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Application of predictive growth curves to global wind capacity.

Growth drivers and limits.

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Abstract

Global primary energy demand is likely to increase by half between 2015 and the middle of the 21st century, which will require new energy capacity to cover growth in consumption. Current primary energy supply is dominated by fossil fuels. These sources are limited in quantity and are unevenly distributed on our planet. Additionally, burning fossil fuels creates a negative externality, causing global warming. The international community has agreed, that increased use of fossil fuels to tackle future energy deficit is unsustainable in the long run. Wind power is an unlimited, clean energy resource, which in theory could partly solve the problem of energy shortage.

This work analyzes the dynamics of wind power capacity at global and regional level. The main finding is that wind capacity follows a logistic growth trend. This gives an opportunity to discover the saturation level and forecast cumulative installed wind capacity into the first half of the 21st century. The study predicts that wind power will cover less than 1% of global primary energy demand in year 2040. The thesis also points to the key drivers of wind capacity and outlines the contribution of those drivers to the forecast for wind power capacity in year 2040.

Acknowledgement

I would like to take the opportunity to thank three people, who guided me in this long and winding journey from a research idea to an academic work. With Evangelos Kyritsis, my supervisor from NHH, we had several long and substantial talks both relating to my thesis and my future steps towards an academic career. All along the journey, I felt his support and participation in all problems I would encounter. Evangelos was always open to my questions and willing to discuss them. Professor Jan Petter Hansen, my external supervisor from University of Bergen, introduced me to the research idea. He and Professor Dag Lorents Aksnes contributed largely to my increased methodological skillset. We had a couple of enjoyable academic discussions with a cup of coffee. It was the first time in my life, that I was drinking coffee with two professors and even having a short academic debate once or twice. I absolutely enjoyed the atmosphere of our meetings and this long journey, which happily ended with this final version of my work.

Contents

1. Introduction

This chapter introduces the reader to background and academic relevance of the research problem. The scientific contribution of the study is outlined here.

1.1 Background

Sustainable and reliable energy supply is fundamental to global economic growth and human development. While energy demand in OECD countries is flattening out (BP, 2016), other parts of the world, in particular Asia, are striving to increase their economic power per capita, which can only be achieved by increased energy consumption. OECD countries make up 1.26bn people, representing only about 17% of global population (OECD.Stat, 2013). An equivalent number of people around the world had no access to electricity as of year 2010. This number is expected to fall to between 319 million and 530 million by 2050. As a result, electricity consumption per capita is forecast to grow globally by between 78% and 111% by 2050 (World Energy Council, 2013). Global energy consumption today is not sustainable in the long run, since it is dominated by depletable fossil fuels (around 80%) (BP, 2016).

Apart from the depletion of the fossil resources, there is concern that exhaust emissions from carbon fuels will make global temperatures warmer by an average of 3–5 °C at the turn of 21st century (Narbel et al., 2014). A group of 1,300 independent scientific experts under the auspices of the United Nations concluded, that gases such as carbon dioxide, methane and nitrous oxide have caused much of the observed increase in Earth's temperatures over the past 50 years (Intergovernmental Panel on Climate Change, 2007).

Billions of people are affected by negative externalities from increased global temperatures, therefore, reducing CO_2 emissions appears extremely necessary (Narbel et al., 2014). Paris Climate Agreement, signed by the leaders of 175 countries at United Nations headquarters in New York, sets an objective to limit global temperature rise to well below 2 °C. Other objectives of the Agreement include fostering climate resilience and adaptation, channeling finance flows towards low greenhouse gas (GHG) emissions (UN News Center, 2016).

According to IRENA report (2015), renewable energy offers an immediate means to decarbonize the global energy mix. Doubling the share of renewable energy by 2030, coupled with energy efficiency, could keep the average rise in global temperatures below 2 °C. The key energy sources of the projected green future are solar and wind (IRENA, 2015). This study attempts to estimate contribution of wind power to the global energy mix of the future.

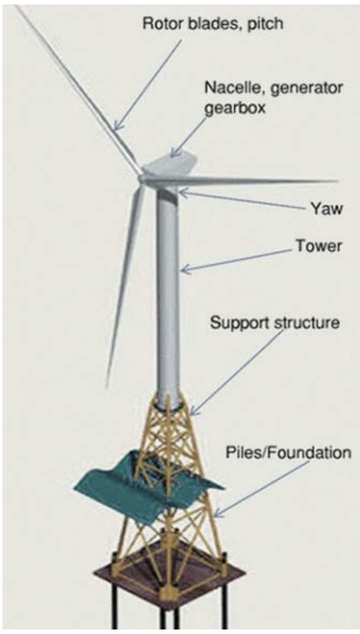


Figure 1.1. *Parts of a wind turbine (Narbel et al., 2014).*

Wind power as a source of energy has been known for centuries. Earlier, windmills were used to mill grain and pump water (Wikipedia, 2016). A majority of modern windmills take the form of wind turbines used to generate electricity. A wind turbine contains a tower that can reach over 150 m in height, a nacelle with the generator and a rotor system (Figure 1.1). The nacelle rotates in order to face the airflow, while the pitch controller orientates the blades to maximize the efficiency of the wind turbine for different wind conditions. The rotational energy is transformed into electricity in the generator, which is wired to an electric grid or a storage system. (Narbel et al., 2014)

Areas with average wind speed between 12 and 17 m/s are considered optimal for wind power installations. Many parts of the world with high average wind speeds have to be excluded from the area available for wind power installation due to geographical remoteness from electricity consumption areas, technical and political constraints. Thus, an upper limit of the economic potential of wind energy is realistically around 5 TW (Narbel et al., 2014).

Between 1990 and 2015, the capacity of wind turbines went up from 200 KW to 4 MW. Even larger wind turbines with a rated capacity of 5–7 MW are tested today (Narbel et al., 2014). In countries, such as Denmark, most economically viable locations have already been filled with wind installations. Therefore, further increase in total wind capacity is only possible through repowering: replacement of old turbines by latest models with higher efficiency. Additionally, an increasing number of countries are experimenting with harvesting wind resources offshore.

Wind power generates no CO_2 emissions other than small amounts during production and installation process. It consumes very little water also. Yet it still has environmental impacts, including visual impact, noise and wildlife disruption (Wind Energy. The Facts, 2016). The most significant challenges facing the wind power are its intermittency and high production costs compared to fossil fuel technologies (REN 21, 2016).

1.2 Relevance

Recent years have seen a large number of reports and publications heralding the 21st century as the age of renewable power both at global and regional level. Expectations, that traditional fossil fuels will lose current dominant role, are running high. The optimistic consensus is that renewables are undergoing exponential growth into the middle of 21st century (IRENA, 2015), (Mathiesen er al., 2011), (IEA, 2010), (Droege, 2009), (DOE, 2016), (EWEA, 2016), (Greenpeace, 2017). In contrast to optimistic predictions, there is a much shorter list of publications making conservative forecasts about development of renewables (Hansen et al., 2016). In particular, Hansen et al. (2016) posit, that wind and solar follow a logistic growth pattern with saturation level of 1.5 TW. Falling growth rates in annual capacity additions and investment, together with stabilization of costs above those of fossil fuels and difficulties with grid integration, have raised question marks about the optimistic trajectory for wind power.

In this thesis, I estimate the trend of wind capacity at the global and regional level. The two trends applied to annual wind cumulative capacity data are logistic and exponential. In particular, fitting a logistic model to the data may help to estimate the upper limit of global wind capacity based on current state of affairs. The logistic equation was originally derived by Verhulst in 1838 to describe the asymptotic growth patterns of biological populations, but is now used in a wide range of different disciplines (Tsoularis & Wallace, 2002). More than 60 years ago, the idea that production from an energy source could follow a sigmoid (logistic) pattern was utilized for forecasting American oil production, known as Hubbert's peak oil theory (Tao & Li, 2007); and later for other energy technologies, including wind energy systems (Xia & Song, 2009). Additionally, this study aims at pointing to the key factors influencing the dynamics of global and regional wind capacity.

Novelty of the study lies in extensive review of global and regional wind capacity development with application of nonlinear regression and subsequent use of adequate selection criteria for establishing the right model. The outcomes of analysis at global and regional level will be compared to build validity of conclusions. The study subsequently forecasts wind power share in the global energy mix in the year 2040.

The outcomes of this study may be relevant for governmental and corporate bodies, active in energy industry. This study intends to shed light on how far the wind industry is from its targets and pinpoint the key factors influencing the progress of wind power.

2. Methodology

The goal of my research is to estimate the trend of growth in cumulative wind capacity globally and at the regional level. This chapter gives an overview of past examples, when curves were fitted to energy time series. It studies relevant growth models. A review of nonlinear and robust curve fitting is performed. Next, I present the 7-step Nonlinear-Curve-Fitting Algorithm by Molutsky & Christopulos (2014). The chapter is concluded by introduction to the model selection criteria.

2.1 Curve fitting energy time series

Analysts often work with data that varies over time, i.e. a time series. A time series is a sequence of data points at successive moments in time, which are spaced at uniform intervals (Höök et al., 2012). Some examples of time series are annual production of electricity from coal-fired plants and monthly production of crude oil in the North Sea. Time series analysis is comprised of various methods for analyzing data to extract meaningful statistics from the dataset.

Time series forecasting is the use of a suitable model to forecast future events based on known past events, i.e. to predict data points before they are measured (Höök et al., 2012). Some examples of time series forecasting are the prediction of future coal production based on historical volume and the extrapolation of historical natural gas discovery trends to assess the potential for new discoveries in the future. A few common methods in time series analysis and forecasting are spectral analysis, ARMA/ARIMA-techniques and various trend estimation approaches, such as the fitting of suitable curves.

A common method of dealing with non-seasonal data that displays a trend, e.g. annual data, is to fit a suitable curve to predict future development. These curves vary from linear to very complex functions. Many time series of energy production produce trends, which can be explained by growth curves. Descriptive growth curves aim to model the time series with relatively few parameters in order to characterize the behaviour of the data studied. Hotard & Ristroph (1984) described the discovery and production of oil and natural gas at the national level, Marchetti & Nakicenovic (1979) talked about technology substitution in energy systems, while Ang & Ng (1992) discussed how growth curves could explain interactions in energy resource analysis, energy demand and fuel substitution. Various forms of growth curves have been utilized for predicting future production of oil (Nashawi et al., 2010) and wind (Xia & Song, 2009).

The “goodness of fit” is determined among others by the deviation of actual data points from corresponding points on the curve, i.e. the magnitude of error. Logically, the best fit to a time series with n points is a (n-1) polynomial. However, polynomials of high degree lack explanatory meaning. This refers to the problem of overfitting, when researcher may find a perfect fit for the sample data, but that fit would have little predictive power for another random sample or the entire population. Models designed to describe observed behaviour or provide forecasts must have a connection to the physical input parameters, generally implying that relatively few parameters should be employed in a model (Höök et al., 2012).

2.2 General Growth Models

Any growth curve can be placed in two different growth mode categories: unbounded and bounded. Within those two large categories we should point out, that unbounded growth may have linear or exponential trend; bounded growth may follow sigmoid or bell-shaped trend. Additionally, sigmoid and bell-shaped curves can be both symmetric (logistic growth) and asymmetric. Figure 2.1 provides examples of exponential, sigmoid and bell-shaped growth curves. In this study we ignore linear growth since my data establish a non-linear trend.

Perpetual growth is often held as an unquestioned belief or even as a fundamental assumption for certain economists (Höök et al., 2012). Some believe that human ingenuity can act as a powerful force, capable of overcoming all possible physical limitations. In essence, those ideas must be seen as the belief in unbounded growth.

The exponential growth model (1) implies continuous unlimited geometric growth. The dynamics of growth depends on three parameters – growth rate, the starting point and time (Tsoularis & Wallace, 2002). In the exponential model, *e* (2.718) is a mathematical constant and time *t* is a variable component, denoted as $t\ (0, 1, 2 \ldots T)$.

$$N(t) = N_0 e^{rt} \quad (1)$$

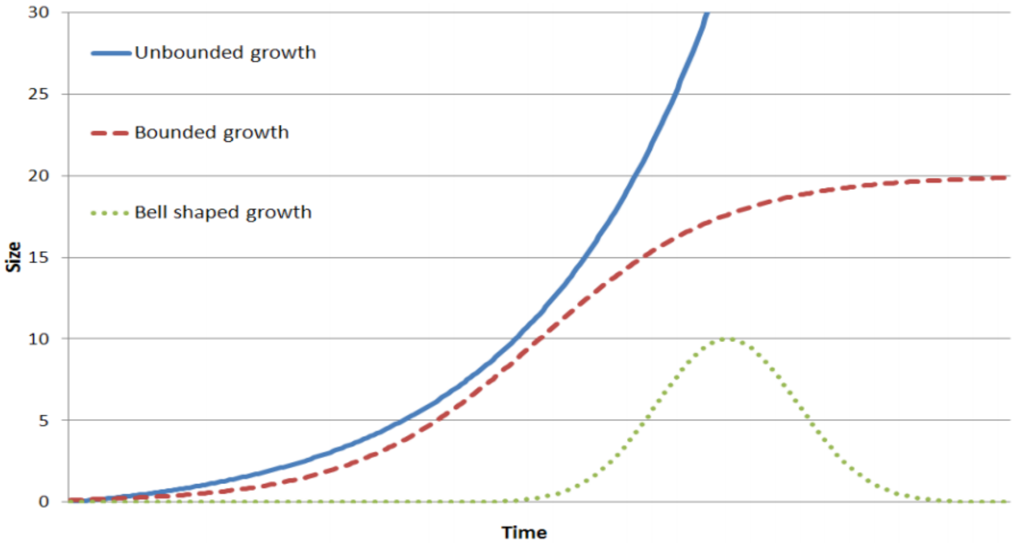


Figure 2.1. *Three growth models (Höök et al., 2012).*

N_0 is the capacity at time $t=0$ and r is a growth rate. The idea behind adding exponential function to the "best fit contest" is inspired by claims in energy industry that renewables and wind energy in particular are undergoing exponential growth far into the future (IEA, 2010), (IRENA, 2015), (DOE, 2016), (Droege, 2009), (EWEA, 2016), (GWEC, 2011), (World Energy Council, 2013).

Fossil fuels are finite resources, because there is an upper limit in total production, determined by their geological availability in the earth's crust. Hydropower has no well-defined upper limit for total energy production, but is subject to a limitation of available rivers to be dammed. This growth dynamics can be described by a sigmoid growth curve. Some of the most well-known sigmoid curves are Gompertz curves, logistic curves, Bertalanffy curves and Weibull (Höök et al., 2012).

Bell-shaped curves may be symmetric or asymmetric. They are often closely related to sigmoid functions and commonly appear as their derivatives. In other words, they may be seen as annual equivalents to a sigmoid behaviour in a time series of cumulative production data. Bell-shaped curves have frequently been used in a wide array of disciplines, but were initially developed to describe and predict growth in biological systems or bioenergetics (Tsoularis & Wallace, 2002).

Verhulst considered that growing population would have a saturation level defined by the environment (as cited in Tsoularis & Wallace, 2002). He added a multiplicative factor, *(1-*

N/K), to the exponential model (1). This factor can be interpreted as a “death component”, which reduces “birth rate” *r*, as population *N* approaches the limit *K*:

$$\frac{dN}{dt} = rN\left(1 - \frac{N}{K}\right) \qquad (2)$$

Expression (2) represents a symmetric bell-shaped curve. The integral of the above expression between time *0* and *T* is a symmetric logistic curve given in expression (3):

$$N(t) = \frac{KN_0}{(K - N_0)e^{-rt} + N_0} \qquad (3)$$

Where N_0 is the population size at time $t=0$ and r is the birth rate. For $r > 0$, the resulting upward growth curve has a logistic shape (Tsoularis & Wallace, 2002).

Logistic growth is characterized by certain key features. The population will ultimately reach its carrying capacity. In mathematical terms this is expressed as:

$$\lim_{t \to \infty} N(t) = K \qquad (4)$$

The population at the inflection point (where growth rate is maximum), N_{inf}, is exactly half the carrying capacity $N_{inf}=K/2$ and the maximum growth rate $(dN/dt)_{max}=rK/4$

Equation (3) can be mathematically transformed into the equation (5) (Claerbout & Muir, 2016), where t_p stands for time of peaking in annual population growth.

$$N(t) = \frac{K}{1 + e^{-r(t - t_p)}} \qquad (5)$$

Hubbert (1959) was among the first to formulate the idea of finite resource simulation curves. He assumed that production starts at zero and ends at zero, when the resource has been fully exhausted. In between, production would go through one or several maxima. The actual shape of a given production curve may vary but its area is limited by the recoverable amount of the finite resource. Today, the derivative of the logistic function in expression (2) is called the Hubbert curve in honour of his pioneering work. It used to be frequently referred to in peak oil discussions (Höök et al., 2012).

Brandt (2007) noted and quantified significant asymmetries in 67 regions between oil production increase and post-peak decline, indicating that less symmetric curves can give better descriptions. There are a few cases of application of asymmetric curves in modelling energy time series. Moore (1966) used Gompertz curves for analyzing and projecting historical supply patterns of oil and other exhaustible natural resources. The asymmetric logistic model has been used for petroleum forecasts by Nashawi et al. (2010). However, asymmetric models commonly suffer from being complex and less straightforward to work with. This complexity is a likely explanation of why they have attracted less attention in recent decades (Höök et al., 2012). Out of similar considerations, I choose to apply symmetric bounded curves, in addition to exponential curve, to my wind capacity data.

The relevance of sigmoid growth pattern for non-fossil energy technologies has been proven by hydro (Gleick, 2012) and nuclear energy (Figure 2.2), which reached maturity at the end of the 20th century. Bounded and logistic curves can be used to model growth in renewable capacity, since some kind of saturation level has to exist even for renewables. If annual doubling of wind power continues for 64 years, the situation quickly becomes totally unrealistic (Höök et al., 2012).

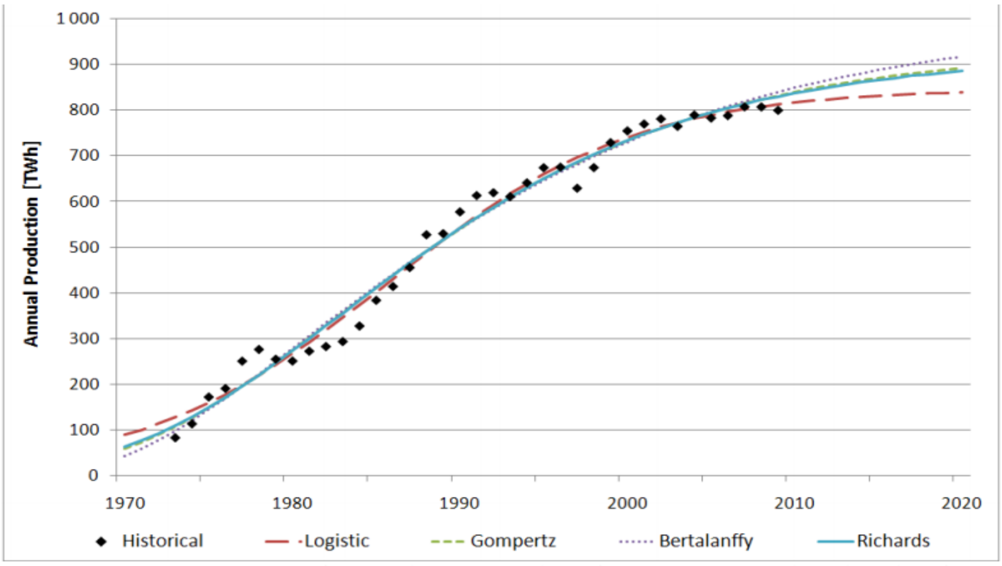


Figure 2.2. *Energy generation of US nuclear power plants from 1973 to 2009 (Höök et al., 2012).*

2.3 Nonlinear curve fitting

Curve Fitting Toolbox in Matlab uses the nonlinear least-squares formulation to fit a nonlinear model to data. A nonlinear model is defined as a nonlinear combination of model parameters with one or more independent variables. For example, Gaussians, ratios of polynomials, and power functions are all nonlinear (Mathworks, 2016).

