Modelling Wind Turbine Diffusion

A Comparative Simulation Study of California and Denmark for 1980-1995

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M.Sc. Thesis

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Summary

Diffusion of renewable technologies have been on makers' minds since the 1970s, because of varying reasons. Expensive energy, depletion of resources and the environmental concerns lead societies to look for alternative energy generation methods. Wind turbines provide a promising alternative for energy generation. It is environmentally friendly, sustainable, and humankind has a long history with wind energy, which makes it familiar. Also, researchers claim that among all renewable technologies, wind energy is the most promising one in terms of cost competitiveness (Menz & Vachon, 2006).

There were two early significant attempts for using wind energy as a source in electricity generation. After the oil crisis, both the United States and Denmark became in favour of wind energy, and implemented various policies to foster wind turbine diffusion.

Both governments put wind energy on their agenda and created policies for wind turbine diffusion, but on the basis of the percentage of installations and development of wind turbines, Denmark is considered much more successful. California had only a 2 percent share of energy for wind turbines in 1994 whereas this value was about 6 percent in Denmark (Sawin, 2001). To understand the differences of policies and their related consequences, this research has been designed.

This research models the diffusion of wind turbines in California and in Denmark with system dynamics simulation. The notions of diffusion from the literature is embedded into the models which are also in line with the diffusion stories of the cases. The results of the study shows that in addition to persistent demand-pull policies of Denmark, the initial conditions there created a more suitable environment for diffusion, due to expensive conventional technologies in and high dependency on imports in Denmark. On the other hand, in California, conventional technologies were cheaper resulting in more efforts to make the wind turbines cost competitive. Besides, California focused on supply-push type of policies and their demand-pull policies were frequently changing and they offered for short periods of time, which could be considered ineffective in familiarity gain with the technology.

Acknowledgements

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I also owe a big thanks to Dr.ir Gönenç Yücel as well, taking this job on top of his duties, nevertheless treating me as one of his own students. The time we spent together on building and structuring the model and his clever suggestions for putting the research into structure was immensely valuable. He always brought forward a set of key questions helping me to re-think of my work, and be critical about it in each step, eventually leading to a grounded model.

Dr.ir Roland Ortt always motivated me with his great enthusiasm and interest in this topic, and his point of view on the model with a different background raised interesting insights on my work. After each meeting with him, I felt excited about what I am doing, and motivated to bring better results. Furthermore, his contribution was quite significant especially in shaping the scope of this project, showing me the limitations and the important factors in the innovation diffusion literature. His suggestions on the focus topic and the way it should be analysed, made my work easier for the later steps in this research.

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Glossary

Aff: affinity

CA: California

DC: Direct Current

DK: Denmark

DOE: Department of Energy, United States

Dmnl: Dimensionless

EAC: equivalent annual cost

IS: Innovation Systems

KPI: key performance indicator

kW: kilowatt

kWh: kilowatt-hour

LCOE: levelized cost of energy

mW: megawatt

NPV: net present value

PURPA: Public Utilities Regulatory Policy Act

QF: Qualifying Facilities

SD: System Dynamics

TSO: transmission system operator

US: United States

WWII: World War II

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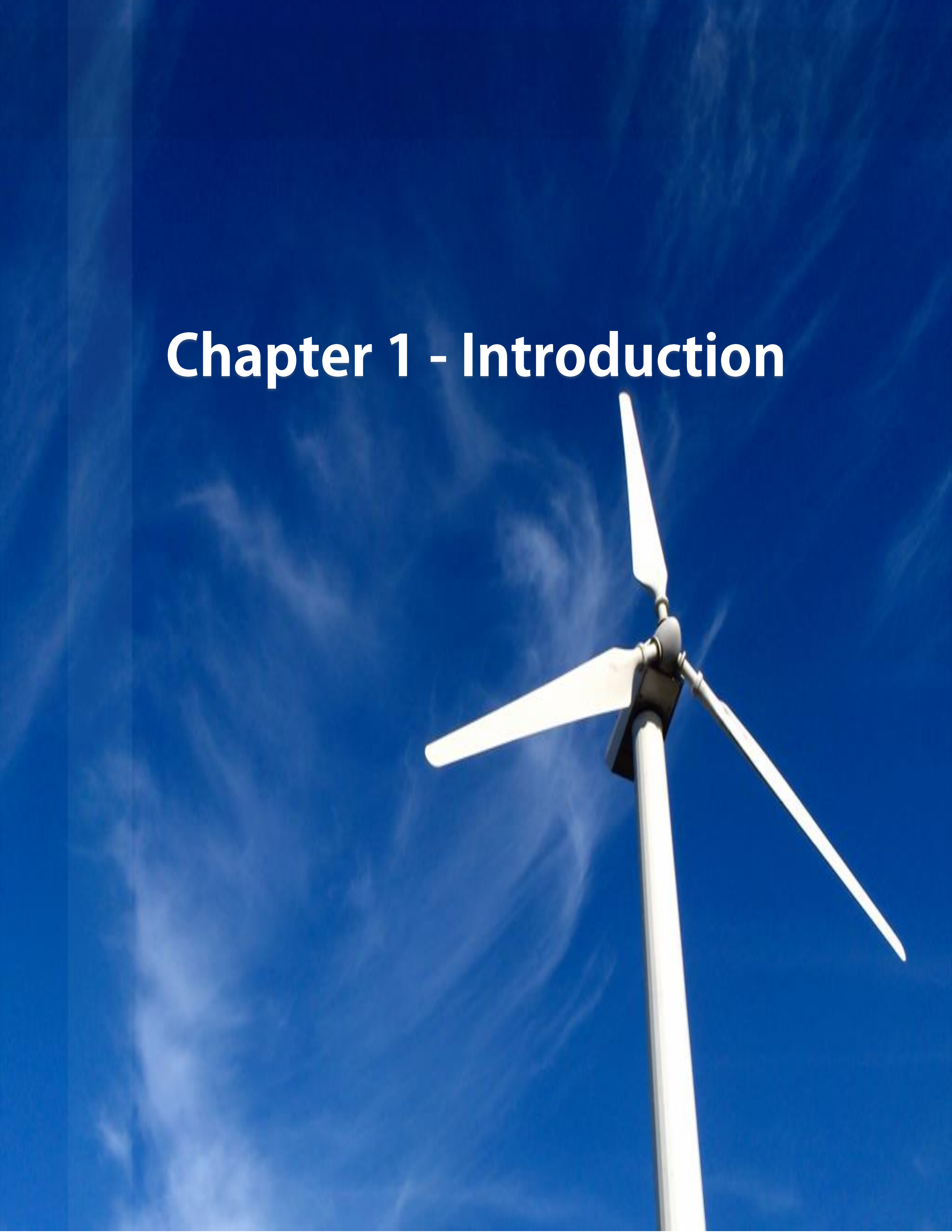
Chapter 1 - Introduction



1. Introduction

1.1. Research Problem

Sustainable technologies are high on the agenda nowadays, due to diminishing natural resources and high levels of greenhouse gases. Therefore, not only governments, but also the private sector has been working on sustainable solutions for a better future. Energy is on top of the list of these sustainable technologies. Many different sustainable energy initiatives have been introduced into the market so far, such as wind turbines, photovoltaic panels, and biomass energy and so on. Among these technologies, wind power has been treated with more attention, because of the promising economic competitiveness of the technology in the market (Menz & Vachon, 2006).

As well as the technological development of these technologies, adoption of these in society represents a challenge for policy makers. Having a promising technology is not enough for people to adopt it, since they might be unsure about the true benefits, they might resist change due to cultural, psychological or economic factors or they might simply not know about the new technology. To overcome these undesired settings in the society and ensure diffusion, policy makers should come up with effective policies having long lasting effects. Abundant research has been done with the focus of *innovation diffusion,* to understand how diffusion occurs. Nevertheless, as many recent investigations state, most of the studies focus on static measures of diffusion, although the phenomenon itself is a process over time (Hekkert, Suurs, Negro, Kuhlmann, & Smits, 2007) (Jacobsson & Johnson, 2000). Static measures can be imagined as having a screenshot of the system at a certain point time, and analysing it only for that captured moment. For instance, as a static measure, barriers to diffusion have been researched widely in the literature, but it is possible to explain the barriers as certain consequences of a mechanism in the system under certain circumstances. For instance, in the study of Kemp Schot and Hoogma, high price of an innovation is shown as a barrier, resulting in low market share and slow learning processes which might decrease cost of the product (1998). However, this interpretation is a static understanding of a dynamic process. To be clearer, if we see the price of the product as a variable, we can see that it is related to many different sources, such as demand, and learning processes. Besides, demand and learning processes are dependent on price as well, and this situation could follow different paths. If the price is high, there might be low demand, therefore learning processes become slower resulting in slow decrease of price. However, this situation could follow a different path as well, demand may be high due to the nature of the innovation even though it is expensive, or there might be extra governmental incentives which temporarily decreases cost and affect the level of adoption. Different levels of variables will result in different end states over time such as *adoption* or *no adoption.* The whole process relating to each of these variables in the system (not in isolation) with an end state is called *mechanism* in this research. A mechanism is defined by Yucel as follows: *"The mechanisms are different manifestations of the change processes and interactions of* *the general scheme"* (Yucel, 2010). It is also possible to see the mechanisms as building blocks of a system, where every mechanism behaves as a wheel inside the clock.

Socio-technical systems are systems too with its underlying social, economic and technological subsystems, therefore it is possible to interpret them with mechanisms. Complex socio-technical systems are a subset of a system, which is comprised of social subsystem having actor interactions, and technical subsystem having the development and compatibility of the technical system that the technology is embedded in. The word complex indicates that there is a strong interdependency between social and technical subsystem both internally and with each other; through many different layers of interaction and feedback effects (Dijkema & Basson, 2009). Diffusion of innovation occurs within a socio-technical system, where the social subsystem consists of suppliers, potential adopters and adopters and technical subsystem indicates the maturity of the technology, and consequently its cost. Since diffusion of innovation is a process going through time within a socio-technical system, and since it is possible to describe a system through a combination of different mechanisms, it should be possible to analyse the diffusion process with the combined interactions of different social and technical mechanisms.

A static interpretation of the barriers, does not help the researchers to come up with effective policy interventions for steering of diffusion of a given technology, because the policies to overcome a certain barrier could have unexpected systemic effects. To illustrate, we take Kemp, Schot and Hoogma's technological barrier example again, and assume that in such a situation, R&D subsidies are given to improve the ill developed technology. Then, although a considerable amount of money has spent on the subsidies and the technology became competitive with incumbent ones, the adoption rate could still be slow, because during this development time, potential adopters may have developed a negative attitude towards the technology. And if this new situation would be treated as a barrier to overcome, policy makers could come up with demand boosting policies. The time lost for overcoming the technological barrier caused negative attitude on potential adopters as a new barrier at a later stage. This example illustrates that barriers are not independent from each other, and time has a role in the appearance and disappearance of these barriers. Therefore, policies based on static interpretation of the mechanisms as barriers would be costly and time consuming and the level of success is also questionable, since the rate of diffusion matters a lot as well as the percentage of adopters in the end.

For this reason, a more dynamic perspective should be adopted for explaining causal, and cyclical and sometimes delayed effects of interventions. In the literature Hekkert et al. have identified the *functions of innovation systems* (2007). These functions are the mappings of general activities that foster or hamper innovation. Most of the functions that he explains resemble the mechanisms defined by Yucel, such as Hekkert's function 2: knowledge development and Yucel's individual and social learning. The importance of a dynamic interpretation of innovation diffusion has been mentioned by other researchers as well. As Jacobsson and

Johnson said, the vast amount of forces that may block the diffusion process of a certain technology are likely to reinforce one another, resulting in system failure (Jacobsson & Johnson, 2000), of course the other way around is also possible.

An analysis of a known case from a different point of view could be useful for bringing new insights to known problems. With this aim, a dynamic understanding of innovation diffusion could reveal the hidden details of the process. If diffusion of innovation would be analysed with this mechanism perspective on a commonly known diffusion story, then it might be possible to observe the contribution of a dynamic perspective on explaining diffusion processes. With this aim, wind turbine diffusion in Denmark and California, US has been chosen as a comparative case study, because of similar settings for the technology diffusion and widely differing diffusion patterns. Figure 1.1 and Figure 1.2 show wind turbine instalment per year in Denmark and US between 1975 and 1999. About 90% of wind turbines installed in the US in these years are located in California (Norberg-Bohm, 2000). When we look at the graphs, the cumulative capacities seem similar, whereas annual capacity instalment varies greatly. After the 1990's Denmark was able to get the leadership in the global wind turbine market (Morales, 2013). For two cases with such similar settings, how could one be able to cover the global market whereas the other was left with unutilized wind turbines? Understanding which mechanisms were active in what ways in these two cases, could bring a holistic and dynamic understanding of the diffusion process. For instance, Kamp claims that in Denmark, the learning by doing (individual learning) mechanism helped the diffusion process, where in contrast this mechanism was rather low in US (Kamp, 2002). To what extent this was true, and what were the other working mechanisms under the process is an interesting question.

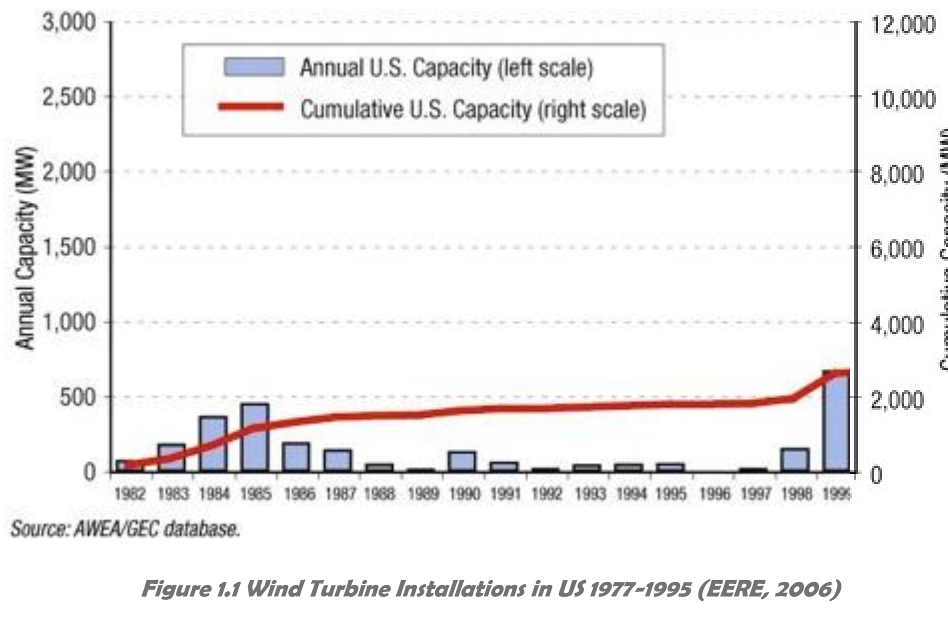


Figure 1.1 Wind Turbine Installations in US 1977-1995 (EERE, 2006)

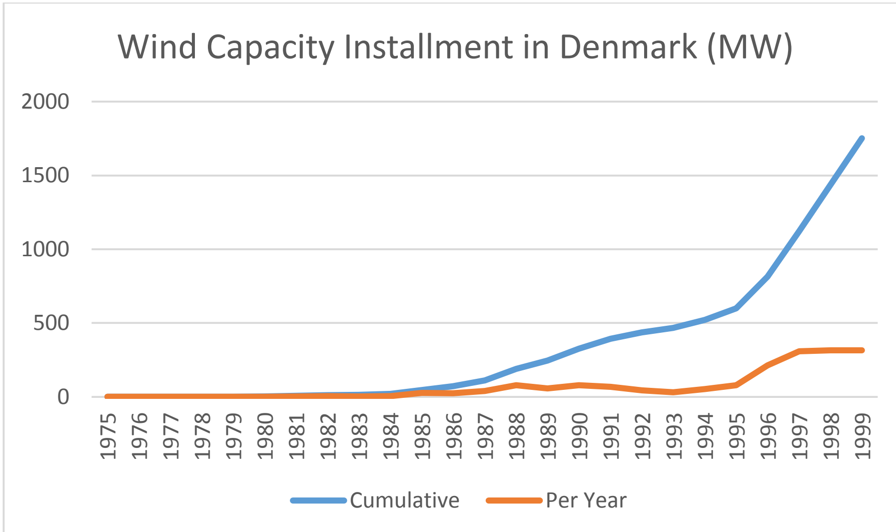


Figure 1.2 Wind Turbine installations in Denmark 1975- 1999 (Spliid, 2012)

To understand why these differences occur, the current methods remain insufficient. Therefore this research aims to explain the reasons behind these differences by looking at the active mechanisms and their interactions with a dynamic point of view.

1.2. Problem Definition

Wind turbine innovation development in the US and Denmark was stimulated for similar reasons around the 1970s which were mainly the oil crisis and environmental concerns (Norberg-Bohm, 2000; Olume & Kamp, 2004). Therefore both governments took action to help wind turbines to diffuse through for electricity generation. However, the diffusion was long lasting in Denmark whereas it was a short term trend in the US. The underlying reasons for different results of these two similar cases are unknown. Current analyses try to explain these results from a static perspective and considering the underlying mechanisms in isolation under a static time frame. These static and isolated approaches ignore the interactions of different mechanisms with each other, and also they provide a discrete understanding of a continuous process to explain the wind turbine diffusion patterns of California and Denmark.

1.3. Research Goal

The objective of this research is to clarify the reasons behind the difference in wind turbine diffusion in Denmark and US with a dynamic analysis approach.

If the underlying reasons of the difference in these two diffusion stories can be revealed, the lessons derived from the past could be useful for developing new policies for renewable energy systems diffusion. The dynamic understanding of the known diffusion story could result in new results differing from the ones in the literature. Besides, the dynamic approach for innovation diffusion could create awareness among policy makers and researchers about different policy analysis tools.

If this research reaches its aim, which is explaining underlying mechanisms of different wind turbine diffusion stories in Denmark and California, then this could be an indication of the necessity to adopt a more dynamic approach for analysing diffusion processes. Also, so far, most studies in the diffusion literature with a dynamic perspective are qualitative (Hekkert et al., 2007). Thus, an attempt to take this qualitative approach into modelling could bring a clear view to benefits and shortcomings of dynamic perspective.

1.4. Research questions

This study aims to answer the following research question:

What are the underlying mechanisms and their relations explaining the commonalities and differences of wind turbine diffusion stories in California US and Denmark?

To have a detailed answer to this question, the following questions are needed to be answered:

- What are the factors that stimulate and/or hinder the adoption of wind turbine technology, and how do these factors relate to each other? (RQ1)
- Which mechanisms are adequate representatives for explaining the relationships among the determined factors? (RQ2)
- What kind of policies have been implemented in California and Denmark for wind turbine diffusion, and what were the aimed mechanisms of these policies? (RQ3)
- How can these differences be explained in a dynamic way?(RQ4)
- What is the contribution of a dynamic analysis to understand the differences of the diffusion stories of the wind turbines in California and Denmark? (RQ5)

The first research questions are aimed at understanding the conceptual relations of different factors playing a role in wind turbine diffusion in general. When these factors are put together, their resemblance to suggested mechanisms of innovation diffusion is assessed with the second research question. The third question brings policies into the picture, by looking at the real cases in California and Denmark, and tries to explain which policy affects which mechanism. Research question 4 is about the implementation of the conceptual model with a chosen methodology, with the purpose of explaining the differences in these two cases in a dynamic way. Then, the research question 5 reflects on the ability of the chosen dynamic method for explaining the differences.

1.5. Structure of the thesis

The structure of the thesis is given in Figure 1.3. It is possible to see this work in three phases. The first one is the conceptualization phase, in which the real life problem is put into a systemic frame. The second phase carries this conceptualization to a simulation model. The final phase is the conclusion phase, where the insights from the research are summarized as well as the limitations.

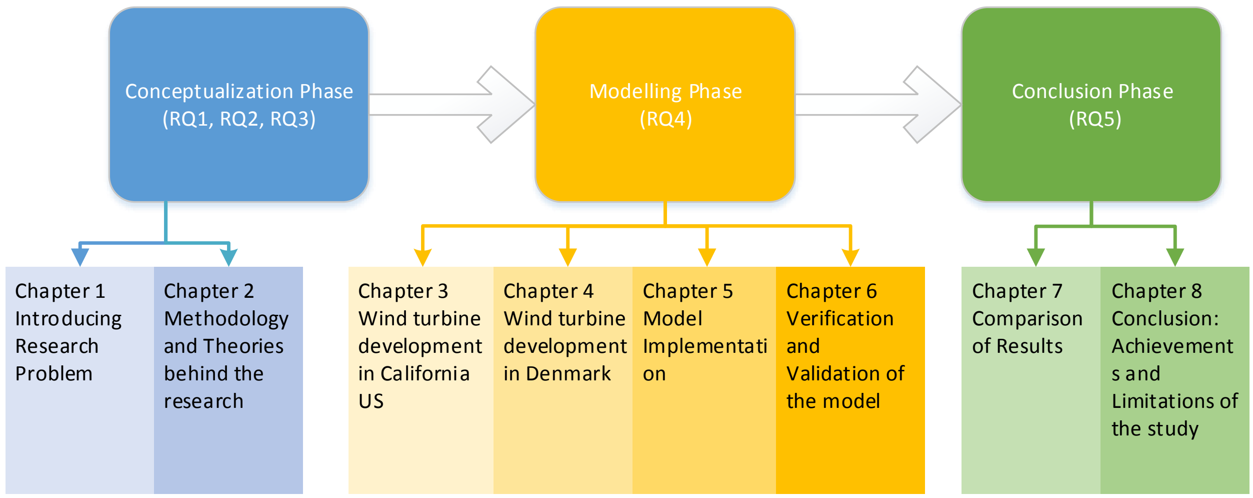


Figure 1.3 Structure of the thesis

- Before going into modelling from the conceptualization, the methodology used for modelling is explained in **Chapter 2.** Also, concepts related with the theory of innovation diffusion are explained.
- The following two Chapters **(Chapter 3 and 4)** include the information about the wind turbine development and diffusion in California, United States and Denmark respectively. First a brief history of wind turbines is introduced, then the structure of the energy market in each country is summarized. The motives of the governments and the society for wind electricity is also explained, as well as the actions taken for realizing the motives. Finally, conceptualization of the socio-technical system of each case is introduced at the end of the chapters.
- **Chapter 5** is about creating a system dynamics model from two conceptual cases. Quantification of the model is also explained as well as the assumptions and finally, a comparative summary is provided at the end of the chapter for summarizing the similarities and differences in both cases from modelling perspective.
- **Chapter 6** is about the verification and the validation of the model, where verification implies "building the thing right" and validation corresponds to "building the right thing" (Boehm, 1981).
- After making sure that the model is working properly and does what is intended, in **Chapter 7**, the initial settings and different policies of both cases are compared and

tested understand the sources of differences. The rate and the cumulative installed capacity of wind turbines would be the main key performance indicators for assessing these differences.

- Finally, **Chapter 8** summarizes the research, and answers the question "what has this model achieved?" Besides, the limitations of the study and suggestions for further research are presented.

Chapter 2

Methodology

2. Methodology

This chapter is separated into two sections. The first section explains the reasons for choosing system dynamics as a model for the interpretation of the dynamic approach. The second section gives brief information on each theory used in the model for building up the reader's knowledge. Then, the third section explains the way these theories have been implemented in the study. Finally, clear steps for the whole research methodology are given.

2.1 Methodology for modelling innovation diffusion dynamically

This study looks for the impact of governmental policies in wind turbine diffusion. A dynamic model is also a requirement for this study, since the current state of the system will have an effect on the upcoming state of the system. For diffusion of wind turbines, the current level of knowledge for example, will have an impact on cost of wind turbines, and the cost of wind turbines will affect the number of wind turbines sold, and therefore the knowledge generated in the next time step. In the end, knowledge is also affected by itself over time, therefore a dynamic representation of the system is needed. One of the suitable methods for dynamic modelling is system dynamics. For understanding the reach of governmental policies in diffusion a suitable approach is a system dynamics simulation model for the following reasons:

- The analysis requires a change in the system over time. Therefore, an approach having temporal features is more suitable for the study. Simulation models of different kind offers this feature, whereas techniques like regression analysis do not have the ability to represent the change over time as effectively.
- A diffusion process is a continuous process, since the accumulation of knowledge and experience curves are not countable (Birta & Arbez, 2007)
- For understanding the relationships among different variables, and tracking where the policy goes, a white box model is needed. System dynamics offer this feature, whereas econometric calculations are looking into the relationships among the variables in isolation and behave as black box models (Melberg, 2000)
- System dynamics is more of a strategic approach rather than being operational, which fits well into governmental perspective. Also this approach do not focus on the exact numeric results, but looks for the behaviour of the system under different circumstances. Once the cause of a behaviour is understood, it is possible to influence this behaviour with different strategies.
- This policy analysis takes an aggregated perspective from top-down approach, because the diffusion is analysed from governmental perspective. Therefore, instead of focusing the detailed interaction structures among the players of the market, the dominant structures in the system should be clarified so that the determination of what went right/wrong should be possible on key variables. The focus here is on the variables

rather than actors, if the significant variables are determined, then necessary actions with related actors can be identified as a following step if desired (Scholl, 2001). Therefore, rather than an agent based modelling having a bottom-up approach, system dynamics approach suits more to the point of view taken in this research.

The next section gives information on how system dynamics works as well as the other theories used in the study.

2.2 Theoretical Framework

The main outcome of this research is a system dynamics based policy analysis for wind turbine diffusion. Therefore system dynamics is main technique for the study, and the other techniques and theories are embedded in it. However, it should be kept in mind that scope of the theories are much more wider and deeper, but the focus on these theories is kept limited according to the boundaries of the cases.

2.2.1 System Dynamics

System dynamics (SD) was introduced to the management world during 1950s by Jay W. Forrester. The main idea of system dynamics is the interpretation of the system in feedback loops, instead of a linear process. It assumes that the complexity of the system comes from its internal causal structure (Meadows & Robinson, 1985). Due to its long existence and popularity, SD is a well-documented modelling approach, making it easy to follow the standard model cycle (Waveren, et al., 1999). However the use of this tool is rather new in the innovation diffusion field (Hsu, 2012; Tsai & Hung, 2014). Therefore, studying diffusion of wind turbines with System Dynamics would be a novel method for diffusion literature, but since the modelling cycle is well established in SD, the model will have strong roots.

SD is a computer based modelling approach for complex systems. It has two main concepts for modelling; feedback loops and stocks and flows. A feedback loop represents a causal path between variables, in which each variable is affected by the previous one. An example for this could be the population loop; if there is high population, births per year will increase, then if there are a lot of births, the population will increase leading to more births per year (Figure 2.1).

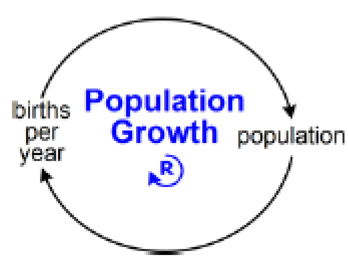


Figure 2.1 Example of a feedback loop

Dynamic behaviour is represented via stocks and flows. Flows go into and out of the stocks, and the level of stocks changes according to the flow rate over time. A common example for this is a population of a society with an inflow (women giving births) and decreasing it with an outflow (death rate) (System Dynamics Society, 2014) (Figure 2.2). A stock can have more than one inflow and/or outflow, and the flows are affected by the feedback loops. There could also be time delays in the system.

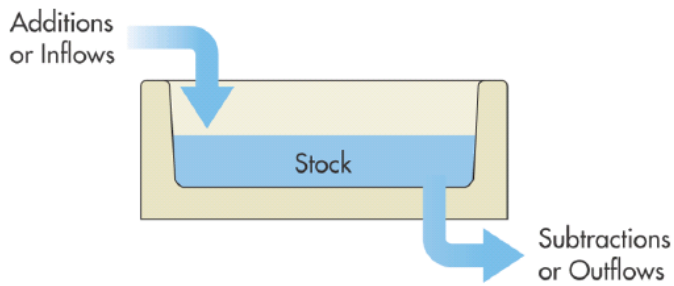


Figure 2.2 Example of a stock and flow relationship

Relationships between the stocks and flows are defined with differential equations. Then the simulation model runs these equations with a given time step over a specific time range. It is also possible to implement non-linear relation between variables in the model. The behaviour of each variable over time can be seen as a graph and table as a result of the simulation.

By creating feedback loops with stocks and flows, and connecting these loops together an appropriate system description can be reached. This way, the system consists of analysable atomic mechanisms. Yet, these mechanisms are analysed within the system, not in isolation. This aspect is crucial in diffusion studies, since a policy (which could be an influence on a certain variable for a certain time period) can affect the final state of the diffusion process. The atomic mechanisms are also existent in diffusion processes, which are explained in the next section.

2.2.2 Diffusion of Innovations

Diffusion of innovation is a field of study looking for the reasons and the rate of adopting an innovation in or through cultures. The idea was introduced by Rogers in 1962 and grew since. His theory tries to explain how, why and at what rate an idea is accepted in a culture or through the cultures (Rogers & Everett, 1983). His theory suggests that there are four main factors driving the diffusion process: the innovation itself, communication channels, time and the social system that the innovation spreads through. Rogers' view on diffusion of innovation is more at the individual level, whereas Bass introduced a more aggregated model in 1969. His model was based on differential equations, and it models the interaction between the adopters and potential adopters on a diffusion process (Bass, 1969). The model principle is "The portion of the potential market that adopts at a specific time t given that they have not yet adopted is equal to a linear function of previous adopters" (Bass, 1969). This way he suggested the diffusion process happens over time, with the interaction of actors and it is about the innovation itself. In both of these theories, the diffusion is considered successful when it follows a stabilization S-curve in Figure 2.3. Later Rotmans discussed different paths that a diffusion process can follow; such as lock-in, backlash, and system breakdown (2005). However, there are quite range of studies discussing the reasons for these different paths. Some of the studies which are also used in analysing diffusion of renewable energy technologies are *barriers to innovation, functions of innovation systems* and *mechanisms of innovation.*

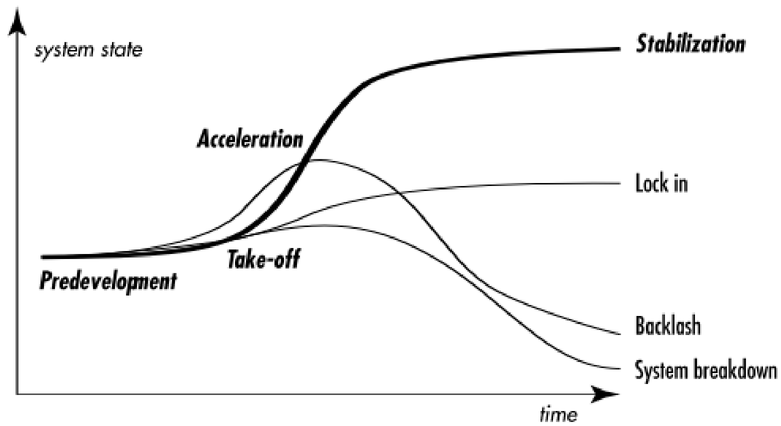


Figure 2.3 Different change paths **(Rotmans, 2005)**

2.2.2.1 Barriers to Innovation

In 1998, Kemp Schot and Hoogma published a paper including barriers for diffusion of an innovation. They grouped these barriers into 7 categories (Kemp, Schot, & Hoogma, 1998):

- Technological factors
- Government policy and regulatory framework
- Cultural and psychological factors
- Demand factors
- Production factors
- Infrastructure and Maintenance
- Undesirable Societal and Environmental Effects of New Technologies

Technological factors are summarized as follows: if there is a new technology, it would probably be ill-developed in terms of user needs, and would be expensive due to low-scale production. Therefore, they need to be optimized, but it might not be possible due to lack of revenue coming from low number of sales. So, the technology would be stuck in ill-developed form and the diffusion will not happen.

Government policy might hinder the diffusion process by creating difficulties in the existing regulatory framework. Also, unclear messages saying that there is a need for a technology for a certain need would result in investing in many technologies, some of which will be ineffective in the end.

Cultural and psychological factors affect the diffusion process as well and they might become barriers for a certain technology. For instance, environmental concern nowadays fosters the diffusion of renewable technologies, but this was not on people's minds 30 years ago. Besides, for some products, such as cars, it is a symbol of status for the consumer which shapes their preferences.

Demand factors are also stated as economic barriers. Consumers are not sure what to expect from the new technology. As a result, their willingness to pay for an unknown product is lower compared to the incumbent technology. The difficulty in changing consumer preferences is seen as a barrier. Also, for some technologies consumers need to change their lifestyles, and this also creates a resistance to buy the product. With these concerns companies are reluctant to offer new technologies. Again, the high price of new technology also results in small-scale production and slow learning curves.

Production factors, or barriers on the supply side implies the cumbersome and long process from prototype to mass production. Most of the manufacturers do not want to risk their core competencies by switching to new technology, because they might lose their market position such as cost leadership or differentiation. For this reason, most of the time new enterprises take the action for launching new products. Yet, new enterprises are short on budget, and they rely heavily on subsidies. Besides, they do not have the ability to produce the technology in large quantities, and consequently learning curves are developing slowly and cost of the product remains high. Finally they do not have the ability to conduct big marketing campaigns so that the customer would be aware of the product.

For some technologies, the infrastructure might needed to be changed as well, and the diffusion might become a chicken and egg problem (Farrell, Keith, & Corbett, 2003). For instance, for the diffusion of electric cars, charging stations should be established, so that customer would not have to worry about running out of battery. Yet, there is a risk that the electric cars would not diffuse anyway, and in that case the charging stations will become useless. Finally, there is a risk of introducing new problems from new technologies, and this will hamper the process of diffusion.

It is possible to see that these barriers are connected to each other. For instance, technological barriers results in expensive products, therefore the consumer does not buy the product (demand barrier) and this results in small-scale production affecting learning curves. Also, the word barrier implies a static meaning, an obstacle that is needed to be climbed over. However, when a deep look is taken into these factors, it is possible to see more of a dynamic structure. The barriers can be seen as certain end states of a mechanism. For instance, as a technological barrier, they suggest that ill developed technology is not able to satisfy the user needs, therefore the adoption rate is low; and the reason for ill development is low scale production. However, it is possible to interpret this as a generic mechanism where the triggering event is production scale and the result is adoption rate. And the low or high level of these factors represent certain functioning of the mechanism under certain conditions.

The contributing feature of this categorization is focusing on the production side of the process, instead of taking only demand into account. The limitation of the study for the purpose of this study is the static understanding of factors influencing diffusion. Therefore, in this study, the factors will be interpreted with their dynamic features and will be used in modelling the diffusion process together with functions of innovations and mechanism of innovation.

2.2.2.2 Functions of Innovation Systems

In 2007, Hekkert et al criticized the existing methods for analysing technology specific innovations, and suggested seven mechanisms which are dynamic *functions of innovation systems*. Innovation Systems (IS) approach has occurred over the last decades, with the combination of evolutionary and institutional theories. The approach claims that diffusion of the technology is both a collective and an individual act (Edquist, 2001). The IS approach takes into account the economic activities of the firms, institutions and the economic structures of the society as well as the technology characteristics, indicating a socio-technical holistic approach to diffusion. On top of this approach, Hekkert et. al introduces the *functions of innovations,* where the entrepreneurial activities of the firms are taken into account in diffusion, and a dynamic point of view is introduced to the approach, saying that these mechanisms' behaviour is time dependent, and they also interact with each other. These functions are defined as follows:

Function 1. Entrepreneurial Activities

As it is mentioned in barriers to innovation, existing manufacturers do not want to take the risk of losing market share and core competencies by focusing on innovations. These activities are carried out by entrepreneurs most of the time, which generates experimental knowledge for the product and strengthens learning-by doing mechanism. Thus, entrepreneurial activities are one of the drivers for innovation to get mature.

Function 2. Knowledge Development

This function is mainly about learning, containing both learning-by-doing and learning-by searching mechanisms. Learning-by-doing and learning-by-searching mechanisms are concepts related to economic theory. Learning by doing stands for the experience gained for a production of a specific product over time by producing it. The learning by doing mechanism implies that "the more one engages in development, the more opportunities exist to reduce costs and improve the product"(Ibenholt, 2002). The same idea is also behind the learning by searching process, but this time, learning is not coming from the production, but from the R&D efforts put into the development of the product both by public and private resources.

These processes are crucial in innovation diffusion as Lundvall once stated (1992). R&D investments, projects and patents are mentioned as a measurement of knowledge development.

Function 3. Knowledge Diffusion through Networks

Exchange of information is as important as knowledge development for a healthy diffusion. The number of members in the network (network size) and the level of interaction among them (network intensity) are the two main drivers for information spread.

Function 4. Guidance of the Search

This function also resembles a barrier defined by Kemp, Schot and Hoogma (1998). If there are many available technologies and there are no clear messages for choosing one, the rate of diffusion would slow down. Thus, the government takes initiative for guiding the market for a certain technology in such situations. These initiatives can be observed via targets of the government and publications.

Function 5. Market Formation

This function implies governmental support for new technologies to compete with the incumbent ones. Creating a protected space for new technologies will make them economically competitive in the market. Creating niche markets is one of the methods for doing so, and another one is offering tax credits or consumption quotas which would create a temporary competitive advantage.

Function 6. Resources Mobilization

Allocation of resources including both human capital and financial resources is also necessary as an input for the other functions. Yet, this function is rather vague and conceptual, since it is quite difficult to measure the mobilization of resources. It can be assumed that this function creates an input for R&D investments, therefore a partial measure for this function can be considered as R&D investments.

Function 7. Creation of Legitimacy

The new technology will compete with the existing ones. For this reason, it is likely to face with opposition as well as support from different parties with different interests. Lobbying or bringing new legislation for adoption of a technology would create a legitimate environment for the new technology. This function resembles the barrier of government policy and regulatory framework explained by Kemp Shot and Hoogma (1998).

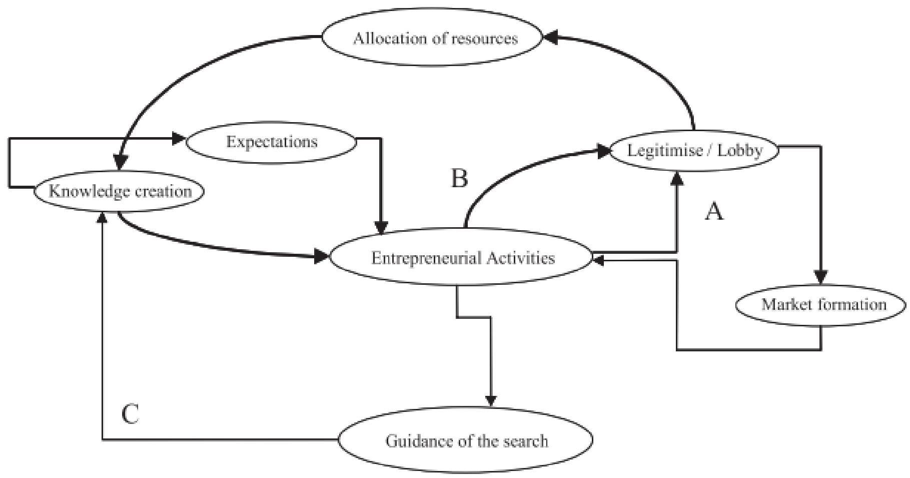


Figure 2.4 Relationship between the functions - motors of change (Hekkert et. al, 2007)

These functions are connected with each other as it is shown in Figure 2.4. Fulfilment of a function would create an impact on others. The Figure shows the relationships of different functions forming a system. For example, with more knowledge, the expectations for the technology will become clearer, and if it is desirable among the consumers, this will increase the entrepreneurial activities. These relationships imply that the model of the system is non-linear with multiple interactions between the functions influencing the performance of the system negatively or positively (Hekkert et al, 2007). The relationship between these functions also implies feedback loops in which the mechanisms are interconnected.

Functions of innovation systems bring the dynamic understanding to the innovation diffusion systems. Yet, these functions remain qualitative so far, and even though it is implied that the relationships exist between them, no quantitative study was found showing the degree of these relationships. This situation creates a motive for system dynamics based analysis of the relationship of the functions.

2.2.2.3 Mechanisms of Innovation

Yucel identifies the main mechanisms which can take place in diffusion studies (2010). He explains mechanisms as atomic parts of the system, which could be linear and/or cyclical (feedback loops). As he stated, not all of the mechanisms are active in every diffusion process, but each process is a unique combination of these mechanisms. The features of the mechanisms are that they should be generalizable, simple, policy-relevant and empirically and/or theoretically grounded. The mechanisms coming from his work and their relationship with the functions can be listed as:

- Experience driven change in option properties: This mechanism stands for knowledge accumulation through actors' experiences. Under the mechanisms resulting in experience driven change in product properties; learning by doing and learning by using mechanisms are explained. In a way, Hekkert also mentions the importance of the learning-by-doing phenomenon, but he claims that the actor who is widely involved in this process is not the big companies but the entrepreneurs. It should be noted that whether the activities are coming from the big company efforts or from the entrepreneurs, the learning-by-doing structure works as an improvement in option properties.

-Scale-driven change in option properties: The number of users of an innovation and also the volume of production has positive or negative effects on diffusion depending on the circumstances and the nature of the innovation. An example for this mechanism of change is crowding process. For instance, if the number of charging stations for electric vehicles remain constant and if there is an unexpected increase in number of electric vehicle owners, the charging stations will be insufficient suddenly, and the availability of the stations will drop dramatically, creating a negative perception on the users.

- Resource driven change in option properties: This mechanism also resembles Hekkert's function 2 and 6, knowledge development and resources mobilization. The allocation of resources could be into the option itself, or the methods of provision as well as the capacity of the provision system. R&D spending is a measurable allocation of resources for an option development, which can be modelled by *learning by searching* mechanism.

- Exogenous Change in option properties: This mechanism considers the global improvement on a knowledge on a certain technology, coming from different socio-technical systems. This difference can come from another social environments, such as if the R&D spending and learning on wind turbine capacities in China leads to a certain improvement, this will be also followed by the Danish manufacturers. Another improvement can come from a technological spillover where a certain improvement on a certain technology could be useful in another one. For instance, developing aerodynamically efficient wind blades is a spillover coming from the aerospace industry.

- **Individual learning:** By using a product actors can improve their information precision about the given technology via direct observation or with experience. Then with time, they can decide the utility of the innovation based on direct observation or by direct experience. This mechanism is also existent in the model, it is modelled with familiarity work of Struben and Sterman (2008). The information gathered from the users are also effective in social learning which is explained below.

- Social learning: This mechanism is about diffusion of information among the actors and it is strongly related with Hekkert's function 3, knowledge diffusion through networks. The interaction between the actors using the innovation and the other ones can influence the rate and the direction of the diffusion process. This mechanism is also based on Bass diffusion model in its simplest form, where the interaction among the adopters and potential adopters affect the diffusion process.

- Learning from external sources: Similar to Struben and Sterman's familiarity model, learning from external sources is also taken into account in Yucel's work (2008) (2010).

Marketing and awareness campaigns, newspapers and scientific reports are the common examples for these sources. These sources are also quite important in shaping actors' knowledge and attitude towards a new technology, playing an important role in diffusion.

-Reference formation and change: Similar to the psychological and cultural barriers mentioned by Kemp, Schot and Hoogma, Yucel mentions the importance of "demand requirements" of the potential adopter, such as personal expectations, social norms which can determine the reference point for assessing an option whether it suits the needs of him/her (1998). Also, regulatory limitations could be interpreted as a reference point playing a role in the actor's decision.

-Commitment formation: If an actor already invests in a certain technology and feels comfortable with using it, it could be difficult to switch to the new technology, event that the new technology offers an economic improvement. Also, the governmental decisions on going for a certain type of new technology among a set of immature new technologies can limit the "competition" and results in leaving the most profitable technology behind. Commitment formation is a phenomenon widely discussed by the researchers, and it could affect a diffusion process negatively or positively depending on the structure of the socio-technical system.

-Preference structure change: Although for a short period of time it is possible to assume that the actors' preferences on a certain structure is fixed, these preferences also change over the long term. For instance, during 1970s, the society was not concerned about sustainability of the world resources, however since 2000, the awareness for the sustainability issue has increased, shaping the consumer demands. There were no green electricity demand during 1970s, but nowadays, some consumers are willing to pay higher electricity rates to consume electricity from green sources. This changes in preferences can lead actors to take action and force the companies and the government to focus on new technologies with different properties.

The major mechanisms from Yucel's work are explained above (2010). The overlap of these mechanisms with the functions of innovations and barriers to diffusion is clear, as the naming suggests. Yet a detailed relationship between these three theories are given in section 2.3.1 Combination of Theories.

2.3. Methodology

This research has explorative features, trying to determine the cause-and-effect relationships among the factors taking a role in diffusion of wind turbine technology in California and in Denmark.

2.3.1. Combination of Theories

As it is explained before this study is based on three pillars: Hekkert's functions, Yucel's mechanisms and the dynamic interpretation of barriers to diffusion which is highlighted by Kemp Schot and Hoogma (2007; 2010; 1998). Table 2.1 shows the concepts that are in this study and the correspondence between them.

Table 2.1 Combination of theories

Function of Innovation Systems (Hekkert et al 2007)	**Mechanisms of Transition (Yucel, 2010)**	**Barriers to Diffusion (Kemp, Schot and Hoogma, 1998)**
F1: Entrepreneurial activities	Experience driven change in option properties	Technological, production and demand factors
F2: Knowledge development	Experience driven change in option properties Resource driven change in option properties	Technological, production and demand factors
F3: Knowledge diffusion through networks	Individual and social learning, Familiarity	Cultural and psychological factors
F4: Guidance of the research	Commitment formation	Government policy and regulatory framework, Demand factors
F5: Market formation	*Not a mechanism but a function affecting the purchasing decision*	Government policy and regulatory framework, Demand factors
F6: Resources mobilization	Resource driven change in option properties	Government policy and regulatory framework
F7: Creation of Legitimacy	Preference structure change	Government policy and regulatory framework

Table 2.1 shows the correspondence between the theories across Functions of Innovation Systems, Mechanisms of Transition and Barriers to Diffusion. Function 1 says that entrepreneurial activities are the key drivers of experience for developing the technology. Yucel also says that experience driven change in option properties help diffusion by accumulation of actor's experiences leading to improvement in product properties. Both concepts address learning-by-doing phenomenon from different approaches. Yet, Yucel does not specify the sources of this learning-by-doing mechanism, whereas Hekkert claims that it is mainly based on entrepreneurial activities. Similarly, Kemp, Schot and Hoogma states that technological barriers due to low performance of new technology is not improved unless a certain level of production triggers the learning by doing mechanism, leading to an improvement in the technology and consequently increased demand. Function 2 refers to learning by searching mechanism and learning by doing mechanism coming from not only the entrepreneurs but from all actors such as big firms and from the research centres. Yucel's experience driven change in option properties covers all learning by doing mechanisms and resource driven change in option properties implies the R&D spending and other resource allocation such as building research centres for a certain technology, and/or industry-government agreements. The negative functioning of these mechanisms can create a range of barriers according to Kemp, Schot and Hoogma, such as ill developed technology, and low

scale of production and consequently low demand. Function 3 is more about the demand side of the diffusion, mentioning the word of mouth coming from adopters and non-adopters. Similarly, individual and social learning of Yucel's mechanisms address the same concepts. These could be treated as a barrier when there is a negative word-of-mouth about the technology, if it does not fit with the expectations and the social norms of the adopters, which is categorized under cultural and psychological factors. Function 4, the guidance of the research represents the determination of the authorities, adopters or the investors to focus on a certain technology among various alternatives. When the guidance is determined and the mind-set is created accordingly, instead of spending a lot of money towards different immature options, all the resources are allocated to the certain technology resulting in considerable improvement. Yucel addresses this issue by explaining the effect of commitment formation to the certain technology. For sustainable technologies, Kemp, Schot and Hoogma mentions that this choice of direction could be a barrier for other technologies for diffusion. Function 5 covers the demand pull type of policies of government such as creating niche markets with pilot programs or offering subsidies. This could be understood as an input fostering the demand for the new technology by affecting certain mechanisms. For example, if a subsidy is offered this would trigger more purchases and it will trigger the individual and social learning mechanisms. From the barrier perspective, it can be seen as a government intervention to the demand barriers. Function 6 behaves as an input to Function 2, where the resources are allocated to contribute knowledge development by the government. Therefore the correspondence to Yucel's mechanisms are the same as Function 2, but since the government is involved, the corresponding barrier is mentioned as governmental policy in Kemp Schot and Hoogma's work. Finally, function 7 stands for the demand for the new technology coming from the bottom, such as advocacy groups working for the legitimacy of the new technology. Yucel mentions this phenomenon by explaining the preference structure change for the actors where all the conventional options are not satisfactory and they look for the new options. However, the existing regulatory framework may hinder the development of the new technology, therefore this could be defined as a governmental barrier from Kemp Schot and Hoogma's perspective.

