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Effects of Climate Elements on the Efficiency of European Electricity Transmission Operators: a DEA Approach

Research Master's Thesis submitted by
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List of Frequently used abreviations

COLS- Corrected Ordinary Least Squares

DEA – Data Envelopment Analysis

DSO-Distribution System operators

ENTSOE-E – European Network of Transmission System Operators for Electricity

IFRS- International Financial Reporting Standards

NRA-National Regulator Agencie

OHL- Overhead Lines

OLS - Ordinary Least Squares

SFA- Stochastic Frontier Analysis

TSO – Transmission System Operator

I Introduction

1 Motivation

Throughout history, technological advancements have made life of mankind easier and less painful. Comparable to the discovery of the wheel, one of the greater advances in technology, was the generation and transport of electricity. While the entirety of the world does not yet have access to electricity, the more economically advanced regions enjoy a constant flow of electricity towards their homes and work places. It is now impossible, especially with the rise of new technologies, such as smartphones and computers, to live without electricity.

But what does it take for electricity to arrive to the end consumer? There are three main actors that play a role in the availability of electricity.

1.1 Electricity Generators

Through the various production plants, energy generators are the first player in the electricity industry. The electricity generators harness nature's energy through different means: coal plants, nuclear plants, windmill farms or even solar power farms. The electricity producers in Europe produced a total net generation of 3,10 million GWH in 2016 (Eurostat,2018). Electricity generators can be categorised in two sections, the firm-capacity generators and the variable-capacity generators. Firm-capacity generators can be switched on and off, while variable capacity generators are dependent on natural factors to produce electricity and can thus only produce a finite amount of electricity at a certain time. Generators also differ in their flexibility, while certain, for example nuclear power plants, are well suited for stable production over a long period of time, others, for example hydro-power plants, can adapt their production depending on the demand on the market. There is one last criteria of distinction, the type of fuel they use to generate electricity. There is first the fossil fuel and nuclear plants that use non-renewable energy, the other plants use renewable or green energy. The produced electricity is then introduced into the Transmission Network.

1.2 The Distribution Network

The last part of the network is the distribution network which connects the transmission network to the end consumers. It also provide the supports and the daily maintenance. The employees of the distribution networks are the people that most of us are familiar with and tend to encounter when it comes down to electricity matters in our homes or living spaces. The distribution operators are usually numerous in countries, in Belgium alone there are eight (Elia s.d.)

1.3 Transmission Network and Operators.

In the middle of the Production and the Distribution there is the Transmission Networks. They are a network of high voltage power lines and cables set up in a grid across long distances. According to a 2016 European Commission briefing on TSO:"*The European transmission grid contains more than 300 000 km of power lines, including 355 cross-border lines*."(Understanding, 2016) Transmission networks are operated by Transmission System Operators (TSO).

The TSOs in Europe are represented by the European Network of Transmission System Operators in Europe (ENTSO-E). The ENTSO-E represent 43 electric TSOs from 36 different European countries. It was formed and given power by the third legislative package for internal energy market of the European Union, was voted in 2009.

The third legislative package for internal energy market contains two directives and three regulations. The directive that concerns the TSO in Europe is DIRECTIVE 2009/72/EC (further called "the directive"). It states that to ensure efficient and non-discriminatory network access, the distributors, producers and transmitters of electricity should be operated by legally distinguishable entities. The management teams of all three participants in the electricity supply chain must be distinct. There are four options for the different member states to achieve a more competitive market.

The advocated option by the European Parliament (EP) and the European Commission (EC) is the "Ownership Unbundling" (Articles 9-12 of the directive). This system ensures the setup of market free of vertical integrations. This option, even though pushed as the favoured one by the EC and the EP, is controversial. The main concern over this solution is the financial aspect as these installations are colossal, plus who can afford to buy them from the electrical companies or how are the companies going to be compensated for their loss (Pollitt, 2008). Pielow (2009) goes further and argues that the investment is not worth the return. Some also argue that there might be inequalities rising due to the different structures of the internal market between the different member states.

The second solution provided in the directive are the Independent System Operators (ISO). The articles 13-16 of the directive give the member states the option to let the current owners of the transmission system keep the ownership, but they would have to transfer the day to day operations to a third party. The transmission operation would thus not only be financed by the owner, but as well by the ISO. This is a derivative of the Ownership Unbundling as, although the production and transmission would remain under the ownership of the same company, it would remove all possibilities of a conflict of interest between management.

Articles 17-23 of the directive provide a third alternative: the Independent Transmission Operator (ITO). Introduced by eight member states, this option allows the original energy company to retain ownership of all the different parts of the transmission network but that exists under its own identity, with their own management but under regulatory control. Investment decisions will be taken jointly by the regulatory authority and by the parent company. One of the main condition for the existence of this format is the setting up of a compliance officer, who will check on the compliance programs set in place by the member states to ensure the exclusion of discriminatory conduct.

The last unbundling option that was given to the member states is referred to as Independent Transmission Operator Plus (ITOP). This gives the option to the states to keep their Transmission Operators as if it was already in place on September 3rd 2009 and "*belongs to a vertically integrated* *undertaking and there are arrangements in place which guarantee more effective independence of the transmission system operator than the provisions of*" Chapter V of the directive.

In chapter IX of the directive, the European Commission sets the definition for the regulatory authorities that need to be put in place in each member state to monitor the internal market and regulate prices. According to this chapter, the regulatory authority should be independent from all other private or public entity, it should have its own budget apart from any other budgets and be protected from any outside influence, so they can assess impartially the situation in their country. The missions given to them by article 36 is to set up, promote and maintain a competitive environment for current actors or potential new entrants. They can resort to fining TSOs if they do not comply with their regulation plans set in place.

This unbundling brought to Europe a new kind of TSOs. Where before only state-run companies where present in the sector, privately owned companies appeared. Following a trend of privatization and neo-liberal ideas, public enterprises were no longer regarded by governments as effective instruments for responding to market failure and, as a result were privatized (Bortoli, Fantini & Siniscalco, 2004).

Due to former experience with privatization, the EU knew that to have a competitive market which would be beneficial to the consumers they needed to put a sort of regulators in place. As most of the time the privatisation led to higher cost and an actual loss of value for the consumer, and sometimes even when there were regulators in place, as for example the privatization of the British railway system (Wellings, 2014).

1.4 Starting Situation

Now that there is a clearer picture of the state of the electric industry in Europe post 2009, we can focus on the two actors that are of more interest for this thesis. The Transportation System Operators and the National Regulators Agency.

The Transportation System Operators have the essential roles of, as their name states it, transporting the electricity with high voltage lines from the production plants to the distribution grids. To make sure that after the unbundling the newly created Transmission System Operator would not take advantage of their natural monopoly (it is extremely costly to set up an entire new Transportation System in a country), even if most companies remained state owned after the unbundling, the European Union provided in the directive a clause that gives the European Union members a legal framework on the setting up of a National Regulator. These Regulators, jointly with the TSOs operating in their country, set the price charged to the customers.

To do so the NRAs set up a regulatory period for which they decide on a regulatory regime. In that regard, regulators have the incentive to benchmark the activities of the TSOs to check for their efficiency compared to similar firms.

2 The Study

As the time progresses, regulators are always trying to find new ways of improving the benchmarking for their regulation. Benchmarking of European TSOs is not an easy task as they have, except for the Germans and the British, no competitors on their own market and evolve in monopoly on the regulated markets. Thus, regulators need to perform international benchmarking. The topic has been profusely covered and experts have helped the different national regulators to put in place toolkits that have helped them estimate the efficiency of their national TSO.

However, one element that seems to have been omitted in these analyses is the climate effect on those TSOs. This thesis aims at answering the question of "Do the different weather conditions affect the efficiency of the European TSOs?"

With this goal in mind I will first perform a thorough literature review on regulatory regimes, benchmarking techniques used in European TSO regulation and the already taken actions regarding weather effects on electric networks. I will then proceed to a quantitative analysis of selected European TSOs to test my hypothesis.

3 Limitations

The limitations of this study are threefold. First off, it is a very specific industry, while the unbundling of transmission operators for both the electricity and the gas happened through the directive, this thesis will solely look at electricity transmission system operators as the climate effects might influence gas transmission operators in a completely different way.

The dataset used for the analytical part is comprised of 18 TSOs. So, it does not include all 43 TSOs from ENTSO-E. The most common reason is that data was not available or not complet. The data is issued of both official databases (ENTSO-E, Bloomberg, and Eurostat), others come from investment websites and the rest from TSOs annual reports found on their websites. There might be some error due to the different ways that these annual reports are set up, although the firms are supposed to follow the International Financial Reporting Standards (IFRS) rules. Two TSOs companies were also reporting in their own currency. Some errors might occur because of that but should be minimal as the use of conversion rates, mentioned in the annual report, was made. Furthermore, some simplifications have been taken regarding the aggregation of data on the network, these will be explained in detailed in the data collection part of this thesis.