In matrix form, nonlinear models are given by the formula:

$$y = f(X,\beta) + \varepsilon \quad (6)$$

where y is an *n-by-1* vector of responses, β is an *m-by-1* vector of coefficients, X is the *n-by-m* design matrix for the model and ε is an *n-by-1* vector of errors.

Nonlinear models are more difficult to fit than linear models because the coefficients cannot be estimated using simple matrix techniques. Instead, an iterative approach is required (Mathworks, 2016). We start with an initial estimate for each coefficient. For some nonlinear models, a heuristic approach is provided that produces reasonable starting values. For other models, random values on the interval *[0,1]* are provided. Next, we produce the fitted curve for the current set of coefficients. The fitted response value $\hat{y}$ is given by:

$$\hat{y} = f(X,b) \quad (7)$$

It involves the calculation of the Jacobian, which is defined as a matrix of partial derivatives taken with respect to the coefficients. In the next step, we adjust the coefficients and determine whether the fit improves. The direction and magnitude of the adjustment depend on the fitting algorithm. Matlab toolbox provides two algorithms – Trust-region and Levenberg-Marquardt. Trust-region is the default algorithm and must be used if you specify coefficient constraints. It can solve difficult nonlinear problems more efficiently than the other algorithms and it represents an improvement over the popular Levenberg-Marquardt algorithm (Mathworks, 2016). Levenberg-Marquardt has been used for many years and proved to work most of the time for a wide range of nonlinear models and starting values (Mathworks, 2016). If the trust-region algorithm does not produce a reasonable fit, and you do not have coefficient constraints, you should try the Levenberg-Marquardt algorithm.

The options of weights and robust fitting for nonlinear models are available. Because of the nature of the approximation process, no algorithm is foolproof for all nonlinear models, data sets, and starting points. Therefore, if you do not achieve a reasonable fit using the default starting points, algorithm, and convergence criteria, you should experiment with different options (Mathworks, 2016).

2.4 Robust Least Squares

It is usually assumed that the residuals follow a normal distribution, and that extreme values are rare. Still, extreme values called outliers do occur. Outliers have a large influence on the fit because squaring the residuals magnifies the effects of these extreme values. To minimize the influence of outliers, we can fit our data using robust least-squares regression.

The Matlab toolbox provides these two robust regression methods - Least absolute residuals (LAR) and Bisquare weights. "The LAR method finds a curve that minimizes the absolute difference of the residuals, rather than the squared differences. Therefore, extreme values have a lesser influence on the fit" (Mathworks, 2016). Bisquare weights "minimizes a weighted sum of squares, where the weight given to each data point depends on how far the point is from the fitted line. Points near the line get full weight. Points farther from the line get reduced weight. Points that are farther from the line than would be expected by random chance get zero weight" (Mathworks, 2016).

For most cases, the Bisquare weight method is preferred over LAR because it simultaneously seeks to find a curve that fits the bulk of the data using the usual least-squares approach, and it minimizes the effect of outliers. Robust fitting with Bisquare weights uses an iteratively reweighted least-squares algorithm (Mathworks, 2016). First, we fit the model by weighted least squares. Second, we compute the adjusted residuals and standardize them. The adjusted residuals are given by

$$r_{adj} = \frac{r_i}{\sqrt{1-h_i}} \quad (8)$$

Where r_i are the usual least-squares residuals and h_i are leverages that adjust the residuals by reducing the weight of high-leverage data points, which have a large effect on the least squares fit. The standardized adjusted residuals are given by

$$u = \frac{r_{adj}}{K*s} \quad (9)$$

Where K is a tuning constant equal to 4.685, and s is the robust variance given by MAD/0.6745, where MAD is the median absolute deviation of the residuals. Third, compute the robust weights as a function of u. The Bisquare weights are given by

$$w_i = \begin{cases} (1-(u_i)^2)^2 & |u_i| < 1 \\ 0 & |u_i| \geq 1 \end{cases} \quad (10)$$

Note that if we supply our own regression weight vector, the final weight is the product of the robust weight and the regression weight. If the fit converges, then we are done. Otherwise, we perform the next iteration of the fitting procedure by returning to the first step.

2.5 Seven steps of nonlinear fitting

In my curve fitting to wind capacity data, I use step-by-step guidance developed by Molutsky & Christopoulos (2004).

	Steps to consider:
Step 1	Clarify your goal. Is nonlinear regression the appropriate fit?
	Are you interpolating unknown values on the curve or making the forecast into the future? Before performing any analysis, plot your data to see whether there is linear dependence of y on x.
Step 2	Prepare your data and enter it into the program.
	You may want to strip your data of outliers and/or normalize your data points.
Step 3	Choose your model.
	Choose one or several curve fits that you want to test on your data.
Step 4	Decide which model parameter to fit and which to constrain.
	You don't have to ask the program to fit all parameters of the model. If there are several parameters whose value is determined from physical relationship in your model, you should fix them as constants before curve fitting starts. You may also choose to constrain certain fitted parameters as greater than zero, depending on the system you analyze.
Step 5	Choose a weighting scheme.

If you assume homoscedasticity in residuals, you should instruct the program to minimize the sum of squared residuals to select the best fit. If you assume heteroscedasticity in residuals, use robust model fit.

Step 6 Choose initial values of fitted parameters.

This step is performed automatically by Matlab Curve Fitting Tool.

Step 7 Perform the curve fitting and interpret the best fit values.

Does the curve visually fit the data well? Are the best fit values scientifically plausible? How precise are the best fit parameter values?

Here one has to look at the upper and lower bounds of 95% confidence interval. The smaller the gap between the two bounds, the more precise is the fit.

Would another model be more appropriate?

Model selection algorithm developed further will answer this question.

2.6 Model selection

In order to determine whether it is exponential or logistic model that better fits the data on global and regional cumulative wind capacity, I use two instrument criteria –RMSE (Root-Mean-Square-Error) and SSE (Sum of squared errors).

I avoid using R squared for comparison of non-linear models since it is not the optimal criterion to that end. R squared is a typical model performance estimate in linear models. However, in non-linear models its meaning can be biased. As Spiess & Neumeyer (2010) point out, "the description of single models when using R squared is not meaningful, as this measure tends to be uniformly high when a set of models is inspected. … Additionally, R squared and even its 'bias corrected' counterpart adjusted R squared are severely biased in favor of models with more parameters when it comes to model selection… R squared is an inappropriate measure when used in the field of nonlinear fitting" (Spiess & Neumeyer, 2010). I can confirm their observation: while modelling wind capacity with exponential and logistic curves, I continuously obtained R squared and adjusted R squared estimates very close to one. In fact, the differences between R squared scores were so small that it was difficult to select between models.

Root-Mean-Square-Error (RMSE) represents the average distance that the observed values fall from the regression line (Statweb Stanford Univesity, 2016).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\widehat{y_t}-y_t)^2}{n}} \quad (11)$$

Where $\widehat{y_t}$ is the fitted value of the model, y_t is the population value, and n is number of observations. Conveniently, it tells you how wrong the regression model is on average using the units of the response variable. Smaller values are better because it indicates that the observations are closer to the fitted line (Frost, 2016). I was able to obtain RMSE estimates while curve fitting in Matlab.

$$SSE = \sum_{i=1}^{n}(\widehat{y_t} - y_t)^2 \quad (12)$$

Sum of squared errors (SSE) is a sum of squared deviations of data points from the model. In fact, SSE is the numerator from RMSE equation. Similar to RMSE, the smaller SSE value indicates a better fit (Wooldridge, 2009). I obtained SSE estimates while model fitting in Matlab.

My model selection algorithm is the following – first, I use RMSE as a selection criterion, where I select the model with the lower RMSE score; if RMSE estimate is not available, I use SSE criterion, where I select the model with the lower SSE estimate.

3. Empirical Findings

In the first section of Chapter 3, I fit logistic and exponential curves to the global cumulative capacity data. In the second section the same procedure is performed on regional wind capacity, upon that both outcomes are compared. Section 3 examines historical wind capacity in Denmark with intention to explain certain findings on global and regional capacity data. Finally, I conclude the chapter with articulation of model implications and proposal for further research.

3.1 Curve fitting global cumulative capacity

The global installed wind capacity has been multiplied nearly 87 times between 1995 and 2015 to reach 435 GW at the end of 2015. China is leading the world in terms of installed capacity, in front of the United States and Germany (BP, 2016). The annual time series for curve fitting were extracted from BP Statistical Review of World Energy from June 2016.

I had two potential curve fitting solutions – to apply logistic curve to cumulative capacity or a bell-shaped curve to annual capacity data. The first option was chosen due to better data availability of cumulative capacity across regions of the world. Now I am ready to start applying the seven curve fitting steps defined in the Methodology Chapter.

Step 1 - Clarify your goal. Is nonlinear regression the appropriate fit? My goal is to forecast global cumulative wind capacity in the year 2040. I have plotted my capacity data in Figure 3.1. Clearly, the data follow a nonlinear trend, so nonlinear regression has to be applied.

Step 2 - Prepare your data and enter it into the program. The data was entered into an Excel spreadsheet. No outliers have been visually detected in the data. I chose not to normalize data to avoid complexity in interpretation. Seasonality is not an issue since I use annual series. The Excel spreadsheet was imported into Matlab software. Next the data was assigned to X and Y variables in Curve Fitting Tool. My X variable is Time running from 0 to 20 (1995-2015), my Y variable is global cumulative wind capacity.

Step 3 - Choose your model. By eyeballing the data, it is plausible to assume, that it follows either logistic or exponential trend. Another option, n-1 degree polynomial, is ignored, since our intention is to come up with a meaningful forecast by fitting as few parameters as possible (Höök et al., 2012).

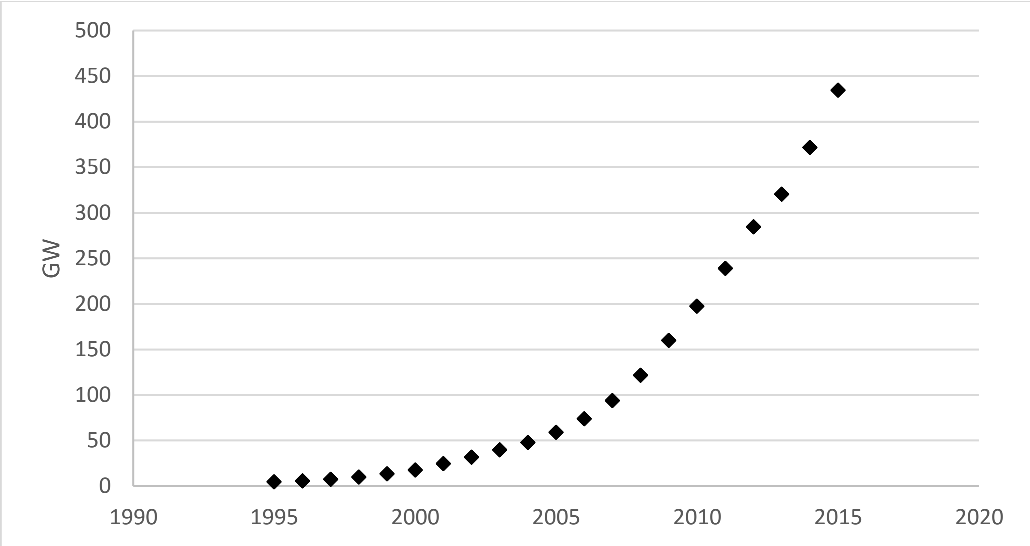


Figure 3.1. *Global cumulative wind capacity (BP, 2016).*

Step 4 - Decide which model parameter to fit and which to constrain. I am fitting logistic (5) and exponential (1) curves to the data series. In the case of logistic curve, I choose to fit three parameters – K, r and t_p. Other studies chose to fit only the last two parameters, constraining K to maximum technically available potential (Xia & Song, 2009). This option has its benefits since fitting fewer parameters often (but not always) improves predictive accuracy for each of fitted parameters by narrowing the 95% confidence interval for each of the fitted values. However, in order to constrain a parameter to a certain value one has to be at least 99% confident that she is using the right constrained value. Otherwise, she risks obtaining meaningless prediction.

In the case of wind, the parameter K is very much uncertain as different studies provide varying estimates (Hansen et al., 2016). Secondly, there is no guarantee that wind capacity will ever reach its technically possible potential, as its future may be compromised by public perception shifts, political, technological and economic changes in the society. Due to all this uncertainty, I choose not to constrain K to any constant, and rather let the software algorithm determine it for me. In the case of exponential curve, I am fitting two parameters – N_0 and r. I could have set N_0 equal the first value in my data series, however I decided not to do so, since my data start in 1995 and the history of wind capacity dates back earlier than that.

Step 5 - Choose a weighting scheme. I perform initial curve fitting with an assumption of homoscedasticity in the residuals. After having obtained the residuals, I perform a Breusch-Pagan test on squared residuals vs t (the only independent variable in the regression) (Wooldridge, 2009). If the null hypothesis of homoscedasticity is rejected at 95% confidence level, I perform robust curve fitting. Either Bisquare weights or LAR robust method are applied, depending on which provides the lower RMSE value. My initial hypothesis of homoscedasticity was rejected on global capacity data in case of logistic (*p-value = 0.000*), and exponential fit (*p-value = 0.014*). Hence, I applied robust fitting. I continuously use the default fitting algorithm Trust-Region (Mathworks, 2016) throughout the work.

Step 6 - Choose initial values of fitted parameters. Matlab Curve fitting tool performed this for me automatically.

Step 7 - Perform the curve fit and interpret the best fit values. Figure 3.2 produces the logistic and exponential curves fitted to the global cumulative capacity series. Initially both curves sit on the data points tightly, so that it is hard to say by eyeballing which of them is the better fit to the data. However, after the year 2010 the exponential curve starts to deviate from the data significantly, whereas the logistic continues to follow that data points.

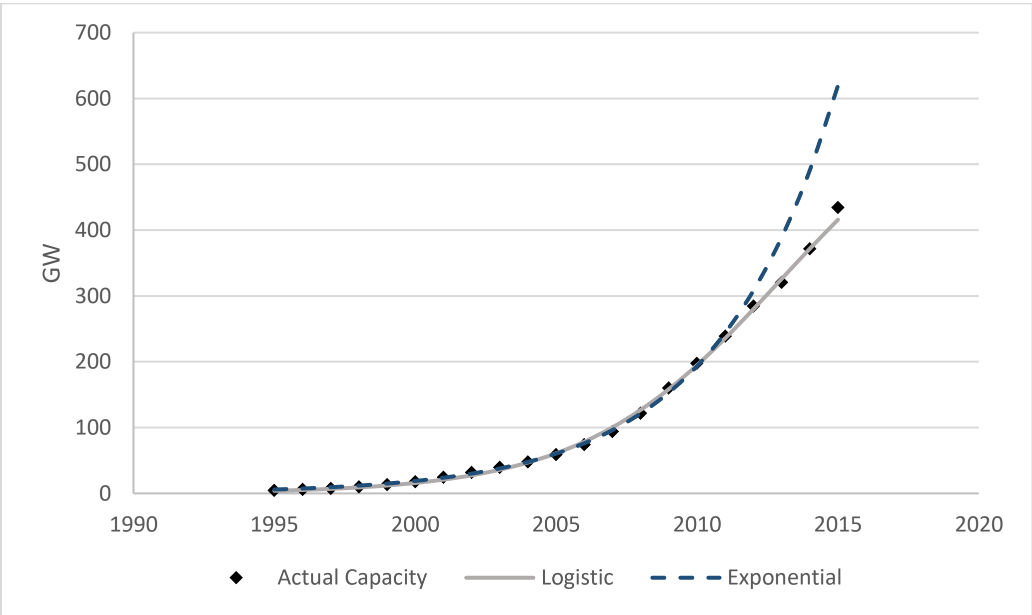


Figure 3.2. *Logistic and exponential curves fitted to global cumulative wind capacity.*

Now let us look at fitting output summarized in Table 3.1. First, we can observe the fitted parameter values produced by logistic and exponential models. For logistic curve, we look at estimated K, r and t_p. Even though somewhat surprising on the background of forecasts made by various bodies in wind industry (IEA, 2010), (GWEC, 2011), (IRENA, 2015), they look scientifically plausible indeed. They are also consistent with other less optimistic studies. (Hansen et al., 2016). The exponential curve also produces scientifically plausible estimates of r. The curves, however, dramatically differ in their estimates of global wind capacity in year 2040. While exponential forecast heralds 208TW of wind capacity in 2040, the logistic produces less than modest estimate, namely 650.3 GW. Looking at carrying capacity for logistic, we see that it saturates at 650.6 GW with the lower 95% confidence bound at 590.6 GW and the upper at 710.5 GW. According to logistic version of reality, the global annual wind installations have already peaked in 2013, with upper and lower confidence bounds allowing peak year to be either 2013 or 2014.

Referring to the Model Selection algorithm formulated in Methodological Chapter, I use two criteria – RMSE and SSE – to determine which of the two hypothesized curves is the better fit to the data. I first look at RMSE value, which is 4.034 for logistic and 5.919 for exponential. Since this parameter shows the average distance of the data points from the fitted curves, I will always select the lowest value, which is 4.034 for logistic. Accordingly, SSE confirms the initial conclusion that logistic fits the data better than exponential. Visualized curve fitting and residuals plot are available in Appendix 7.2.

Table 3.1. *Logistic and Exponential Models. World.*

	Logisitc					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	650.6	0.284	2013	650.3	292.9	4.034
95% Upper bound	710.5	0.300	2014			
95% Lower bound	590.6	0.267	2013			
	Exponential					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	N/A	0.232	N/A	208684	665.7	5.919
95% Upper bound	N/A	0.238	N/A			
95% Lower bound	N/A	0.227	N/A			

K(GW) – carrying capacity (the upper asymptote of logistic curve)
r – growth rate of cumulative capacity
t(p) – is the year of peaking annual installations of new capacity
2040(GW) – is the model specific forecast of cumulative capacity in year 2040
SSE – Sum of squared errors
RMSE – Root-Mean-Squared-Error

Figure 3.3 depicts the eventual logistic model of global wind capacity. In addition, the graph shows forecasts of capacity by various energy-related bodies. Those forecasts clearly make an impression that the industry expects solid growth at least into 2040s. Their assumption may be either exponential or linear dynamics of growth up until the middle of the century. My model does not confirm those expectations.