Note that not all of these mechanisms are active in wind turbine diffusion in California and Denmark. Function 4 and Function 7 is not observed in the stories of diffusion in these cases, because the only promising technology for that time in terms of cost competitiveness was claimed to be wind turbine technology, removing the doubt in guidance of the research. Also, this diffusion was supported and steered by the government from the beginning, therefore there was no need for creation of legitimacy in these diffusion stories. The next section will explain the methodology in a step by step manner from creating a conceptual model with these functions to implement those within a system dynamics model.

2.3.2. Steps in the Methodology

Figure 2.5 shows the followed steps for building this study. At first, a literature survey is done simultaneously to explore the wind turbine diffusion stories of two cases, and the theories in innovation diffusion which fits into these stories (Chapter 2, 3 and 4). Then the knowledge of these two searches are combined into a conceptual model. The conceptual model is transferred to a working model with no data in Vensim[1] Then the necessary data is collected from various sources, mainly energy related websites, such as the Energy Information Association (EIA) in the U.S. Two different models with different data but with the same concepts is created as a result. The policies which are found in literature survey are implemented for each case (Chapter 5). Then verification and validation study is conducted for ensuring the usefulness of the model (Chapter 6). Finally, policy testing study is done for determining the most and the least effective policies that have been used in these cases and their influences on wind turbine diffusion (Chapter 7). Then the insights gathered from the study is explained (Chapter 8).

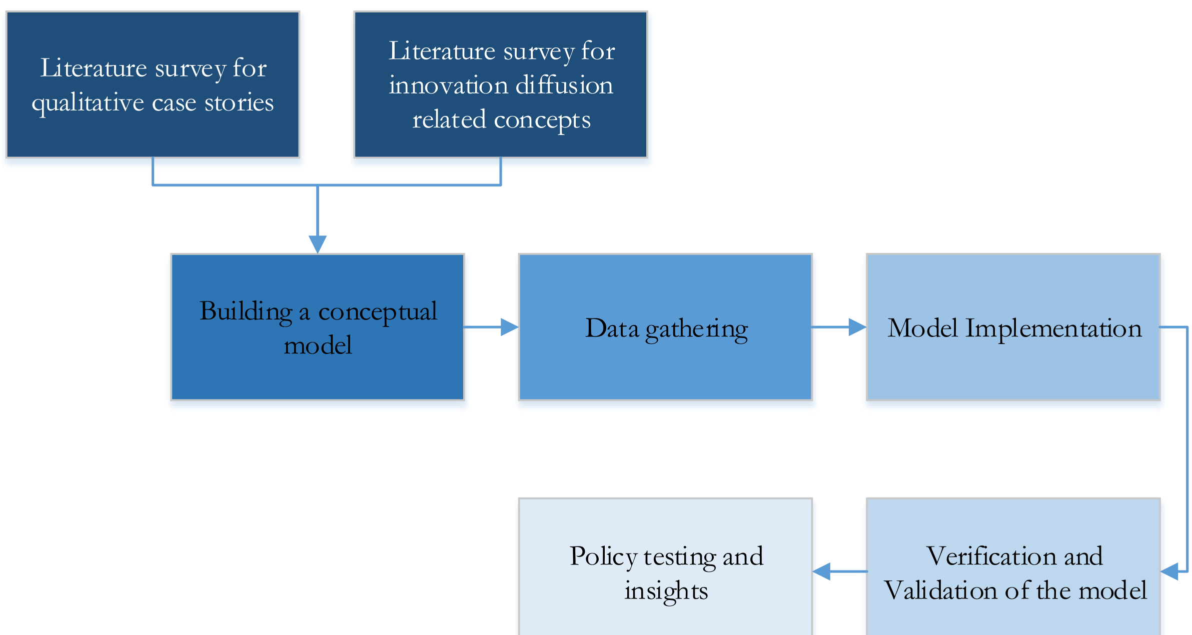


Figure 2.5 Methodology

In this chapter, theoretical framework and the methodology for the study is given. In the next two chapters, the qualitative knowledge about wind turbine diffusion in California and in Denmark is provided respectively.

[1] System Dynamics simulation software

Chapter 3

Development of Wind Turbines in California, US

3. Development of Wind Turbines in California, US

The Unites States is one of the prime movers in taking initiative in wind turbine technology, together with Denmark and Germany. However, about 95% of the wind turbines in U.S. were installed in California, due to state policies and favourable weather conditions (Sawin, 2001). Also, for population size and geographic perspective, California is more comparable to Denmark than the all of the United States. Therefore, California is chosen as one of the case studies for wind turbine diffusion. The following sections give information about the history of wind turbines in the United States, general organization of the energy market, federal and state based motives and policies for fostering wind turbine diffusion, and finally conceptual system description of California.

3.1 History

Wind mills have a long history. However, the attempts to generate electricity from wind power started in late 1800s. The world's first power plants were built in New York and in Berlin (Hau, 2006). However, with the world wars and energy generation technologies from fossil fuels shifted the researchers' attention from wind turbines. A milestone in wind turbine development was achieved in the 1940s in United States with 1250 kilowatt (kW) two-blade wind turbine. However, this wind turbine had a permanent breakdown in 2 years (Heymann, 1998). This effort, however, did not trigger further researches in US, because of the conclusion that wind power is much more expensive compared to conventional fuels (Sawin, 2001). The real motivation for focusing wind turbines as an energy source occurred in the 1970s, when the oil crises had been faced. With the oil crises and the acid rains, a search for different energy generation technologies had accelerated (Norberg-Bohm, 2000). Traditional knowledge of wind mills and the previous attempts at wind electricity generation led the government to build on existing knowledge and focus on wind turbines.

3.2 Energy Market Structure in United States

Before explaining the government's role in the wind turbine development and diffusion in United States, an introduction of the relevant actors and their relations is necessary for a comprehensive understanding.

The electricity has three main processes, owned by different stakeholders. Generation, transmission and distribution. The deregulated market resulted in a different combination of responsibilities of utilities. Some of the utilities have their own generation plants, however, most of them are only involved in distribution. The ownership of these utilities are both public, private and cooperative. The electricity market in the US was under heavy regulation since early 1970s, but with the oil crisis and changed governmental mind-set, a series of legislations for deregulation has been introduced. This situation ended the monopoly of electricity generation of utilities, and nonutility participants emerged (EIA, 1994). The transmission network is controlled by non-profit organizations called Independent System Operators (ISO) for reliable electricity market.

The federal government of United States intervene with the electricity market via regulations and incentives with different public institutions: Department of Energy (DOE), Environmental Protection Agency, Federal Trade Commission and Nuclear Regulatory Commission. Apart from federal institutions, states also have the power to determine their own electricity agendas in line with the federal strategies.

Currently, wind power constitutes 4.13% of the United States' electricity generation, where in total 13% of the electricity is coming from renewables (including hydropower) (EIA, 2013). This number was almost 0% before 1970s and it was still quite low (below 1%) until 2000s. The policies that have been implemented by the states and federal government to reach this increase in percentage is given in the next section.

3.3 Wind turbine Motives and Policies in California

There were two main drivers in the US for focusing on wind technology. The first one was the concern of high oil prices starting with the oil crises, and continuing with the Persian Gulf War, and the second driver was the environmental concerns; including acid rain, urban smog and lately the climate change (Norberg-Bohm, 2000). With these concerns, there were several policy attempts to find different energy generation alternatives. It is possible to categorize these policies in supply-push and demand-pull policies, where supply-push policies aim to stimulate innovations, whereas demand-pull policies tries to create a market for new technologies.

Supply push technologies are easily visible from R&D spending. Until 1977, the R&D budget was rather low for all energy types, but the Department of Energy decided to increase the budget about six times (Norberg-Bohm, 2000). Yet, with the change of the government policy with Reagan's administration, the budgets were cut drastically and it remained low until 1999 (Norberg-Bohm, 2000). In Figure 3.1 R&D spending for energy over time can be observed. In total, from 1975 to 1988, the US spent $427.4 million on R&D only for wind technology.

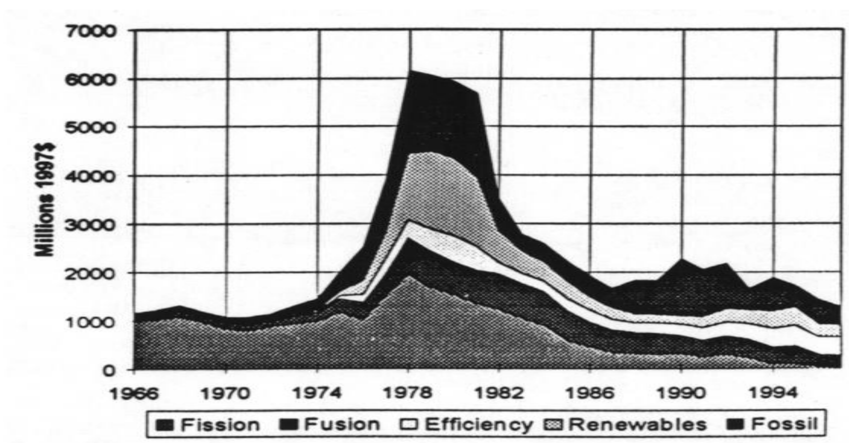


Figure 3.1 Energy Technology R&D Budget Authority of DOE and Predecessor Agencies, 1966 to 1997 (Norberg-Bohm, 2000)

R&D efforts on wind turbines followed two paths. The first path was about creating a large, cost-competitive wind turbine. The program called Mod Program, and it was carried by NASA and DOE jointly. The aim was to reach about 3 to 5 mW wind turbine, and about half of the R&D spending for the 1970s used in this program. The program was unsuccessful in reaching its target, but with the researches it gathered a considerable amount of experimental data on grid connection (Norberg-Bohm, 2000). One of the designs of these wind turbines is shown in Figure 3.2.

Figure 3.2 MOD-1 (rotor diameter 61 m, 2000 kW, 1979) (Hau, 1998)

The second path was about smaller wind turbine innovation, under the support of DOE. They provided R&D subsidies to work on the technology, and in the end, these efforts resulted in 12 key innovations, such as rotor size improvements, 7 of them related to total or partial public funding, 3 of them coming from the private sector. The source of remaining two is unknown (Norberg-Bohm, 2000).

Demand pull policies in the US started with the Public Utilities Regulatory Policy Act (PURPA), which was published in 1978 and implemented in 1981. This policy required utilities to purchase power from "qualifying facilities" which are defined as small renewable heat and/or electricity generators (Martinot, Wiser, & Hamrin, 2005). PURPA is the ancestor of the feed in tariff of today, however the cost calculation was different. The cost was determined as "avoided cost", which is the marginal cost for a public utility to produce one unit of power (IEPA, 2014). The calculation of this cost was left to the states, but its aim was to approximate the avoided costs to the utilities (Martinot, Wiser, & Hamrin, 2005).

In 1980, California offered a 25% state tax credit for investments in wind power, where there was also a 25% tax credit from the federal government. Federal tax credit had ended in 1985, and state tax credit was reduced in 1985 and ended in 1987 (Sawin, 2001).

California took the PURPA act to a further stage by offering long term contracts at a fixed electricity price for the first 10 years, in which the contract duration varies between 15 to 30 years (Martinot, Wiser, & Hamrin, 2005). This was a real stimulant in the California wind market, but only for a short period of time. This offer started at the end of 1983 and continued until 1985. The effect of this offer on wind turbine installations can be observed in Figure 3.3.

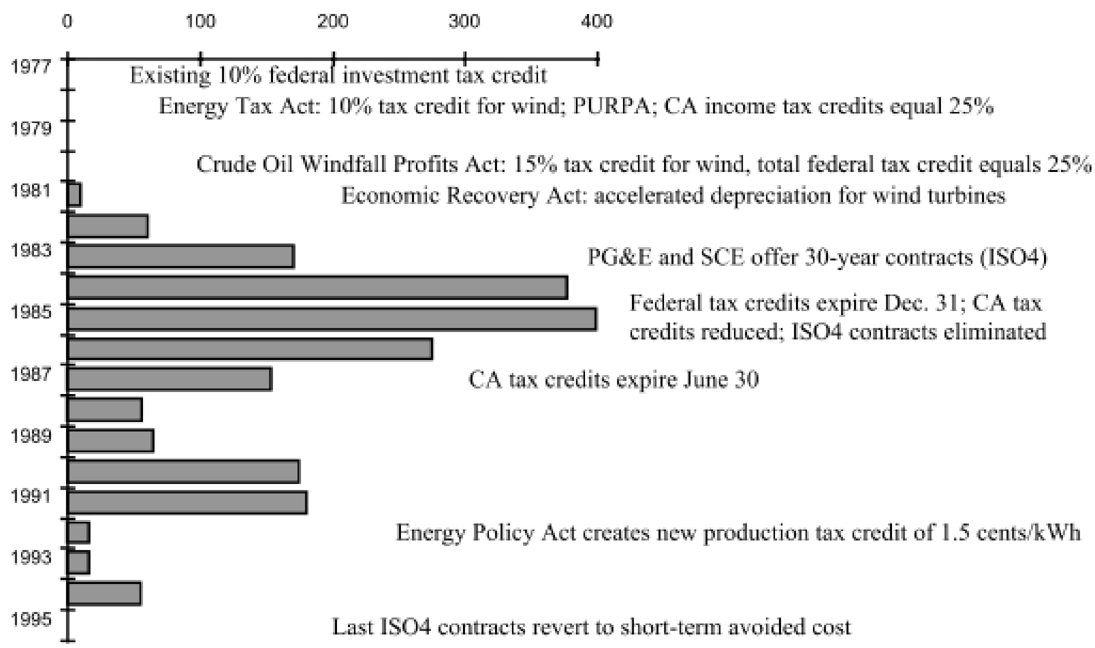


Figure 3.3 Annual Wind Turbine Installations (megawatts) (Norberg-Bohm, 2000)

In 1991, there was a new tax credit for wind power. The federal government offered 1.5 ¢/kWh reduction on electricity cost for wind with the Energy Policy Act.

Apart from these effective policies, there were other attempts which remained impotent. Since 1970, US regulated SO_2 and NO_x emissions with Clean Air Act. However, instead of going for renewables, investors went for gas turbines, enabling them to meet with sulphur caps with no additional equipment (Norberg-Bohm, 2000). Also, paying for the fines for exceeding the caps was still more profitable than going for coal-free technologies (Norberg-Bohm, 2000).

Overall, for supply-push efforts, big projects were not really fruitful, while a focus on existing small scale wind turbines brought useful innovations. Demand-pull policies were effective at the time of implementation, but they were scattered and fluctuating. Therefore the wind turbine installations in California followed a wavy path which did not result in continuous installations ensuring persistence.

3.4 Conceptualization of the Case

Conceptualization is structured by answering the following questions (Albin, 1997):

- What are the active actors and what are their aims and responsibilities?
- How do the actors interact with each other?
- In what kind of environment do they interact? What are the boundaries of the environment?
- What are the basic mechanisms in the system?
- What are the key variables in the model?

The conceptualization process is structured with the reverse engineering style, by choosing the starting point as *installed wind turbines*. Before starting to explain this process, the introduction of actors with their motives and concerns is presented in Figure 3.4. Since the model's purpose is policy analysis, an aggregated point of view has been chosen, therefore, the interaction among the actors responsible for generation, transmission and distribution is treated as one actor called utility. The reasoning for this simplification is the fact that for the time period of 1980-1995, environmental concern of the end consumers was low, therefore there were no green-electricity demand coming from the end of the electricity supply chain, and the only main driver was cost for utilities, which was the same for also other actors (Norberg-Bohm, 2000). In addition to utilities, wind turbine producers are the second main actor, having learning processes and determining cost and get benefits from R&D subsidies. The final actor is the government, aiming to help the utilities to install wind turbines by making wind turbines cost competitive, and offering subsidies to producers.

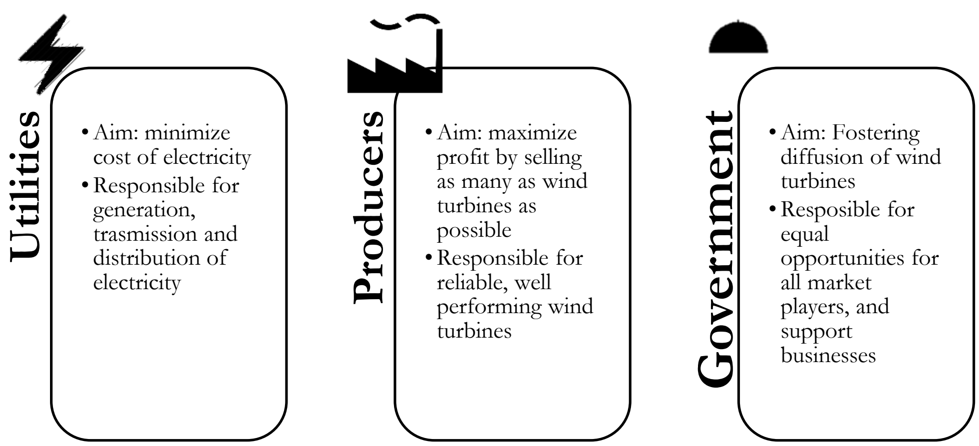


Figure 3.4 Actors, their aims and responsibilities

As well as the actors' own actions, their interactions are important for understanding decision flows. An action sequence diagram is shown in Figure 3.5 for showing the relationships between the actors. This diagram shows the interaction of actors, where the vertical lines can be seen as the time axis. The arrows shows the action happening between corresponding actors. Some of the actions are continuous throughout the process, therefore those are shown in dashed lines.

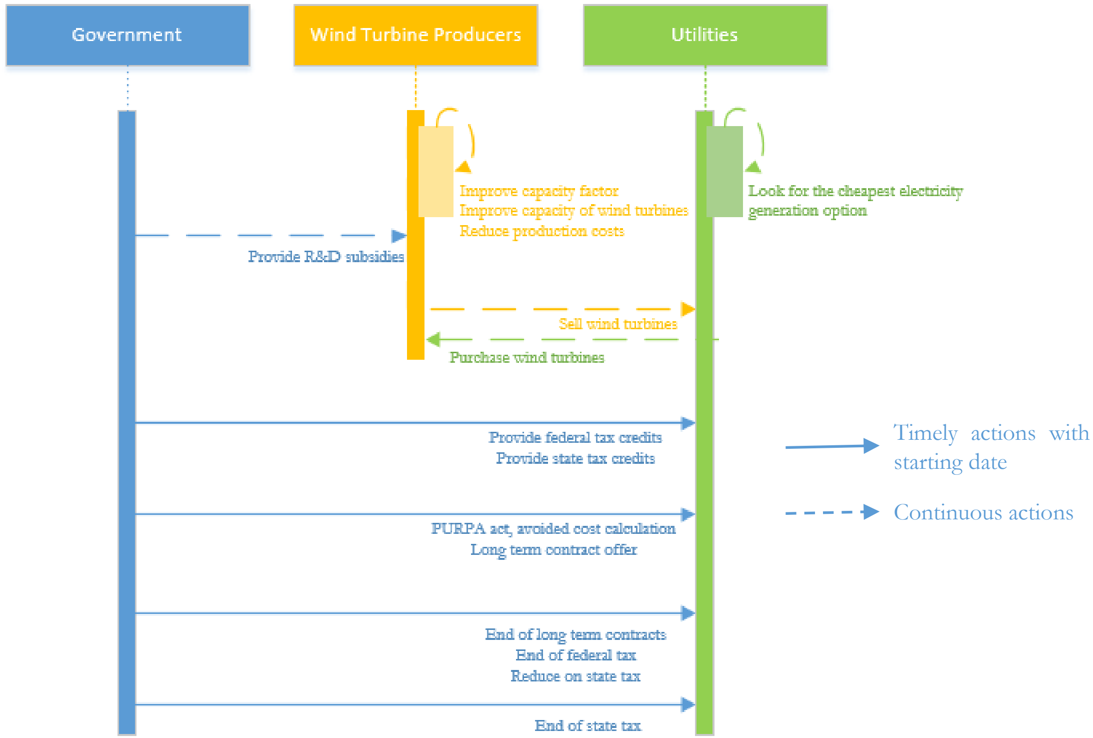


Figure 3.5 Action Sequence Diagram

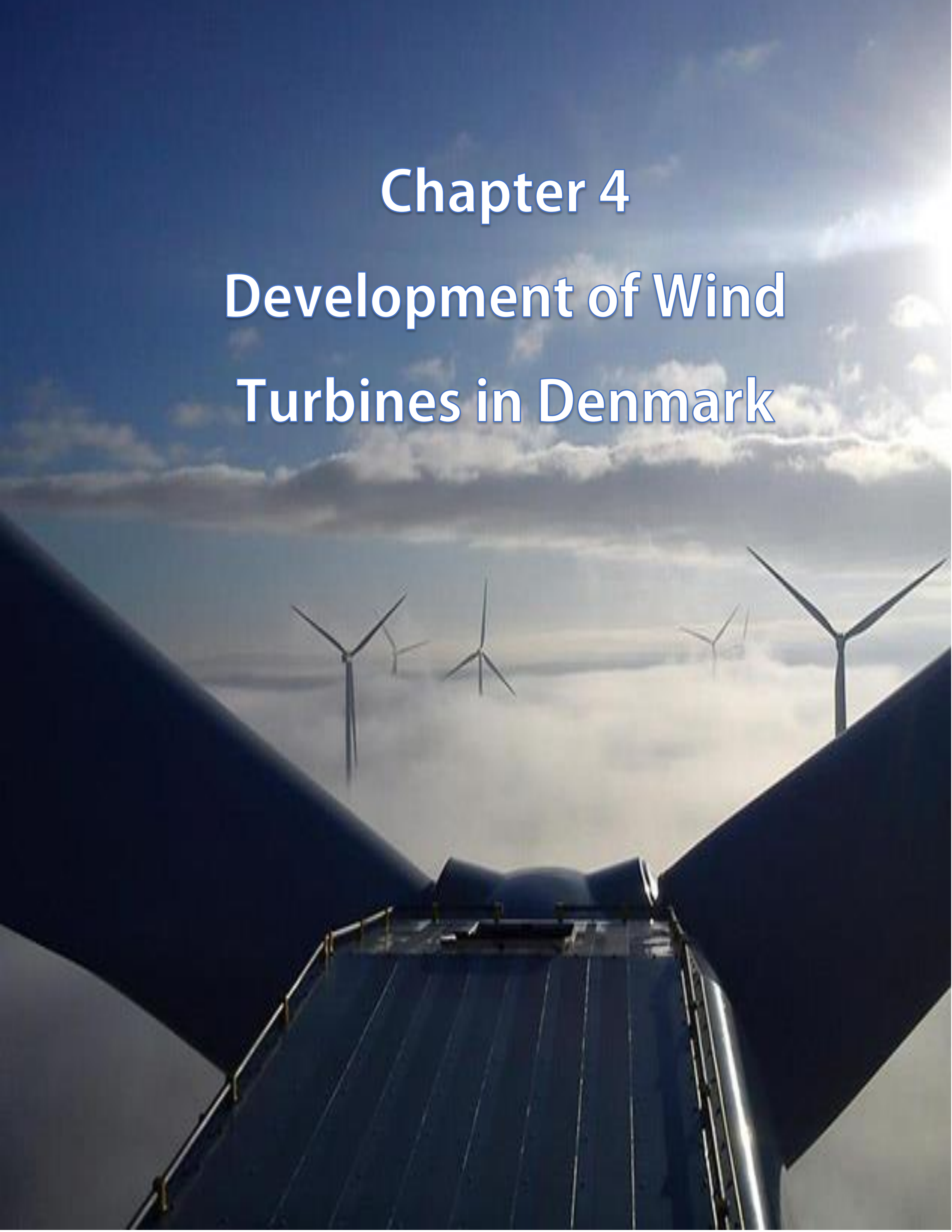
After defining the actors and their interactions, it is time to define system boundaries. The duration of the analysis is from 1980 to 1995, because this is the only time period, a considerable amount of wind turbines are installed. The physical boundary is defined at the beginning, as California. Wind turbines were the only promising renewable technology at the time in terms of cost competitiveness (except from hydropower), therefore the other renewable technologies are not considered (Menz & Vachon, 2006).

In a nutshell, California's wind turbine producers learned from learning by doing with DOE's subsidies on small scale wind turbines, but that was not the only source of knowledge. Learning by searching with significant R&D investments which focused on large wind turbines brought a valuable knowledge to wind turbine technology. From the adopters' side, the utilities focused on profitability of wind turbines, and they did not take initiatives on wind turbine diffusion which could have strengthened the knowledge share.

Before explaining the remaining questions in this description phase, the Denmark story will be analysed in the same way. Then the remaining questions for both cases will be answered together in Chapter 5.

Chapter 4

Development of Wind Turbines in Denmark



4. Development of Wind Turbines in Denmark

This chapter gives information about the wind turbine diffusion in Denmark and related policies fostering and/or hampering it. The next section gives a brief history of wind turbine development in Denmark before 1970s, the second section takes a look at the energy market structure in Denmark, and the third section explains the motivations for wind turbine diffusion and related policies. The final section puts all the information in a frame and structures the conceptualization of wind turbine diffusion in Denmark.

4.1. History

Denmark's story with turbines started way before the 1970s, with the contributions of the Danish physics professor Poul la Cour. In 1903 he created a windmill producing direct current (DC) electricity named 'Klapsejler' (Heymann, 1998). His windmill helped Denmark to survive fuel shortages in World War II (WWII) (Kamp, 2002). With time, the aerodynamic structure of wind turbines was developed with la Cour's efforts.

During WWII there were other efforts for generating electricity from wind mills. F.L. Smidth's windmill 'Aeromotor' had maximum capacity of 70 kW with two or three blades. However, after WWII, small windmills offering decentralized electricity with direct current were quickly replaced by centralized fossil fuel based power plants (Kamp, 2002). However, the efforts for building wind turbines did not stop completely. Johannes Jull worked on wind turbines during the 1940s and 1950s and he even built a 200 kW turbine with a 24 meter rotor in 1956 with the support of government which was named 'Gedser'. The main design criteria of this wind turbine was based on la Cour's design, which promotes simplicity. The designs of Danish wind turbines are still based on the principles of Gedser design (L. Kamp, 2002). This wind turbine was tested for ten years until 1967. In total, it produced 2.2 million kWh of electricity (Gipe, 1995). However, the Danish government reported that it is not possible for wind turbines to compete with the fossil fuels for electricity generation from an economic perspective in 1962 (Kamp, 2002). Therefore, for economic reasons the operation of the Gedser turbine was stopped (Heymann, 1998). However, with the oil crisis in 1973, Denmark went back to focusing on wind energy.

As of 2013, 33.2 % of Denmark's electricity generation is coming from wind energy (Danish Wind Industry Association, 2013). Additionally, with the experience they gained, Denmark has a large share in the global wind turbine market (Morales, 2014). To understand how Denmark reached such high percentages, the next section will introduce the electricity market structure in Denmark briefly. Then in the next section, the motives and policies for wind turbines in Denmark will be explained.

4.2. Electricity Market Structure in Denmark

The Danish electricity market was liberalized at the end of the 1990s (European Commission, 2007). With the new structure Grid companies and Transmission system operators (TSO's) maintain monopoly activities. The generation of electricity is rather competitive, with generation companies and independent producers such as owners of wind turbines. It should be noted that Denmark allowed from the beginning to own power companies by consumer cooperatives and municipalities (Bergman, 2003). Therefore, the liberalization process did not have significant effects on the electricity generation structure.

The main structure of the relationship among the actors are similar to United States. There were three main processes; generation, transmission and distribution. From the deregulation act, generation activities were not get affected significantly, since Denmark allowed private cooperatives to have their own power generation facility. The prices were regulated by the government for having a secure market. Also, even though environmental concerns were high on the agenda, there was no specific demand for green electricity coming from the consumers. Instead, environmental concern only resulted in high preference of wind turbines over nuclear energy. The cooperatives' main focus was also on profits, and they worked closely with the utilities, therefore it is assumed in this research that the aims of the cooperatives are covered under the aims of utilities.

Danish electricity generation was heavily based on fossil fuels, and the second major source was coal. However, Denmark has little fossil fuel, and consequently, they were highly dependent on imports (before the 1970s, Denmark was not exploiting the oil and gas reserves in the North Sea) (Heymann, 1998).

Currently, Denmark has two separated transmission systems, where the eastern one is connected to Nordic market (NORDEL) and the western one is the synchronous grid of Continental Europe (Gellert, 2011). With the North Sea reserves and wind production, the country produced 156% of its electricity need in 2007, and exported the remaining 56%. (European Commission, 2007).

4.3. Motives and Policies for Wind Energy in Denmark

The motivation for focusing on wind turbines in Denmark was also coming from the 1973 oil crisis. In 1973, 94% of Denmark's energy supply was coming from imported oil and the rest was mainly based on coal, which was also imported (L. Kamp, 2002). Similar to United States, Danish wind turbine policies followed two paths: supply-push and demand-pull. Under the supply-push policies Risø National Laboratory and Technical University of Denmark started a Wind Power Programme, to develop knowledge about large wind turbines (Van Est, 1999). In the first phase of this programme, 35 million DKK was spent on developing wind turbines, and 82% of this budget went to development of large wind turbines. Within this programme, a formal Danish team visited the United States to co-operate and exchange knowledge about with turbines. However, The American wind turbine producers did not approach this idea positively. After the meeting, the development of wind turbines in Denmark and the United States followed different paths (Kamp, 2002).

Apart from putting R&D efforts into wind energy, the Wind Power Programme directly involved the utilities in the programme, since they will be the potential buyers of the technology. This involvement helped utilities to become more familiar with the technology from the development phase, which could be also interpreted as a demand-pull policy regarding large wind turbines (Kamp, 2002). The efforts to build large wind turbines continued until 1990. Gedser turbines, the Nibe turbines (Figure 4.1), Masnedø turbines and Tjæreborg were the results of large wind turbine development efforts triggered by mainly learning by searching mechanisms (Sawin, 2001). However, the utilities could not reach the expected performance from large wind turbines, therefore the government abolished the programme around 1990 (Kamp, 2002).

Figure 4.1 Nibe A and Nibe B, 1979 (Hau, 2006)

It should be noted that Denmark had little knowledge about aerospace principles, therefore their wind turbine designs were not that affected by the aerospace industry. Yet, the lack of this potential spill over had no effect on developing quality wind turbines (Kamp, 2007).

The development of small scale wind turbines in Denmark started independently from R&D spending, with the efforts of small entrepreneurs. These entrepreneurs were in favour of small, locally owned power plants instead of centralised power plants. Besides, the society was environmentally conscious, therefore their mind-set was highly in favour of renewables instead of nuclear energy (Sawin, 2001). Therefore the Danish government provided clear aims to the producers by stating that they want to reach 10% wind share in electricity generation by 2000 (Olume & Kamp, 2004). In 1979, the Danish Ministry of environment ordered utilities to provide wind turbine access to the grid and pay the fair rates for the electricity they generated. They provided 30 percent of the investment cost payment. This reduction was given to buyers of wind turbines, not to the producers (Buen, 2006). It should be kept in mind that, this subsidy was given to the wind turbines which are approved by Risø Test Station assuring quality. Also a Danish wind atlas was published showing the best locations for siting wind turbines in 1980-1981.

In 1985, there was an agreement between the government and utilities for 10 years. Utilities were able to buy the wind generated electricity by paying 85 percent of its price. This policy resulted in increase in wind turbine installations (Figure 4.2).

In 1986-87 investment subsidy was reduced to 20% and 10% respectively. And this subsidy was removed totally in 1989 (Kamp, 2002). Also the criteria for receiving the investment subsidy were tightened. In 1988, there was a new agreement between the government and the power companies to install 100 mW wind power at the end of 1990. However, this agreement was only totally realized at the end of 1992 (Buen, 2006).

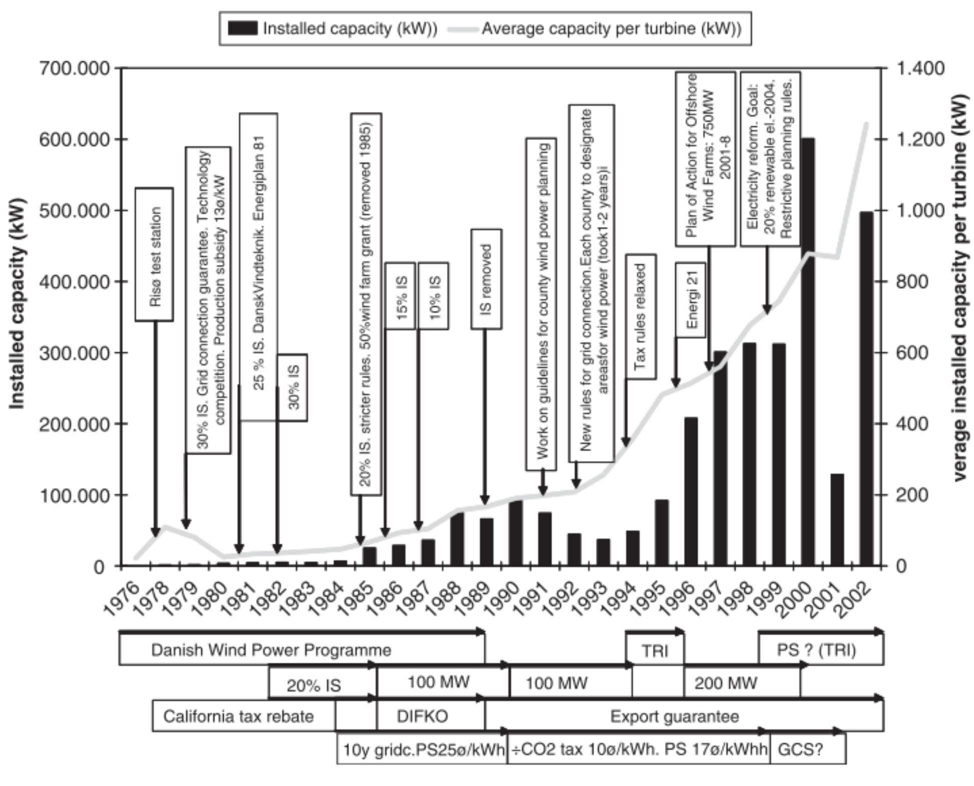


Figure 4.2 Wind turbine installations in Denmark and related policies (Buen,2006)

In brief, similar to California, large scale wind turbine efforts were not that successful. Nevertheless, during these efforts the government involved the utilities in the development process, which triggered a learning by interacting mechanism. Also, the government was clear with their aim to reach 10% energy production from wind energy by 2000, which created awareness and security in the market. Demand-pull policies were effective for initiating the demand, but their long-lasting effects are open for discussion.

4.4. Conceptualization of the Case

For conceptualization of the Denmark story the same steps will be followed as in the California case.

Conceptualization is structured by answering the following questions (Albin, 1997):

- What are the active actors and what are their aims and responsibilities?
- How do the actors interact with each other?
- In what kind of environment do they interact? What are the boundaries of the environment?
- What are the basic mechanisms in the system?
- What are the key variables in the model?

In Denmark there are actually four actors instead of three in the California case. Because some of the wind turbines were owned privately at that time. However, since utilities are the buyers of this electricity, and they are interested in the producing costs, for modelling purposes this separation has no significant impact. Besides, most of the time, installation costs were shared between the wind farm owner and the utility meaning that they have partial ownership of the farm. For this reason, again the utilities will be considered as the wind turbine owners as well. The relationship among the actors and their motives are also the same as California case which is shown in Figure 4.3. The reason for having the same actor framework in both cases is due the similar mind-set of these actors. For example, the utilities in both cases were mainly concerned about the profit due to deregulation of the energy sector in both countries. Producers have global goals for selling wind turbines with maximum profit, and they also exported their wind turbines showing that the aims of the producers did not change according to their location. Finally, both the governments in Denmark and in the United States have the priority of secure energy supply, and for this specific case they focused on wind energy as an alternative source. Environmental concerns were existent, however, this resulted in only for the preference of wind energy instead of nuclear energy (Buen, 2006). In addition to utilities, wind turbine producers are the second main actor, having learning processes and determining costs and get the benefits from R&D subsidies. The final actor is the government, aiming to help the utilities to install wind turbines by making wind turbines cost competitive, and offering subsidies to producers.

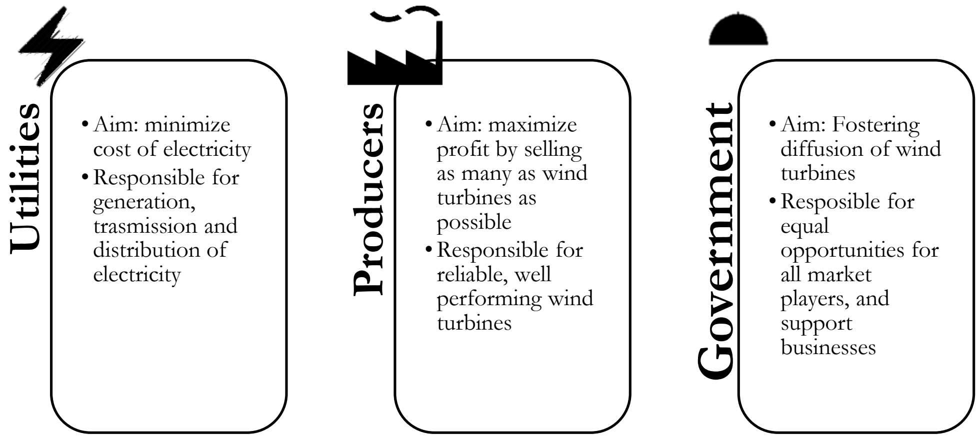


Figure 4.3 Actors, their aims and responsibilities

As well as the actors' own actions, their interactions are important for understanding decision flows. An action sequence diagram is shown in Figure 4.4 for showing the relationships between the actors. The vertical line represents the timeline. The arrows shows the actions happening between corresponding actors. Some of the actions are continuous throughout the process, therefore those are shown in dashed lines.

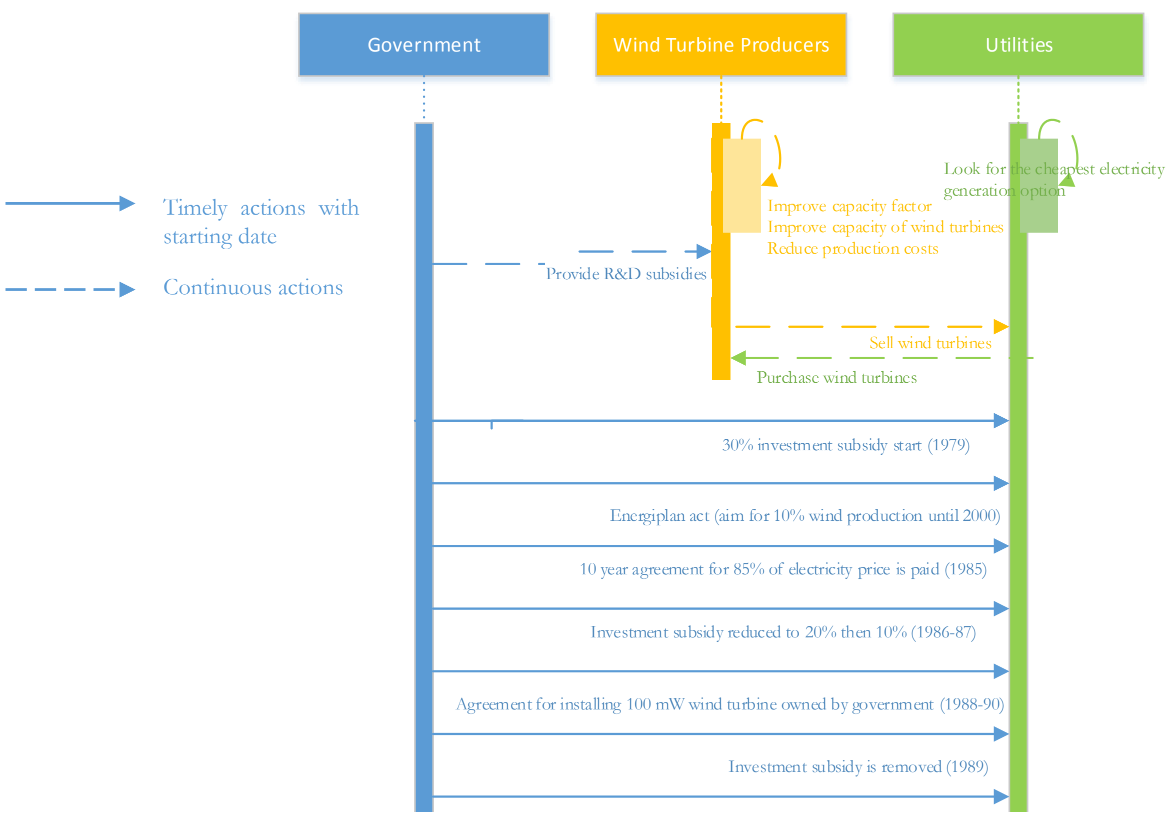


Figure 4.4 Action Sequence Diagram

After defining the actors and their interactions, it is time to define system boundaries. The duration of the analysis is from 1980 to 1995, to be consistent with the California case. The physical boundary is defined as Denmark. The choice of wind power is coming from Denmark's governmental aims, stating that wind power is the only alternative to conventional energy generation (Danish Energy Authority, 2001).

When we look at the overall history of wind turbine diffusion in Denmark, we see that Danish producers learned building good wind turbines with mainly experimenting on small scale wind turbines (learning by doing). There were also R&D efforts with the research centres and governmental efforts resulting in extra knowledge for improvement of wind turbines (learning by searching). Due to the determination of government on having wind turbines as an energy alternative, the willingness of the society to adopt wind turbines instead of nuclear energy and the efforts of Danish Windmill Owners Association; the knowledge share among the adopters was strong implying the importance of Knowledge Diffusion via Networks function of Hekkert. Also, the decision making mechanism of adopters, which were the utilities, was based on maximizing profits.

Explanation of the remaining questions are given in the next chapter since the system is quite similar to the system in California. A common model with different parameters is created in Chapter 5, showing the common key variables and active mechanisms in the system.

Chapter 5 - Model Implementation

5. System Description

This chapter builds on the previous three chapters. Chapter 2 introduces the theoretical framework to be used for building the model, whereas Chapter 3 and 4 gives the storyline of the model for California and Denmark case respectively. The following diagram shows the structure of this chapter (Figure 5.1).

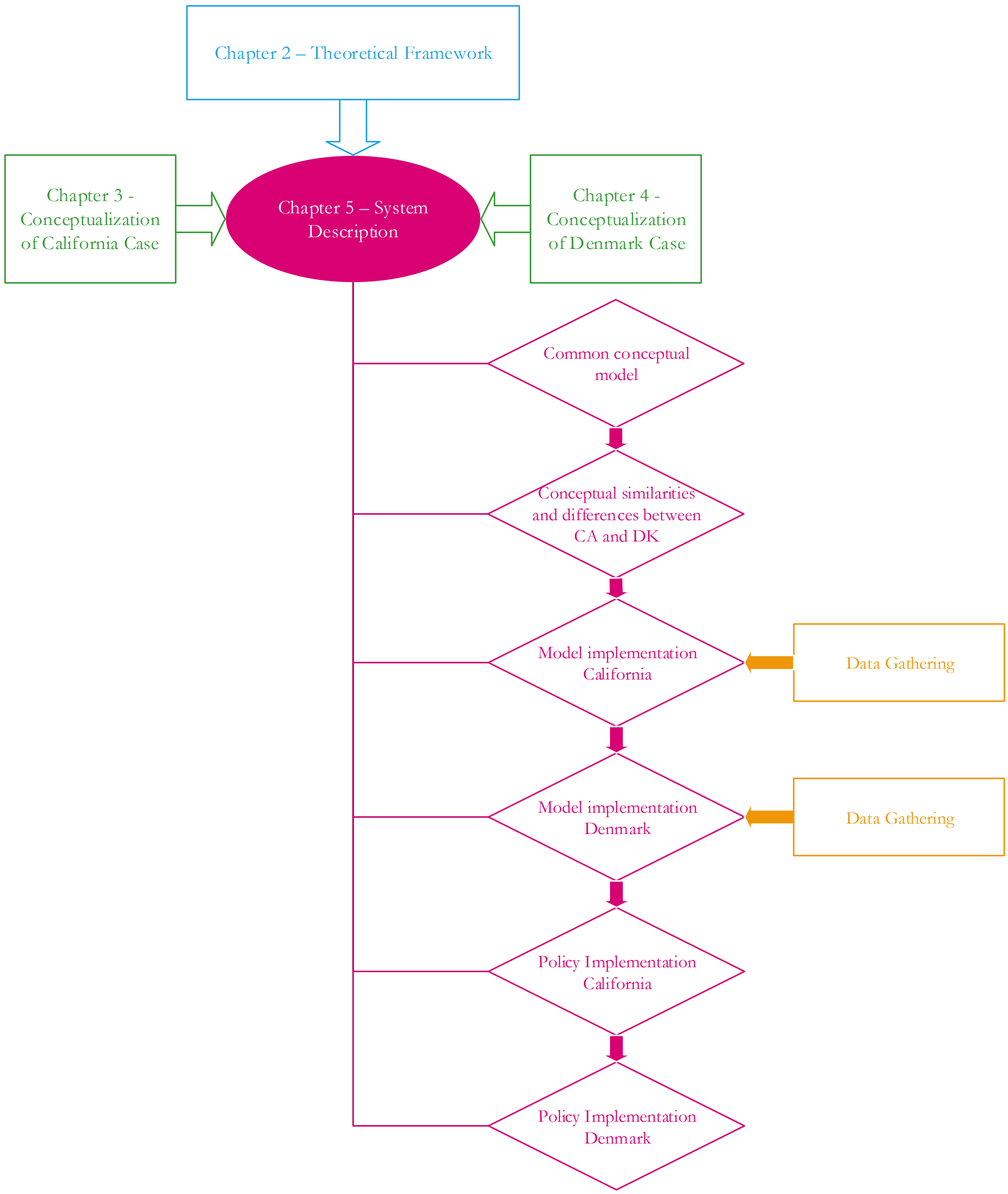


Figure 5.1 Structure of System Description

As Figure 5.1 suggests, first the conceptualization questions which were not answered in Chapter 3 and 4 will be answered. Then, the active mechanisms in the diffusion will be explained with their theoretical relations one by one. In the third section, a common conceptual model will be built. Before going through the model implementation, the conceptual differences in the cases will be underlined. The fourth and fifth sections will be about implementation of the conceptual model into a working one, for California and Denmark respectively. Data gathering processes and the sources will be also explained in these chapters. After building the working models, policies and their interpretation and implementation into the model will be explained. Finally the initial results of the model will be presented as base cases. However, conclusions coming from these models will not be highlighted here, since validation of the model is necessary (Chapter 6).

5.1. Finishing up the Conceptualization Phase

In the conceptualization phases of California and Denmark, these two questions were left unanswered:

- What are the basic mechanisms in the system?
- What are the key variables in the model?

The reason for postponing the answers of these questions is the great similarity of the two cases. The first three questions answered in Chapter 3 and 4 implies that the structure of the cases looks similar. First of all, the main actors in both cases and their aims and responsibilities are the same. Secondly, the decision making mechanism of adopters, which is a based on costs is the same because in both cases the actors aim to maximize their profits. When we look at the Table 2.1. and compare it with the qualitative knowledge coming from Chapter 3 and 4, we see that both in California and in Denmark, some of the learning is occurred via learning by searching, triggered by R&D investments. Also, both cases showed improvement on capacity factors, and investment costs by time, where learning-by-doing phenomenon is observed. Also, as it is observed in every diffusion story, knowledge diffusion via networks were visible, where the adopters communicate with each other about wind turbine technology. The active mechanisms are mainly learning by doing, learning by searching and knowledge diffusion through networks. There were no competition of an alternative renewable technology at the time, therefore resource allocations and the guidance of the search were only focused on wind energy. The existence of these active mechanisms/functions show that both cases can be represented with the same structure. Of course, the functioning of these mechanisms differ in both cases, but the concepts in the cases will be the same.

To determine the key variables, three different sources are used. The first one was based on the historical results, and the factors which cannot be assessed quantitatively are also based on these historical results. For example, the learning rates for capacity factor of wind turbines and their investment costs are determined by sensitivity studies by looking at the best fit to the historical data in terms of results. For this reason, wind turbine installations per year, capacity factor of wind turbines over time and similar performance measures are determined. Secondly, the policy based variables are determined, such as R&D investments, and subsidies. The third source of variables is coming from the literature. Since the active mechanisms are conceptualized in Chapter 2, the variables affecting these mechanisms are gathered from the literature and they put together in feedback mechanisms. There was an iterative and simultaneous process in determining the mechanism and the key variables, therefore even though one is presented before the other in this report, it is not possible to say that one follows the other in conceptualization. Since both of the systems have the same structure, the same key variables and mechanisms are active in both of them. Thus, key variables for these cases are shown in Table 5.1.

Key variables for wind turbine diffusion are separated into two categories as endogenous and exogenous. Endogenous variables are the ones affecting and being affected from other variables, whereas exogenous variables are the ones only affecting the other variables, but not getting affected. Also, the variable actor relation is shown in the parenthesis of each variable. "U" stands for utilities and "P" stands for producers. There are no variables regarding government, since the government is not affected by those (exogenous actor). The change of these variables over time will be the outcomes of the model. It should be noted that there will be more variables in the model implementation to be able to meaningfully represent the real world, however the outcomes of the change in those variables are secondary results, therefore they are not presented in the table.