Lastly only some weather parameters were considered in this study as they emerged from previous study as the most relevant one. But since there is no study on electric TSO in Europe the whole spectrum of weather parameters could be considered in later studies.

II Literature Review

The focus of this literature review will be on the regulatory tools of NRA, benchmarking process' to evaluate the efficiency of the TSOs and a look at what has been done in the climatologic environment. Some big works have already been produced for the European Commission and will be the basis of this thesis. Although the focus of this paper is Europe and the organisations that work and evolve in the European Economic Space, the literature review does not focus solely on this geographical limitation but will draw some content from other regulated markets such as the United States.

As most large infrastructures, transmission networks are natural monopolies. And as Agrell and Bogetoft (2013) mention. *"Monopolies have limited incentives to reduce costs and will tend to underproduce and overcharge the services provided since they are not subject to the disciplining force of the market. For electricity distribution, the monopoly characteristic is accentuated by the fact that there are no close substitutes for the offered services and that demand is relatively inelastic."* They were referencing the DSOs in this paper, but the same applies to TSOs, where there is most of the time no alternative and they are historically rooted in place.

1 Regulatory regimes

The regulation of utility operators can be seen as a game between the regulators and the firms. The firms possess the information on their technology and their costs that regulators need. It also often not in the best intention of the firms to report information correctly. (Baron and Myerson, 1982) These problems can be somewhat countered with the use of benchmarking. (Agrell and Bogetoft, 2017)

A lot of regulatory regimes have been put in place throughout history. In Europe, the regimes that are being used recently can be categorized in three groups: Cost-recovery, Fixed-price and Yardstick regimes.

1.1 Cost-recovery regimes

Cost-recovery regimes (cost of service, cost-plus, rate of return,…) put in place a price that will fully cover the cost of the operator, sometimes with a mark-up factor on top. A reimbursement for a period t can be illustrated as in Agrell and Bogetoft (2017).

$$R^k(t) = C_{OpEx}^k(t) + D^k(t) + (r + \delta)K^K(t)$$

C_{OpEx}^k the operating expense, D^k the depreciation of fixed assets, r the investment rate, δ the markup factor, and K^k the total investment.

While relatively simple in appearances there are some caveats. Firstly, two of those terms in the calculation of the reimbursement, namely the depreciation and the investment, depend heavily on accounting practices and the allocation of asset ownership. (Massurato, 2017). In this model there is not incentive to reduce costs as it would reduce the reimbursement. Furthermore, it takes a considerable amount of resources to verify the information. Therefore, this regime is not often considered the main regime but more as a negotiation and consultation-based regime. (Agrell & Bogetoft, 2017).

1.2 Fixed price regimes

Facing the problems from cost-recovery regimes, Littlechild(1983) launched a high powered regime at the start of the British Telecommunication privatisation. In this new regime firms could retain any realized efficiency gains.

In Price-cap, as the name would suggest, the price or revenue is caped for a certain regulatory period. A simple model of price-cap for a firm, with a predicted productivity level x_g and an individual requirement on firms, $x_{i,}$ to mirror the level of the past cost, thus setting up a catch-up target. For period t the revenue of firm I can be put as:

$$R_i(t) = C_i(0)(1 - x - x_i)^t \; for \; t = 1 \dots T$$

With $C_i(0)$ the cost of firm i in period 0 and Ri(t) the revenue in period t.(Agrell &Bogetoft,2005). This is also the introduction of cost reduction incentive via the fixed payment. To maximize profit they will need to reduce cost.

This kind of regimes are also called ex-ante regimes as illustrated in figure 1 the regulators focus on past regulatory period to estimate x and x_i .

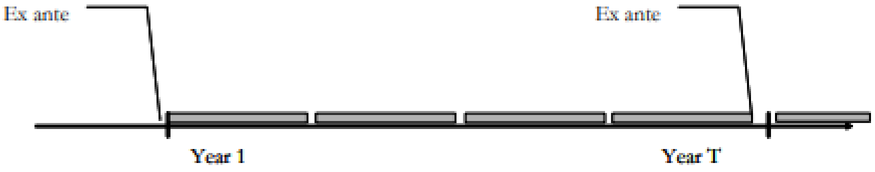

Figure 1: Ex-Ante Specification

Figure 1: Ex-Ante Specification (Source : Agrell & Bogetoft,2017)

The biggest challenge regulators face in this regime is the setting of the first period as they have to "*strike a careful balance between informational rents, incentives for restructuring and bankruptcy risk*".(Agrell & Bogetoft,2007).

Agrell, Bogetoft and Tind(2005) highlight other caveat of the regime, such as if the cap is too tight, the firm risks bankruptcy, but the most important one is that the CPI-X model that we have seen above does not allow change in the output profile, disincentivising the innovation of new products and the augmentation of the quality.

1.3 Yardstick Regimes

The drive of the yardstick regimes is to mirror the market, not by estimating ex-ante product cost development but by taking real life observations (Agrell & Bogetoft, 2017). This regime is considered ex-post as the regulators set the price for the period after the period passed, as visualised in Figure 2. Thanks to this ex-post approach, the dynamic and environmental aspect can be integrated in the cost as they have already happened.

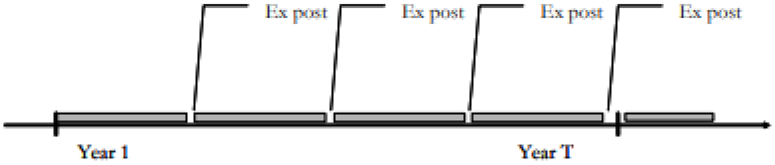

Figure 2: Ex-Post Specification (Source: Agrell & Bogetoft,20017)

For a regulated firm k in period t and h ϵ K, K being the set of all other firm operating on the market with similar conditions, a simple for of yardstick regime could be a follow:

$$R^k(t) = \frac{1}{K-1}\sum_{h\neq k} C^h(t) \qquad t = 1,2,\ldots T$$

In this example, the average price is taken as the regulatory price. Of course, there are other ways to aggregate data, and if the firms are not identical a simple average is certainly not applicable.

The caveats of such techniques are threefold. Firstly, to establish a yard stick regime, there needs to be comparators available with correlated operating conditions, which is not always the case. Secondly, if the comparators are not numerous and are subject to the same regulatory regime, collusion may happen. Lastly, prior to the yardstick regime a "t*ransient period of asset revaluation or franchise bidding*" needs to be assessed otherwise the firm might face sunken cost or bankruptcy. (Agrell & Bogetoft 2017).

In the regulation of European TSO there is a clear preference for the revenue cap, but the idea that the regimes are not pure need to be kept in mind. While the basis can be Revenue cap, many other costs can be regulated at the same time in the regime.

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2 Technology

The efficiency is defined by Bogetoft and Otto (2011) as the use of the least resources to generate the most products. In the case inputs of TSOs input and outputs. Thus, a production plan T (a technology) for a firm i producing m outputs $y_i \in R_+^m$ using n inputs $x_i \in R_+^n$.

$$T = \{(x, y) \in R_+^n \times R_+^m | x\ can\ produce\ y\}$$

This technology, T, needs to fulfil certain conditions (Shepherd, 2015).

Free disposability: If a combination of (x,y) is part of T, another combination (x’,y’) with x’ and y’ with $x' > x$ and $0 \leq y' \leq y$ and thus produces less outputs with more inputs must belong to T as well.

Convexity: T is assumed to be convex. Given this assumption we know that if (x_1,y_1) and (x_2,y_2) belong to T then a mixture of both should belong to T as well. Thus for $\alpha \in [0,1]$:

$$(x_1, y_1), (x_2, y_2) \in T \ \rightarrow (x, y) = \ \alpha(x_1, y_1) + (1 - \alpha) * (x_2, y_2) \ \in T$$

Returns to scale: The shape of technology T (and by extension the efficiency frontier) is defined by its returns to scale. This will be addressed further in section 3.1.

Ultimately, it is the efficiency of these technologies that are being benchmarked by NRAs

3 Benchmarking

As we have seen, to put in place for some of those regulation regimes, regulators need benchmarking to assess the other firms on the market. To benchmark TSOs on an efficiency basis the NRAs have all kinds of methodologies at their disposition. These methodologies can be divided in two categories the top-down approaches and the bottom-up approaches.

