et al. (2006) carried out a DEA and an SFA examination simultaneously and found a high degree of correlation between them. Coelli and Perelman (1999) also investigated the parametric and the DEA method in parallel (the former also with LP and also with COLS estimation methods), and found that the three procedures yielded reliably similar results. Graham (2008) compared results from the decomposed TFP method (created in such a way that it is comparable to the DEA method) and the DEA method, here also, the investigations yielded broadly the same rankings. Yoshida and Fujimoto (2004) examined data processed with the EW-TFP and also with the DEA method, both techniques lead to the same results. Parkan and Wu (1999) however found that the OCRA method gave similar results to DEA if and only if the DEA weights were restricted to remain around the OCRA calibration constants. Jayanthi et al. (1999) found no significant correlation between the
efficiency values produced by the OCRA and DEA method. From this summary it can be concluded that the majority of the methods seem to lead to the same results. Only the OCRA method appears to be problematic. Also bearing in mind the difficulties in connection with the method it is perhaps reasonable not to utilize the technique in question, but the rest of the methods can be employed safely and they will provide reliably similar results. Thus it can be stated that the methods enumerated in the present study – except for OCRA – can all be individually and reliably applied for the efficiency measurement of transport systems.

Figure 3.2. Links between the methods
(source: own research)

Before the revision of the literature, the measures utilized for efficiency evaluation seemed to be distinct, and this feeling was reinforced contemplating the traditional classification of the techniques (i.e. a) methods using an index, b) methods using a production function, c) non-parametric methods). The systematization of the techniques (in Figure 3.1. and throughout Section 3.3.) followed this classical idea. However, now it can be seen that there are very strong inner links between the methods, which even overlap at times. Figure 3.2. explains this discovered inner topography of the techniques. Naturally, the traditional indices have a very close relation to the decomposed TFP index (link 1), as they are its origin. MPI and MLPI have also much in common with the decomposed TFP index (2), as they use similar methods for the evaluation of different components in efficiency. At the same time MPI and MLPI cannot exist without the non-parametric methods (DEA, OCRA, FDH, hereinafter referred to as DEA) (3), or the SFA method (4), since they provide the input for the indices. The decomposed TFP and the DEA method are also very close (5), as the former can be construed in such a way that it becomes very similar to DEA. The decomposed TFP is also a “relative” of the econometric
methods (like SFA) (6), as their handling of components contributing to efficiency is very much alike (a functional relation is present). While SFA and DEA are the two sides of the same coin (7): they estimate the same thing with and without the error term. Finally, EW-TPF method is the one which unites the most from the different methods seeing that its roots are in the simple indices (8), it is a relative of the decomposed TFP (9), it is based on function forms similar to those of SFA (10), and creates an efficiency index based on distance functions, just as DEA (11).

Thus with Figure 3.2. and the relations enumerated I would like to stress the finding that the efficiency analysis techniques in the transport sector are not distinctly standing methods, but rather they create a network of solutions from which the researchers has to select a procedure or a combination best suiting his needs. Consequently and according to our basic hypothesis, it can indeed be stated that the techniques scrutinized show overlapping elements in their methodologies (Markovits-Somogyi, 2011d).

3.5 Conclusion

From the review of the literature it is evident that numerous methods exist for ex-post efficiency measurement. Having thoroughly investigated them, it has become clear that most of them stand on strong mathematical basis and are well accepted within the scientific community (the only exception is OCRA which is further not to be understood under the term “efficiency evaluation methods”). Perusing several studies looking into the correlation and validity of these different techniques, it has also been revealed that all of these efficiency evaluation methods may reliably be used for authentic efficiency evaluation.

Investigating the different databases of road freight transport and logistics companies available and possibly available for the purpose of efficiency evaluation, it was realized that there were not enough data at hand for conducting parametric efficiency assessments, and so it would have been necessary to include many estimations. This, in turn, would have reduced the reliability of the results. Furthermore, the scope of such a thesis would not have enabled the in-depth analysis of several different methods in parallel. Thus, it was reasonable to choose one efficiency measurement method and such a method that is of a non-parametric character.

Having reviewed the literature of non-parametric methods, the most reliable and widely used technique turned out to be data envelopment analysis. This is why it was selected as the efficiency evaluation technique to be utilised further in the present thesis. Even though the literature review above has shown that DEA provides results robust enough as compared with other techniques, it is the intention of the present thesis to
show that DEA can also be reliably used for efficiency evaluation in the road freight sector. Thus, a verification of this will be presented in Section 5.1.
4. Detailed discussion of data envelopment analysis and its application in the transport and logistics sector

4.1 Detailed discussion on the mathematical background and variants of DEA

Data envelopment analysis is a non-parametric evaluation method, and this is the basic characteristic that can be used best to give some introductory remarks about the way it functions.

It is a common feature of parametric efficiency assessment methods that they presume a function which characterizes the relationship between the resources used by a company (inputs) and the products or services it produces (outputs). Supposing that there are two inputs (e.g. capital and labour) and one output (e.g. number of products), this relationship can be imagined as a three dimensional surface, which is basically the production function, while the space below is the production possibility set.

Meanwhile non-parametric methods do not require the knowledge of the production function before the analysis, but they utilize experimental data. Imagining the same three dimensional space, the companies can be positioned here as individual points if their coordinates (three in the given example: use of labour, use of capital, number of products produced) are known. Data envelopment analysis determines a surface enveloping these points in space, and calls the evolving surface efficiency frontier. Those companies whose points are located in the efficiency frontier will be regarded as efficient, while the others are less efficient. Moreover, by calculating the distance of these points from the efficiency frontier, the degree of inefficiency can be established as well.

Advantages and disadvantages of DEA are a direct consequence of the way the method works: it is clearly an advantage that there is no need to have a priori assumptions about the production function of the given area. Also, it has to be mentioned that DEA enables the joint evaluation of multiple inputs and multiple outputs, which may even be of diverse nature, like monetary and technological parameters. A further benefit is the possibility to employ DEA on a relatively small sized sample. The basic thumb rule in the literature regarding the minimum sample size stipulates that the number of decision making units (DMUs) shall be at least three times the sum of the number of inputs and outputs (Bazargan and Vasigh, 2003).
Nevertheless, a disadvantage of DEA is the fact that it does not relate the efficiency of the decision making units to an absolute scale, but it determines a relative efficiency where the DMUs are compared to their most efficient peers. Furthermore, when conducting the analysis, special attention shall also be paid to outliers. These and also companies of very different profile shall be kept out of the final sample (Markovits-Somogyi, 2012c). The process of adapting DEA is shown in Figure 4.1.

![Figure 4.1. The process of adapting DEA](Source: own edition)

Finally, it has also to be emphasized, that DEA is linear. The function to be optimized is ratio-based (output/input), which would be very difficult to solve without the existence of predefined constraints. It becomes linear exactly because a limiting condition is introduced to the denominator.

**4.1.1 The basic method: DEA CCR**

The basic idea behind the DEA efficiency estimator is the ratio of outputs to inputs, and this way it is a very good measuring technique of the efficiency indicated by the definition given in Section 2.4., where efficiency is defined as “the ratio of the services and other results produced by the road freight transport or logistics firm and the resources utilised for this production.”
Thus, a company is more efficient, if it can produce a larger number of outputs with the same quantity of inputs (output oriented approach), or else, if it can produce the same amount of outputs with a smaller quantity of inputs (input oriented approach). With this ratio in mind, the efficiency of the observed DMUs can be evaluated by forming a best practice frontier as based on the performance of the best achieving companies and comparing the rest to them. This leads us to the most basic DEA method, the CCR [named after the initial of the authors, Charnes, Cooper, Rhodes in (Charnes, Cooper, Rhodes, 1978) who created the model as based on the idea of Farrel (1957)], the most vital characteristic of which is that it deals with constant returns to scale (for this reason also called CRS model). This means that the DMUs investigated operate at the most efficient scale size.

The CCR DEA model can be described as follows (Cooper et al., 2004): let us assume that there are \( n \) DMUs to be evaluated. Each DMU consumes \( m \) different inputs and produces \( s \) different outputs. Thus, e.g. DMU \( j \) consumes \( x_{ij} \) of input \( i \), and produces \( y_{rj} \) of output \( r \). We also assume that \( x_{ij} \geq 0, \ y_{rj} \geq 0 \), and for each DMU, there is at least one positive input and one positive output. From these, the ratio of outputs to inputs is used to measure relative efficiency \( DMU_j = DMU_0 \), the DMU to be evaluated relative to the ratio of all \( j = 1, 2, \ldots, n \) DMUs.

Thus, the function to be maximised is:

\[
\max h_0(u,v) = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}
\]

(4.1)

where: \( u_r, v_i \) are weights; \( y_{r0}, x_{i0} \) are the observed input/output values of DMU \( 0 \) (DMU to be evaluated).

The following constraints are introduced so as to give a limit to the values:

\[
\sum_{r=1}^{s} u_r y_{rj} \leq 1 \quad j = 1, 2, \ldots, n, \quad (4.2)
\]

\[
\sum_{i=1}^{m} v_i x_{ij} \quad j = 1, 2, \ldots, n, \quad (4.2)
\]

and \( u_r, v_i \geq 0 \).

Using the Charnes–Cooper transformation (Charnes et al. 2004), this leads us to the following equivalent linear programming problem:

\[
\max z = \sum_{r=1}^{s} \mu_r y_{r0}
\]

(4.3)
\begin{align*}
\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} \nu_i x_{ij} & \leq 0 \\
\sum_{i=1}^{m} \nu_i x_{i0} & = 1 \\
\mu_r, \nu_i & \geq 0
\end{align*}

where: \((u, v)\) change to \((\mu, \nu)\) as a result of the Charnes–Cooper transformation. The equivalent dual LP problem of (4.3) is:

\begin{equation}
\theta^* = \min \theta
\end{equation}

subject to

\begin{align*}
\sum_{j=1}^{n} x_{ij} \lambda_j & \leq \theta x_{i0} & i = 1, 2, ..., m; \\
\sum_{j=1}^{n} y_{rj} \lambda_j & \geq y_{r0} & r = 1, 2, ..., s; \\
\lambda_j & \geq 0 & j = 1, 2, ..., n.
\end{align*}

This formula is also called the ‘Farrel model’ as it was created by Farrel. However, he did not apply the dual theorem of linear programming (by virtue of which \(z^* = \theta^*\), and either problem can be solved) and hence was not able to make the connection between the models introduced above.

Formula (4.4) is also called the ‘strong disposal’ or ‘weak efficiency’ model as it ignores non-zero slacks. Should we want to take them also into account, we have to use the following modified model that is also called the envelopment model:

\begin{equation}
\min \theta - \varepsilon \left( \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)
\end{equation}

subject to

\begin{align*}
\sum_{j=1}^{n} x_{ij} \lambda_j + s_i^- & = \theta x_{i0} & i = 1, 2, ..., m; \\
\sum_{j=1}^{n} y_{rj} \lambda_j - s_r^+ & = y_{r0} & r = 1, 2, ..., s; \\
\lambda_j, s_i^-, s_r^+ & \geq 0 & \forall i, j, r
\end{align*}

where: \(\varepsilon\) is a non-Archimedean element defined to be smaller than any positive real number.

The dual linear program of this model, also known as the multiplier model, is:

\begin{equation}
\max z = \sum_{r=1}^{s} \mu_r y_{r0}
\end{equation}

subject to
\[ \sum_{j=1}^{m} \mu_j y_{ij} - \sum_{i=1}^{n} v_i x_{ij} \leq 0 \]

\[ \sum_{i=1}^{n} v_i x_{i0} = 1 \]

\[ \mu_i, v_i \geq \varepsilon > 0 \]

Using these formulae, a DMU \( 0 \) is efficient if and only if \( \theta^* = 1 \) and \( s_i^- = s_r^+ = 0 \) for all \( i, r \), and it is weakly efficient if \( \theta^* = 1 \) and \( s_i^- \neq 0 \) and/or \( s_r^+ \neq 0 \) for some \( i \) and \( r \) in some alternate optima (Cooper et al. 2004). Formulae (4.5) and (4.6) represent the input-oriented DEA CCR models (envelopment and multiplier form). The output oriented model is also very similar, and makes difference in the values to be maximized/minimized.

### 4.1.2 The BCC model

The DEA BCC [named after Banker, Charnes and Cooper in (Banker, Charnes and Cooper, 1984)] model incorporates an additional constraint, the convexity constraint:

\[ \sum_{j=1}^{n} \lambda_j = 1 \]  \( (4.7) \)

which enables to take into account the non-constant returns to scale (for this reason also called variable returns to scale, VRS model).

**Table 4.1. Studies applying the CCR and/or the BCC DEA method**

<table>
<thead>
<tr>
<th>Source</th>
<th>CCR</th>
<th>BCC</th>
<th>Transport mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adler and Berechman, 2001</td>
<td>✓</td>
<td></td>
<td>airports</td>
</tr>
<tr>
<td>Barros and Dieke, 2008</td>
<td>✓</td>
<td>✓</td>
<td>airports</td>
</tr>
<tr>
<td>Barros, 2008</td>
<td>✓</td>
<td>✓</td>
<td>airports</td>
</tr>
<tr>
<td>Cullinane and Wang, 2005</td>
<td>✓</td>
<td>✓</td>
<td>ports</td>
</tr>
<tr>
<td>Jitsuzumi and Nakamura, 2010</td>
<td></td>
<td>✓</td>
<td>railways</td>
</tr>
<tr>
<td>Martin and Roman, 2001.</td>
<td>✓</td>
<td>✓</td>
<td>airports</td>
</tr>
<tr>
<td>Pacheco and Fernandes, 2003.</td>
<td></td>
<td>✓</td>
<td>airports</td>
</tr>
<tr>
<td>Pina and Torres, 2001.</td>
<td>✓</td>
<td>✓</td>
<td>urban public transport</td>
</tr>
<tr>
<td>Sampaio et al., 2008</td>
<td>✓</td>
<td>✓</td>
<td>public transport</td>
</tr>
<tr>
<td>Wu and Goh, 2010.</td>
<td>✓</td>
<td>✓</td>
<td>ports</td>
</tr>
<tr>
<td>Yoshida and Fujimoto, 2004</td>
<td>✓</td>
<td>✓</td>
<td>airports</td>
</tr>
</tbody>
</table>

(Source: own research)

Undoubtedly, in most of the cases the possibility of variable returns to scale has to be considered. That is why several studies employ both techniques at the same time, and if the efficiency values do not match, there is scale inefficiency and the companies at hand
display variable returns to scale. In these cases the original DEA CCR value can be decomposed into scale inefficiency and “pure technical inefficiency” (Coelli, 1996). Table 4.1. shows a selection of studies which apply CCR, BCC or both of the methods in the transport sector (Markovits-Somogyi, 2011a).

4.2 Application of data envelopment analysis in the transport and in the logistics sector

As it has been seen in the previous section, the major question when constructing a DEA study is the proper selection of inputs and outputs. In order to choose the right ones, a literature review is presented below which summarizes the relevant findings from DEA applications in the transport and logistics sector (Markovits-Somogyi, 2011c). The examination of the transport sector is essential, because, as it will be discussed in detail later on, very few examples of DEA applications can be found in the road freight transport and logistics sector; while transport is the industry, which is very similar and in some cases even overlaps with logistics; thus it is a good field for gathering experience about applications.

4.2.1 Transport sector

Review of applications

Reviewing the literature to be found on the application of DEA a very broad and colourful picture emerges. In this appraisal 69 studies on the method have been gathered in order to enable the examination of the data, the supporting methods and the inputs and outputs chosen. These studies were elaborated either directly in the papers listed in the references, or were reported in the same articles (Azadeh et al., 2008; Barros, 2008; Barros, Peypoch, 2009; Bazargan, Vasigh, 2003; Cullinane et al., 2005; Good et al., 1993; Hamdan, Rogers, 2008; Jitsuzumi, Nakamura, 2010; Karlaftis, 2004; Martin, Roman, 2001; Odeck, 2006; Pacheco, Fernandes, 2003; Sampaio et al., 2008; Tongzon, 2001; Yu and Lin, 2008; Yu, 2010; Wu, Goh, 2010, etc.). We have to be aware that not always were all the data available to work with: sometimes the chosen inputs or outputs were not mentioned, or the reference to the place of application was missing. Nevertheless for most of the studies the data needed were accessible, and of course it is only this information that is included in this study for further investigation.

Figure 4.2. shows the distribution of the studies among the different transport modes. As it can be seen clearly, the majority of the studies deal with airports and ports; these two represent more than 50% of the studies. Public transport companies and railway companies also have a significant share, while airlines are only mentioned in 4 studies.

When talking of public transport companies we have to be aware that this is not a homogenous group. Urban just as well as rural companies, or the blend of the two have
been investigated with the DEA; and in some cases these were companies operating buses only, in other cases there was mix of fleet (bus, underground) present. However, this is not a factor which prevents us from comparing these studies, as the methodology and their chosen inputs/outputs were remarkably similar. Even the mixed fleet did not pose a problem for the application of DEA, since the “number of equivalent vehicles” could homogenize the fleet from the point of view of selected input.

Figure 4.2. The distribution of the studies found in the literature (number of studies) 
(source: own research)

Figure 4.3. shows the distribution of the DEA studies among the different continents showing the share of the different transport modes as well. It is evident that the most DEA applications can be found in Europe, Asia (the Near East and Japan having an important role) and North-America. Although it is not indicated in the figure, 11 out of the 12 studies coming from North-America originate from the United States of America.

Looking at the share of different transport modes, we find that the majority of studies in Europe deal with airports and the public transport, while in Asia the port efficiency is investigated the most. The curiosity into railway efficiency is nearly evenly distributed between these two continents, but it has a smaller share.

Figure 4.4. presents the frequency of the number of DMUs in the samples of the DEAs investigated. Three outliers in the range above 70 have been excluded from the data so as to make the graphical representation simpler. Nonetheless these outliers also reveal an interesting phenomenon to be observed in the choice of the number of DMUs. All three of these outliers (all of them above 150) belong to studies in the public transport area. This shows that the researchers of this transport mode have a much larger provisional data set to choose from, and are less limited by lack of data. The reason for this might be the requirement of public spendings being transparent.
Figure 4.3. The distribution of the DEA applications among the continents according to modes of transport

(source: own research)

Figure 4.4. Frequency of the number of DMUs investigated

(source: own research)

Figure 4.4. indicates also that the number of DMUs in the DEA applications cluster around thirty (the average being 29.22), and the huge majority is between 15 and 40. (See descriptive statistics in Table 4.2.) On the one hand this can be explained by the data available (we shall remember that the DMUs in the transport sector would for instance be airports, ports or railway companies), but it is also explained by the fact that there is a desired correlation between the number of inputs/outputs and the number of DMUs. As a thumb rule the number of observations should be three times greater than the number of the inputs plus outputs; and the number of DMUs should be equal or larger than the product of the number of inputs and outputs.
From the review of the studies it seems that it is mainly output orientation that is preferred for the evaluation of airports and ports. This is rather reasonable as these dispose of facilities (e.g. runways, terminal buildings, terminal area of ports) which are difficult and/or very expensive to extend, and as such, most of the inputs chosen for the DEA would be hard to alter. For the evaluation of public transport organizations and railway companies the input orientation can also be a viable choice (and indeed it is observed among the DEA studies), as they dispose of more inputs (e.g. number of vehicles) that can be flexibly changed.