What could the explanation for such low saturation level be? First, in spite of falling production costs (at least until recently), wind power is at present more expensive (at global level), than established energy alternatives, such as coal and gas. Until grid parity is eventually achieved, continuous subsidizing of wind power is needed in the deployment process. For a number of developing countries the opportunity cost of investment in wind energy is too high. As Hansen et al (2016) put it, regional plans for ruling out subsidies towards renewable energy without compensating with other marked changing strategies will very likely only strengthen the marked contribution to a logistic pattern.

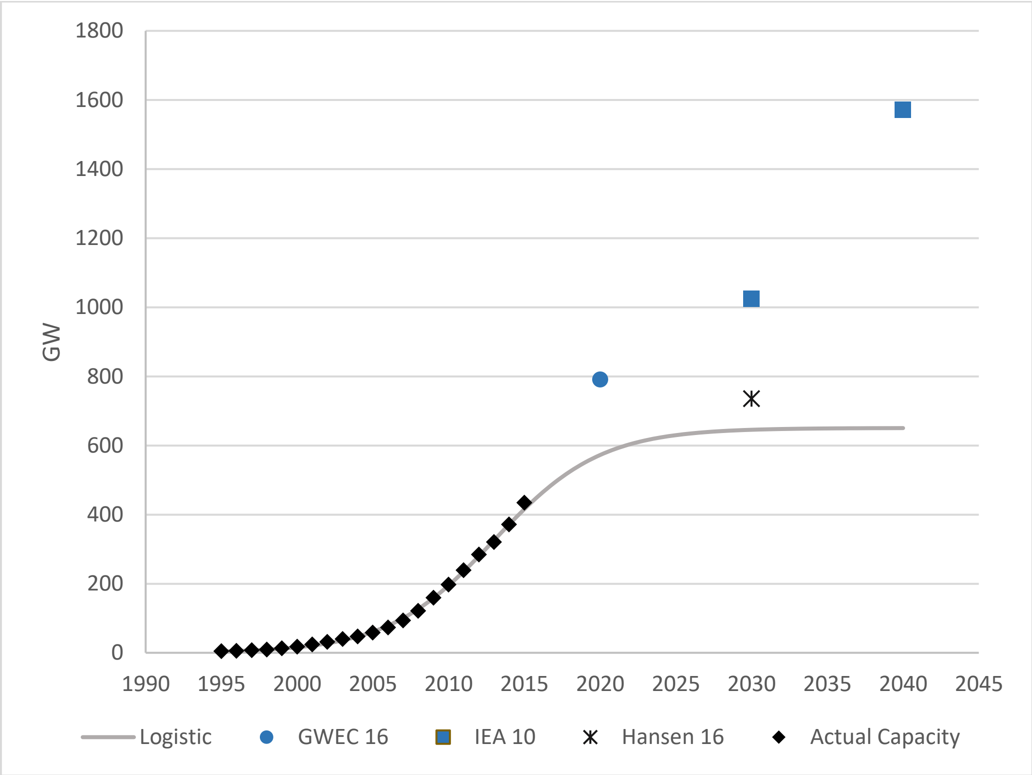


Figure 3.3. *Modelled logistic global wind capacity and its forecasts.*

In addition to relatively high direct costs, wind energy commands high indirect costs. Figure 3.4 illustrates extreme volatility in wind resource and electricity prices in January 2007 in Denmark. Intermittency complicates using wind as base load source, since its variability may cause electricity price spikes during peak consumption hours as shown in Figure 3.4 (right). Wind power producers usually do not know exactly how strong the wind next month will be, as well as they cannot be sure about how many days in the upcoming summer the whole farm will stand idle because of storm season. As a result, it becomes difficult for wind investors to forecast future returns (Kropyvnytskyy, 2016).

Use of wind power as base load source requires investment in another balancing source (e.g. natural gas fired plant), which would be easy to scale up and down following the electricity demand. This would come as indirect cost to wind capacity. The possible solution to that problem is developing state-of-art storage technology, which would help to smooth intermittency of wind. However, we are clearly not there yet (Timilsina et al., 2013).

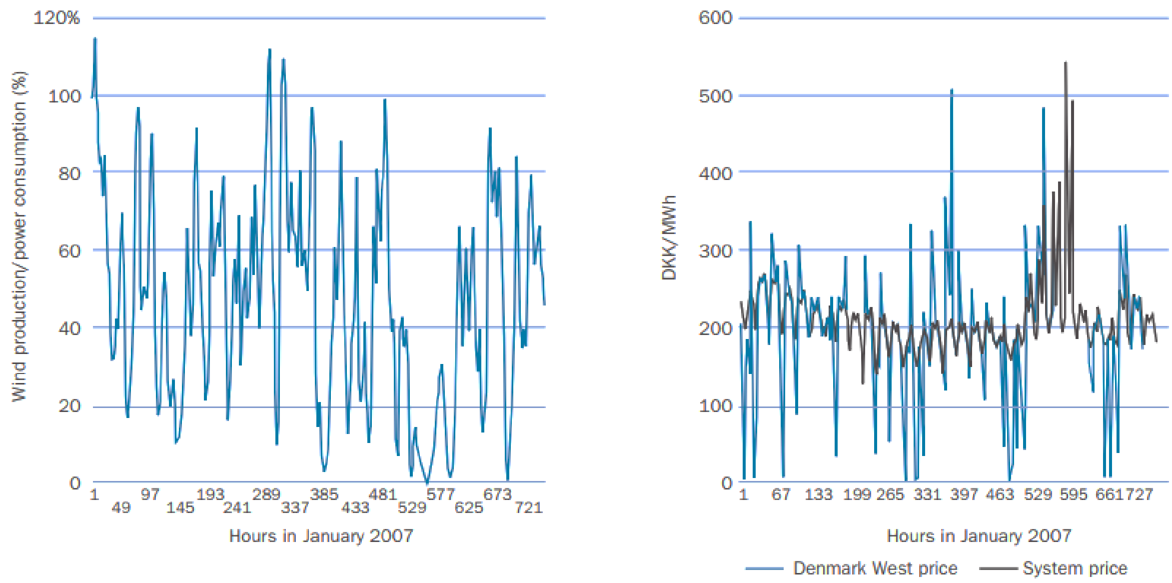


Figure 3.4. *An example of wind resource volatility in Denmark in January 2007. Left graph shows hourly share of wind in total electricity consumption. Right graph shows spot hourly price of electricity in Danish kroner per MWh (EWEA, 2009).*

Another difficulty with wide deployment of wind power is geographical remoteness of optimal sites with high average wind speed. For example, in China the best wind resources are concentrated in the North of the country, whereas the major demand centers are located on the Eastern and South-Eastern coasts, hundreds or even thousands kilometers away. That requires large investments in expansion of transmission grid - another indirect cost of wind power. As the lowest hanging fruits are picked first, so is the picture with wind installations. The majority of cost efficient locations for wind have already been developed (Timilsina et al., 2013). Further expansion would require more significant decline in direct costs coupled with continuation of governmental subsidies and major grid investment.

Short material life times in wind turbines, typically 20-25 years, imply that future global production capacity will increasingly be needed to replace decommissioned installations. Major decommissioning will start in early 2020s, 20 years after large installations of wind began in Europe and North America. This would require much more annual capacity installations in order to replace the retired generation and increase cumulative capacity.

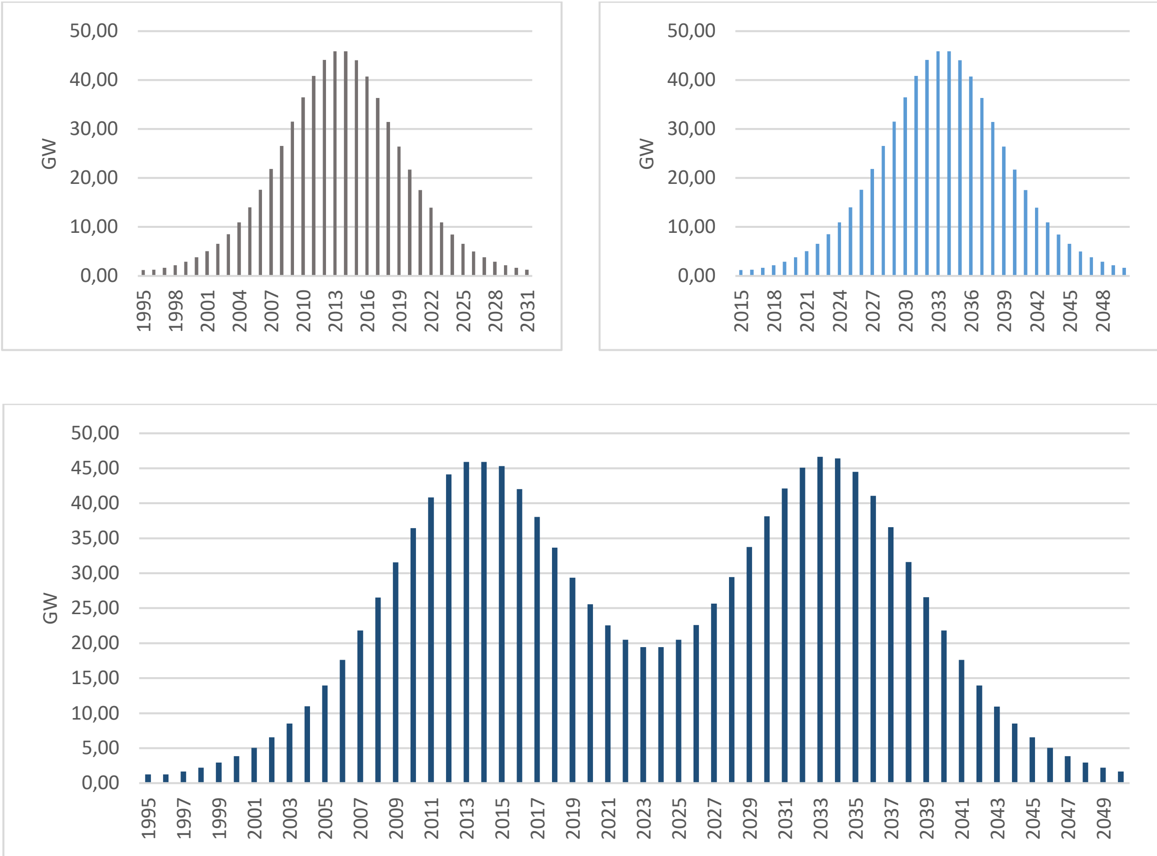


Figure 3.5. *Modelled annual new capacity installations(grey), substitution for retired installed capacity(blue) and total annual installations (dark blue), given 20 year long life cycle.*

The sigmoid logistic curve models the cumulative installed generation capacity. Its derivate, a grey bell-shaped curve in Figure 3.5 (grey), models new annual capacity installations. As discussed above, the annual new capacity installations have likely peaked around 2013. In order to guarantee, that cumulative capacity does not fall due to decommissioning, substitution for retired capacity has to be provided, as shown in Figure 3.5 (blue). Thus, we get the bottom chart in Figure 3.5 (dark blue), showing the combination of new and substitution capacity. The chart has two humps. The first hump symbolizes the peak of modelled new capacity in 2013. The second hump is the peaking of modelled substitution capacity 20 years later in 2033.

Finally, wind power tends to cannibalize its own revenue streams through depreciating market energy prices in the hours of high production and low demand (Hansen et al., 2016). This puts negative pressure on profit margins for a wind investor.

3.2 Curve fitting regional cumulative capacity

Availability of regional data on cumulative wind capacity allows me to perform similar analysis at regional level. Having obtained the estimates for each region, we will add them together to get a global picture. In the end, we will compare conclusions made on global and regional data sets. I found cumulative annual regional capacity data in the same BP report (2016) as the global data.

Eurasia[1] (Appendix 7.2). Eurasia includes all of Europe, Turkey and former USSR. Europeans were the first to start deploying wind power at the industrial scale in 1990s and remain the second largest market for wind capacity after Asia&Pacific today. Wind power's share of total installed capacity in European Union has increased six-fold since 2000, from 2.4% in 2000 to 15.6% in 2015. Wind power is placed third after gas and coal in EU power mix as of 2015. In cumulative terms, Germany remains the EU country with the largest installed capacity (45 GW), followed by Spain (23 GW), the UK (14 GW) and France (10 GW) (GWEC, 2016).

In 2015, the European Commission (EC) launched its vision for a unified energy strategy aiming at coordinating the energy policy of the 28 Member States. The main priorities of the strategy are security of supply, integrated internal energy market, energy efficiency, emission reductions, and research and innovation. According to Global Wind Report (2016), among the key predicaments for wind energy in Europe are sudden changes in legislation in a number of EU member states. They make it hard for investors and developers to plan investments in new wind energy assets as well as in repowering and retrofitting existing assets. In addition, the EU power sector suffers from overcapacity caused by uneconomical and inefficient fossil fuel power plants being artificially kept online by public subsidies. That in turn causes electricity prices to drop, undermining the business case for investing in new power capacity (GWEC, 2016).

Table 3.2 produces the outcome of logistic and exponential curve fitting. By looking at RMSE, we find the logistic fit more optimal compared to exponential. After going through the residuals graph for Eurasia in Appendix 7.2, we again can confirm that logistic residuals sit

[1] Includes all countries in Europe, Turkey and Former USSR.

closer to empirical data. In the case of Eurasia, we can now say that cumulative capacity follows a logistic rather than exponential development.

The logistic curve forecasts saturation level of 219.4 GW for Eurasia's wind cumulative capacity. This can be compared to official estimates 600 GW for Europe excluding Turkey and CIS in 2050 made by EWEA (2016). The difference by the factor of 2.7 is striking and rather alarming. Logistic model also informs us that annual new capacity installations in Europe have already peaked some time between 2010 and 2013.

Table 3.2. *Logistic and Exponential Models*. Eurasia.

	Logisitc					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	219.4	0.218	2011	218.93	92.3	2.403
95% Upper bound	250	0.239	2013			
95% Lower bound	188.8	0.198	2010			
	Exponential					
	K(GW)	r	t(p)		SSE	RMSE
Forecast	N/A	0.135	N/A	4686.76	628.3	6.079
95% Upper bound	N/A	0.147	N/A			
95% Lower bound	N/A	0.123	N/A			

K(GW) – carrying capacity (the upper asymptote of logistic curve)
r – growth rate of cumulative capacity
t(p) – is the year of peaking annual installations of new capacity
2040(GW) – is the model specific forecast of cumulative capacity in year 2040
SSE – Sum of squared errors
RMSE – Root-Mean-Squared-Error

North America[2] (Appendix 7.2). The US is the single largest market globally in terms of total installed capacity after China. The US total installed wind capacity reached 74 GW, Canada finished the year with over 11 GW of total installed capacity making it the seventh largest market globally, with wind power was supplying approximately 5% of Canada's electricity demand. Mexico installed an impressive 713 MW of new capacity to reach the total capacity of 3 GW by the end of 2015 (GWEC, 2016). Providing adequate transmission is a key to continue to enable the build out and delivery of wind power to all parts of the continent. Value

[2] Includes Canada, USA and Mexico.

needs to be placed on proposed long-distance, high-voltage lines connecting wind energy resource areas to population centers (GWEC, 2016).

In Table 3.3, RMSE of 2.921 (logistic) is lower than 3.518(exponential). If we assess fitted graphs and the residuals plot in Appendix 7.2, we can state, that cumulative capacity in North America follows logistic development, rather than exponential.

From the table we observe that annual new capacity wind installations have already peaked in magnitude in 2011 and will be decreasing further on. Official bodies expect that by 2030 USA alone will install between 224 GW of wind power across 47 states (DOE, 2016). The logistic curve, however, predicts the saturation level at around 118.4 GW for the entire region.

Table 3.3. *Logistic and Exponential Models. North America.*

	Logistic					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	118.4	0.327	2011	118.4	76.8	2.191
95% Upper bound	136.7	0.372	2012			
95% Lower bound	100.1	0.281	2010			
	Exponential					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	N/A	0.250	N/A	77324.44	210.4	3.518
95% Upper bound	N/A	0.266	N/A			
95% Lower bound	N/A	0.234	N/A			

K(GW) – carrying capacity (the upper asymptote of logistic curve)
r – growth rate of cumulative capacity
t(p) – is the year of peaking annual installations of new capacity
2040(GW) – is the model specific forecast of cumulative capacity in year 2040
SSE – Sum of squared errors
RMSE – Root-Mean-Squared-Error

Latin America[3] (Appendix 7.2) saw 3,652 MW of new capacity come online, bringing total installed capacity to over 13 GW in 2015. Brazil led Latin America in 2015 with 8.72 GW of total capacity. Uruguay has a goal to generate as much as 38% of its power from wind by the end of 2017 and added almost 316 MW, bringing its total installed capacity to over 845 MW in 2015. Chile added 169 MW of new capacity to reach a total installed capacity of almost 1

[3] Includes Latin American countries south of Mexico and Caribbean.

GW in 2015. One of the key barriers to wind development on the continent is the lack of sufficient transmission lines in the areas with the largest wind power potential (GWEC, 2016).

RMSE score of 0.166 is lower for logistic model than 0.182 for exponential (Table 3.4). The logistic model predicts that the peak in annual installations for the region will be in between 2015 and 2021. Moreover, the upper limit of capacity is going to be below 199.8 GW. GWEC (2011) predicts installation of 93 GW for the entire Latin America by 2030. My logistic curve predicts saturation of 62.39 GW of total capacity by 2040.

Table 3.4. *Logistic and Exponential Models*. Latin America.

	Logisitc					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	62.39	0.455	2018	62.39	0.414	0.166
95% Upper bound	199.8	0.512	2021			
95% Lower bound	4.979	0.399	2015			
	Exponential					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	N/A	0.404	N/A	48945.3	0.532	0.182
95% Upper bound	N/A	0.422	N/A			
95% Lower bound	N/A	0.386	N/A			

K(GW) – carrying capacity (the upper asymptote of logistic curve)
r – growth rate of cumulative capacity
t(p) – is the year of peaking annual installations of new capacity
2040(GW) – is the model specific forecast of cumulative capacity in year 2040
SSE – Sum of squared errors
RMSE – Root-Mean-Squared-Error

Africa (Appendix 7.2). South Africa is the current leader in cumulative installations in this region with just over 1 GW of cumulative capacity. Egypt saw a new wind farm with total capacity of 200 MW come online in 2015. This brought Egypt's total installed capacity up to 810 MW. Egypt expects to source 20% of its energy from renewable sources by 2030. Morocco had 787 MW cumulative capacity at the end of 2015 (GWEC, 2016).

Africa is still in the early stage of Wind power development. In the early stage of installations, it becomes harder to distinguish between exponential and logistic trends. If one looks at the actual data of cumulative capacity for Africa, she would see that the data points for years 2014 and 2015 are located much higher than the preceding trend. Given that years 2014 and 2015 seem to be outliers, it becomes harder to establish the actual trend in cumulative capacity.

After applying logistic curve to the full data, including 2014 and 2015, I came up with an estimate of carrying capacity for Africa of 2TW, which in present looks unrealistic. This violates my curve fitting algorithm (Molutsky & Christopoulos, 2004). My decision was to apply exponential and logistic fitting to reduced dataset with removed data points for 2014 and 2015.