Top-down approaches are comparative efficiency modelling that compares companies, business units or other aggregates between similar companies. The peculiar challenge of top-down approaches is the availability of similar companies to perform the comparison. It might be difficult for national regulators to find identical TSOs as the ones operating in their country, as most of the time, the TSOs are monopolies and have no competition on their markets. However, performing an international comparison is possible. To do so we need to focus on the consistency of comparators (Oxera 2013).

The bottom-up approaches tend to be based on detailed information. By looking at the different cost elements and possible cost reduction, a global assessment gets build. Then those cost reductions are aggregated to create an overall cost reduction target (Oxera 2013).

While both types of approaches are interesting and have their valid points in this paper the focus will be put on top-down approaches[1] as they are the ones used in TSO benchmarking on the European market now.

Top down approaches can also be categorised in different groups, the main sub group is the frontier-based analysis. The frontier-based analysis approaches rely on the establishment of comparable entities that will set a frontier of efficiency. The three main top down approaches that we have seen in use for the bench marking of the TSO are part of this frontier base group: Data Envelopment Analysis (DEA), Corrected Ordinary Least Squares (COLS), and Stochastic Frontier Analysis (SFA), these three accounts for 78% of the benchmarking done by regulator[2] if the NRAs use any type of benchmarking (Haley & Pollitt, 2009).

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[1] For more info on bottom-up approaches see Oxera(2013)

[2] This percentage is worldwide.

3.1 Data Envelopment Analysis (DEA)

A DEA is a deterministic non-parametric approach to frontier based analysis. A DEA consist of a comparison between indicators of efficiency that are generalised, in order to compare Decision Making Units (DMU), in this case TSOs, with multiple inputs and outputs (Berg, 2010). To compare the efficiency of the different DMU, a frontier is calculated putting the DMUs that are performing the best on that frontier for combinations of input-output combinations. The efficiency of a DMU is then measured as the distance from this frontier. The DMUs being on the frontiers are thus considered 100% efficient. As you can see in figure 3 with companies A, B, C and D forming the frontier and thus being 100% efficient while companies E, F and G are not 100% efficient.

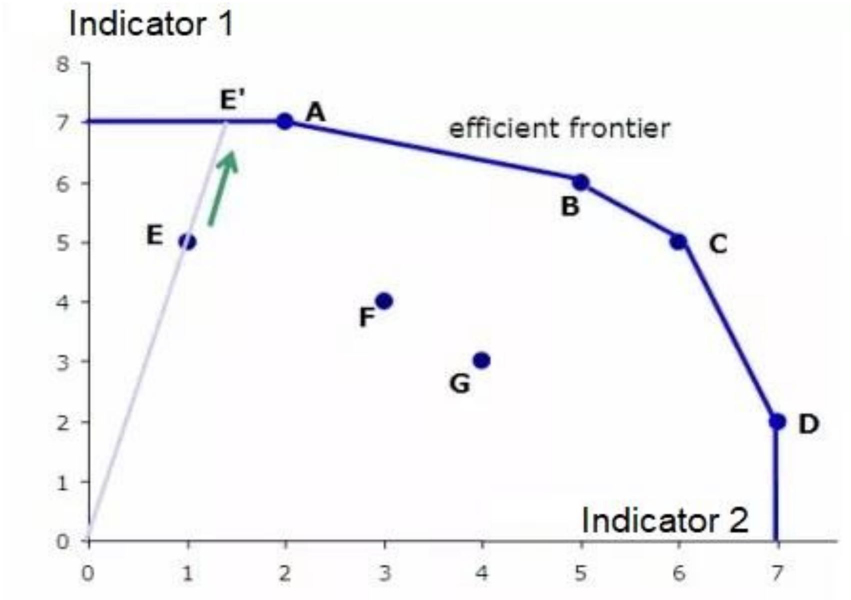

Figure 3: Frontier of a Data Envelopment analysis (Source: Analyticsdefined[3])

Data envelopment analysis can be categorised into two different models, the variable return to scale (VRS) (Banker, Charnes & Cooper, 1984) and the constant return to scale (CRS) (Charnes, Cooper

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[3] Source : https://analyticsdefined.com/data-envelopment-analysis-in-r/

& Rhodes, 1978). In the VRS the changes happening to the output and the input are not proportional to each other. whereas in CRS, the changes to output and input are proportional. The VRS has two sub models that are the decreasing returns to scale and the increasing returns to scale (non-decreasing return to scale). The decreasing returns to scale, means that the more input the DMU uses, the least output it will get. The increasing returns to scale works inversely.

The linear program that needs to be solved to get an efficiency score for the i-th firm within N firms for a CSR model is as follows (Niellesen & Pollitt 2010).

$$\min_{\theta,\lambda} \theta$$

s.t.

$$-y_i + Y\lambda \geq 0,$$

$$\theta x_i - X\lambda \geq 0,$$

$$\lambda \geq 0$$

Where θ is a scalar and λ a Nx1 vector of constants. X and Y are respectively KxN input and MxN output matrices. While y_i and x_i represent the output matrices of the company i-th firm. This equation is then solved for all N firms. An additional constrain is added λ=1 for the DEA with variable return to scale.

While classic DEA performs well on the evaluation of the static efficiencies, depending on the choice of the input and outputs the results may variate if the DMUs are subject to uncontrollable variable. Therefore, a dynamic component is added to the data envelopment analysis. This approach was first proposed by Nemoto and Goto (1999) and was later, by themselves, applied to the Japanese electrical grid in Nemoto and Goto (2003).

The advantages of a DEA are that DMUs are compared with an actual efficient one and not some estimated measures and that you do not need specific information on cost and production functions. (Jamasb, Newbery,Pollitt, & Triebs, 2006)

The main caveat is that it does not allow for a stochastic element, considering the entire difference of efficiency as inefficiency, and does not leave space for noise in the data. (Jamasb et al, 2006)

In the regulatory setting, DEA has been used a lot by regulatory organs in Europe. Most notable examples are Norway with the benchmarking of local DSOs accounting for the age of the grids, and Finland which, also to analyse the DSOs of its country, used DEA with the total expenditure (TOTEX) as sole input to set regulatory price for the control periods. One of the most notable work on benchmarking of European TSO is the e^3Grid Project (Sumicsid, 2008). The approach, used in this intermediate report, is a composed static and Dynamic DEA, in which the opportunity was given to all the TSO to submit operator specific conditions, such as activation taxes or forced esthetical maintenance. They would then these conditions put through a series of verification to see if it was a valid claim from the operator.

3.2 Corrected Ordinary Least Squares (COLS)

COLS is based on a simple regression model, Ordinary Least Squares (OLS). The OLS estimates parameters of a linear regression model. It chooses a parameter and applies the least squares principle onto it (Goldberger, 1964). The subtility is that for the calculation of the constant parameter of the COLS the upwards to the maximum of its variance, so that the frontier now represents the efficiency frontier and not the average efficiency as seen in figure 4 (Greene, 2008)

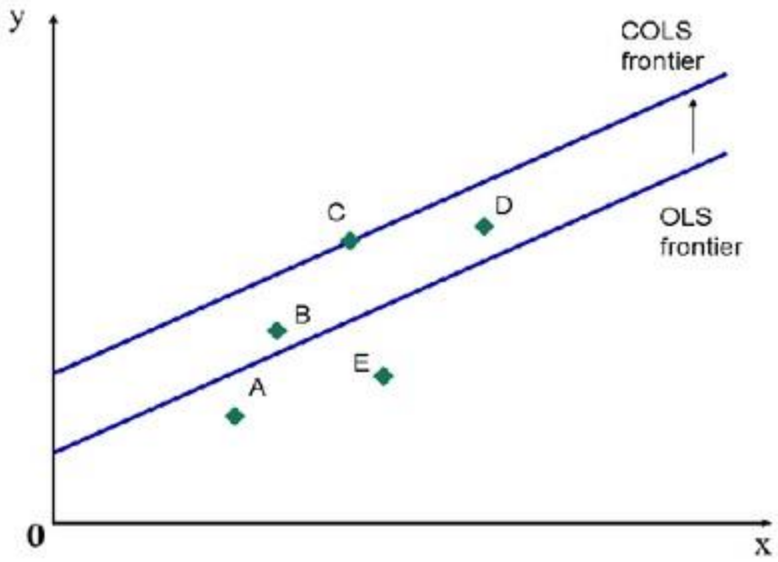

Figure 4 COLS Frontier Shift

While COLS is easy to use, there are some drawbacks. To use COLS you will require assumption on the technology used in the production process. Furthermore,
COLS presents the same problem as the DEA. There is no allowance for stochastic error. The residual is considered entirely as inefficiency. (Jamasb et al, 2006)

COLS also has been used in the regulatory world to benchmark the efficiency of companies. Most notably in the UK, not only by Ofgem, the electricity regulator, but also, by Postcomm, the postal service regulator and by Ofwat, the water and sewage services regulator (Oxera 2013).