Table 5.1 Key Variables in Wind Turbine Diffusion

Endogenous Variables	**Exogenous Variables**
Wind turbine installations (U)	R&D subsidies (P)
Familiarity with the wind turbines (U)	Initial investment cost of wind turbines (P,U)
LCOE of wind (P, U)	LCOE of natural gas, oil, hydropower and nuclear (U)
Wind turbine capacity factor (P)	Operation cost of wind turbines (U)
Affinity with the wind turbines (U)	Initial wind turbine capacity factor (P, U)
Affinity with the conventional techs (U)	Average annual electricity demand (U)
R&D based knowledge stock (P)	Effectiveness of users, and non-users(U)
Learning by doing experience stock (P)	Tax credits (U)

The reason for having wind turbine installations as a key variable is obvious, since it is the main outcome that we are interested in the model. Familiarity with the wind turbines is also a key variable, because it represents the percentage of utilities who are aware that the wind turbine is an option for generating electricity. Levelized Cost of Electricity (LCOE) of wind is also crucial, which is explained in section 5.1.4, because it represents the cost of installing wind turbines and producing electricity from it. Wind turbine capacity factor is another variable affected from learning-by-doing and learning-by-searching mechanisms, and it influences the performance of wind turbines, leading to an impact on LCOE. Affinity with the conventional technologies and the wind turbines are also significant, because these variables are results in utilities' decision making to install wind turbines. R&D based knowledge stock has a direct effect on learning-by-searching mechanism, and learning by doing experience stock has a direct effect on learning-by-doing mechanism, therefore they are also considered as key endogenous variables.

The exogenous variables are also important since they have an impact on the endogenous ones. R&D subsidies have direct effect on R&D based knowledge stock, initial investment cost of wind turbines is the starting point for learning-by-doing and learning-by-searching mechanisms, LCOE of other technologies affects the decision of the utilities whether installing wind turbines are profitable or not, so as the operation cost of wind turbines. Also, initial wind turbine capacity factor stands for another reference point for learning-by-doing and learning-by-searching mechanisms. Average annual electricity demand has an effect on determining the demand increase per year and subsequently the new installations for electricity generation. Effectiveness of the users and non-users affects the familiarity where the relationship is explained in section 5.1.5. The next question which should be answered is the relationship among these variables. To answer this question, each mechanism will be shown in the context of wind turbine diffusion.

5.1.1. Learning by doing mechanism

This mechanism was present both in Hekkert's work and Yucel's work (2007; 2010). The implementation of this mechanism in wind turbine diffusion case is conceptualized as in Figure 5.2.

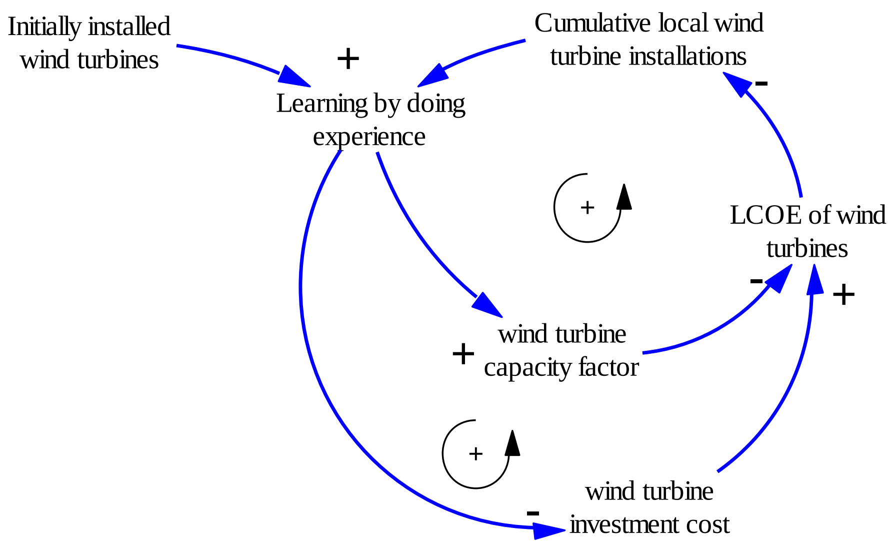


Figure 5.2 Learning by doing mechanism in wind turbine diffusion

As the Figure 5.2 shows, there is a positive relationship between the cumulative installations of wind turbines and learning by doing experience. Experience accumulation results in better capacity factors which decreases the costs and increases the installations of wind turbines, since people learn on building better and more efficient processes with experience. Similarly, experience increases productivity and as a result investment cost of wind turbines decreases, resulting in decrease in LCOE and higher wind turbine installations. It should be noted that Hekkert's function 1, entrepreneurial activities are embedded in this learning by doing mechanism in an aggregated way.

This mechanism is widely accepted in economic theory and its role in wind turbine diffusion is highlighted by many studies (Ibenholt, 2002; Kamp, 2007; Kemp, Schot, & Hoogma, 1998; Klaassen, Miketa, Larsen, & Sundqvist, 2005; Kobos, Erickson, & Drennen, 2006). Thus this mechanism is one of the main feedback loops in wind turbine diffusion.

5.1.2. Learning by Searching Mechanism

This mechanism is also strongly mentioned by Hekkert in Function 2 and 6, and by Yucel's *resource driven change in option properties.* The same variables are being affected by the learning-by-searching mechanism, which are the capacity factor and investment cost of wind turbines. It should be noted that in real learning processes, other things are improved as well such as rotor blades. However, the capacity factor and investment cost variables carry the improvements on other parts of wind turbines since they are the two key indicators of performance and cost. Figure 5.3 shows the relationship between R&D spending and LCOE of wind turbines.

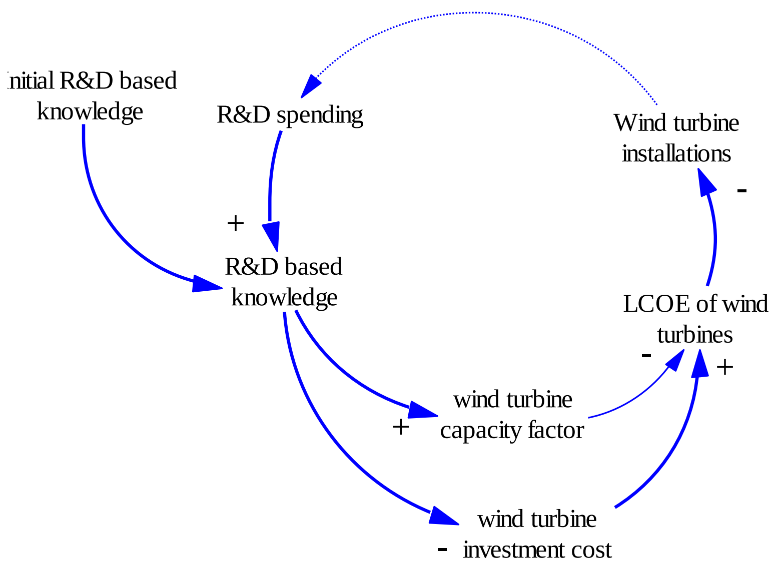


Figure 5.3 Learning by searching mechanism in wind turbine diffusion

The dashed arrow implies that there could be a relationship between wind turbine installations and R&D spending, which could be negative, however, this possible relationship is ignored in the conceptual model, since there is no indication of such relationship in the literature and governmental R&D supports are highly affected by authorities' points of view.

5.1.3. Combining Learning-by-doing and Learning-by-Searching mechanisms

Both of these mechanisms influence the same factors, but measuring the contribution of them separately is not possible. To model the effects of these mechanisms on *capacity factor* and *investment cost* Klaassen et al's work on two factor learning curves is taken as base knowledge (2005).

With the experience of a certain technology, producers learn efficient ways to produce the product and therefore the cost decreases. The relationship between learning and cost reduction has been found in many empirical studies (Argote & Epple, 1990; Dutton & Thomas, 1984). As a common formula, one factor learning curve is as follows (Koomey & Hultman, 2007):

$$SPC = A \,.\, \left(\frac{CC}{CC_0}\right)^{-\propto} \tag{1}$$

Where SPC is investment cost per unit for the technology (specific cost) and CC is the cumulative capacity at a given time divided by the cumulative capacity at time 0 (CC_0). – α is the learning factor, and A is the specific cost at time 0.

This formulation indicates that there is a constant percentage learning rate causing the decrease in cost. However, there is no separation between different learning styles in this formula, so that learning by doing and learning by searching stand together in it. Hence, this traditional formula do not help the policy makers in allocation of R&D resources (Klaassen et al., 2005). To overcome this problem, Kouvaritakis et al offered the following formula, including cumulative R&D expenditures in addition to cumulative installed capacity (2000). In this model, there was a depreciation of R&D knowledge as well. However, this is ignored in this study, since there was no proof of missing knowledge on such a short time period of 15 years (1980-1995). Additionally, in a one-factor learning curve, learning-by-doing is measured with cumulative capacity, and that only depreciates with lifetime of the technology, which is about 20 years, and the forgetting feature is ignored. To have a more consistent formula, forgetting the knowledge coming from learning by searching structure is also ignored. The modified 2 Factor Learning Curve formula is as follows:

$$SPC = A \,.\left(\frac{CC}{CC_0}\right)^{-\propto} .\left(\frac{KS}{KS_0}\right)^{-\beta} \tag{2}$$

In this formula (2) KS is the knowledge stock at a given time, where KS_0 is the initial knowledge stock. β represents learning by searching index. The remaining symbols are the same as (1) These separate parts of the formula represent the percentage improvements coming from learning by doing and learningy by searching respectively, and to reach the total improvement on specific cost these values are multiplied.

The learning also occurs for performance improvement. For example, with time, the capacity factor of wind turbines increases. To model this learning curve the same formula is used, but with a percentage increase in performance. The following formula is used for calculating learning curves for performance increase:

$$PF = PF_0 \,.\left(\frac{CC}{CC_0}\right)^{\delta} .\left(\frac{KS}{KS_0}\right)^{\theta} \tag{3}$$

Equation (3) has the same logic as equation (2). PF stands for performance at a given time, where PF_0 is the initial performance. Learning rates for different performance measures can be different, therefore for each measure the values of δ and θ would be different.

5.1.4. Purchasing Decision of Wind Turbines

The purchasing decision is based on the levelized cost of energy (LCOE) calculation. During the 1980s, there were environmental concerns but those concerns were only coming from the governmental perspective. Therefore, actors' decisions were mainly affected by the cost of generating electricity (Norberg-Bohm, 2000). Also, the only promising renewable technology in terms of cost competitiveness was wind turbines (compared to conventional technologies; such as nuclear power, coal power and oil based power plants) (Menz & Vachon, 2006). For this reason the utilities' purchasing decision is based on LCOE comparison of different technologies, which is modelled as conventional technologies vs. wind. The separation of preference among conventional technologies is modelled in an aggregated fashion, since the power mix of conventional technologies did not change significantly in the duration of the model, and the detailed preferences of conventional technologies are the out of the scope of this study.

Levelized cost of energy (LCOE) is a common method for calculating electricity cost. It is the cost of electricity to reach the break-even point over the lifetime of the project for generating it from a specific source (NREL, 2013). It takes investment cost, fuel cost, operation and maintenance cost into account, and gives an aggregated cost which makes it possible to compare electricity cost coming from different sources. It can be written as the following formula (IEA, 2005):

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t \; + \; M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \tag{4}$$

$\mathbf{I_t}$ = investment cost at year t

$\mathbf{M_t}$ = operations and maintenance cost in the year t

$\mathbf{F_t}$ = fuel cost in the year t

$\mathbf{E_t}$ = Electricity generation in the year t

r = discount rate

n = lifetime of the project

This formula calculates the net present value (NPV) of each cost for year t and divides this total cost by the electricity generation at year t discounted into year 1. However, this common method is not very suitable for system dynamics method in its current form, because SD is a time based simulation, and NPV calculations in SD is not very reliable. The reason for this is due to the nature of system dynamics simulation. For calculating NPV, the costs for the whole lifetime should be known, but SD simulations progress step by step over time and do not have memory on the values for the whole period. Therefore, another way of dealing with calculating LCOE should be implemented into the simulation. To solve this problem, instead of calculating NPV of each cost, the equivalent annual cost of investment cost is calculated and time dependent costs are left at their time t. Equivalent annual cost (EAC) is the cost per year of owning and operating an asset over its lifetime (Short, Packey, & Holt, 1995).

$$EAC = \frac{I_0.r.(1+r)^n}{(1+r)^n - 1} \tag{5}$$

I_0 stands for the investment costs for the technology (Stoft, 2002). After calculating EAC of investment cost, LCOE at time t is calculated in the model as follows (NREL, 2000):

$$LCOE_t = \frac{EAC}{E_t} + M_t + F_t \tag{6}$$

This final version (6) is used for cost calculation of different technologies, which would be more suitable for system dynamics working principles.

In the model, there is another variable called affinity which is used for modelling actors' decision making process. This variable represents the actors' possibility of purchasing an option under a certain performance. It is generally modelled exponentially as follows (Struben & Sterman, 2008). This formula is based on standard multinomial logit choice models in the literature. It is a commonly used choice framework for modelling consumer choice among different options in the consideration set. In our case the consideration set is wind turbine vs. conventional technologies:

$$a_j = a^* \exp(-\beta \left[\frac{LCOE_j}{LCOE^*} - 1\right]) \tag{7}$$

a^* represents a reference affinity for the reference LCOE value $LCOE^*$. The reference value stands for an normal value that the adopter has an idea about. For example, an actor decides whether the given LCOE of the available options are expensive or not by comparing it with the reference LCOE*. If the given LCOE is more expensive than the reference value, the affinity decreases and vice versa. The reference values are determined separately for conventional technologies and for wind turbines. For conventional technologies, the average LCOE of all times is taken as $LCOE^*$ and then affinity at this value is assigned as 1, because, at an average price of electricity generation cost, the utilities will go for the conventional methods. After determining reference values of conventional technologies, wind turbine reference values are determined accordingly. Assuming that if wind turbine is competitive with the conventional technologies, the affinity to the wind turbines is assigned to 1 with lower reference LCOE* value, since it is a relatively new technology and utilities will have questions in their mind for going for a new technology. Besides there will be switching costs of the utilities for moving to a new technology, due to limited experience and unknowingness of the new technology. This way affinity is modelled as a decision making process of utilities for purchasing wind turbines.

5.1.5. Knowledge Diffusion through Networks and Familiarity

For modelling familiarity, a qualitative understanding of methods is used and this understanding is harmonized with Struben and Sterman's familiarity work. The third function of Hekkert emphasizes the importance of exchange of information among adopters (2007). Also, Kamp states that the learning by interacting mechanism was strong in Denmark, which was one of the main reasons of successful wind turbine diffusion (2002). Therefore, a mechanism representing this exchange of information is essential.

Hekkert mentions that it is possible to measure function 3 with network size and network intensity. To model that, the network size is measured not with the number of utilities, but *total installed capacity* in California and in Denmark. The percentage of wind turbine capacity represents the share of wind turbine installations in an aggregated way. Network intensity is represented by the variables; *effectiveness of contacts with users* and *effectiveness of contacts with non-users*. Users stand for the utilities who already installed wind turbines. Non-users stand for all utilities except having wind turbines. Familiarity increases with the total social exposure coming from effectiveness of users, non-users and external stimulants such as marketing. This increase is called familiarity gain and it is represented with n_t. The effectiveness of users are calculated by multiplying the share of wind turbines over total installed capacity with the familiarity at that time and the effectiveness ratio of users on potential adopters. The remaining share represents the share of non-users in the network which is also multiplied by familiarity and the effectiveness ratio of the non-users. It is assumed that there is a positive relationship between the network intensity and effectiveness of contacts, since in a network having strong relationships, word of mouth would be stronger. The marketing ratio is then added to the formula as an extra motivation in familiarity gain. The formula is shown below (Struben & Sterman, 2000):

$$n_t = \alpha + c_i F\left(\frac{W}{N}\right) + c_j F(1 - \frac{W}{N}) \tag{8}$$

In the familiarity gain formula which is illustrated in 8, α represents the social exposure gained by marketing/awareness programmes, c_i represents the effectiveness ratio of users, F represents familiarity value at that time, W represents the installed mW of wind turbines, N represents the total installed capacity for electricity generation in mW and finally c_j represents the effectiveness ratio of non-users on adoption.

Familiarity represents the awareness percentage of the utilities with the wind turbines. It is a number between 0 and 1. It also decays over time, since people lose familiarity if the social or direct exposure to that technology is low. The decay is modelled with the following exponential function (Struben & Sterman, 2000):

$$\emptyset_t = \emptyset_0 \frac{\exp(-4\varepsilon(n_t - n^*))}{1 + \exp(-4\varepsilon(n_t - n^*))} \tag{9}$$

In this function which is a characteristic logistic function, n_t represents the social exposure from users, nonusers and awareness campaigns at time t. n^* represents the reference rate of social exposure where familiarity decreases at half of the normal rate. The greater the exposure, the slower is the decay. $\emptyset_0$ Is the *maximum familiarity decay rate*. Familiarity decreases fastest when n_t is small. ε stands for the slope of the decay rate at a given point. It is assumed that ε is $1/n^*$ which normalizes the elasticity of the familiarity decay to exposure at 1.

After introducing the variables affecting the familiarity, the structure of the mechanism is shown in Figure 5.4.

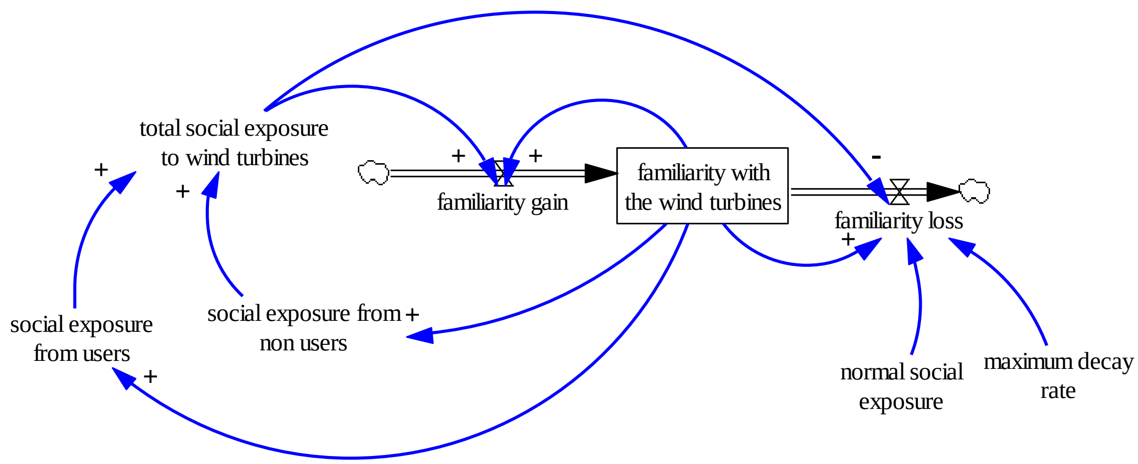


Figure 5.4 Familiarity mechanism

As can be seen in the picture, familiarity increases with the total social exposure and decreases with time. The distinction between the users and non-users is done by looking at the share of wind turbine capacity in total installed capacity for electricity generation.

All main mechanisms and decision making processes are now explained. In the next section, how these structures put together is illustrated.

5.1.6. Combining the Mechanisms

In a model representing wind turbine diffusion, the mechanisms introduced in the previous sections should be put together in a meaningful way. Figure 5.5 shows the conceptual diagram of the model, where every mechanism is integrated.

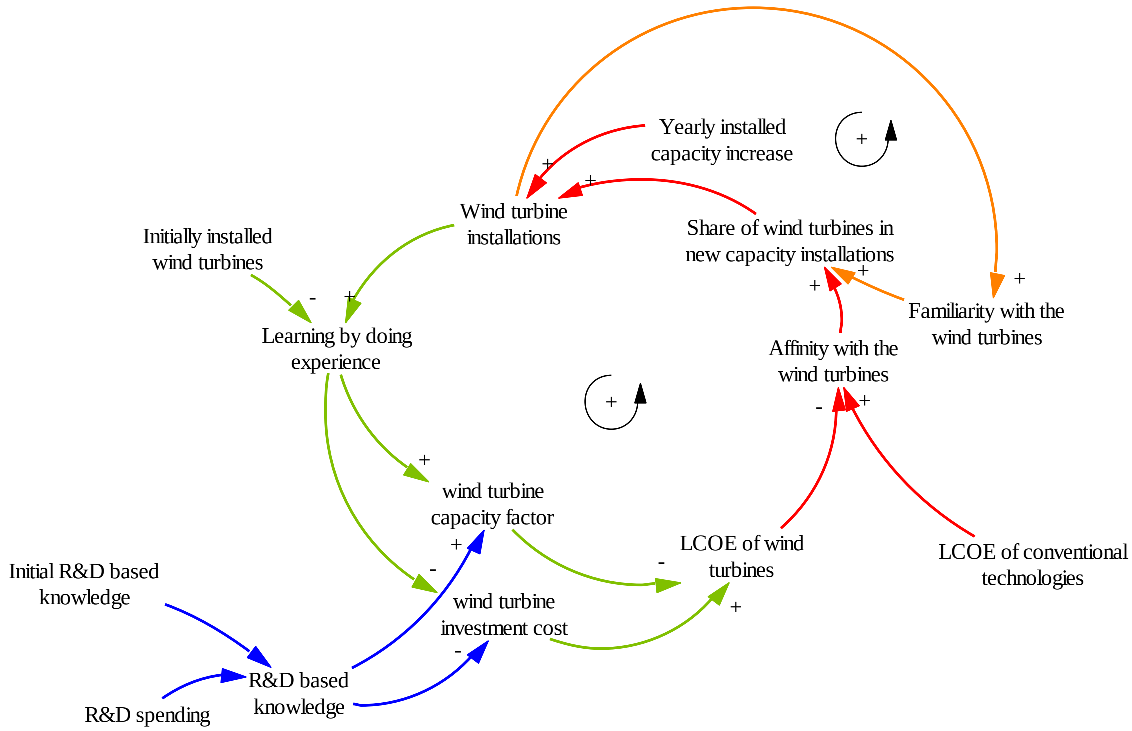


Figure 5.5 Conceptual Diagram of Wind Turbine Diffusion Model

In brief, there are two main things influencing wind turbine installations. The familiarity with them and the affinity with them. Familiarity increases with installations and decreases with time. Affinity is a way of comparing wind turbines with other technologies, and deciding the level of fondness towards wind turbines. This comparison is based on LCOE comparison of wind turbines and conventional technologies. LCOE represents the price of electricity at which electricity should be generated from a power source to break even over the lifetime of that power plant (NREL, 2013). Therefore, it is a calculation method including both performance and cost related factors, like capacity factor and investment cost, which are improved over time with learning by doing and learning by searching mechanisms. Demand is modelled with *yearly installed capacity increase* which represents the total capacity increase for electricity generation. The main diffusion structure is the same for California and Denmark, since actors' responsibilities, decision making structures and the motives are the same. However, there are differences between them in terms of strength of different loops, and the policies strengthening or weakening these loops. The conceptual differences between these two cases are explained in the next section.

5.2. Differences between California and Denmark and Main Assumptions

When we look at the numerical data, we see a lot of differences between California and Denmark, such as the R&D spending of governments. However, there are some other differences coming from qualitative data, and they should be explained before going to data gathering and model implementation phase. Also there are other assumptions regarding the mechanisms themselves which should be made clear. These conceptual differences and assumptions are as follows:

- The network intensity and knowledge share was stronger in Denmark, because in Denmark there were wind associations and they were publishing informative magazines about wind turbines. Such an organization was not present in California (Kamp, Smits, & Andriesse, 2004; Norberg-Bohm, 2000).
- The learning by doing curve is stronger compared to learning by searching curves (Kamp, 2007; Klaassen et al., 2005).
- The learning by doing mechanism is only affected by locally produced wind turbines.
- The learning by searching mechanism is not state based, but country based, therefore R&D spending of whole country for wind energy is more realistic, since R&D based knowledge spreads through fast and also most of the activities were in California in Unites States.
- Installed capacity increases with the same yearly rate, which is the average rate of actual yearly increases.
- There is no distinction between onshore and offshore wind turbines since there were no significant attempts in installing offshore wind turbines during 1980s and 1990s.
- The source of production (whether it is locally produced or imported) is not modelled in detail, because the model focuses on the installation of wind turbines. However, this simplification might affect the learning curves. For instance, if Denmark sold 2000 wind turbines to California during 1985, and the production of these turbines increased the knowledge of Danish producers (Norberg-Bohm, 2000). To compensate this omission, learning rate factors were increased in which the results imitate real data.
- Utilities purchase the wind turbines and operate them, so there is no third actor as wind turbine operator.
- There is no inflation, and all money values are in the form of dollar value of 1980.

These assumptions are the ones that should be considered while implementing the model. The next section explains the implementation process of the model with data sources.

5.3. Implementation of the model

The conceptual model is turned into a working model in Vensim. There were four views of the model, the first one is mainly modelling the wind turbine installation process, the second view represents the modelling of capacity increase, the third view shows the learning processes and finally the fourth view shows the familiarity modelling. The visualization of these views can be seen in Appendix A. Also detailed explanations of them are given under the figures in the appendix. For checking the detailed equations, please see Appendix B.

After constructing the model, the data should be filled in for each case. The data source for each variable is shown in Table 5.2 and 5.3 respectively for California and Denmark with implementation notes. When these data are installed, a simulation of two cases without policy interventions is attained.

Table 5.2 Data Sources for California

Variable	Data Source	Notes
Interest rate	(Sawin, 2001)	The same interest rate is used for calculating LCOE of conventional technologies.
Operation and Maintenance Costs		The numbers are taken from Sawin's work (2001)averaged out, and for having realistic results they are also compared with the report published by Lantz, Wiser, & Hand (2012).
Capacity factor	(California Energy Commission, 2002)	The reference value in 1980 was 12% and in 2000 was 24%. The learning curve fix is made according to these reference values.
Average lifetime of different technologies	(Tidball, Bluestein, Rodriguez, & Knoke, 2010)	
LCOE of oil, natural gas, nuclear power and hydropower	(EIA, 1996; EIA, 2014; Koomey & Hultman, 2007)	It was not possible to find LCOE's directly. Instead, investment cost, O&M cost and fuel costs are found separately and LCOEs are calculated.
Consumption percentages for oil, natural gas, nuclear power and hydropower	(EIA, 1999)	The percentages are calculated by the given total volumes
Installed capacity for electricity generation, and average increase	(EIA, 2013)	
Initial investment cost of wind turbine per kW	(Sawin, 2001)	Also the yearly decrease of this cost is modelled internally with the learning curves, real data used as a reference.
Capacity of a wind turbine	(Hau, 2005)	
R&D spending	(Kammen & Nemet, 2006)	
Strength of learning curves	(Azevedo, Jaramillio, Rubin, & Yeh, 2013)	α and β values show a significant difference for different sources. Therefore they were adjusted in the model with trial and error.
Variables used for modelling familiarity	(Struben & Sterman, 2008)	The initial values are taken from Struben's and Sterman's work, but to be able to reach more realistic results sensitivity testing is done for these variables, and their final values are determined accordingly.
Time delay of R&D information	(Klaassen et al., 2005)	

For Denmark, most of the variables are the same, but the values of these variables differ. The sources for Danish case data is shown in Table 5.3

Table 5.3 Data Sources for Denmark

Variable	**Data Source**	**Notes**
Interest rate	(Sawin, 2001)	These interest rate was taken from Danish market data
Operation and Maintenance Costs	(Chabot, 2012) (Morthorst, 2009)	The values are converted to 1980 dollar value, as it is done with the other monetary variables.
Capacity factor	(Lantz, Wiser, & Hand, 2012) (Bach, 2012)	The initial capacity factor was 11% and it has increased to 25% by 2000. The calibration for the model is done with these reference values.
Average lifetime of different technologies	(Tidball, Bluestein, Rodriguez, & Knoke, 2010)	
LCOE of oil, coal and natural gas	(BP, 2014; EIA, 1996; EIA, 2014; Koomey & Hultman, 2007)	Investment cost, O&M cost and fuel costs are found separately and LCOEs are calculated. Same values are used for conventional technologies in Denmark with the assumption that these mature technologies have similar prices in the world. Also, for conventional technologies, the power plants are rather inexpensive, but most of the cost is coming from fuel price, which is different for Denamark. Also, interest rates are used for calculating Danish LCOE's are different.
Consumption percentages for oil, coal and natural gas	(Danish Energy Authority, 2001)	The percentages are calculated by the given total volumes.
Installed capacity for electricity generation, and average increase	(EIA, 2013)	Apart from United States, EIA has statistics of other countries, including Denmark.
Initial investment cost of wind turbine per kW	(Lantz, Wiser, & Hand, 2012)	Also the yearly decrease of this cost is modelled internally with the learning curves, real data used as a reference.
R&D spending	(Sawin, 2001)	
Strength of learning curves	(Lanz, Wiser & Hand, 2012)	α and β values were not present, instead the investment cost decrease is given as a graph, the values are determined by sensitivity testing with the best fit for the historical results
Variables used for modelling familiarity	(Struben & Sterman, 2008)	The initial values are taken from Struben's and Sterman's work, but to be able to reach more realistic results sensitivity testing is done for these variables, as well as taken the qualitative information about stronger relationships among the actors and their final values are determined accordingly.

After putting all data into the model, policy interventions are added to each case. The details of this process are explained in the following section.

5.4. Policy implementations in the model

With a chronological order of implementation of policies, at first California policy interventions and how it is embedded in the model is explained, then the same process will be followed for the Denmark case.

5.4.1. Policy implementations for California

Energy tax credits from the state and the government

In 1980, the total of these credits were resulting in about a 50 percent reduction in electricity generation costs from wind turbines. These tax reductions continued until 1985. In 1985, federal tax credit was ended (25 percent). Also in the same year, state tax was reduced to 10 percent and it was removed in 1987 (Sawin, 2001). To implement this policy, a percentage reduction in *LCOE of wind* is modelled with a STEP function. This way, the tax reductions with the same percentages are reflected in the model as cost reduction.

The PURPA Act

The PURPA act has two different policy interventions. The first one is the avoided cost subsidy which was given between 1983 and 1987 and the second one is the long term contract offers with an electricity price guarantee between 1983 and 1985.

The avoided cost policy required utilities to purchase power from qualifying facilities (QFs) including the wind turbine owners (Norberg-Bohm, 2000). Then, utilities bought the electricity from these facilities at avoided cost. Avoided cost is the marginal cost for the utility to produce one more unit of electricity (IEPA, 2014). Since QFs decrease the utility's need to produce this additional power, they pay the price to QF which is equal to the production cost of the utility. To model this policy intervention, between 1983 and 1985, if the LCOE of wind is more than the LCOE of conventional technologies, the difference is decreased from LCOE of wind, making the cost of wind same as conventional technologies. The remaining extra costs are assumed to be paid by the government.

Under the PURPA act, California was offering long term contracts which had a guaranteed electricity price for 10 years. This offer started at 1983 and finished in 1985 (Martinot, Wiser, & Hamrin, 2005). This is not a reduction of cost, but a guarantee of profit, which gives an opportunity to wind turbine owners to make relatively the same profit as the conventional technologies for ten years. However, in the model, the profit is not modelled, because there is not a distinction between the expenses and revenues. To be able to create a similar effect, cost reduction is used. For modelling this, the new LCOE offer for these long term contracts is calculated by taking the average LCOE of conventional technologies, and adding an extra costs (which was 25 1980$/mWh) since the state would not be able to cover the exact profit coming from wind turbines. Then an extra demand with this new LCOE is determined with the same affinity structure, and a new share of wind turbines of the total demand is installed. The logic behind this way of implementation is to imitate the profit that the producer makes, not by increasing the revenues, but by decreasing the costs. Note that 25 dollar value is chosen after a sensitivity analysis with the results of yearly installations of wind turbines, because there were no data showing the profits of these contracts.

Energy Policy Act

Under this policy, the federal government offered 15 $/mWh reduction on electricity cost for electricity generation from wind energy in 1990-1991 (Sawin, 2001). This is also modelled with STEP function by reducing 15 dollars from LCOE of wind for the given period.

R&D Funding

R&D expenditures changed significantly according to the governmental policies. Therefore it is modelled as an exogenous variable changing over time (with lookup function) (Sawin, 2001). All dollar values are converted to the 1980 dollar value (Figure 5.6).

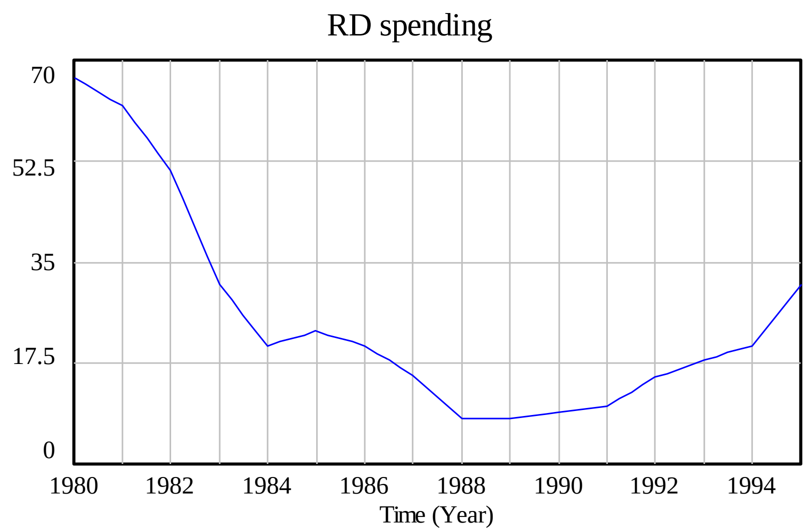


Figure 5.6 R&D expenditures of US (1980 million $)

5.4.2. Policy implementations for Denmark

Investment Subsidy

In 1979, the Danish Ministry of environment provided 30 percent of the investment costs to utilities. This offer was reduced to 20 percent in 1986 and 10 percent in 1987. In 1989, it was totally removed with the belief that wind turbines had become cost competitive (Kamp, 2002). To model this policy, a STEP function is created with the related percentages and years, and a reduction of this cost is directly applied to investment cost, not to LCOE of wind.

EnergiPlan act

With this policy, it is made clear that the government focuses on wind based energy and wishes to reach a 10 percent wind share in electricity generation in 2000. This clear aim is interpreted as an external exposure to familiarity, since these acts creates a secure feeling in the investor by decreasing the uncertainty of the future. Therefore, *external exposure to wind turbines* as a variable is added to familiarity until 1987. The reason for stopping in 1987 is the loss of trust to the wind turbines due to failures of some wind turbines. The government also revised their goals and put the subsidies back at about this time, indicating that they were also not deterministic about their goals towards the end of 1980s (Kamp, 2002).

10 Year Agreement between the Government and the Utilities

In 1985, an agreement between Danish government and the utilities was made for 10 years. According to this agreement, utilities were paying the wind generated electricity price at 85 percent of its actual price (Buen, 2006). To model this, 15 percent decrease in *LCOE of wind* is modelled with STEP function from 1985.

100 MW Wind Turbine Agreement

In 1988, on behalf of the government, utilities were to install 100 mW wind power by the end of 1990. However, the target was reached at the end of 1992. The detailed distribution of these installations per year is not known. Therefore, this agreement is modelled with a decreasing RAMP function for the given time period which reaches 100 mW in 1992. This addition is directly added to *yearly local installations.*

R&D expenditures

R&D spending of Denmark was also changing with time, therefore it is modelled as a time based lookup function with 1980 $ value. Figure 5.7 shows Danish R&D spending for wind turbines (Sawin, 2001).

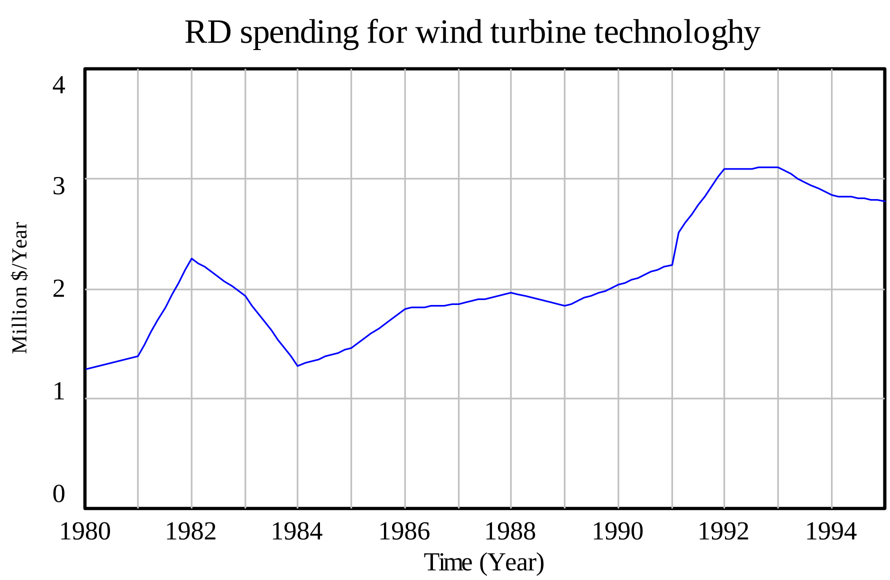


Figure 5.7 R&D expenditures of Denmark (1980 million $)

After implementing all these policies as the way they are explained. The following initial results are gathered, which will be used as a base case for the next chapters. The following figures show the real vs. model results for yearly installed capacity for California and Denmark respectively.

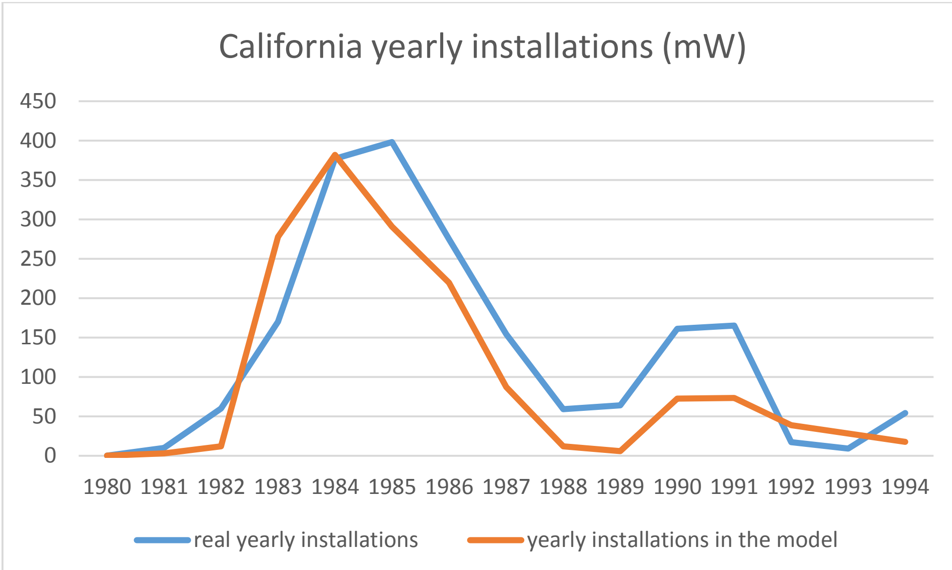


Figure 5.8 Yearly installed capacity - California real data vs. model results

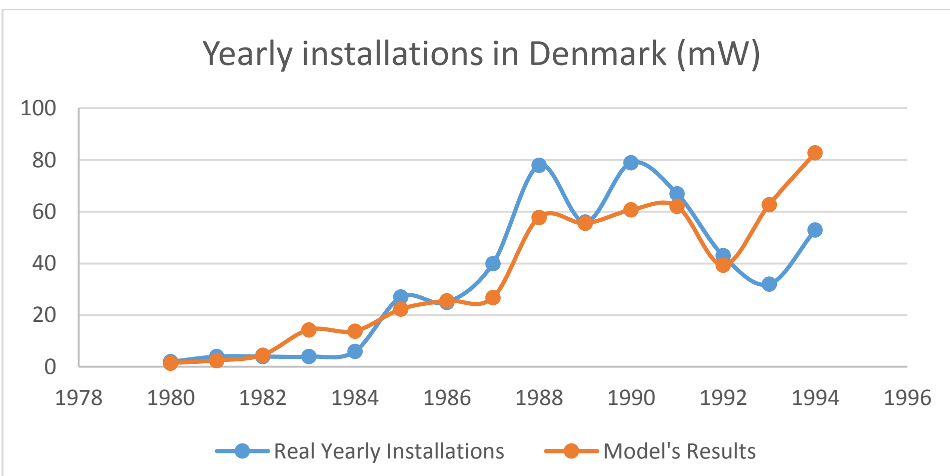


Figure 5.9 Yearly installed capacity - Denmark real data vs. model results

As Figures 5.8 and 5.9 shows, the model is able to capture the major changes in wind turbine installations. Since the aim is to catch the behaviour instead of the exact data, the results of the model is promising. However, without a validation study the model is not trustworthy, for this reason the next chapter will be about the verification and the validation of the model.

Chapter 6 - Verification and Validation

6. Verification and Validation

The aim of this chapter is to test the model from various aspects to understand whether the model fits its purpose or not. This way, the purposefulness and the usefulness of the model will be analysed. It should be noted that all models are wrong since they are the simplified, limited versions of reality (Sterman, 2000). However, this does not necessarily mean that all models are useless. If the model's representation of the real world shows plausible results for the purpose, then it can be a helpful tool for understanding the system at hand. Therefore, various tests have been suggested in the literature for showing the usefulness of the model. The next section offers a verification and validation design for the model created for diffusion of wind turbines in California and Denmark by combining some of the widely used methods in the literature. Then the second section in this chapter explains the implementation process of these tests, and finally the last section reflects on the results from the tests, and gives a conclusion about the usefulness of the model.

6.1. Verification and Validation Design

Verification stands for checking whether the model is coded into the simulation correctly. It verifies the relationship between the simulation model and the conceptual model, and looks for flaws that might occur during the implementation process. On the other hand, validation analyses whether the conceptual model, and consequently the simulation model represents the reality adequately keeping the purpose in mind. It could be interpreted as quality assurance of the model (Yucel, 2013).

Many different tests for verification and validation are suggested in the literature, which are both qualitative and quantitative. However, choosing one of these tests and implementing it would be insufficient, because the aspects that these tests are focusing on are different. For this reason, the following verification and validation design is constructed by combining Sterman's and Barlas' work. The design can be seen in Figure 6.1 (Sterman, 2000; Barlas, 1996).

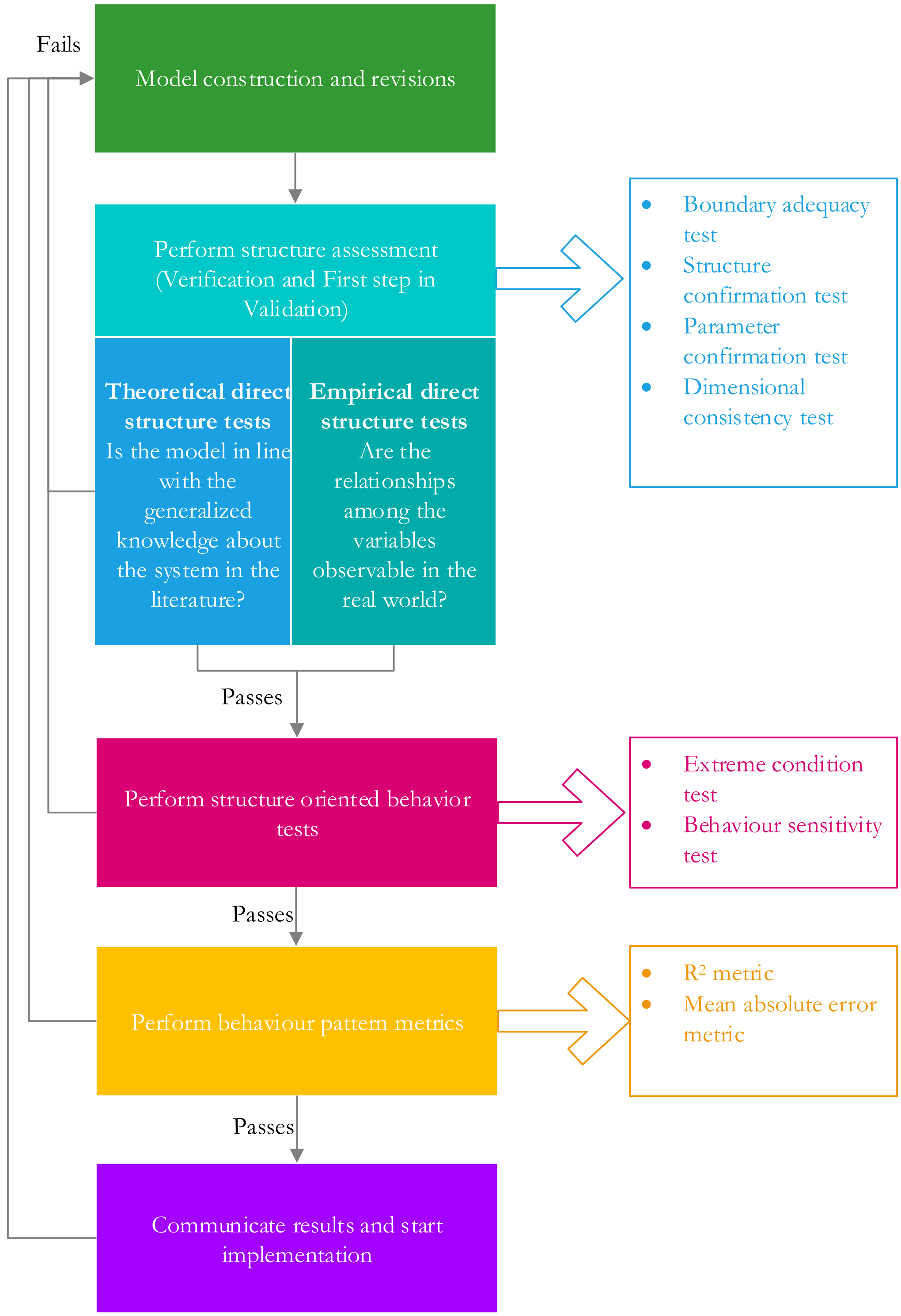


Figure 6.1 Verification and Validation Design (Barlas, 1996; Sterman 2000)

This design starts with a structure assessment test which looks at whether the model is consistent with the real world and also with the literature. This step has a qualitative nature. *Boundary adequacy test* analyses whether the model has all the necessary feedbacks or not, and also checks for the presence of unnecessary feedbacks. *Structure confirmation test* looks for whether the level of aggregation is appropriate, the representation of decision rules conforms to reality and model structure is consistent with the descriptive knowledge of the system (Sterman, 2000). *Parameter confirmation test* checks whether all parameters have real world counterparts, and if not whether they are acceptable (they are acknowledged in theory). *Dimensional consistency test* looks for the units in equations and checks whether the units of the right hand side of the equations are consistent with the left hand side of the equations without having parameters with no real world meanings (such as $\$^3/mWh^2$). If the model passes all of these tests, then it is possible to say that the model is structurally valid (Barlas, 1996). Then the second phase of validation is performed which are *Structure oriented behaviour tests*.

Structure oriented behaviour tests are conducted quantitatively on the simulation itself and looks at the behaviour changes in the model under different circumstances. *Extreme condition test* evaluates the validity of the equations by checking the plausibility of the simulation results under extreme conditions and comparing the results with the logical expectations in real world for the same extreme conditions (Barlas, 1996). For example, if the price of wind turbines is extremely high, no one would buy the product, therefore there will not be any learning coming from learning-by-doing process. *Behaviour sensitivity test* looks for the model's behaviour change and its sensitivity to parameter responses. The sensitivity could be in three forms: Numerical sensitivity, behavioural sensitivity and policy sensitivity. Numerical sensitivity stands for the change in a parameter resulting in the numerical values of the results. Behavioural sensitivity stands for a change in a parameter resulting in the behaviour mode of the model, such as if the adoption of wind turbines grows exponentially instead of reaching an S-curve. Policy sensitivity stands for a change in a parameter reversing the impact or desirability of an applied policy (Sterman, 2000). When these structure oriented behaviour tests are passed successfully by the model, it is possible to conclude that the model behaves realistically under different circumstances, and the next step in validation can be conducted.

The final step in validation checks the fit of the model behaviour with the real world data. R^2 metric and mean absolute error (MAE) metric are two of the commonly used statistical metrics looking for the fit of model data with the real world data. This final step built on previous steps shows that the model is not only structurally satisfactory but also able to reproduce similar outcomes as the real world.

To measure the effectiveness of these tests key performance indicators (KPIs) should be defined. For testing diffusion of wind turbines model, the following variables are chosen as KPIs:

- *Total installed capacity of wind turbines*
- *LCOE of wind*
- *Yearly local installations of wind turbines*
- *Percentage of wind turbine capacity*
- *Familiarity with the wind turbines*

LCOE of wind has the *capacity factor* and *investment cost per kW* in it, and these two variables are affected by learning by doing and learning by searching mechanisms. Both *yearly local installations of wind turbines* and *total installed capacity of wind turbines* are chosen as KPIs because it is possible to have different installation rate per year and have the same cumulative total capacity of wind turbines in the end. *Percentage of wind turbine capacity* is also important for checking the diffusion not only in absolute numbers but also in percentage of installed capacity. *Familiarity with the wind turbines* is a necessary but not sufficient condition for diffusion of them, therefore as a performance indicator, it can give insightful results.