Table 4.2. Descriptive statistics of the number of DMUs

<p>| | |</p>
<table>
<thead>
<tr>
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</tr>
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<tbody>
<tr>
<td>Average</td>
<td>29.22</td>
</tr>
<tr>
<td>Modus</td>
<td>19</td>
</tr>
<tr>
<td>Median</td>
<td>28</td>
</tr>
<tr>
<td>Deviation</td>
<td>13.79</td>
</tr>
</tbody>
</table>

(Source: own research)

The calculation of allocative or overall efficiency next to technical efficiency can be observed in several DEA studies independently of transport mode.

Comparison of the inputs and outputs used

As it has been already mentioned, the number of inputs and outputs chosen for a DEA are quite restricted. First, one has to adhere to the thumb rule which demands that the number of observations be three times the number of inputs plus outputs, and the number of DMUs be equal or larger than the product of the number of inputs and outputs. Given a dataset, sometimes the authors are forced to choose less inputs and/or outputs than desired. Then, there is also the tendency that the more the inputs/outputs, the more DMUs prove to be efficient (Bunkoczi and Pitlik, 2009).

Figure 4.5. shows the frequency of the number of studies opting for a given number of inputs, while Figure 4.6. presents the same for the outputs. It is clear that the number of inputs cluster around 3 and 4, whereas the number of outputs tends to be 1 or 2. This means that in the most cases 3 or 4 inputs are used (theoretically covering the traditional labour, capital and energy inputs as highlighted in (Sharma and Yu, 2010) to produce 1 or 2 outputs. (This coverage is only theoretical, as it will be seen in the detailed analysis of the inputs and outputs.)

The same tendency is more or less also valid when looking at the number of outputs distributed among transport modes (see Figure 4.7), although “airports” show a more even distribution. Regarding the number of inputs, both “airports” and “ports” show a more even distribution (see Figure 4.8).
Finally, let us examine the inputs and outputs themselves. The appendix contains all the inputs and outputs gathered from the studies where they were selected for the evaluation of airports, ports, public transport companies, railways and airlines (see Appendix 1). It is not unexpected that the more studies are available for a given transport mode, the wider the variety of the inputs and outputs chosen.

Labour (as number of employees or the cost of labour) is an input omnipresent in the studies and some sort of measurement unit is also nearly always vindicated for capital as well. But energy consumption as input is only applied in the evaluation of public transport companies, although it could be employed in DEAs of airlines and railways as well.
A new category, “facilities” has been introduced in the classification of inputs (even though it can be regarded as part of “capital” inputs) because the factors listed here seem to constitute a vital and integral part of the inputs, especially for airports and ports. However it is mildly surprising that there was only one study that employed more technical inputs, like a “dummy z variable for slot coordinated airports”, and a “dummy z variable for time restrictions” (Pels et al., 2003), although the technical facilities at an airport (e.g. availability of ILS) or the level of air traffic control can significantly contribute to the performance of an airport.
Regarding the outputs, they could be ordered into two main categories: operational and fiscal outputs. Operational outputs are the measurement units created from the physical movement of vehicles or passengers and cargo, while fiscal outputs are the ones which can be expressed in some monetary unit. The listings in the appendix also indicate that generally the number of inputs is higher, and maximum one or two outputs are chosen for the DEA study (Markovits-Somogyi, 2011c).

4.2.2 Logistics and road freight transport
In spite of its strong mathematical background and its reasonable structure, which makes it adept for the efficiency evaluation of firms active in the road freight transport and logistics sector, there are relatively few examples of DEA applications to be found in the Hungarian or even in the international literature. By analysing the available scientific papers, it seems that mainly Chinese authors employ DEA in the different fields of logistics. It is true that these papers are not always fully accessible, and also, sometimes their methodology is not fulfilling all the requirements of a proper DEA investigation. This way their results have to be treated accordingly, and also this is the reason why there is room for appropriate application.

Li and Cheng (2007) investigate the logistics efficiency of 5 wheat suppliers, as based on 5 inputs (storage capacity, information system construction cost, machine equipment overall cost, total order fulfilment cycle time, customer responding time) and 7 outputs (order accomplishment rate, order punctual rate, product qualified rate, information transmission accuracy, information sharing degree, flexibility of amount, flexibility of time). The results of the study are disputable though, because the necessary number of DMUs in this case would be at least 24 if the thumb rule present in the literature is to be applied, namely, that the number of DMUs should be at least two times as much as twice the sum of the number of inputs and outputs (Azadeh et al., 2008). An even stricter thumb rule is applied by Bazargan and Vasigh (2003), who claim that the number of DMUs should be calculated in the following way:

\[ n \geq \max \{m \times s; 3(m+s)\} \] (4.8)

where

- \( n \) is the number of DMUs,
- \( m \) is the number of inputs,
- \( s \) is the number of outputs.

It is evident that the investigation mentioned above fulfils neither of these constraints. However, it might serve as a good basis for further application.
The study of Jiang (2010) solves the problem explained above by using principal component analysis (PCA), just as it is used by Janoshalmi, 2010. This method decreases the number of inputs and outputs by creating specially aggregated inputs and outputs. Jiang investigates the efficiency of the logistics network of 25 cities (and with the help of these, regions) employing DEA. At the beginning, 13 is the sum of inputs and outputs which is then decreased by PCA. It is interesting to see that his work does not evaluate firms but regions; the inputs characterize the level of economic development, and the accessibility of transport, while the output is freight transport performance in tonne-kilometres realized on different elements of the transport network. Jiang and Fu (2009) carry out the assessment of 31 regions in a similar manner, by using 6 inputs and 2 outputs.

Liu and Wu (2007) analyze the efficiency of logistic enterprises with the help of the Malmquist productivity index. As input, total assets and shareholder’s equity were used, while the outputs were net profit and major business revenue. It is remarkable that only financial type of indicators have been selected for the evaluation, and thus one of the most important advantages of DEA has not been made use of: namely its applicability for assessment along characteristics of different dimensions. Shen and Chen (2008) evaluate the scale efficiency of 17 logistics companies, but here also only monetary inputs and outputs are used. Hui and Dong (2008) analyze the sustainability of the logistics sector, while He et al. (2006) carry out an assessment into the logistics competitiveness of the different Chinese regions. Finally, the study by Fülöp and Temesi (2002) has to be mentioned who use DEA for the efficiency evaluation of industrial parks which can be viewed as a peer application to the logistics field (Markovits-Somogyi and Bokor, 2010).

As to the field of road freight transport, the applications are even more scarce. There was only one study found to evaluate the efficiency of road haulage companies (Cruijssen et al., 2006). The authors used the inputs: “total assets” and “hours worked”, as well as the outputs: “added value” and “profit/loss for the year before taxes” to assess 82 companies active in the Flemish road transportation sector. The authors did not include any technological parameters into the investigation, and they did not endeavour to provide a full ranking of the companies.

4.3 Conclusion

After introducing the mathematical background of DEA, the present section aimed to analyse the existing applications of the method from the point of view of their input-output structure. It was found that the overwhelming majority of the studies apply DEA in the transport sector, the applications in the logistics and road freight transport field are scarce. It was important to investigate the input-output structure of the available
applications, because the most difficult part of creating a DEA model is the appropriate development of its input-output structure. For this reason, the inputs and outputs utilized in the different studies were investigated, and a comprehensive list was created regarding the transport applications (see Appendix 1.). These serve as guidelines for the development of the model applied in the thesis.

Albeit few, the investigation of the existing applications in the logistics and road freight transport field was also vital, because this revealed what had already been done in this area. From this it can be concluded, that DEA has been utilized in the logistics and road freight transport sector mainly from a financial aspect, technological parameters are seldom included into the investigations. There are also studies which do not adhere to the thumb rule regarding the minimum sample size. It can also be stated that the application in the logistics and road freight transport sector generally do not intend to provide full ranking of the decision making units. These are the points where the present thesis adds value to the DEA literature. In the following applications, it is always the aim to include technological parameters into the examinations, to take into consideration the thumb rule relevant to the investigation, and finally, with the modified methodology introduced in Section 6. to provide full ranking of the DMUs.
5. Adapting traditional data envelopment analysis to the road freight transport and logistics field

Having reviewed the existing applications in the literature, it has become clear that there are several different fields within road freight transport and logistics, to which DEA could successfully be adapted for the efficiency analysis of the decision making units. As a result of the diverse nature of these areas and the resulting differences in data availability, which is always a constraint to practical scientific research, different approaches have been taken in the individual cases.

Even though the analysis of literature showed that the efficiency rankings provided by data envelopment analysis are reliably similar to those delivered by other methods, still, it seemed important to demonstrate within the framework of the thesis that DEA delivers dependably similar results to other methods in this specific field as well. Thus, first, a particular DEA model is created as based on real life data with the aim of comparing the ensuing ranking values with efficiency rankings achieved by another method, namely the complex efficiency index.

Subsequently, an extended DEA model is adapted to the case of road haulage companies. Here, the aim is to investigate how technological and environmental parameters can be integrated into efficiency analysis, and illustrate how aspects beyond the financial viewpoint can be incorporated into efficiency assessment.

Then, DEA is adapted to the Hungarian logistics centres with the aim of showing which input-output structure is the most viable for investigating these companies. Here, the predominant means of research is clustering, keeping in mind that logistics centres in themselves may be rather dissimilar. Thus, it is essential to form a subgroup that can reliably be investigated. The resulting input-outputs structure is then tested by sensitivity analysis, and by incorporating theoretic considerations does the final structure evolve.

As a last adaptation of traditional DEA and a macroeconomic example, the method is also used to model the logistic efficiency of European countries. The examinations themselves were carried out on the one hand, with the DEAP software, version 2.1 (Coelli, 1996) (the case of logistics centres), and on the other hand, by GAMS 23.6 (Rosenthal, 2012).

5.1 Verifying the use of data envelopment analysis

It is well known that data envelopment analysis assesses efficiency along the lines of several inputs and outputs, thus it can take into consideration not only financial results,
but also other operational or technological parameters. This is one of its most important merits, but this is also what makes it difficult to compare its results with other, purely financial indicators. However, often it is a requirement to demonstrate that the results provided by DEA are valid and reliable. In order to overcome this problem, a DEA structure including solely financial factors as inputs and outputs was set up, and the resulting values were compared to an applicable financial indicator. The chosen financial indicator was the complex efficiency index (CEI) which, in its different forms, is used for comparing the efficiency of different companies (Pap, 2009), as already indicated by the literature review on efficiency assessment methods (see Section 3.1, Eq.3.3).

First, the following form of CEI is utilized:

\[
CEI = \frac{NVP}{0.1TA + 1.8LC}
\]  

where  
NVP  net value of production,  
TA  tied-up assets,  
LC  labour costs (estimated by “staff costs”)\(^3\).

These can be calculated the following way:

\[
NVP = GAV − D = (GVP − CS) − D = [TS − CGS − VSS + OW ± V] − CS − D
\]  

where  
GAV  gross added value  
D  depreciation  
GVP  gross value of production  
CS  contracted services  
TS  total sales  
CGS  cost of goods sold  
VSS  value of services sold  
OW  own work capitalized  
V  variations in self constructed assets

Tied-up assets is calculated as the sum of intangible assets, tangible assets and stocks. For the relevant DEA analysis, inputs chosen were the tied-up assets, the staff costs, while the net value of production was the selected output.

In order to carry out the analysis on real life data, the accounting data of 33 Hungarian road haulage companies were collected from the database of the Hungarian Government.

\(^3\) The accounting based terminology was translated from Hungarian as based on Act C of 2000 on Accounting.
The names of the firms originate from the relevant database of MKFE (Association of Hungarian Road Hauliers). Only those firms were selected from this database, who stated road haulage as their main profile, and who appeared not to be involved in any other business activity. One of the companies seemed to have registered, as tied-up assets, zero, thus it was excluded right at the beginning from the database as an outlier. Out of the remaining 32 companies some had recorded a non-zero value as “costs of goods sold”. They were also excluded from the sample, as this indicated that their profile is not solely that of road haulage. The methodological examinations outlined above were conducted on the remaining 29 road haulage companies. The basic financial data of these companies are shown in Table 5.1., in thousand HUF, for the year 2010, the last year for which such financial data were available.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
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<th>3</th>
<th>4</th>
<th>5</th>
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<td>17682</td>
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<tr>
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<td>6774</td>
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<td>9515</td>
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</tr>
<tr>
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</tr>
<tr>
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<td>557848</td>
<td>3669</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5.1. Basic financial data of the investigated companies

Results of the examination are shown in Figure 5.1, where the firms are ordered according to their CEI rank. To understand the results, it has to be known that DEA assigns the efficiency value of 1 to the efficient units, while the less efficient are given lower values between 0 and 1. CEI indexes are absolute values, in this case all above 1.

It can be seen that the two series of values display the same trend. Indeed, the Spearman correlation of the ranks established by the given values is 87.27%. Thus, it can be stated that the two kinds of assessments provide a reasonably similar order of the decision making units. In Figure 5.1. it can also be seen that there are four companies,
which do not follow the pattern indicated by the complex efficiency index. In order to investigate their role, a further analysis was conducted, where a different form of the complex efficiency index, \( CEI' \) was used, as suggested by Drechsler (1981).

\[
CEI' = \frac{NVP}{0.1NE + 1.5LC}
\]  

\[(5.3)\]

The ensuing results, with the companies ordered according to their modified CEI index, are shown in Figure 5.2. Again, it can be seen that the rankings correlate well with each other. Indeed, their Spearman correlation is even higher than previously, with a value of 89.41%. At the same time it shall be noted that there are two firms (No. 5 and 25), which behave as outliers in both of the DEA rankings. Scrutinizing their input and output data, an interesting phenomenon can be revealed. These two are the only ones in the sample, who have higher labour costs than is their value of tied-up assets. Thus, this affirms what is already known from the literature, that firms with an operational structure different from the majority of the sample will function as outliers in the DEA investigation. Hence, the examination was carried out once again, but omitting the companies in question (the
results are shown in Figure 5.3). The Spearman correlation of the resulting ranking orders was 96.4%.

Figure 5.2. The ranking scores of the 29 companies using modified CEI and DEA (Source: own research)

Figure 5.3. The ranking scores of the 27 companies using modified CEI and DEA without the outliers (Source: own research)
These numerical results verify that data envelopment analysis is sufficient for the efficiency analysis of road hauliers, and the resulting rankings are reassuringly similar to those obtained by traditional financial evaluation methods, provided that the companies investigated have similar operational structures (Markovits-Somogyi, 2012c).

5.2 Assessing the efficiency of companies active in the road freight sector
- A microeconomic adaptation

One of the most vital advantages of DEA is its inherent possibility to include non-financial aspects into the efficiency evaluations. This way it can be an appropriate tool to create assessments parallel with pure financial analysis extending also to different technological and environmental parameters. The present subsection adapts DEA to road haulage companies using real life data collected from the Hungarian road freight sector.

The most essential part of creating a model in DEA is always the question of inputs and outputs. Such factors have to be selected which represent the operation of the given type of enterprise well and are at the same time available to the researcher. As based on the nature of activities performed and also with view on the financial analysis performed earlier, theoretically the following basic factors could be included as inputs or outputs in an efficiency investigation of the companies in question (Markovits-Somogyi, 2012b):

**Inputs**
1. Data regarding equipment. The number and age distribution of
   - trailer trucks,
   - lorries, and
   - other vehicles.
2. The number of employees or the labour costs (the latter available as accounting data).
3. Costs of operation.
4. An indicator regarding the geographical area of operation (the companies active in densely populated areas may be in more advantageous position as compared to others).
5. Data regarding sustainability (e.g. relating to the composition of the vehicle fleet, the environmental category of the engine may provide important information regarding sustainability).

**Outputs**
6. Transport performance (or total distance performed by the trucks). Ideally this would be available in tonne-kilometres or in a similar value but in practice usually
it can only be obtained as an average of kilometres performed by the individual vehicles.

7. Net income or net value of production (available as accounting data).
8. Data regarding quality of operations (timeliness, percent of payload arriving safely).

So as to be able to carry out the efficiency analysis in practice and to be able to extend the investigation to technological or even environmental aspects, data beyond those available from account were needed. Thus, road haulage firms have been contacted with a questionnaire survey. The contact data of 49 road haulage companies have been gathered with the help of MKFE (Association of Hungarian Road Hauliers). Taking into consideration their field of operation, 40 have been contacted with a questionnaire via email. This method yielded 3 results only (and only 2 of those were relevant), so in a second round a phone survey was carried out. This, together with the previous results yielded a database of 14 road haulage companies. These were already screened, thus this final sample included only those who were active in international freight transport (Markovits-Somogyi, 2012a). This way it could be assured that only firms with the same profile are included in the sample.

With view on the theoretical input-output structure outlined above and in order to facilitate the process of input-output selection, the questionnaire was aimed to collect information on the following:

- Is the company active in international freight transport? (Only those replying affirmative were kept in the sample.)
- Does the company have any other profile above road freight transport, which contributes to its revenues? (The DMUs giving a confirmatory answer were excluded from the sample.)
- The number of different vehicles utilized and their distribution along environmental categories.
- The geographic area where the company is active.
- The total kilometres run by the vehicles of the company.
- Financial data of the companies were collected from the web based database of the Hungarian Government (Ministry of Public Administration and Justice, 2012).

The base case for investigation was the input-output structure utilized in the financial evaluation, where the results were compared to the complex efficiency index (see Section 5.1). Unfortunately, as indicated above, the technological and environmental data for all the 29 companies were not available due to refusal of responding, thus, only a sample of 14 firms could be investigated with this input-output structure. This sample is created
from 12 companies featuring in the financial analysis, plus 2 further firms who were ready to give answers to the questions of the questionnaire. Then, 1 further company was excluded from the sample, as it had already been identified as an outlier in the financial analysis. Hence, the following investigations are carried out on the remaining sample of 13 decision making units (DMUs). Even though the sample is small, the results are methodologically fully eligible, as DEA can be applied to any sample size, provided that the number of DMUs is at least three times as much, as the sum of the number of inputs and outputs (Bazargan and Vasigh, 2003). DEA CRS was applied on the sample.