3.3 Stochastic Frontier Analysis (SFA)

Statistical Frontier Analysis was introduced by Aigner, Lovell, & Schmidt. (1977) and Meeusen and van den Broeck(1977) simultaneously. The maximum likelihood estimator used in SFA is asymptotically more efficient than the COLS estimator (Coelli, Prasada Rao., & O'Donnell, 2005). As mentioned before, the SFA allows the separation of random shocks and statistical noise from inefficiency by decomposing the error terms in two parts. (Rosko, M. D., & Mutter 2008).

The equation for a total cost approach an SFA looks like this .

$$TC_i = \beta_i x_i + \varepsilon_i$$

$$i = 1, \dots \dots \dots, n$$

With TC_i, the total cost for the TSO to produce a total output, x_i is a vector of logged factors explaining the TSOs costs. β is vector of unknown parameters that will be estimated and ε is the error term, that is decomposed as follows:

$$\varepsilon_i = v_i + u_i$$

With v_i representing the statistical noise and u_i represents the proper cost inefficiency (Anaya and Pollitt 2017). The separation of the residual (ε_i) is illustrated in figure 5 with the illustration of SFA frontier compared to the COLS and OLS approach.

It is a nice way to not assume that the residual represents inefficiency. As Cullinane, Wang, Song & Ji (2006) mention it in their comparative approach on the efficiency of container ports, DEA has its advantages compared to SFA as it has more freedom for the data, not imposing a specific functional relationship between output and input, "*nor any specific statistical distribution of the error terms*"(Cullinane et Al 2006). But they also agree with the fact that regular DEA cannot cope with the measurement of random shock or errors and will instead attribute it to inefficiency which will lead inevitably to estimation errors.

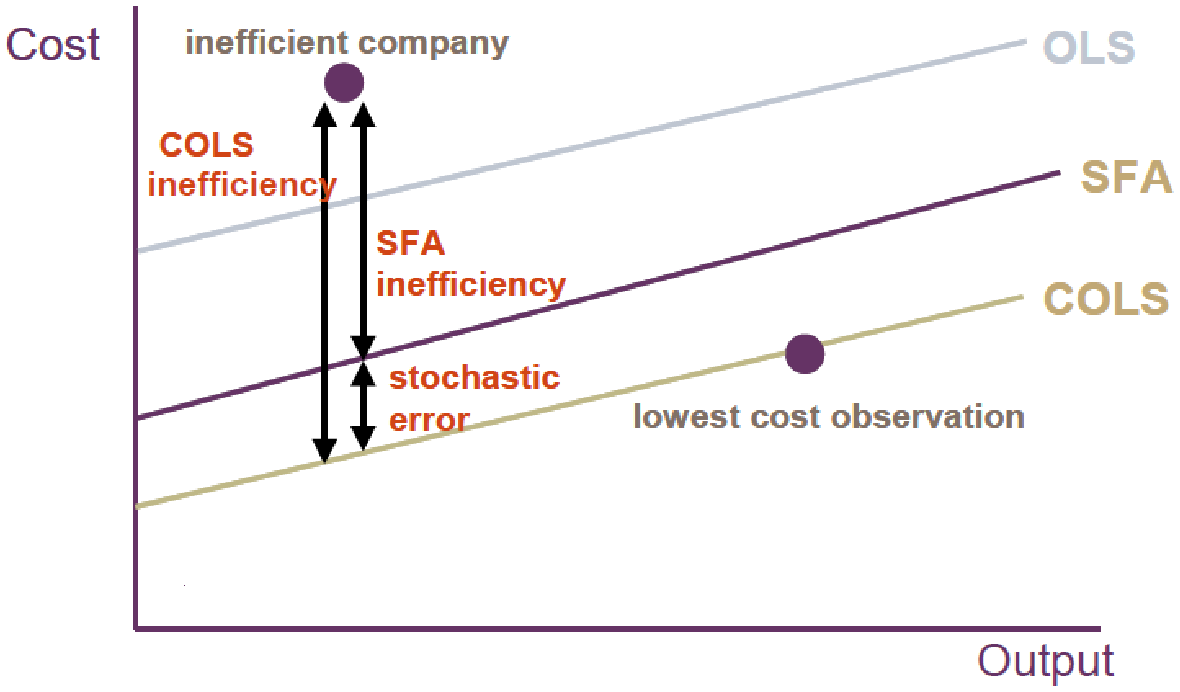

Figure 5: Comparison of SFA, OLS and COLS Fronties (Source: Oxera 2013)

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The idea of separating the residual is attractive. But the main caveat of SFAs and the reason why it is not used more commonly in the regulation of TSOs in Europe is the need for an extensive dataset. Otherwise the SFA will not converge and the results will not be considered as robust. This caveat can be slightly countered by the use of panel data over the course of a long period. Taking data over a period also permits to calculate the Malmquist index to compare the productivity efficiency's evolution over time. (Kumbhakar & Lovell, 2003)

The second caveat, while less influential, is that an assumption needs to be made on the distribution of the inefficiency term. If the wrong one is selected, it might lead to the introduction of bias (Kumbhakar & Lovell, 2003)

In regulation SFA has been used profusely, but rarely for TSOs. In Finland the electricity DSOs were regulated between 2008 and 2011 based on a SFA benchmarking of their TOTEX: while

Portugal uses SFA to benchmark the OPEX of the DSOs. Germany on the other hand uses since 2009 a DEA-SFA model to regulate the DSOs.(Haney &Pollitt 2009).

In other industries, Ofcom regulated British Telecommunication using a TOTEX SFA benchmarking. To compare it to the biggest dataset possible Ofcom normalised British Telecommunications dataset so it could be compared to US companies (Nera 2008). Royal mails performances were also assessed by Postcomm using SFA, for the period of 2006 to 2010 (Postcomm, 2006).

4 Weather and the Electric Grid

The literature on the weather effects on electrical grids is not that extensive. As Over Head Lines (OHL) are hanging between pylons they are constantly exposed to the element of the weather. Billinton and Wu (2001) prove that the number of failures tend to increase during extreme climatic events. Rostein and Halbig (2012) also discuss the fact that weather affects not only the producers and distributors of electricity but also the TSO. As the OVH are exposed to the elements, the different temperatures can increase the loss of power in dissipation, the violent wind and rain can cause overlapping and circuit shortage or in the case of a violent storm pylons can fall and create a disturbance in the grid. Keener (1997) goes even further and says that about 90 percent of power outage during summer are caused by lightning.

The weather not only affects the physicals side of the business but also the electricity consumption. As temperature rises, so does the use of refrigerating electric device, such as air conditioning. (Hor Watson, & Majithia ,2005) In the same way, when the temperature drops the consumption of electricity rises, especially in countries where heating is performed through electricity such as France. RTE(2017) estimates that for each degree below the national seasonal average, the consumption of electricity increases by 2400MW. This number is equivalent to the consumption of the city of Paris.

The majority of studies performed on electricity and climate effect have been focused on the distributor. Although it is not the same player in the electric supply chain, it faces the same challenges as the transmission operator and we can learn from those studies. In Anaya and Pollitt (2017) they based themselves on data from Mills (2012) and data from the U.S. Department of Energy to establish that between 2007 and 2016, 49 percent of power outages were to be attributed to weather events as demonstrated in Figure 6.