Table 3.5 produces the outcome of curve fitting to the reduced data set. This time the results look scientifically plausible. RMSE score is lower for logistic, thus it is selected as the optimal model. My logistic trend predicts total capacity plateau at 4.32 GW. The peak of annual new installations is estimated between 2008 and 2019.

Table 3.5. *Logistic and Exponential Models. Africa.*

	Logisitc					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	4.32	0.278	2014	4.32	0.069	0.070
95% Upper bound	7.92	0.353	2019			
95% Lower bound	0.72	0.203	2008			
	Exponential					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	N/A	0.215	N/A	647.26	0.087	0.076
95% Upper bound	N/A	0.237	N/A			
95% Lowe bound	N/A	0.193	N/A			

K(GW) – carrying capacity (the upper asymptote of logistic curve)
r – growth rate of cumulative capacity
t(p) – is the year of peaking annual installations of new capacity
2040(GW) – is the model specific forecast of cumulative capacity in year 2040
SSE – Sum of squared errors
RMSE – Root-Mean-Squared-Error

Mid. East (Appendix 7.2) is another challenging region for forecasts, very much for same reasons as Africa. Jordan saw the 117MW Tafila plant commissioned last September. In Israel, two new projects are being commissioned - the first for over 20 years - at Gilboa (11.9MW) and Sirin (9.35MW). However, the country's permitting process remains painfully slow and there are concerns about a proposed revision to the support mechanism. In Kuwait, Elecnor is building a 10MW demonstration plant at Shagaya. Work is also planned to start this year on Libya's first utility-scale plant, a 27MW facility at Msallata. Overall, the current progress in in the region is negligible. The reasons behind it are clear - political instability and lack of economic backing from governments (Wind Power Monthly, 2016).

Here, as in case with Africa, I treat the data point for 2015 as an outlier and remove it prior to curve fitting. This way I am able to get a realistic prediction for 2040. Looking at RMSE (Table 3.6) score, we select the logistic curve as explanatory model. The logistic curve predicts the upper limit of wind capacity at below 0.31 GW. This means that there is very little, if any, capacity growth expected in the region until 2040.

Table 3.6. *Logistic and Exponential Models. Mid. East.*

	Logistic					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	0.20	0.250	2010	0.20	0.002	0.011
95% Upper bound	0.31	0.357	2014			
95% Lower bound	0.10	0.143	2005			
	Exponential					
	K(GW)	r	t(p)		SSE	RMSE
Forecast	N/A	0.141	N/A	6.47	0.002	0.012
95% Upper bound	N/A	0.166	N/A			
95% Lower bound	N/A	0.115	N/A			

K(GW) – carrying capacity (the upper asymptote of logistic curve)
r – growth rate of cumulative capacity
t(p) – is the year of peaking annual installations of new capacity
2040(GW) – is the model specific forecast of cumulative capacity in year 2040
SSE – Sum of squared errors
RMSE – Root-Mean-Squared-Error

Asia&Pacific[4] (Appendix 7.2). For the seventh year in a row, Asia was the world's largest regional market for wind power, with capacity additions totaling nearly 33 GW in 2015. The two biggest markets here are China and India (GWEC, 2016).

China added 30 GW of new capacity in 2015, the highest annual number for any country ever. There is a shift in attitudes among high-level government officials in China, as many high-level government officials are now concerned about the extreme air pollution in major cities, and express the desire to reduce air pollution and curb climate impacts. The government set itself a target of peaking GHG emissions by 2030. It is now actively designing and implementing a national carbon market. The 13th Five-Year Plan includes an objective for non-

[4] Includes countries of Southern, Eastern, South-Eastern Asia and Pacific.

fossil renewable energy consumption to reach 15% by 2020 and 20% by 2030. For wind power, the target is to reach cumulative installed capacity of 250 GW by 2020 (GWEC, 2016).

Difficulties however continued in transmitting China's wind power from turbines to population centers due to infrastructure bottleneck. Curtailment is a reduction in the output of a generator from what it could otherwise produce given available resources, typically on an involuntary basis. Operator-induced curtailment typically occurs because of transmission congestion or lack of transmission access, but it can occur for a variety of other reasons, such as excess generation during low load periods, voltage, or interconnection issues (NREL, 2014). Curtailment rose in 2015 to an average 15%, up from 8% in 2014, with 33.9 TWh of potential generation kept from the grid. This practically means lost revenue to wind investors (GWEC, 2016).

India continued to be the fifth largest annual market globally, adding 2,623 MW of new wind power to reach a total of 25 GW. India committed to installing 60 GW of wind by 2022. Further, India made a commitment to raise the share of non-fossil fuel power capacity in the country's power mix to 40% by 2030 (GWEC, 2016).

Wind power grew at a moderate pace in Japan in 2015, installing 245 MW in 2015 compared to 140 MW in 2014. Cumulative installations crossed the 3 GW mark at the end of 2015. Japan government gives less than moderate support to wind installations. Australia and New Zealand saw combined installed capacity rise to just over 4 GW in 2015, with Australia adding 380 MW of new capacity (GWEC, 2016).

Let us determine, whether it is exponential or logistic curve that better models the development of wind installations in the region (Table 3.7). RMSE score is lower for logistic, meaning that the capacity follows an asymptotic trend. This can also be confirmed by looking at fitted models and residuals plot in Appendix 7.2.

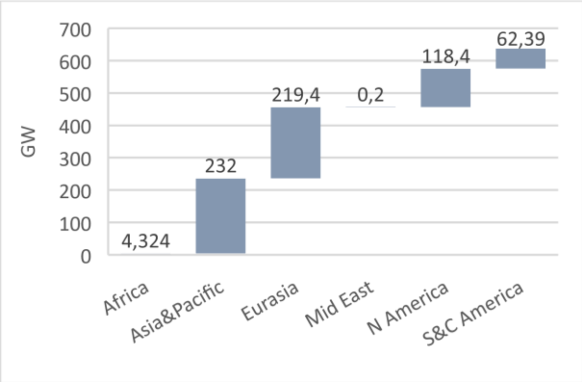
According to logistic model annual new capacity installations in the region peaked between 2012 and 2013. The carrying capacity is estimated at 232 GW. This is the largest estimate of all other regions. Yet it falls short of the expected 900 GW in 2030 (IEA, 2010) by almost a factor of 4.

Table 3.7. *Logistic and Exponential Models*. Asia&Pacific

	Logisitc					
	K(GW)	r	t(p)	2040(GW)	SSE	RMSE
Forecast	232	0.426	2012	232	70.29	2.096
95% Upper bound	253.1	0.460	2013			
95% Lower bound	211	0.393	2012			
	Exponential					
	K(GW)	r	t(p)		SSE	RMSE
Forecast	N/A	0.248	N/A	94954.1	1083	7.981
95% Upper bound	N/A	0.276	N/A			
95% Lower bound	N/A	0.220	N/A			

K(GW) – carrying capacity (the upper asymptote of logistic curve)
r – growth rate of cumulative capacity
t(p) – is the year of peaking annual installations of new capacity
2040(GW) – is the model specific forecast of cumulative capacity in year 2040
SSE – Sum of squared errors
RMSE – Root-Mean-Squared-Error

Let us draw a line under regional assessments and look at the entire picture of the world in 2040. After going through each part of the world and assessing their potential in wind capacity, I found out that in all of the cases the cumulative capacity follows logistic development. In all my curve fitting instances the logistic model fitted the data better than exponential. The logistic remains hardly distinguishable from exponential curve until it reaches the midpoint, where the slope of the tangent line applied to annual change in capacity becomes equal zero. Since the logistic curve is symmetric, it travels the same distance from midpoint to the upper asymptote, as it made from the lower asymptote to the midpoint. Thus, the upper asymptote is largely determined by location of midpoint, where the acceleration of growth turns negative. Whenever the data start to follow the asymptotic trend, the parameter K of the logistic is able to catch this dynamics and adjust accordingly. This observation is confirmed by most curve fitting instances, except two – Eurasia and Asia&Pacific. I assume that in those two cases the data was lacking curvature required by an exponential curve. Thus the software algorithm fitted the exponential so (minimizing RMSE) that it started deviating from the logistic later then midpoint of the logistic curve.



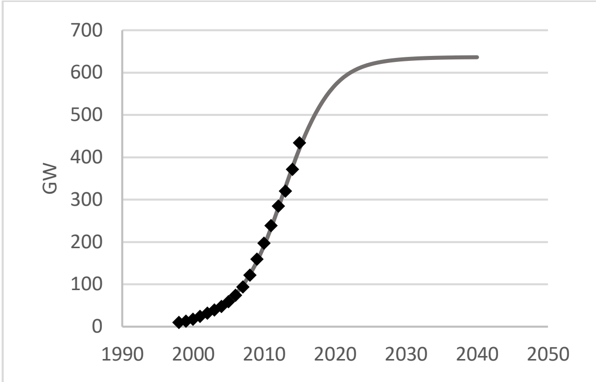


Figure 3.6. *Regional contributions to total global wind capacity in 2040(left) and modelled cumulative combined regional capacity (right).*

Figure 3.6 shows regional contributions to global wind capacity, which all-together amounts to 636 GW in 2040. We see that Asia&Pacific is the largest contributor to global wind capacity with 232 GW, Eurasia being the second largest adding up 219.4 GW. Distant third is North America with just 118 GW. The smallest contributor is Mid. East with just 0.2 GW in 2040.

The logistic curve fitted on global data predicts carrying capacity saturation at 650 GW, with the lower 95 % confidence bound at 590.6 GW and the upper at 710.5 GW. Thus, my combined regional estimate for 2040 lies within 95% confidence bounds estimated by logistic model of global capacity. Hence, the estimate on the global data has been confirmed by regional dynamics. If we assume 650 GW as the forecast of installed wind capacity in 2040, we can obtain the percentage of global primary energy demand covered by wind in the same year.

From the forecast of primary energy demand in Appendix 7.1, we assume that the world will require 25TW of primary energy supply in 2040. Next, we have to take into account the typical capacity factor for wind, which can be assumed at 35% (Narbel et al., 2014). We multiply total capacity of 650 GW by 0.35 to obtain 227.5 GW actual energy produced per year. Next, I divide 227.5 GW by 25 TW to get 0.91% of total primary energy demand supplied by wind in 2040. This is a very low estimate, making wind just a marginal source in global energy mix of the future.

The logistic model shows that current progress made by wind industry is far too little to be able to talk about the future dominated by renewables, at least in relation to wind power. The wind capacity was expanding in some isolated parts of the world, like Denmark and Germany and China; however, the overall global picture is far from bright. What exactly drives wind capacity up will be the topic of the following chapter.

3.3 Relevant Case of Denmark

Renewable energy and the efficient use of energy have played a central role in Danish energy policy for more than three decades. Denmark is the first mover in the wind industry. As of 2015, 42% of total Danish electricity consumption is supplied by wind (Energinet, 2016). Abundant with wind and shallow seas nearby, the total offshore wind power in Denmark made up 1270 MW in 2015, including the newly installed 400 MW large-scale offshore wind farm at Anholt. This amounts to a quarter of total wind energy capacity, estimated at 5 GW as of 2015 (Danish Wind Industry Association, 2016).

In the 1970s, rising environmental awareness, the oil crisis and the anti-nuclear debate had a major impact on the reformulation of the Danish government's energy policy. In the 1980s, the government focused its policy on reducing dependence on fossil fuels and subsidizing clean energy sources. Under its energy plans, the Danish government was Europe's first country to bring in large subsidies for its nascent wind industry, including the feed-in-tariff system, which was successfully replicated in Germany. The industry also received significant subsidies for R&D in the late 1970s and the 1980s. The country is also a pioneer in the use of environmental taxation, with a range of primary energy taxes introduced since the 1980s. These taxes were designed inter alia to reduce air pollution and CO_2 emissions, encourage energy efficiency, and support renewable energy (IRENA, 2013).

Cooperatives have played an important role in the development of wind power by helping create public acceptance. Their engagement has ensured that communities directly benefited from wind power development, especially in the form of profit sharing from electricity generation from renewable energy sources and from lower energy taxes. The planning responsibility for offshore wind farms is currently managed at government level, while the planning of onshore wind farms is collaborative.

In the early 1990s, a new energy plan provided a feed-in tariff for wind, which led to rapid growth in the wind sector between 1994 and 2002. Coordinated government support mechanisms such as long-term R&D support, premium tariffs for wind electricity generation and ambitious national targets helped the domestic wind industry to mature. However, with a change in government in 2001, and the phasing out of the feed-in tariff there was stagnation in the wind sector until the end of 2008 (IRENA, 2013).

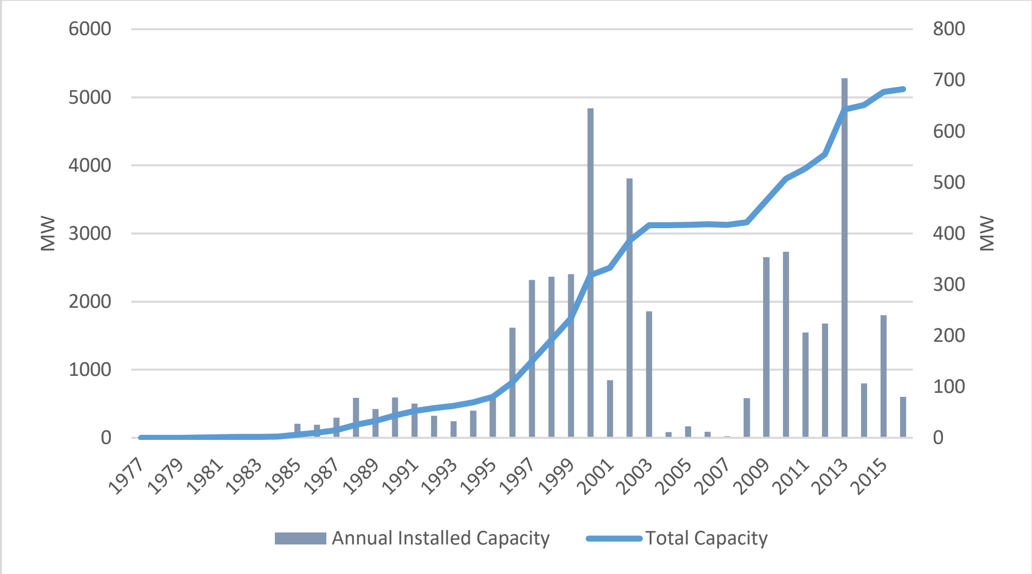


Figure 3.7. *The dynamics of Denmark's wind capacity (Enegistyrelsen, 2016).*

Figure 3.7 depicts wind capacity dynamics in Denmark between late 1970s and the present. First of all the annual capacity additions, including new capacity and substitution of retired capacity, make the case or my assumption in Figure 3.5. There I predict that global annual installations will establish two humps (peaks). The first hump is driven by peak in new capacity installations; the second hump is caused by peak in substitution capacity.

The second interesting observation from this graph is the dynamics of total capacity. We can observe a plateau between 2003 and 2008. This was the period, when the government phased out feed-in-tariffs. The dynamics between 1977 and 2008 can be approximated by a sigmoid curve; however, the curve seems to be non-symmetric. If we were to fit a sigmoid to the total capacity data back in early 2000s, we would have concluded that Danish capacity has a saturation level just over 3 GW and it is not expected to grow further. Yet after 2008, we see upward dynamics in total capacity again. This case reminds me of a paper by Meyer and Ausubel (1999), where they describe a model with logistically varying limits.

They modify equation 2 by turning carrying capacity constant *K* into a variable *K(t)*. They say that *K(t)* can be a function in its own right. *K(t)* may vary sinusoidally, exponentially, logistically and linearly. In their study, Meyer & Ausubel (1999) attempt to study the dynamics of population in England from the Middle Age until the present. They choose to implement logistic variation in carrying capacity *K(t)*. Thus, they arrive at a model establishing bi-logistic growth, where a growth trajectory nearing the initial carrying capacity or ceiling starts growing again to a second, higher, carrying capacity (Meyer & Ausubel, 1999). This bi-sigmoidal trend is very likely to be the case for Danish wind capacity.

In 2009, the wind market in Denmark was revived due to the United Nations Climate Change Conference in Copenhagen 2009, and the setting of a long-term European target for promoting electricity generation from renewable energy sources. Over the last ten years, some sections of the local communities have been protesting against any further building of onshore wind turbines across the country. This has made private sector development of wind farms very cumbersome in the last decade. Another big challenge to further development of wind capacity in Denmark are electric grid bottlenecks. The transmission system operator is supportive of the further wind development, and has designed a comprehensive plan on how to tackle the problem. Energinet plans to supply 50% of the demand with wind power by 2025 (IRENA, 2013).

Denmark is a pioneer in Wind energy; it has much longer history with wind installations, than rest of the world. Thus observing the current dynamics in Danish wind sector we may be having a peek into the future for the global wind industry. What can be learned from the case of Denmark?

First, Danish wind capacity, indeed, established sigmoid trend, although not logistic. Secondly, a sigmoid trend may have several capacity ceilings. After the first ceiling is saturated, a plateau may appear, and then the second stage of sigmoid growth may begin. In fact, there might be more than two such stages of growth. In case with my prediction for Wind capacity in 2040, I have a plateau stage which starts in 2020 after 90% of carrying capacity is saturated. My plateau stage lasts for 20 years, which may be a bit too long, at least by looking at the Danish case. It is possible that the new growth loop in total capacity will begin around 2030. The application of such model with varying limits to various energy systems can be an interesting topic for further research.

Another takeaway from Denmark’s wind history is the importance of government subsidies for continuation of capacity growth. The plateau, located between years 2003 and 2008, was caused by phasing out of feed-in-tariffs. The influence of government subsidies on wind power capacity will be discussed in the following chapter.

3.4 Implications and further research

The important limitation in current research work is data availability. When performing may forecast, I had annual capacity data running between 1997 and 2015 (19 data points). The quarterly or monthly data were not available. The econometric consensus has it that a sound regression with predictive power should have at least 10 data points for each parameter fitted. (Frost, 2015) In case with the logistic curve I had three fitted parameters for 19 data points, which is short of above stated consensus requirement. Despite that, low RMSE scores on logistic fits suggest relatively accurate performance of the chosen models. Most importantly, the regional model has verified the predictions on global data for carrying capacity.

Two more issues with performed curve fitting can be observed in residual plots in Appendix 7.2. Logistic and Exponential residuals plotted against independent variable establish a pattern, pointing to autocorrelation. Autocorrelation does not violate the estimates of coefficients, however, it adversely affects standard errors, which compromises validity of test statistics (Wooldridge, 2009). Similar issues were encountered in other works attempting to simulate energy capacity with a logistic trend (Höök et al., 2012), (Hansen et al., 2016). Other studies chose to avoid providing residual plots (Xia & Song, 2009), (Marchetti & Nakicenovic, 1979) (Nashawi et al., 2010). It would have been interesting to apply an autoregressive logistic curve (de Pinho et al., 2013) to wind capacity, which may be the point of departure for further research. In addition, it would be interesting to see if wind capacity will establish the logistic pattern with several capacity ceilings as described above.

The realization of my forecast dwells on many uncertainties, e.g. future development in wind costs, availability of reliable storage, public perception of Climate Change, breakthroughs in other competing technologies, prices and availability of fossil fuels, etc. Significant change in any of the specified major factors can validate or invalidate my forecast. It would be very interesting to look at other renewable energy sources, e.g. solar, and perform a similar analysis of global and regional trends in investment and capacity to see if they follow a logistic trend.