The input and output data of the investigated companies are shown in Table 5.2. TA, LC, and NVP stand for tied-up assets, labour costs and net value of production, respectively. These are the financial indicators utilized in the previous section as well. “Km” stands for the total distance performed by the companies’ vehicles in the year 2010. These data originate from the questionnaire.

Table 5.2. Input and output data of the investigated companies

<table>
<thead>
<tr>
<th>Orig. No.</th>
<th>New No.</th>
<th>TA</th>
<th>LC</th>
<th>NVP</th>
<th>Km</th>
<th>Env</th>
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<td>654381</td>
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<td>159032</td>
<td>441000</td>
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</tr>
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<table>
<thead>
<tr>
<th>Orig. No.</th>
<th>New No.</th>
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<th>LC</th>
<th>NVP</th>
<th>Km</th>
<th>Env</th>
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</tr>
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<td>298964</td>
<td>190790</td>
<td>557848</td>
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<td>2.33</td>
</tr>
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<td>98174</td>
<td>923000</td>
<td>310000</td>
<td>1.14</td>
</tr>
</tbody>
</table>

(Source: own calculations as based on data from (Ministry of Public Administration and Justice, 2012) and on a self-conducted survey)

Public and scientific awareness is turning more and more towards the sustainability of operations (Tánczosné and Török, 2007), thus it was justified to extend the investigations to the aspect of sustainability as well. “Env” is an environmental index, which is created as based on the distribution of the vehicle fleet among the environmental categories, which is also based on data included in the questionnaire. If the whole fleet consists of vehicles in the EURO-V. category only, this index is 1, while a fleet of vehicles solely in the EURO-III. category will get a 3. The companies having mixed fleet were assigned an
environmental index reflecting the ratio of the vehicles’ distribution. The index was created in a “the lower the better” fashion, thus enabling to include it as an input into the investigation.

The structure of the different DEA investigations can be seen in Table 5.3. As it can be seen, Model “A” is identical with the original financial analysis conducted in Section 5.1. Then, as a technological parameter, the total distance performed by the vehicles of the company is included in the second investigation (Model “B”), as an estimator of transport performance. It was also considered to include the technological indicator “cumulated vehicle number” (an aggregated marker representing the composition of the vehicle fleet) into the investigations, but, as expected, preliminary calculations showed that it was not independent from the value of tied-up assets.

Model “C” shifts the emphasis from technological to environmental characteristics, and includes the sustainability related indicator “Env”, described above, into the investigation. The independence of parameters “Env” and “TA” was calculated, because it was supposed that there would be a correlation between these factors; since a more environmentally friendly fleet must be more expensive. However, the calculations did not find a significant correlation. Moreover, even if the data had correlated, neither of the indicators would have be excluded from the investigations, as they capture different aspects of operation, and it is exactly by this shift of view that technological and environmental aspects can also be taken into consideration.

Finally, Test “D” includes all the available variables.

<table>
<thead>
<tr>
<th>Table 5.3. Input and output structure of the different DEA models</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Models</strong></td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>A</td>
</tr>
<tr>
<td>B</td>
</tr>
<tr>
<td>C</td>
</tr>
<tr>
<td>D</td>
</tr>
</tbody>
</table>

(Source: own research)

It has to be noted that Model “D” cannot be viewed as methodologically valid, as, taking into account the thumb rule of DEA literature, here the number of DMUs should at least be 5 * 3 = 15, and our sample consists only of 13 DMUs. Thus, the result of Test “D” is only included as a curiosity.
It is also to be emphasized, that, as based on the theoretical considerations, there are further input and output factors that could be incorporated into the basic DEA structures shown in Table 5.3. However, the researcher is often limited by lack of data, and this was the case here as well. Thus, due to the size of the sample it was not possible to enlarge the number of inputs or outputs and include data on e.g. the geographic location of the firms etc. Nonetheless, these would have only served as steps refining the results achieved so far, and it is believed that the basic structures presented in the thesis are representing well the way the given companies operate and they can be viewed as a correct basic input-output structure for the phenomenon examined.

The results of the investigations are shown in Table 5.4, and the rankings are depicted by Figure 5.4. (It is important to keep in mind, that here the best rank is 1, and the worst is 13, while looking at DEA weights, the best weight is 1, and then, the lower value represent worse efficiencies.) It can be seen, that more and more DMUs get efficient as the number of the inputs and outputs is increased. This is to be expected from the characteristics of data envelopment analysis.

Table 5.4. The DEA weights resulting from the different DEA models

<table>
<thead>
<tr>
<th>No. of DMUs</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
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</thead>
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<td>1.00</td>
<td>1.00</td>
</tr>
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<td>0.725</td>
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<td>5</td>
<td>0.695</td>
<td>0.789</td>
<td>0.695</td>
<td>0.831</td>
</tr>
<tr>
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<td>0.801</td>
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</tr>
<tr>
<td>7</td>
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<td>0.792</td>
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<td>0.442</td>
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<td>0.643</td>
<td>0.668</td>
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</tbody>
</table>

(Source: own research)

The results from model “A” match very well with those from a pure financial analysis: calculating the Spearman correlation between the ranks achieved by the modified complex efficiency index and by Model “A”, yields a value of 92.45% Then, as emphasis shifts from financial features to technological and environmental parameters, this
correlation gets naturally lower (51.92%; 42.58%; 17.58% between CEI’ and Model “B”, “C” and “D”, respectively).

**Figure 5.4.** Ranking results from Models A to D  
(*Source: own research*)

Figures 5.5. and 5.6. represent the same ranking values, but as compared to the rankings achieved by Model „A”. In Figure 5.5. it can be seen, that including the technological parameter only does not shift the rankings drastically, they display the same trend (Spearman: 64.97%, at 0.99 significance level for the sample size of 13, this is considered significant, see Appendix 2. for the significance levels), but there are, of course, differences in the ranking.

**Figure 5.5.** Ranking of Model B as compared to Model A  
(*Source: own research*)
This is especially noteworthy in case of Firm 11, who gets a far better ranking when including this technological parameter. Naturally, and as expected, including the environmental characteristic shifts the ranks significantly (Figure 5.6., Spearman: 41.07%).

![Figure 5.6. Ranking of Model C as compared to Model A](Source: own research)

Having seen the different rankings achieved by data envelopment analysis, it can be stated that this method is capable of including technological and environmental parameters into the investigations of efficiency. It has been seen that in case of pure financial analysis, its results match well the results from financial indicators, while its advantage is that it can be extended to include further, non-financial parameters.

5.3 Analysing logistics centres – A microeconomic adaptation

Several different notions can be understood under logistics centres. In order to be clear about what is being evaluated in the present subsection, it is of utmost importance to define “logistics centre” itself and identify which type or subtype can be analysed.

Logistics centre is a place which concentrates logistics supply, and to a smaller extent, logistics demand as well; and where basic logistics services are provided, (e.g. conventional storing, moving and transport services, transport preparation, or even combi-terminal and finishing services are available)\(^4\). According to this definition, “Terminals” [as in (SEALS, 2008)] can all be seen as logistic centres. These are: airports, seaports, inland shipping terminals, road-rail terminals and distribution centres. This categorization is done on the basis of the transport mode present at the logistics centre, and the scope or public availability of the services is less emphasized. Looking at these different categories, in general a Hungarian logistics expert would only mark inland

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\(^4\) Own definition as based on (Prezenszki, 1998) and (Bakos, 2011.)
shipping terminals, road-rail terminals and distribution centres as “logistics centres” although the first two categories also fulfil the requirements of the definition. However, from what has been learned above about the transport applications of data envelopment analysis, it is clear that DEA is widely used for the evaluation of airports and seaports, hence, independently of whether they are regarded as logistics centres or not (Knoll, 1995), it can be stated that DEA is adequate for their investigation. As there is ample evidence for such applications, this study will not further go into this direction.

Looking closer at inland shipping terminals, road-rail terminals and distribution centres, another way of their categorization emerges, as based on the qualification system of Hungarian Logistics Service Centers (MLSzKSz, 2011). According to this, logistics centres may be intermodal, regional, local or private logistics centres. The last category overlaps greatly with that of “distribution centres” in the previous clustering. Distribution centres, i.e. logistics centres operated privately by companies to take care of their inbound and/or outbound logistic activities differ in several features from the publicly available logistics centres and thus they cannot be evaluated together with the latter ones. Not only is information regarding their operation inaccessible but also their service profile is different from that of public logistics centres. Thus they are excluded from the focus of the present study.

Consequently, in view of the Hungarian logistics industry, intermodal, regional, local inland shipping terminals, road-rail terminals and public (road to road) distribution centres will be understood under the notion of “logistics centres” in the framework of the present thesis.

Even with this categorization, there is a huge variety of logistics centres which cannot always be compared to one another. Thus it might be necessary to form further clusters to only compare those logistics centres with each other which are similar in their profile. Keeping all this in mind, the first step can be taken to evaluate the efficiency of Hungarian logistics centres.

5.3.1 First model

Methodology
In order to carry out the investigations, statistic data of 26 Hungarian centres have been collected but the final sample includes only 12 companies, because data for all the inputs and outputs were available only for these firms. Here the thumb rule to be found in the literature has also to be adhered to, according to which the number of observations should be three times greater than the number of the inputs plus outputs; and the
number of DMUs should be equal or larger than the product of the number of inputs and outputs (Bazargan and Vasigh, 2003). Consequently and also based on theoretical considerations (Markovits-Somogyi and Bokor, 2011), only 3 inputs and 1 output is included in the investigation in the first tests. The inputs selected are the surface size of offices, number of employees and surface of available storage space (including external storage facilities). The output considered was the volume of total sales revenue, and in a second examination the goods traffic. The output oriented DEA model was used, as these firms are relatively free to alter the level of their inputs and their aim is output maximization. The linear programming problems were solved by the DEAP software, version 2.1 (Coelli, 1996) and the data utilized are real-life data of logistics centres from the year 2005.

Results
As it can be seen from the mathematical background outlined above, in DEA a firm is efficient if its efficiency ranking is 1. These efficient companies lie on the frontier created by the model and the rest of the enterprises are compared to the achievement of these firms. In the first step a basic efficiency analysis of the 12 companies was carried out, examining constant and variable return to scale (CRS and VRS) efficiency. The output selected here was the total sales revenue. The results are summarized in Figure 5.7.

![Figure 5.7. CRS and VRS efficiencies as based on total sales revenue](Source: own research)

Here it can be seen that firms number 6, 10 and 12 are efficient both under constant and under variable return to scale i.e. they are also scale efficient. Whereas firms number 1, 3, 5 and 11 could significantly improve their efficiency if they operated at scale efficient size. Although their VRS efficiency is high, their aggregate efficiency is low and this is due to the fact that they are scale inefficient. As it is known, CRS efficiency (or aggregate efficiency) is decomposed into pure technical efficiency (VRS efficiency) and scale
efficiency; CRS and VRS efficiency are not the same when there are scale inefficiencies in the case of some DMUs. This is due to the fact that DEA VRS draws a tighter frontier around the sample points and thus provides technical efficiency scores that are higher (or equal) to those of CRS (Coelli, 1996).

Data envelopment analysis also reveals that they operate under increasing returns to scale, thus they could improve their efficiency if they increased their inputs.

In the next step the output of total sales revenue has been exchanged to goods traffic. The main question was how this change influences the efficiency ranking of the firms. From Figure 5.8. containing the results it is clearly visible that firms number 10 and 12 remain efficient, whereas number 6 loses its potentials, and number 1 joins the group of efficient firms. The gap between CRS and VRS efficiency opens up in case of firms 2, 4, 7 and 8.

We could see that firms number 10 and 12 remain efficient independently of the output chosen: this could be due to the fact that they do not only successfully utilize their inputs for maximizing the volume of freight forwarded, but their business policy is also adequate to translate this to maximum profits. Whereas firm number 1 is efficient in maximising the goods traffic with the given levels of input but it does not seem efficient in converting that to total sales revenue as its efficiency ranking falls sharply once total sales revenue is regarded as output. The contrary can be observed in case of firm number 6, which is efficient in creating total sales revenue while it is not so efficient when we regard the amount of freight forwarded.

Apart from these absolute results it is worth looking at the change of scale efficiencies. It is interesting to note that the change in output factor, i.e. the change from total sales

![Figure 5.8](image-url)
revenue to volume forwarded does not alter the direction of return to scale. This can be seen clearly from Table 5.5. (irs = increasing returns to scale, drs = decreasing returns to scale).

**Table 5.5. Comparing efficiencies of scale**

<table>
<thead>
<tr>
<th>Total sales revenue</th>
<th>Goods traffic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>irs</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>irs</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
</tr>
<tr>
<td>5</td>
<td>irs</td>
</tr>
<tr>
<td>6</td>
<td>-</td>
</tr>
<tr>
<td>7</td>
<td>-</td>
</tr>
<tr>
<td>8</td>
<td>-</td>
</tr>
<tr>
<td>9</td>
<td>-</td>
</tr>
<tr>
<td>10</td>
<td>-</td>
</tr>
<tr>
<td>11</td>
<td>irs</td>
</tr>
<tr>
<td>12</td>
<td>-</td>
</tr>
</tbody>
</table>

(Source: own research)

Firms number 5 and 11 remain clearly increasing return to scale meaning that they should undoubtedly increase their scale efficiency via enlarging their inputs. The “irs” feature has vanished in case of firms 1 and 3 but it is evident that the direction of scale has not changed, they represent a constant returns to scale when investigating the goods traffic. At the same time decreasing return to scale has emerged in case of all the other companies which are not efficient in the second examination. This indicates that on this level there is scale inefficiency due to too big input volume.

**Inclusion of two outputs**

As highlighted before, the setup of DEA in this investigation has been created in such a way that it enables the inclusion of a maximum number of inputs and outputs. Adhering to the strictest thumb rules in literature this number could not be enlarged as there is a severe constraint on the size of our data set. There are some authors however, who are claim that this stringent requirements can be relaxed and who include a higher number of inputs and outputs. Wu and Goh in (Wu and Goh, 2010) for example argue that the number of DMUs should minimally only be two times as much as the sum of the number of inputs and outputs. Thus, keeping in mind the widely accepted way of carrying out data envelopment analysis, it was opted for executing a further DEA in which the total number of inputs and outputs was 5, with the number of DMUs being 12. The aim with this further exercise was to see how the efficiency ranking would be influenced if both total sales revenue and goods traffic were included in the examination. The outcome is summarized in Figure 5.9., where the crosses indicate the results in question.
It is very interesting to note that in case of nearly all DMUs, the new efficiency ranking equals the highest efficiency ranking of the two previous tests. There is one exception though: DMU number 3, which performs equally low if the output considered is the total sales revenue or the goods traffic, but if both of them are included in the investigation its efficiency rises above 0.8.

![Figure 5.9. Comparison of DEAs with 1 and 2 outputs](source: own research)

**Comparison of local and global companies**

Efficiency distribution has been scrutinized from another angle as well: that of the ownership of the companies. 8 out of the 12 companies investigated are locally owned firms whereas the rest are multinational enterprises present in the country. Figure 5.10. shows the average CRS, VRS and scale efficiencies of the global and local companies, separately for the three test setups (1-2: where the only output is total sales revenue and goods traffic, respectively, and 3: where they are both included).

When the only output included is the total sales revenue, it is very interesting to see that the average CRS efficiency of the global and local firms do not differ significantly. When this is separated into VRS efficiency and scale efficiency, a very different picture emerges: global enterprises seem to be much more scale efficient (0.977) than their local counterparts (0.505) whose strength seems to lie in achieving pure technical efficiency (0.732). These dissimilarities smooth out though when the view is changed to the output of “goods traffic”. When including both of the outputs into the examination, the results for the global firms show that relatively low VRS and scale efficiency values contribute to the low aggregate (CRS) efficiency. On the other hand, the CRS efficiency of the local
companies is significantly higher than in the single output models (0.563 versus 0.263 and 0.328), and this is explained by the high VRS efficiency value (0.828). From these results it can be concluded that the efficiency of global firms present in the Hungarian market seems to originate from their scale efficiency, while pure technical efficiency is higher in case of their Hungarian counterparts.

![Efficiencies of globally and locally owned logistics centres](image)

**Figure 5.10.** Efficiencies of globally and locally owned logistics centres
*(Source: own research)*

**Discussion**

Before moving on, there is one point which needs to be further discussed. When looking at the efficiency results in absolute values it is more than evident that there are some DMUs (2, 4, 8 and 9) the efficiency of which are very low indeed and that does not change with the change in output. The reason behind this seemingly very weak performance is undoubtedly a point that needs to be further investigated. As for now, two facts could supposedly and partially explain these results. Without spelling out their names, it can be said of all the companies in question are logistics centres with multiple base and not only active in Hungary. Then, it is also true that as based on their subscribed capital, at least half of the firms concerned are partially owned by investors from abroad. These facts might explain why the DEA setup with the structure outlined in the study yielded those very low efficiency results. *(Markovits-Somogyi et al., 2011)*

**5.3.2 Sensitivity analysis**

As it has been seen, in the case of some firms, the efficiency values resulting from the previous research proved to be very low. The aim of the following section is to examine whether the changes in the input-output structure could alter this feature. For this
purpose first it is investigated how the exclusion of the individual inputs contributes to the change in the efficiency ranking (Markovits-Somogyi and Bokor, 2012a).

The base case

Before starting the examination, the base case has to be presented. The model that we take as the basis of investigation is the third, compiled model from the previous investigation. This means, that the inputs here are the surface size of offices, the number of employees and the surface of available storage space (excluding external storage facilities). The output considered is both the volume of total sales revenue and the goods traffic; and the number of DMUs is 12. The output oriented DEA model is used, as these firms are (partly in short term, partly in mid term) relatively free to alter the level of their inputs and their aim is output maximization.

![Figure 5.11. Efficiency values in the base case](Source: own research)

Figure 5.11. shows the constant (CCR) and variable (BCC) returns to scale, and pure scale efficiencies in the base case scenario. As it has been seen already, DMUs 2, 4, 8 and 9 have very low CCR and BCC efficiency scores. In the further examination only the DEA BCC method is going to be applied. It has to be noted, however, that DEA CCR and BCC values differ in case of the decision making units which do not operate scale efficiently. The reason behind this is that DEA BCC draws a tighter frontier around the sample points and the resulting efficiency values are equal or higher than the DEA CCR scores. It is reasonable to look only at the DEA BCC scores, as most of the DMUs do not operate under constant returns to scale, and further, DEA BCC will yield the same results as DEA CCR for those who do.