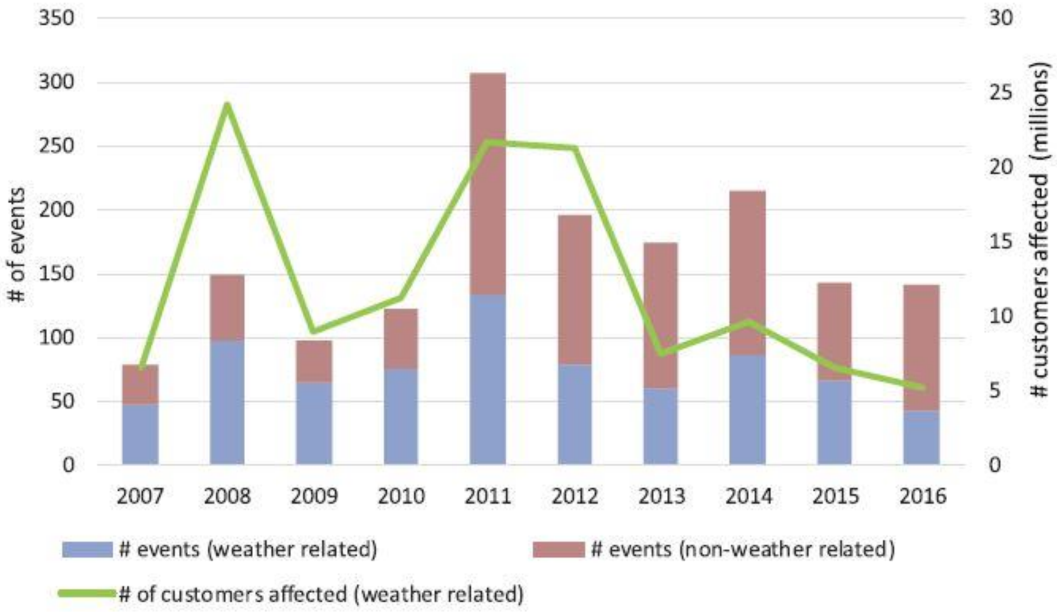

Figure 6: Number of Customers Affected by Power Outages (Source: Anya & Pollitt 2017)

Using this data Anaya and Pollitt (2017) show that the yearly average economic cost of power outages in the US is between US$ 27.4 and US$ 43.3 billion.

With estimations as high as that, the question remains why are there not more research on the subject. There could be several reasons for that, but the main reasons identified by Anaya and Pollitt (2017) are first that data on weather is relatively difficult to find and secondly that interest in the weather is relatively new, especially in the context of benchmarking utilities providers, but as Asner et al (2009) note, the rapid velocity of climate change is bound to take us into climatic uncharted territory in the future as we stray each year further from what is known as the seasonal average.

The findings on the relations between electric firms’ efficiency and weather effects diverge from study to study. This is probably due to the different methodology and the different variables used in the models proposed by those studies. Some studies such as Kornhonen and Syrjänen(2003) and Yu, Jasmab & Pollitt (2009) suggest that including the climatic variable does not have any significant effects on the efficiency of electric distributors, but then again they solely focus on single countries respectively Finland and the United Kingdom. But when the findings do note an impact on the efficiency, it is a negative impact and mostly due to extreme weather conditions (Jamasb, Orea & Pollitt, 2012).

III Practical Part

1 Methodology

1.1 Problematic

Europe’s electricity transmission system operators have now been unbundled and are mostly operating as monopoles on their home market. Therefore, regulators have been put in place to regulate the price and the activity of those TSOs. Throughout the literature, we have seen that regulators have put in place a multitude of tools to be as fair as possible in their benchmarking always adding more variables and making exceptions according to special situations. One of the external factors that TSOs must deal with is the climate. Surprisingly while weather variables have been included in a couple of studies in Europe and outside Europe, it has never been used to check for its effects on the efficiency of European TSOs. Furthermore, the weather extremes, especially regarding the temperature, are reaching higher limits every year (Royal Meteorological Institute).

1.2 Research Question and Hypothesis

After thorough examination of the current situation, the research question that will drive the practical part of this thesis is:

“Do climate variables affect the efficiency of European electricity Transmission system operators?”

Thus, the H0 will be:

H0: Climate variables do not affect the efficiency of European Transmission operators.

1.3 Model Selection

To verify my hypothesis, I will perform a quantitative analysis on a collected dataset.

While not many studies have been done regarding the effects of the temperature on electricity transmission system operators, there is one there is one similar study that I will consider.(Llorca, Orea & Pollitt, 2016). The main objective of this thesis is to determine whether some climate variables have an effect on the efficiency of the TSOs and if this is the case, should it be taken into account for the benchmarking of said TSOs when performing international benchmarking.

1.3.1 Benchmarking Method

As I have shown in the literature review, there are multiple benchmarking techniques available. At the start of this thesis, I had my mind set on using the Stochastic Frontier Analysis as it made the most sense since I was trying to determine the effect of weather on inefficiency, and the separation of the residuals into a stochastic term and noise term would have greatly helped in this endeavour. However, after multiple attempts, with many different models, I had to admit that it would not be possible to run an SFA as it would not converge. Therefor I opted for an analysis based on a DEA. This technique is well established in Europeans regulatory scene and has the benefit of not needing a consequent dataset.

For this thesis the use of a DEA with VRS and input orientation is made. The input orientation focuses on minimizing the input to produce a given amount of outputs, while the output orientation will try and maximize the output for a given amount of input. The input orientation was chosen because TSOs are required to transport the electricity produced (or coming from other regions) to the DSO, industrial clients or other TSOs. It is not them which push the level of outputs for their industry.

1.3.2 Temperature effects

To analyse the effects of temperature, I include uncontrollable weather variables. There are five main models for the analysis of uncontrollable variables in DEA available (Yang & Pollitt, 2009): the separation model, the one-stage model, the two-stage model, the three-stage model, the four-stage model.

The separation model divides the research sample in subgroups based on categorical variable which represents the environment in which the firms evolve. A new DEA frontier is then constructed for the different subsets. But there are drawbacks to this model. First the only variables that it can be applied to, need to be categorical (e.g. private or public ownership of the company). Secondly the subdivision of the original sample reduces the discriminating power of the DEA. Therefore, some firms may appear efficient in the new subsets while they were not in the original data sample. And lastly, as Yang and Pollitt(2009) point out, the comparison of all the firm's efficiency score would be meaningless as they are not generated with the same efficiency frontier.

The one-stage model, as its name would suggest, includes the uncontrollable variables directly into the DEA model, together with the outputs and inputs (Banker & Morey 1986). While it seems straight forward, and allows the accommodation of multiple variables, it does have its drawbacks too. One needs to decide in advance what the effects of the uncontrollable variable will be. Due to the addition of more variables in the base model some firms will become efficient.

The two-stage model starts off with a regular DEA model with the construction of an efficiency frontier and efficiency scores for the firms of the sample set. Then the efficiency score are regressed against a set of uncontrollable variables. Since the efficiency score are all in the interval of [0,1] we cannot use a regular regression but need to use *limited dependent variables,* such as a Tobit regression or an exponential model. The advantages of the two-stage model are the easiness to interpret the results and the capability of including multiple uncontrollable variables in the regression. No firms will become efficient as you do not add any more variables in the base model and lastly you do not require to have prior assumption of the influence of said variables on the efficiency of the firms. But there are also drawbacks, firstly the output surplus and the input slacks are not considered, and secondly, if the variable used in the regression and in the first stage are highly correlated, there might appear a bias on the estimates of the regression (Coelli et al, 2005).

The three-stage model, introduced by Fried et al. (2002), starts off as the others with a regular DEA. A stochastic frontier analysis (SFA) is then used in the second stage to regress the slacks against a set of chosen uncontrollable variables. As Yang and Pollitt (2009) point out, the stochastic frontier found here is to be considered as the minimum slack achievable in a noisy environment. The inputs are then adjusted based on those estimated coefficients. The third stage is then a DEA again but using the adjusted inputs. The advantages of this technique are that it can use all the information that is present in the input slack, and it can accommodate multiple uncontrollable variables. The drawbacks of this model, on the other hand, are more technical as it will run a high cost in time and computational effort (Yang & Pollitt, 2009)

The four-stage model, also introduced by Fried et al(1999), starts with a standard DEA. During the second stage, the total input slack is regressed against uncontrollable variables using a Tobit regression. The estimated parameters of the second stage are then used to estimate the allowed input slack in the third stage, those inputs will then be adjusted. The fourth stage is then a DEA with the use of the adjusted inputs from stage three. This model shares the similar advantages and drawbacks as the three-stage model but is considered less sophisticated as it does not account for a stochastic element.

For this thesis I will use the two-stage model to check the influence of the climate variables on the TSOs. While it is true that it has some drawbacks, it is not only an easy to interpret model, but also an established approached in the literature. Furthermore Yang and Pollitt(2009) find a high correlation between the efficiency scores of two-stage model and the others, indicating that it might not matter which one you choose, while noting the three-stage model would remain superior.