The next section performs the tests explained in this chapter with the logical order shown in Figure 6.1. Some of the tests are qualitative and general, therefore direct influence on KPIs will not be stated for those, whereas for the others the results of the test for each KPI will be shown.

6.2. Implementation of the tests

This section starts with structure assessment tests. If the model passes these tests, structure oriented behaviour tests will be conducted. If the model fails, the modifications for making the model will be applied and the same tests will be conducted again until the model passes those. This procedure will be followed for the other steps as well, which are structure oriented behaviour tests and behaviour pattern tests.

6.2.1. Structure Assessment Tests

The following tests aim to check whether the model is consistent internally and it adequately represents the notions in the literature as well as in the real world. Boundary adequacy test, structure confirmation test, parameter confirmation test, and dimensional consistency test will be conducted respectively.

6.2.1.1. Boundary Adequacy Test

This test is qualitative in nature, looking for the sufficient representation of the real world in the model. It compares the feedbacks in the model by checking unnecessary exogenous variables and the exogenous variables which could be important in the model, so which should be represented endogenously (Sterman, 2000).

For the wind turbine diffusion model, the full list of exogenous variables is given in Appendix C. As it can be observed immediately, most of these variables are not affected by the wind turbine diffusion. One critical variable which could be also modelled as endogenously is *operation cost of wind turbines,* which could be interrelated with the performance of wind turbines, and indirectly with learning mechanisms. However, in the literature, no study was found explaining this relationship. Also, the operation cost has a small effect on *LCOE of wind turbines* due to its small value compared the equivalent annual cost of wind turbines. In sum, there is not a significant effect of modelling *operation cost* of wind turbines exogenously.

Another critical variable could have been the *average lifetime of wind turbines,* since that variable would also be influenced by learning mechanisms, but the lifetime of wind turbines did not change significantly since 1970s. Considering the duration of the model, taking this variable as constant is an acceptable assumption which would not have crucial impacts on the model behaviour.

It is possible to say that the model confirms the boundary adequacy test by making important variables endogenous. Additionally, the model has all important feedbacks and does not include the extra feedbacks in line with the descriptive story and the literature as it is explained in Chapter 5.

6.2.1.2. Structure Confirmation Test

Structure confirmation test looks for whether the level of aggregation is appropriate, the representation of decision rules conforms to reality and model structure is consistent with the descriptive knowledge of the system (Sterman, 2000).

This model analyses the diffusion of wind turbines from a governmental perspective. Therefore, the level of aggregation is designed accordingly, and the detailed trade interactions in the market are omitted. Decision rules of the utilities are based on LCOE, which includes the capacity factor and the cost, so in a sense it has both cost related factors and the performance related factors in an actor's decision making, which is similar to real life. Besides, LCOE is also frequently used in investment decisions for power plants. Again, as it is stated in the previous section, the descriptive story fits to the model as it was shown in Chapter5. Thus, it is possible to conclude that the model passes structure confirmation test.

6.2.1.3. Parameter Confirmation Test

Parameter confirmation test checks whether all parameters have real world counterparts, and if not whether they are acceptable (they are acknowledged in theory). As the names of the variables suggest, most of them have real world counterparts. But there are some variables which are not observable in real life, therefore the justification for each of them is explained in Appendix D.

As the explanations in the justification table shows, it was unavoidable to have variables not having real world counterparts, but these variables are existent in the literature and therefore they are often used (Ibenholt, 2002; Klaassen, Miketa, Larsen, & Sundqvist, 2005). Thus, the validity of the model from parameter perspective is also sufficient.

6.2.1.4. Dimensional Consistency Test

Dimensional consistency test looks for the units in equations and checks whether the units of the right hand side of the equations are consistent with the left hand side of the equations without having parameters with no real world meanings (such as $\$^3/mWh^2$). In the model, the variables having real world counterparts have consistent units with the real world. For the parameters not having real world meaning, if it is appropriate, "dimensionless" (Dmnl) is chosen as a unit. Dmnl unit is acceptable for the factors representing percentages, or for the factors that are not possible to assign a meaningful unit. The units of each variable is shown in Appendix B. An explanation is necessary for the variables related with *familiarity with the wind turbines* stock. This stock can be understood as a percentage, and its value changes between 0 and 1 as a multiplicative factor. Therefore, if there would be a unit of this factor, it would add an extra dimension, whereas in real life this value captures the cognitive processes that the utilities learn information about to wind turbines to consider it as an option. If everyone is familiar with wind turbines this value reaches 1, and if no one is familiar with the wind turbines this value is 0. Apart from their implication as a percentage, in the familiarity study of Struben and Sterman, this value was also modelled as dimensionless (2008).

Another variable set that might raise a question is the alpha and beta values on learning curves. These values are also representing learning rate in literature, therefore they should be dimensionless. For affinity, to have a units of measure, *aff* is assigned as an arbitrary unit. That also does not affect the consistency of units. There was no need for parameters with meaningless units for ensuring dimensional consistency. Finally, when the "units check" test is conducted in Vensim, the program did not give any errors, except warning messages regarding table functions of LCOE. Ideally, in system dynamics, table functions should be dimensionless. However, in this model, table functions are used as a way of importing external data into the model, by taking the x axis as time, and y axis as the imported date. With this kind of usage it can be considered okay to have units for those variables.

With the justifications for variables with no dimension, the units are consistent in the model with no futile units. Therefore it is possible to conclude that the model is valid from dimensional perspective.

This last test has been also passed by the model, which was the last step in ensuring structural validity. The results of these tests show that the model is structurally valid, therefore it is possible to conduct structure oriented behaviour tests.

6.2.2. Structure Oriented Behaviour Tests

Structure oriented behaviour tests are conducted quantitatively on the simulation itself and looks at the behaviour changes in the model under different circumstances. *Extreme condition test* evaluates the validity of the equations by checking the plausibility of the simulation results under extreme conditions and comparing the results with the logical expectations in real world for the same extreme conditions (Barlas, 1996). *Behaviour sensitivity test* looks for the model's behaviour change and its sensitivity to parameter responses. In this section, both of these tests will be conducted and according to the results, whether the modifications will be done in the model, or the last phase of validation will be implemented.

6.2.2.1. Extreme Condition Tests

For this test it is necessary to have some hypotheses for extreme conditions. If the model behaves as expected under given extreme conditions, then it is possible to conclude that the model behaves realistically under supreme conditions. The hypotheses to be tested are listed below:

- If *LCOE of wind* is extremely high compared to conventional alternatives, there will not be any wind turbine installations.
- If *LCOE of wind* is extremely low compared to conventional alternatives, the percentage of wind turbines installed will increase rapidly.
- If *familiarity with the wind turbines* is zero, there will not be any wind turbine installations.
- If *familiarity with the wind turbines* is 1, there will be a considerable increase on yearly installations.
- If the alpha values for learning by doing are zero, the LCOE decrease would be quite low. (Learning would come only from R&D expenditures which is less strong than learning by doing).
- If the beta values for learning by searching are zero, the LCOE decrease would be lower than the actual model, but it will get affected less, compared to alpha values.
- If both alpha and beta values are zero, there will not be any learning effect on *capacity factor, capacity, investment cost* and consequently on *LCOE of wind.*

These hypotheses are tested one-by-one both for California case and Denmark case. The results for each hypothesis are shown in Appendix E. The results show that the model behaves realistically under extreme conditions.

6.2.2.2. Behaviour Sensitivity Test

This test looks for the changes in model's behaviour for the changes implemented in exogenous variables. In other words, it looks for the sensitivity level of the model for the changes in variables. All exogenous variables are altered with 10 percent for conducting this test with random uniform distribution. Both univariate analysis, where the variables are changed one-by-one is conducted, and multivariate analysis where some variables are altered simultaneously is conducted. The results are shown in Appendix F. As the results suggest, the model is quite robust to changes in variables, it is numerically sensitive to most of the realistic alterations. Also for the variables having no real wold counterparts, the sensitivity testing showed that the model is only numerically sensitive to these variables, indicating that the assumptions of the quantification do not cause a significant difference in the model. Note that sensitivity analysis is quite important also for the variables not having real world counterparts. The variables in this model such *as maximum decay rate, effectiveness of contacts with users, non-users* are all variables with no real world meaning, but supported from the literature. Yet, the results of sensitivity analysis showed that these variables only affect the model in a numerical way, and do not interfere with the model's behaviour at a significant level validating model's robustness. When we look at the results, we see that alpha and beta values have a greater numerical sensitivity, which can raise questions. However, since alpha and beta values represent the learning rates in percentages, 10 percent sensitivity analysis already means a significant change. Learning with 80 percent and 72 percent rate has immediate effects on cost reduction, and people are sensitive to price changes for adoption, and as a result learning rates affect the model numerically. Yet, this does not need to be considered as a flaw in the model, because if the improvements in cost and capacity factor of the wind turbines were to be higher in real life, it is sure that the adoption rate would have increased.

There are some combinations of variables causing behavioural sensitivity after 75 percent confidence bounds, which should be taken into account while testing policies. However, to reach this effect, many combinations of policies is required to alter all of the variables, which is unrealistic. Therefore, if the policy testing is conducted carefully, the model is reliable according to the sensitivity results.

6.2.3. Behaviour Pattern Tests

For making a statistical comparison between real installations and the model's results, R^2 and Mean Absolute Error/Mean (MAE/Mean) metrics are calculated. These tests are looking for point by point to fit of model's results with the real data. R^2, which is called coefficient of determination, measures the variance changes of the model compared to real data. If the model shows the exact behaviour with the real data, then R^2 is one. If the result is 0, it means that the covariance of the real data and the model's results is 0. Therefore, the closer R^2 is to 1, the better fit is obtained.

MAPE measures the average error between the model's results and real data. Since the yearly installations during 1980s is close to 0, MAPE does not show realistic results, because the percentage change becomes too high even though the real change between values are not that high. For example, if there is 0 mW installations in real data and this value is 1mW in the model, it is not possible to calculate the MAPE value (Sterman, 2000). Therefore, instead of using MAPE, MAE/Mean test is used. This test, also brings the average error of the model I terms of percentage, by taking the means of the real data and the model's results into account. The formulas for R^2 test and MAE/Mean tests are shown below:

$$R^2 = \frac{1}{n}\sum \frac{(X_d - \overline{X_d})(X_m - \overline{X_m})}{S_d \qquad\qquad S_m} \tag{10}$$

$$MAE = \frac{1}{n}\sum |X_m - X_d| \tag{11}$$

$$\frac{MAE}{Mean} = \frac{MAE}{Mean} - \frac{MAE}{\overline{X_d}} \tag{12}$$

where

$$\bar{X} = \frac{1}{n}\sum X\,; \quad s = \sqrt{\frac{1}{n}\sum (X - \bar{X})^2} \tag{13}$$

The reason for using both R^2 and MAE/Mean tests is because they measure different things. MAPE/Means shows the percentage error of the data, but two data series with different structures could have the same value for MAE/Mean. To see the fit in terms of pattern of data R^2 test is also important. Having both of these results will give a healthier understanding for the fit of model's data into real results.

These tests are conducted for three different KPIs, which are investment cost per kW, yearly installations and cumulative installations in mW. The reason for choosing these variables is because the only available data on a yearly basis was these factors. Also, yearly and cumulative installations fit behaves as a test for the whole model, whereas investment cost per kW is a specific test for the sub-model of learning curves.

In Table 6.1 the results of these tests for California and Denmark is shown. For seeing the yearly numbers, please see Appendix G.

Table 6.1 R-square and MAE/Mean Test Results

		R^2	MAE/ Mean	Comments
California	Investment cost per kW	0.96	0.01%	This result shows that the learning curve fit of California case is quite good, because learning factors of alpha and beta fits with the literature, and the results fit quite well with the real data.
	Yearly installations	0.82	11%	The R^2 fit of this data is also acceptable since it can still be considered as 80 percent fit. Also MAE/Mean is about ten percent, which is higher compared the other results but in absolute terms 11 percent of error is acceptable.
	Cumulative installations	0.96	1.87%	The results show that cumulative installations fit well with the real data.
Denmark	Investment cost per kW	0.88	1.34%	The results show that cumulative installations fit well with the real data.
	Yearly installations	0.73	1.33%	The reason for having a low R^2 value for this variable is due to government's installation of 100 mW during 1988-1992. The actual installations per year is not known, but in the data there were two hunches which is assumed to be the installations coming from government. However, due to modelling considerations, this installation is done in the model by installing 25 mW per year, which has a different pattern than real data.
	Cumulative installations	0.98	2.75%	The results show that cumulative installations fit well with the real data.

As the high rate of R^2 tests and low percentage errors of MAE suggests, the model is able to reproduce the real life data successfully.

6.3. Discussion of the results and Conclusion

The validation study concludes that the model fits to the purpose, there are no missing or extra feedback loops compared to real story and it fits well with the theory in innovation diffusion literature. Besides, the model behaves as expected under extreme conditions, and it is robust to changes in variables within 10 percent range. Finally, the model is able to generate realistic results with an acceptable error margin. As a result of these validation studies from different perspectives, it is possible to conclude that the model is able to capture the main mechanisms in real innovation diffusion stories of California and Denmark, from the governmental perspective. In brief, this Chapter shows that it is safe to use this model with the purpose of comparing the governmental policies for wind turbine diffusion in Denmark and California. The next chapter explains the main similarities and differences between the initial settings of California and Denmark, and then it explains the base case results in a comparative manner. Then policy testing is done in both cases to see the effectiveness of different policies on the model.

Chapter 7 - Comparison of the Cases

7. Comparison of the Cases

The stories of California and Denmark are well known for wind turbine diffusion in the literature. This chapter explains these differences by using the models created. First, the model's base case results are discussed in a comparative manner. Then, the differences between the model's initial settings are explained where there are no policies. Thirdly, policy-by-policy the differences and the effects of these policies on the installations are explained. Finally, the insights gathered from this comparison are explained.

7.1. Comparison of the Model Outcomes of California and Denmark

The initial results of the model were given in Chapter 5 in Figure 5.8 and Figure 5.9. Since the validation of the model is provided in Chapter 6, it is safe to reflect on these results. California has two waves of installation, the first wave is coming from the combination of the PURPA act and the long-term-contracts. These demand-pull policies offered a cost competitive environment for wind turbines, but they did not last long. When they are cancelled, again the wind turbine demand decreased significantly, because the level of adoption did not lead to a learning curve making the wind turbines cost-competitive. Then the second wave also came from the demand-pull policy of 15 $/mWh reduction on the LCOE of wind turbines, making the option competitive again. Yet, this does not help the utilities to keep the demand growth. As is clear from the Figure 5.8, California's adoption level goes back to the start level once the demand-pull policies removed. The reasons behind this loss is due to the low familiarity ratio among the utilities, their network were weak and there were no attempts to bring them together or keep them informed about the new technology. In addition, the utilities in California were not that vulnerable to the oil price compared to Denmark as it is explained in Section 7.2.

When we look at the model's results and the real results of Denmark in Figure 5.9., the increasing trend of the graph stands out. The reason for this is twofold. First, after a certain level, wind turbines become cost-competitive, not because Denmark improved the wind-turbines tremendously, but because the conventional alternatives were quite expensive for Denmark. The second reasons is that the mind-set of the society and the government was clear from the beginning, showing a determination and hence increasing familiarity towards wind turbines. Also the policy implication of *government installing wind turbines of 100 mW* resulted in as a temporary boost in installations, because it is not a policy directed to the causes of adoption, but it is directed to the end result. Yet, note that this installations improved the learning curves and familiarity, but not directly.

The model's results show a good fit to the real data, and it promise plausible explanations for the fluctuations of the graphs in both cases. To understand the causes of differences in these two cases, the initial settings of the models, and the effectiveness of policies are tested in the following sections.

7.2. Initial Settings for California and Denmark

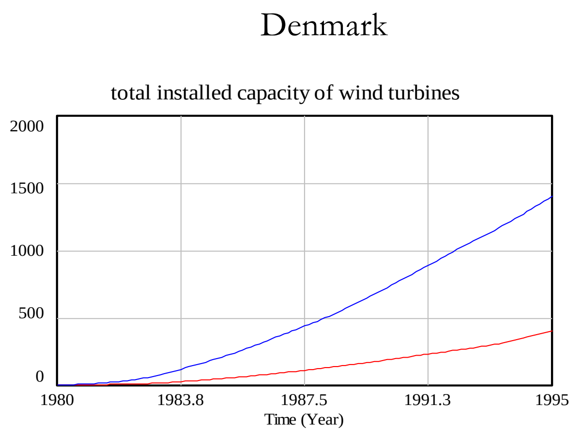
Although the active mechanisms for California and Denmark are claimed to be same, there are important differences in the initial settings triggering these mechanisms. These differences are illustrated in the model by determining the initial values of variables as well as the values of exogenous variables. The initial values for the variables for both cases are given in Table 7.1.

Table 7.1 Initial Settings of California and Denmark Model

Variable	CA	DK	Comments
Alpha value for learning by doing on capacity factor	1.07	1.07	Capacity factor learning did not show significant changes between CA and DK, therefore in the model, this variable is treated as a global value with the same values.
Alpha value for learning by doing on investment cost	0.88	0.95	When we look at the investment cost at 1980 and investment cost at 1995, we see that CA had much impressive learning curve compared to DK. (For investment costs, the lower the alpha value, the greater the learning impact, since it represents the percentage reduction on the cost). To capture this effect in the model, alpha and beta values of CA is given higher than DK. Also, as Hekkert et. al mentions, learning by doing is hugely affected from entrepreneurial activities (2007). In Denmark the entrepreneurs were producing agricultural equipment before, therefore they learned slowly with trial and error (Karnoe & Garud, 2001)
Beta value for learning by searching on capacity factor	1.04	1.04	Since capacity factor is treated as a global value, this learning effect is also the same. The reason it is lower than alpha value is based on literature (Kamp, 2002).
Beta value for learning by searching on cost	0.90	0.96	The reason to have lower value for CA which results in better cost reduction is due to available data. Note that these beta values are also less effective compared to alpha values which is based on literature (Kamp, 2002)
Effectiveness of contacts of nonusers	0.38	0.45	Since the communication among potential adopters in DK was higher than CA due to published Naturlig Energi magazine where the performances of wind turbines was made public (Kamp, 2004). This magazine helped them to For this reason, the effectiveness of contacts of non-users are assumed to be 15% less in CA.
Effectiveness of contacts of users	0.68	0.8	Communication between the users of wind turbines were also higher in DK due to Wind Meetings where knowledge and experience were shared between manufacturers, owners and researchers. They also established Danish Windmill Owners Association (Kamp, 2004). For this reason, the effectiveness of contacts of users are assumed to be 15% less in CA.
Initial familiarity	0.25	0.25	Initial familiarity with the wind turbines were low but not zero for both cases. Both CA and DK had historical experiences with wind turbines (see Chapter 3 and 4) and they were familiar with the windmills. There were no real indication of familiarity difference between two cases in the literature, therefore they are assumed to be the same.
Initial installed capacity for electricity generation	55000	7072	This number is based on EIA data, reflecting the real values.
Initial investment cost of wind turbines per kW	2500	1322	This data is taken from the literature and converted to 1980's dollar value. (Sawin, 2001; Lantz et al 2012).
Interest rate	0.66 (mean)	0.77 (mean)	The interest rates are also taken from the literature (Sawin, 2001).

	0.0265 (stdev)	0.0172 (stdev)	
Maximum decay rate	0.42	0.42	Maximum decay rate for both cases are assumed to be same, because this value represents the reference value for forgetting rate. Due to differences in cultures this number could differ, but in general, people tend to forget the new technology when the exposure is not frequent enough (Struben & Sterman, 2008). Since this situation is valid both for CA and DK the same value is used in the simulation.
Normal social exposure	0.20	0.20	Similar to maximum decay rate, this value represents the reference value for forgetting rate. When it is 0.2 it means that familiarity decays with the half of the maximum decay rate. Since maximum decay rate is assumed to be the same for both cases, it is reasonable to take the same reference value for normal social exposure, ensuring the decay behaves the same for both cases.
Operation cost of wind turbines	14.19 (mean) 3.53 (stdev)	12.73 (mean) 3.391 (stdev)	These costs change over time, therefore their mean and standard deviation is given in the table.
Percentage increase of installed electricity capacity per year	2.5%	2.5%	This values are also calculated on average, by looking at the net changes of installed capacity between 1980 and 1995 (EIA, 2012). The average capacity increase per year for both cases turned out to be the same
Sensitivity value for wind turbines	1	1.8	The reason for taking Danish utilities' sensitivity values higher than California is due to market's results. When weighed average cost of conventional methods and LCOE of wind is examined, it is observed that standard deviation of the prices is much higher in Denmark compared to California. This situation implies an insecure market structure with more sensitive buyers to price. The numbers are calibrated with the fit to historical data. For both values DK values are 1.8 times higher than CA.
Sensitivity value for conventional technologies	0.54	1	
Weighted average cost of conventional methods (Average LCOE)	24.87 (mean) 2.607 (stdev)	61.61 (mean) 11.63 (stdev)	These values are based on historical data. Since the value changes over time the mean and the standard deviation is given in the table. As it can be seen, the prices are more stable in California.
LCOE of wind	31.75 6.95	56.83 19.68	These values are calculated by the model, but to show the changes in the price over time it is added to the table.

As the comments in Table 7.1 indicate, the main differences between California and Denmark is coming from effectiveness of users and effectiveness of non-users, as well as the learning rates regarding investment cost.



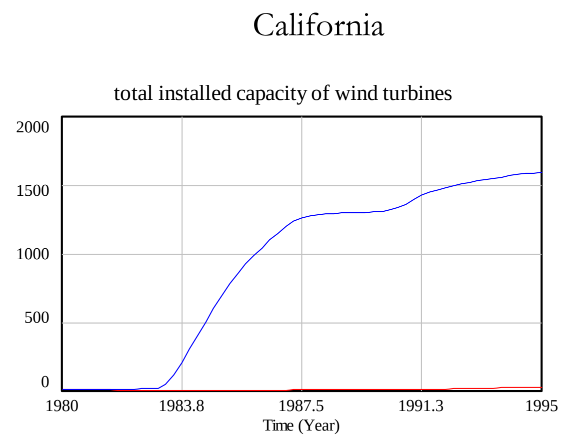


Figure 7.1 Simulated Wind Turbine Installations with and without Policies in DK and CA

As is clear from Figure 7.1 the initial settings lead to a considerable amount of installations in Denmark whereas there are few installations in California. The reasons for this can be explained with these combined effects of variables:

- First of all, utilities in Denmark are more sensitive to price changes in energy, because they purchase all of the resources from outside at very high prices compared to California. This situation results in easy switching to a new energy alternative, since their satisfaction with the current ones are not that strong.
- Secondly, the effectiveness of users and non-users for triggering adoption is higher in Denmark, and this is beyond the power of government, because this effectiveness was coming from the bottom, where the investors and entrepreneurs worked together for effective communication in Denmark. Such a movement is not observed in California case. When the effectiveness of users and non-users is stronger, this triggers the feedback mechanism of familiarity, and familiarity has a multiplicative effect on demand share of wind turbines. In a way, it is a percentage value representing the rate of utilities who are aware of the advantages and disadvantages of wind turbines. Without awareness it is not possible to consider the wind turbines as an option. This ratio was higher in Denmark as a result of triggering more adoption.
- The learning curves were also effective in these results, but in a subtle way. The key criterion for adoption is to have a profitable value for wind turbines compared to conventional technologies, not to have the lowest value in the global market. Since the cost of conventional technologies was already high in Denmark, with the cost reductions coming from learning curves, it was easier to reach the desirable LCOE in Denmark. On the other hand, in California, the cost of generating electricity from conventional sources was already cheaper, and as a result, the learning curves had to be more effective to reach a desirable cost. For this reason, Denmark was more

promising for wind turbine diffusion initially, which already creates an advantage for the diffusion process.

It is also important to look at the stimulating effects of the policies implemented by local and federal governments, because as Figure 7.1 shows, the diffusion without any intervention was not satisfactory in both cases (It was less than 0.5% both for Denmark and California). In Chapter 5, the kind of policies followed by the authorities and how these policies were implemented in the model was illustrated now, the results of these policies are shown in the next section in a comparative manner.

7.3. Policies and their effects on wind turbine installations for California and Denmark

Here, for the policies existing in both cases, the results with and without that policy is compared in both cases. For policies having similar mind-set but different implication, a similar comparison is also conducted. For unique policies which is non-existent in the other case, what-if analysis is done by adding that policy to the lacking case. The results are compared and analysed policy-by-policy.

7.3.1. Effect of R&D efforts on wind turbine installations

R&D efforts basically triggers the learning by searching mechanism, which leads to a decrease in LCOE of wind turbines, increasing the attractiveness of wind turbines as an energy generation option. However, to what extent these R&D investments are effective? The models suggest the following results:

California Denmark

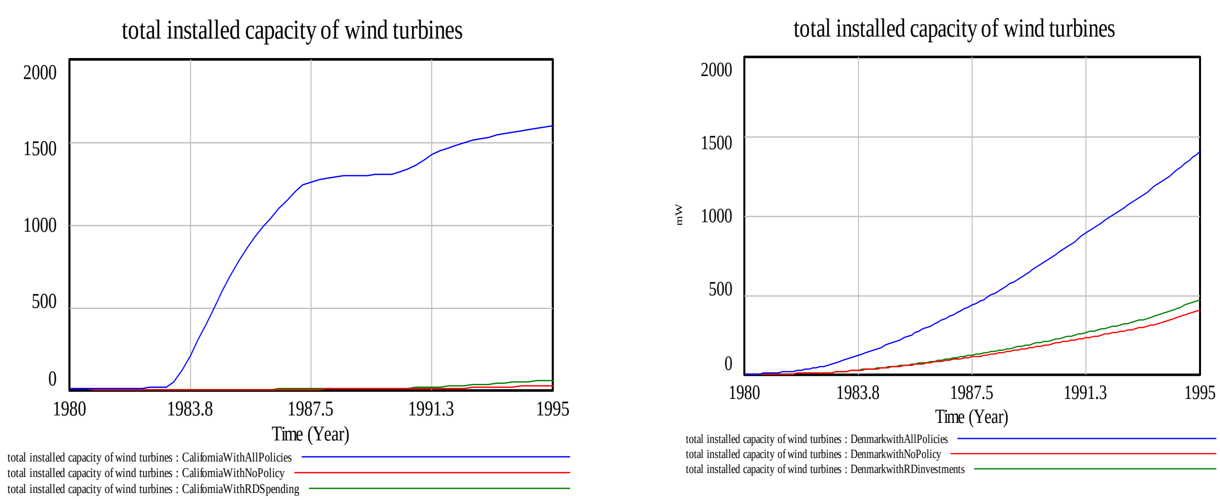


Figure 7.2 Effect of R&D investments on cumulative wind turbine installations

As Figure 7.2 shows, there is a little improvement in wind turbine installations with R&D efforts. It is important to note that, in total the United States spent 538.5 million (in 1980 $)

from 1980, where in total it spent 200 million from 1970 to 1980 for R&D of wind turbines. On the other hand Denmark spent 33.9 million from 1980 to 1995, and they spent 12.5 million from 1970 to 1980 which was treated as an initial value (Sawin, 2001; Norberg-Bohm, 2000). These results show that, learning by searching mechanisms are not enough for effective diffusion, because it takes time to reach a cost competitive results for a new technology only by learning by searching. In the meantime, since the new technology is expensive, there is no or little adoption, and this situation results in a decrease in familiarity, because familiarity requires a certain ratio of social exposure. One of the main sources of social exposure is the adopters, and the word of mouth coming among non-adopters about the technology, which is not triggered effectively in this policy.

To show that the importance of the amount spent for R&D research, the amount spent for the U.S. is used as an input in the Denmark case and the results are compared with the original ones. The graph showing these results are shown below:

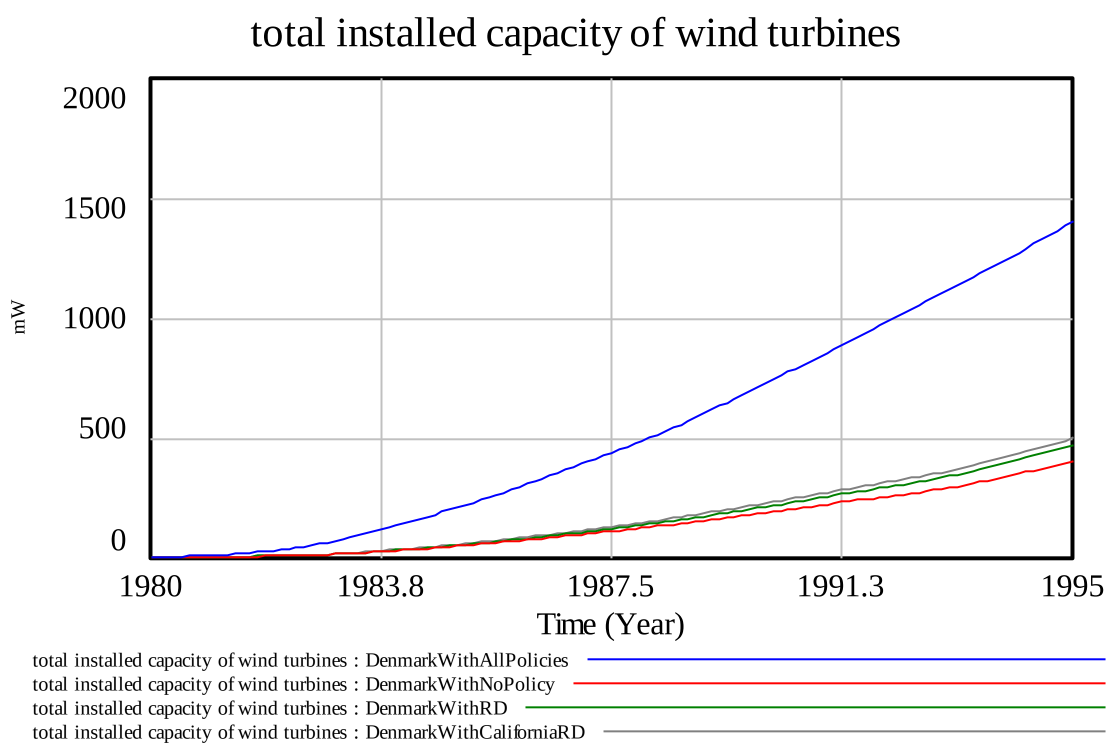


Figure 7.3 Comparison of R&D spending of California and Denmark on Denmark Case

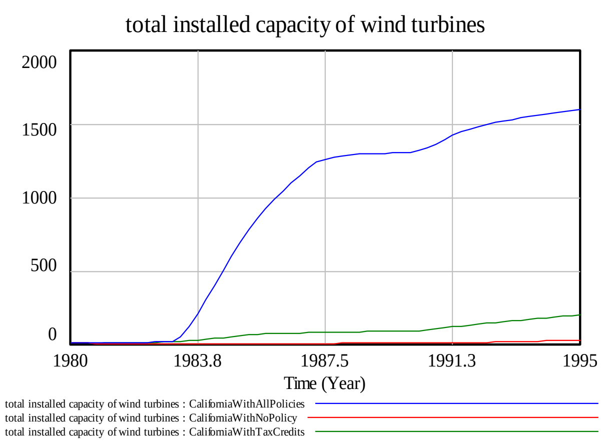
As the previous explanations supports, Figure 7.3 shows that there is a little effect of R&D spending when it is used as only policy instrument. However, it should be noted that, with the learning by doing mechanism, the R&D efforts become more important, because it is a percentage improvement on top of the learning by doing mechanism. When there are few installations, the learning-by-doing mechanism remains ineffective, and the additional improvement coming from learning-by-searching mechanism becomes insufficient by itself.

Although the graph is not shown here, when Denmark's R&D spending is added to California model, similar results are obtained.

7.3.2. Effect of subsidies on wind turbine installations

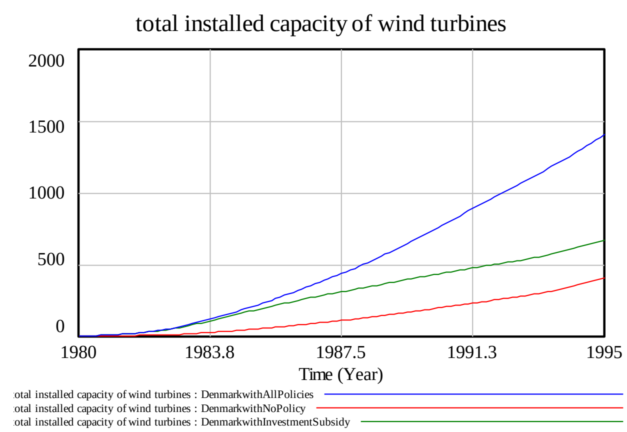
In California, subsidies were offered in terms of tax credits. From 1980 to 1985 the tax credits were directly targeted to the LCOE of wind turbines, and the value was about 50%. In 1985 this value was reduced to 25%, then to 10% and finally to zero in 1987. In addition to this tax reduction, under the Energy Policy Act, 15 $ per mWh reduction is applied to the LCOE of wind turbines. In Denmark, there were two types of subsidies. From 1980 until 1989, there is investment subsidy, which behaves like a tax reduction directly on investment cost. It started with 30% and then reduced to 20% in 1985, 15% in 1986, 10% in 1987, and removed in 1989. In addition to this tax reduction, the government agreed with the utilities to offer 15% reduction in the LCOE of wind turbines starting from 1985. In the following graphs, the effects of these reductions on installations will be shown one-by-one.

California

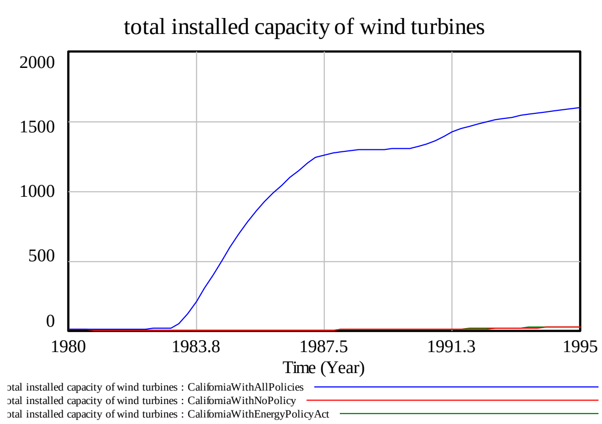


Effect of tax credits

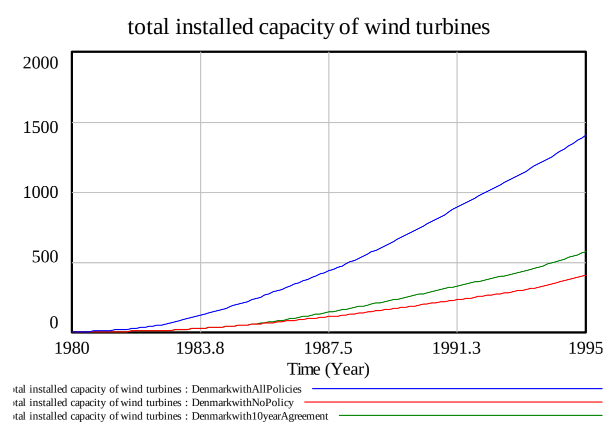
Denmark



Effect of investment subsidies



Effect of Energy Policy Act



Effect of 10 year agreeement

Figure 7.4 Effects of subsidies on wind turbine installations

As the graphs in Figure 7.4 shows, the subsidies in general are more effective than R&D efforts, but they do not contribute to the diffusion significantly. The Energy Policy Act remains ineffective when it is implemented in isolation, because since the learning by doing mechanism is inactive due to low installations, the cost reduction is not enough to make wind turbines competitive with a 15 $ subsidy per mWh. It is also important to note that the effect of investment subsidies is similar to the subsidies offered on LCOE, because a significant part of LCOE belongs to investment cost in wind turbine technology, since there is no fuel cost and little operation cost.

7.3.3. Effect of PURPA Act on wind turbine installations

An equivalent form of the PURPA act was not in the agenda of Danish government at that time, therefore here the results are shown for California and also the policy is artificially added to Denmark model to observe the possible effects on Denmark. PURPA basically works like a feed-in tariff and government offers to compensate for the extra cost of generating electricity from wind turbines compared to conventional technologies. This policy was active in California between 1983 and 1987. This policy is implemented to Denmark model with the same values. The results are shown below:

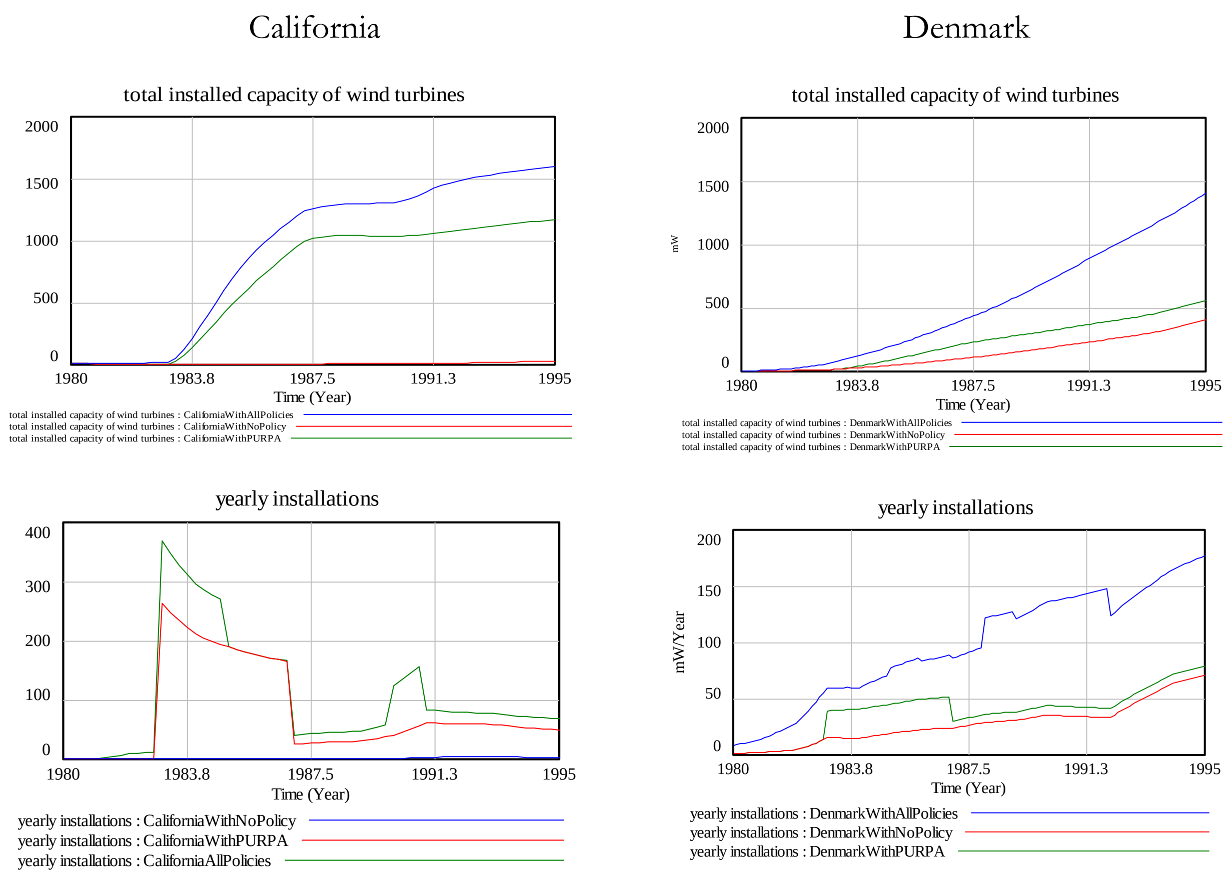


Figure 7.5 Effect of PURPA act on wind turbine installations

To have a better understanding of the PURPA act on installed wind turbines, both yearly installations and cumulative installations are shown in Figure 7.5. This figure shows that the effect of PURPA is stronger in California, whereas it is possible to reach a better result with combination of all policies in Denmark. The most effective policy of California is PURPA, since it makes the wind turbines cost competitive leading to adoption. The same effect was expected in Denmark normally, but the reason for not having such high installations in Denmark is due to the model settings. In Denmark, conventional technologies are already high for the utilities, therefore they do not consider the same LCOE for wind turbines and conventional technologies with a high level of affinity. The level of affinity is not that strong in Denmark with PURPA act, therefore, even though the installation rate increases due to the better price offer for the LCOE of wind, it is not as effective as California case.

7.3.4. Effect of EnergiAct on wind turbine installations

EnergiAct represents the determination of Danish government the setting wind turbines as the only energy alternative and determining persistent goals for wind turbine share in energy generation. This policy has a soft effect similar to marketing, making the option visible to the customers. However, such a mechanism is not observable in California, due to rapidly changing policies and governmental mind-set towards renewables. Therefore, to see the possible effects of EnergiPlan act on California's installations, this policy is added to the California model. The results are shown below:

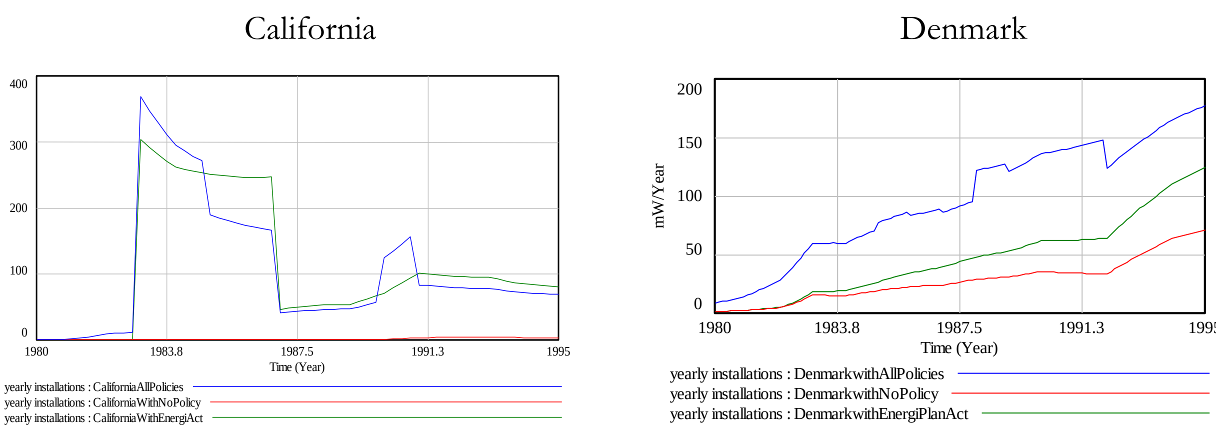


Figure 7.6 Effect of EnergiPlan Act on wind turbine installations

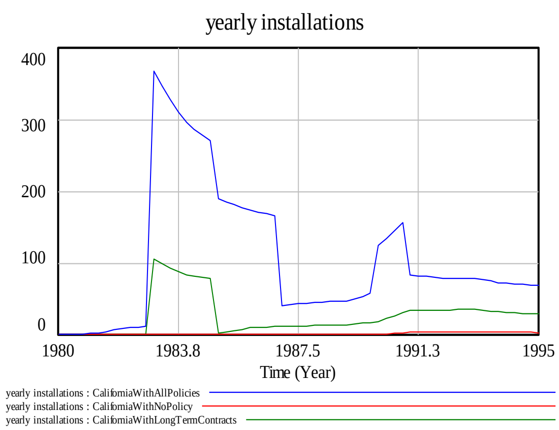
In Figure 7.6 for California, the effect of EnergiPlan is showed in combination to PURPA act, because EnergiPlan act do not trigger significant adoption in isolation. The reason for this is because even though the people are aware of the wind turbines as an alternative, it remains expensive compared to conventional methods and therefore there is little preference for it. However, if we make sure that there is a certain potential demand (coming from PURPA act in this case) then we can see the importance of awareness creation. If we look at both Figure 7.5 and Figure 7.6, we see that indeed the effect of PURPA has strengthened with EnergiPlan.

On the other hand, in Denmark, this act plays a significant role due to two reasons, firstly; there is already demand for wind turbines when there is no policy around due to expensive alternatives, secondly; familiarity with the technologies decay non-linearly, and since the percentage of adoption is more in Denmark, the decay gets slower. When the extra exposure coming from EnergiPlan is added to this value, its effect becomes more than the added value due the non-linear nature of familiarity decay.

7.3.5. Effect of Long-term contracts on wind turbine diffusion

California offered long term contracts with a fixed electricity price which is close to conventional technologies. There was no such an offer in Denmark, therefore this policy is implemented to the Denmark model to see the possible effects. The results are shown below:

California



Denmark

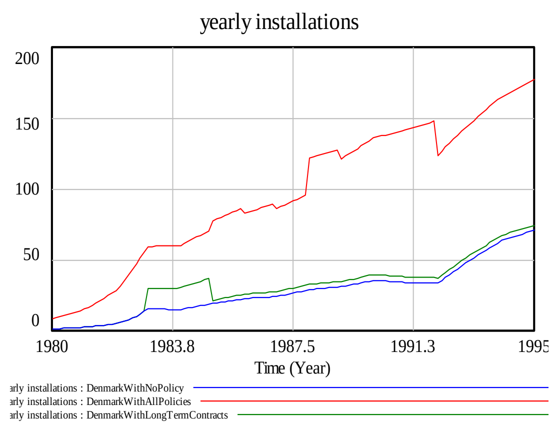


Figure 7.7 Effect of Long Term contracts for wind turbine installations

The Figure 7.7 shows that the effect of long term contract policy is similar in both cases. Not that the long term contracts were offered only between 1983 and 1995, which explains the bump in the graphs at that time. It is clear that this bump has a temporary effect on wind turbine installations as expected. It also adds value to the wind turbine installations in total, but it is not as significant as PURPA act for California.

7.3.6. Effect of Government installing wind turbines on wind turbine diffusion

The Danish government decided to install wind turbines of 100 mW with government funding with an agreement with utilities from 1988 to 1992. There was no such an attempt in California, therefore to show the possible results this addition is modelled to see the possible effects.

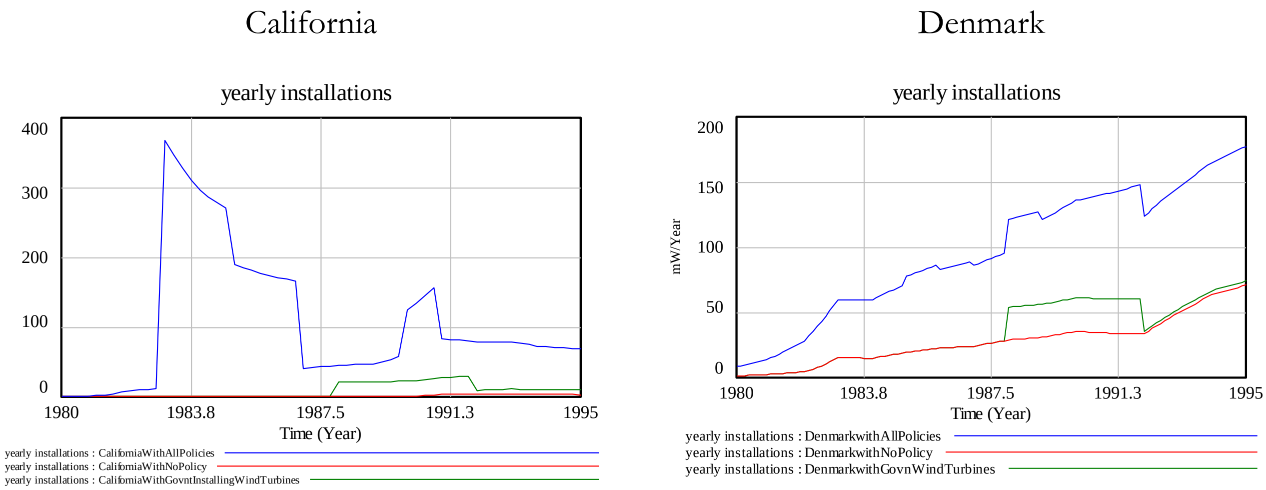


Figure 7.8 Effect of government installing wind turbines on diffusion

Figure 7.8 Shows that the effect of governmental installation has a temporary bump in the installations. Also, the familiarity changes were checked for this external installation and the model shows almost no change in familiarity. The reason for this is because this installations are coming externally, it is an additional mW to yearly need of demand, and it does not affect the yearly installations done by utilities or cooperatives. Therefore, the share of wind turbine installations do not change, and in total the percentage of wind turbines on installed capacity changes insignificantly, since 100 mW has less than 0.1% effect on the share. This value affects the social exposure from users and non-users but since the impact itself is quite small, there is no long-lasting effects of government installations of wind turbines.

It is also important to look at the combined effects of policy interventions, due to the possibility of one-policy hindering or amplifying the other. To understand whether this kind of influence exists in the models, the models run with all policies except one of them, where the non-existent policy is altered across all policies. However, the results showed that there is no such a thing showing that combination of the policies perform worse than the sum of these policies. To see the results please see Appendix H.