Effect of the change in inputs

The sensitivity analysis was carried out in the following way: each of the inputs was ceteris paribus excluded from the input-output structure and the resulting efficiency ranking was recorded. Figures 5.12., 5.13 and 5.14. show how the exclusion of the office
area, the number of employees and the internal storage area respectively contributed to the change in efficiencies.

**Figure 5.12.** Change in BCC efficiency values due to the exclusion of office area as input  
(Source: own research)

Figure 5.12. shows that the efficiency score of only one DMU is affected by the exclusion of office area from the inputs. In practice this means that only in case of DMU 5 did the efficient utilization of office area contribute to the high score received in the base case scenario. But this change does not in any way affect the very low efficiency scores observed in case of DMUs 2, 4, 8 and 9.

In Figure 5.13. it can be seen how the efficiency values change if the number of employees is excluded from the inputs. It is interesting to note that three out of the four DMUs of very low efficiency value (DMUs 4, 8 and 9) are influenced by this modification but their scores are even further reduced. However, the change in the values does not lead to significant changes on their part: it is just a proportionate reduction in the absolute value. Thus we can state that their results are not very sensitive to the exclusion of this input and this is not the reason of their low efficiency.

Nevertheless, it is also important to note that the efficiency value of DMU number 11 changes significantly as the number of employers is excluded from the inputs. From this it can be concluded that a major part of its efficiency is due to the fact that it can produce its output with a workforce smaller than that of its peers.
Figure 5.13. Change in BCC efficiency values due to the exclusion of the number of employers as input  
(Source: own research)

Figure 5.14. Change in BCC efficiency values due to the exclusion of the size of internal storage area as input  
(Source: own research)

Figure 5.14. depicts the change in efficiency values due the exclusion of the internal storage area from the inputs. The main visible effect of this modification is the reduction of the efficiency of several DMUs. This is a very understandable tendency, as the decision making units investigated are logistic centres, and the size of their internal storage area is a significant parameter of their operation as there is a very strong relation between this value and the volume of goods handled, and obviously this also influences total sales revenue.

It is also worth to be noted that the efficiency of DMUs number 5 and 10 are seriously influenced by this modification meaning that their efficiency is largely due to the efficient
utilization of their storage area. The scores of the DMUs with originally low efficiency value are reduced even further but to a smaller extent.

Effect of the change in outputs

In the following section the effect of the changes in the output structure is investigated. Figures 5.15. and 5.16. show how the ceteris paribus exclusion of the volume of total sales revenue and the goods traffic, respectively, influences the efficiency rankings.

Figure 5.15. represents the effects of the exclusion of total sales revenue. It is well visible that the efficiency scores of DMUs 3, 6 and 9 are significantly reduced due to this modification meaning that their financial success contributes largely to their overall efficiency in the base case. The change also affects several other decision making units which indicates that this output contributes noticeably to the final ranking. It is worth noting that the efficiency score of DMU number 7 has increased by this exclusion. The results of the originally low DMUs are not higher, only that of DMU number 8 has augmented slightly.

Finally, in Figure 5.16. it can be seen how the exclusion of the goods traffic from the circle of outputs changes the efficiency scores. As expected this modification also changes the efficiency values of many DMUs including all the decision making units of originally low ranking. The direction of change is in all cases negative, i.e. the resulting values are lower than the original.

![Figure 5.15. Change in BCC efficiency values due to the exclusion of total sales revenue as output](Source: own research)
Discussion

First it has to be stated that the efficiency scores of the DMUs of originally low efficiency value have not changed significantly in any case (Markovits-Somogyi and Bokor, 2012a). This means that the reason of their inefficiency cannot be entirely explained by the exclusion of any of the individual inputs or outputs. However, supposing that all the decision making units, i.e. logistic centres operate in the market, there has to be further features which lead to such inefficiency that can be seen in the numerical results. The profile of these DMUs has to be further investigated in depth in order to reveal the eventual underlying reasons.

Table 5.6. Effect of the different inputs and outputs on the efficiency values

<table>
<thead>
<tr>
<th>DMUs</th>
<th>offices</th>
<th>employers</th>
<th>storage area</th>
<th>total sales</th>
<th>goods traffic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>2</td>
<td></td>
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<td>x</td>
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<td>3</td>
<td></td>
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<td>x</td>
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<td>4</td>
<td>x</td>
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<td>5</td>
<td>xx</td>
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<td>6</td>
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<td></td>
<td></td>
<td>xx</td>
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<tr>
<td>7</td>
<td></td>
<td>x</td>
<td>x</td>
<td>xx</td>
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<td>8</td>
<td>x</td>
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<td>xx</td>
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<td>11</td>
<td></td>
<td>xx</td>
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<tr>
<td>12</td>
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</tbody>
</table>

(Source: own research)
Second, it can be declared that the examination of the input-output structure has unveiled the relationships between the efficiency of the different decision making units and the inputs and outputs. These results are summarized in Table 5.6. ‘xx’ shows a strong connection, where the input/output in question alters the efficiency score by at least 0.5; while ‘x’ refers to a weaker connection, where the efficiency value is changed by less than 0.5. Looking at Table 5.6, it becomes clear that the ‘size of offices’ influences the smallest number of DMUs, thus this is the factor that could first be omitted from the DEA model. At the same time it is obvious, that ‘storage area’ and ‘total sales’ are influencing the most DMUs, consequently they are to be included in the model at any expense.

5.3.3. Second model
With the experiences gained in the sensitivity analysis, a new DEA setup is being created in this subsection and is applied to a smaller number of DMUs. As it has already been highlighted in the introductory paragraphs, logistics centres are very diverse, and thus they are often difficult to be compared with each other. This heuristics is also proven numerically by the first DEA runs presented in Section 5.3.1. As it has been seen in the sensitivity analysis, the very low efficiency values of the DEA setups in 5.3.1 must be due to the fact that logistics centres as such are very different even among themselves. This is why a smaller cluster of logistics centres is created in the present subsection. Only logistics service centres are included in this examination, and the input-output structure is modified as based on the experiences of the sensitivity analysis. “Storage area” including external storage facilities is an input, “total income” features as an output and a further output, “warehouse utilization level” is also integrated in the model. Due to lack of data, this structure enables the investigation of 9 DMUs only but, with the given input-output structure this number fulfils the requirements of the thumb rule. The results can be seen in Figure 5.17.

![Figure 5.17](image.png)

**Figure 5.17.** The resulting efficiency values from the second application (output oriented approach)  
(Source: own research)
Although it is reasonable to evaluate the VRS (BCC) values, the CRS efficiency values should not be neglected either. There it can be seen that numerous firms have very low efficiency values which is indicating that further slight modification regarding the input-output structure might be desirable which leads us to the third application in practice.

### 5.3.4 Third model

Here a further input, *total number of employees*, is incorporated into the model. It should be noted that this way the number of inputs and outputs are somewhat higher than desirable but using the rule introduced by Wu and Goh (*Wu and Goh, 2010*) referred to before, this can also be acceptable. Independence analysis was carried out for the inputs and outputs, which showed that *storage area* is independent of the *total number of employees*, and *total income* is also independent of *warehouse utilization level*, thus they can be investigated within the same DEA model.

The results are shown in Figure 5.18, which indicate that the input-output structure of this model is viable as the efficiency values are relatively evenly distributed between 0.0 and 1.0. and none of the efficiency values are too low in the sample.

![Figure 5.18](image)

*Figure 5.18. The resulting efficiency values from the third application (output oriented approach) (source: own research)*

Regarding the absolute values themselves, it can be seen that in the CRS approach the main tendencies are the same as in the previous DEA run. DMUs 2, 7 and 9 perform remarkably well, while 1, 3 and 4 are among those who have the most room for
improvement. Comparing the results with constant (CRS) and variable (VRS) returns to scale, it is obvious that the CRS and VRS values are very different and there are huge scale inefficiencies in the cases of DMUs 1, 3 and 4. Here, the reason of inefficiency is that these companies do not operate at an economic scale. The CRS and VRS efficiencies are the same for DMUs 5, 7 and 9; and they are nearly equal for DMUs 2, 6 and 8. Thus, here it can be stated that these firms operate at an efficient scale and – if inefficient, as is the case for 6 and 8 – their inefficiencies are due to pure technical inefficiency and not due to scale inefficiency.

From the analysis conducted above it can be seen that data envelopment analysis is capable of evaluating the efficiency of logistic service centres, given that a homogenous database is available containing the main information about the operation of these logistics centres. It should also be highlighted that DEA is even able to show whether the inefficiency of certain companies lies in scale inefficiency or pure technical efficiency.

5.4 Evaluating the logistics efficiency of European Countries – A macroeconomic adaptation

Having seen the different applications of DEA in the logistics field, it has become clear that there are basically no studies looking into the logistics efficiency of the different European countries, although such an evaluation would be feasible. Of course, just as in case of all DEA examinations, the researcher is much limited by lack of data which has to be circumvented by the meticulous planning of the DEA structure. The biggest problem is the lack of information on country level regarding the investment in the logistic field. This is why three different structures have been created, and all these have been investigated by data envelopment analysis (Markovits-Somogyi, 2011b).

Table 5.7. shows the input and output structure of the three different DEA runs (A1, A2 and B) that have been carried out. The source of data concerning inputs 1 to 5, and outputs 1 and 2 is the database of EuroStat (EuroStat, 2011), while outputs 3 and 4 originate from the 2010 LPI survey (Arvis et al., 2010), all data originate from the year 2009. The main difference between the cases is the following: in Model “A” the investment (or the “cost”) of the logistics sector was not taken into account by any means, while in Model “B” it was estimated by using inputs 4 and 5. Models “A1” and “A2” differ in as much as “A2” does not take into consideration the GDP per capita ratio. Although methodologically the structure incorporated in “A1” is the most defendable one, an investigation without the differences in GDP was also to be carried out, as outstandingly high GDPs created outliers in the sample, as it will be observable later on.
Figures 5.19. to 5.21. present the results of the different DEA examinations (the numerical results are also included in Column I. of the Table in Appendix 6.). Model “A1” is methodologically the most viable DEA run, as it incorporates the GDP per capita in Purchasing Power Standards. It is, however, this feature that leads to very low efficiency levels being assigned to traditionally rich countries, as Luxembourg, Switzerland and Norway which have very high GDP levels. In this examination, Bulgaria, Germany, Latvia, Poland, Romania and Turkey turned out to be the logistically most efficient countries.

Table 5.7. Description of inputs and outputs in the different models

<table>
<thead>
<tr>
<th>Models</th>
<th>A1</th>
<th>A2</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inputs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Length of motorways/1000 inhabitants</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>2. Length of railway network/1000 inhabitants</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>3. GDP per capita in Purchasing Power Standards</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Staff costs in the transport and storage sector</td>
<td></td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>5. Gross investment in tangible goods</td>
<td></td>
<td></td>
<td>x</td>
</tr>
<tr>
<td>Outputs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Road transport performance (million tonne-kilometres)</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>2. Rail transport performance (million tonne-kilometres)</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>3. Quality</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>4. Timeliness</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

(Source: own research)

Excluding the GDP per capita input from the DEA structure (Figure 5.20.) yields significantly different results regarding the ranking of the countries (although the absolute efficiency values do not change considerably in case of the countries mentioned above, but there are other nations whose efficiency score decrease to a higher degree). It is interesting to note that Germany, Latvia, Poland and Turkey still perform remarkably well in this DEA structure too, whereas in “A2” Hungary gets assigned an efficiency score of 0.211 instead of the 0.664 in Model “A1”.

The idea behind Model “B” was to include somehow the logistics costs of the different countries and thus try to take into account the amount spent in the logistics sector. As it has been established that there is no indicator available which would reliably signify the logistics cost of different countries (Olaja, 2011), other measurement units have been selected to try and include this feature in the investigation. This is why “Staff costs in the
transport and storage sector” and “Gross investment in tangible goods” have been integrated in the DEA structure.

![Graph of logistics efficiency of European countries](image1)

**Figure 5.19.** Logistics efficiency of European countries (*Model “A1”*)
*Source: own research*

![Graph of logistics efficiency of European countries](image2)

**Figure 5.20.** Logistics efficiency of European countries (*Model “A2”*)
*Source: own research*

Unfortunately, due to lack of data, only 25 countries could be examined in this test, and the results have to be evaluated very cautiously, since this way only the more lax thumb rule regarding the number of necessary DMUs could be fulfilled. This is also visible in the results (see Figure 5.21.), where a large number of countries are seemingly efficient.
However, it should still be noted that Germany, Latvia and Poland perform very well in this DEA run also. This seems to indicate that these countries can convert their inputs into outputs with a high efficiency level.

![Figure 5.21. Logistics efficiency of European countries (Model “B”)](image)

(Source: own research)

### 5.5 Conclusion

After verifying the utilization of data envelopment analysis, the present section has shown three subsectors in road freight transport and logistics where DEA can successfully be utilized. Since the applications in the literature are very scarce for this field, the aim was to adapt a proper DEA structure to these areas and highlight the advantages inherent in DEA. It has been shown that the well parameterized DEA model is capable of evaluating the efficiency of the DMUs and it can thus incorporate technological or even sustainability factors. When done so, it can be applied as a tool parallel with pure financial analysis.

However, it has also been seen that there are some constraints to its utilization: the number of decision making units needs to be sufficiently large, in order to be able to correctly analyse the effect of different parameters. This thumb rule regarding sample size is often difficult to be adhered to, and it would be beneficial if it could be circumvented. Also, DEA cannot always provide full ranking of the decision making units, which is a limitation of the method.
6. The problem of full ranking

As it could be seen from the previous adaptations, DEA does not fully rank the decision making units: all DMUs lying on the efficiency frontier are considered efficient and thus there might be several units with an efficiency value of unity. The more the number of inputs and outputs relative to the sample size, the more units will be found efficient. To be able to distinguish the performance of these units, numerous ranking methods have been developed since the introduction of the DEA technique.

The present section first gives a brief overview of the main approaches presented in the literature. It must be noted that several of these solutions are not distinct measures that can easily be categorized into one or the other group of applications, the approaches frequently overlap. Hence, the aim was to give a clear and concise picture of the models at hand and list them below the heading which is the most revealing as to the content of the method (Markovits-Somogyi, 2011e).

Then, it is shown how one of these methodologies, DEA combined with AHP (analytic hierarchy process) introduced by (Sinuany-Stern et al. 2000), can be further developed to make its results more distinctive. The ensuing method, hereafter referred to as modified DEA/AHP is then to be adapted to the road freight transport and logistics field, and it is demonstrated how it can provide a full ranking even in the cases where traditional DEA is not applicable due to methodological constraints.

6.1 Different full ranking methods within DEA

6.1.1 Super-efficiency
Perhaps super-efficiency is the most well known, most widely applied and researched full ranking method in DEA. In the field of transport, for instance, Adler and Berechman (2001) evaluate 26 airports of Western Europe, North America, and the Far East with the super-efficiency DEA method, Bazargan and Vasigh (2003) apply super-efficiency for the ranking of 45 US airports, Hirshhausen and Cullmann (2010) treat the problem of outliers with this technique in their study, while Wu and Goh (2010) utilize the method to investigate the efficiency of 21 container ports (Markovits-Somogyi, 2011a). The idea of super-efficiency as developed by Andersen and Petersen (1993), Banker et al. (1989) and Banker and Gifford (1988) is that the best practice frontier is created first without evaluating DMU_0, and then with its inclusion. Next the extent to which the envelopment frontier becomes extended is investigated. With this procedure, DMU_0 may even be
attributed an efficiency value higher than unity. Mathematically the super-efficiency DEA method can be summarized in the following way:

$$\min \delta_0 = \theta_0^i - \varepsilon \left( \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$$ (6.1)

subject to

$$\theta_0^i x_{i0} = \sum_{j=1, j \neq 0}^{n} \lambda_j x_{ij} + s_i^- \quad i = 1, ..., m;$$

$$y_{r0} = \sum_{j=1, j \neq 0}^{n} \lambda_j y_{rj} - s_r^+ \quad r = 1, ..., s;$$

$$\sum_{j=1, j \neq 0}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0, j \neq 0$$

$$s_i^- \geq 0 \quad i = 1, ..., m;$$

$$s_r^+ \geq 0 \quad r = 1, ..., s;$$

$$\theta_0^i \geq 0$$

where $\delta_0$ is the value to be minimized, and the index $s$ of $\theta$ refers to super-efficiency.

The problem with super-efficiency DEA is that under certain conditions infeasibility occurs which limits the applicability of the technique. Seiford and Zhu (1999) provided in their article the necessary and sufficient conditions under which the problem becomes infeasible. Being aware of this shortcoming, several authors endeavoured to develop the super-efficiency technique further. Chen (2004) tries to circumvent the problem of infeasibility by utilizing both the input and output oriented DEA model and achieves full ranking by measuring the input saving or output surplus present. Jahanshahloo et al. (2007) rely onto the super-efficiency method developed by Hibiki and Sueyoshi (1999), and they incorporate a novelty into it: their new ranking system for the appraisal of extreme efficient DMUs is independent of the inefficient DMUs. Their basic idea is to measure the distance by which the given efficient DMUs move the frontier from the inefficient DMUs. Lotfi et al. (2007) adapt super-efficiency DEA to the case of exogenously fixed inputs as based on the model of Banker and Morey (1986) who have already dealt with the question of exogenously fixed inputs and outputs. Lee et al. (2011) also seek to characterize input savings and output surplus with the scores and strive to increase or decrease the inputs and outputs in a way that the frontier is reached by the DMU which contributed to infeasibility. Chen and Deng (2011) further develop the model of Jahanshahloo et al. (2007) and in their model the efficiency ranking of an efficient unit depends on the efficiency changes of all inefficient units after the given DMU is excluded.
from the reference set, whereas the performance of an inefficient DMU is characterized by the efficiency values resulting from the exclusion of each efficient unit from the reference set.