4. What drives wind capacity upward

In IRENA's report on the success story of Danish wind industry, it is specified which factors played the main role in growth of wind installations in the country. They key factors were efficient and supportive government, well-developed policies and pricing mechanisms, broad *public involvement through cooperatives and wide support from Danish society* (IRENA, 2013). *The high costs of green transformation were passed on to the public. Denmark's households pay the highest electricity bills in the entire EU 28. Another European country with large share of electricity supplied by wind, Germany, sits just behind Denmark in the list of European household electricity prices* (Eurostat, 2016).

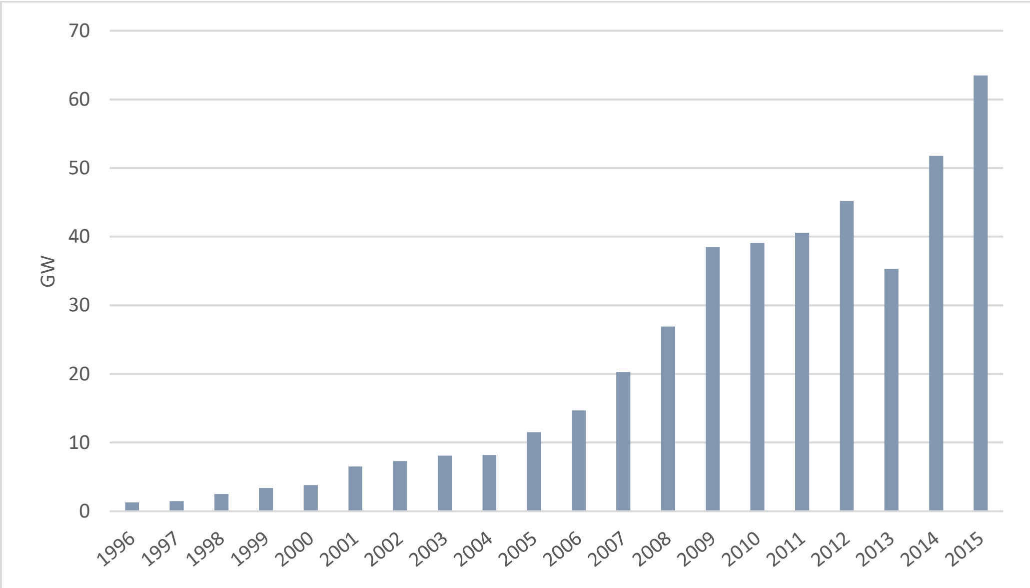


***Figure 4.1**. Global annual wind capacity additions (GWEC, 2016).*

In this chapter, we will look at major factors fostering development of wind capacity around the globe. Investment is the main driver of capacity. Meanwhile, resource availability, declining installation costs, high prices for gas and coal, supportive government policies and investment in infrastructure drive up wind power investment.

4.1 Investment

Analogous to biological systems, where environmental resources such as food and habitat enable growth of living organisms, wind capacity growth requires investment and available area with good wind conditions as minimum requirements. Investment is the mechanism that gives birth to new wind capacity, however, not necessarily with immediate effect, since there are several types of investment.

R&D investment is aimed at improving the efficiency of wind technology and comes from various public and private sources. A perennial target of wind R&D has been to reduce the weight of the nacelle at the top of the tower – because weight at the top requires the entire structure to be made with additional strong material, pushing up the capital expense. One way to grow the offshore wind industry is to open new markets, particularly in those regions where sea depths make conventional fixed-bottom projects impossible. This requires the development of floating wind turbines. Hywind Scotland Pilot Park is an example of such an R&D project. R&D investment causes growth in total capacity indirectly (Frankfurt School - UNEP Collaborating Center for Climate & Sustainable Energy Finance, 2016).

Asset Finance of utility-scale projects are the largest category of renewable energy investment. This type of investment is directly related to new capacity installations and repowering. Six of the top 20 global wind deals in 2015 were for offshore projects in China. The largest project in onshore sector was Mexico's Nafin wind farm portfolio, at an estimated $2.2 billion with nameplate capacity of 1.6GW (Frankfurt School - UNEP Collaborating Center for Climate & Sustainable Energy Finance, 2016).

Public Market Investment allows private and institutional investors to contribute to expansion of wind energy globally and locally. It includes Initial Public Offerings (IPOs), Private investment in public equity, Convertibles and Over-the-counter (OTC) investment (Frankfurt School - UNEP Collaborating Center for Climate & Sustainable Energy Finance, 2016). Wind power stocks have largely underperformed the global stock markets between 2012 and later stage of 2016 (Bloomberg Markets, 2016).

Venture Capital investment is rather untypical for wind industry due to large initial sums of capital investment required, which are affordable only for institutional investors and major corporations. In early 2015, however, French start-up Ideol, a designer of floating foundations for offshore wind farms, received $4.4 million in a second seed-funding round. The company recently signed a deal with the China Steel Corporation, the largest integrated steel maker in Taiwan, to jointly develop turbines using Ideol's technology (Frankfurt School - UNEP Collaborating Center for Climate & Sustainable Energy Finance, 2016).

Wind is the largest sector for acquisition transactions among renewables. In 2015, corporate M&A went up 161% on the year before at $10.7 billion. This type of investment activity shows a growing trend (Frankfurt School - UNEP Collaborating Center for Climate & Sustainable Energy Finance, 2016).

Debt is the principal investment mechanism in wind power. In 2015, commercial banks provided most of the project-level debt for wind farms in established markets such as Europe, North America, China and India. Bonds have been an alternative to conventional bank project finance for many years. A significant proportion of the green bond issuance also came from development banks and utilities.

Utilities continued to be an important source of equity finance for renewable energy projects at the development or preconstruction stage. Institutional investors such as insurance companies or pension funds tend to be more risk-averse and therefore interested in the predictable cash flows of an operating stage of a project (REN 21, 2016).

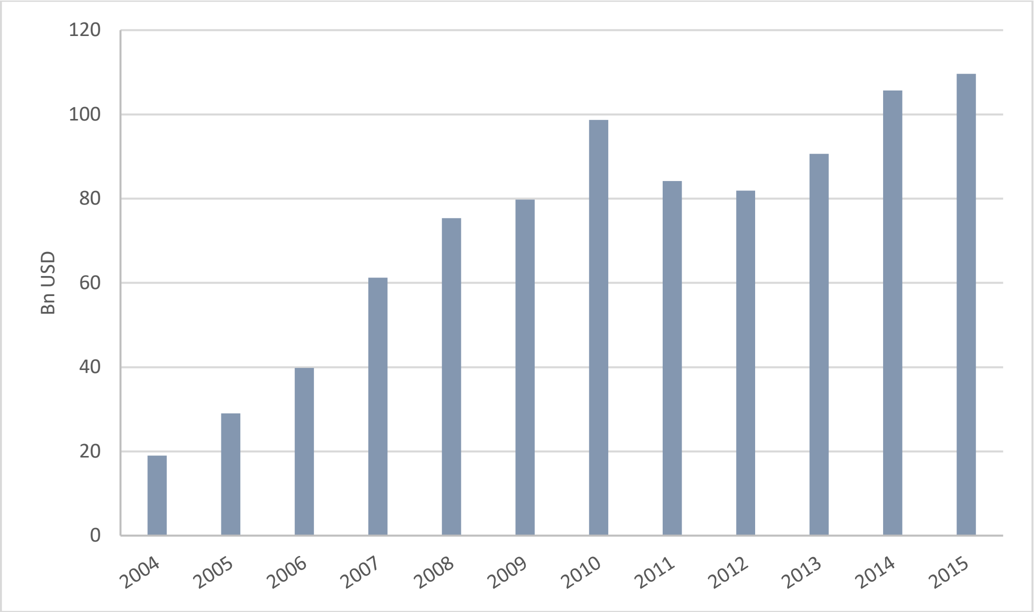


Figure 4.2. *Global annual investment in wind power (Frankfurt School - UNEP Collaborating Center for Climate & Sustainable Energy Finance, 2016).*

Wind Power is ranked second in terms of received investments in 2015 after solar power. Wind power attracted $109.6bn in new investment globally in 2015. Together wind and solar contributed to 94.7% of new investment in renewables. Previously the majority of investment in renewable capacity came from developed countries; however, in 2015 the developing countries have taken over leadership. In particular, significant role in global expansion of renewables is played by China, India and Brazil. Compound annual growth rate (CAGR) for wind investment between 2004 and 2015 has been 15.72%.

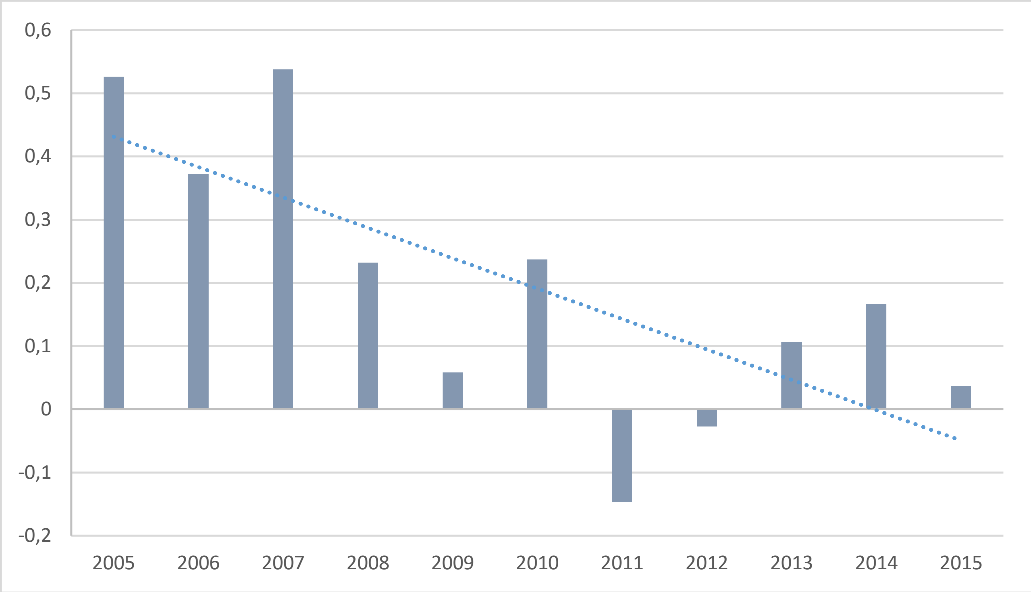


Figure 4.3. *Annual growth rates in global annual wind investment*

Annual growth in wind investments has seen steadily declining rates. Figure 4.3 displays a linear trend applied to annual growth rates as a function of time. The line produces a negative slope of -0.048 significant at 95% level. The fact that annual growth in investment is significantly declining creates at expectation of sigmoid trend in the path of future investment. According to the linear model, annual growth rates in investment turn negative in 2015.

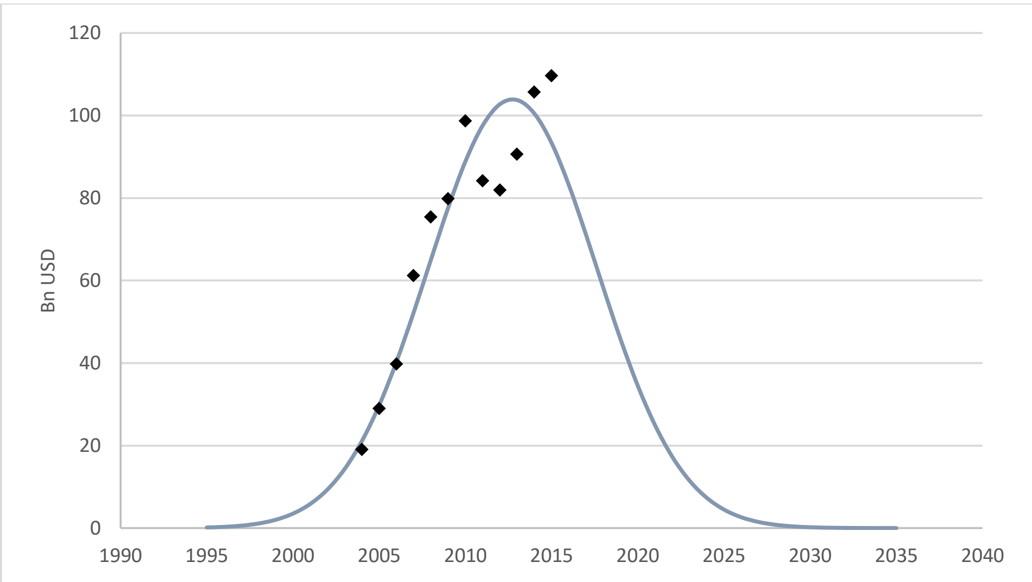


Figure 4.4. *Hypothesized bell-shaped trend in annual wind investment*

Figure 4.4 produces hypothesized bell-shaped development of annual wind power investment. To get this model I converted annual investment data to logs (Appendix 7.3), applied a parabolic trend to logs as a function of time ($R^2=0.94$), extended the data backward and forward and then exponentiated the cuve back to bn USD. The curve is peaking in 2013, the same year as new annual capacity in my model.

This observation contrasts with renewable energy industry's views on investment in the future. IRENA's analysis (2015) shows that global annual investment in renewables can reach USD 900 billion by 2030(about 9 times more than currently). "In order to avoid lock-in with unsustainable energy systems, annual investments between now and 2020 should reach USD 500 billion(about 5 times more than currently), almost a doubling from current levels of investments" (IRENA, 2015). My study does not observe any significant growth in annual invesmtent. It rather reports the opposite conclusion – the growth is slowing down in a significant way.

4.2 Levelised Cost of Electricity (LCOE)

The Levelised Cost of Electricity (LCOE) has been designed with the idea of allowing for comparisons between energy sources on a unit cost basis over the lifetime of different energy technologies/projects. Three distinct elements, namely capital costs, operation and maintenance costs and fuel costs, are evaluated under the LCOE approach (Narbel et al., 2014).

$$C_{LCOE} = \left[\frac{R * c_p}{H * f}\right] + \left[l * \left(\frac{c_0}{H * f}\right)\right] + \left[l * \left(\frac{c_f}{H * f}\right)\right] \quad (13)$$

$$R = \frac{r * (1 + r)^T}{(1 + r)^T - 1} \quad (14)$$

$$l = \frac{r * (1 + r)^T}{(1 + r)^T - 1} * \frac{(1 + e)}{(r - e)} * \left[1 - \left(\frac{1 + e}{1 + r}\right)^T\right] \quad (15)$$

In the first square bracket of expression (13) we have c_p which stands for initial capital outlay to install wind turbine and connect it to the grid; f is a capacity factor, meaning the percentage of hours out of total 8760 hours per year, H, which the turbine was producing power at 100% of its capacity. R (14) is the share of the plant cost that the income must cover over each year of operation such as to balance out the whole project at the end of the plant life. The wind turbine in itself accounts for most of the total investment as it makes between 68–84 % of the total investment cost (Narbel et al., 2014).

Table 4.1 *LCOE Cost components*

LCOE Components			
c_f	Fuel cost USD/MW	H	Hours per year
c_0	O&M cost USD/MW	l	Levelization factor
c_p	Investment at t=0 USD/MW	r	Discount rate %, $r \neq e$
e	Escalation rate %, e≠r	R	Capital recovery factor
f	Capacity factor %	T	Plant life in years

In the second square bracket (13) we have c_0, which are variable and fixed O&M costs, grouped together. It is plausible to assume that O&M costs will grow, as the power facility is aging. To correct for that we employ levelization factor *l (15)*. This factor depends on the discount rate *r* and on an escalation rate *e* measuring by how much the O&M costs are expected to increase annually.

Operation and maintenance costs in the case of wind power are relatively low, compared to other electricity generating technologies. O&M costs are generally between 1 - 4 cents/KWh and include various insurances, overhead costs, spare parts and labour costs. Generally, O&M costs increase with the age of the wind turbine (Narbel et al., 2014).

The third square bracket contains the cost of fuel, labelled as c_f. When the fuel costs for a year are known; these can be transformed into a unit cost basis by integrating a levelization factor, the capacity factor and the number of hours in a year. The parameter *e* in the levelization factor for O&M and fuel costs are going to have different values.

The formula is the general case for comparison between various electric power sources including coal, gas, nuclear, hydro and other non-hydro renewables. Wind power is dependent on wind to produce electricity. As wind is a free commodity, no fuel costs need to be borne by the producer. Thus, we are able to transform the formula in order to adjust it to specifics of wind power.

According to Ragheb (2015), LCOE for wind has to include government incentives and tax credits. Thus, we can come up with adjusted formula for wind LCOE:

$$C_{LCOE} = \frac{R*c_p+l*c_o}{H*f} - S_t \quad (16)$$

Where S_t stands for government subsidies in USD/MWh, for example, depreciation tax credit or Production Tax Credit (PTC).

An important parameter in this formula is r, the discount rate, which is hidden in R and l parameters. The discount rate is chosen depending on the cost and source of investment capital. It implies the balance between debt and equity financing as well as perceived riskiness of the project. It should also consider the inflation effect; therefore using real interest rate is advisable. As we can observe from R, $\lim_{r\to 0} R = 0$ and from l, $\lim_{r\to 0} l = 0$, and hence $\lim_{r\to 0} C_{LCOE} = 0$. Thus, we have mathematically proven that low interest rates are beneficial for development of wind energy.

Another interesting parameter is capacity factor f. A typical capacity factor for a wind turbine is in the range 25 – 40 %. At first glance, one may think that the higher the capacity factor, the lower is LCOE. This may follow from equation (13). However, in reality the capacity factor is less important since the cost of wind is equal to zero. The capacity factor would vary between different models of a turbine; likewise, the cost of the turbine will increase with growth in capacity factor. Overall what counts is the lowest possible cost per MW of energy produced, not capacity factor by itself (Ragheb, 2015).

A typical project lifetime T is equal 20 years (Narbel et al., 2014). Now let us find LCOE for a utility scale wind turbine with nameplate capacity of 2 MW. In order to perform the calculation, we will have to make some reasonable assumptions about various parameters as presented in Table 4.2. We keep parameter S_t equal to zero this time and will use it later for comparison with this base case.

Table 4.2 *Assumptions for LCOE calculation.*

Parameter	Value	Units
Turbine and installation cost	4,000,000[5]	USD
Capacity factor	30	%
O&M cost	4,000	USD/year
r	5	%
e	1	%
T	20	years
Capacity	2	MW
H	8,760	hours

First, we estimate Capital recovery factor (14):

$$R = \frac{0.05 * (1 + 0.05)^{20}}{(1 + 0.05)^{20} - 1} = 0.08$$

Second, we find levelization factor (15):

$$l = \frac{0.05 * (1 + 0.05)^{20}}{(1 + 0.05)^{20} - 1} * \frac{(1 + 0.01)}{(0.05 - 0.01)} * \left[1 - \left(\frac{1 + 0.01}{1 + 0.05}\right)^{20}\right] = 1.094$$

Third, we obtain c_p and c_o:

$$c_p = \frac{4000000\ USD}{2MW * 8760\ hours * 0.3} = 761.04\ USD/MWh$$

$$c_o = \frac{4000\ USD}{2MW * 8760\ hours * 0.3} = 0.761\ USD/MWh$$

[5] The estimate from the website windustry.org

Finally, C_{LCOE} (13) is:

$$C_{LCOE} = 765.04USD/MWh * 0.08 + 0.761USD/MWh * 1.094 = 61.90USD/MWh$$

Thus, we have obtained LCOE estimate for a 2 MW turbine with exploitation of 20 years and project discount rate of 5%. In per kilowatt-hour basis, LCOE is 0.0619 USD/KWh.