7.4. Conclusion

The differences between California and Denmark cases are twofold. First the initial settings in Denmark shows that it provides a more suitable environment for wind turbine diffusion with a stronger network, expensive LCOE of conventional alternatives, high sensitivity of adopters to price due to a fluctuating and expensive market, and a positive mind-set towards wind turbines. On the other hand, in California, the conventional alternatives were already cheaper which requires wind turbines to be improved much more to be cost competitive. Also, people have no interest in building networks regarding wind turbines, which also resulted in decreasing familiarity with the wind turbines and consequently less installations. Apart from that, the market was more stable in conventional technologies, which made the utilities to be reluctant in switching into a new technology. All of these initial conditions resulted in a less promising environment for wind turbine diffusion in California compared to Denmark.

Although the initial settings were in favour of Denmark, the policy interventions exist to counteract these negativities. From a policy making perspective, we see that the most effective policies in both cases are in demand-pull policies by offering subsidies and feed in tariffs. The Denmark case showed that it is also important to create awareness about the new technology to increase its adoption rate. The models' results also showed that the direct interventions on installing wind turbines such as long term contracts in California and the government installing wind turbines in Denmark has temporary effects on diffusion whereas the effects of stimulating markets also impacts the adoption in the future due to increased familiarity and triggered learning by doing mechanism. R&D efforts also improve the adoption, but it has effects to a certain extent, therefore spending vast amounts on R&D is not a desirable policy in isolation according to the results of the model.

Chapter 8 - Conclusion and Reflection

8. Conclusion and Reflection

8.1. Answers to research questions

This research aimed to answer the research question: *What are the underlying mechanisms and their relations explaining the commonalities and differences of wind turbine diffusion stories in California US and Denmark*? To have a detailed answer for this question, the following 5 research questions are answered:

- **What are the factors that stimulate and/or hinder the adoption of wind turbine technology, and how do these factors relate to each other? (RQ1)**

  The factors fostering or hindering the decision processes are studied by different researchers. Three different points of view are taken in this research to explore these factors. Hekkert et. al and Yucel offers a dynamic understanding of the diffusion stories, whereas the research of Kemp, Schot and Hoogma takes the issue from a static perspective by analysing the barriers. (2007; 2010; 1998). In general, knowledge diffusion via networks, learning by doing and learning by searching improvements on the technology have positive effects on diffusion, but the adoption may be negatively affected by the high costs of the new technology, psychological and cultural factors and the threat of the new technology to the market players in the incumbent technology.

- **Which mechanisms are adequate representatives for explaining the relationships among the determined factors? (RQ2)**

  The adoption of an innovation is affected by various mechanisms related to different actors such as the government, the adopters and the producers. The wind turbine diffusion stories showed that the active mechanisms were the same both in California and Denmark case; which are learning-by-doing mechanism, learning-by-searching mechanism, and familiarity gain with word of mouth from users and non-users. These three mechanisms set the base of both diffusion stories, with the LCOE based decision making process of adopters.

- **What kind of policies have been implemented in California and Denmark for wind turbine diffusion, and what were the aimed mechanisms of these policies? (RQ3)**

  Various policies were implemented with the aim of fostering the diffusion. R&D efforts in both countries triggered the learning by searching mechanisms which resulted in improvement in LCOE, and the subsidies offered by the governments helped the wind turbines to be more cost competitive, and as a result the demand is increased. The increased demand helped the producers to sell more wind turbines and triggered the learning by doing mechanism, which also improved the cost competitiveness of wind turbines. The EnergiPlan act in Denmark helped the potential adopters to be aware of the benefits of wind turbine technology in more detail, and since they knew more about the technology, their probability of purchasing one increased, resulting in higher demand. Also, the Danish government installed 100 mW of wind turbines which helped learning by doing mechanism. Long-term contracts in California, offered an alternative way of making wind turbines cost competitive with the conventional technologies, and they helped gaining knowledge about wind turbines. All installations helped gaining familiarity with the wind turbines, but to reach an effective level of familiarity, the exposure coming from the users, non-users and the awareness campaigns should be frequent and strong enough, which is not ensured with all the policies, such as the Danish government installing 100 mW wind turbines.

- **How can these differences be explained in a dynamic way? (RQ4)**
  To analyse these differences in a dynamic way, System Dynamics (SD) is chosen as a methodology. The reason for choosing SD is based on its features such as: it is a white-box modelling tool, the model has strategic point of view, it is a continuous simulation environment, taking an aggregate perspective and it offers dynamic simulation environment. The method of analysis should be over time since diffusion itself is a process over time, and it should be continuous due to non-countable features of the diffusion such as accumulation of knowledge. Besides, a white-box model is needed to track the deep effects of a policy in the process. This study aims to explain the differences in the cases from the policy perspective which focuses on the overall picture of the system rather than the detailed market relations among the actors, which requires a strategic tool as well. Last but not the least, a dynamic approach is needed, since the current state of the system has an effect on the next step the system would take. A methodology having this feature is needed for reaching a reliable analysis. The methodology of system dynamics offers all of these features, therefore it is chosen as the suitable methodology for simulating wind turbine diffusion. Another contribution this research reached is the ability to test the different, even non-existent policies in simulation environment. This way the possible effects of a policy could be tested in advance. This way of what-if analysis is not possible with regression analysis, or other common methods used in analysing innovation diffusion stories.

- **What is the contribution of a dynamic analysis to understand the differences of the diffusion stories of the wind turbines in California and Denmark? (RQ5)**
  In a nutshell, the system dynamics method revealed that not only the policies resulted in better diffusion in Denmark, but also the initial conditions played a role in this diffusion. Also, the effect of the policies on mechanisms are revealed with the system dynamics method with its transparent structure. Also, the existence of mechanisms were in the literature for some time, and the researchers accepted that there is an interaction of these mechanisms, however the implementation of these interactions is not widely tested yet. This study also provides an example for testing different mechanisms not in isolation, but with their interaction resulting in a systemic diffusion.

As these sub research questions answer, the underlying mechanisms resulting in a successful diffusion story in Denmark and a failure in California comes both from the initial conditions and the main nature of the policies used. Denmark's persistence in creating demand for wind turbine installations resulted in effective diffusion in the end, whereas California's high efforts in R&D did not contribute to the diffusion much. Also, Denmark's electricity was already expensive, which makes the wind turbine easier to reach a cost competitive level, whereas in California this required a lot of effort. The mechanisms which were active in the diffusion process were the same in both cases, implying that the structure of the diffusion story was the same, with different values of parameters. Learning-by-doing, learning-by-searching, and knowledge diffusion via networks were the main observable ones triggering the diffusion. The way actors make their choices were also important in diffusion, and the environmental concern was only at the government's mind at that time, leading to cost based decision making of the utilities.

8.2. Conclusion

Modelling wind turbine diffusion with system dynamics was able to answer the research questions raised at the beginning of this research. The aim of the study was to explain the differences of wind turbine stories between California and Denmark, and the model results showed that the differences is coming from not only the policy attempts but also the initial conditions of these countries, which are highly affected by energy generation costs. Yet, without any policy intervention, neither California, nor Denmark would be able to reach the observed diffusion rate, which is much higher compared to no-policy cases. The results showed that demand-pull policies were more effective compared to supply-push policies in fostering adoption, because demand-pull policies not only results in immediate installation increasing familiarity with the technology, but also triggering learning-by-doing mechanism, which is more effective than learning-by-searching mechanism in wind turbine diffusion. Among demand-pull policies, the ones which interfering with the regular market were more effective compared to direct installations. For example, subsidies offered for adopting wind turbines and PURPA act in California were the most successful ones in fostering installations. Additionally, Denmark case showed that creating awareness about the new technology is also quite important, because the preference to wind turbines over conventional technologies are highly affected from familiarity. After reaching a certain level of familiarity, the installations start to accelerate, but a soft threshold for this familiarity should be passed. In California, this soft threshold is not reached, because the effectiveness of non-users were low, the percentage of adopters also remained low making the effectiveness of users obsolete, and finally there was no awareness creation coming from the government with constant changing policies and with no clear aim.

In brief, Denmark was already in an advantageous position for wind turbine diffusion, but without policy interventions none of the cases would be successful. California could have spent more money on demand-pull policies instead of investing too much on R&D efforts, which might result in higher adoption. Another issue with the California's policies was the constant changing nature of policies. Before understanding the effectiveness of a policy, a new policy is introduced, and within 2 to 3 years, it is changed again. These policies help to foster installations, but these frequent changes creates disruptions in installations and make their effects temporary. When there is a disruption, the familiarity decreases, therefore, re-gaining that familiarity takes time.

What this research reached scientifically is also worth considering. First, it should be realized that most of the innovation diffusion analysis studies focus on the demand side of the story, where supply side also has an importance. This inadequacy is stated by Hekkert (2007) and Kemp, Schot and Hoogma (1998), yet the number of studies taken the supply side into account is limited in number. Therefore this study indicates the importance of the supply side of the diffusion story as well as it captures the demand side. Another important point is the possibility of testing new policies on a known case which is not possible with regression analysis. For instance, EnergiPlan act is tested in California, which was originally only existent in Denmark, and the effects of this act on California is derived from the model's results. Of course, "all models are wrong" (Sterman, 2000), therefore we cannot conclude that the model would give the exact results, yet having this data at hand would be useful for analysing the effectiveness of the policies and for developing new policies. Lastly, modelling this cases with system dynamics provided a combined view for active mechanisms in the diffusion, and as a result it was possible to make a quantitative work on observing the interactions of mechanisms.

8.3. Suggestions and future work

This research can only be seen as an early and humble attempt to explain the innovation diffusion with a more dynamic approach, compared to widely used methods such as regression analysis. This study showed promising results in modelling innovation diffusion, by looking at the diffusion stories which occurred in the past. This way it was possible to observe the abilities of the system dynamics method in capturing the different diffusion paths. This could be an indication for future studies, with the suggestion of forecasting the direction of a certain technology in the society with planned policies. In a way, it is possible to move from a reflective study to an explorative study with system dynamics.

Another issue realized in this research is about the diffusion of innovation literature itself. Different attempts to give the diffusion studies a more dynamic approach have been tried, but these attempts remained theoretical so far. This study was also an attempt to apply these theoretical suggestions into case studies. To test the validity of these theories, more case studies should be conducted with the other well-known diffusion stories. This way, the strength of these theories will be supported.

In the literature of technology based innovation systems, similar issues are mentioned by different researchers, but a common framework showing the relationships of these theories do not exist to the author's knowledge. A common framework showing these similarities and the common issues raised by different researchers could be a useful guide for the following diffusion studies. In chapter two, the Table 2.1. can be interpreted as a preliminary attempt for creating such a framework.

It should be noted that the conditions and the mind-sets of the actors has changed in wind turbine diffusion since 1980s. At that time, the knowledge about environmental hazards coming from the conventional technologies were only at the initial stage. Therefore, there was no green demand coming from the consumers, and the utilities only focused on the profit side of generating electricity. Yet, this is not the case in today, the amount of environmentally friendly consumers increased, demanding green energy from the utilities even at a higher price. The change of this mind-set offers a new research area, for understanding the change in people's mind-set and the factors affecting this change. Apart from that, the actor's mind-sets should be reflected on diffusion studies for more realistic results.

8.4. Reflection

8.4.1. Reflection on the methodology

System dynamics simulation is chosen as an educated guess for analysing the diffusion story of wind turbines in California and Denmark. Yet, of course it is possible to analyse it with different methods. A close competitor for system dynamics is agent-based modelling, which is becoming popular among the researchers studying innovation diffusion. Agent-based modelling also provides a suitable platform for diffusion studies because it makes it possible to simulate the autonomous actions of actors, which could easily be the adoption in this case, and assess the effects as a system as a whole. With this methodology, actor based, bottom-up simulation models can be developed enabling an emergent behaviour as well. However, for the aim of this study, agent based modelling did not fit the purpose as much as system dynamics. Because, agent-based simulation has an actor perspective, the underlying structures, which are mechanisms in this case are not clear. In a way, from structural point of view, agent-based modelling behaves like a black-box model and it makes it difficult to trace the chain of events causing the results of the simulation. Besides, agent based modelling is focusing on the micro-level decision making structures of actors, however one of the aims of this study is to reveal the strategic set of actions from governmental perspective. With a different point of view to the same case study, agent-based modelling could reveal different important points, yet it is not possible to conclude that one method is better than the other since they take different perspectives for understanding the same phenomenon. The choice of system dynamics for this research was an educated guess, taken without analysing all the different methods precisely. Yet, this educated guess includes a logical but quick analysis for the choice of methodology. Regression analysis and econometric models were not dynamic in nature, agent-based simulation was more focused on the actor perspective rather than the underlying structure, and system dynamics was offering a good fit to for this purposes. Therefore, system dynamics is chosen as a methodology, which was taking a risk at the beginning, but worked well in the end.

8.4.2. Reflection on the model

In this section the aim is to reflect on the model's ability and validity for this research. Also, what kind of improvements could be done in the model will be discussed as well. The created model is a simple one, but it was able to capture the main dynamics of the diffusion stories of California and Denmark. A simple model was not that easy to create, because on the one hand you should ensure that every variable is put into the model in a transparent way, and no significant mechanism is left out to reach reliable results. With this aim, most of the time spent in this research was put into building the model, starting from the literature survey and learning about the histories of diffusion in California and Denmark. The validation study also showed that the model is robust to changes, and behaves as expected under extreme conditions which increases the validity of the model. However, no model is perfect by nature. One of the main purposes of the model is to simplify reality in an understandable way, but this means that some of the factors affecting the behaviour of the model are left out from the beginning. Therefore, this model does not fully explain what really happened in wind turbine diffusion in California and Denmark, but it can point at the main important reasons in the story. Also, there is another limitation of this model, which is the part trying to quantify the qualitative knowledge. To overcome this limitation, all soft variables are based on the literature, which could be interpreted as a commonly accepted existence of those variables, supporting the structure of the model. However, the exact quantification of these variables is based on experimentation with the model, which has no real counterpart, therefore it is impossible to ensure the truth of these variables. To deal with this problem, the qualitative statements from the literature on wind turbine diffusion stories are taken as base points and the improvements on the values are done by looking at the model's results.

Another limitation of the model is the way the structure is created and the policies are implemented. System dynamics offers a flexible modelling environment, therefore it is possible to model a phenomenon in a thousand different ways. This is both an advantage and a disadvantage. The advantage is coming from the freedom of the modeller to put his/her notion to the model in a more flexible way, but this way threatens the validity of the model. Because, reaching the desired result is not the aim of this study, but reaching the desired result with the right interpretation of the story and correct way of implementation to the simulation software matters more. Therefore, as much as possible, the model's structure tries to reflect on the mechanisms available in the literature. Yet, for implementing the policies in the model has no literary proof, since they are case based, provisional methods. There is no proved way out of this problem, therefore the policies are implemented with logical processes by checking their effects on each variable, and ensuring that there is no non-sense response in any of the variables.

A controversial situation can be spotted from the relation between the assumptions and the conclusions. The model is structured based on the statement saying that learning-by-doing has stronger effect compared to learning-by-searching effect. Then, the conclusion is also reflects the same. To what extent this conclusion is valid based on this assumption? To test that, in the model, I changed the beta and alpha values with each other and observed the results, when all policies, and when solely R&D policies are active. The results showed that there is an improvement when the parameter values are interchanged, yet, still the effect of R&D policies on adoption stays limited. This test is made in the Danish model, and the results showed that only 50 mW extra installation occurred cumulatively at the end of the simulation. Note that, the case stories also qualitatively indicate the same result. The United States spent a considerable amount of money for research and development compared to Denmark, yet the Danish government was more successful in stimulating adoption. Therefore, even though the assumption looks like a weakness of the model, the results support the assumption both quantitatively and qualitatively.

After stating these limitations of the model, the benefits of it should not be overlooked. This model assisted in tracking the effects of policies on the mechanisms, which could be seen as a novelty in innovation diffusion. With regression analyses, it is possible to observe the overall effects of policies on the diffusion, but it is not possible to understand the way that policy enhance or diminish the rate of diffusion. With system dynamics modelling, the relationships can be revealed, which could be a promising tool for policy makers in transition studies. Another benefit of the model is in determining the main active mechanisms in the diffusion. For instance, if we put all possible mechanisms and remove each of them one by one with a simplified model of the same problem, and if we reach the similar results we can prioritize on the effectiveness of the mechanisms on the diffusion. This is partially done in policy testing in Chapter 7 from the policy perspective, but for an extension of the study, the effects of other mechanisms on the model could be tested resembling to a what-if analysis.

For extending the model, other implications are also possible. At the beginning, the idea was also look for the imports of each country to the other and their effects on diffusion, but due to time constraints this is not realized. But, researching the wind turbine installations from the market perspective could bring new insights to the diffusion stories, because we know that Denmark not only uses wind energy as one of the main energy sources in the country, but they have a significant market share in the global market. A number of studies could be done focusing on the limitations of the model as a follow up research.

8.4.3. Reflection on the work

Building this research took a lengthy process with various challenges in different steps. As it is shown in Figure 2.5. there were seven different steps in the research from beginning to the end, which are:

- Literature survey for qualitative case stories
- Literature survey for innovation diffusion related concepts
- Building a conceptual model
- Data gathering
- Model Implementation
- Verification and the Validation of the model
- Policy testing and the insights.

The difficulties experienced in each of these steps are explained below:

Literature survey for qualitative case stories & innovation diffusion concepts
Before deciding on my research topic, I only heard about innovation diffusion, but I was not knowledgeable about the theory. When I started reading, I realized that it has a very wide spectrum focusing on different styles of innovation diffusion and reflecting on different challenges encountered. Therefore, the first challenge was about narrowing down and finding the related concepts in the theory. To be able to determine the related concepts I had to learn about the diffusion stories of wind turbines from various sources. The focus was mainly on the scientific publications, to increase the reliability of the knowledge gathered. The more I read about the case stories, the more innovation diffusion literature made sense to me. In the end, I ended up with two detailed stories of wind turbine diffusion and a bunch of concepts relating to diffusion of innovation. Another issue is about the statement in the literature saying learning-by-doing has a stronger effect than learning-by-searching mechanism. This is a qualitative statement regarding wind turbines, but whether this is a general condition or a specific to this story is controversial. I believe that this was the case for wind turbine technology, because even from the 1980s, the technology was in a usable condition, so it was sort of developed. Before reaching this point, it is necessary to focus on learning-by-searching as well. And there is not a real way of measuring the effects of learning-by-doing and learning-by-searching on the performance or cost improvement. Therefore, in the model I tried to keep them close, even though I assigned a higher effectiveness ratio for learning-by-doing.

Building a conceptual model
During my literature search, the relationships and the feedback loops started to take shape in my mind with the possible idea of using system dynamics as a method. The stories explained in the literature seemed a suitable input for SD simulation, therefore I searched for the applications of SD on innovation diffusion in the literature. There were some attempts, but the number of them were quite limited, and most of them have a narrower focus. When I

looked at the features of SD and the concerns of authors' on reflecting on the limitations of current methods on analysing SD, I realized that there is a good match among the two. After looking at all the features of SD and seeing whether it satisfies the expectations of the research, I concluded that SD is a good approach. Doing so, I started building the conceptual model with the feedback loops and the relationships of these feedback loops with each other. Since there was no similar study in the literature that could assist me, I modelled different parts of the conceptual model by taking different references from the literature. For the parts not existing in the literature, expert opinion is used as a feedback. The initial conceptual model is not exactly used in the implementation, because due to the challenges encountered in the implementation, the mistakes in the conceptual model was realized and fixed accordingly.

Data gathering

This was one of the most time consuming parts of the research. It is impossible to find the exact data that you want, therefore, a new method of calculating those data should be found. In this case it was the LCOE's of different technologies. After 2000, the LCOE's of different energy sources are available on the web, but prior to 2000, it is hard to come by this data. Therefore, the LCOE's are calculated manually with the found investment costs, operation costs and fuel costs of that time, and finding all of this information took some time. Also, some data is not available by nature, such as the familiarity of the potential adopters to wind turbines. It is not measurable, therefore based on the qualitative knowledge found in the literature, assumptions are made for this kind of data. After finding the data, it was time for implementing the model.

Model Implementation

After having the conceptual model and the data, it was rather a straightforward process to implement the model. However, this part requires a detailed modelling of the variables, and therefore some points which are overlooked in the conceptual model had to be re-designed. For example, for modelling the familiarity mechanism, at first, the Bass model of diffusion was used. However, during the implementation it is realized that this model does not fully fit into the story with a little number of actors (number of utilities are much limited compared to the whole society). Besides, there were too many degrees of freedom that this model brought, in which some of them were inexplicable in the wind turbine diffusion context. Therefore, another way of modelling this familiarity mechanism has to be found. In the end, Struben and Sterman's work (2008) suited much better in modelling this mechanism. It is adapted according to the nature of this study.

Verification and Validation

After building the model it should be ensured that the model is trustable. For this reason, the verification and the validation study is designed. The design of the study is also based on the literature, making sure that the model is acceptable from different perspectives such as structure, or dimension. The steps to be followed were clear in this part of the research, and they are followed point-by-point. The results showed that the model is robust to parameter changes and behaves realistically under extreme conditions. Thus, it was possible to move forward with the study to generate useful insights from the model.

Policy Testing and the Insights

This part was designed for making use of the created models. The models were created with a purpose of understanding the differences between two cases. Therefore, as well as the policies, the initial settings in these models are compared. Then, the policies which are similar to each other are compared in isolation and their effects on diffusion is discussed. Then the policies which are unique to a case tested into the other case resembling to a what-if analysis. This process was time consuming, but useful for generating insights. The process of generating insights is more of a cognitive work, by comprehending and interpreting the results and tracking back the reasons of these results.

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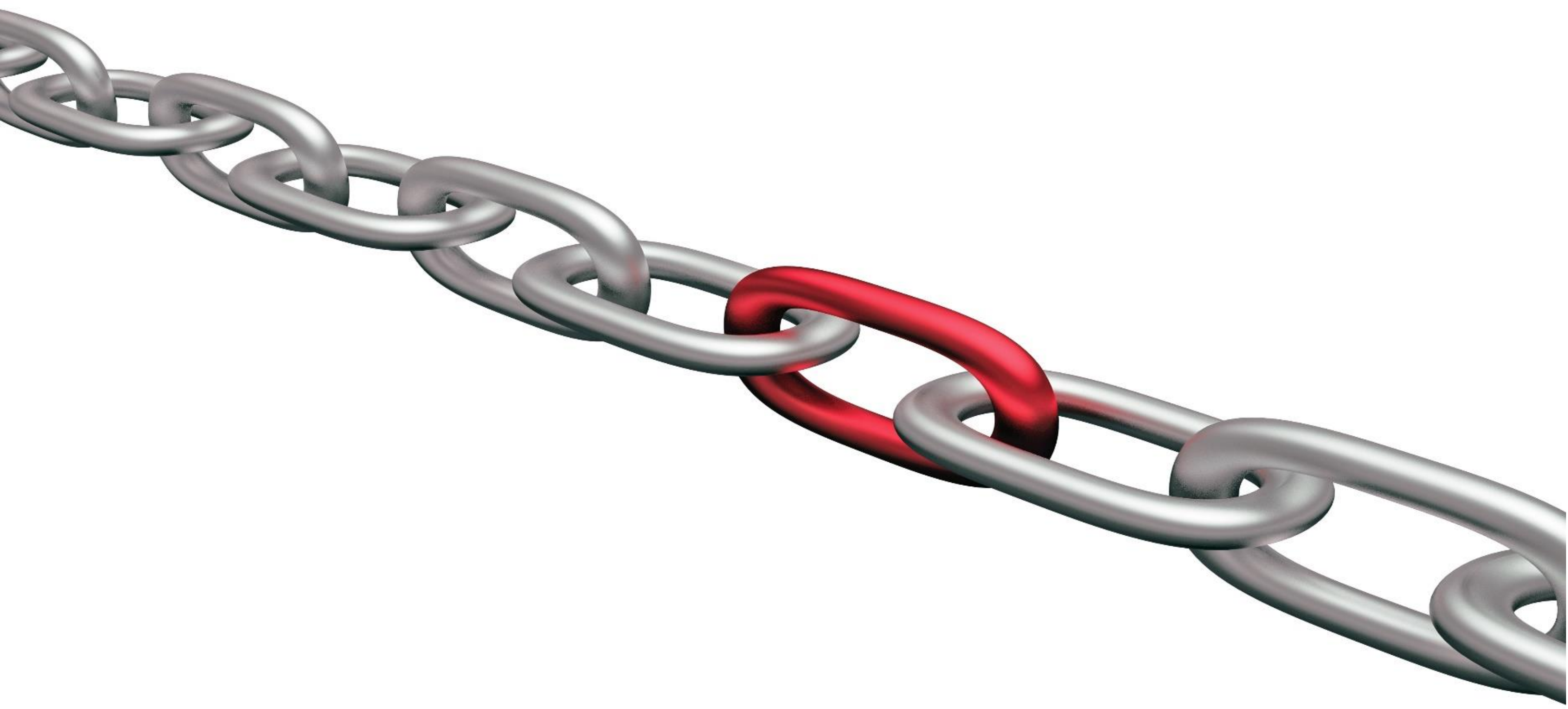


Appendices

Appendix A – Model implementation

Appendix A.1. – First view: Wind turbine installation process

The picture of this view is separated into 4 main subsections. The first subsection is about LCOE's of conventional technologies, second subsection is about LCOE of wind, third subsection shows the decision making mechanism by comparing LCOE's and final section shows the wind turbine installations. After partial representation of these subsections, the combined version will be shown at the end.

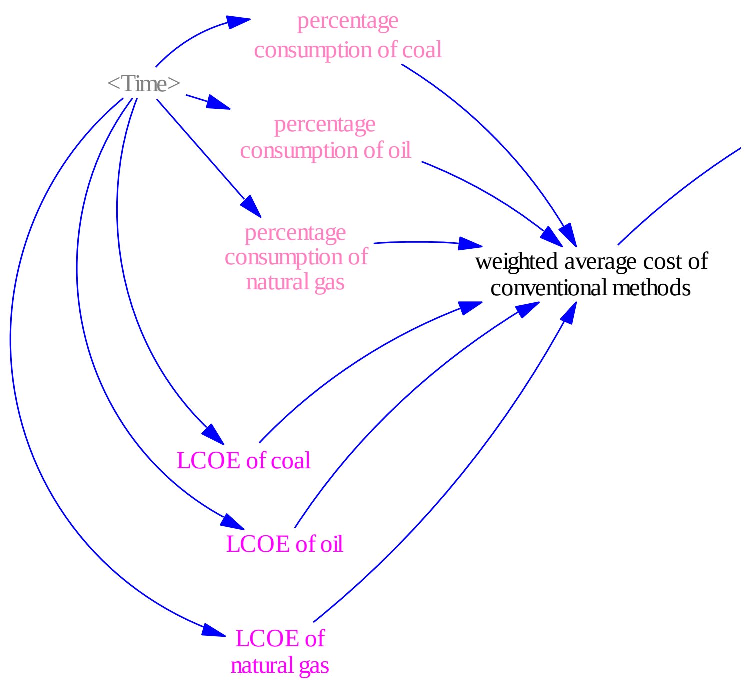


Figure U.0.1 LCOE modelling of conventional technologies

For modelling LCOE's of conventional technologies, at first the power mix of the case is determined. Figure U.1 shows Denmark case. In Denmark, main electricity sources were oil, coal and natural gas. Their LCOE's are calculated separately with the same interest rates which are also used for wind. The reason for calculating the weighted average cost of conventional technologies is to have an idea of average cost of electricity with conventional methods. Then this weighted average is treated as the LCOE of conventional methods in the model.

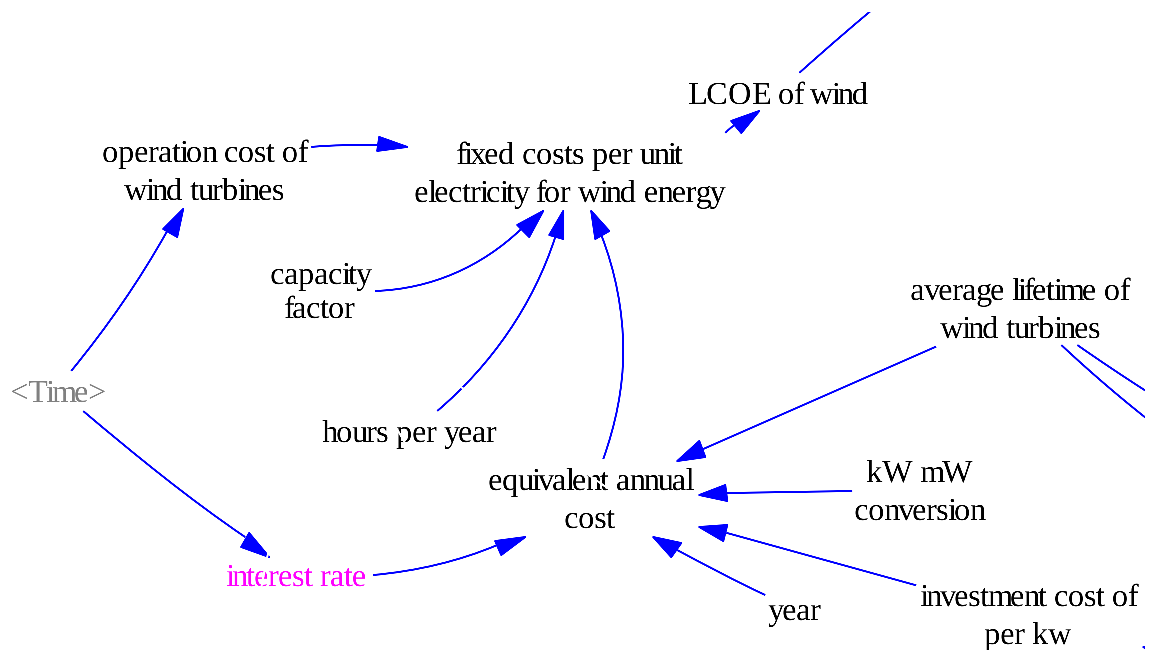


Figure U.2 LCOE modelling of wind turbines

For modelling LCOE of wind, the same formula explained in Chapter 5 is used. The calculation of LCOE is done within the model this time, because this is an immature technology and the learning curves have not been reached to plateau as conventional technologies. Learning curves affect capacity factor and investment cost of wind turbine, and consequently LCOE of wind decreases with time.

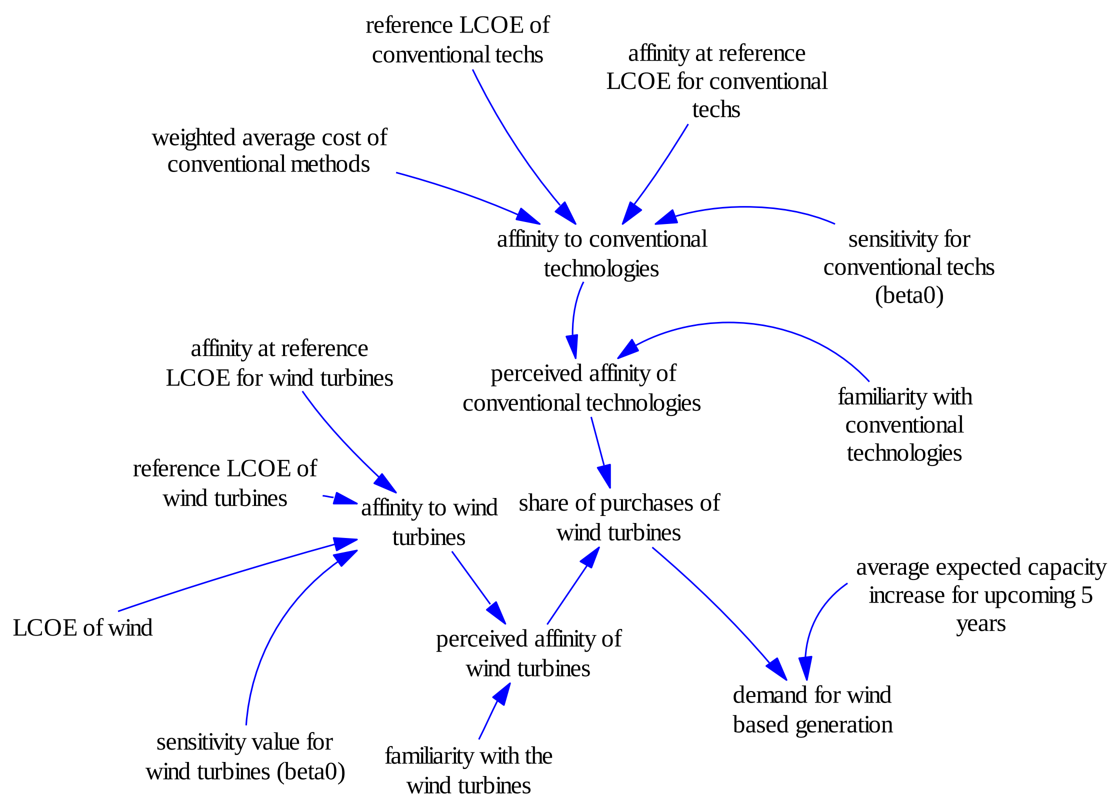


Figure U.3 Decision making modelling for wind turbine purchases

This part of the model compares LCOE of wind turbines with LCOE of conventional technologies, and then determines the percentage share of wind turbines for newly installed capacities. LCOE of conventional technologies is the average of *weighted average cost of conventional methods* over time, which is 60$ for Denmark. Affinity with the conventional technologies at this price is assigned to 1, assuming that utilities will install the methods that they already know of, on the average price. Reference LCOE of wind turbines is a bit less than the reference value of conventional techs, which is 55$ for Denmark. The affinity at this price is assigned to 1 for wind turbines. These values say that if wind turbines offer the same performance (cost related performance) with the conventional technologies, it will still be considered a little bit inferior, due to the prejudice over a new technology. Yet, if it is a bit cheaper than the conventional ones, then this prejudice is left.

Perceived affinity of wind turbines is the multiplication of affinity value with the familiarity, since to be able to decide on buying something an actor should be aware of its existence. Familiarity with the conventional technologies is assumed as 1, due to mature nature of these technologies. Share of purchases of wind turbines is calculated by dividing perceived affinity of wind turbines to total perceived affinity. This comparison is the percentage share of people who would consider buying wind turbines. Then this value is multiplied with the average expected capacity expectations of the utilities and the share is installed as wind turbines.

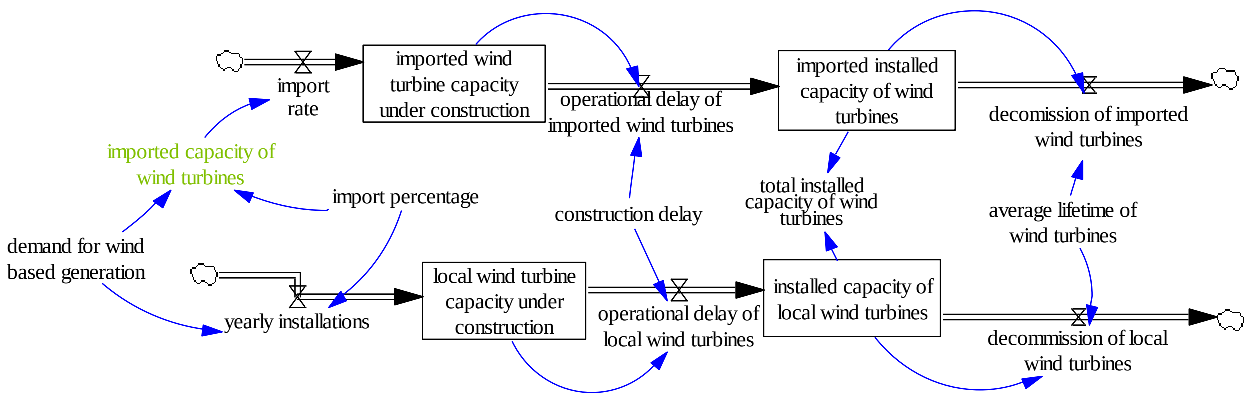


Figure U.4 Installation of wind turbines

The part of the model in Figure U.4 represents the yearly installations of wind turbines. As an assumption 15% of the wind turbine demand is imported. The construction of wind turbines is 6 months and decommission of the wind turbines are determined by their age, where the lifetime of wind turbines is 20 years. Total installed capacity of wind turbines shows the cumulative capacity installed coming from imported and local manufacturers.

Appendix A.2. – Second view: Installed Capacity

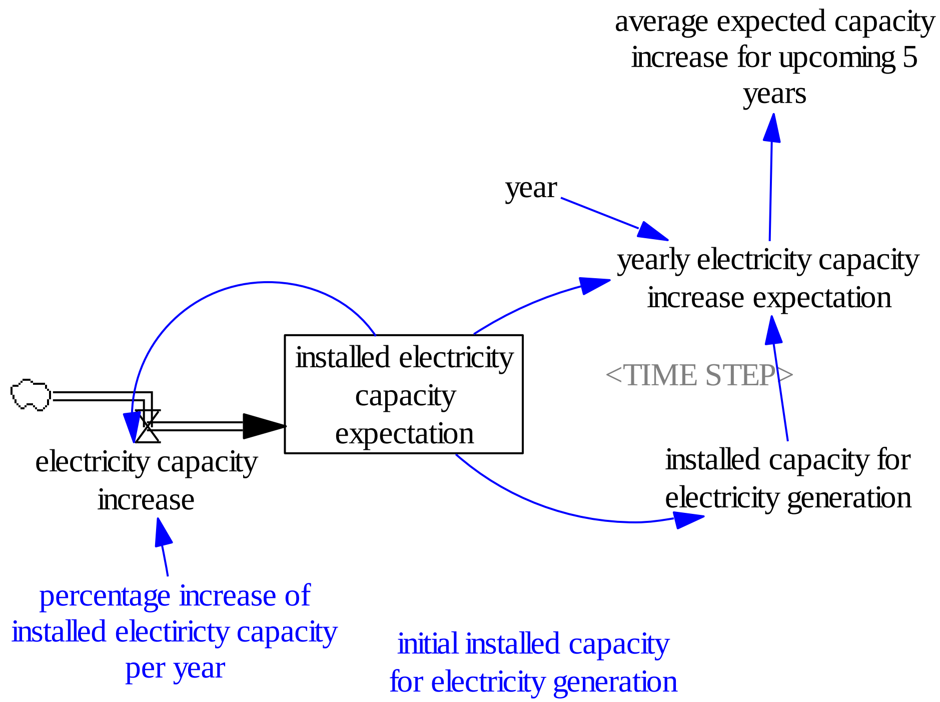


Figure U.5 Installed capacity and Demand modelling

This view is based on the assumption that for each new installation increasing electricity capacity, some of this increase will be done with wind turbines. Therefore the installed capacity of California and Denmark at 1980 is found, and their average percentage increase is calculated. *The installed electricity capacity expectation* and *installed capacity for electricity generation* are both the same values, however for calculating the yearly increase, *installed capacity for electricity generation* has a delay of one year. Then for introducing the uncertainty of this increase, *average expected capacity increase for upcoming 5 years* is calculated by focusing 5 years from that point in time, by looking at last 5 years energy increase. This forecasting is done by the model itself.

Appendix A.3. – Third view: Learning mechanisms

This view is separated into two parts, modelling learning by searching mechanism, and modelling learning by doing mechanism. Figure U.6 shows the modelling of learning by searching mechanism:

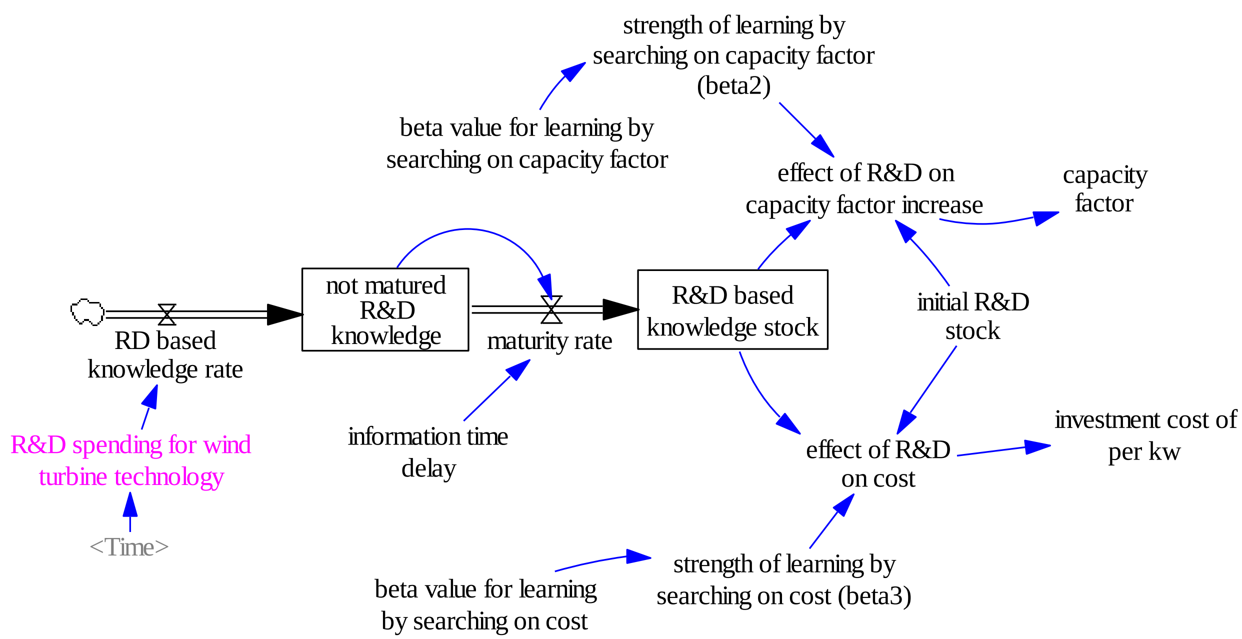


Figure U.6 learning by searching mechanism in the model

Here in this mechanism, according to Klaassen et al's work, there is a maturity time for R&D spending to turn into useful knowledge. In general this delay time is assumed to be three years (Klaassen et al., 2005). Therefore in this model, the delay time for mature knowledge is also set to three years. The variable *R&D spending for wind turbine technology* is a lookup function imitating the real R&D spending of governments. When the knowledge matures, it accumulates into *R&D based knowledge stock*. *Initial R&D stock* is calculated by adding the spending before 1980. Then according to the formula in Chapter 5, effect of R&D on cost and capacity factor is calculated and the results are reflected into capacity factor and investment cost. Note that in the figure initial values of capacity factor and investment cost is not shown, however in the model, these values are also used to calculate their current values. Initial values are gathered from historical data.

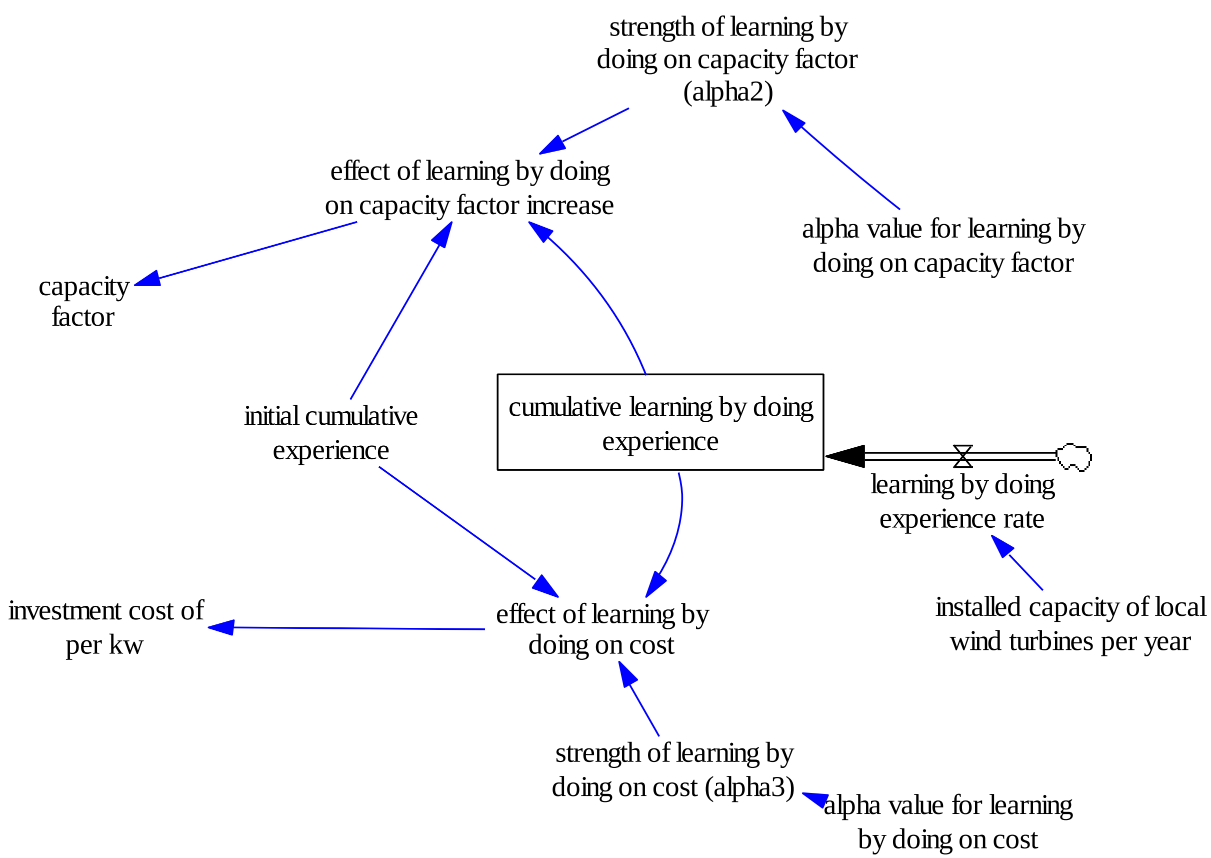


Figure U.7 learning by doing mechanism in the model

Learning by doing mechanism is modelled similarly. The measure for learning by doing is the *installed capacity of local wind turbines per year* and *initial cumulative experience* is the total installed wind turbine capacity in California and Denmark before 1980, which were

8 and 5 mW respectively. Again, this figure does not show, but initial values of capacity factor and investment cost of wind turbines are also in the model.

Appendix A.4. – Fourth view: Modelling Familiarity

This view shows how the familiarity with the wind turbines is modelled. The implementation of this structure is shown in Figure U.8:

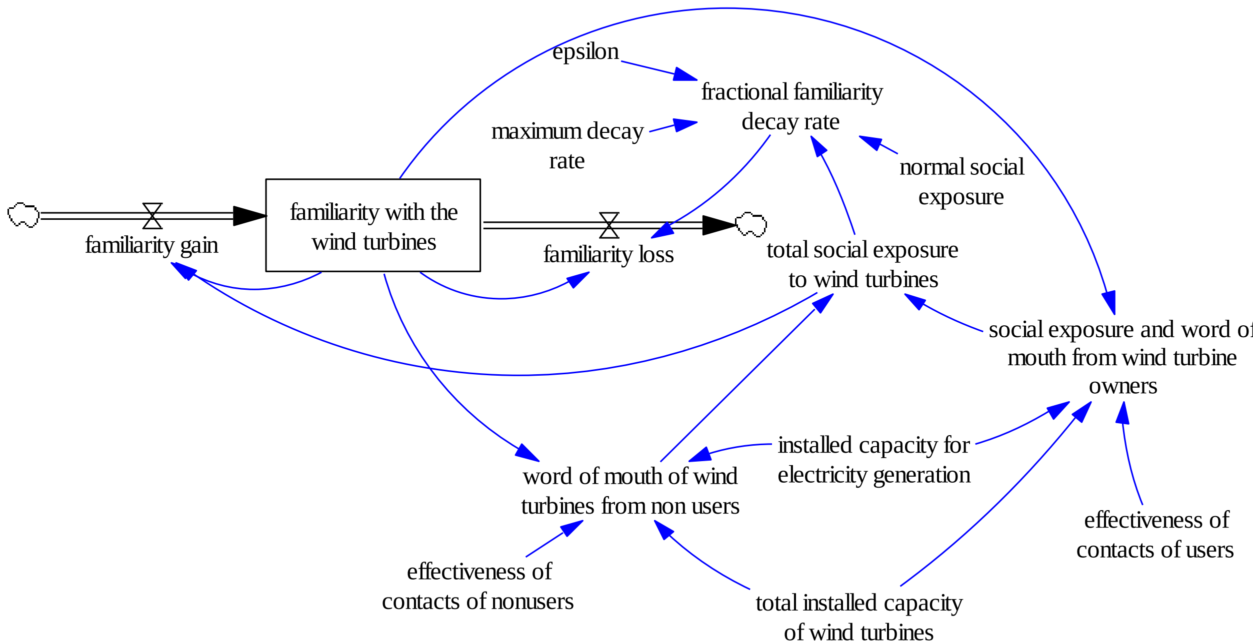


Figure U.8 modelling familiarity with the wind turbines

As it was explained in Chapter 5, familiarity increases with total social exposure to wind turbines from users and nonusers, and it decays with time, depending on the exposure level and reference rates. To understand this mechanism better, it should be thought that there are 2 platforms: wind turbine and conventional technologies. The share of wind turbine installation over total capacity gives the share of wind turbine users in an aggregated way. Then, for non-users, the word of mouth mechanism works, where this mechanism is strengthened with the visibility of wind turbines for users. These word of mouth mechanisms are related with familiarity as well; if many utilities are aware of wind energy option, more people will talk about it, so that social exposure increases. This is the last mechanism, which connects to the first view in modelling perceived affinity (See Figure U.3).