6.1.2 Cross-efficiency
In traditional data envelopment analysis the weights evaluating a given DMU are used only to characterize the DMU in question. Sexton et al. (1986) suggested the introduction of the cross-efficiency DEA method which includes a self and a peer evaluation of the DMUs as well. Thus, the individual decision making units are not only assessed by their own weights but the weights of all the other DMUs are also incorporated into the value judgement. In practice this is carried out by a cross-efficiency matrix which is created as follows:

\[
h_{kj} = \frac{\sum_{i=1}^{m} x_{ik} y_{ij}}{\sum_{j=1}^{n} x_{jk} y_{ij}} \quad k = 1, \ldots, n; j = 1, \ldots, n; \quad (6.2)
\]

where \( h_{kj} \) is the score given to unit \( j \) in the DEA run of unit \( k \), when unit \( j \) is evaluated (Adler et al., 2002), and it is always true that \( 0 \leq h_{kj} \leq 1 \). The values in the diagonal of the cross-efficiency matrix, \( h_{kk} \), are the values returned by the traditional DEA model. To achieve full ranking, \( \bar{h}_k \), the average cross efficiency score of unit \( k \) is introduced:

\[
\bar{h}_k = \frac{\sum_{j=1}^{n} h_{kj}}{n} \quad (6.3)
\]

This score is more representative of efficiency than the traditional DEA-score, as all the elements of the cross-efficiency matrix are included in it but one has to be aware that at the same time the connection to the multiplier weights is lost (Adler et al., 2002). An interesting extension of the cross-efficiency method is the maverick index \( M_k \) developed by Doyle and Green (1994) which measures the deviation between the DMUs peer scores and the original DEA score in the following way:

\[
M_k = \frac{h_{kk} - e_k}{e_k} \quad (6.4)
\]

where

\[
e_k = \frac{1}{n-1} \sum_{j \neq k} h_{ij}
\]
The higher this \( M_k \) maverick value, the more the given DMU can be considered a maverick, i.e. its self evaluated score might be high parallel with a low peer evaluation.

### 6.1.3 Benchmark ranking method

The simplest benchmark ranking method is the approach when it is counted how many times a given DMU is peer to the other decision making units. Obviously this solution will not necessarily provide full ranking, as the resulting number may be equal in case of different DMUs. A more sophisticated method is developed by Torgensen et al. (1996) which also investigates the extent to which the different DMUs are peers to each other and through this benchmarking procedure full ranking is achieved. The technique consists of two steps: first a traditional, slack based DEA model is solved and \( V \), the set of efficient DMUs is determined. The DMUs which have slack values of zero belong to this set. Then the following model is applied to all decision making units:

\[
\frac{1}{E_k} = \max \theta_k \quad (6.5)
\]

subject to

\[
- \sum_{j \in V} \lambda_{kj} x_{ij} - s_{ik}^- = -x_k^i \quad i = 1, \ldots, m;
\]

\[
\sum_{j \in V} \lambda_{kj} y_{ij} - \theta_k y_{ik}^- s_r^r = 0 \quad r = 1, \ldots, s;
\]

\[
\sum_{j \in V} \lambda_{kj} = 1
\]

where \( V \) is the set of efficient units.

Finally, the individual reference weights created by the previous model are aggregated and this benchmarking measure ranks the decision making units:

\[
\rho_k^r \equiv \frac{\sum_{j \neq k} \lambda_{jk} (y_{kj} - y_{kj})}{y_r^p - y_r} \quad (6.6)
\]

\( \forall k \in V, r = 1, \ldots, s, \)

where

\[
y_{kj}^p = \frac{y_{kj}}{E_k} + s_r^r
\]
6.1.4 Common weights

6.1.4.1 Applying minimum weight restriction

If developed purposefully, the utilization of common weights can contribute to achieving a full ranking. The main goal of Wang et al. (2009) is to introduce a minimum weight restriction and as a side effect, common weights are also achieved. [Imposed weight restrictions to incorporate value judgement are widely researched within DEA but as these methods originally do not necessarily and purposefully provide a full ranking, they are not explicitly discussed here. The reader is referred to the theory of assurance regions developed by Thompson et al. (1986) and to the cone ratio DEA approach of Charnes et al. (1990) and further developed for example by Talluri and Yoon (2000)].

Wang et al. construct a maximin weight model and use this to reach full ranking:

\[
\begin{align*}
\text{maximize} & \quad \varepsilon \\
\text{subject to} & \quad \sum_{i=1}^{m} v_i = 1 \\
& \quad \sum_{r=1}^{s} u_r \hat{y}_{r0} - \sum_{i=1}^{m} v_i \hat{x}_{i0} = 0 \\
& \quad \sum_{r=1}^{s} u_r \hat{y}_{rj} - \sum_{i=1}^{m} v_i \hat{x}_{ij} \leq 0 \quad j = 1, \ldots, n; \\
& \quad u_r \geq \varepsilon \quad r = 1, \ldots, s; \\
& \quad v_i \geq \varepsilon \quad i = 1, \ldots, m.
\end{align*}
\]

where

\[
\begin{align*}
\hat{x}_{ij} &= \frac{x_{ij}}{\sum_{k=1}^{n} x_{ik}} \quad i = 1, \ldots, m; j = 1, \ldots, n; \\
\hat{y}_{rj} &= \frac{y_{rj}}{\sum_{k=1}^{n} y_{rk}} \quad r = 1, \ldots, s; j = 1, \ldots, n
\end{align*}
\]

are the normalized inputs and outputs and \( \varepsilon \) is not the usual, non-archimedean infinitesimal used in the traditional two-stage DEA model, but a decision variable, not necessarily very small and set to be the maximin input and output weight of DMU_0.

\[
\varepsilon^* = \max_{u_r, v_i} \left\{ \min_{r} (\min_{i} u_r, \min_{i} v_i) \right\}
\]

(6.8)
Thus to achieve full ranking the following steps have to be taken: 1) perform a normal DEA CCR to identify the efficient units 2) run the maximin weight model to find the maximin weight of each DMU 3) set weight restrictions and reassess the efficiencies of the DMUs with the weight restrictions incorporated in the judgement 4) rank the units as based on the new efficiency scores. Apart from utilizing common weights for the achievement of full ranking, the approach of Wang et al. includes further two novelties as compared to the traditional solutions: normalizing the input and output data and using minimum weight restrictions. The maximin theory is also applied by Troutt (1995) who developed a maximin efficiency ratio model which also creates common weights for evaluation.

\[
\max_{u,v} \left( \min_k \frac{\sum_{j=1}^{s} u_j y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \right)
\]

subject to

\[
\sum_{i=1}^{r} u_i y_{rj} \leq 1 \quad j = 1, ..., n;
\]

\[
\sum_{i=1}^{r} v_i x_{ij} \geq 0 \quad \text{for } r = 1, ..., s; i = 1, ..., m.
\]

6. 1.4.2 Statistical analysis

Common weights are also achieved by different multivariate statistical analyses and these can also lead to full ranking. For instance, canonical correlation, linear discriminant analysis or the discriminant analysis of ratios can be employed. Friedman and Sinuany-Stern (1997) use canonical correlation (CCA) to determine a scaling ratio score:

\[
T_j = \frac{W_j}{Z_j} \quad j = 1, ..., n;
\]

where

\[
Z_j = V_1 x_{1j} + V_2 x_{2j} + ... + V_m x_{mj}, \quad W_j = U_1 y_{1j} + U_2 y_{2j} + ... + U_s y_{sj}
\]

Here, the task of CCA is to find the vectors \( U' (U_1, U_2, ..., U_s) \) and \( V' (V_1, V_2, ..., V_m) \) which maximize a given coefficient of correlation between the composite input, \( Z \) and the
complex output, W. Sinuany-Stern et al. (1994) utilize linear discriminant analysis and develop the following one-dimensional linear function:

\[ D_j = \sum_{r=1}^{s} u_r y_{rj} + \sum_{i=1}^{m} v_i (-x_{ij}) \quad j = 1, ..., n \]  (6.11)

Value \( D_j \) is used for ranking, where the DMU with the highest \( D_j \) value is the most efficient decision making unit. Both of the above described models are only feasible when the weights are non-negative. Discriminant analysis of ratios combined with a non-linear search optimization algorithm can also be used for ranking but there is no guarantee that the solution found is globally optimal (Adler et al., 2002). A newly developed approach is that of Wang and Luo (2011) who aim to reach full ranking by the following regression analysis, the authors provide two different models (Eq. 6.12, 6.13):

minimize \[ z = \sum_{j=1}^{n} \left( \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \right)^2 \]  (6.12)

subject to
\[ u_r \geq 0 \quad r = 1, ..., s; \]
\[ v_i \geq 0 \quad i = 1, ..., m. \]

minimize \[ J = \sum_{j=1}^{n} \left( \sum_{r=1}^{s} u_r y_{rj} - \theta^* \sum_{i=1}^{m} v_i x_{ij} \right)^2 \]  (6.13)

subject to
\[ \sum_{r=1}^{s} u_r \left( \sum_{j=1}^{n} y_{rj} \right) + \sum_{i=1}^{m} v_i \left( \sum_{j=1}^{n} x_{ij} \right) = n \]
\[ u_r \geq 0 \quad r = 1, ..., s; \]
\[ v_i \geq 0 \quad i = 1, ..., m. \]

Solving either of the models yields common weights for fully ranking the decision making units.

### 6.1.5 Slack based DEA

Another way of approaching the question of full ranking is taking into account the slacks present in the slack-adjusted DEA model. It was Bardhan et al. (1996) who first created an index as based on the slacks to determine the order of DMUs. The Measure of Inefficiency Dominance (MID) (see Eq. 6.14.) was only utilized to rank the inefficient
units. (Some argue that the traditional DEA score is not even appropriate for ranking the inefficient DMUs, as these efficiency values are based on different weights and are thus incomparable.)

\[
0 \leq 1 - \frac{\sum_{r=1}^{m} s_{r}^{-} + \sum_{r=1}^{s} s_{r}^{+}}{m + s} \leq 1
\] (6.14)

Tone (2002) suggests a similar approach by creating the index \( \rho \) and utilizing that for the development of a super-efficiency like efficiency measure, where \( \rho \) is the objective function to be minimized. Hence, this method could also be viewed as a variant of the super-efficiency technique.

\[
\rho = \frac{1 - \frac{1}{m} \sum_{r=1}^{m} s_{r}^{-}}{1 + \frac{1}{s} \sum_{r=1}^{s} s_{r}^{+}}
\] (6.15)

Du et al. (2002) acknowledge the viability of the method by pointing out that the slack-based super-efficiency method is always feasible and they also present an extension to the model.

Chen and Sherman (2004) also use slacks for the development of a non-radial super-efficiency DEA model. With stepwise proportional changes in the inputs and outputs the slacks in the radial method are eliminated and thus full ranking is achieved. It must be noted that this leads to the incorporation of value judgments.

### 6.1.6 Multi-criteria decision making methods

Several efforts have been made in literature to combine or employ in parallel data envelopment analysis and a multi-criteria decision making (MCDM) method. Some authors even argue that DEA itself is a MCDM technique [e.g. (Troutt, 1995)]. It shall be noted, however, that MCDM is usually applied prior to decision making or project execution, while DEA is more often utilized for the evaluation of schemes already implemented (Adler et al., 2002). One way of merging MCDM with DEA is the incorporation of preferential information into the model. As mentioned earlier, this can be done for instance by limiting the values of weights (assurance region or cone-ratio models). A different solution may be the selection of preferred input/output targets, or even the creation of hypothetical DMUs. These solutions, however, do not always guarantee full ranking. An example from (Troutt, 1995) can be found in the section...
‘Common weights’ as his method can be categorized under both headings. The multi-criteria decision making method most frequently integrated with DEA is analytical hierarchical process (AHP). Sinuany-Stern et al. (2000) develop a combined approach where a pairwise comparison of the decision making units is carried out first, using the DEA approach modified to cater for this situation. (See Eq. 6.16.) Then, in a second run, the DMUs are also investigated using a cross-efficiency solution (Eq. 6.17.). The resulting values are used for the creation of a pairwise comparison matrix serving as the basis of the AHP study. (This method is to be referred to hereinafter as DEA/AHP).

\[
E_{AA} = \max \sum_{r=1}^{s} u_r Y_{rA} \tag{6.16}
\]

subject to

\[
\begin{align*}
\sum_{i=1}^{m} v_i X_{iA} &= 1, \sum_{r=1}^{s} u_r Y_{rA} \leq 1, \sum_{r=1}^{s} u_r Y_{rB} - \sum_{i=1}^{m} v_i X_{iB} \leq 0 \\
u_r &\geq 0, r = 1, ..., s, v_i &\geq 0, i = 1, ..., m.
\end{align*}
\]

\[
E_{BA} = \max \sum_{r=1}^{s} u_r Y_{rB} \tag{6.17}
\]

subject to

\[
\begin{align*}
\sum_{i=1}^{m} v_i X_{iB} &= 1, \sum_{r=1}^{s} u_r Y_{rB} \leq 1, \sum_{r=1}^{s} u_r Y_{rA} - E_{AA} \sum_{i=1}^{m} v_i X_{iA} &= 0 \\
u_r &\geq 0, r = 1, ..., s, v_i &\geq 0, i = 1, ..., m.
\end{align*}
\]

The method developed by Sinuany-Stern et al. has been applied for instance by Guo et al. (2006) for supply chain evaluation. Royendegh and Erol (2009) also build upon the idea of (Sinuany-Stern et al., 2000) but extend the method to ANP (analytic network process), the more generalized form of AHP. Zhang et al. (2006) combine DEA with AHP for 4PL vendor selection but their approach is different. After the construction of an input-output structure, AHP is utilized for a preliminary data analysis with the help of which the importance of the different criteria is determined. The results of the AHP are then used as preferential information in a modified DEA model. A pairwise comparison matrix is created with the evolving efficiency values and then AHP is applied again for the evaluation of the matrix.

6.1.7 Application of fuzzy logic

The fuzzy approach is used in different, wide-ranging fields (see e.g. Orbán and Várlaki, 2009; Harmati et al., 2008; Várlaki, 1999; Földesi et al., 2008). Very interesting and unusual path for ranking is taken by Wen and Li (2009) who utilize fuzzy information in
data envelopment analysis and as a side effect full ranking is achieved. The core of their method, the fuzzy DEA model is the following:

\[
\max \theta = Cr \left\{ u^T \tilde{y}_0 \geq 1 \right\}
\]

subject to

\[
Cr \left\{ u^T \tilde{y}_j \leq u^T \tilde{x}_j \right\} \geq 1 - \alpha \quad j = 1, ..., n;
\]

\[
u, v \geq 0
\]

where \( \alpha \geq 0.5 \), \( \tilde{x}_j \), and \( \tilde{y}_j \) are fuzzy variables characteristic of DMU\(_j\), \( u \) and \( v \) are considered vectors and \( Cr \) is the credibility measure. Then DMU\(_0\) is \( \alpha \)-efficient, if \( \theta^* \geq \alpha \), where \( \theta^* \) is the optimal solution of model (20).

Due to the complexity of the technique, it is difficult to solve it with traditional methods, so a hybrid intelligent algorithm is applied and fuzzy simulations are used together with a genetic algorithm. Another way to combine fuzzy logic and DEA is that of Karsak (1998) and Hougaard (1999), who first run a traditional DEA model and then use fuzzy logic to incorporate expert knowledge into the evaluation (2002).

### 6.1.8 Shadow prices

Alirezaee and Afsharian (2007) also take a different approach to full ranking. Without changing the DEA model, they introduce a new aspect.

\[
F(x, y) = 0
\]

is seen as the efficient production function, and \( \sum_{i=1}^{s} u_i y_{ij} \) and \( \sum_{i=1}^{m} v_i x_{ij} \) is viewed as the total revenue and the total cost for the \( j \)th DMU, respectively. Then

\[
\sum_i \frac{\partial F}{\partial x_{ij}} x_{ij} + \sum_j \frac{\partial F}{\partial y_{ij}} y_{ij} = 0
\]

while

\[
\left[ \sum_{i=1}^{s} u_{ij} y_{ij} - \sum_{i=1}^{m} v_{ij} x_{ij} \right] \leq 0
\]

is called profit restriction for the \( j \)th DMU. Using these formulae, a balance index is created which for each DMU is the sum of quantities of profit restrictions of other DMUs. DMU\(_i\) will be ranked higher than DMU\(_j\), if DMU\(_i\) is efficient, but DMU\(_j\) is not; or in another case, when the efficiency score of both DMUs is the same, but DMU\(_i\)'s balance index is more negative.
6.2 The DEA-PC (pairwise comparison) methodology

Having studied the different full ranking possibilities within DEA, it has become clear that there is a way to improve one of the methods listed above. The work of \textit{(Sinuany-Stern et al., 2000)} was found particularly inspiring (see Section 6.1.6) and appreciating its results, the original method is improved by enabling the pairwise comparison matrix to be nonreciprocal which contributes to the possibility of a more accurate evaluation \textit{(Markovits-Somogyi, 2012c)}. Even more so, since in the course of applying DEA in practice (see Section 5.), it has been revealed that the thumb rule in connection with the number of DMUs to be found in the literature is very difficult to be adhered to. According to this rule the number of observations should be three times greater than the indices of the inputs plus outputs; and the number of DMUs should be equal or larger than the product of the indices of inputs and outputs \textit{(Bazargan and Vasigh, 2003)}. Some authors are less strict in their conduct, Wu and Goh \textit{(Wu and Goh, 2010 and Chung and Hwang, 2005)} for example argue that the number of DMUs should only be minimally two times as much as the sum of the indices of inputs and outputs. However, under certain conditions even this requirement might be difficult to satisfy. The new technique proposed and called DEA-PC (pairwise-comparison) intends to provide a solution for both the problem of full ranking and the difficulty inherent in the thumb rule cited above \textit{(Fülöp and Markovits-Somogyi, 2012)}.

The DEA/AHP method is based on the following DEA-like approach:

\[
\begin{align*}
F_{AB} &= \max \sum_{r=1}^{s} u_r Y_{rA} \\
\text{subject to} & \sum_{i=1}^{m} v_i X_{iA} = 1 \\
& \sum_{r=1}^{s} u_r Y_{rA} \leq 1 \\
& \sum_{r=1}^{s} u_r Y_{rB} - \sum_{i=1}^{m} v_i X_{iB} \leq 0 \\
& u_r \geq 0, r = 1, \ldots, s, v_i \geq 0, i = 1, \ldots, m.
\end{align*}
\]

where

- $F_{AB}$ is the efficiency value,
- $Y_{rA}$ is the amount of output $r$ produced by unit A,
- $X_{iA}$ is the amount of input $i$ utilized by unit A,
- $r = 1\ldots s$ are the number of outputs,
- $i = 1\ldots m$ are the number of inputs,
- $u_r, v_i$ are the weights to be found,
A, B are the two units to be compared with each other.