2 Data

2.1 Data gathering

2.1.1 TSO selection

For the empirical analysis we use a panel data set of 18 European electricity transmission system operators for a period of 2015-2017. The TSOs chosen for this thesis are Austrian Power Grid AG from Austria, OST sh.a from Albania, Elia System Operator from Belgium, ČEPS a.s. from Czechia , Elering AS from Estonia, RED electroca from Spain, Fingrid Oyj from Finland, RTE from France, IPTO from Greece, Terna from Italy, Litgrid from Lithuania, AST from Latvia, Crnogorski from Montenegro, Tennet operating in both the Netherlands and Germany, Statnett from Norway, REDE from Portugal and SEPS from Slovakia . Both the National Grid of Electric Transmission (United-Kingdom) and Creos (Luxembourg) were initially included in the data test but were removed due to the ambiguity of the data. On one hand the National Grid claims in 2016 to operate 14.000 kilometres of OHL but in 2017 and 2015 their annual report claims only 7.200 kilometres. Furthermore, they operate the Scottish transmission network, without owning it which made for ambiguous interpretation of the financial data as it was not clear what part of the expenses went for which grid. Creos was removed because although the data was good, the financial data included both the Electric and Gas transmission part and no separate financial results could be found.

These TSOs come from all over Europe and are thus exposed to very different climatic environments throughout the year. Most of the TSOs selected are the sole operators in their countries but some are spread across multiple countries or do not cover the entirety of the country. The selection of these TSOs was done regarding multiple factors. The main factor is the availability of data, secondly TSOs in this data set are all part of ENTSO-E. They are thus regularly compared for benchmarking.

Regarding the choices of output and input, as important as it may seem, there is no overwhelming consensus in the literature over what should be employed.

2.1.2 Intput Selection

An evident choice for the input in our situation is the Total Expenditure (*TOTEX*), calculated through the sum of the Capital Expenditure (*CAPEX*) and the Operational Expenditure (*OPEX*). The CAPEX is the growth in capital, the investments made in property, plants and equipment (PPE). On the other hand, the OPEX is the cost of running the normal business operations such as the cost of products, for instance the electricity that is transmitted, the cost of wages and retirement plans, and other operating costs. These data have mainly been collected through the usage of the Bloomberg database. As not all the data was available on said database, the rest was found using the companies' annual financial reports. These are the formulas used to calculate the CAPEX and the OPEX from the annual reports of period t.

$$CAPEX_t = Deprication \,\&\, Amortisation\ of\ fixed\ assest_t + PPE_t - PPE_{t-1}$$
$$OPEX_t = Operation\ cost + Labour\ costs + \ other\ operating\ costs$$

This data is usable as all these annual financial statements are redacted and compiled according to the International Financial Reporting Standards. We will however use the Producer Price Index (PPI) as an inflation adjustment. These are weighted indexes of price at the producer level. These indexes[4] are on a 2010 basis, meaning the PPI was 100 for the year 2010. This adjusted value is variable *TOTP*.

2.1.3 Output selection

As outputs the common choice in the literature are the Peak Load (*PL*), representing the maximum load on the network for an hour throughout the year and Total Load (*TOTL*) as per the total load transported by the TSO throughout the year. The first one can be interpreted as potential investment requirements and the second one more as a reflexion on the daily operating cost of the business. This information is either readily available on the yearly factsheets of ENTSO-E or in the annual

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[4] Taken from Eurostat or tradingeconomics

reports of the companies. In figure 7 and 8 the ratio of this outputs separately to the TOTEX can be seen.

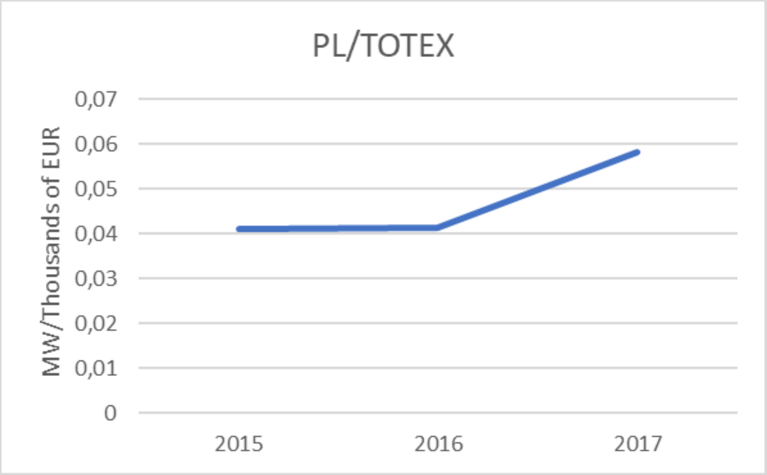

Figure 7: Ratio Peak load over Total Expenditure

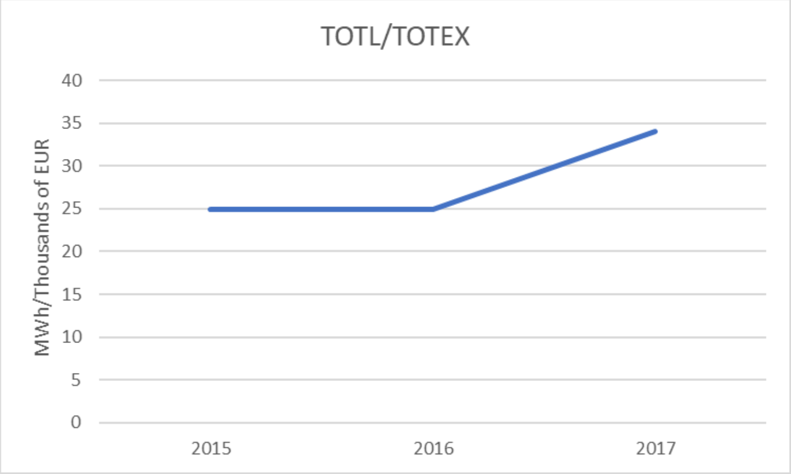

Figure 8: Ratio Total Load over Total Expenditure.

As we can see, they follow similar evolution relatively equal between 2015 and 2016 then a sharp increase in 2017. This might be interpreted in a relative increase of efficiency in our sample and thus the outputted MW per euro seems to be increasing.

Next to the output, there are some cost drivers (that will be considered as outputs in the analysis) that need to be considered. The obvious cost drivers suggested by the literature for a TSO are its length of network of underground cables and overhead lines and the number of transformers operated (Jamasb & Pollitt, 2000). This data is collected on the ENTSO-E data platform and in some cases annual reports. The network length is the full length and not the circuit length. While the cable (*CABLE*) length is taken in an aggregate way over the different voltages, the length of the overhead lines is separated in two different sections the High Voltage (*LINEHV*), up to 220 KV, and the Extra High Voltage (*LINEEHV*), between 220 and 800KV, and taken together in *LINETOT*. For the transformer I took total capacity (*TRACAP*) per TSO. While both, the number of transformer and the total capacity, have been used in the literature, there is a preference for the capacity as it better reflects the cost of operation.

2.1.4 Climatic Data

The climate data were collected from the National Center for Environmental Information's (NCEI) online climate data platform[5]. This platform regroups the data from land stations across the globe. The three chosen parameters to measure the effects of the weather on the efficiency of the TSOs, are the absolute lowest temperature of the year (*TEMPMIN*), the absolute maximum temperature of the year (*TEMPMAX*) and the max windspeed of the year (*WSP*). The choice of these climate variable is based on past studies where temperature maximums and minimums are said to be the preferred variables to check the impact of temperature on the efficiency (Valor, Meneu & Caselles, 2001). As the NCEI is an organisation part of the United States of America, all the data was in Fahrenheit degrees and Knots. Not a problem as such but as this thesis targets an European environment, I converted them back into Celsius degrees and meters per second. This data was collected per country. In the case of TSOs that cover more than one country, such as Tennet, the weather stations were then selected in accordance with the territory in which the TSO operates.

Table 1 contains the statistical resume of the dataset.

---

[5] https://www7.ncdc.noaa.gov/CDO/cdoselect.cmd?datasetabbv=GSOD&countryabbv&georegionabbv

	UNITS	MIN	MEAN	MAX
TEMPMAX	°C	27 ,60	37 ,76	47 ,22
WSP	m/s	14 ,46	28 ,85	43 ,98
TEMPMIN	°C	-42 ,38	-21,9	-5,22
PL	MW	576	17659	94497
TOTL	TWH	3 ,20	107 ,61	546 ,00
CABLE	km	1 ,0	913 ,3	5563 ,0
LINESHV	km	461 ,6	9216 ,3	54563 ,0
LINESEHV	km	373 ,5	5894 ,4	22028 ,0
LINESTOT	km	835 ,1	15110 ,8	65518 ,0
TRACAP	MVA	3672	58237	282829
OPEX	thousand €	8522	626633	3707278
CAPEX	thousand €	1300	401894	2521000
TOTEX	thousand €	14325	1028527	5116312
PPI		93 ,80	103 ,23	113 ,19
TOTP	thousand €	14212	1017255	5144349

Table 1: Statistical Resume of The Data Set.