Appendix A.5. – Full pictures of the views

This section of the appendix shows the full visualization of 4 views to show the connections. It should be noted that this picture is for Denmark without policy implementation.

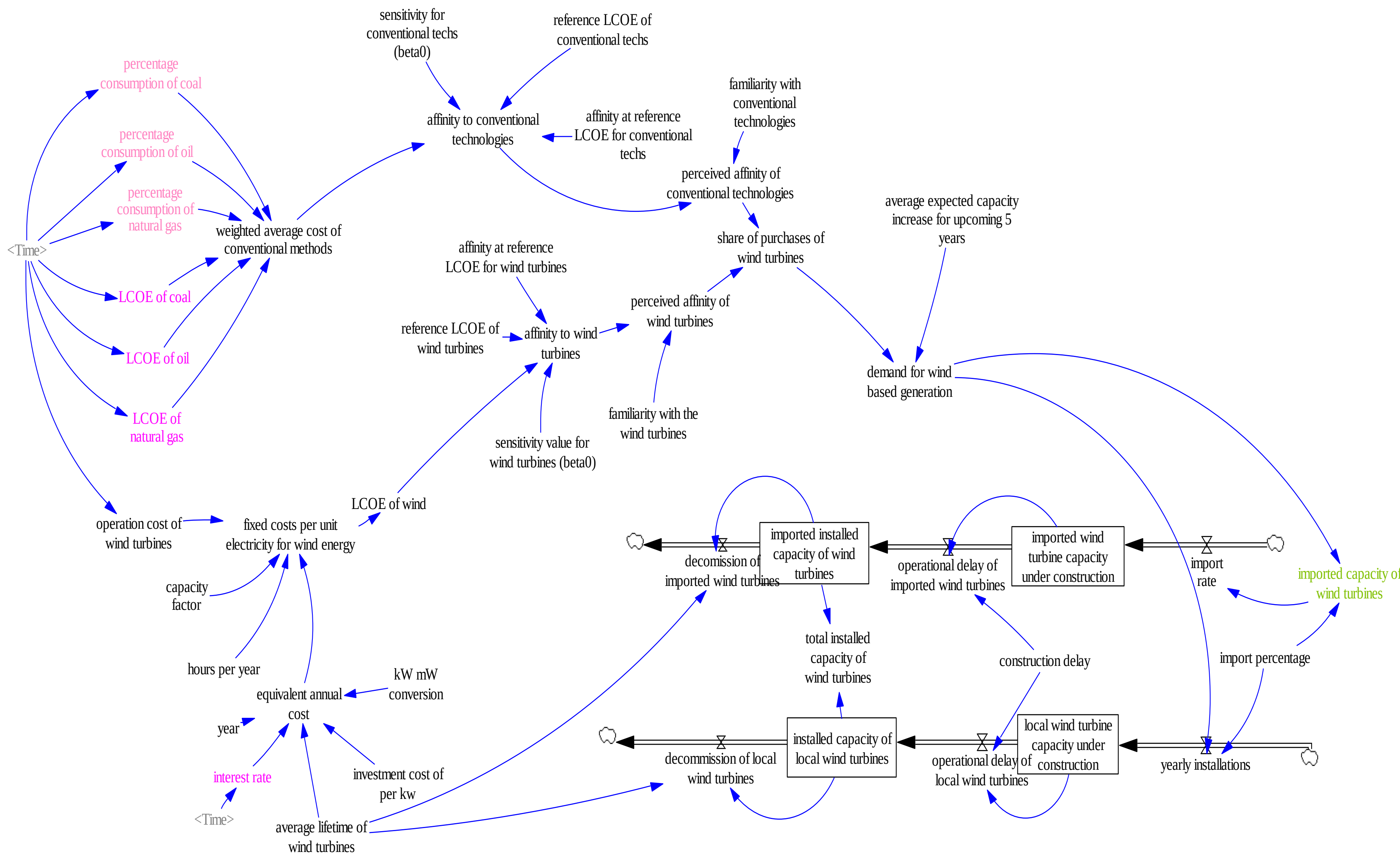


Figure U.9 Screenshot of view 1: Wind turbine installations

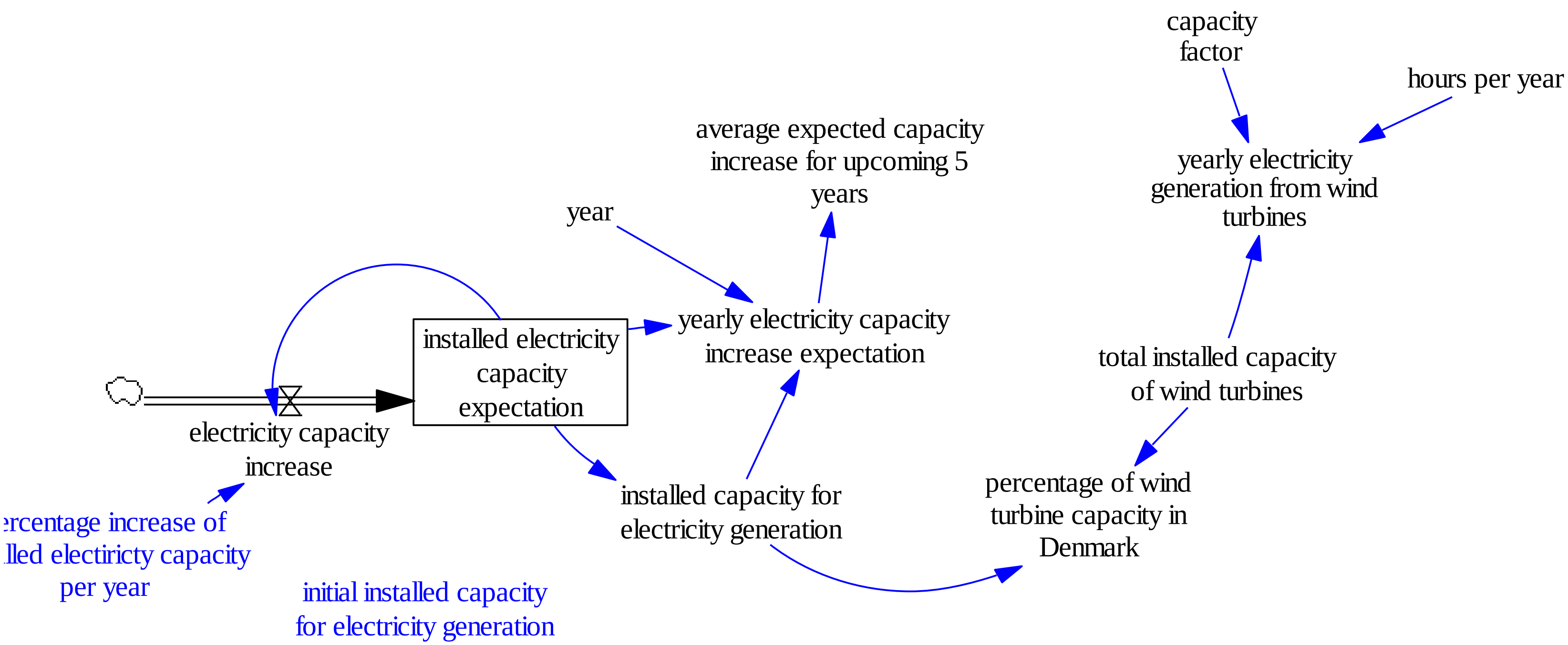


Figure U.10 Screenshot of view 2 : Installed Capacity for Electricity Generation

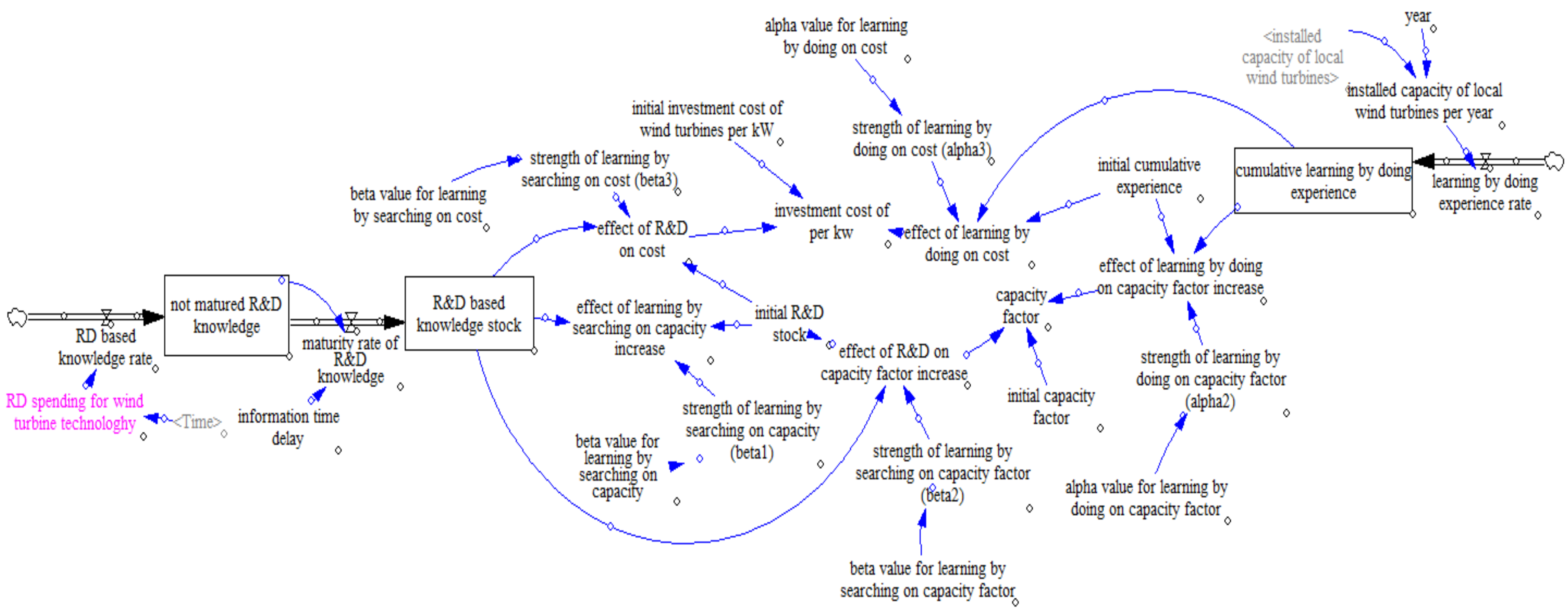


Figure U.11 Screenshot of view 3 : Learning Curves

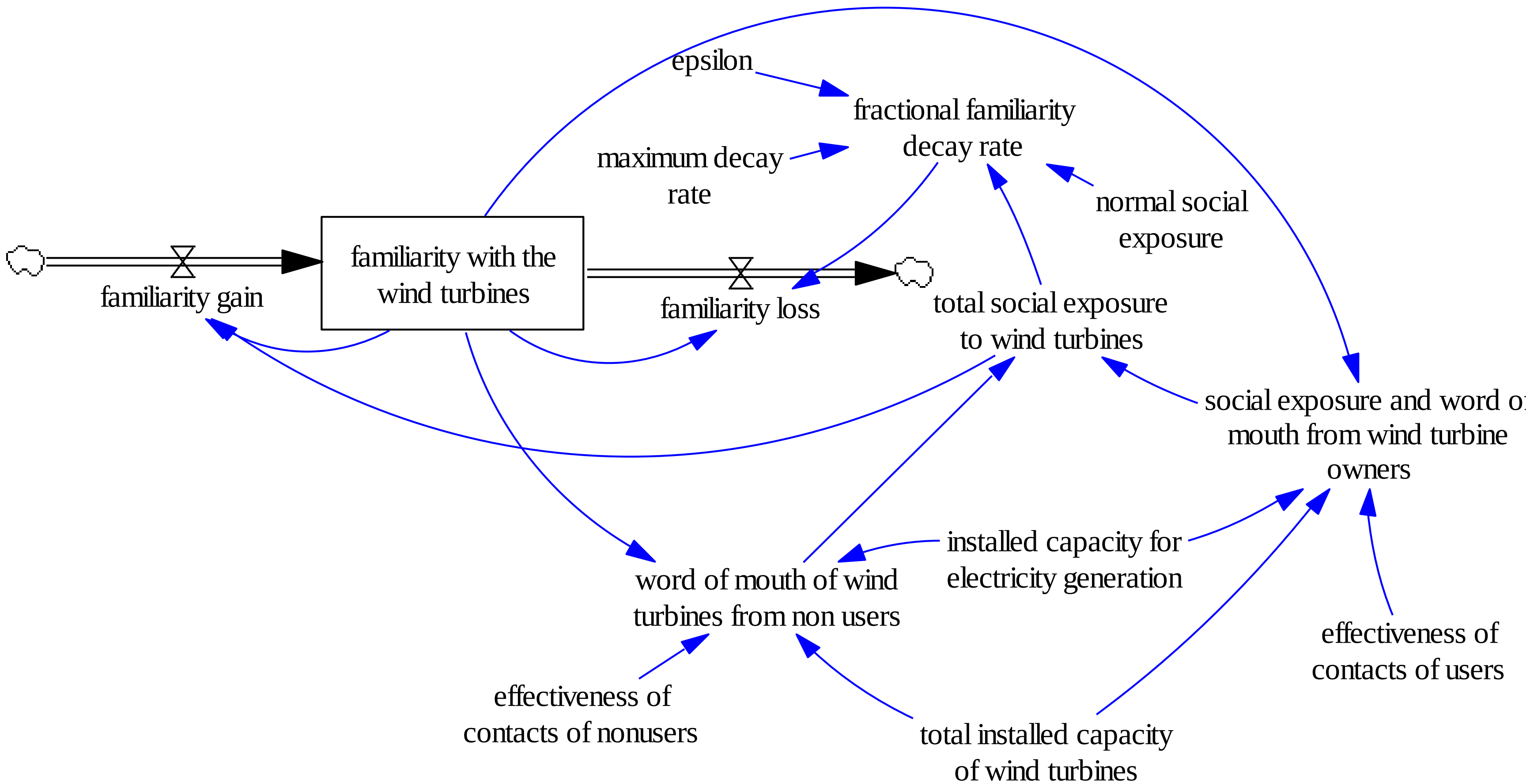


Figure U.12 Screenshot of view 4: Familiarity with the wind turbines

Appendix B – Names, Formulas and the Units of Variables

The table below shows the names, equations and the units of the variables used in both cases. Note that some of the variables exist only one of the cases if it is a policy based variable. Also for different values used in the cases are shown with a dash.

Variable	Formula(Denmark/California)	Unit
Percentage consumption of coal	Lookup with Time	Dmnl
Percentage consumption of oil	Lookup with Time	Dmnl
Percentage consumption of natural gas	Lookup with Time	Dmnl
LCOE of coal	Lookup with Time	$/mWh
LCOE of oil	Lookup with Time	$/mWh
LCOE of natural gas	Lookup with Time	$/mWh
Weighted average cost of conventional methods	LCOE of natural gas*percentage consumption of natural gas + LCOE of oil*percentage consumption of oil + LCOE of coal*percentage consumption of coal	$/mWh
Operation cost of wind turbines	Lookup with time	$/mWh
Capacity Factor	initial capacity factor*effect of R&D on performance increase*effect of learning by doing on performance increase	Dmnl
Hours per year	8760	h
Equivalent annual cost	(investment cost of per kw*interest rate*(1 + interest rate)^average lifetime)/((1 + interest rate)^average lifetime - 1)* kW mW conversion	$/mw
Investment cost of wind turbine per kW	initial investment cost of wind turbines per kW*"effect of R&D on cost"*effect of learning by doing on cost*(1-investment subsidy)	$/kW
kW mW conversion	1000	kW/mW
Fixed costs per unit electricity for wind energy	(equivalent annual cost)/ (hours per year * capacity factor) + operation cost of wind turbines	$/mWh
Avoided cost compensation for wing	MAX(LCOE of wind-weighted average cost of conventional methods,0)	$/mWh
PURPA act implementation	STEP(avoided cost compensation for wind, 1983) - STEP(avoided cost compensation for wind, 1987)	$/mWh
LCOE of wind	fixed costs per unit electricity for wind energy*"10 year agreement between government and utilities"	$/mWh
LCOE of wind coming from long term contracts	weighted average cost of conventional methods + 20	$/mWh
10 year agreement between government and utilities	1 - STEP(0.15, 1985)	Dmnl

Sensitivity value for wind turbines (beta0)	1.8/1	Dmnl
Reference LCOE of wind turbines	43/20	$/mWh
Affinity at reference LCOE of wind turbines	1	aff
Affinity to wind turbines	affinity at reference LCOE for wind turbines*EXP(-"sensitivity value for wind turbines (beta0)"*(LCOE of wind/reference LCOE of wind turbines-1))	aff
Reference LCOE of conventional techs	60/28	$/mWh
Affinity at reference LCOE for conventional techs	1	aff
Sensitivity for conventional techs(beta0)	1/0.54	Dmnl
Familiarity with conventional technologies	1	Dmnl
Perceived affinity of conventional technologies	affinity to conventional technologies*familiarity with conventional technologies	aff
Perceived affinity of wind turbines	familiarity with the wind turbines*affinity to wind turbines	aff
Share of purchases of wind turbines	perceived affinity of wind turbines/(perceived affinity of wind turbines + perceived affinity of conventional technologies)	Dmnl
Average expected capacity increase for upcoming 5 years	FORECAST(capacity increase expectation per year,5,5)	mW/year
Demand for wind based generation	average expected capacity increase for upcoming 5 years*share of purchases of wind turbines	mW/year
Yearly installations	demand for wind based generation*(1-import percentage) +government agreement for installing wind turbines	mW/year
Import percentage	0.15	Dmnl
Imported capacity of wind turbines	demand for wind based generation*import percentage	mW/year
Import rate	imported capacity of wind turbines	mW/year
Imported wind turbine capacity under construction	INTEG(import rate-operational delay,0)	mW
Construction delay	0.5	year
Operational delay of imported wind turbines	imported wind turbine capacity under construction/construction delay	mW/year
Imported installed capacity of wind turbines	INTEG(operational delay of imported wind turbines-decommission of imported wind turbines,0)	mW
Decommission of imported wind turbines	imported installed capacity of wind turbines/average lifetime of wind turbines	mW/year
Average lifetime of wind turbines	20	year
Local wind turbine capacity under construction	INTEG(yearly installations-delay until turbines are operational,0)	mW

Operational delay of local wind turbines	local wind turbine capacity under construction/construction delay	mW/year
Installed capacity of local wind turbines	INTEG(operational delay of local wind turbines-decommission,5)	mW
Decommission of local wind turbines	installed capacity of local wind turbines/average lifetime of wind turbines	mW/year
Total installed capacity of wind turbines	installed capacity of local wind turbines + imported installed capacity of wind turbines	mW
Percentage increase of installed electricity capacity per year	0.025	1/year
Initial installed capacity for electricity generation	7072/55000	mW
Electricity capacity increase	installed capacity expectation per year*(percentage increase of installed electricity capacity per year)	mW/year
Installed electricity capacity expectation	INTEG(electricity capacity increase, initial installed capacity for electricity generation)	mW
Installed capacity for electricity generation	DELAY FIXED(installed electricity capacity expectation, 1, initial installed capacity for electricity generation)	mW
Yearly electricity capacity increase expectation	installed electricity capacity expectation-installed capacity for electricity generation	mW/year
Percentage of wind turbine capacity in Denmark	total installed capacity of wind turbines/installed capacity for electricity generation*100	Dmnl
RD Spending for wind turbine technology	Lookup function with time	Million $/year
RD based knowledge rate	RD Spending for wind turbine technology	Million $/year
Not matured R&D knowledge	INTEG(RD based knowledge rate-maturity time,0)	Million $
Maturity rate of R&D knowledge	"not matured R&D knowledge"/time delay of the info	Million $/year
Information time delay	3	year
R&D based knowledge stock	INTEG(maturity rate of R&D knowledge, initial R&D stock)	Million $
Initial R&D stock	12.5	Million $
Beta value for learning by searching on capacity factor	1.04/1.04	Dmnl
Beta value for learning by searching on cost	0.96/0.9	Dmnl
Strength of learning by searching on capacity (beta1)	LOG(beta value for learning by searching on capacity, 2)	Dmnl
Strength of learning by searching on capacity factor (beta2)	LOG(beta value for learning by searching on capacity factor, 2)	Dmnl
Strength of learning by searching on cost (beta3)	LOG(beta value for learning by searching on cost, 2)	Dmnl

Effect of learning by searching on capacity increase	(R&D based knowledge stock/initial R&D stocK'')^strength of learning by searching on capacity (beta1)	Dmnl
Effect of R&D on capacity factor increase	(R&D based knowledge stock"/initial R&D stock)^strength of learning by searching on capacity factor (beta2)	Dmnl
Effect of R&D on cost	(R&D based knowledge stock/initial R&D stock)^strength of learning by searching on cost (beta3)	Dmnl
Installed capacity of local wind turbines per year	installed capacity of local wind turbines/year	mW/year
Learning by doing experience rate	Installed capacity of local wind turbines per year	mW/year
Cumulative learning by doing experience	INTEG(learning by doing experience rate, initial learning by doing experience)	mW
Initial cumulative experience	5	mW
Alpha value for learning by doing on capacity factor	1.07/1.062	Dmnl
Alpha value for learning by doing on cost	0.947/0.88	Dmnl
Strength of learning by doing on capacity (alpha1)	LOG(alpha value for learning by doing on capacity, 2)	Dmnl
Strength of learning by doing on capacity factor (alpha2)	LOG(alpha value for learning by doing on capacity factor, 2)	Dmnl
Strength of learning by doing on cost (alpha 3)	LOG(alpha value for learning by doing on cost, 2)	Dmnl
Effect of learning by doing on capacity increase	(cumulative learning by doing experience/initial cumulative experience)^strength of learning by doing on capacity (alpha1)	Dmnl
Effect of learning by doing on capacity factor increase	(cumulative learning by doing experience/initial cumulative experience)^strength of learning by doing on capacity factor (alpha2)	Dmnl
Effect of learning by doing on cost	(cumulative learning by doing experience/initial cumulative experience)^strength of learning by doing on cost (alpha3)	Dmnl
Initial investment cost of a wind turbine per kW	1322/2500	$/kW
Initial capacity factor of a wind turbine	0.12	Dmnl
Investment subsidy	0.3 - STEP(0.1, 1986) - STEP(0.1, 1987) - STEP(0.1, 1989)	Dmnl
Familiarity gain	total social exposure to wind turbines*(1-familiarity with the wind turbines)	Dmnl/Year
Familiarity with the wind turbines	INTEG(familiarity gain-familiarity loss,0)	Dmnl
Familiarity loss	familiarity with the wind turbines*fractional familiarity decay rate	Dmnl/Year
Fractional familiarity decay rate	EXP(-4*epsilon*(total social exposure to wind turbines-normal social exposure))/(1+EXP(-4*epsilon*(total social exposure to wind turbines -normal social exposure)))*maximum decay rate	1/Year
epsilon	5	Year/Dmnl
Maximum decay rate	0.425	1/Year
Normal social exposure	0.2	1/Year

Word of mouth of wind turbines from non-users	(installed capacity for electricity generation-total installed capacity of wind turbines)/installed capacity for electricity generation*familiarity with the wind turbines*frequency and effectiveness of contacts of nonusers	1/Year
Social exposure and word of mouth from wind turbine owners	(total installed capacity of wind turbines/installed capacity for electricity generation)*frequency and effectiveness of contacts of users*familiarity with the wind turbines	1/Year
Effectiveness of contacts of nonusers	0.45/0.3825	Dmnl/Year
Effectiveness of contacts of users	0.8/0.68	Dmnl/Year
Awareness campaigns for wind turbines	STEP(0.02,1981) - STEP(0.02, 1987)	Dmnl/Year
Total social exposure to wind turbines	awareness campaigns for wind turbines + social exposure and word of mouth from wind turbine owners + word of mouth of wind turbines from non-users	1/Year

Appendix C - List of exogenous variables

1. Percentage of consumption of coal
2. Percentage of consumption of oil
3. Percentage of consumption of natural gas
4. LCOE of coal
5. LCOE of oil
6. LCOE of natural gas
7. Operation cost of wind turbines
8. Interest rate
9. Reference LCOE of conventional techs
10. Reference LCOE of wind turbines
11. Affinity at reference LCOE for conventional technologies
12. Affinity at reference LCOE for wind turbines
13. Average lifetime of wind turbines
14. Construction delay
15. Effectiveness of contacts of non-users
16. Effectiveness of contacts of users
17. Import percentage
18. Initial capacity
19. Initial capacity factor
20. Initial cumulative experience
21. Initial installed capacity for electricity generation
22. Initial investment cost of wind turbines per kW
23. Initial RD stock
24. Maximum decay rate
25. Normal social exposure
26. Percentage increase of installed capacity per year
27. Sensitivity for conventional techs (beta)
28. Sensitivity value for wind turbines (beta)
29. Beta value for learning by searching on capacity factor
30. Beta value for learning by searching on cost
31. Beta value for learning by searching on capacity
32. Alpha value for learning by doing on capacity factor
33. Alpha value for learning by doing on capacity
34. Alpha value for learning by doing on cost

Appendix D - Justification of the variables not having real world counterpart

Variable	Justification
Affinity at reference LCOE for conventional techs and for wind turbines	Affinity represents the performance related consideration of the buyer at a reference value (Struben & Sterman, 2008). This value is based on the following assumptions: -For conventional technologies, reference LCOE is chosen as the average of the values over time in the model. Then for this value affinity is chosen as 1, since utilities would prefer the conventional technologies if they have reasonable price. -The assumption behind the reference value for LCOE of wind turbines is also based on the LCOE of conventional technologies. If wind turbines have the same LCOE with conventional technologies, then there will not be any reason for a utility to not choosing wind turbines. However, since wind technology is relatively new, this might have negative effect on the customer, s/he would need an extra incentive to go for wind. As a result, reference LCOE of wind turbines are chosen about 5 dollars less than the average LCOE of conventional technologies. For that LCOE, the affinity is chosen as 1.
Sensitivity for conventional techs and for wind turbines	This sensitivity parameter captures two factors: the impact of random factors and population size effects on heterogeneity, and individual sensitivity to performance. However, in practice these values are not identifiable and they are represented with β (Ben-Akiva & R., 1985). In the model this value is calibrated with sensitivity analysis where the results of *yearly installations* were compared with historical data. As expected, the sensitivity to wind turbines are higher than sensitivity to conventional techs, because uncertainty with the wind turbines are higher since it is a new technology. People would be more concerned about the price changes of wind turbines, which could be permanent, because the technology is not mature. The sensitivity to price changes is higher in Denmark compared to California, because the price volatility is higher in Denmark, implying an insecure market.
Alpha values for learning by doing on capacity factor, capacity, and cost	Alpha values are coming from the literature of learning curves. Therefore, the existence of these values are acceptable in the model. For finding the appropriate alpha values, a sensitivity analysis has been conducted, by comparing each factor with its historical counterpart. For example, capacity of wind turbines were only 75 mW in 1980, and they increased to 300 mW in 1995 (Lantz, Wiser, & Hand, 2012) . To reach the same performance improvement in the model, sensitivity analysis is conducted. After reaching the corresponding values, a comparison of those with the literature on *learning curves for renewable energy* and *wind turbines* is made. It is shown that alpha and beta values are similar to these studies. Note that there is no separation between alpha and beta values in the literature expilicitly, therefore their combined effects are taken as a measure (Ibenholt, 2002; Klaassen et al., 2005; Koomey & Hultman, 2007)
Beta values for learning by searching on capacity factor,	These values represent the similar concept with alpha values. They are the learning coming from learning by searching processes. For finding the appropriate beta values, a sensitivity analysis has been conducted. It should be noted that, the performance of the variables getting affected from alpha and beta values are closely related, and it is not possible to separate them. Only qualitative knowledge known

capacity and cost	for this issue is the claim by Kamp saying that learning by doing efforts were more effective than learning by searching efforts in wind turbine development (2007). Therefore, the analysis of alpha and beta values have been analysed together with the assumption alpha>beta. The comparison with the literature for these values are conducted together with the alpha values as it is explained above.
Maximum decay rate	This value is also adapted from Struben and Sterman's familiarity study (2008). Familiarity is a soft variable, so its decay is not easy to measure. This value represents the familiarity decay speed when the social exposure is lowest. In Struben's and Sterman's study, this value was 1. Yet, their model represents the regular consumers in which awareness of the technology could decay much rapidly, due to fast changing trends in consumer preferences and due to their cultural and social concerns. Besides, their motives to adopt the technology is not solely based on performance and cost, soft concerns such as status symbol plays a role. Last but not the least, more social exposure is required to be familiar with the technology (number of potential car owners is much more than number of utilities in the society). Therefore, as a combined effect of these different factors with the wind turbine diffusion, it is assumed that the familiarity decays much slower for wind turbines. A base case for this low rate is chosen as 30 percent arbitrarily. Then, a sensitivity analysis has also been conducted for this value for both cases. This value is set the same in both cases on purpose, because it is a soft variable which makes it difficult to explain the reasons behind different values. Besides, since the utilities' aims and responsibilities are assumed to be the same both in Denmark and California, having the same maximum decay rate.
Normal social exposure	This number represents the level of social exposure required to minimize the familiarity decay. When the social exposure is high enough, there is no decay in familiarity. Normal social exposure behaves as a reference value for representing familiarity decay. This number is the reference rate of social exposure where familiarity decreases at half of the normal rate. This value is directly transferred from Struben and Sterman's work with the idea behind that it should be *at least* as easy as regular transition studies to get familiar with the technology under certain level of exposure due to tightened network. Besides, decision makers in this case are constantly looking for the advantageous options in the field, whereas regular consumers are not that active for searching a new technology. Since familiarity decays slower in this model, the same rate of normal social exposure is acceptable considering the term *at least*. This value is set the same in both cases on purpose, because it is a soft variable which makes it difficult to explain the reasons behind different values. Besides, since the utilities' aims and responsibilities are assumed to be the same both in Denmark and California, having the same maximum decay rate.
Epsilon	Epsilon is the decay rate at the normal social exposure. In the model created by Struben and Sterman, the value was equal to 1/normal social exposure representing the slope of familiarity decay, therefore it is taken the same in this model. Also sensitivity testing has been conducted, and the results showed that for the 10% change in epsilon, the changes in numerical results of the model were insignificant.
Effectiveness of contacts of nonusers	These values represent the influence of non-users on each other for deciding the adoption of wind turbines. In general, in transition studies, these numbers are low. In Struben and Sterman's work, where they were modelling electric vehicle

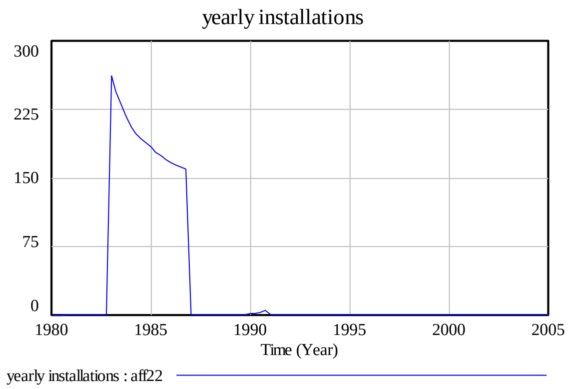
	transition, they have chosen this values as 0.15 (2008). In our model, the same value has been used for California case. It should be noted that Struben and Sterman claimed that this number was more optimistic compared to real life. However, they were modelling regular consumers, in which the communication among potential users are rather low, compared to networks among utilities. The number of utilities are lower, and the communication among them are stronger due to lobbying activities and/or their associations. Consequently, 0.15 is not that optimistic in wind turbine diffusion context. It should be noted that this value was 10 percent more in Denmark, because the communication among the customers were stronger in Denmark (Olume & Kamp, 2004). Additionally, a sensitivity analysis has also been done for this value and comparison for *yearly installations* has been done as well with the historical data.
Effectiveness of contacts of users	These values are quite similar to the values *effectiveness of contacts of non-users*. The only difference here is that owners of wind turbines influence the potential adopters. Since the information is coming from direct experience, the validity of it and consequently the effect of it is much stronger. This value is chosen as 0.8 for California case and it is increased 10 percent for Denmark case where 10 percent is chosen arbitrarily (in line with the increase in *effectiveness of contacts of nonusers)*. Also a sensitivity test is conducted and the results show that the numerical changes of *yearly installations*, and *familiarity with the wind turbines* are insignificant due to low number of adopters.

Appendix E - Extreme value test: Hypotheses and results

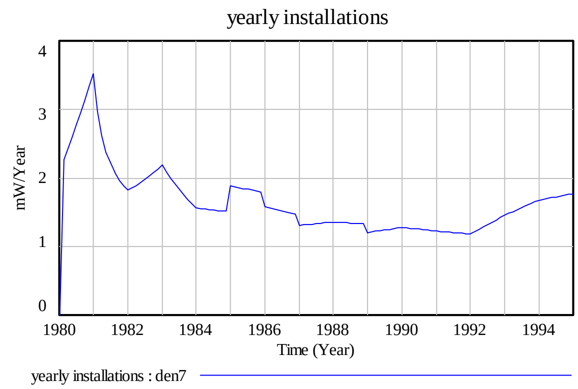
- *If LCOE of wind is extremely high compared to conventional alternatives, there will not be any wind turbine installations:*

To test this hypothesis LCOE of wind is multiplied by five in each model. The results are as follows:

California



Denmark



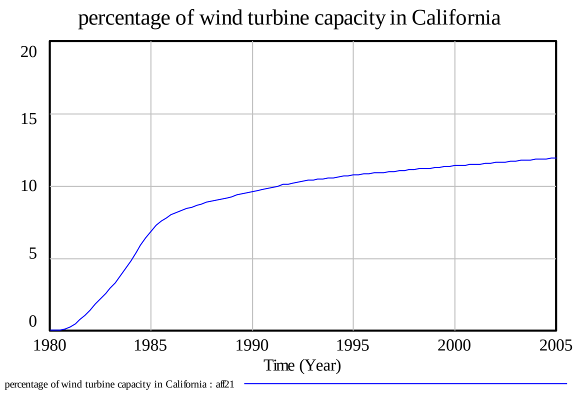
The reason for having non-zero installation between 1983 and 1986 is the result of policy PURPA act. That act was offering LCOE of wind with the same cost of conventional technologies, therefore there are still installations. When we disable that policy, the *yearly installations* are zero at that time. Also, there is a policy in 1991 offering 15 dollar subsidy per mWh. Due to that policy, about 3-4 mW of installations occur but that number is quite low not affecting the validity.

The installations per year are ranging from 1 to 3.5 megawatts per year, which can be considered insignificant, so that the hypothesis can be accepted as true. The reason for this small installations, is due to strong network in Denmark, the familiarity does not decrease so quickly.

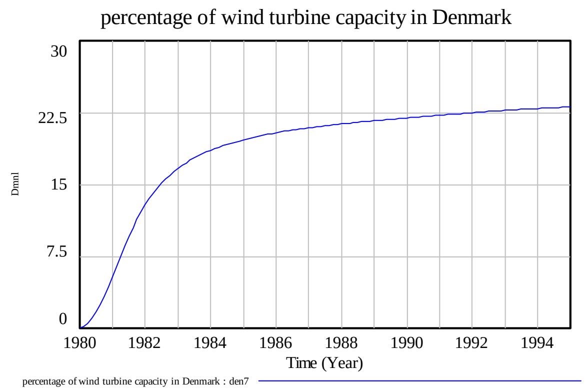
- *If LCOE of wind is extremely low compared to conventional alternatives, the percentage of wind turbines installed will increase rapidly:*

For testing this hypothesis, the LCOE of wind turbines was divided by 5 this time to ensure it is low enough compared to conventional alternatives.

California



Denmark



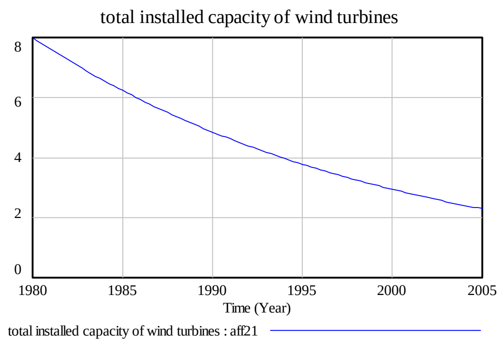
As expected, the percentage share of wind turbine capacity compared to all installed capacity in California, the share increases rapidly to 10 percent in 1990. The reason for not having 100 percent is based on the assumption that there are no replacements of existing power plants, only new installed capacity is shared among different alternatives. The reason there is a slow increase after reaching 10 percent is the familiarity process in California increases slowly.

Also as expected, the percentage share of wind turbine capacity increases rapidly and reaches a plateau since the additions are only coming from new power plants, there is no replacing of existing power plants with the wind turbines. Also, the familiarity process is stronger in Denmark due to higher communication among the actors, therefore percentage share of wind turbines are higher in Denmark.

- *If familiarity with the wind turbines is zero, there will not be any wind turbine installations.*

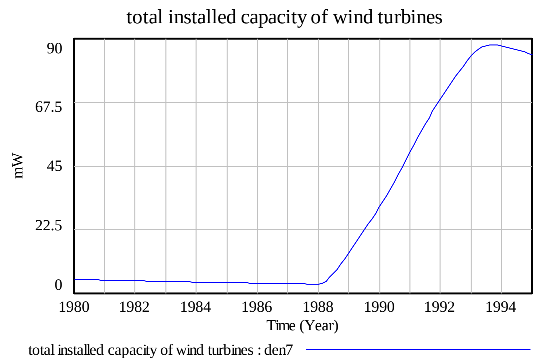
To implement this test, effectiveness of contact with users and effectiveness of contacts with non-users are set to zero. This ensures that there is no familiarity gain in the model, and also initial value for familiarity is set to 0 to ensure that the utilities are not familiar with the wind turbines.

California



This graph shows the total mW of wind turbines installed cumulatively over time. The yearly installation graph was 0 all the time as the hypothesis suggests, therefore another KPI is shown in this graph for better visualization.

Denmark

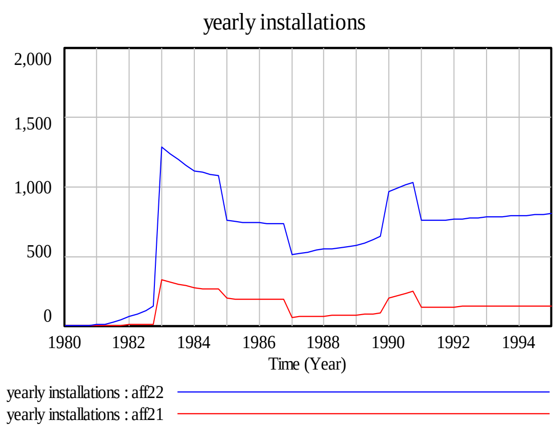


The reason there is an increase in Denmark for installed capacity after 1988 is because of the governmental decision to install 100 mW wind turbine capacity which belongs to the public. When that policy is disabled, the results are as expected, there are no wind turbine installations.

- *If familiarity with the wind turbines is 1, there will be a considerable increase on yearly installations.*

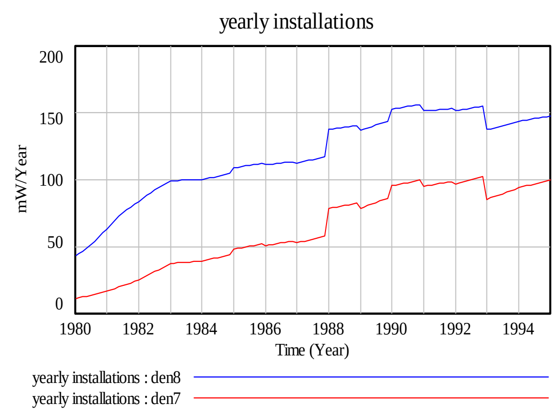
To make familiarity 1, the initial stock of familiarity is set to 1 and effectiveness of contacts with users and effectiveness of contacts with non-users are also set to 1. This way only influence on adoption will be the LCOE comparison of wind turbines and other alternatives, resulting in higher installed capacity compared to calibrated model.

California



When familiarity is set to one for the model, there is a significant increase in yearly installations as the hypothesis suggested.

Denmark

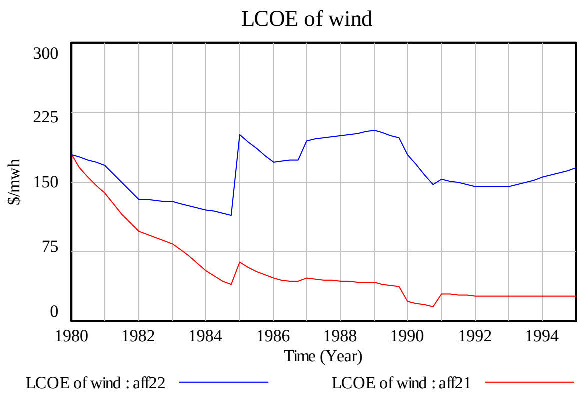


Also in Denmark, there is a significant increase in yearly installations, as expected. However the difference of increase is lower in Denmark than California. The reason for this is because familiarity with the wind turbines in Denmark is already stronger than California case. Besides, in concrete numbers, the yearly capacity demand of Denmark is lower than California's demand.

- *If the alpha values for learning by doing are zero, the LCOE decrease would be quite low. (Learning would come only from R&D expenditures which is less strong than learning by doing).*

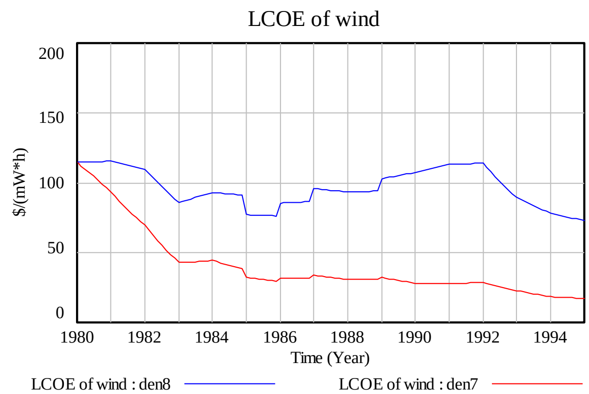
For this test, alpha values are set to 1 for each variable, meaning that there is no effect of learning by doing in the model. The rest of the variables (including beta values) are left the same as the base model.

California



This graphs shows the change in LCOE. The blue line is the result of extreme condition test, and the results show that except from some fluctuations due to interest rate and R&D expenditures, LCOE of wind do not decrease significantly.

Denmark

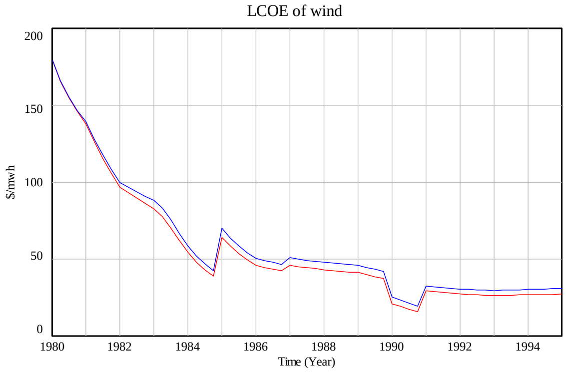


Denmark showed similar results as California, as expected.

- *If the beta values for learning by searching are zero, the LCOE decrease would be lower than the actual model, but it will get affected less, compared to alpha values.*

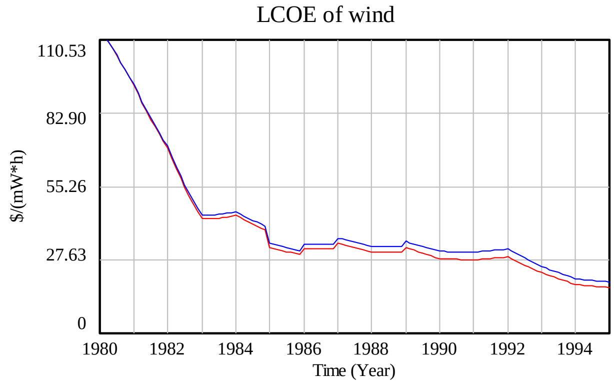
For this test, alpha values set back to their original values and beta values are all set to one, meaning that there is no effect of learning by searching mechanisms in the model.

California



Effect of R&D expenditures are effective, but only slightly, as the hypothesis suggests.

Denmark

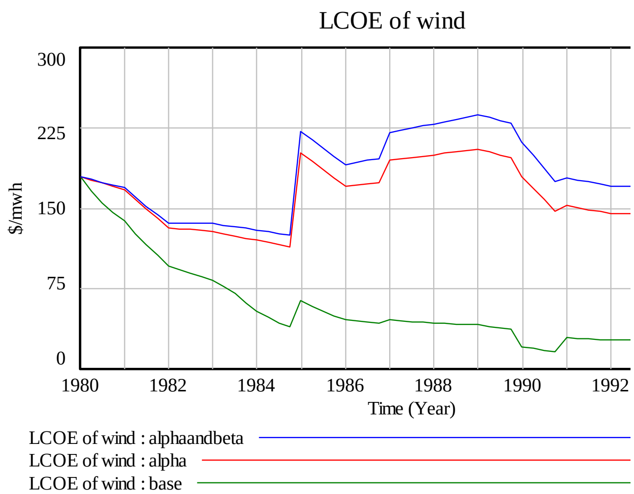


Denmark showed similar results as California, as expected.

- *If both alpha and beta values are zero, there will not be any learning effect on capacity factor, capacity, investment cost and consequently on LCOE of wind.*

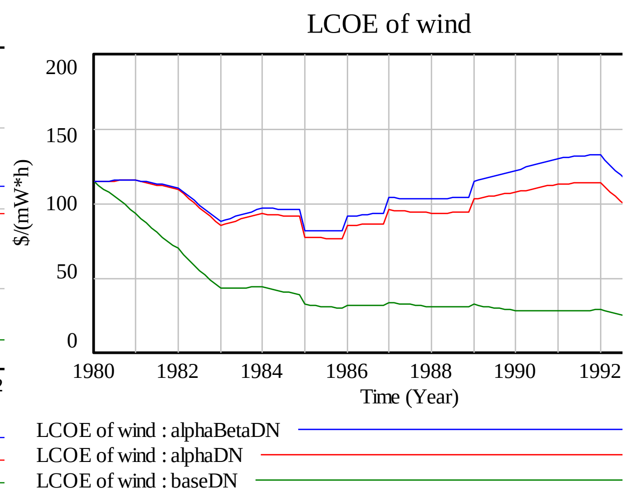
For testing this hypothesis, both alpha and beta values are set to 1, and comparison is made with the case where only alpha values are set to 1.

California



In this graph green line represents the base case, where both learning by doing and learning by searching factors are active. For red line, only learning by searching mechanism is active and the LCOE decreases slightly. When both of these mechanism are deactivated (blue line) the cost decrease is only affected from interest rates.

Denmark



Denmark showed similar results as California, as expected.

Appendix F - Sensitivity Analysis Results

Appendix F.1. Univariate Sensitivity Analyses

For all exogenous parameters in the model a sensitivity analysis is conducted with 10 percent increase/decrease for the value of each variable. 1000 simulations for each parameter is run with the random uniform distribution. The sensitivity analysis results with confidence bounds are given for related KPIs per parameter below (Not shown KPIs indicate that the model is not numerically sensitive to that parameter, but *yearly installations* KPI is not shown unless stated otherwise, because there is no parameter between *yearly installations* and *total installed capacity of wind turbines* which could generate different results for these two KPIs.):

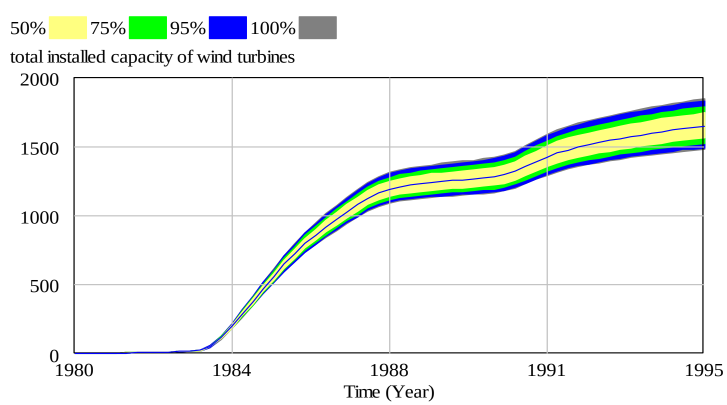
Affinity at reference LCOE for conventional technologies and Affinity at reference LCOE for wind turbines:

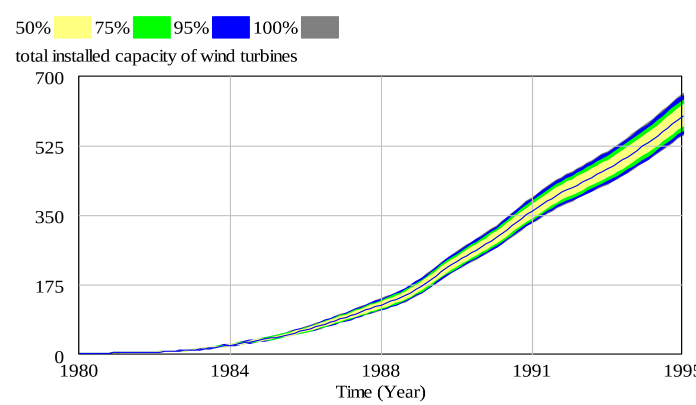
This parameter had the value of 1 in the base simulation. Since it affects directly the preference for wind turbines, the installations are affected directly. The results show that the model is only numerically sensitive to this parameter. The reason for there is little sensitivity in LCOE is the learning curves coming from learning by doing is less sensitive, since LCOE depends on many factors. Also, perceived affinity is determined by taking the percentage affinity of wind turbines to total affinity, therefore, 0.9 affinity of conventional technologies corresponds to 1.1 affinity for wind turbines. As a result, sensitivity analyses are the same for these parameters.