It should be noted that in the original method, $E_{AA}$ is used for denoting the efficiency value. Here, however, $F_{AB}$ is used, in order to emphasize that this is a comparison where unit A is prioritized before unit B. The change from F to E is necessary to avoid confusion with a different efficiency value later on. Applying the same notations, the modified approach is the following:

\[
\hat{F}_{AB} = \max \sum_{r=1}^{s} u_r Y_{rA}
\]

subject to

\[
\sum_{i=1}^{m} v_i X_{iA} = 1
\]

\[
\sum_{r=1}^{s} u_r Y_{rB} - \sum_{i=1}^{m} v_i X_{iB} = 0
\]

$u_r \geq 0, r = 1, ..., s, v_i \geq 0, i = 1, ..., m.$

where $\hat{F}_{AB}$ is the modified efficiency value.

When equations (6.22) and (6.23) are compared, two differences are observable. First, it can be seen that the second constraint regarding the weighted sum of the outputs is missing. This is the elementary difference between the two models, since here a comparison of efficiency values is enabled which is not limited by a maximum value. If that constraint is left untouched, the resulting efficiency value will very frequently be the unity and thus real distinction is not achieved between the two DMUs (Fülöp and Markovits-Somogyi, 2012). Second, it shall also be noted that the semi-inequality in the third constraint of Eq. (6.22) is changed to equality in Eq. (6.23). This can be done because any optimal solution will fulfill this constraint as an equality and we are only interested in optimal solutions.

In essence, $\hat{F}_{AB}$ can also be calculated the following way:

\[
\hat{F}_{AB} = \max_{r \in S} \frac{Y_{rA}}{Y_{rB}} = \max_{r=1, ..., s} \frac{Y_{rA}}{Y_{rB}} \cdot \max_{i=1, ..., m} \frac{X_{iB}}{X_{iA}}
\]

This can be proven by the subsequent reasoning: let us look at a basic feasible solution of (6.23). The special structure of the problem indicates that any basic feasible solution will contain exactly two positive variables: one from the $v_i$ and one from the $u_r$ variables. These shall be denoted $i_0$ and $r_0$. Then, it is clear that $v_{i_0} = 1/X_{i_0A}$ and
\[ u_{r0} = v_{i} X_{iB} / Y_{iB} = \frac{X_{iB} / X_{iA}}{Y_{iB}} \]

and the value of the objective function is:

\[ Y_{iA} / X_{iA} \]

\[ Y_{iB} / X_{iB} \]

which is to be maximized by finding the relevant pair of \((r_0, i_0)\). This implies (6.24) directly (Fülöp and Markovits-Somogyi, 2012).

The pairwise comparison of all the decision making units is carried out by both of the methodologies, but the resulting values are then used in slightly different ways. The original method uses the efficiency values \((F_{AB})\) to create a reciprocal pairwise comparison matrix, but for that, a further value is also calculated. The best cross evaluation is defined by the following equation:

\[ E_{BA} = \max \sum_{r=1}^{m} u_r Y_{rB} \]  

subject to

\[ \sum_{i=1}^{m} v_i X_{iB} = 1 \]

\[ \sum_{r=1}^{s} u_r Y_{rB} \leq 1 \]

\[ \sum_{r=1}^{s} u_r Y_{rA} - F_{AB} \sum_{i=1}^{m} v_i X_{iA} = 0 \]

\[ u_r \geq \varepsilon, r = 1, ..., s, v_i \geq \varepsilon, i = 1, ..., m. \]

where

\( E_{BA} \) is the best cross evaluation,

\( \varepsilon \) is an Archimedean element defined to be smaller than any positive real number.

Then, \( F_{AB} \) and \( F_{BA} \) are used to create a reciprocal pairwise comparison matrix which is similar to the pairwise comparison matrices used in AHP. The major difference is that while in traditional AHP the values in the matrix are the results of subjective evaluations, in DEA/AHP, these values come from objective calculations. The only subjectivity in DEA might be the result of how the input-output structure is developed. The DEA/AHP method creates the elements of the \( n \times n \) matrix \( A = [a_{jk}] \) from the following values:

\[ a_{jk} = \frac{F_{jk} + E_{jk}}{F_{kj} + E_{kj}} \]  

where

\( a_{jj} \) is 1.
The full rank of the decision making units is then established by determining the weights of the eigenvector of the matrix. However, as it was shown by (Fülöp and Markovits-Somogyi, 2012), often the matrix created the way described above yields problems. If the following conditions

\[ Y_{rA}/X_{iA} < Y_{rB}/X_{iB} \text{ for all } (r, i) \]  

or

\[ Y_{rA}/X_{iA} > Y_{rB}/Y_{iB} \text{ for all } (r, i) \]  

are not met, the equality \( F_{jk} = E_{kj} = F_{kj} = E_{jk} = 1 \) will hold, which happens very often, if the cases are randomly generated or real life problems. This means that the resulting pairwise comparison matrix will contain very many 1s, which means that in fact the given decision making units are not distinguished from each other. Thus, in these cases the original method cannot fully rank the decision making units.

In the new method it is proposed to create the \( n \times n \) pairwise comparison matrix \( A = [a_{jk}] \) from the values

\[ a_{jk} = \hat{F}_{jk}, \quad j, k = 1, \ldots, n. \]

In this case, it is not necessary to create a best cross-efficiency value, because the resulting \( a_{jk} \) values in themselves are sufficient for a balanced comparison. It is true, that \( \hat{F}_{AB} \) is a biased value, in as much as it is constructed using the single output and the single input which is the best from unit A’s point of view (see Eq. 6.24.) but at the same time using \( \hat{F}_{BA} \) for comparing B with A ensures the same advantage for unit B. Thus, looking at the entirety of the matrix, the level playing field is assured for all the DMUs.

Here (and also at looking at Eq. 6.24.) it becomes clear that the resulting matrix will not be reciprocal, as \( \hat{F}_{AB} \) will not be necessarily equal to \( 1/\hat{F}_{BA} \). In original AHP, where the elements of the matrix are the results from subjective comparisons, this might be a problem, because there, it is the consistency of the matrix that ensures the eligibility of the results. Here, however, where the data are the results of an objective methodology, the consistency of the matrix is not a prerequisite anymore.

In both of the methods, ranking weights have to be elicited from the resulting matrix. The DEA/AHP technique, just as AHP (Duleba, 2009), uses the eigenvector method for this purpose. That is, the vector \( w \) is to be determined which satisfies the following conditions (Rapcsák, 2007):
\( Aw = \lambda_{\text{max}} w \)  
subject to 
\[ \sum_{i=1}^{n} w_i = 1 \quad w \in \mathbb{R}^n \]
where 
\( \lambda_{\text{max}} \) is the maximum eigenvalue of the pairwise comparison matrix, and 
\( w_i \) are the ranking weights.

Although this method was developed for eliciting ranking weights from reciprocal matrices, it was shown that the method can be extended to non-reciprocal matrices as well (Koczkodaj and Orlowski, 1999; Sekitani and Yamaki, 1999). Moreover, the logarithmic least square method and the weighted least square method can also be used to tackle the problem of determining the ranking weights from the pairwise comparison matrices (Fülöp and Markovits-Somogyi, 2012). Inevitably, one cannot give a definite answer to the question of which of the techniques is the best. This question is argued but is undecided in the more general multi-attribute decision making, too. However, tests on numerical examples carried out with DEA-PC show that the correlations between the resulting rankings are satisfyingly high. The applications of DEA-PC presented below will rely on the eigenvector method.

Finally, regarding the choice of the name, DEA-PC: first, the method was referred to as “modified DEA/AHP methodology”, since Sinuany-Stern et al. (Sinuany-Stern et al., 2000) called their method “DEA/AHP methodology”. However, certain differences between traditional AHP (Saaty, 1980) and DEA-PC justified a new terminology to be introduced. These differences are the following: a) there is no hierarchy, which is one of the main characteristics of AHP b) it is not the elements of the Saaty-scale which are used in the procedure c) the values are not subjectively created, but are the result of a DEA like pairwise comparison d) consistency does not play a role in the procedure e) the evolving matrix is not reciprocal.

### 6.3 DEA-PC applied on micro level

#### 6.3.1. Full ranking of road haulage firms

Having introduced the theoretical background of DEA-PC methodology, the next step is to adapt it to the field of road freight transport and logistics. First, its applicability to road haulage companies is investigated. To begin with, the pure financial examination already introduced in Section 5.1 is carried out with the new method. The input and output parameters are those listed in Table 5.1, excluding the outliers identified (Firms No. 5. and 25.).
The results of the investigation are shown in Table 6.1, where the firms have been ordered according to their CEI' value. It is important to note that DEA/AHP and DEA-PC does not issue efficiency values of 1 to the most efficient firms: their utmost aim is to provide a full ranking, which is achieved by values in a different range than that of traditional DEA. Nonetheless, to make data more transparent, two further columns, indicated by DEA/AHP' and DEA-PC', are inserted, in which data are recalculated in a way where the most efficient unit is assigned the value of 1.

Table 6.1. Results from the financial investigation with the different methods

<table>
<thead>
<tr>
<th>Firm</th>
<th>CEI'</th>
<th>DEA</th>
<th>DEA/AHP</th>
<th>DEA/AHP'</th>
<th>DEA-PC</th>
<th>DEA-PC'</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.862217</td>
<td>1.0000</td>
<td>0.05981</td>
<td>1</td>
<td>0.07267</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>6.841099</td>
<td>1.0000</td>
<td>0.03866</td>
<td>0.64638</td>
<td>0.0542</td>
<td>0.745837</td>
</tr>
<tr>
<td>3</td>
<td>6.258109</td>
<td>0.9138</td>
<td>0.04074</td>
<td>0.681157</td>
<td>0.04527</td>
<td>0.622953</td>
</tr>
<tr>
<td>4</td>
<td>6.055687</td>
<td>0.8838</td>
<td>0.04265</td>
<td>0.713091</td>
<td>0.04324</td>
<td>0.595019</td>
</tr>
<tr>
<td>5</td>
<td>5.859561</td>
<td>1.0000</td>
<td>0.03721</td>
<td>0.622137</td>
<td>0.05734</td>
<td>0.789046</td>
</tr>
<tr>
<td>6</td>
<td>5.575095</td>
<td>0.8134</td>
<td>0.04274</td>
<td>0.714596</td>
<td>0.04023</td>
<td>0.553598</td>
</tr>
<tr>
<td>7</td>
<td>5.407009</td>
<td>0.7883</td>
<td>0.04585</td>
<td>0.628992</td>
<td>0.04527</td>
<td>0.631072</td>
</tr>
<tr>
<td>8</td>
<td>4.824027</td>
<td>0.7034</td>
<td>0.04209</td>
<td>0.703728</td>
<td>0.03829</td>
<td>0.526902</td>
</tr>
<tr>
<td>9</td>
<td>4.74995</td>
<td>0.7048</td>
<td>0.0448</td>
<td>0.749039</td>
<td>0.05105</td>
<td>0.702491</td>
</tr>
<tr>
<td>10</td>
<td>4.50253</td>
<td>0.8013</td>
<td>0.03618</td>
<td>0.604916</td>
<td>0.04586</td>
<td>0.631072</td>
</tr>
<tr>
<td>11</td>
<td>4.484318</td>
<td>0.6542</td>
<td>0.03881</td>
<td>0.648888</td>
<td>0.03285</td>
<td>0.452043</td>
</tr>
<tr>
<td>12</td>
<td>4.134212</td>
<td>0.6027</td>
<td>0.0398</td>
<td>0.665441</td>
<td>0.03523</td>
<td>0.484794</td>
</tr>
<tr>
<td>13</td>
<td>4.068846</td>
<td>0.6673</td>
<td>0.04154</td>
<td>0.694533</td>
<td>0.04771</td>
<td>0.65653</td>
</tr>
<tr>
<td>14</td>
<td>4.011135</td>
<td>0.7039</td>
<td>0.04143</td>
<td>0.692694</td>
<td>0.05008</td>
<td>0.689143</td>
</tr>
<tr>
<td>15</td>
<td>3.801236</td>
<td>0.6990</td>
<td>0.04044</td>
<td>0.676141</td>
<td>0.04967</td>
<td>0.683501</td>
</tr>
<tr>
<td>16</td>
<td>3.362572</td>
<td>0.4906</td>
<td>0.03272</td>
<td>0.547066</td>
<td>0.02432</td>
<td>0.334664</td>
</tr>
<tr>
<td>17</td>
<td>3.28388</td>
<td>0.5647</td>
<td>0.03729</td>
<td>0.623474</td>
<td>0.04022</td>
<td>0.553461</td>
</tr>
<tr>
<td>18</td>
<td>3.17492</td>
<td>0.4630</td>
<td>0.03259</td>
<td>0.544892</td>
<td>0.02436</td>
<td>0.335214</td>
</tr>
<tr>
<td>19</td>
<td>3.011425</td>
<td>0.4389</td>
<td>0.03431</td>
<td>0.57365</td>
<td>0.0284</td>
<td>0.390808</td>
</tr>
<tr>
<td>20</td>
<td>2.974077</td>
<td>0.4335</td>
<td>0.03329</td>
<td>0.556596</td>
<td>0.02629</td>
<td>0.361772</td>
</tr>
<tr>
<td>21</td>
<td>2.958501</td>
<td>0.4318</td>
<td>0.03001</td>
<td>0.501756</td>
<td>0.02113</td>
<td>0.290766</td>
</tr>
<tr>
<td>22</td>
<td>2.832255</td>
<td>0.4128</td>
<td>0.03294</td>
<td>0.550744</td>
<td>0.0264</td>
<td>0.363286</td>
</tr>
<tr>
<td>23</td>
<td>2.199795</td>
<td>0.3208</td>
<td>0.02516</td>
<td>0.420665</td>
<td>0.01721</td>
<td>0.236824</td>
</tr>
<tr>
<td>24</td>
<td>1.819116</td>
<td>0.2774</td>
<td>0.02611</td>
<td>0.436549</td>
<td>0.01908</td>
<td>0.262557</td>
</tr>
<tr>
<td>25</td>
<td>1.764887</td>
<td>0.2651</td>
<td>0.02676</td>
<td>0.447417</td>
<td>0.01993</td>
<td>0.274253</td>
</tr>
<tr>
<td>26</td>
<td>1.595079</td>
<td>0.2327</td>
<td>0.01845</td>
<td>0.308477</td>
<td>0.0116</td>
<td>0.159626</td>
</tr>
</tbody>
</table>

(Source: own research)

From the results it can be seen that traditional DEA does not give full ranking, it considers three firms as efficient. Whereas, both DEA/AHP and DEA-PC achieve full ranking, and the
Spearman correlation between the rankings of DEA/AHP, DEA-PC and the CEI’ index is 81.32% and 81.75%, respectively. This means, that the results from the full ranking methods are reasonably similar to those achieved by the pure financial indicator (Markovits-Somogyi, 2012c). Here, at this sample size and data structure the benefits of DEA-PC over DEA/AHP are not yet obvious, these are to be highlighted in the further investigations.

Subsequently, the same models have been adapted to DEA-PC as already investigated with traditional DEA in Section 5.2, Table 5.3. For ease of understanding, the given Table is repeated here as Table 6.2. As already mentioned in Section 5.2, the extended evaluation could only be carried out on a sample of 13 decision making units (see Table 5.2 for input and output data), which construed a serious limitation in case of traditional data envelopment analysis. However, DEA-PC is not limited by the size of the sample, as the comparisons are carried out pairwise.

Table 6.2. Input and output structure of the different DEA/AHP models

<table>
<thead>
<tr>
<th>Models</th>
<th>Inputs</th>
<th>Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Tied-up assets (TA)</td>
<td>Labour costs (LC)</td>
</tr>
<tr>
<td>A</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>B</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>C</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>D</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

(Source: own research)

The base case (Model “A”) is again the pure financial analysis, where inputs are tied-up assets and labour costs, and the output is the net value of production. The resulting weights are shown in Appendix 3., where the firms ordered according to CEI’ index. Figure 6.1. shows the rankings received by using these weights, ordered according to the DEA-PC rankings. The columns represent rankings, thus they are the shorter, the better for the given DMU.

The Spearman correlation between the ranking received by DEA/AHP, DEA-PC and the CEI’ value is 86.81% and 82.42%, respectively, so again it can be stated that even on this smaller sample, the full ranking methods provide reasonably similar rankings.

Subsequently, as a technological parameter, the sum of distance covered by the vehicles was included into the investigations (Model “B”). Here, it was the aim to extend the examinations with such an operational parameter that enables the comparison of the companies from the technological side as well. The ensuing ranking weights are shown
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again in Appendix 3., while the rankings themselves are depicted in Figure 6.2, in the order of DEA-PC ranks.

![Figure 6.1. Rankings from the two methods in Model “A”](source: own research)

![Figure 6.2. Rankings from the two methods, in case of Model “B”](source: own research)

It is important to note that the DEA/AHP method does not provide a full ranking. It can be seen, that several companies (Firms No. 2, 6, 13, 11) are accorded the same weights, hence the same rankings, so the full ranking procedure does not reach its aim. When looking at the pairwise comparison matrix in the given case (see Appendix 4.), the
phenomenon indicated in Section 6.2 becomes visible. The conditions required by Eq. 6.28. and 6.29 are not met, and the pairwise comparison matrix thus includes very many 1s. This way several companies cannot be distinguished from each other, and full ranking is not reached. Whereas, the DEA-PC pairwise comparison matrix (see Appendix 5.) created by using the \( \hat{F}_{AB} \) values, as in Eq. 6.24., will be able to ensure full ranking.

In Model “C”, a parameter representing sustainability is included into the investigation. For a detailed description of this parameter, see Section 5.2. The ensuing weights are to be found in Appendix 3., and the rankings are shown in Figure 6.3.

Model “D” (see Figure 6.4) includes all of the parameters investigated individually up until now. This is the input-output structure that cannot be investigated with traditional DEA methodology, due to the limited size of the sample. However, the full ranking procedures DEA/AHP and DEA-PC should be adequate for their investigation.