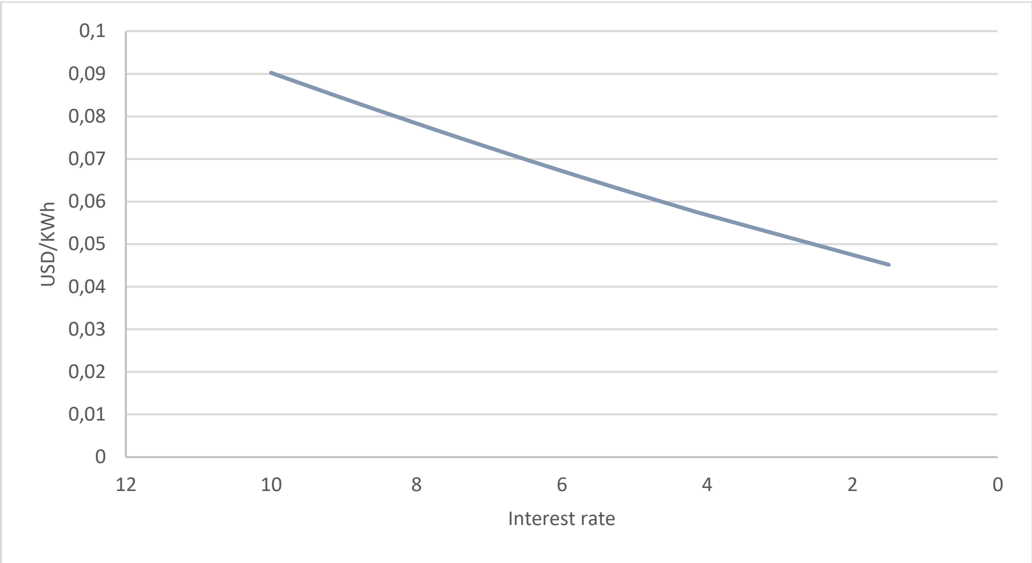


Figure 4.5. *Dependence of LCOE on interest rate r (%)*

Figure 4.5 shows variation of LCOE with change in interest rate. With halving of interest rate from 10% to 5%, LCOE has fallen by one third.

Based on historic data in Appendix 7.4 , wind LCOE fell from an estimated USD 0.25/KWh in 1983 to around USD 0.06/KWh in 2013 (Narbel et al., 2014). Increased capacity factors (due to technology improvements) and declining wind turbine costs each have accounted for around one-third of the reduction in LCOE since 1983; the remaining one-third is due to other capital cost reductions and declining operation and maintenance costs. I have estimated CAGR on averaged LCOE for onshore and offshore wind between 1995 and 2015 at -3%. In Appendix 7.5, one can find prediction trend for onshore and offshore wind between 2016 and 2040, made by US National Renewable Energy Laboratory (NREL). They expect LCOE onshore to stabilize at the level of 0.048 USD/KWh, whereas offshore wind cost decline from current 0.16 USD/KWh will stop at around 0.1 USD/KWh, making it twice more expensive compared to onshore technology.

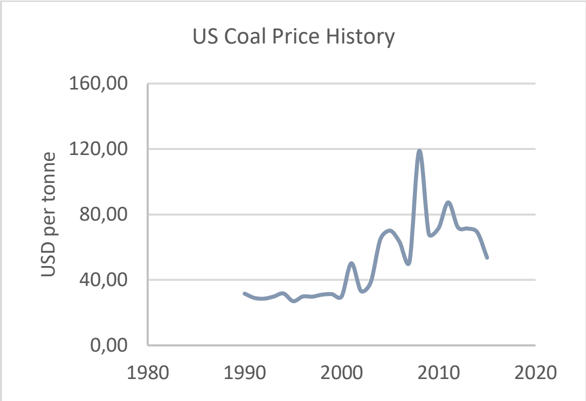
4.3 Competing Fuels

The two dominant elements in global energy mix are coal and natural gas. As of 2010, they covered 48% of human energy needs (Narbel et al., 2014).

Coal has for centuries been used for domestic heating, but today most of the coal is used for fueling electric power plants. In fact 41 % or 8,700 TWh of the electric energy produced globally in 2010 came from coal-fueled plants. Coal is one of the most abundant fossil fuels on Earth, and usually easier and cheaper to explore and produce than other fossil fuels such as oil and natural gas. The biggest issue with coal is that it is a top emiter of green-house gases among all fossil fuels. Burning of coal emits the following harmful particles: CO_2, SO_2, NO_x, CO, organic compounds and particulate matter. The major effluent from the coal-fueled power plant is of course carbon dioxide (CO_2) which is the product of burning carbon (coal) in an oxygen rich environment. CO_2 is believed to be the main contributor to global warming (Narbel et al., 2014).

Overall, the global production and consumption of coal have increased over time. Almost all of the additional production took place within non-OECD countries, parallel to the growth of their energy needs. The share of the production taking place in OECD countries fell from 56 % in 1971 to 26 % in 2012.

Over the past decades, environmental pressures have forced the coal power plants to become more efficient in terms of emissions and the average efficiency of new coal based power plant is steadily increasing around the planet. Yet, as these power plants have a long economic life (over 40 years), the average efficiency is only slowly improving. The current policies, dictated by Paris Agreement, require all nations, that ratified the Agreement, to contribute to curbing emissions globally, by limiting average temperature increase to 2 C compared to preindustrial period. This would require a steep decrease in the use of coal in the next decades.



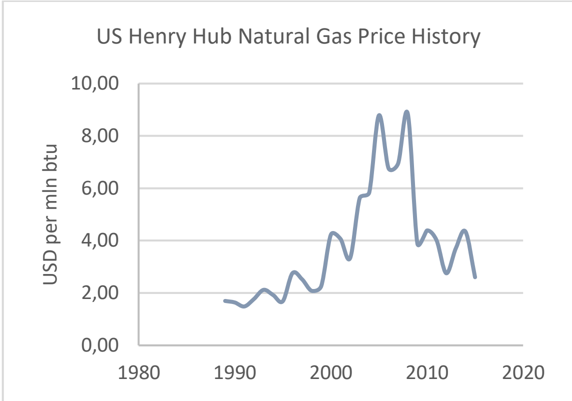


Figure 4.6. *Historical prices for coal and natural gas in the US* (BP, 2016).

Between 35 and 70 % of the LCOE for coal-fired power plants is related to the cost of fuel (Figure 4.6.). At the moment, coal is one of the cheapest electricity generating technologies and even a moderate increase in the price of coal should not impact this statement. LCOE for a typical black coal power plant in US stood at around 0.04[6] USD/KWh in 2015. However, major environmental regulations, as, for example, required installation of Carbon Capture Technology are expected to increase LCOE above 0.1 USD/KWh (EIA, 2016).

Figure 4.7. produces the dynamics of coal LCOE following growth in prices of coal. We can observe that a price of 110 USD/tonne is required in order to reach grid parity with wind. Average coal price in US in the period 1990-2015 was 50.48 USD/tonne. Let's assume that utilities purchase electricity at 0.05 USD/KWh (Ragheb, 2015) from the owners of coal plant and owners of wind farm. Since electricity markets globally are dominated by coal and gas-fired plants, it is plausible to assume that market prices for electricity are determined by the cost of electricity production from those fossil fuels. At that price coal invesors will receive profit of 0.05 USD/KWh-0.04USD/KWh=0.01USD/KWh. Meanwhile the investor in wind is losing money, since his profit is 0.05USD/KWh-0.062USD/KWh= -0.012USD/KWh. We ignore taxes and subsidies.

[6] Neither Carbon Capture, nor Carbon price included in the estimate.

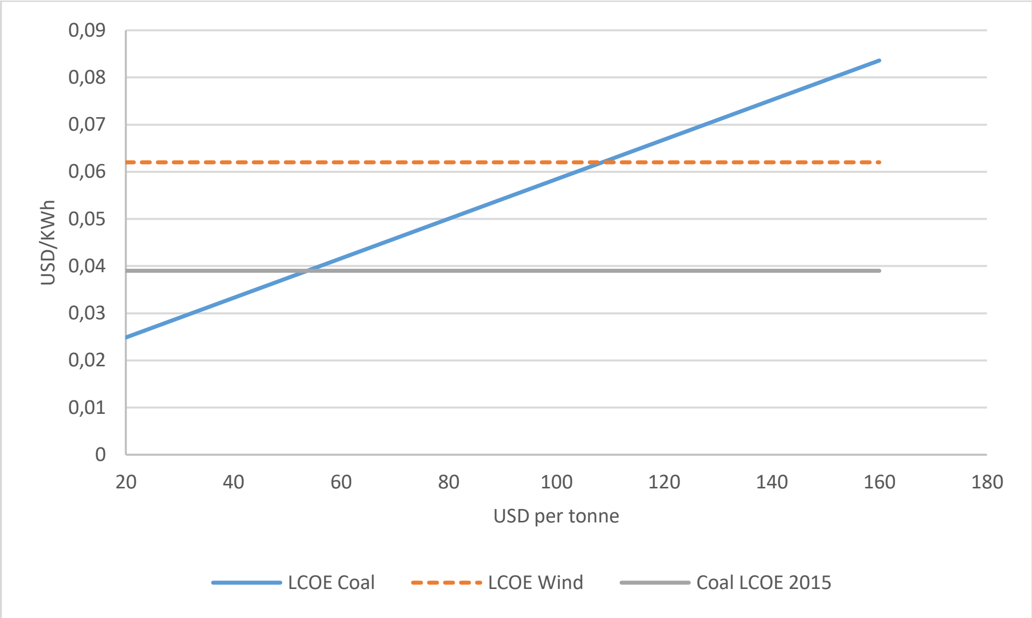


Figure 4.7. *Change in coal LCOE as a function of coal price. Price data from BP (2016)*

Natural gas is used as a fuel by combined heat and power plants (CHP). The capital costs necessary to build a gas-fired power plant are low and the construction times short compared to other fossil fuel-based technologies. In addition, natural gas power plants combine a very high operational flexibility, high efficiency levels and a comparatively low carbon emission compared to other fossil fuel energies such as coal. These characteristics naturally make natural gas attractive to the eyes of many plant operators, investors and governments. Historically, the transformation of natural gas into electricity has been gaining in importance and the natural gas consumption has risen steadily over the past decades.

Fuel cost makes up between 61% and 87% of gas LCOE (Figure 4.6). The average LCOE estimate in US in 2014 was 0.05[7] USD/KWh (Narbel et al., 2014). Figure 4.8 shows the influence of gas prices on LCOE of natural gas power plant. We see that gas price above 7 USD/mmbtu is needed for gas to reach grid parity with wind. Average gas price in US between 1989 and 2015 has been 3.78 USD/MMBtu. Let us assume that public utilities offer the price of 0.055 USD/KWh to gas and wind investors. The owners of gas plant (LCOE at 0.034 USD/KWH) will have a profit margin of 0.021 USD/KWh. Meanwhile the owners of wind park (LCOE at 0.062 USD/KWh) will end up with negative profit margin of -0.007

[7] Neither Carbon Capture, nor Carbon price included in the estimate.

USD/KWh. We ignore taxes and subsidies. Again, it turns out that investing in wind capacity is not economically profitable.

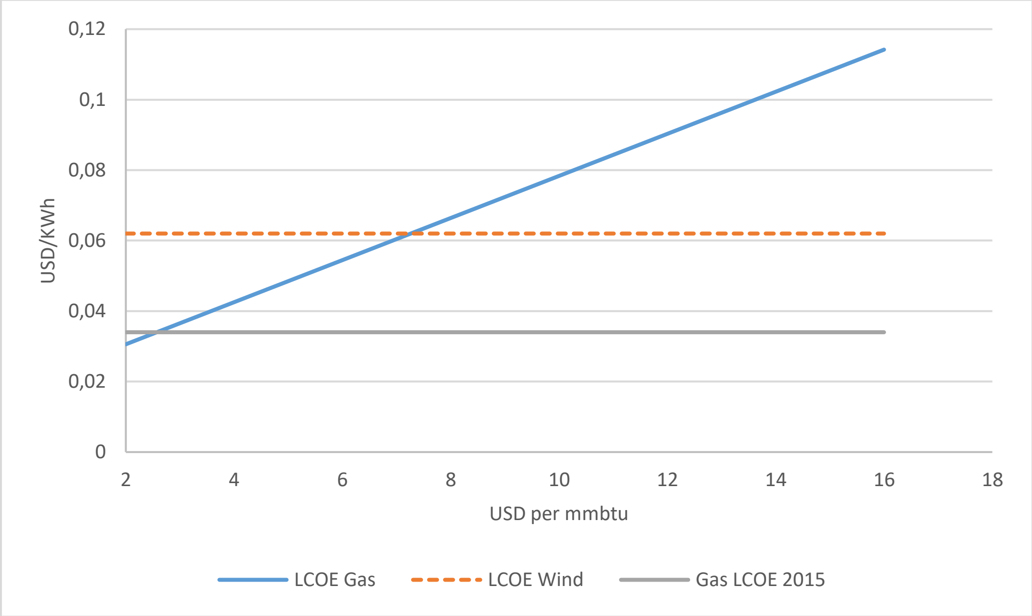


Figure 4.8. *Change in gas LCOE as a function of gas price. Price data from BP (2016).*

4.4 Government policies

Many countries have developed strategies to encourage wind power development to address their commitments to control CO_2 emissions. It is important to note, that renewable policies are practiced on the national and subnational level, when certain regions of a country unilaterally pursue their own targets and policies.

Worldwide, targets for renewable energy continue to be a primary means for governments to express their commitment to renewable energy deployment. As of year-end 2015, renewable energy targets had been pledged by 173 countries at the national or state/provincial level (REN 21, 2016). Targets also have been adopted at the regional level, incorporating joint commitments by several countries. Targets are introduced in a variety of ways, ranging from announcements by governments or heads of state to fully codified plans accompanied by quantifiable metrics and compliance mechanisms. For example, the EU built on its 2020 targets by establishing a long-term objective of a minimum of 27% of final renewable energy consumption by 2030. Notably, Hawaii announced its intention to become the first US state to run entirely on renewable power, setting an RPS mandate for 100% renewables by 2045 (Timilsina et al., 2013).

The main policy instruments countries employ include feed-in tariffs (FiTs), capital subsidies, tax incentives, tradable energy certificates, mandatory targets, renewable energy portfolio standards, priority in dispatching and guarantee to access transmission lines and long-term contracts. Among these policy instruments, FiTs are the most common.

In a pure FiT system, producers get a fixed price per unit of electricity fed into the grid for a specified period of 5 to 20 years. Investors favor this type of policy instrument as future prices are known in advance, therefore suppressing revenue risks. In that sense, FiTs are effective and result in the quick installation of renewable energy capacity, if they are sufficient. As of mid-2012, most developed and some developing countries introduced FiTs for wind energy (REN 21, 2016). However, FITs have the drawback of being immune to fluctuations in electricity demand and/or electricity spot market prices. Consequently, more and more countries, including Germany, Denmark, Slovakia, Finland and the United Kingdom, are moving into specialized forms of FiT such as fixed premium, feed-in premium with cap and floor prices and sliding premium (Ragwitz et al., 2012).

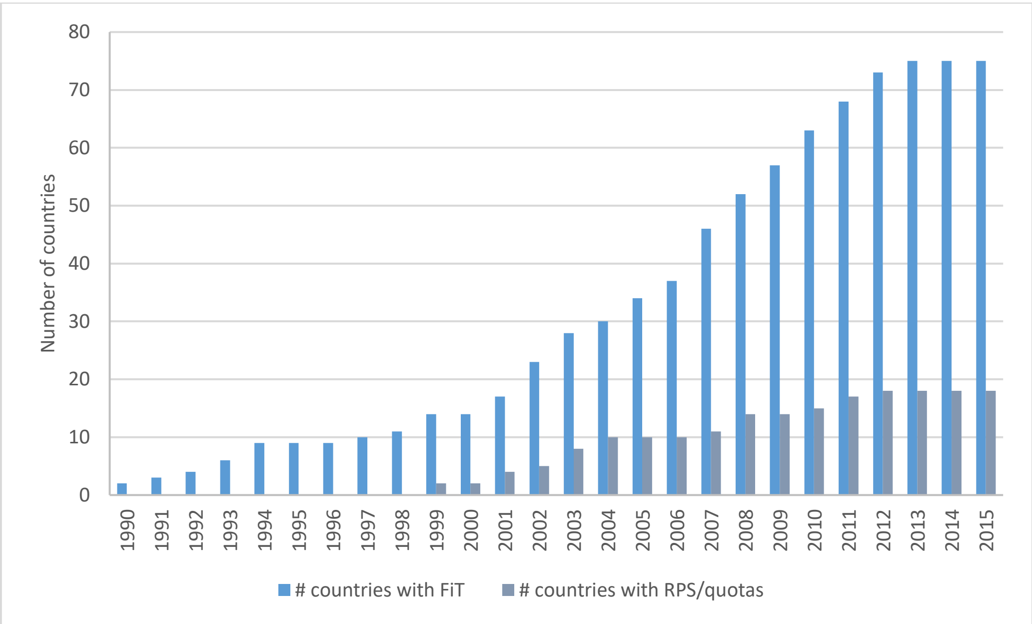


Figure 4.9. *Renewable Policies Worldwide (REN 21, 2016)*

As of year-end 2015, feed-in policies (feed-in tariffs and feed-in premiums) remained the most widely adopted form of renewable power support. FiT tariffs for renewables have been introduced in 75 countries (Figure 4.9). It is remarkable that the number of countries with renewable policies stopped growing after 2013. The dynamics in policies looks very similar to dynamics in global annual investments in Figure 4.2.

In addition to regulatory policies that stimulate increased renewable electricity generation, renewable obligations or mandates that require the deployment of renewable power capacity are in use worldwide. Electric utility quotas or Renewable Portfolio Standards (RPS) is the most common mandate in use at the national level to promote renewable power. A paper by Bird et al. (2005) finds that RPS had significant positive effect on wind investment in Texas, Minnesota and Iowa. A similar conclusion is made in the study of US policies by Menz & Vachon (2006). RPS policies were in place nationally in 18 countries by year-end 2015. The overall pace of new adoption at the national level has slowed significantly in recent years, and no new additions were made at the national level in 2015 (REN 21, 2016).

Figure 4.10 produces a different reality for our wind park: before the owner with LCOE of 0.062 USD/KWh had to sell produced electricity at the market price of 0.05 USD/KWh and hence was losing money on the investment. Now with the introduction of FiT by the local government, she can sell electricity at 0.08 USD/KWh and hence end up with profit of 0.018 USD/KWh. In this example we do not account for taxation. Thus investment in wind has become profitable, and more such investment can be expected as long as FiT is in place. In that case the price of coal is becoming irrelevant to the wind investor.