California

Denmark

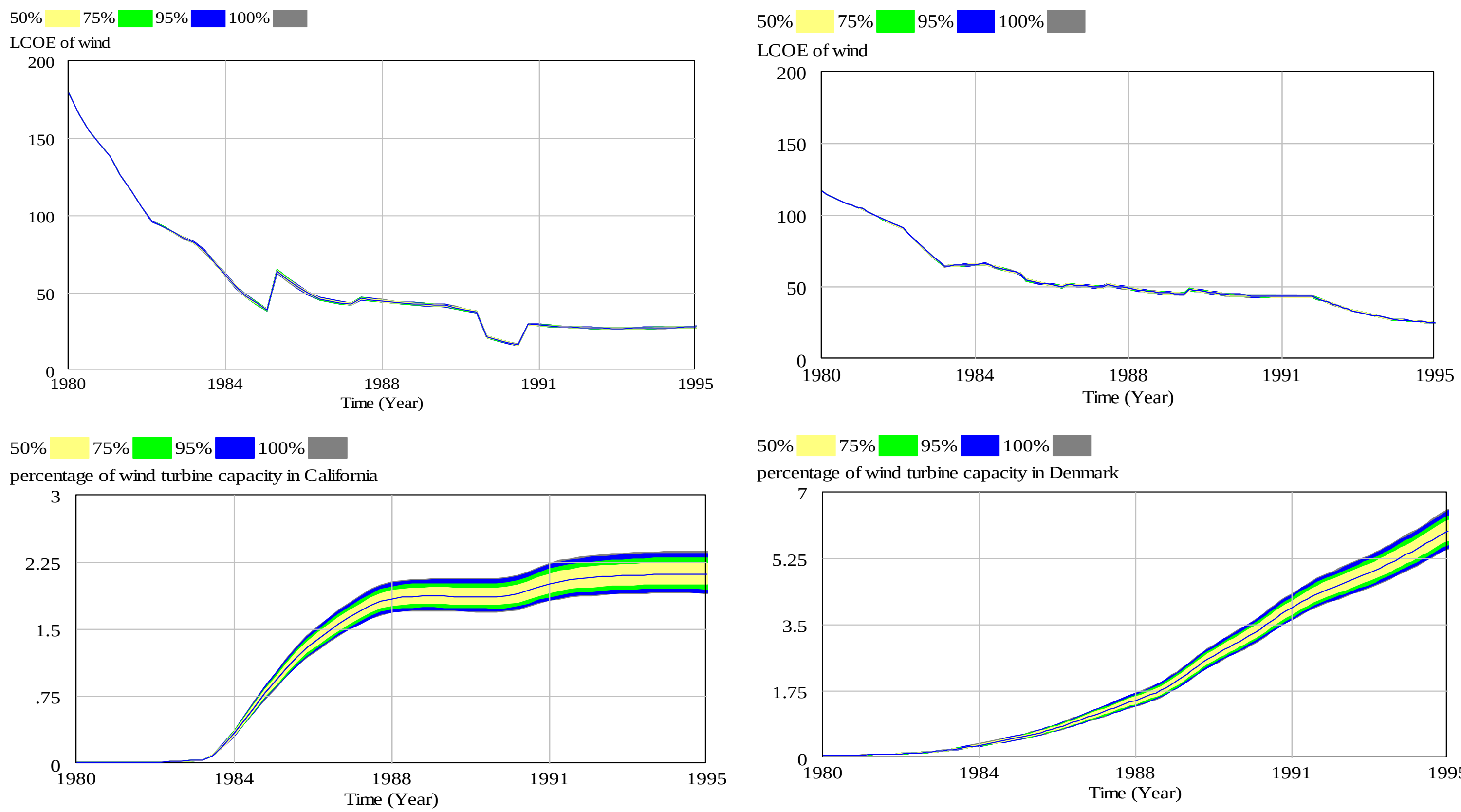
Total installed capacity of wind turbines





LCOE of wind

Percentage of wind turbine installations

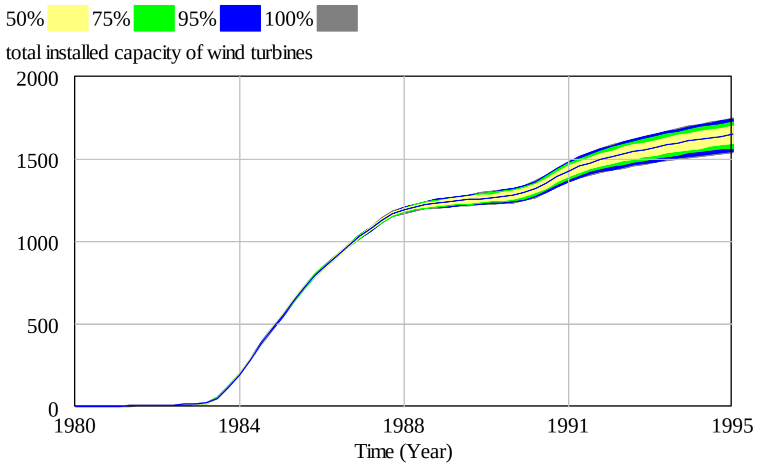


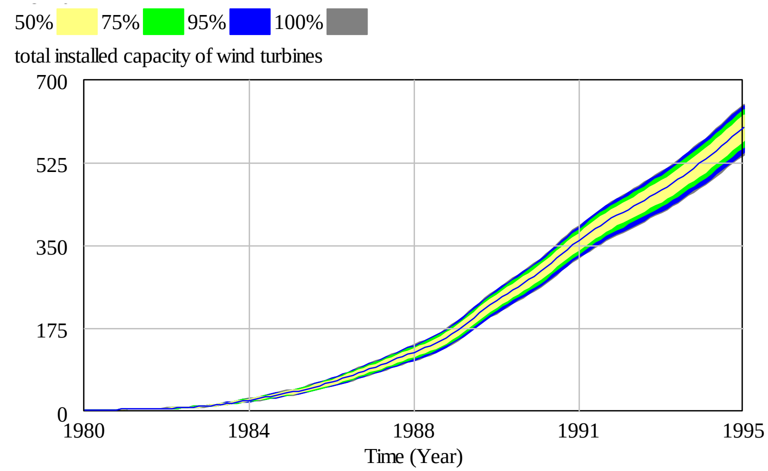
Average Lifetime of Wind turbines

Although this value is based on real life data, which is commonly accepted as 20 years for wind turbines, it has important effects on LCOE of wind turbines. The results of sensitivity analysis according to this parameter is shown below. The results show that the model is numerically sensitive to average lifetime of wind turbines, and this sensitivity is not strong. Again, familiarity with the wind turbines is not affected from this value because the percentage change of wind turbine share is not strong enough.

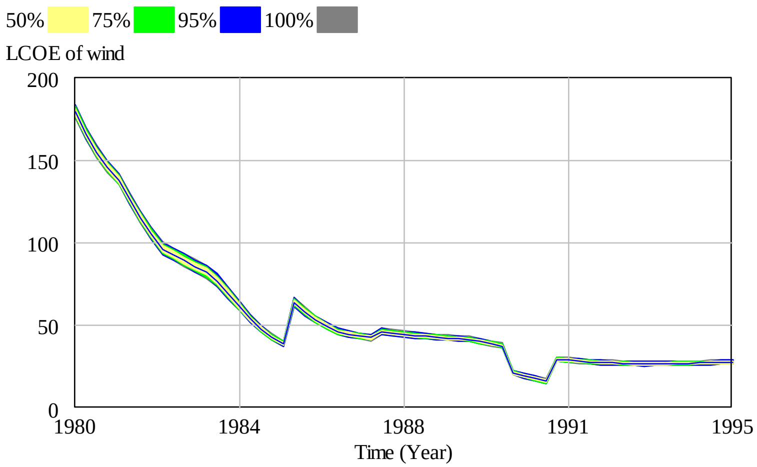
California *Denmark*

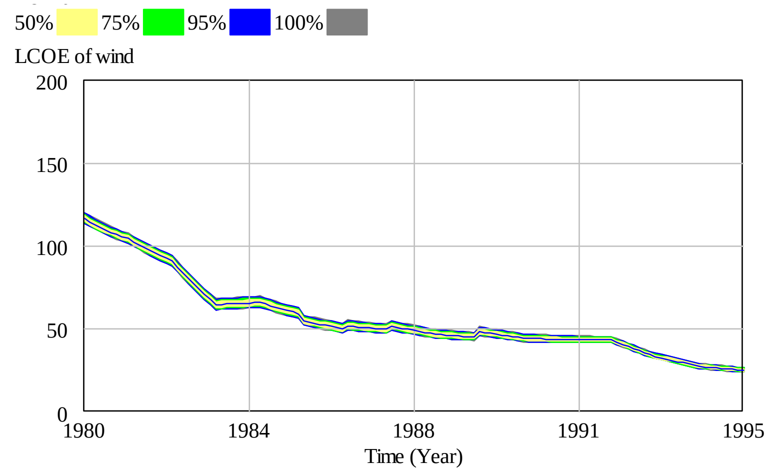
Total installed capacity of wind turbines



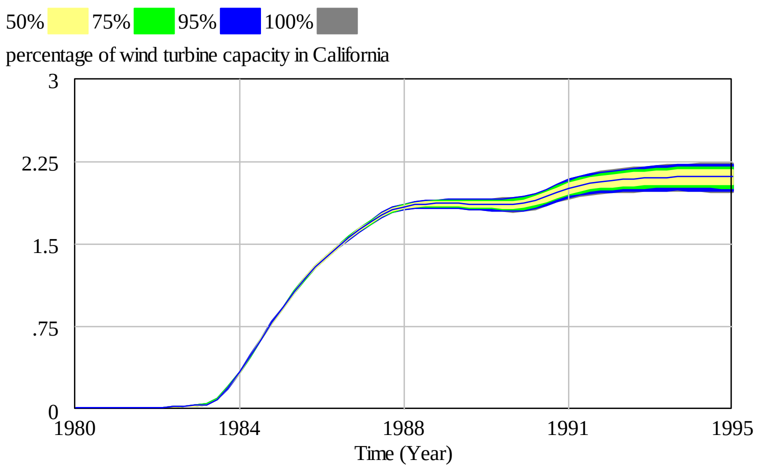


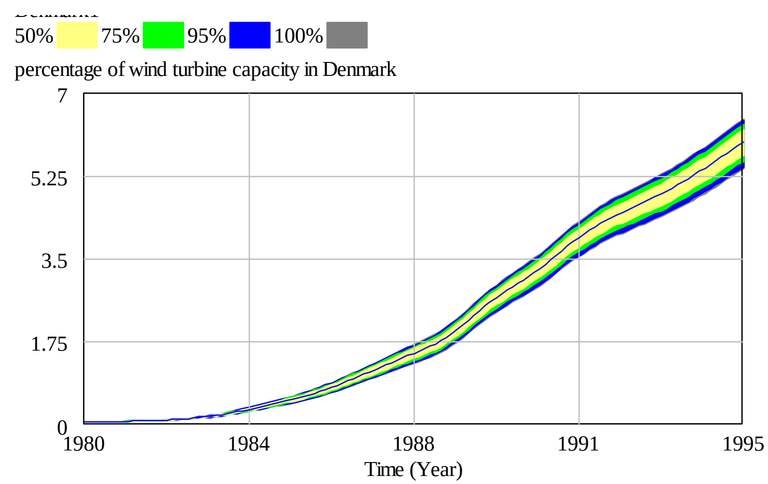
LCOE of wind





Percentage of wind turbine installations





Construction Delay:

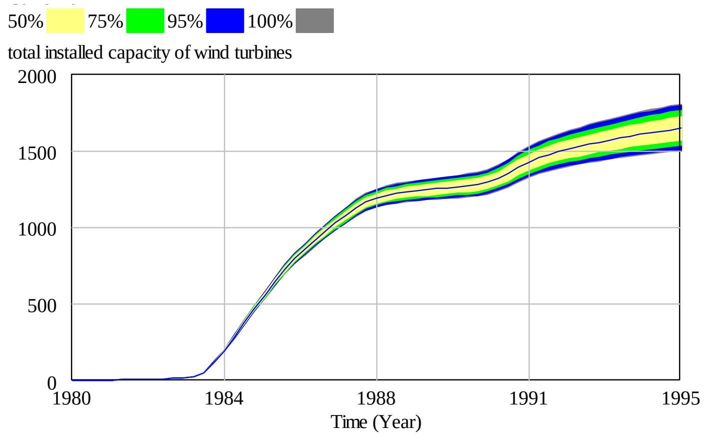
Ten percent alteration of this value did not change the model significantly even from the numerical perspective. This result is acceptable, since there is only a insignificant effect of this factor on learning curves (it affects knowledge accumulation via learning by doing) and these values are even get less significant in LCOE calculation.

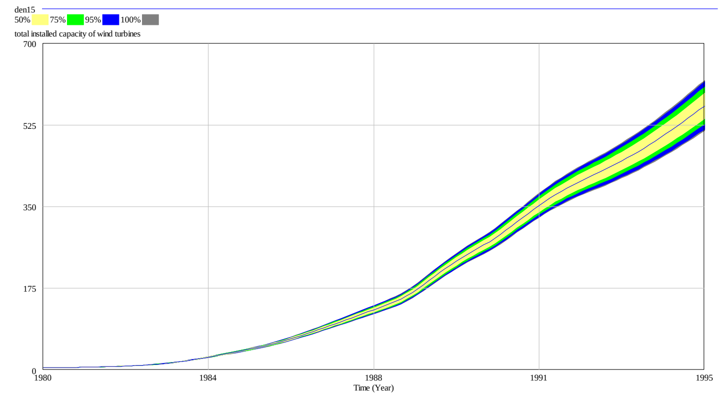
Effectiveness of Contacts of nonusers:

The changes of this parameter affects all KPIs, because it directly affects familiarity. When familiarity is changed, perceived affinity for the technology is changed immediately, resulting in change in installations. The results show that the model is numerically sensitive to this value.

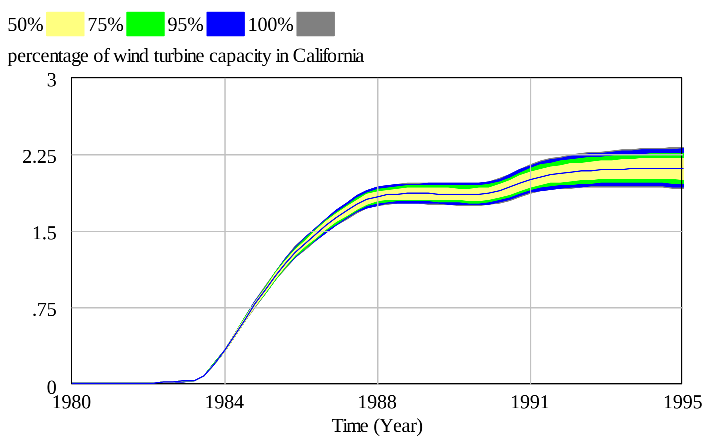
California | Denmark

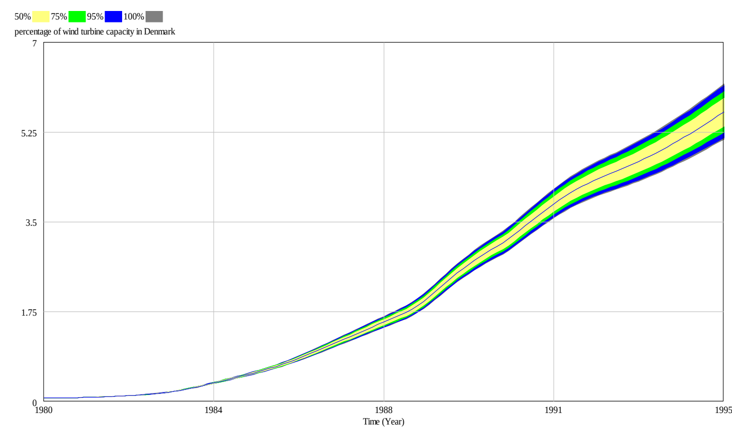
Total installed capacity of wind turbines



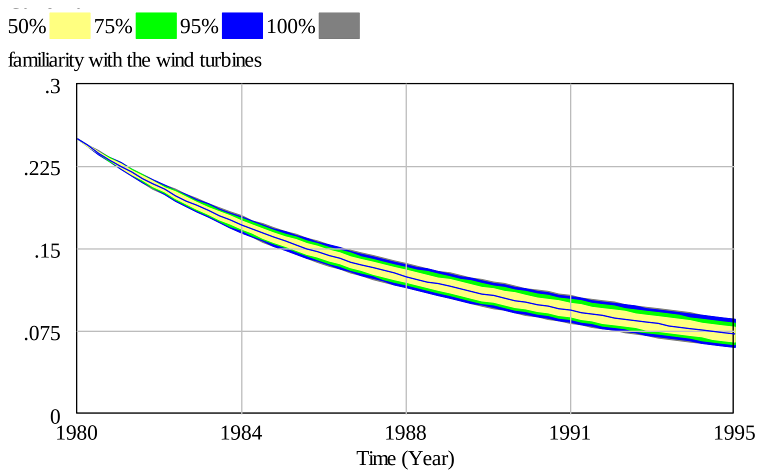


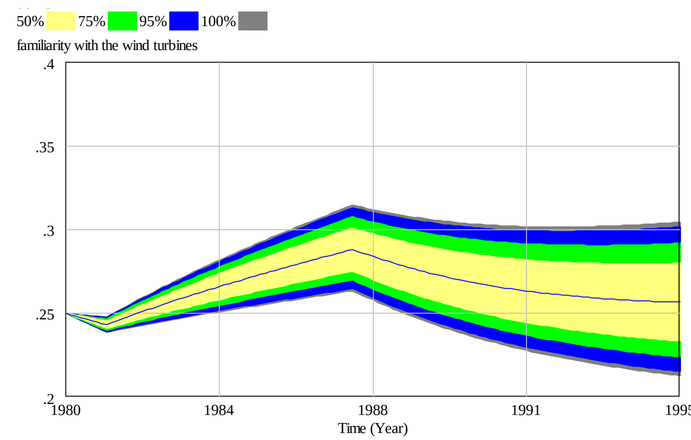
Percentage of wind turbine installations





Familiarity with the wind turbines



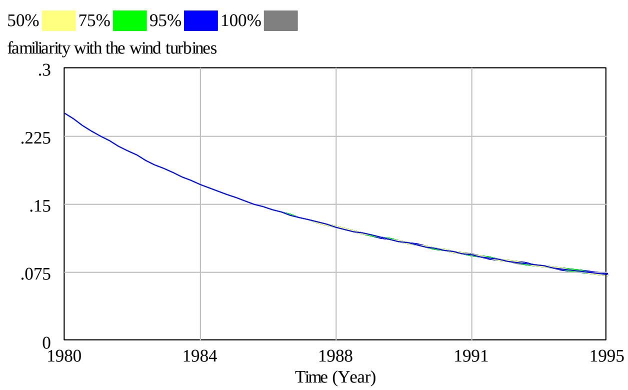


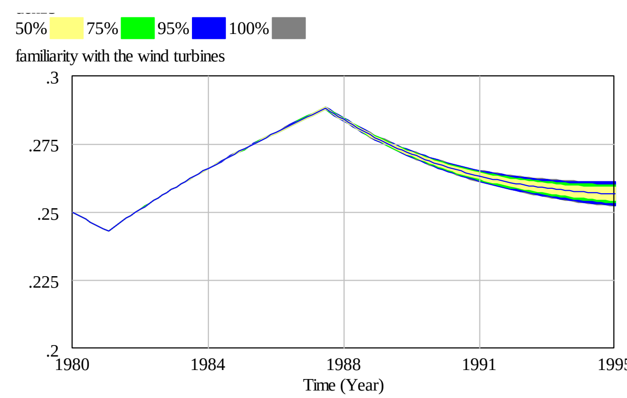
Effectiveness of Contacts of users:

Since the adoption is only about 2.5 percent in California and about 6 percent in Denmark, the effectiveness of contacts of users did not affect the model's results significantly. Only for Denmark, the familiarity with the wind turbines changed a bit after 1988, due to increased percentage of users which has no significant effects on other KPIs.

California *Denmark*

Familiarity with the wind turbines





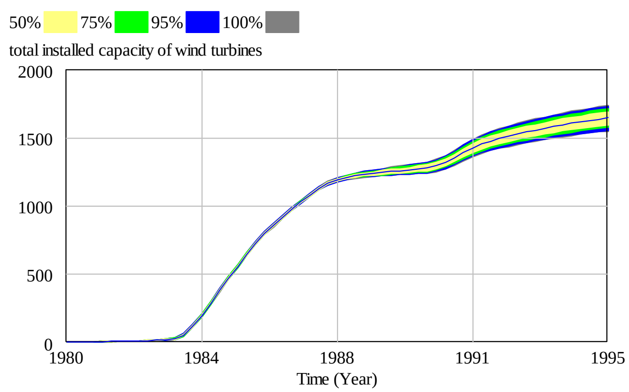
Initial Capacity Factor & Initial Investment Cost:

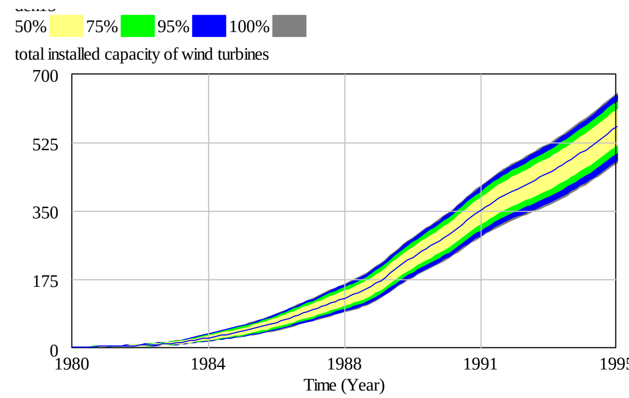
This value was also taken from the literature, but sensitivity analysis is required to see whether the model behaves differently if there is a mistake with the assumption. The results show that only numerical sensitivity is in question regarding this parameter. Yet, since the aim of system dynamics is to capture the behavior of the system, numerical sensitivity is acceptable. The results are shown below. The reason for there is no change in California's familiarity is due to low percentage of adoption which is under normal social exposure. As expected, changes in initial investment cost showed similar results.

California

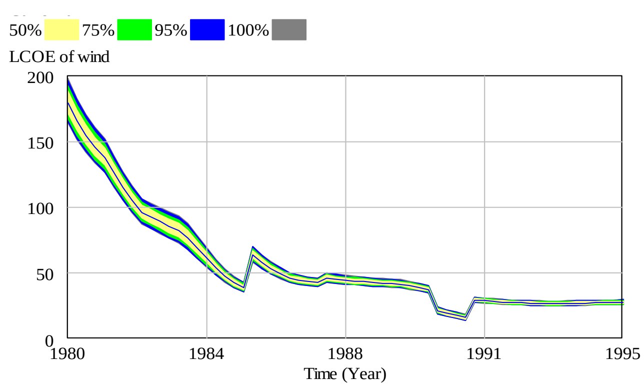
Denmark

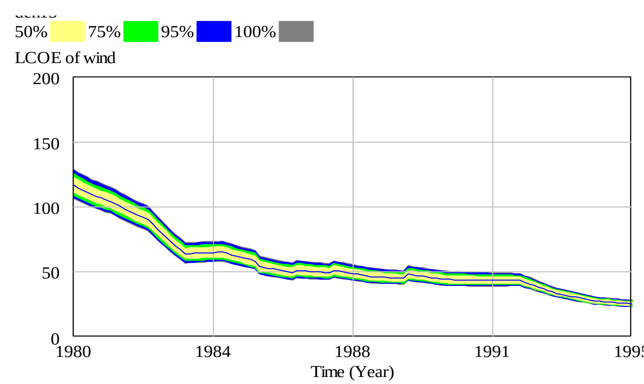
Total installed capacity of wind turbines



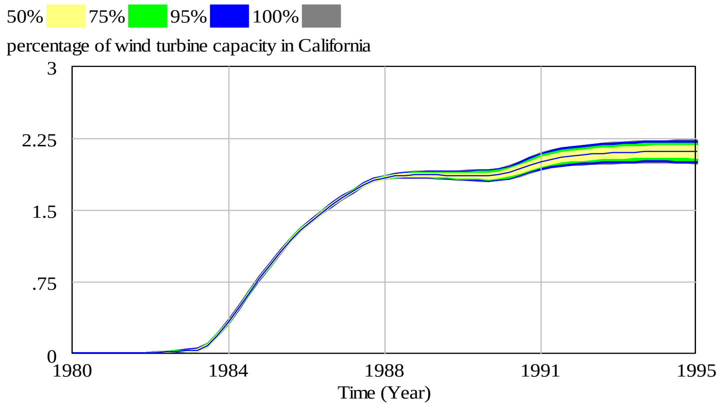


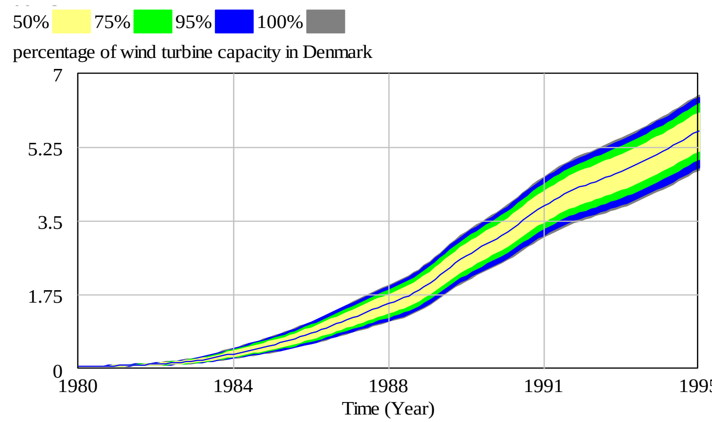
LCOE of wind



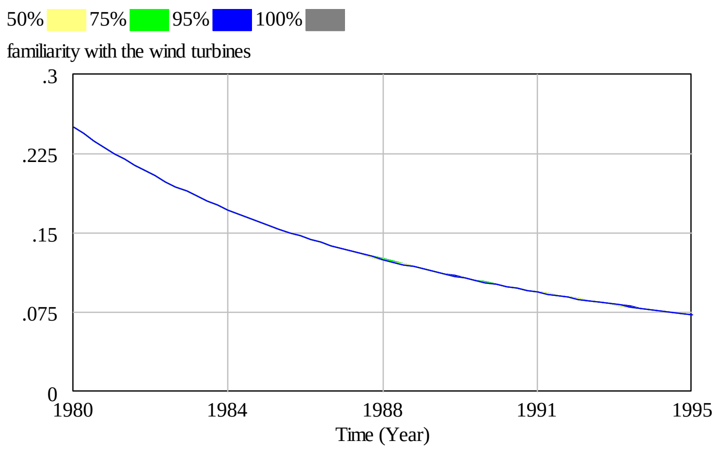


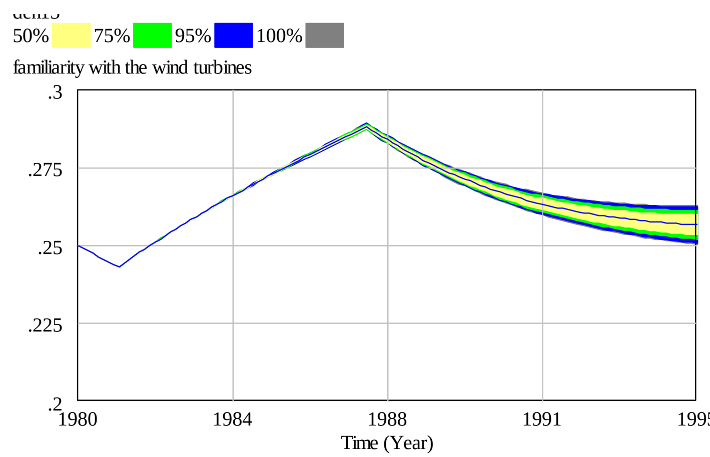
Percentage of wind turbine installations





Familiarity with the wind turbines





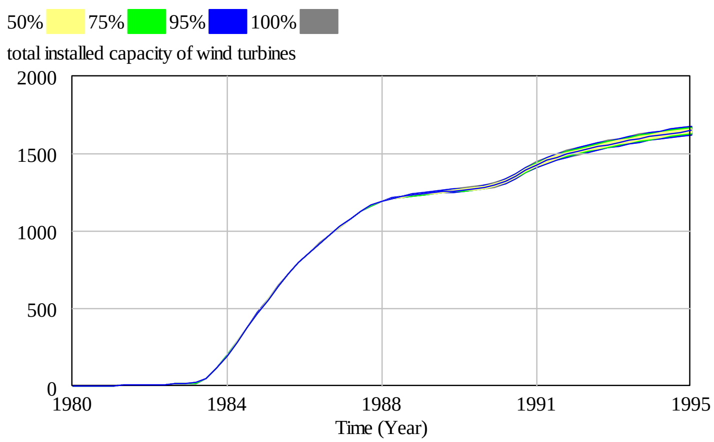
Initial Cumulative Experience & Initial R&D stock:

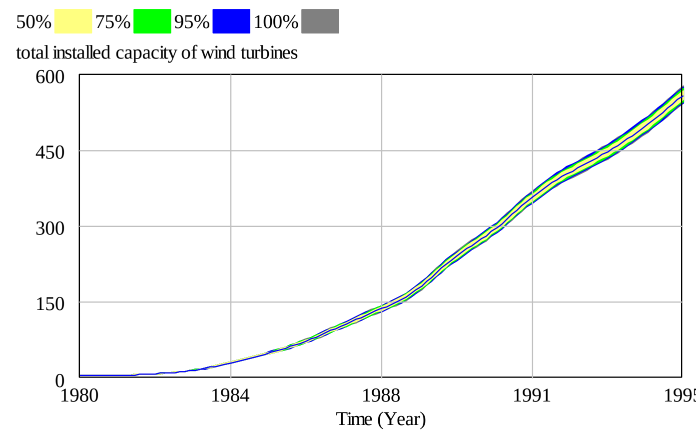
The 10 percent change in this value showed only numerical sensitivity and this sensitivity was so low that it can be ignored. For illustration, *total installed capacity of wind turbines* graph is shown below. It can be concluded that, if there is no significant difference between initial cumulative experiences, both cases can be considered equal in terms of starting point for diffusion from experience perspective. (Only 8 mW of wind turbine capacity was installed in California and this value was 5 mW in Denmark) Also the results for initial R&D stocks were the same. The reason for this small change is the initial experience stocks affect the rate of learning curves not the ultimate result that the learning curve reaches. Therefore its effect on LCOE is rather small, resulting in small difference in total installed capacity of wind turbines.

California

Denmark

Total installed capacity of wind turbines



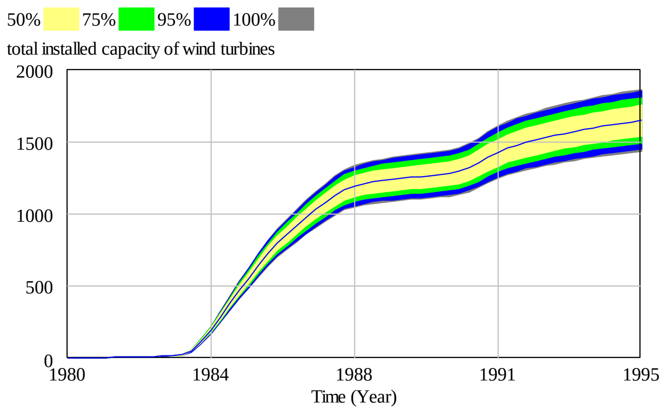


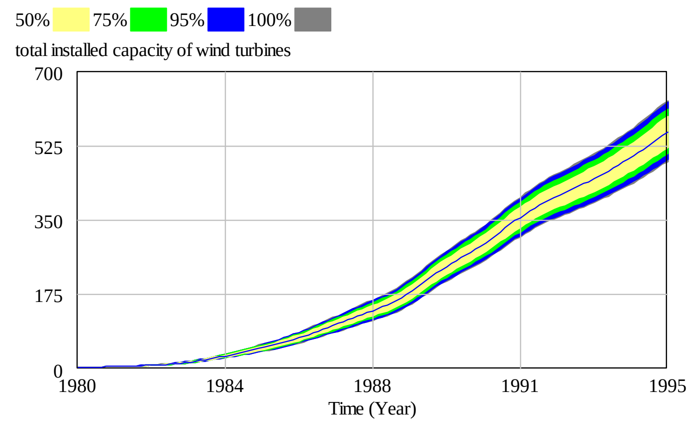
Initial installed capacity for electricity generation & Percentage increase of installed capacity per year

As expected, this value only affects the results of the model in absolute terms, not in percentages. If there is an increase in total demand, the number of installed wind turbines increases as well, but the percentage share of this distribution is not affected significantly. Thus, below only *total installed capacity of wind turbines* and *percentage of wind turbine installations* are shown. The results were similar for *percentage increase of installed capacity per year* since it alters the installed capacity in a similar perspective.

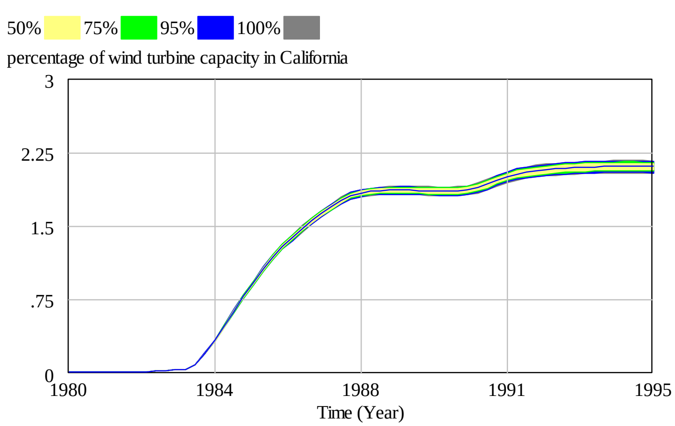
California | *Denmark*

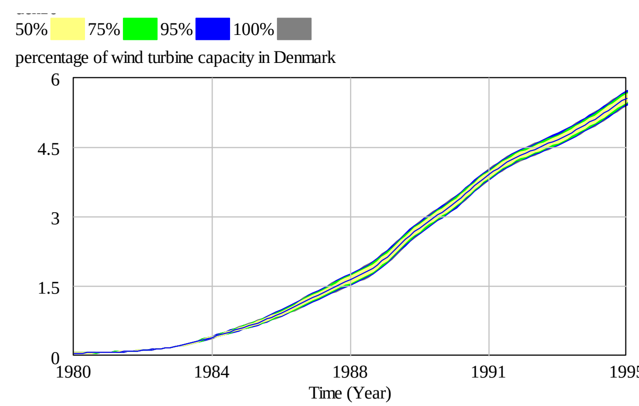
Total installed capacity of wind turbines





Percentage of wind turbine installations





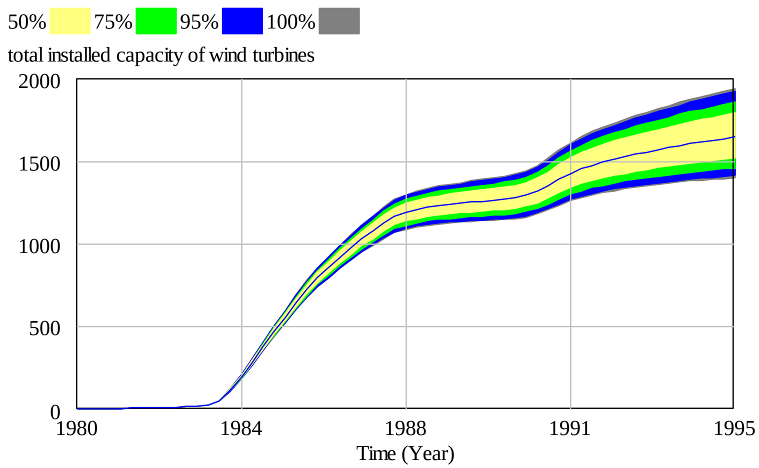
Maximum Decay Rate:

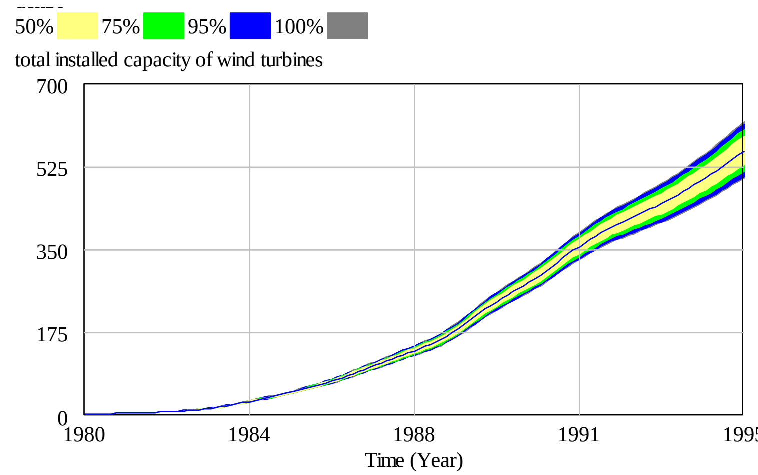
Also the results of the changes in this parameter results in numerical sensitivity of the model. The most sensitive KPI is familiarity with the wind turbines, since the forgetting of technology increases when this decay rates. According to the changes in familiarity, the demand for wind turbines changes as well, affecting percentage of wind turbine capacity and total installed capacity of wind turbines. This value has no effect on LCOE, since the ultimate decrease in learning curves depends on accumulated knowledge.

California

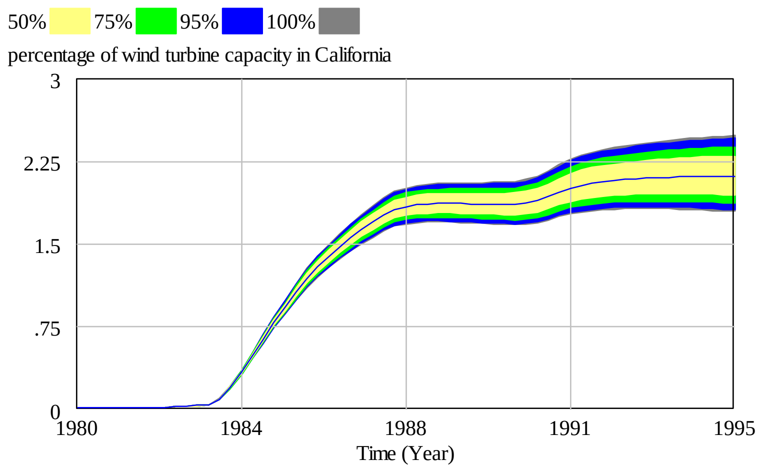
Denmark

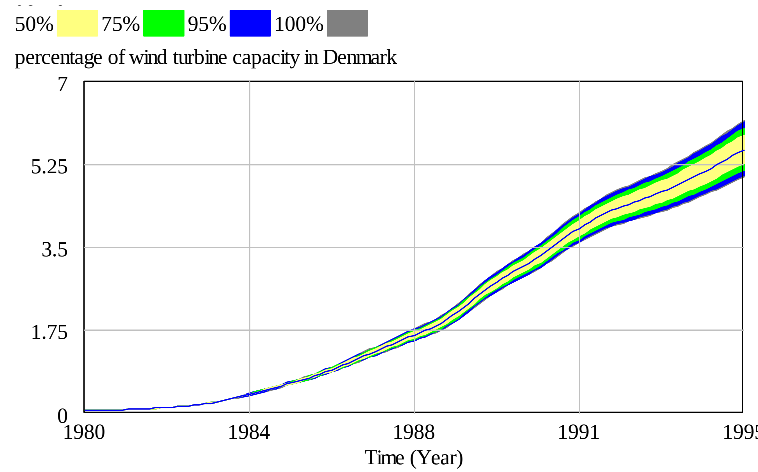
Total installed capacity of wind turbines



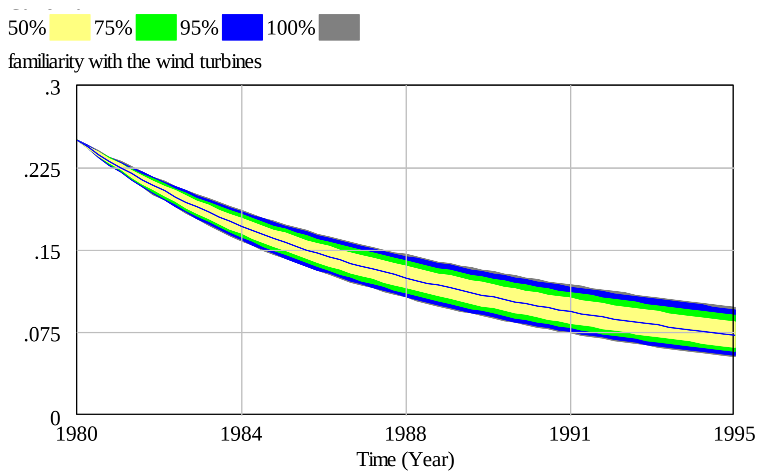


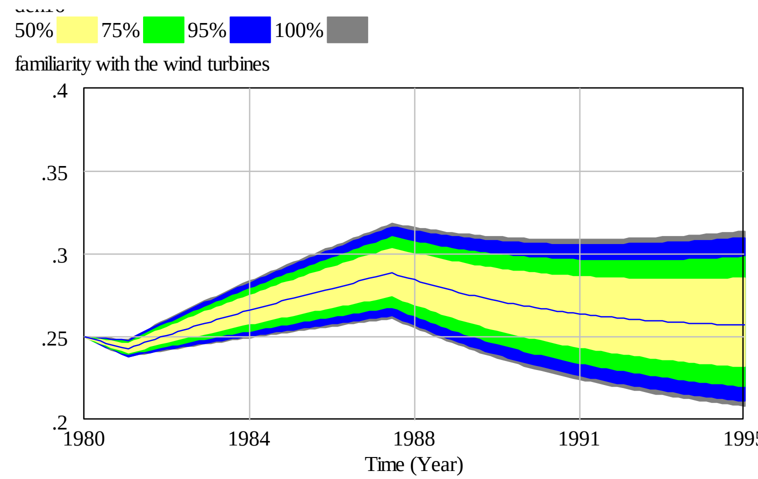
Percentage of wind turbine installations





Familiarity with the wind turbines



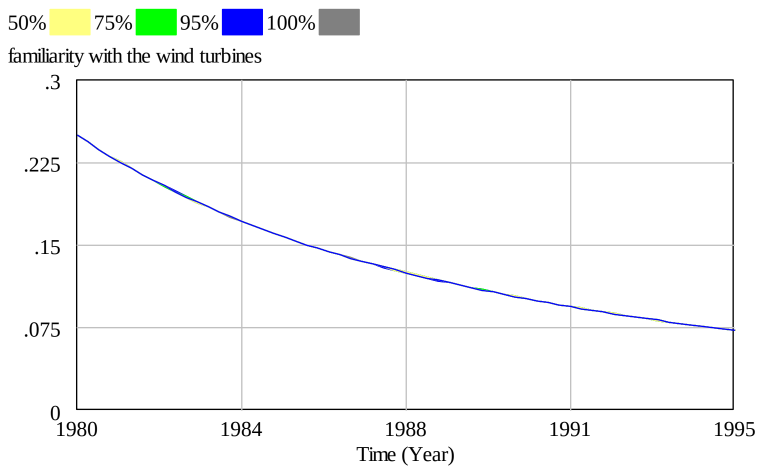


Normal Social Exposure:

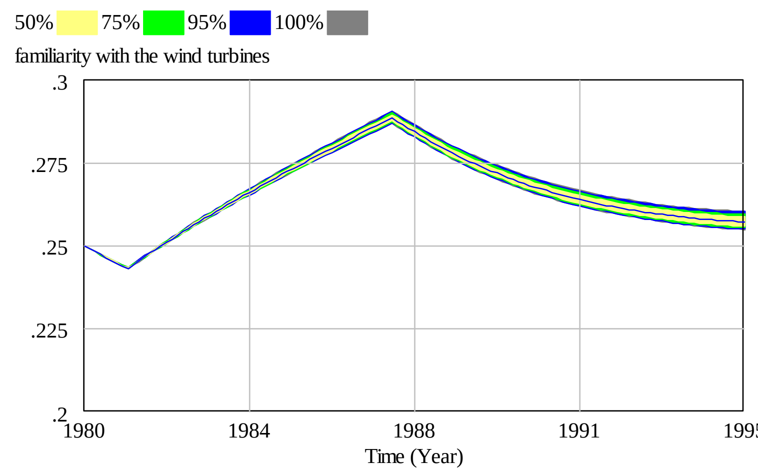
Ten percent change in this level does not affect the model behaviour numerically, except for the familiarity for Denmark. The reason that California is not affected but Denmark is affected is because Denmark reaches over 5 percent wind turbine installation percentage, which is higher than normal social exposure.

Familiarity with the wind turbines

California



Denmark



Sensitivity value for conventional technologies & Sensitivity value for wind turbines:

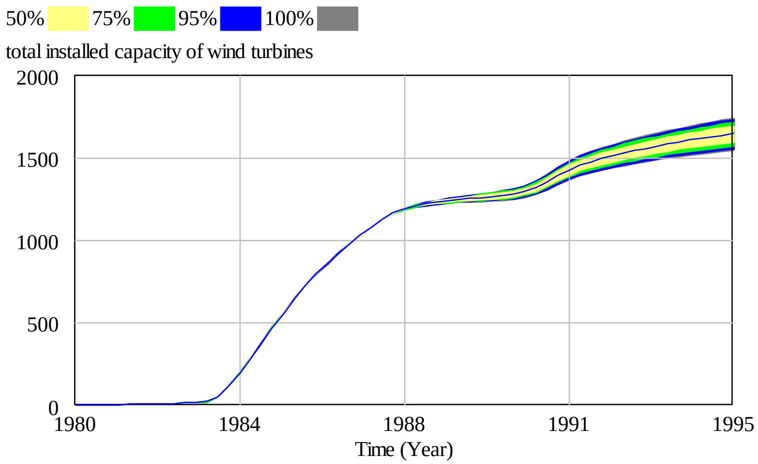
These values represent the buyers' sensitivity to price changes for conventional technologies or wind turbines respectively. Only slight numerical sensitivity is observed for these values which could be considered insignificant.