Nevertheless, the phenomenon observed by Model “B” happens in Model “D” as well, where even more firms remain undistinguished from each other (see Figure 6.4, Firms No. 2, 6, 3, and 5; and Firms No. 10, 11, 12 and 13.). Consequently, it can be stated that DEA/AHP does not always provide full ranking, and the examples on road haulage companies have shown the same phenomenon experienced by other numerical examples from the literature (Fülöp and Markovits-Somogyi, 2012). Thus, it is reasonable to use the DEA-PC technique, if full ranking is to be achieved.
When comparing the results of the DEA-PC method in the different models, it can be seen, that the change of aspects provides significantly different rankings. Figure 6.5. includes all the DEA-PC rankings in all the four models. It can be seen, how the shift of aspects from purely financial to technological and/or environmental factors alters the ranking of the individual DMUs. For instance, Firm No. 10 ranked 12th and 11th in Models “A” and “B” becomes 1st, when sustainability is included in the examinations. Whereas, the ranking of Firm No. 4. gets worse (from 2 to 6, 9 and 10), when technological and then environmental characteristics are incorporated into the input-output structure.
This subjective observation is also reinforced by the numbers themselves. When the rankings of Models B, C and D are compared to the rankings from Model A, Spearman correlations of 63.74%; -9.34% and -33.52% can be calculated. Thus, it can be seen that indeed, the change from financial to non-financial parameters alters the evolving rankings significantly.

6.3.2. Full ranking of logistics centres
As a third field of adaptation, DEA-PC is also applied to logistic centres. Based on the experiences gathered in Section 5.3, these decision making units are analysed with the input-output structure created in the “second” and “third” model (see Sections 5.3.3 and 5.3.4, and Table 6.3 here), and only logistics service centres are included into the examinations. As before, to make data more transparent, DEA-PC’ values are calculated by assigning the most efficient unit the value of 1, and recalculating the efficiency values of the rest of the units.

<table>
<thead>
<tr>
<th>Table 6.3. The input-output structure of the investigated models</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Inputs</strong></td>
</tr>
<tr>
<td><strong>Storage area</strong></td>
</tr>
<tr>
<td>Second model</td>
</tr>
<tr>
<td>Third model</td>
</tr>
</tbody>
</table>

(Source: own research)

The aim of the investigations was to provide a full ranking of the logistics service centres, and taking into account the results from Section 6.3.1, only the DEA-PC method is applied here, which can reliably deliver full ranking of the decision making units. The ranking weights yielded by the traditional DEA method and by DEA-PC are shown in Table 6.4. The Spearman correlations between the rankings obtained by the traditional DEA method and the new method are 92.08% and 80.00% for the second and the third model, respectively. So, it can be established that the acquired rankings provide reasonably similar results to those delivered by the traditional method.

The rankings themselves, are shown in Figure 6.6 (Second model), and Figure 6.7 (Third model), ordered according to their DEA-PC rankings. Just as from the weights in Table 6.4, it is clear from these diagrams as well, that traditional DEA does not deliver full ranking, while DEA-PC is able to do so. Looking at the final order of the centres, to be read from the horizontal axis of Figures 6.6 and 6.7, it can be also seen, that the inclusion of the
“total number of employees” changes the order only in the 2nd and 3rd place, between Centres 2 and 9.

Table 6.4. The resulting ranking weights in the different models

<table>
<thead>
<tr>
<th>Firms</th>
<th>Second model</th>
<th>Third model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DEA</td>
<td>DEA-PC</td>
</tr>
<tr>
<td>1</td>
<td>0.04300</td>
<td>0.01164</td>
</tr>
<tr>
<td>2</td>
<td>0.85000</td>
<td>0.15914</td>
</tr>
<tr>
<td>3</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>4</td>
<td>0.07400</td>
<td>0.02527</td>
</tr>
<tr>
<td>5</td>
<td>0.14900</td>
<td>0.03986</td>
</tr>
<tr>
<td>6</td>
<td>0.06600</td>
<td>0.02186</td>
</tr>
<tr>
<td>7</td>
<td>1.00000</td>
<td>0.63257</td>
</tr>
<tr>
<td>8</td>
<td>0.10500</td>
<td>0.01953</td>
</tr>
<tr>
<td>9</td>
<td>1.00000</td>
<td>0.09011</td>
</tr>
</tbody>
</table>

(Source: own research)

Figure 6.6. The rankings of the logistics service centres in the second model

(Source: own research)

Thus, it can be stated that DEA-PC is capable of fully ranking logistic service centres according to their efficiency, and the sample size does not limit so severely the investigations as in the case of traditional data envelopment analysis.
6.4 DEA-PC applied on macro level – Full ranking of European Countries

The DEA-PC methodology was also to be adapted on macroeconomic level, thus the investigations introduced in Section 5.4 have been set forth with this aim. The same input-output structures were tested with the DEA-PC methodology as described previously (Models “A1”, “A2” and “B”, see Table 5.7 in Section 5.4) , where European countries were analysed using the traditional DEA approach (Markovits-Somogyi and Bokor, 2012b).

The numerical results from the DEA-PC investigation of the countries with the three models are shown in Column II. of the Table in Appendix 6. The ranking weights drew the attention to a very interesting phenomenon: it has become obvious that Latvia is an outlier in the sample, as its efficiency value was exceedingly higher than that of the rest. Looking closer at the input-output data has soon revealed the reason for that: Latvia’s highway network is exceedingly short and this has led to its efficiency value being so large. It is the merit of the DEA-PC methodology that it has been able to point to this fact.

Subsequently new DEA runs have been carried out without the data of Latvia. Although the weights were dissimilar (see Figure 6.8. and Column III. in the Table included in Appendix 6.), the evolving rankings were not significantly different from the rankings gained in the DEA-PC including Latvia. The ranks showed a Spearman correlation of
83.42%, 80.41% and 87.04% in Models “A1”, “A2” and “B1” respectively all of which can be considered significant as based on the relevant significance levels (see Appendix 2).

It has to be emphasized that DEA-PC in itself is not expected to yield the value of 1 for the most efficient unit. This is a full ranking procedure thus the results show weights which can discern all the units and create full ranking. Hence, the unit with the highest weight is automatically considered as the most efficient DMU. In Figure 6.8. the recalculated values are shown, where 1 is assigned to the most efficient unit.

**Figure 6.8.** Ranking weights in the DEA-PC method without the outlier Latvia

(source: own research)

Figure 6.8 also shows the final full ranking: the data have been ordered according to the values of “A1” which can be considered as the most viable test setup. Here again it can be seen that some countries with low GDP get high ranks. Also it is observable that all the countries have different ranking weights, thus DEA-PC can create full ranking. It is important to note that this order cannot directly be compared with the ranking created by DEA CCR in the first stage because there the outliers were not omitted. For this reason a further DEA CCR test has been carried out without the data of Latvia. Since “A1” was methodically the most viable case, only the results thereof are considered.
Figure 6.9 presents the rankings with the new DEA-PC and traditional DEA CCR method. The data have been ordered by the DEA-PC ranking. It should be noted that the diagram incorporates the absolute rankings and not the ranking weights, thus the smaller the number, the higher the ranking. The rankings correlate significantly, the Spearman correlation between them is 65.92% which is higher than the critical value required at a significance level of 0.99 (see Appendix 2). Thus it can be stated that the full rank is satisfyingly reflecting the original order but it also has the advantage of being able to rank all the decision making units.

![Figure 6.9. Ranking orders with DEA-PC and DEA CCR method without the outlier](source: own research)

### 6.4.1 Comparison with an international survey

The Logistics Performance Index (LPI) is a set of indicators that measures, in the form of an international survey of the World Bank, the performance of the trade logistics environment of countries (Olaja, 2011). It uses more than 5000 individual country assessments made by nearly 1000 international freight forwarders to compare the trade logistics profiles of 155 countries (Arvis et al., 2010). Thus it can be viewed as an objective indicator of the different countries’ logistics performance. The country assessments are based on six pillars which measure how „easy” or „difficult” a country’s trade logistics is seen from the outside. These six independently assessed indicators are the following:

- Customs and other border procedures
- Transport and IT infrastructure & services
- Availability of affordable shipments
- Logistics competence and quality
- Tracking and tracing of shipments
• Timeliness of shipments

Apart from the Logistics Performance Index, which is the international part of the survey, it also comprises a domestic part which evaluates the performance of the respondents’ countries.

The significance of the LPI survey from the point of view of the present DEA and DEA-PC research is twofold. First, with its indicators it provides important data regarding the quality of logistics performance: it enables the incorporation of quality aspects into data envelopment analysis. This is what has already happened in both the DEA and the DEA-PC investigation where “Timeliness of shipments” from the international survey and “Quality” from the domestic part have been used as output in the DEA and DEA-PC tests. Second, it provides an even bigger opportunity by offering evaluative data in form of the fourth indicator called “Logistics competence and quality”. It has to be noted that this indicator is independently assessed and neither of the input indicators mentioned above have been utilized for the development of this measurement. Hence, it can be freely used as a benchmark against which the results of DEA and DEA-PC can be compared.

In its content “Logistics quality and competence” is exactly what efficiency in logistics is about: it reflects the logistics performance of the different countries. Thus, it appears to be viable to compare this ranking with the DEA and DEA-PC results (the scores themselves are presented in Table 6.5). Therefore, in the following the ranking derived from the “Logistics quality and competence” score of the LPI survey and the results of the traditional DEA and the DEA-PC in case A1 are compared with each other. Table 6.6 shows the Spearman correlations of the different rankings for the preliminary investigations on 29 European countries, while Table 6.7 presents the correlations using the second DEA and DEA-PC run where the sample was considered without the outlier, Latvia, and the number of elements was n = 28. To enable back checking, the critical values of complete independence in Spearman correlation are presented in Appendix 2.

First, it can be seen, as mentioned earlier, that with values 53.24% and 65.92%, traditional DEA and DEA-PC correlate well in both of the cases which means that the two rankings are satisfyingly similar, as expected. Then, comparing the rankings from the “Logistics quality and competence” indicator and the traditional DEA investigation, an interesting phenomenon can be discovered. The correlations are negative and at a significance level of 0.05 they are in both cases significant. (The test without the outlier is even significant at a 0.01 significance level.) This means that the two rankings show opposite results. What can be the reason behind this behaviour?

The answer lies in the characteristics of data envelopment analysis itself. If countries are to be ranked along absolute values then the “Logistics quality and competence” rank will
be the adequate one to be considered. Here, the absolute competence of the country is reported without taking into account other, external circumstances. This is analogue to asking which animal is the strongest. Undoubtedly, the absolute answer would be the elephant. At the same time, if all circumstances are considered, the right answer would be the ant. This is how data envelopment analysis also takes into consideration all external factors and abilities and provides a ranking order by ensuring a level playing field for all decision making units. Here, countries with smaller possibilities are expected to perform less than countries with large GDPs which are expected to perform proportionally better. The negative correlation can also be explained by the fact that the “Logistics quality and competence” rank correlates significantly with GDP (Spearman correlation 76.70%), while GDP is considered as an input in data envelopment analysis.

**Table 6.5. Logistics quality and competence (LQC) ranking scores of the selected countries in the international LPI survey (1 – lowest score, 5 – maximum score)**

<table>
<thead>
<tr>
<th>Countries</th>
<th>Belgium</th>
<th>Bulgaria</th>
<th>Czech Republic</th>
<th>Denmark</th>
<th>Germany</th>
</tr>
</thead>
<tbody>
<tr>
<td>LQC</td>
<td>4.13</td>
<td>2.85</td>
<td>3.27</td>
<td>3.83</td>
<td>4.14</td>
</tr>
<tr>
<td>Countries</td>
<td>Estonia</td>
<td>Ireland</td>
<td>Greece</td>
<td>Spain</td>
<td>France</td>
</tr>
<tr>
<td>LQC</td>
<td>3.17</td>
<td>3.82</td>
<td>2.69</td>
<td>3.62</td>
<td>3.87</td>
</tr>
<tr>
<td>Countries</td>
<td>Italy</td>
<td>Latvia</td>
<td>Lithuania</td>
<td>Luxembourg</td>
<td>Hungary</td>
</tr>
<tr>
<td>LQC</td>
<td>3.21</td>
<td>2.96</td>
<td>2.85</td>
<td>3.67</td>
<td>2.87</td>
</tr>
<tr>
<td>Countries</td>
<td>Netherlands</td>
<td>Austria</td>
<td>Poland</td>
<td>Portugal</td>
<td>Romania</td>
</tr>
<tr>
<td>LQC</td>
<td>4.15</td>
<td>3.7</td>
<td>3.26</td>
<td>3.02</td>
<td>2.68</td>
</tr>
<tr>
<td>Countries</td>
<td>Slovenia</td>
<td>Slovakia</td>
<td>Finland</td>
<td>Sweden</td>
<td>United Kingdom</td>
</tr>
<tr>
<td>LQC</td>
<td>2.84</td>
<td>3.15</td>
<td>3.92</td>
<td>4.22</td>
<td>3.92</td>
</tr>
<tr>
<td>Countries</td>
<td>Norway</td>
<td>Switzerland</td>
<td>Croatia</td>
<td>Turkey</td>
<td></td>
</tr>
<tr>
<td>LQC</td>
<td>3.85</td>
<td>4.32</td>
<td>2.53</td>
<td>3.23</td>
<td></td>
</tr>
</tbody>
</table>

(Source: Arvis et al., 2010)

**Table 6.6. Correlation between the rankings in case A1, considering all the countries in the sample**

<table>
<thead>
<tr>
<th>For all DMUs</th>
<th>Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEA – DEA-PC</td>
<td>53.24%</td>
</tr>
<tr>
<td>Log. qua. – DEA</td>
<td>-40.99%</td>
</tr>
<tr>
<td>Log. qua. – DEA-PC</td>
<td>9.16%</td>
</tr>
</tbody>
</table>

\( n = 29 \)

(Source: own research)

Finally, looking at the correlations between the “Logistics quality and competence” rank and the DEA-PC rank, it can be stated that no correlation exists. This is due to the fact that
DEA-PC is halfway between traditional DEA and absolute scoring, like LPI. It takes into account factors like GDP but their influence is not omnipotent.

**Table 6.7. Correlation between the rankings in case A1, without the outlier**

<table>
<thead>
<tr>
<th>Without outliers</th>
<th>Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEA – DEA-PC</td>
<td>65.92%</td>
</tr>
<tr>
<td>Log. qua. – DEA</td>
<td>-47.04%</td>
</tr>
<tr>
<td>Log. qua. – DEA-PC</td>
<td>41.05%</td>
</tr>
</tbody>
</table>

*n = 28*(

(Source: own research)

### 6.5 Conclusion

After enumerating the different techniques capable of providing full ranking within data envelopment analysis, the present section introduced the DEA-PC methodology, which is capable of fully ranking the decision making units in a reliable way. This novel method, which can be applied for efficiency analysis in any known DEA-application field, is a technique further developed from the original DEA/AHP method (*Sinuany-Stern et al.*, 2000).

It has been shown, both theoretically and also by practical examples from the field of road freight transport, that, contrary to the original DEA/AHP technique, DEA-PC always provides full ranking. Furthermore, the modified method has been adapted to evaluate road haulage companies by taking into account technological and environmental parameters as well.

As an additional microeconomic adaptation, the DEA-PC methodology has also been utilized for evaluating logistics service centres, based on the input-output structures identified earlier. Then, on macroeconomic level, DEA-PC was also adapted to the efficiency assessment of European countries, and the results were compared to the outcomes of a major international survey. DEA-PC was capable of revealing the differences between absolute “logistics quality and competence” and the input-output ratio oriented efficiency.

Throughout the investigations, DEA-PC has proven to be a reliable full ranking method capable of identifying outliers, and not so severely limited by the size of the sample as traditional data envelopment analysis.
7. New scientific results

7.1 Defining efficiency, clustering the available ex-post efficiency assessment and analyzing techniques; and investigating the existing applications and the possibility of extension

I have processed the available efficiency definitions and delimiting these, I have created the most adequate efficiency definition that can be used in road freight transport and logistics, with special view on its applicability later on. According to this, efficiency can be defined as “the ratio of the services and other results produced by the road freight transport or logistics firm and the resources utilised for this production.” (See Section 2.2).

As based on this efficiency definition I reviewed and categorized the relevant evaluation techniques, and taking into consideration the practical aspects of road freight transport and logistics, I recommended the use of DEA (Data Envelopment Analysis). (See Section 3.)

I critically evaluated the method of data envelopment analysis and investigated its existing applications in the transport sector. As based on this, I have shown that it is possible to adapt DEA to the road freight sector and in the logistics field, with a special view on the possible inclusion of technological and environmental parameters. (See Section 4.)

The definition of efficiency was developed with the aim of assessing already operating decision making units (DMUs). There are different methodologies in the literature available for this purpose (techniques using indexes, parametric and non-parametric methods). All of these dispose of a very wide background, methodological toolbox and area of utilization. Keeping in mind practical applicability, the investigations were limited to non-parametric methods, because here it is not necessary to have a priori assumptions about the inner operational structure before the efficiency analysis, thus, their input data need is also significantly lower. Within non-parametric methods, the general methodological background of data envelopment analysis is developed in much detail, and a sufficient number of practical applications are available. The literature review revealed 69 studies utilizing data envelopment analysis in the field of transport. The detailed research into the transport applications was aimed to gain sufficient expertise in the development of input and output structures, which is the most complicated part of DEA modelling (see Section 4.2.1).
The review also showed that in road freight transport and logistics there are very few adaptations available, and these often only include financial parameters. Sometimes, these existing models can also be methodologically questioned. Thus, this justifies the need for elaborating DEA adaptations to the road freight transport and logistics sector.

**Relevant own publications:** (Markovits-Somogyi, 2011a); (Markovits-Somogyi, 2011d); (Markovits-Somogyi and Bokor, 2011); (Markovits-Somogyi, 2011c); (Markovits-Somogyi and Bokor, 2010); (Markovits-Somogyi et al., 2010).

### 7.2 Specifying DEA models in the area of road freight transport and logistics

<table>
<thead>
<tr>
<th><strong>I adapted special DEA models to road freight transport and logistics both on microeconomic and on macroeconomic level</strong> (see Section 5.). The models were tested on practical applications.</th>
</tr>
</thead>
</table>

First, in the case of road freight transport companies, I verified the DEA-rankings as based on a pure financial analysis (Section 5.1), then, the input-output structure was extended to include technological and environmental parameters. The evolving DEA structures were tested on real-life data collected from financial databases and through phone surveys (see Section 5.2). Then, within the framework of a second micro-economic adaptation, by an iterative and heuristic process I adapted the DEA-method to the efficiency assessment of logistics service centres from a complex technological and economic viewpoint (see Section 5.3). I refined the evolved input-output structure by way of sensitivity analysis.

On macroeconomic level, relying on existing applications, I created the technological and economic parameter system applicable for the efficiency evaluation of the logistics efficiency of European countries (see Section 5.4).

**Relevant own publications:** (Markovits-Somogyi, 2011b); (Markovits-Somogyi and Bokor, 2012a); (Markovits-Somogyi et al., 2011).