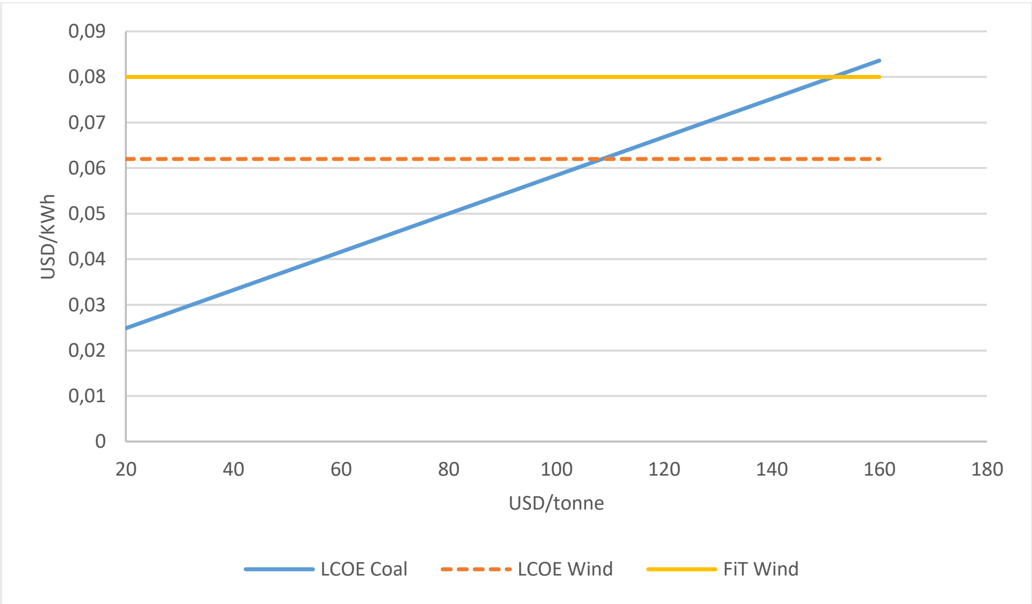


Figure 4.10. *Coal LCOE as a function of coal price. Introduction of FiT for wind power.*

Direct subsidies and tax credits are also common instrument used by policymakers. Most developed countries and some developing countries have provisions to provide capital subsidies (on investment and/or operation) or other forms of aid to renewable energy producers. In the United States, for example, a wind energy production tax credit (PTC) is used to encourage investment in wind generating capacity. It provides an income tax credit of 2.3 ¢/KWh in the US, that is adjusted annually for inflation and is valid for the first 10 years of production, but it applies only to large-scale power installations, while the existence of the program is subject to the whims of Congress. Since 1992, the Congress let the PTC for wind expire four times before eventually extending it again, giving birth to a boom and bust cycle in the installation of new wind power capacity (Ragheb, 2015).

Let us look at a different situation for our wind power producer. This time the local government has kept the market price for purchase of electricity at 0.05 USD/KWh, however they introduced PTC of 0.022USD/KWh with duration of 20 years instead (Figure 4.11). Effectively it is denoted as S_t in equation (16). If PTC equals 0.022 USD/KWh, our wind investor's LCOE drops to 0.04 USD/KWh. Now he is selling electricity at profit of 0.05 USD/KWh – 0.04 USD/KWh = 0.01 USD/KWh. In this example we do not account for taxation. As long as PTC keeps wind LCOE below the market price for electricity, the owner is willing to invest further into wind capacity. The price of natural gas becomes irrelevant.

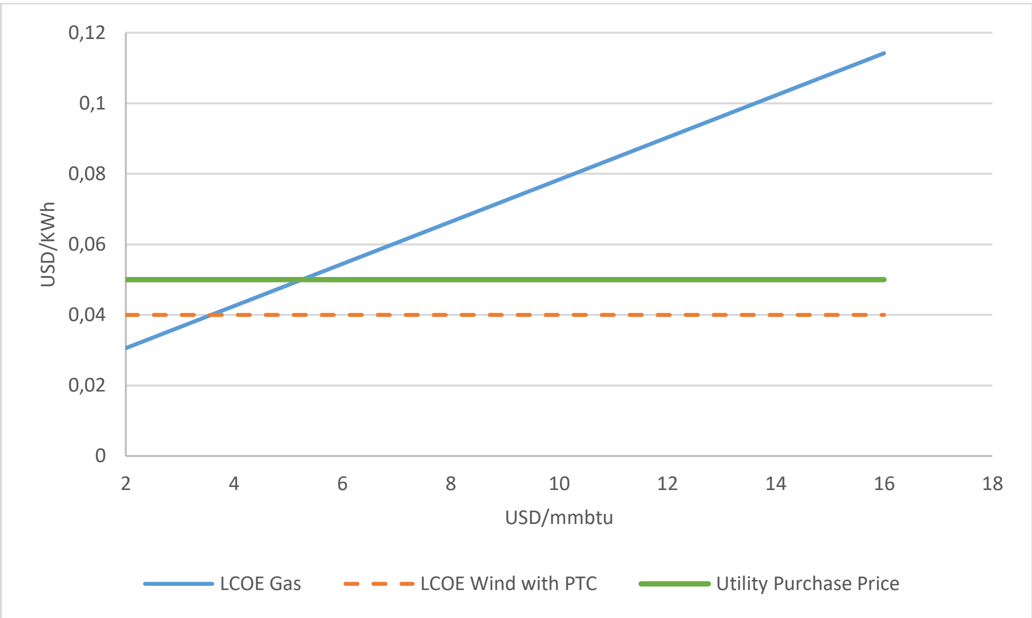


Figure 4.11. Gas LCOE as a function of gas price. Introduction of PTC for wind power.

Australia, Japan, California and some European countries have introduced tradable Renewable Energy Certificates (tRECs), also known in Europe as Tradable Green Certificates (TGC) to promote all forms of renewable energy. Under such a system, power companies are required to meet a given renewable energy target (in terms of installed capacity or share of electricity sold). Power companies will either be able to build new capacity or buy tRECS on the secondary market to meet their renewable energy targets (Timilsina et al., 2013).

The selection of policy instruments is highly influenced by national situations. Most countries have introduced more than one policy instrument. The small contribution of wind power to the global electricity supply mix implies that existing policies are not sufficient or existing fiscal incentives are too small. Since wind power is more capital intensive compared to conventional fossil fuel fired generating technologies, the relatively high capital costs continue to be an obstacle to the adoption of wind power at the scale supported by its potential.

The above examples show, how policy intervention may swing the investment choice in favour of wind, applied to onshore wind technology. The application of such policies to offshore wind would be the same in principle, but would require much higher magnitude of subsidizing. According to NREL estimation (Appendix 7.5), offshore LCOE is currently in the region of 0.16 USD/KWh and is not expected to drop below 0.1 USD/KWh any time soon.

As long as governments ignore the cost of externalities related to burning fossil fuels, fossil fuels may stay a cheaper alternative to produce electricity, than wind. Hence, wind would require constant subsidies in order to remain economical. If, however, governments will choose to add reasonable carbon tax to fossil fuel prices and mandate carbon capture technology, wind may become affordable without subsidies. These measures will likely increase electricity bills for households in the short and medium run, as they have done in Denmark and Germany.

4.5 Grid and storage

Introducing significant amounts of wind energy into the power system entails a series of economic impacts - both positive and negative. If high wind times coincide with peaking demand levels, introduction of wind may reduce electricity prices in the area. Meanwhile, additional balancing cost in a power system arises from the inherently variable nature of wind power, requiring changes in the configuration, scheduling and operation of other generators to deal with unpredicted deviations between supply and demand. Additional transmission lines and capacity need to be provided to reach and connect present and future wind farm sites and to transport power flows in the transmission and distribution networks (EWEA, 2009).

A key constraint facing wind energy development internationally is bottlenecks in the electrical transmission grid. One reason is that good wind resources are frequently found in remote, sparsely populated areas with (thermally) limited transmission capacity to other parts of the electrical grid, where electricity is consumed.

For a given wind climate, cost minimization per KWh usually implies a capacity factor of around 30%. Wind speeds statistically follow a skewed distribution, high wind speeds occur only very rarely, whereas low wind speeds are very frequent. This means that if electrical interconnections are dimensioned to meet the maximum power output of wind farms, they will be used relatively inefficiently. However, when several wind farms are sufficiently geographically dispersed within a transmission-congested area, their peak production will almost never coincide (EWEA, 2009).

Wind turbine energy production may vary from hour to hour, just as electricity demand from electricity customers will vary from hour to hour. In both cases this means that other generators on the grid have to provide power at short notice to balance supply and demand on the grid. Wind generation can be reliably forecast a few hours ahead, so the scheduling process can be eased and balancing costs lowered (EWEA, 2016).

Large balancing areas offer the benefits of lower variability. They also help decrease the forecast errors of wind power, and thus reduce the amount of unforeseen imbalance. Large areas favour the pooling of more cost-effective balancing resources. In this respect, the regional aggregation of power markets in Europe is expected to improve the economics of wind energy integration. However, such extra interconnection will add up to infrastructure costs.

The problem of long-term variability may be more difficult to cope with than short-term variability. If the wind does not blow for a week when we are close to the annual peak power demand, this might lead to a very tight capacity balance on the power system, implying at least high prices if not technical problems.

A study in 2007 has found that grid upgrade in Germany will cost 0.03 EURO/KWh of wind generation (EWEA, 2009). Germany has been the European renewable leader by a large margin in the recent years. According to leaked plans from the German Federal Network Agency (Bundesnetzagentur), published in Süddeutsche Zeitung (Oltermann, 2016), the government has had to halve its original target for expanding its windfarms in northern flatlands because it cannot extend its power grid quickly enough to the energy-hungry South.

China has been building two wind turbines every hour. This is the world's biggest program of turbine installation; double that of its nearest rival, the US. Nevertheless, the IEA warns - China has built so much coal-fired generating capacity that it is turning off wind turbines for 15% of the time (Harrabin, 2016). The problem is that coal-fired power stations are given priority access to the grid. In the province of Gansu, windmills had to be shut down 39% of time this year, because there is not enough capacity on the grid.

Both China and Germany found themselves in infrastructure bottleneck, meaning that installing more renewable capacity is uneconomical until the missing transmission infrastructure is put in place. Similar level of grid curtailment occurs in India (Manley, 2016), another large market for renewables.

Another option that could potentially reduce the high cost of grid expansion is energy storage. A paper by Ayodele & Ogunjuyigbe (2015) does an overview of storage technologies currently available. They split storage technologies into four major categories: Electrical storage, Mechanical storage, Chemical storage and Thermal storage.

An example of Electrical storage is Superconducting Magnetic Energy Storage (SMES). In this technology, energy is stored in the magnetic field of superconducting coil. Excess power is injected into the superconducting coil, which stores energy in the magnetic field. When power is needed, the current is generated in the magnetic field. This technology has high energy efficiency (about 97%) since energy is not lost due to thermodynamic losses associated with other energy technologies. SMES has short response times, meaning it can deliver required power at short notice. The big drawbacks of this technology are short storage duration and immaturity (Ayodele & Ogunjuyigbe, 2015).

Mechanical storage is represented by flywheel (short storage duration) and Pumped Hydroelectric Storage (long storage duration). Flywheel transforms excess power into kinetic energy. It has high peak power capacity, high efficiency and rapid response. The biggest issues are low energy density, high cost and short-term storage duration. Pumped Hydroelectric Storage (PHS) is a mature technology. It has large storage capacity and long duration of storage, however, moderate efficiency. Difficulty of wide utilization of PHS lies in high costs, specific topographic area requirements, and possible adverse impact on the environment (Ayodele & Ogunjuyigbe, 2015).

One of Chemical storage technologies are lithium ion batteries (medium storage duration). Li-ion batteries are a fast evolving technology. Such batteries have short access time, high energy density and efficiency. High cost, however, still prohibits wide utilization. Finally, Thermal storage is used in Cryogenic energy storage.

Ayodele & Ogunjuyigbe (2015) find that none of the studied technologies can solve the problem of energy storage alone. Thus, they suggest a combination of those and other technologies could be the answer. For example, in a country, like Norway, hydroelectric storage looks as a natural solution, since the country possesses suitable topography and already has more than 90% of power sourced from this source. If the cost of batteries will significantly decrease, this option may become a viable solution in the future. Ideally, the balancing of supply and demand would require a combination short-duration, high response and long-duration storage solution. SMES could be used for the former and PHS for the latter.

4.6 Implications and further research

This chapter is answering an ambitious question – what drives wind capacity upward. To find the clue I analyzed a large body of literature including industry reports, assessments and forecasts of governmental and international organizations and academic literature. As consequence, this work has come up with a hypothesized mechanism, which drives wind capacity up. First, my qualitative (not quantitative) conclusion is that capacity is caused by investment. An indication of that (yet not a proof) is strong observed positive correlation between the two ($Corr_{C,I} = 0.93$). My other hypothesis is that investment in wind power is driven by the following key factors: resource availability, declining cost of wind, increasing cost of competitive sources (coal and gas), predictable future-oriented government policy for wind power together with investment in grid and storage. I have read literature that performed quantitative research on those factors separately (Menz & Vachon, 2006), (de Pinho et al., 2013), (Kneifel, 2008), however none of the sources familiar to me had combined all the above-mentioned factors in a regression. The big challenge here is lack of sufficient data for the entire world on several parameters; however, I can assume that such analysis may be possible at the level of a country or a state.

5. Conclusion

Global primary energy demand is likely to grow by 50% between 2015 and 2040. Fossil fuels currently produce around 80% of global primary energy supply. It has been confirmed, that there are enough fossil resources to supply increased consumption at least until the end of 21st century. The ongoing increase in average temperatures on Earth requires cutting down on CO_2 emissions into the atmosphere. It has been stated by Intergovernmental Panel on Climate Change, that burning fossil fuels in electricity production is the main contributor to increased CO_2 concentration in the atmosphere. Paris Climate Agreement, signed by 175 countries sets an objective to limit global temperature rise to well below 2 °C, by limiting GHG emissions. Renewable energy is endorsed globally as one of the main tools for reducing CO_2 levels and satisfying increased demand for power.

This study applies growth curves to cumulative wind capacity in order to understand its dynamics and make a forecast for its future development. It has been found, that global cumulative wind capacity follows a logistic trend with saturation level of around 650 GW, much lower than consensus in the industry. Furthermore, the study analyzed the dynamics of cumulative wind capacity at the regional level. The combined estimate lies within 95% confidence bounds of the estimate from analysis on global data. According to the findings, wind power is going to supply less than 1% of global primary energy demand in 2040.

The mechanism that drives wind capacity is investment. Growth in global annual wind investment has been declining. A linear regression on annual growth rates in wind power investment predicts, that global investment in wind power peaked in 2014.

Investment is driven by several key parameters. Decline in LCOE contributes to growth in investment. Onshore wind LCOE has almost reached its minimum potential, while offshore is highly uncompetitive with other alternatives. There is urgent need for further continuous cost declines. The costs of the competing technologies - coal and gas – have been declining, which is harmful for investment in wind power. Government subsidies are required for further expansion of investment, yet some governments start to phase them out, others introduce them short-term, while energy investment requires long-term policy stability. Governments have to introduce substantial carbon tax for fossil fuels to create level playing field in the energy market. Finally, insufficient infrastructure and lack of cheap and reliable electric storage technologies are major predicaments for further investment in wind capacity.

My research concludes that, unless the above-mentioned barriers are overcome, wind power is unlikely to become a major contributor to global energy mix in the 21st century.

This study has performed a comprehensive analysis of global and regional wind power capacity and investment. It would be interesting to perform a similar research on solar capacity and investment to see, if future with solar power, as a major energy source, is about to arrive. Subsequent study might also estimate a predictive model for wind (and solar) power utilizing the driving factors, specified in my research, as model parameters.

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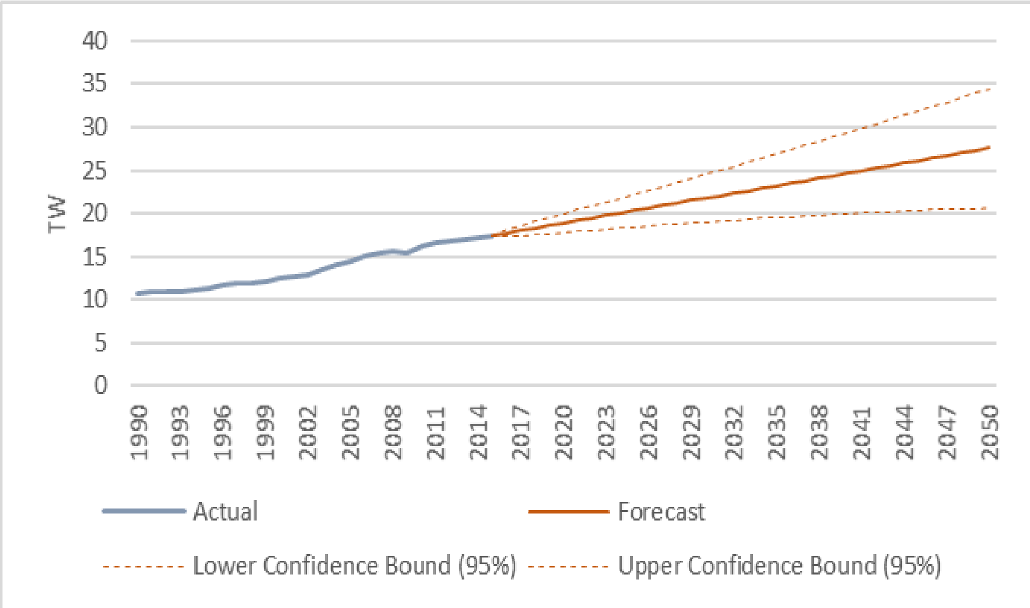
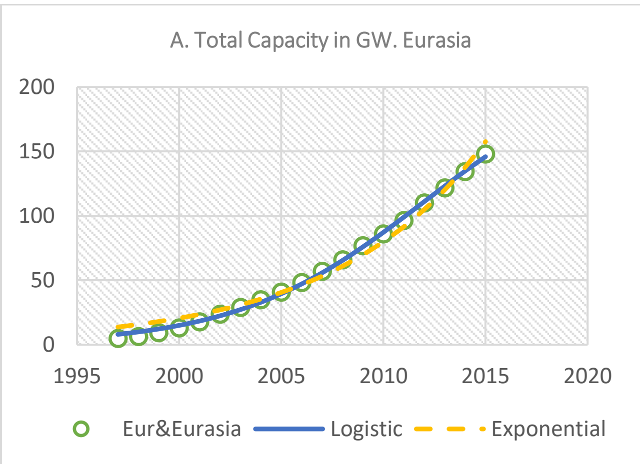
7. Appendix

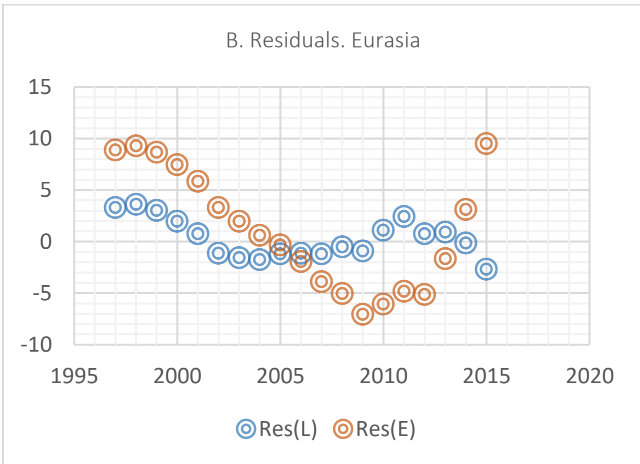
7.1

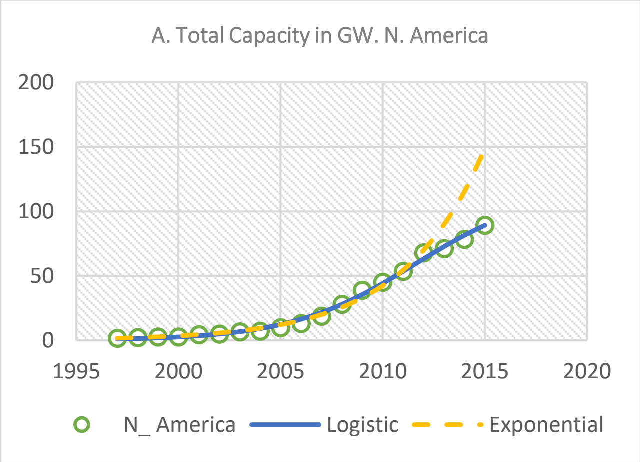


Global Primary Energy Consumption Forecast based on BP data (2016).