2.2 Statistical analysis of parameters

In order to decide which parameters, I should include in the DEA model, I decide to run a simple statistical analysis of said parameters.

2.2.1 Function selection

The first step to perform an analysis is to decide of a functional form of our function. The obvious choice for a function would be a linear-one production function as we have one input and multiple outputs (cost drivers included). However, this would not be a judicial choice as we might encounter trouble with our data set as there is some heteroscedasticity present, which is normal as we are dealing with TSOs from big countries (i.e. RTE, Tennet) and TSOs from small countries (i.e.

Elering or ČEPS). To counter that, I will opt for a log-linear function. Well known in the econometric field, one of the advantages of the log-linear form is having the ability to fit the data in a better way, especially regarding the size of the TSOs in the dataset. The regression coefficient can also be interpreted as production elasticity.

The log linear formula takes a general form as follows:

$$\log x_i = \beta_0 + \sum \beta_i \log y_i$$

With: X_i the input of firm i

Y_i the output of firm i

β the coefficient of the output

Due to his logarithmic aspect and the fact that log(0) would return an error, in the case that a TSO did not have any CABLES I replaced them by 1. Log(1)= 0 thus this solves the problem.

2.2.2 Analysis of a Simple Linear Regression using OLS

In order to decide which parameters to include I will use a step-wise backwards selection with different models, removing the least significance each time. In the table 2 you can see the different models analysed with the adjusted R² of the model.

Parameters (log)	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
PL	x	x	x		x	
TOTL	x	x			x	
CABLES	x	x	x	x	x	x
LINESHV	x	x	x	x		
LINESEHV	x					
LINESTOT					x	x
TRACAP	x	x	x	x	x	x
Adjusted R²	0.792	0.8014	0.8044	0.8072	0.8013	0.8067

Table 2[6]: Regression Models and their adjusted R²

---

[6] In green the parameter that were significant and in red the least significant parameters

Out of this parameter analysis, three parameters stand out and will be included in our DEA model, *CABLES*: representing the length of the cables, *LINESTOT*: the total length of overhead lines, and *TRACAP*: the capacity of the transformers.

While the model with the HV lines was slightly more significant, it made no managerial sense for me to include the lower voltage lines and not the higher voltage ones. Thus, the parameter from M6 will be further utilized.

Here is the summary of the model.

```
summary(M6)

Call:
lm(formula = log((D$TOTP) * 100) ~ log(D$CABLES) + log(D$LINESTOT) + 
    log(D$TRACAP))

Residuals:
    Min      1Q  Median      3Q     Max 
-2.2833 -0.1593  0.1132  0.3090  1.1655 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)       7.4894     0.9590   7.810 3.28e-10 ***
log(D$CABLES)      0.3204     0.0424   7.557 8.10e-10 ***
log(D$LINESTOT)  -0.3520     0.1775  -1.983   0.0529 .  
log(D$TRACAP)     0.7044     0.1174   5.999 2.20e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6718 on 50 degrees of freedom
Multiple R-squared:  0.8177,   Adjusted R-squared:  0.8067 
F-statistic: 74.75 on 3 and 50 DF,  p-value: < 2.2e-16
```

To test for multicollinearity, I used the maximum Variance Influence Factor (VIF) technique as referred to by O’brien (2007).

```
vif(M6)
   log(D$CABLES) log(D$LINESTOT)   log(D$TRACAP) 
       1.998704        4.395762        3.060358
```

We do not reach the critical threshold of 5 thus it is safe to assume that there is no multicollinearity problem.

I am however surprised by the coefficient for *linesTOT* as it does not have the expected sign.It appears to be correlated to another explanatory variable (TRACAP). However, as we do not expect multicollinearity problems and that the p-value is significant, which would not be the case if it were highly correlated, thus, I decide to leave it in the model.

Testing for Heteroscedasticity with the Breusch-Pagan test we obtain a p-value of 0.0723. With a p-value below 0.1 we can assume that the Gauss-Markov theorem hold and that the estimators are the best linear unbiased estimators. (Plackett, 1950)

```
	studentized Breusch-Pagan test

data:  log((D$TOTEX/D$PPI) * 100) ~ log(D$Cable) + log(D$linesTOT) + 
log(D$TRACAP)
BP = 6.8528, df = 3, p-value = 0.07674
```

From the coefficients we can learn something about the return of scale of our production function. As they can be interpreted as production elasticities as it is related to a Cobb Douglas production function (Cobb & Douglas, 1928). The sum of the coefficient can give us an indication on the return of scale of our function. If the sum of estimated-coefficient of our OLS is more than one, it would mean a decreasing returns to scale, if it equals to one, it would mean a constant returns to scale, and if it is less than one, it would mean an increasing returns to scale.

$$0.3204 \ + \ (-0.3520) + 0.7044 = 0.6728 < 1$$

Thus, we can consider that our model has increasing returns to scale(non-decreasing returns to scale) . This information will be useful for the calculation of efficiency scores with a DEA.

3 Empirical analysis & results

This part is divided as follows, first the technical efficiency will be calculated using a DEA, followed by the second stage of the two-stage model to find out if the weather parameters have any effects on the technical efficiency of TSOs.

For the empirical analysis I will use the technique explained by Kao and Liu (2014) to aggregate my dataset over the time periods, taking the average of all the parameters to perform the following analysis. The aggregated dataset can be found in Appendix A. In order to perform those analysis, I make use of the R program and the “Benchmarking” package developed by Bogetoft and Otto(2011).

3.1 Data Envelopment Analysis

As suggested in the methodology and the data pre-analysis, I will opt for a DEA with increasing return to scale, also called non-decreasing return to scale, and with an input orientation, as the TSOs do not decide the amount of electricity they have to transport. Table 3 offers a recapitulative list of information concerning the DEA model. In Agrell et al (2013) a DEA model is defined for benchmarking. I will inspire myself from this work to perform the first stage of the Two-stage analysis.

DEA model	
Input	TOTEX
Outputs	Cables
	linesTOT
	TRACAP
Orientation	In-put Oriented
Return to scale	Increasing return to scale

Table 3: Recapitulation of the DEA Model

In Appendix B you can find the TSOs with their respective technical efficiency score per year and for the aggregated dataset.

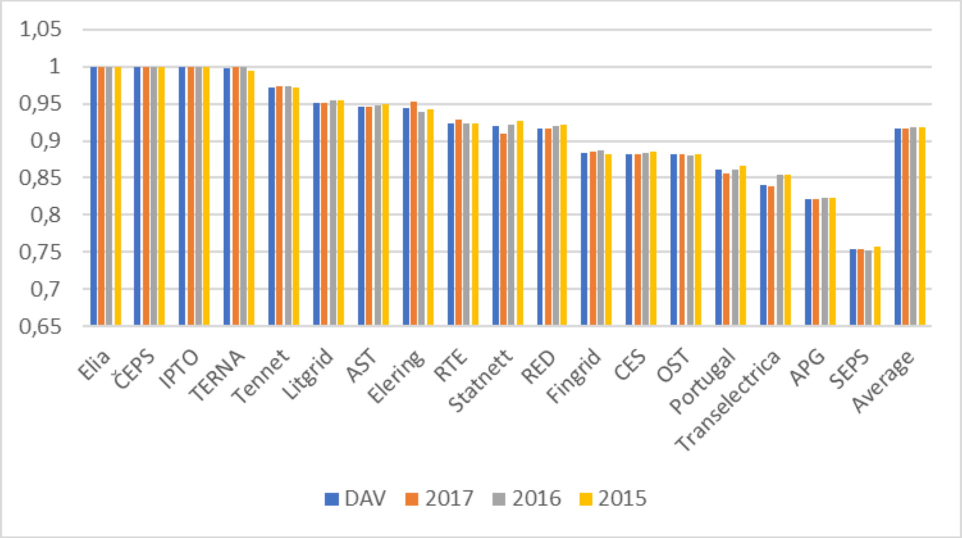

Figure 7[7]: Technical efficiency score of TSO per year

Looking at these efficiency scores, we can see that it seems constant over the years and that the TSOs perform as overall relatively well with an average score always around 0,91.

The dominance test proposed in Agrell et al(2013) is then used to control for outliers. Outliers are overly efficient firms with an abnormal set of technology, the inclusion of it in the dataset will affect the efficiency score of other TSOs. The dominance test looks at the proportional difference between the sum of the efficiency score of a firm with the potential outlier included (E(k;K))and when TSO i isexcluded (E(k;K\i)). (Banker, Rajiv & Natarajan, 2011). The test statistic is T is used in this dominance test.