### 7.3 Developing a new method for full ranking within DEA

<table>
<thead>
<tr>
<th><strong>A new method, called DEA-PC (pairwise comparison) has been developed for full ranking within the framework of data envelopment analysis (see Section 6.2.).</strong></th>
</tr>
</thead>
</table>

The DEA-PC method can be described by the following equation:
\[ \hat{F}_{AB} = \max \sum_{r=1}^{s} u_r Y_{rA} \]  

subject to

\[ \sum_{i=1}^{m} v_i X_{iA} = 1 \]

\[ \sum_{r=1}^{s} u_r Y_{rB} - \sum_{i=1}^{m} v_i X_{iB} = 0 \]

\[ u_r \geq 0, \quad r = 1, \ldots, s, \quad v_i \geq 0, \quad i = 1, \ldots, m. \]

where

- \( \hat{F}_{AB} \): the efficiency value resulting from the pairwise comparisons,
- \( A, B \): index of the two, compared decision making units (DMUs),
- \( X_{ij}, Y_{ij} \geq 0 \): the input and output values of the decision making unit to be evaluated (DMU \( u_0 \)),
- \( j = 1, 2, \ldots, n \): number of DMUs,
- \( i=1, 2, \ldots, m \): number of inputs,
- \( r=1, 2, \ldots, s \): number of outputs,
- \( u_r, v_i \): the weights determined by the linear program.

The received \( \hat{F}_{AB} \) efficiency values are ordered into a pairwise comparison matrix known from the AHP method. Full ranking is then obtained by the coordinates of the eigenvector of the matrix.

Reviewing the full ranking techniques available within the DEA family, I have established, that modifying the existing DEA/AHP method an efficiency assessment tool disposing of a much higher distinction power can be created. After appropriate adaptation, this method is capable of delivering a full ranking in the area road freight transport and logistics as well, and so it can contribute to the enhancement of decision making processes.

**Relevant own publications:** (Markovits-Somogyi, 2011e); (Fülöp and Markovits-Somogyi, 2012); (Markovits-Somogyi, 2011f)

**7.4 Full ranking on micro- and macroeconomic level**

I verified the use of the road freight transport and logistics efficiency assessment method extended with the new full ranking feature on microeconomic level, both for the case of road haulage companies and for the case of logistics service centres (see Section 6.3.).
I verified the use of the road freight transport and logistics efficiency assessment method extended with the new full ranking feature on macroeconomic level by integrating novel aspects into the logistics efficiency assessment of countries. I delivered a full ranking of European countries as based on their logistics performance, and evaluated the results as compared to the outcomes of an independent international survey (see Section 6.4).

As based on the real life data of road haulage firms, I demonstrated by numerical results that the DEA-PC method dispenses of a higher distinction power as compared to the original DEA/AHP method, and it can provide a full ranking more reliably. Beyond conducting pure financial analysis, serving the purposes of verification, I extended the novel DEA-PC methodology to technological and environmental parameters, with the help of which complex technological and economic efficiency assessments became possible (see Section 6.3.1).

Using the input-output structure developed by previous investigations (see Section 5.3), I adapted the new DEA-PC method to the case of logistics service centres, where it has again been proven that the modified technique is capable of delivering full ranking and is less sensitive to the sample size as compared to traditional DEA (see Section 6.3.2).

I demonstrated with a practical application how the new DEA-PC full ranking method can be adapted to the macroeconomic level by presenting the logistic efficiency assessment of European countries. I compared the ensuing results to the relevant indicator of the LPI survey (Logistics Performance Index). I have established that, due to its concept and refined algorithm, the recommended new efficiency assessment technique provides more balanced results for decision making.

Relevant own publications: (Markovits-Somogyi, 2012a); (Markovits-Somogyi, 2012b); (Markovits-Somogyi, 2012c); (Markovits-Somogyi, 2011b); (Markovits-Somogyi and Bokor, 2012b)

8. Practical applicability of the results and possibilities of further development

The use of parametric methods is often very much constrained by lack of data. Frequently, they require a very detailed data structure and in-depth data, which is not accessible to the researcher or even to the managerial level of the company; or if they are obtainable, they might not be consistent enough to be usable for comprehensive research. It has been shown that data envelopment analysis – for full ranking
complemented with the DEA-PC approach – can be utilized in the cases when such detailed data are not available, and it can provide an efficiency evaluation using the input-output data of the decision making unit. Hence, it is a method that can be applied more easily and cost-efficiently than parametric methods.

As it has been seen, the main aim of utilization is to give a rank of decision making units. It is specifically capable of providing an evaluation where a larger number of firms or organizations are to be assessed in the presence of a limited number of factors (inputs and outputs). Thus, it is capable to provide a horizontal view of all the companies in the given field. If a business decision maker is interested to know the place of his/her company among its rivals, DEA and DEA-PC can provide him/her with this insight. Especially so, if it is not only financial aspects that are to be evaluated. By including all the relevant technological and environmental factors, DEA and DEA-PC can rank the companies from a holistic, technological-economic viewpoint. This is achieved even by scarce data availability, which is a merit; as business decision makers usually do not dispose of detailed information about the operation of their rivals. When the efficient decision making units are determined, their way of operation should be scrutinized, and if possible, the best practices are to be followed. This can enhance the operation of the company in question. Furthermore, by investigating economies of scale with the help of DEA, and also the ratio of allocative and pure technical efficiency, a guideline is given to the company, regarding how to proceed.

At the same time, DEA and DEA-PC can also be utilized in cases where the decision maker would like to establish the ranking of companies excluding his/her own. To give concrete examples: the executive officer of a producing firm would like to choose a supplier as based on different aspects. In this case DEA and DEA-PC can be an appropriate complementary tool to financial analysis. It could also be used as a supplementary tool in tendering, where the public administration has to select applicants as based on different aspects. Moreover, as it was demonstrated, it can also be applied on the macroeconomic level, thus it can also be utilized as an appropriate tool for the efficiency assessment of regions or even countries. It can also be applied this way by public administrations.

Advantage of the method, as mentioned before, is its ability to provide results using relatively easily accessible and not too detailed data, and the fact that it does not need an a priori assumption about the production function. However, it has to be known that the method is sensitive to outliers, and this might necessitate the need for preliminary statistical analyses. Also, as it is a relative method, the decision maker needs to be aware that the ranking provided will be relative, only extending to the decision making units involved in the investigation. Furthermore, the validity of the results relies strongly on the input-output structure utilized in the examinations, thus it is recommended to seek the
help of an expert when developing a model in a new field. Generally, in the field of transport and logistics, it can be stated, that the inputs shall involve at least one factor from the following areas: capital, labour and – if possible – energy. Whereas, outputs usually extend to the two fields of financial and operational results.

Regarding the data used in the investigations: the constraint regarding the number of inputs and outputs has to be kept in mind, namely that the number of decision making units shall be at least three times the sum of the number of inputs and outputs. If this condition is not fulfilled, DEA cannot be applied. However, DEA-PC is not limited by this condition as it was partly developed with the purpose of overcoming this hindrance, so this new method can still be applied if this prerequisite is not met. Even though the microecomic applications presented in the dissertation had very small sample sizes, this is the reason why they can still be viewed as methodologically valid\(^5\). Moreover, DEA-PC is capable of analysing more complex input-output structures as well.

Nonetheless, it needs to be stressed, that DEA and DEA-PC is able to investigate efficiency and efficiency only. It is always necessary to complement it with some further assessment method or approach that explores effectiveness – the question whether the intended results are reached. Colloquially, DEA examines whether “things are done right”, while it is also to be seen whether “the right things are done”. This double sidedness of efficiency and effectiveness has always to be kept in mind when evaluating the achievement of “obligatory expectations” and the efficiency factors providing competitive advantage.

Regarding further scientific research, the models created for the efficiency evaluation of road freight transport companies and logistics centres could be extended to include parameters which explain different additional sides of efficiency. So, in case the view is to be shifted for example more towards sustainability, supplementary input and/or outputs can be incorporated into the models. Naturally, this enlarges the data need, and an increased sample size is inevitable as well.

A further possible step forward, including theoretic research, is to develop valid models for the case of parametric methods as well, and carry out in-depth comparative analysis on the results gained by these different methods. Even though e.g. stochastic frontier analysis is a widely accepted parametric method, it is seldom utilized in the Hungarian freight transport and logistics field. As mentioned above, the need for detailed data availability is much higher in this case, but provided they are obtainable, it would be of

\(^5\) Before developing the DEA-PC method, it was also considered to test the traditional DEA method with the help of non-real life, created data (and thus, on much larger samples), but due to the concept underlying data envelopment analysis, which necessitates the development of the efficiency frontier as based on real data, this approach was abandoned.
academic interest to adapt this method to the Hungarian road freight transport and logistics sector, and then – keeping in mind the different concept of the methods – the results could critically be compared with those of DEA and/or the modified DEA/AHP method.

The results and methodological approaches included in the thesis can well be incorporated into the different courses taught at the Faculty of Transportation Engineering and Vehicle Engineering at BSc and MSc level, such as the courses “Decision Making Methods”, “Logistics Management”, “Project management”, “Transport Economics” and “Operation of Logistics Systems”. Incorporating DEA and modified DEA/AHP methodology into the agenda adds value on the theoretical side of the courses, while DEA case studies can contribute to making the courses more practice oriented.
Acknowledgement

It would not have been possible to create the present PhD Thesis without the help of many supporting persons. First, and foremost I would like to acknowledge the aid received from my supervisor, Zoltán Bokor, who was always ready to consult new ideas regarding DEA adaptations and guided me through the research. I am also thankful to all the other colleagues of the Department of Transport Economics, who contributed with their questions, remarks and comments to raising the standards of the document. Here, I am especially grateful to Katalin Tánczos, Enikő Legeza, Zoltán Nagy, Botond Kövári and Ádám Török. I am also grateful to the pre-opponents and reviewers of the dissertation, Szabolcs Duleba, Gábor Kovács, Ferenc Mészáros, Péter Várlaki and Ágnes Wimmer who provided me with valuable comments.

Carrying out the analyses would not have been feasible without proper data sources, thus I am particularly thankful to Zoltán Bende from the Association of Hungarian Road Hauliers (MKFE), who helped me construct the questionnaire to be sent to the road freight transport companies, and who also instructed me about the availability of MKFE contact details. I am really grateful to Gergely Gecse from the Ministry of National Development as well, who provided me with data of logistic centres and with information about the public government data sources, and the LPI questionnaire.

As there are rather few Hungarian DEA applications, I was very glad to be able to receive help from experts who had already experience in this particular field. A special thanks goes to Krisztina Tibenszkyné Fórika from Zrínyi Miklós National Defense University, who gave me the initial guidance needed to take the first steps forward, and to János Fülöp from the Computer and Automation Research Institute, Hungary Academy of Sciences, who was always ready to help me out with minor and not so minor methodological questions.

Finally, I am also grateful to my family: my husband, my sons, my parents and parents-in-law, who stood beside me during this challenging period.
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Motivation – Efficiency) Közgazdasági és Jogi Könyvkiadó, Budapest


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140. Tibenszkyne, F. K. (2007) Az oktatás hatékonyságának mérése a ZMNE 2006-ban végzett hallgatóin a DEA módszer segítségével (Measuring the efficiency of education applying the DEA method to the data of students graduated at ZMNE in 2006), Hadmérnök on-line scientific publication Vol. 2. 149-165.


Relevant own publications


14. **Markovits-Somogyi, R., Bokor, Z (2012b)** Assessing the logistics efficiency of European countries by using the DEA-PC methodology (submitted to Transport)


Appendix 1. Selected inputs and outputs in case of different transport modes

<table>
<thead>
<tr>
<th>Airports</th>
<th>Inputs</th>
<th>Outputs</th>
</tr>
</thead>
</table>
| **Labour** | • labour expenditures / price of labour / payroll  
• number of employees  
**Capital** | • capital input / capital invested / accumulated capital stock / capital (proxied by the book value of physical assets)  
• price of capital  
• intermediate expenses  
• other input – the residual of total operating costs (excluding capital input)  
• operating expenses / operational costs  
• non-operating expenses  
• capital expenditures  
• materials expenditures  
**Facilities** | • number of runways  
• length of runway(s)  
• size of the runway area  
• number of passenger terminals  
• size of the airport ramp area  
• size of passenger terminal area / size of the airport area / airport surface area  
• size of the apron area  
• number of check-in desks  
• size of departure lounge  
• number of gates  
**Operational** | • number of planes / aircraft movement  
• number of passengers / passenger loading / commuter movement  
• amount of cargo/freight (pounds, tons) handled  
• amount of mail cargo handled  
• general aviation / number of other operations  
• percentage of on time operations  
**Fiscal** | • turnover  
• operating revenues  
• aeronautical revenues / aeronautical sales  
• non-aeronautical revenues / commercial sales  
• other revenues  
• sales to planes  
• sales to passengers  
**Other** | • handling receipts  
• summed variables (specific to the given methodology)  

- number of aircraft parking positions at the terminal
- number of remote aircraft parking positions
- number of baggage collection belts
- number of baggage claim units
- size of the baggage claim area
- number of public parking spaces
- curb frontage

**Expenditures not to be paid by the airport**
- airport charge
- access cost

**Operation**
- dummy $z$ variable for slot coordinated airports
- dummy $z$ variable for time restrictions

**Other**
- minimum connecting times
- distance to the nearest city centre

<table>
<thead>
<tr>
<th>Ports</th>
<th>Inputs</th>
<th>Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Labour</strong></td>
<td></td>
<td><strong>Operational</strong></td>
</tr>
<tr>
<td>number of port authority employees (proxied by the number of stevedoring labour)</td>
<td></td>
<td>container throughput (number of containers handled)</td>
</tr>
<tr>
<td>number of container terminal workers</td>
<td></td>
<td>total cargo handled (tons)</td>
</tr>
<tr>
<td>labour expenditure</td>
<td></td>
<td>ship working rate</td>
</tr>
<tr>
<td><strong>Capital</strong></td>
<td></td>
<td>number of ships</td>
</tr>
<tr>
<td>depreciation charges</td>
<td></td>
<td>ship calls</td>
</tr>
<tr>
<td>other expenditures</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Facilities</strong></td>
<td></td>
<td><strong>Fiscal</strong></td>
</tr>
<tr>
<td>number of berths</td>
<td></td>
<td>revenue obtained from rental of port facilities</td>
</tr>
<tr>
<td>total length of the berth / container berth length</td>
<td></td>
<td></td>
</tr>
<tr>
<td>number of cranes</td>
<td></td>
<td><strong>Other</strong></td>
</tr>
<tr>
<td>number of tugs</td>
<td></td>
<td>service level</td>
</tr>
<tr>
<td></td>
<td></td>
<td>user satisfaction</td>
</tr>
</tbody>
</table>
- number of quayside gantries
- number of quay cranes
- number of transfer cranes
- number of yard gantries
- ship-shore container gantry cranes
- number of reach stackers
- number of straddle carriers
- terminal area of ports
- total length of the terminal
- total quay length

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Labour</strong></td>
<td><strong>Operational</strong></td>
</tr>
<tr>
<td>labour hours (transport, maintenance, administration)</td>
<td>passenger trips / number of passengers transported</td>
</tr>
<tr>
<td>total number of employees</td>
<td>passenger-km</td>
</tr>
<tr>
<td>total labour costs</td>
<td>seat km</td>
</tr>
<tr>
<td><strong>Capital</strong></td>
<td></td>
</tr>
<tr>
<td>cost/km</td>
<td>total annual vehicle miles</td>
</tr>
<tr>
<td>cost/traveller</td>
<td>total annual ridership</td>
</tr>
<tr>
<td>subsidy/traveller</td>
<td>km/employee</td>
</tr>
<tr>
<td>operational costs</td>
<td>km year/inhabitant</td>
</tr>
<tr>
<td>services cost systems</td>
<td>km of the route served by the company</td>
</tr>
<tr>
<td>utilities costs</td>
<td>average speed of the buses</td>
</tr>
<tr>
<td>insurance costs</td>
<td>load coefficient (passenger-km over number of places available-km and population density)</td>
</tr>
<tr>
<td>personnel costs</td>
<td>1/accident rate</td>
</tr>
<tr>
<td>fuel costs</td>
<td>1/accident frequency</td>
</tr>
<tr>
<td>other variable costs</td>
<td><strong>Fiscal</strong></td>
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<tr>
<td>number of buses / total number of vehicles operated / number of equivalent vehicles</td>
<td>total service and companies gross revenue</td>
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<tr>
<td>number of buses operated (under 35 seats, above 35 seats)</td>
<td>operating revenue (as a proxy when passenger-km not available)</td>
</tr>
<tr>
<td>total number of seats</td>
<td>equipment</td>
</tr>
<tr>
<td><strong>Energy</strong></td>
<td>fuel/100 km</td>
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127
• fleet gallons/fuel
• amount of fuel consumed

**Other**
• km of route
• directional miles
• effective driving hours
• average speed
• average fleet age
• population density
• input density index

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<tr>
<th>Railways</th>
<th>Inputs</th>
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<td>• passenger-train-kms</td>
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<td>• length of lines</td>
<td>• freight-train-kms</td>
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<td></td>
<td>• number of passenger cars</td>
<td>• passenger-kms</td>
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<td>• number of freight cars</td>
<td>• ton-kms</td>
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<td>• number of train cars and electric multiple units</td>
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<tr>
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<td>• fix assets</td>
<td>• train-car-kms</td>
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<tr>
<td></td>
<td>• operating expenditure</td>
<td>• externality (relative annual growth rate per capita taxable income)</td>
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<th>Railways</th>
<th>Inputs</th>
<th>Outputs</th>
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<tr>
<td><strong>Labour</strong></td>
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<td>• passenger-ton-kms</td>
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<td>• flight operation staff</td>
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<tr>
<td><strong>Facilities</strong></td>
<td>• number of the aircrafts</td>
<td>• operational revenue by passenger-km</td>
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<tr>
<td><strong>Capital</strong></td>
<td>• operational costs</td>
<td>• earnings before interests and taxes</td>
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<td>• residual expenditure</td>
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Appendix 2. Significance levels for Spearman correlation in case of different sample sizes

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(Source: Zwillinger, 1996)
Appendix 3. The resulting ranking weights in the different models

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(Source: own research)
Appendix 4. The DEA/AHP pairwise comparison matrix from Model “B”

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+     | Firm6  | Firm7  | Firm8  | Firm9  |
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Appendix 5. The DEA-PC pairwise comparison matrix from Model “B”

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Appendix 6. Ranking of European Countries

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<th>III. DEA/AHP without outliers</th>
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