7.2 Curve fits to regional and global capacity data (BP, 2016) with residual plots.



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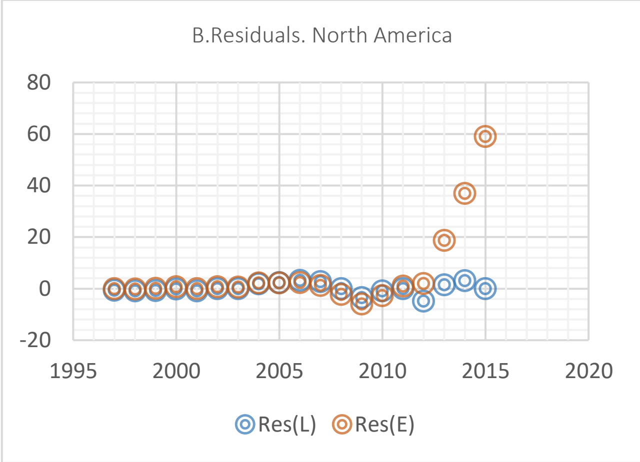
200
150
100
50
0
1995
2000
2005
2010
2015
2020
N_ America
Logistic
Exponential


B.Residuals. North America
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40
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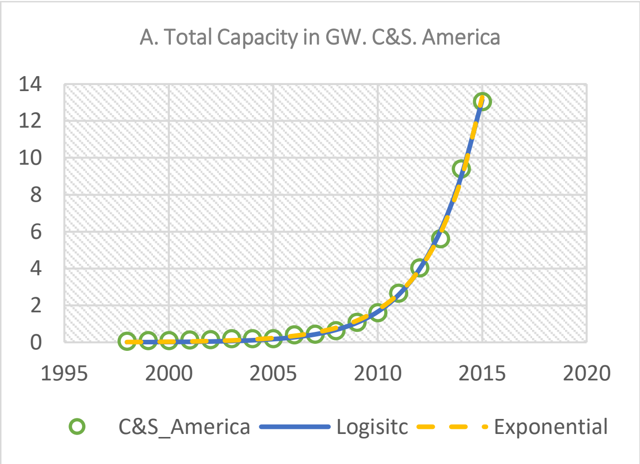
A. Total Capacity in GW. C&S. America
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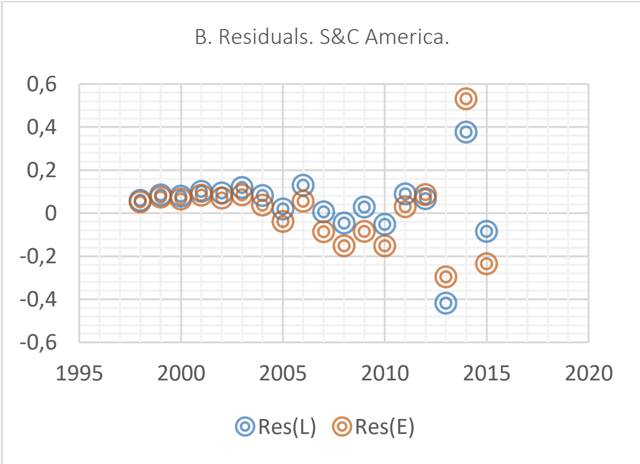
Exponential


B. Residuals. S&C America.
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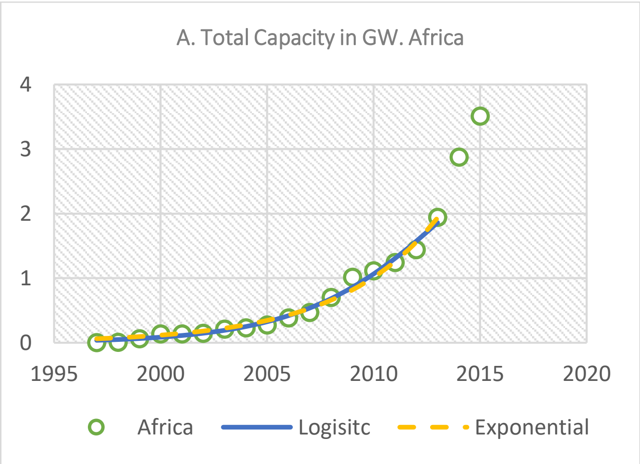
A. Total Capacity in GW. Africa
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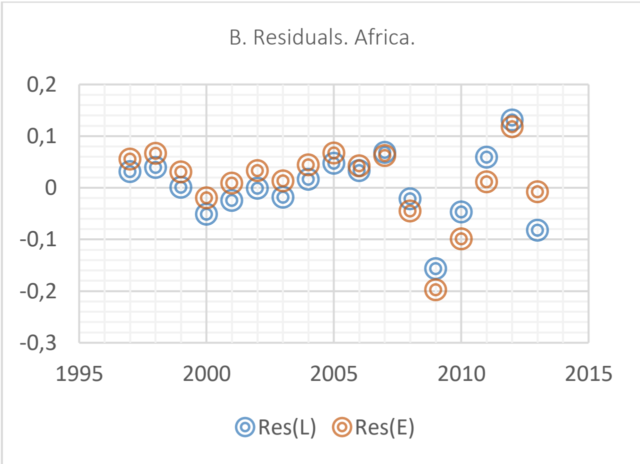
Africa
Logisitc
Exponential


B. Residuals. Africa.
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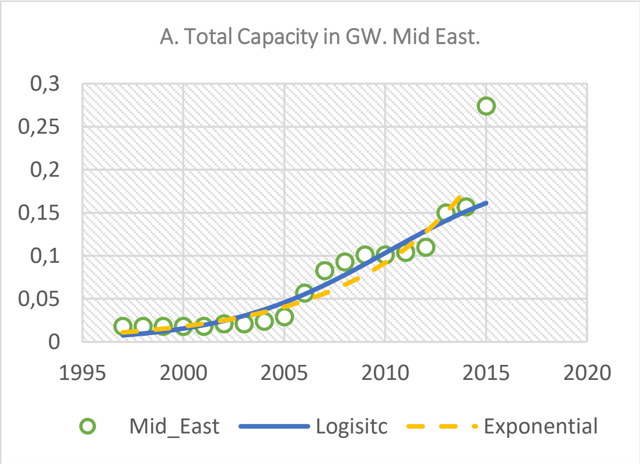
2015
Res(L)
Res(E)


A. Total Capacity in GW. Mid East.
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0,25
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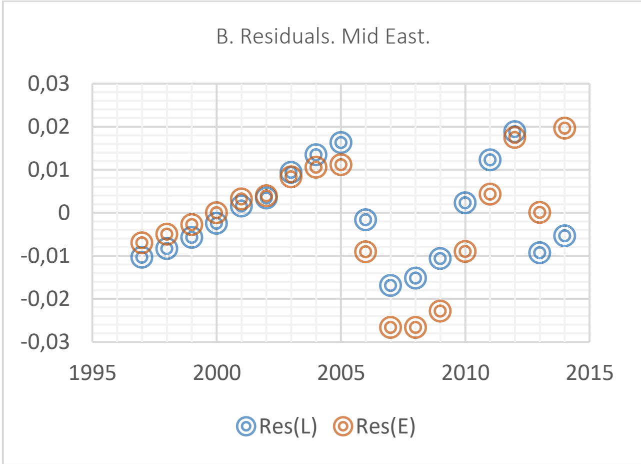
2000
2005
2010
2015
2020
Mid_East
Logisitc
Exponential


B. Residuals. Mid East.
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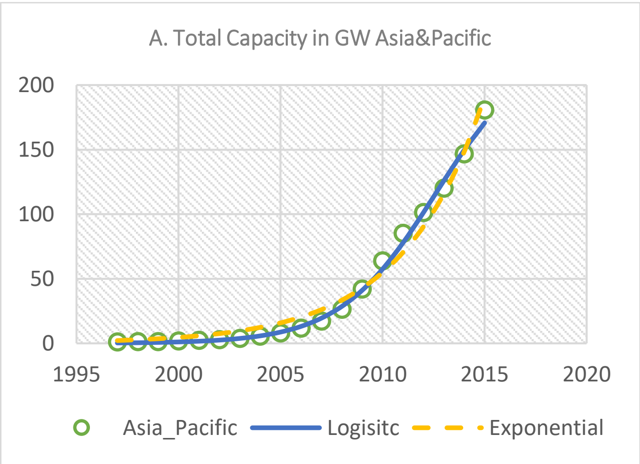
Res(E)


A. Total Capacity in GW Asia&Pacific
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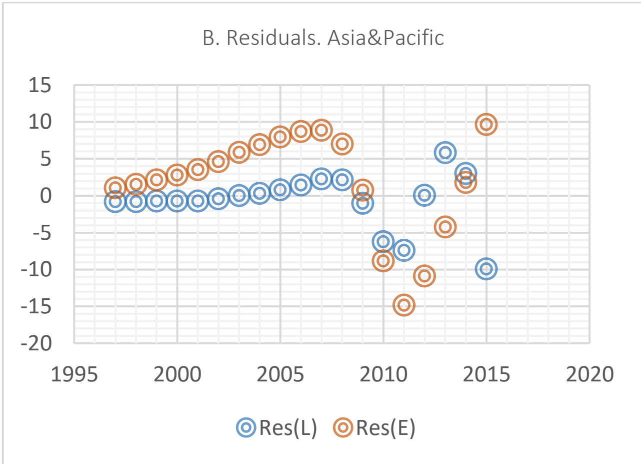
Asia_Pacific
Logisitc
Exponential


B. Residuals. Asia&Pacific
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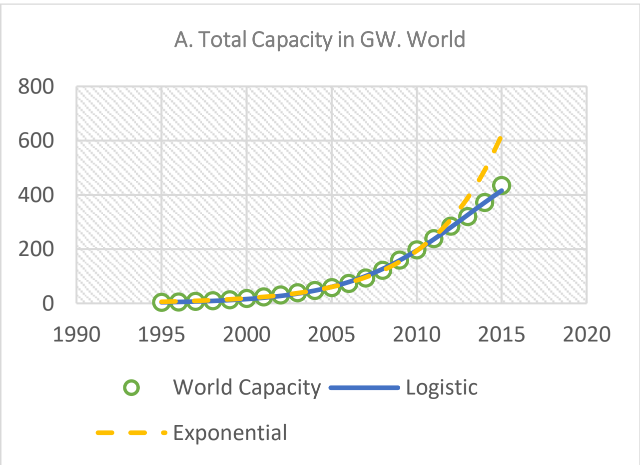
Res(L)
Res(E)


A. Total Capacity in GW. World
800
600
400
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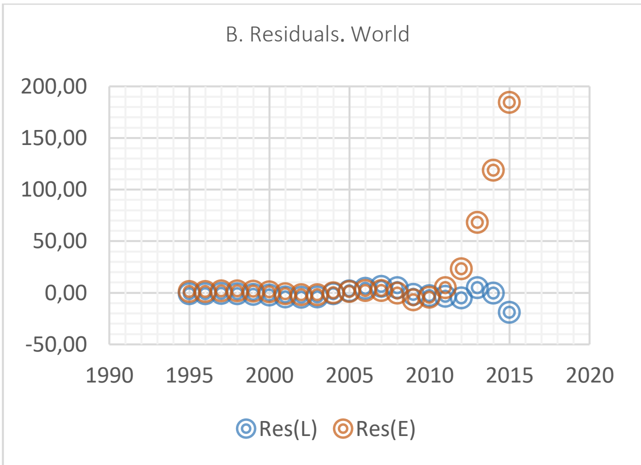
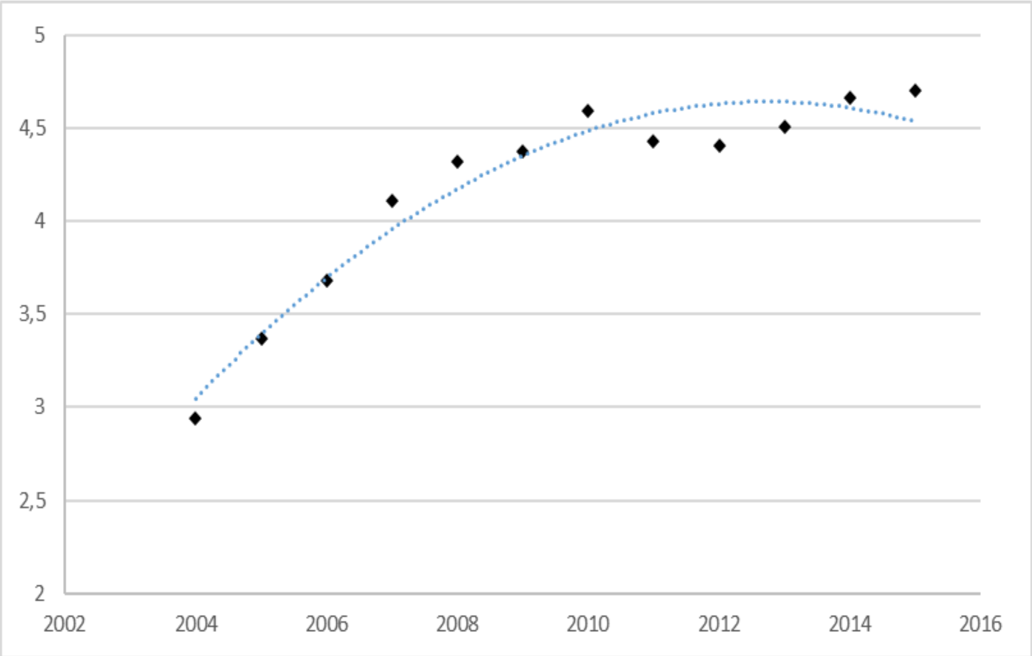
2020
World Capacity
Logistic
Exponential

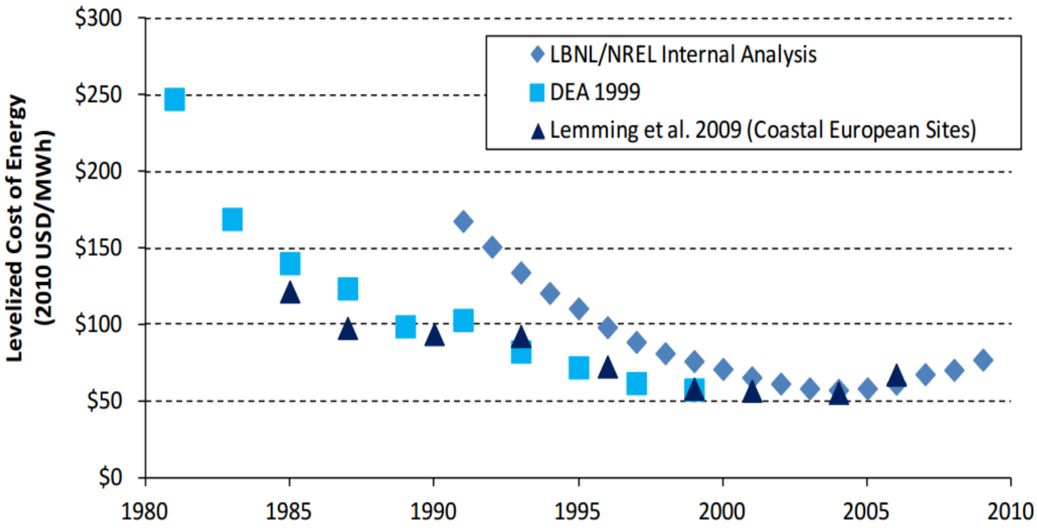

B. Residuals. World
200,00
150,00
100,00
50,00
0,00
-50,00
1990
1995
2000
2005
2010
2015
2020
Res(L)
Res(E)

7.3



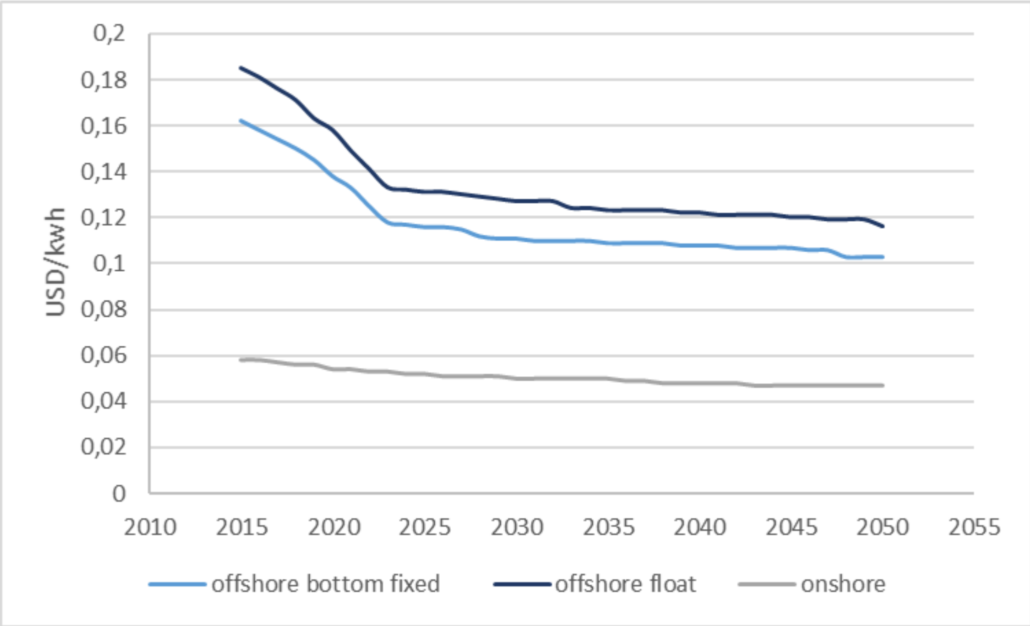
Parabolic trend applied to logs of annual global investment. (R^2 .=0.94)

7.4



Estimated LCOE for wind energy between 1980 and 2009 for the United States and Europe (excluding incentives) (NREL, 2012)

7.5



Forecast Wind LCOE development (OpenEI, 2016)