---

[7] (the scale of the graph is chosen to render the difference in efficiency visually ascertainable)

$$T = \frac{\sum_{k\epsilon K\backslash i}(E(k;K\backslash i) - 1)^2}{\sum_{k\epsilon K\backslash i}(E(k;K) - 1)^2}$$

T is designed so that if the T < 1 it means that the TSO i had an influence on the efficiency of the others. The three TSOs that are obtaining 100% efficiency every time are tested this way and are recognised as outliers.

After the dominance test, the super-efficiency test is calculated. According to Bogetoft and Otto(2011), the idea behind super efficiency is that efficient firms on the frontier do not have an incentive to improve their efficiency score. Thus, the super-efficiency test calculates the efficiency without the upper limit of 1. The idea is that outliers will exceed it, and not span the technology thus giving a more reliable score to the other firms. The simplex is once more solve through a function, namely sdea, of the “Benchmarking” package for R.

```
> summary(dea)
Summary of efficiencies
IRS technology and input orientated efficiency
Number of firms with efficiency==1 are 0 out of 18
Mean efficiency: 0.944
---
  Eff range      #    %
  0.7<= E <0.8   1  5.6
  0.8<= E <0.9   6 33.3
  0.9<= E <1     8 44.4
        E ==1    0  0.0
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.7540  0.8819  0.9222  0.9435  0.9670  1.2220
```

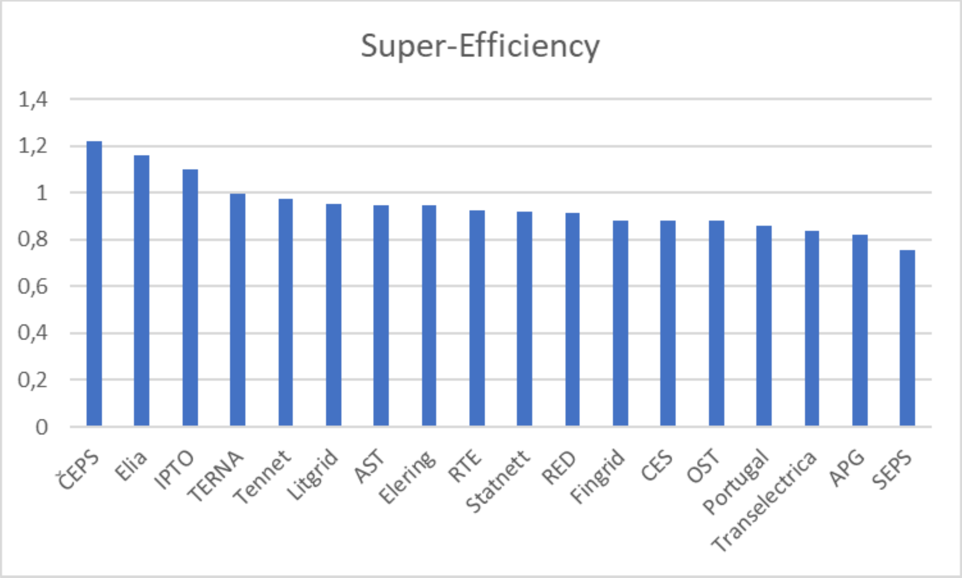

Figure 8: Super-efficiency of TSOs

On figure 8[8], our three previously suspected outliers have super efficiencies values above 1. Following the Agrell et al(2013) and the German Ordinance for Incentive Regulation, a TSO is considered an outlier if he :"exceeds the upper quantile limit by more than 1,5 times the inter-quantile range."(Agrell et al,2013). Translated into a formula:

$$E > q(0.75) + 1{,}5[q(0.75) - q(0.25)]$$

The limit for our model is 1.0946 with a respective efficiency score of 1.1631, 1.2216 and 1.1011, Elia, CEPS, and IPTO are categorised as outliers. Their efficiency score will be set at 100% (or 1) and their inputs and outputs will be considered as determining the technology frontier. A final DEA is then performed with these settings. Table 4 shows the efficiency scores of this final DEA. Those will be used in the second stage.

---

[8] Detailed Efficiency score in Appendix C

TSO	Efficiency
ELIA	1
CEPS	1
IPTO	1
TERNA	0,9808
Tennet	0,9239
RED	0,9125
Litgrid	0,91
RTE	0,9059
Elering	0,9039
AST	0,9035
Statnett	0,8841
CES	0,8827
Fingrid	0,8819
OST	0,8816
Portugal	0,847
Transelectrica	0,8302
APG	0,8124
SEPS	0,754

Table 4: Efficiency Score of TSOs with our Base Model DEA

3.2 Stage Two: Testing the hypotheses

As mentioned in the methodology part of the thesis, I opted for a two-stage model. Table 5 to 7 shows the correlation coefficient of the weather variables with the three outputs used in our DEA of the total data set.

	CABLES	**TEMPMAX**	**WSP**	**TEMPMIN**
CABLE	1			
TEMPMAX	0,019	1		
WSP	0,076	0,060	1	
TEMPMIN	0,250	0,756	-0,277	1

Table 5: Correlation *CABLES* with Weather Variables

	LINESTOT	**TEMPMAX**	**WSP**	**TEMPMIN**
LINESTOT	1			
TEMPMAX	0,491	1		
WSP	0,494	0,059	1	
TEMPMIN	0,294	0,755	-0,276	1

Table 6: Correlation LINESTOT with Weather Variables

	TRACAP	**TEMPMAX**	**WSP**	**TEMPMIN**
TRACAP	1			
TEMPMAX	0,377	1		
WSP	0,581	0,060	1	
TEMPMIN	0,323	0,756	-0,277	

Table 7: Correlation TRACAP with Weather Variables

The correlation coefficients between the weather variables and the DEA variables are all below the wished threshold of 0.5 except for the correlation between the windspeed and total capacity of the transformers. Thus, if there is significance level found in the second stage, we may suspect a small bias.

For the second stage regression I will use the regular OLS. I would have preferred to use the Tobit regression as suggested, but with a sample size of 18 it is not possible, as it is too small. As we want to regress the technical efficiency of our TSO against the weather variables, the form used is linear and not log linear because temperatures come in the negative form and, the temperature and windspeeds are all respectively in the same range and we can assume homoscedasticity. The regression formula will thus have a form like this:

$$TE_i = \beta_0 + \beta_1 TEMPMAX_i + \beta_2 WSP_i + \beta_3 TEMPMIN_i$$

The summary of the regression is as follow.

```
lm(formula = eff$Efficiency ~ Dav$TEMPMAX + Dav$WSP + Dav$TEMPMIN)

Residuals:
      Min        1Q    Median        3Q       Max 
-0.139380 -0.024202 -0.000599  0.025951  0.116095 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)   
(Intercept)  1.113e+00  2.693e-01   4.132  0.00102 **
Dav$TEMPMAX -3.955e-03  6.284e-03  -0.629  0.53927   
Dav$WSP     -7.063e-05  2.559e-03  -0.028  0.97837   
Dav$TEMPMIN  2.758e-03  3.082e-03   0.895  0.38603   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.07061 on 14 degrees of freedom
Multiple R-squared:  0.0731,   Adjusted R-squared:  -0.1255 
F-statistic: 0.368 on 3 and 14 DF,  p-value: 0.7772
```

With p-values ranging from 0.386 to 0.97837, the weather variables are not significant in the explanation of the efficiency. Furthermore, with a F-statistic of 0.368 and an adjusted R^2 of -0.1255 we can clearly see that the independent variables are not explanatory. In conclusion to this analysis, we do not find significant evidence to reject H0.

IV Conclusion

Since the unbundling of TSOs in Europe, the regulators have been trying to implement more stable and fairer bench marking models, including most of elements possible that could influence the financial results of the TSOs. It is in this optic that this thesis attempts seeing whether weather elements have an impact on the efficiency of electricity TSOs in Europe.

To analyse this, the use of a two-stage DEA was made. Performing a DEA on 18 TSOs and then regressing the technical efficiencies of the DEA against the weather variables. The analysis did not produce any significant results. Therefore, H0 can not be rejected.

This thesis is of importance to both the regulators as they can now focus on other external parameters that could affect the performance of TSO. The groundwork is also set up to test a bigger sample. As priorly said, the data used for this thesis was the one available online, this could be extended to all the ENTSO-E members with proper usage of the data acquiring channels.

This thesis also calls for further analysis as not all the weather variables have been analysed. We could test more variable such as snow, rain and storm days. The use of more advanced DEA could also be done to get an even more robust efficiency score while I doubt the results would differ as the p-values where so high.

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