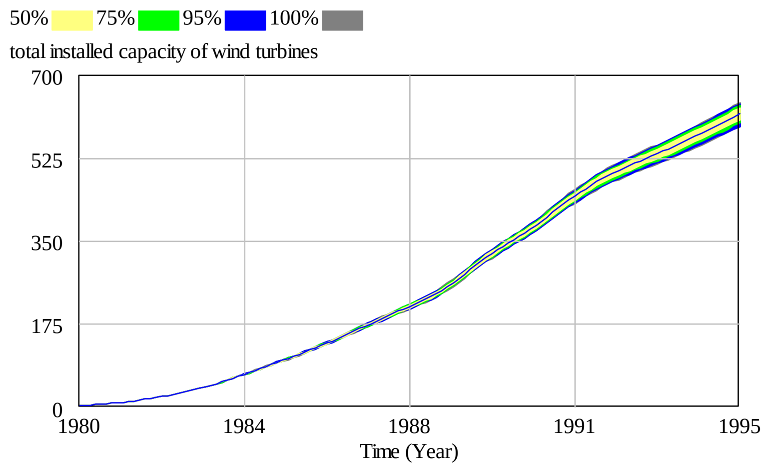
Beta value for learning by searching on cost & Beta value for learning by searching on capacity factor:

These values affect the ultimate decrease on cost and ultimate increase on capacity factor with learning by searching mechanism. Since these values affect LCOE (not the slope but the real value), the installations are numerically sensitive to this value. The results are shown below:

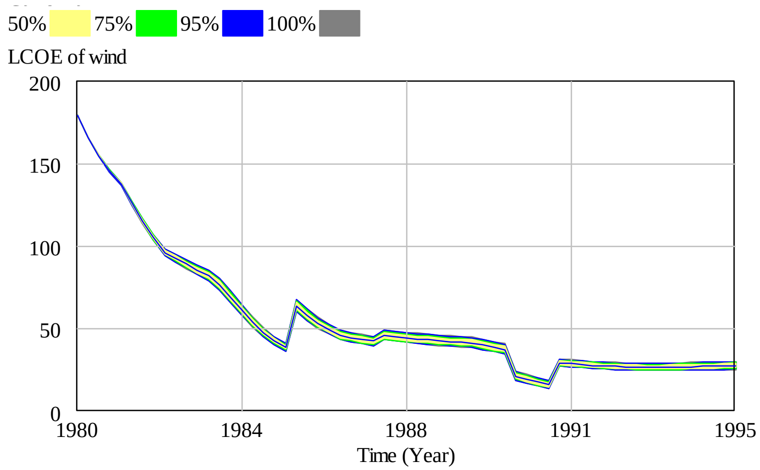
California *Denmark*

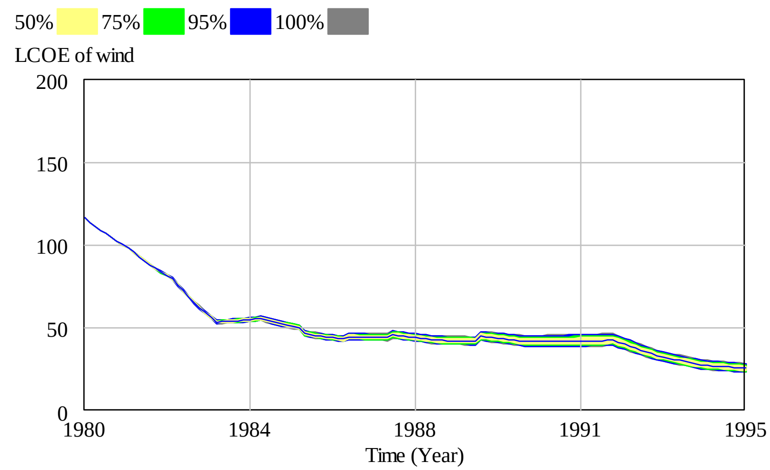
Total installed capacity of wind turbines



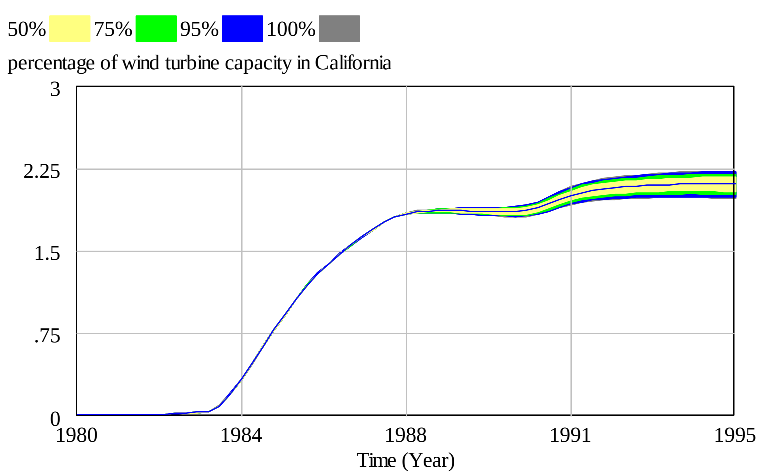


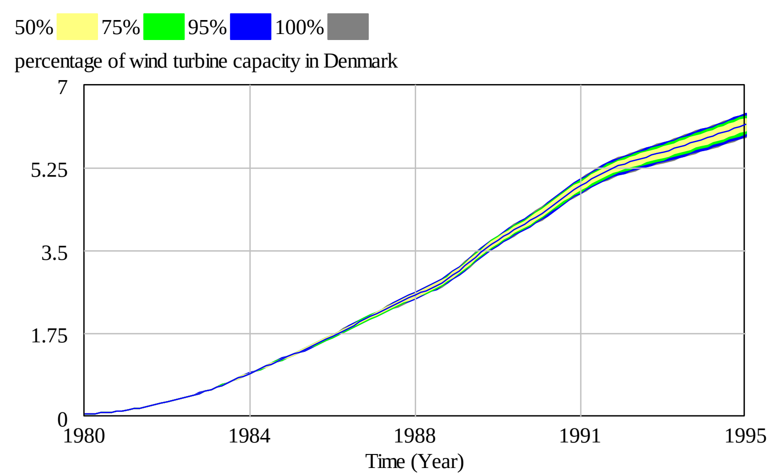
LCOE of wind





Percentage of wind turbine installations





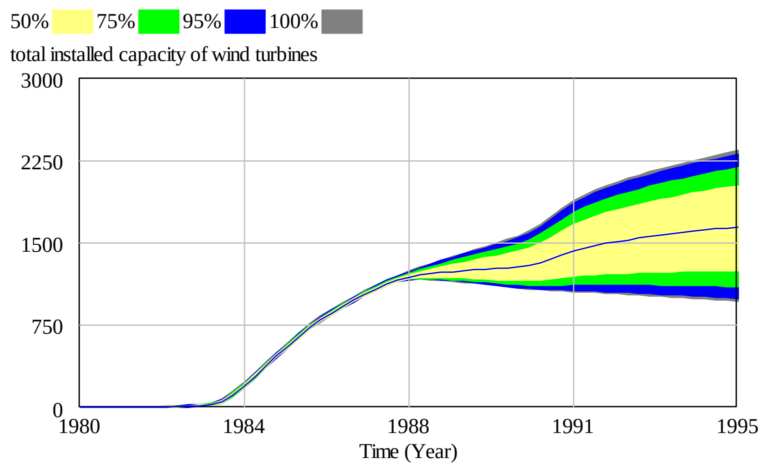
Alpha value for learning by doing on cost & Alpha value for learning by doing on capacity factor:

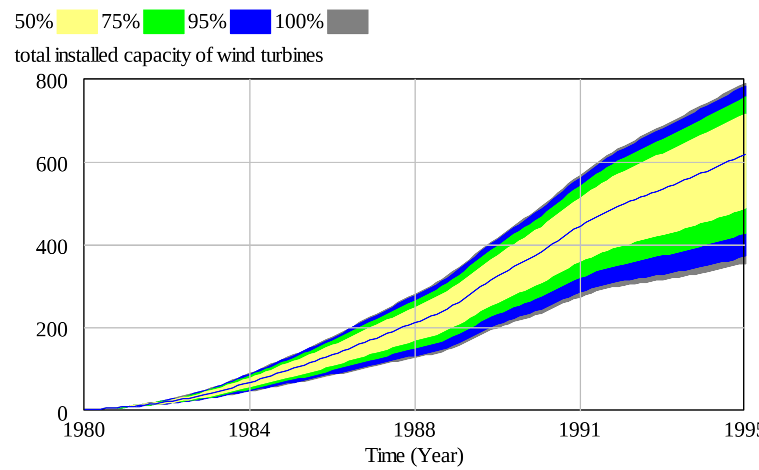
These values affect the ultimate decrease on cost and ultimate increase on capacity factor with learning by doing mechanism. Since these values affect LCOE (not the slope but the real value), the installations are numerically sensitive to this value in the 95% confidence bounds. There is a behaviour change in the graphs but this is caused by increasing the values over the real possible value. For instance, alpha value for learning by doing on capacity factor has to be above 1. If it is lower than 1 it means that with time capacity factor decreases, showing inferior performance, which is unrealistic. When the sensitivity analysis is done with considering these bounds, there was no behaviour change. The results without the bounds are shown below to illustrate the point better. The results for cost and capacity factor was similar. Again, for familiarity, there is not real change in California but the results are sensitive in Denmark. This is due to higher percentage of adoption in Denmark, which goes higher than normal social exposure.

California

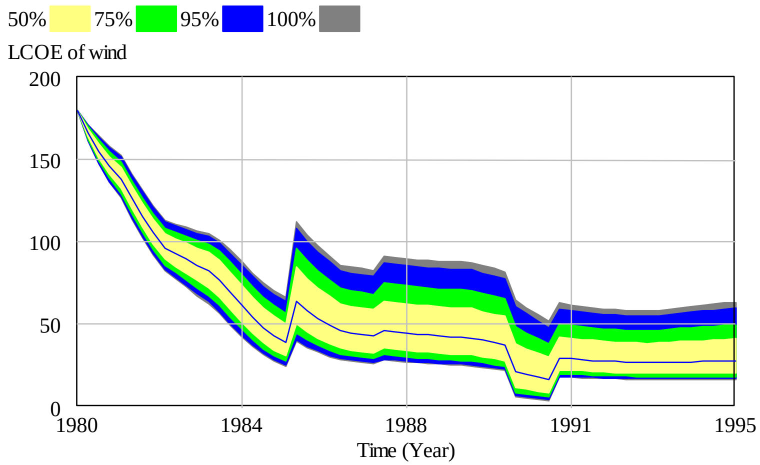
Denmark

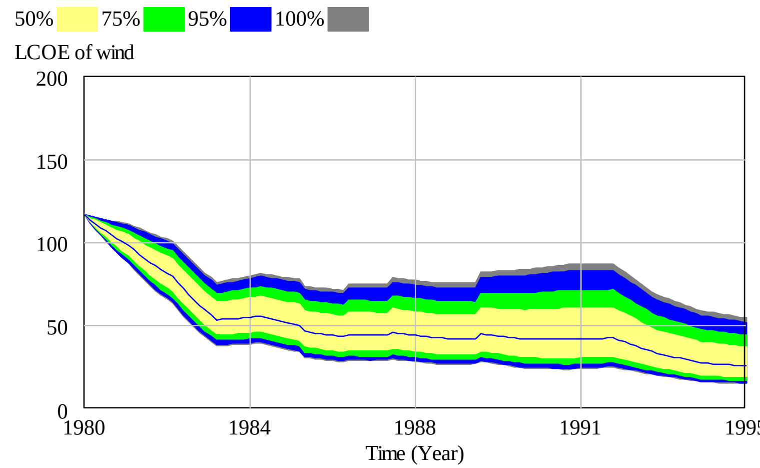
Total installed capacity of wind turbines



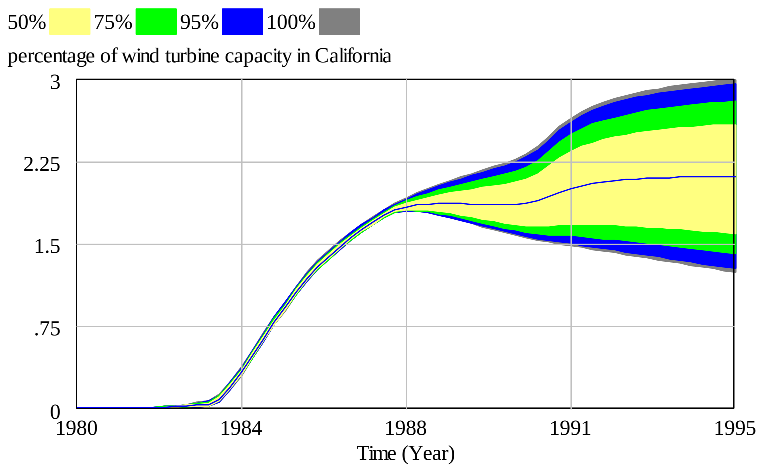


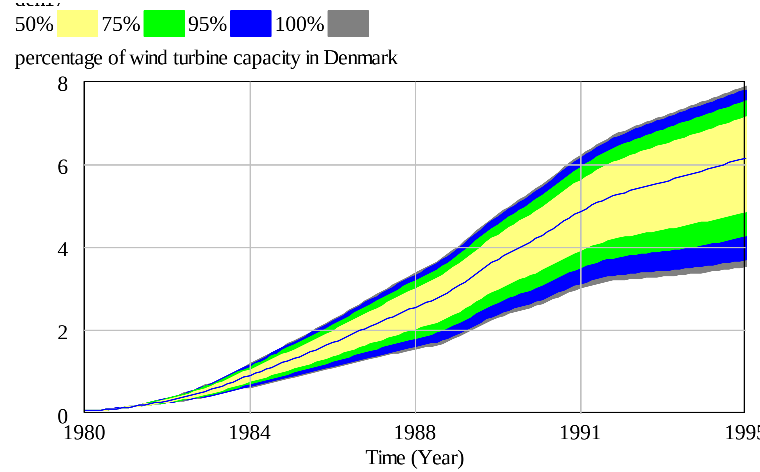
LCOE of wind



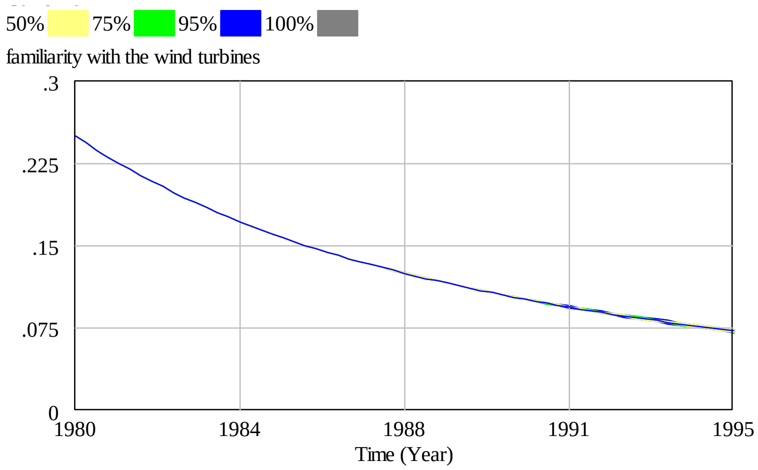


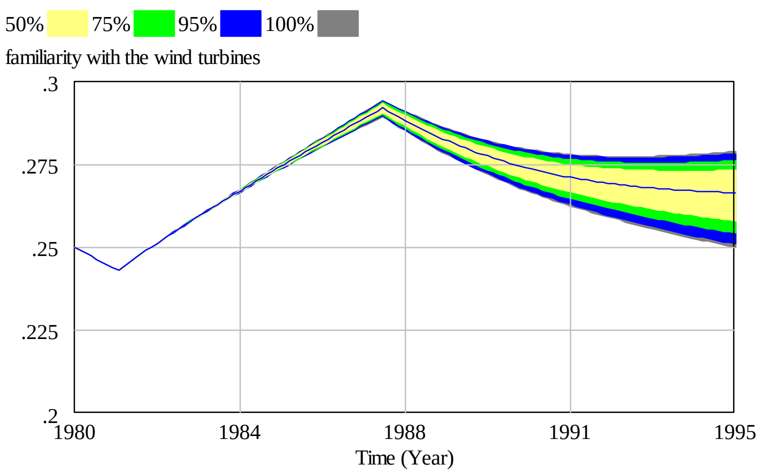
Percentage of wind turbine installations





Familiarity with the wind turbines





Appendix F.2. Multivariate Sensitivity Analyses

After making these univariate sensitivity analyses, multivariate sensitivity analyses are done by combining closely related variables. For example, for familiarity; effectiveness of users and non-users, maximum decay rate and normal social exposure are the main variables affecting the feedback loops. Therefore their combined effects are also investigated with sensitivity analysis. The descriptions of each of these multivariate sensitivity analyses are given below:

- Multivariate sensitivity analysis for testing variables related with familiarity
- Multivariate sensitivity analysis for testing variables related with learning curves
- Multivariate sensitivity analysis for testing variables related with affinity (purchasing decision)

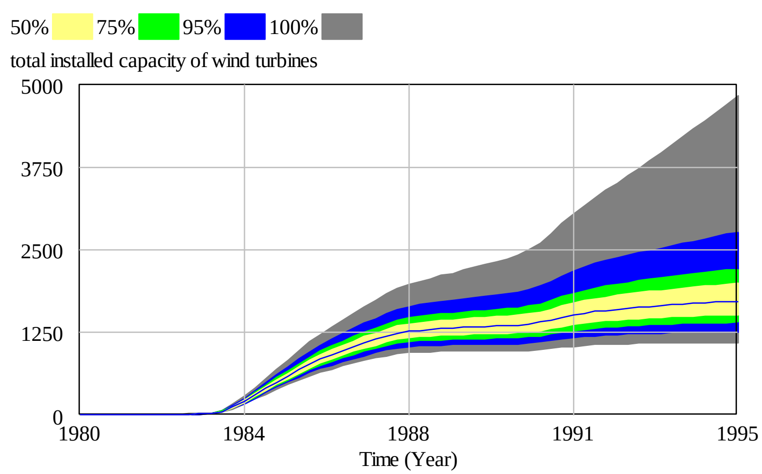
Again, each of the variables are changed 10 percent with random uniform distribution. The simulation is run 1000 times number of variables altered.

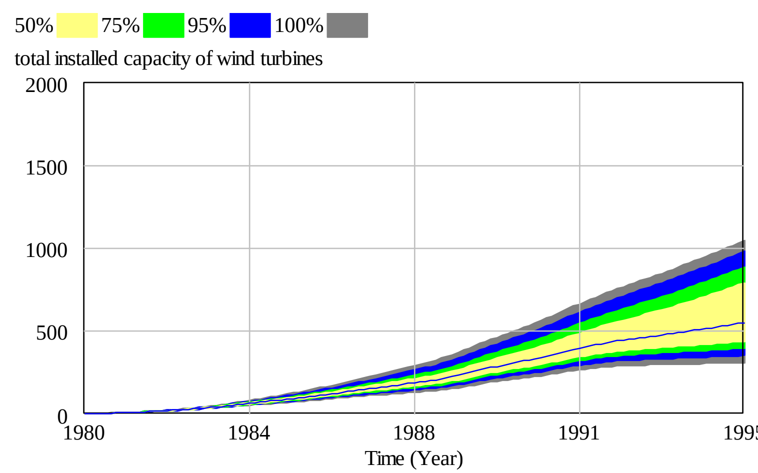
- Multivariate sensitivity analysis concerning Familiarity: *effectiveness of users, effectiveness of nonusers, maximum decay rate, normal social exposure, initial familiarity:* 5000 runs with 10% alteration of values with random uniform distribution.

California

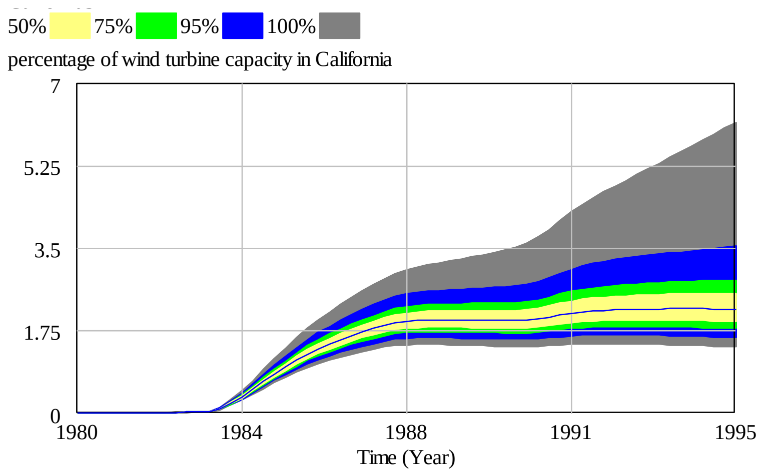
Denmark

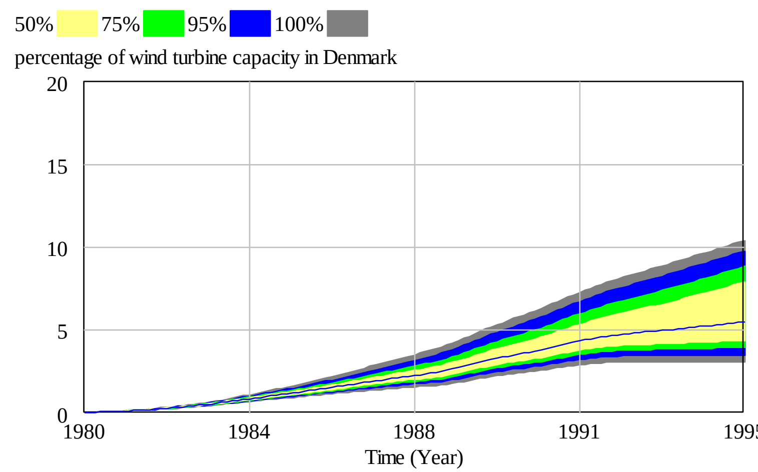
Total installed capacity of wind turbines



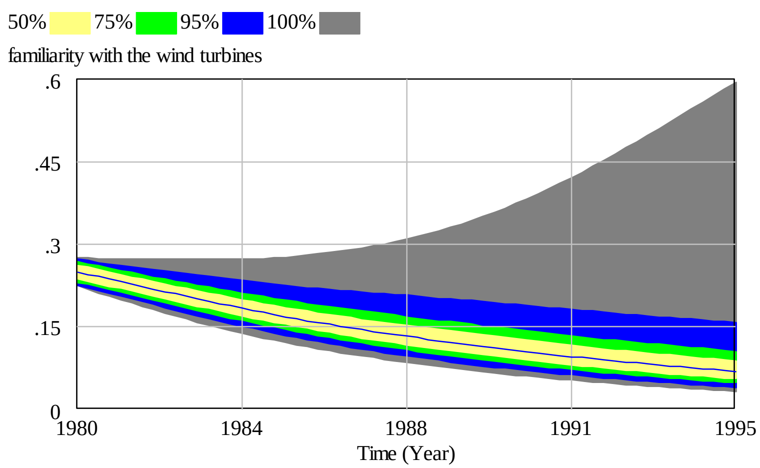


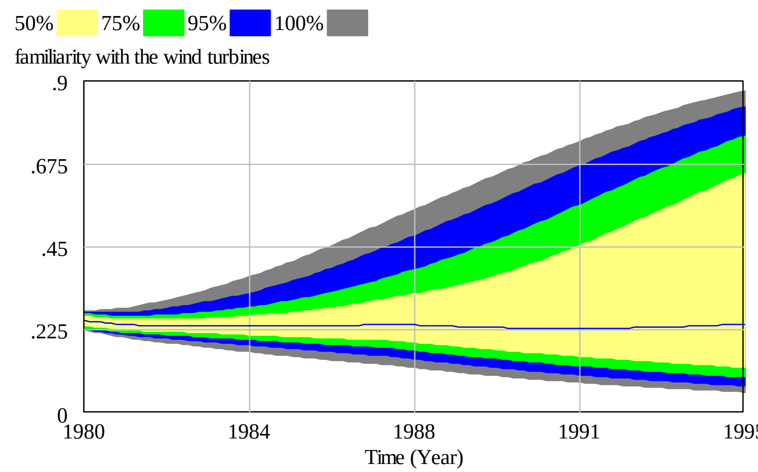
Percentage of wind turbine installations





Familiarity with the wind turbines





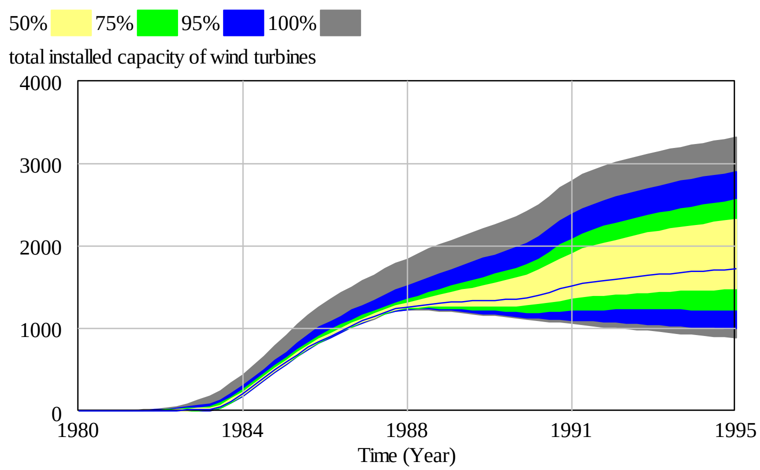
The results for California is only numerically sensitive under 95% confidence bounds. But for Denmark, the familiarity is behaviorally sensitive to combined effect of variables influencing familiarity. This behavior change does not result in significant behavior change in the model for installed capacity and the percentage of installed capacity, since familiarity only increases the demand. As it was explained before, the reason for Denmark to be behaviorally sensitive to familiarity is due to high level of adoption which is more than normal social exposure. This way, familiarity decays quite slowly, and it get closer to well-known S-curve. Same situation only happens for California for 5 percent of the simulations.

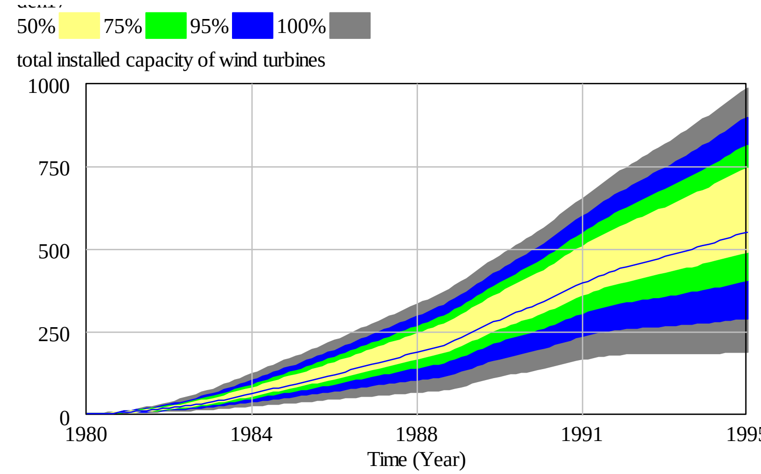
- Multivariate analysis regarding learning curves: *alpha values for learning by doing on cost, alpha value for learning by doing on capacity factor, beta value for learning by searching on cost, beta value for learning by searching on capacity factor, initial RD stock initial cumulative experience (initial installed capacity), initial investment cost per kW, initial capacity factor* are changed with 10 percent random uniform distribution over 8000 runs.

California

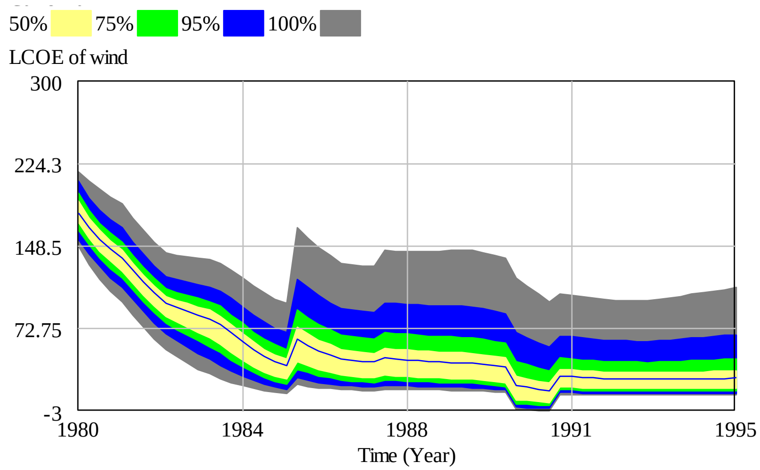
Denmark

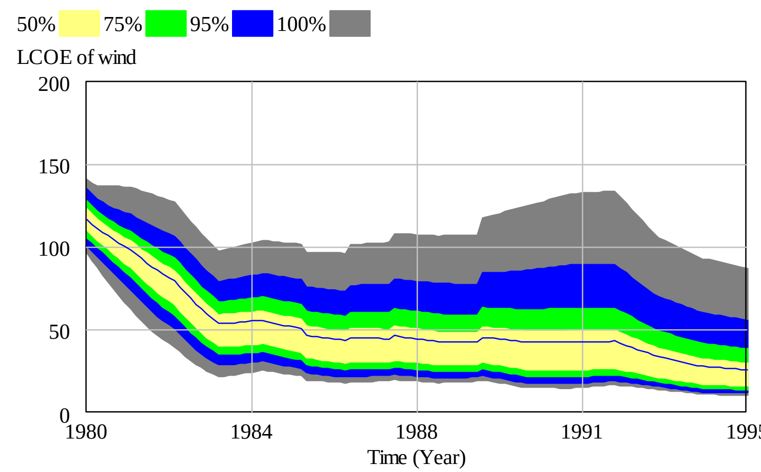
Total installed capacity of wind turbines



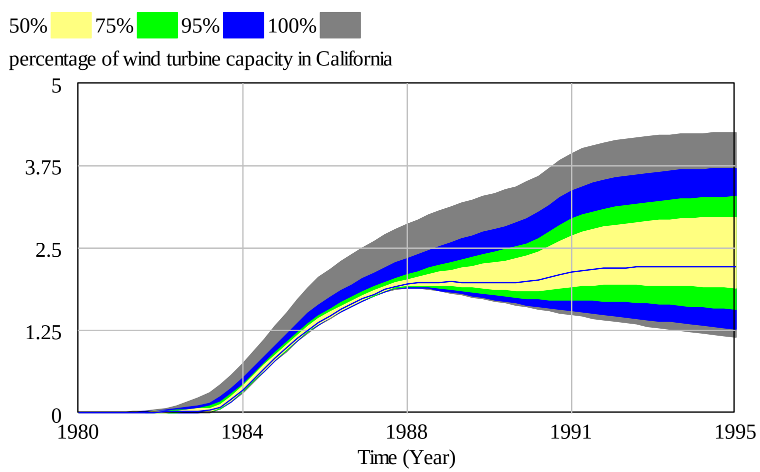


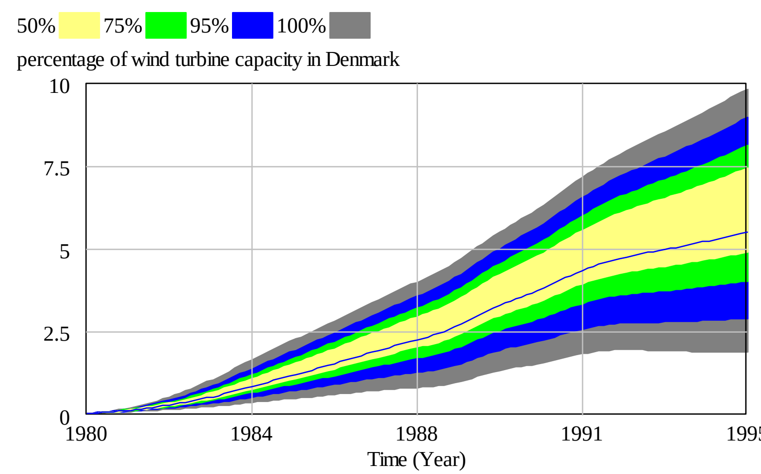
LCOE of wind



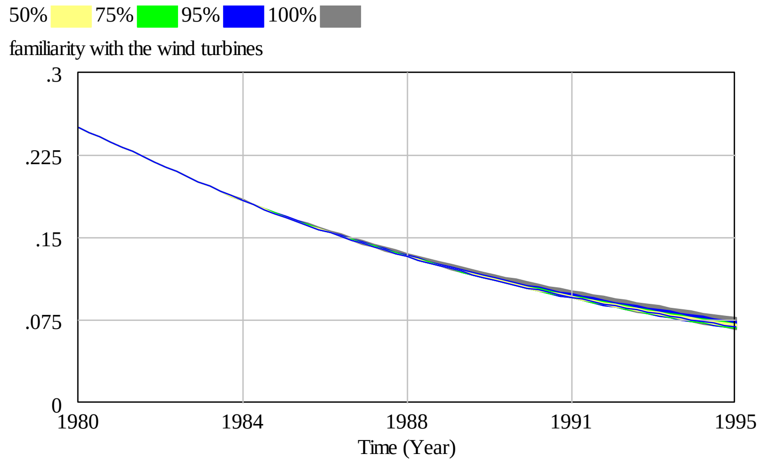


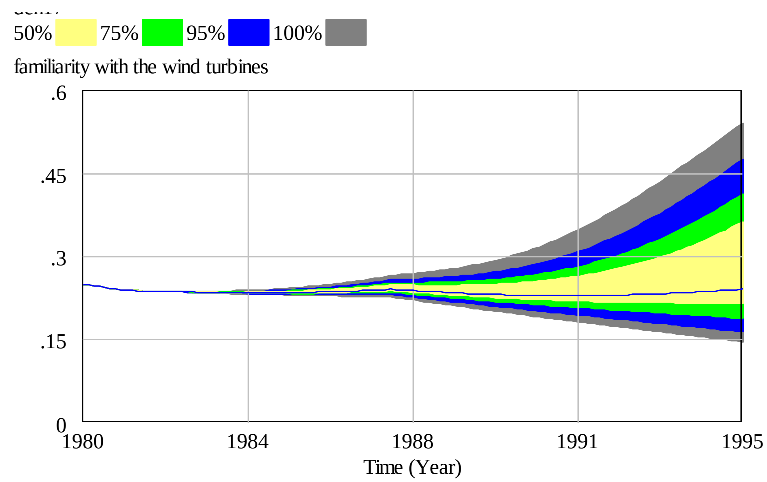
Percentage of wind turbine installations





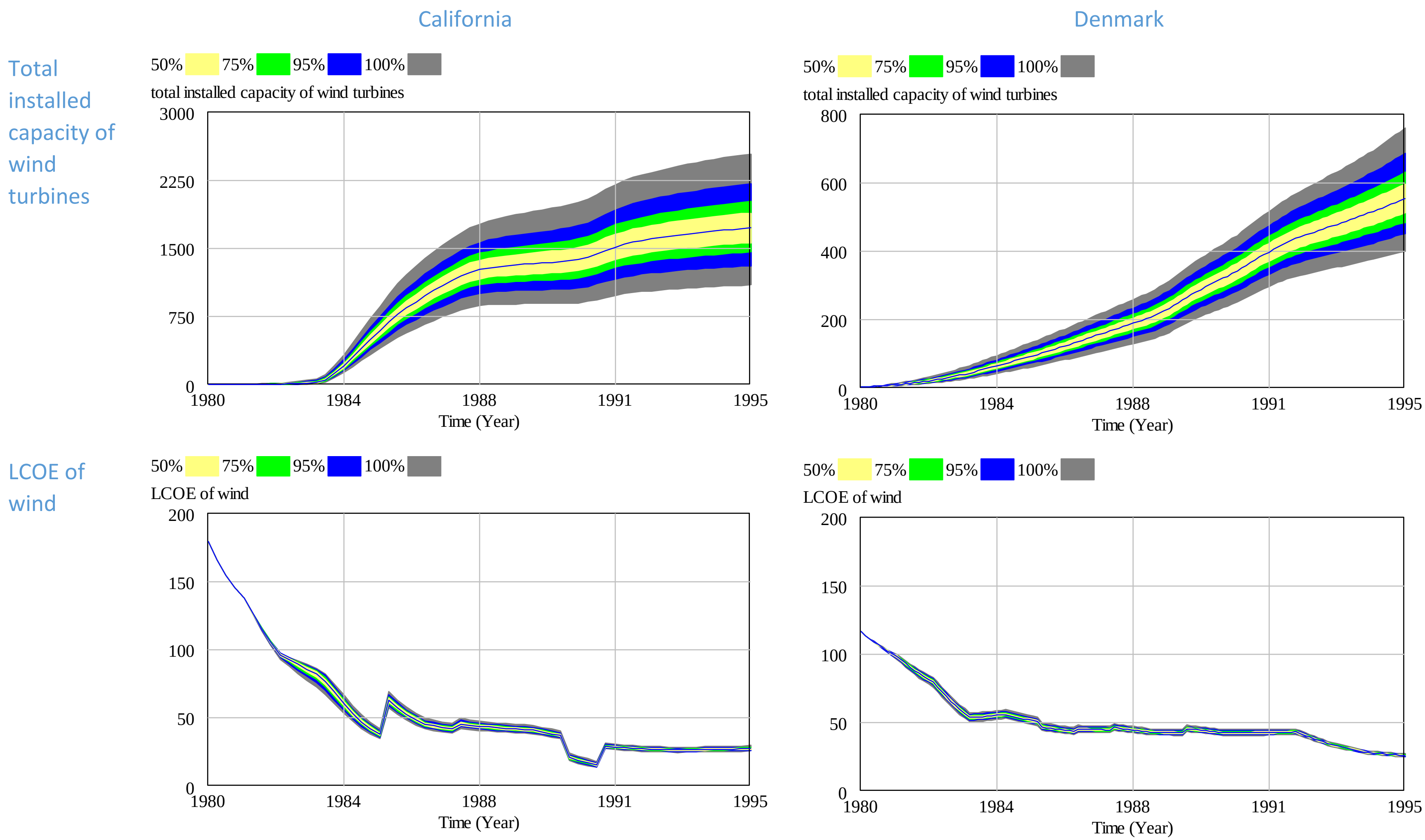
Familiarity with the wind turbines





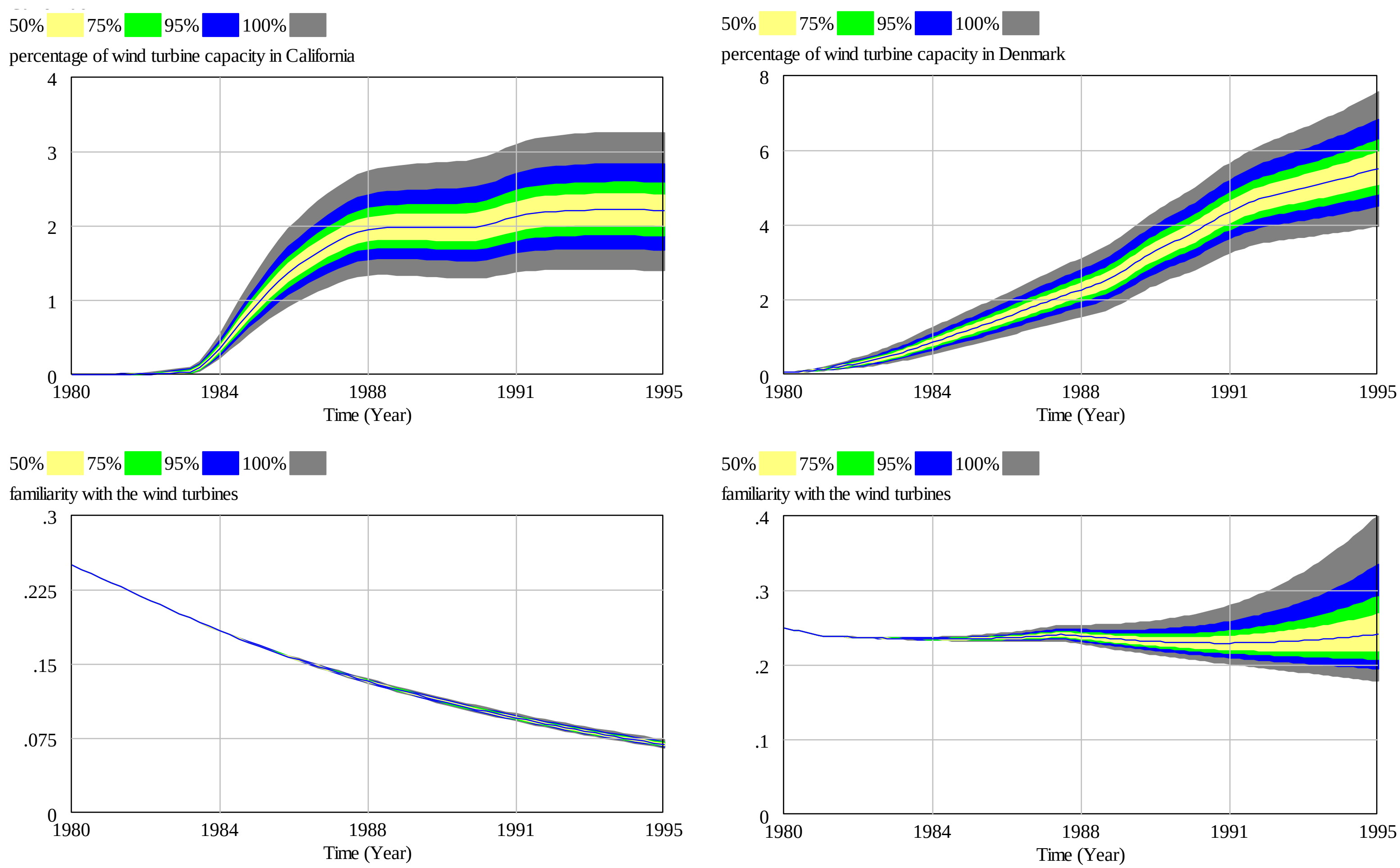
The results show that the model is numerically sensitive to combined changes in learning curves more that 75 percent of the confidence bounds. Behavior change is in California is coming from the comparison of LCOEs of conventional technologies and wind turbines, resulting in expensive wind turbines and lower rate of adoption due to slow learning. For Denmark, even though the learning curves get slower, wind turbines remain advantageous to conventional technologies, because Denmark's energy cost is high. Familiarity sensitivity difference between California and Denmark is due to level of adoption as it is explained before.

- Multivariate analysis share of wind turbine purchases: *affinity ay reference LCOE of wind turbines, reference LCOE of wind turbines, affinity at reference LCOE of conventional technologies, reference LCOE of conventional technologies, sensitivity value for wind turbines, sensitivity for conventional technologies* are changed with 10 percent random uniform distribution over 6000 runs.



Percentage of wind turbine installations

Familiariy with the wind turbines



Model's response to sensitivity analysis regarding affinity is numerical sensitivity. The reason there is no behavior sensitivity for this analysis, is because LCOE of wind turbine remains at the same advantage compared to LCOE of conventional technologies, unlike previous analysis. Therefore, utilities adoption level differs in percentage, but there is no behavior change. Familiarity sensitivity difference between California and Denmark is due to level of adoption as it is explained before.

Appendix G – R^2 and MAE/Mean Tests Results

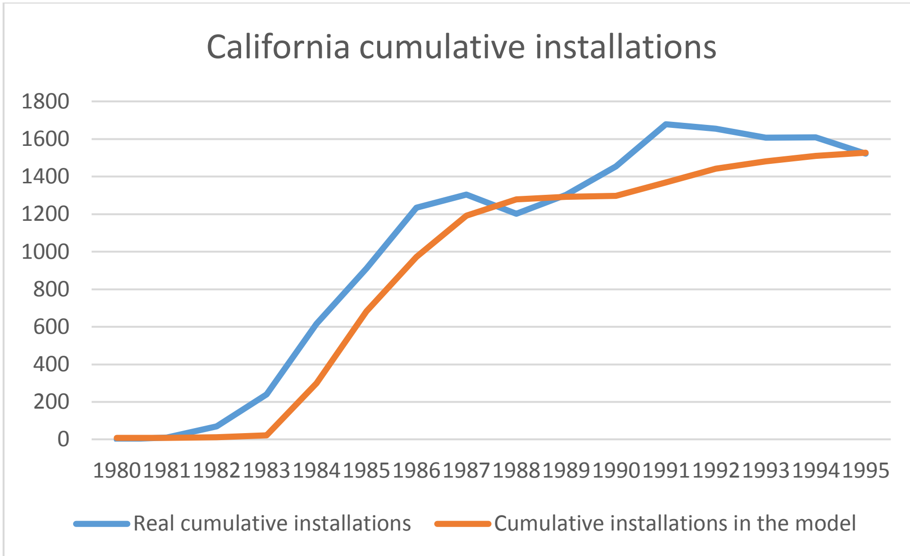
Here the tables show the real data, model's data and the results of these tests, as well as the graphs of the data both for California and Denmark.

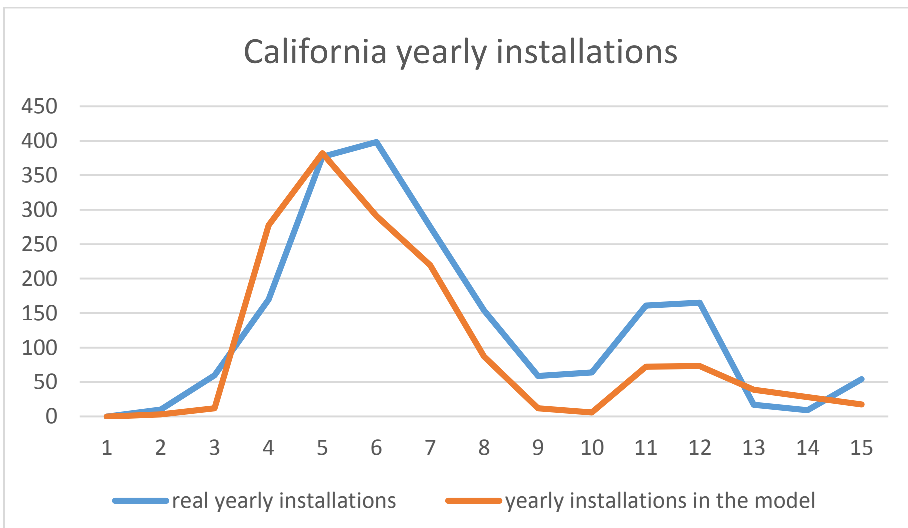
Denmark R2 and MAE/Mean tests

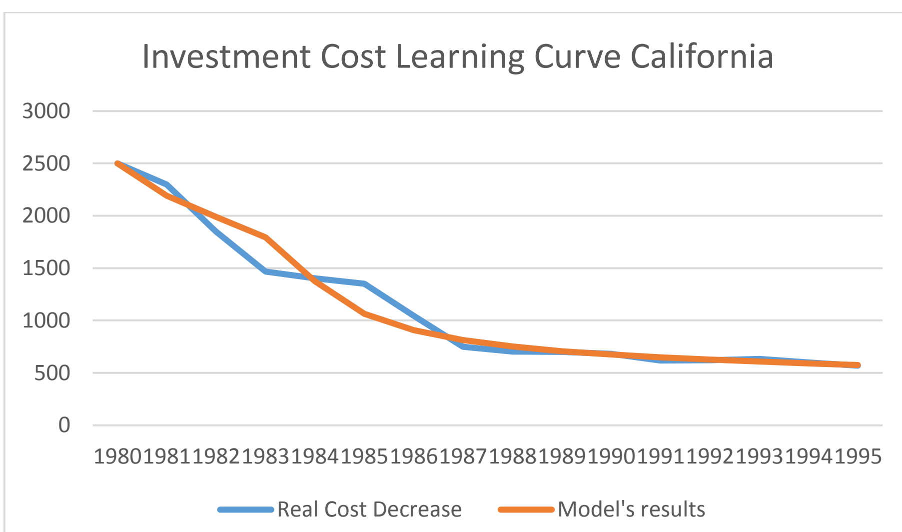
	investment cost		cumulative installations		yearly installations	
	real	model	real	model	real	model
1980	1322	1322.00	2	5.00	2	1.40
1981	1322	1248.06	6	6.09	4	2.41
1982	1360	1195.01	10	9.12	4	4.56
1983	1284	1145.09	14	16.19	4	14.32
1984	1265	1091.72	20	31.04	6	13.76
1985	1209	1042.04	47	48.62	27	22.28
1986	1133	998.38	72	73.75	25	25.57
1987	1058	959.49	112	104.08	40	26.80
1988	982	925.85	190	135.94	78	57.84
1989	1095	895.92	246	185.26	56	55.51
1990	1076	868.11	325	242.24	79	60.71
1991	1020	843.12	392	300.26	67	62.08
1992	982	820.78	435	358.17	43	39.31
1993	906	800.83	467	407.81	32	62.75
1994	831	783.00	520	470.23	53	82.81
1995	793	766.64	599	552.86	79	96.69
R^2	0.88		0.98		0.73	
MAE/Mean	1.34%		2.75%		1.33%	

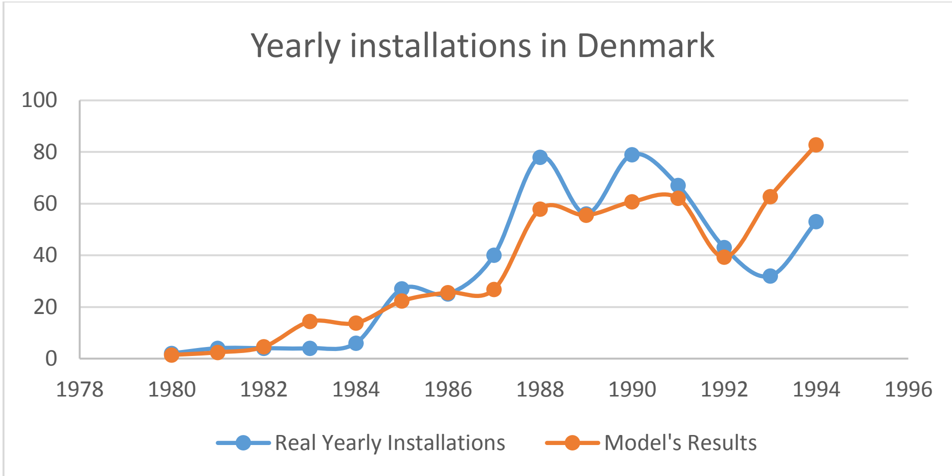
California R2 and MAE/Mean tests

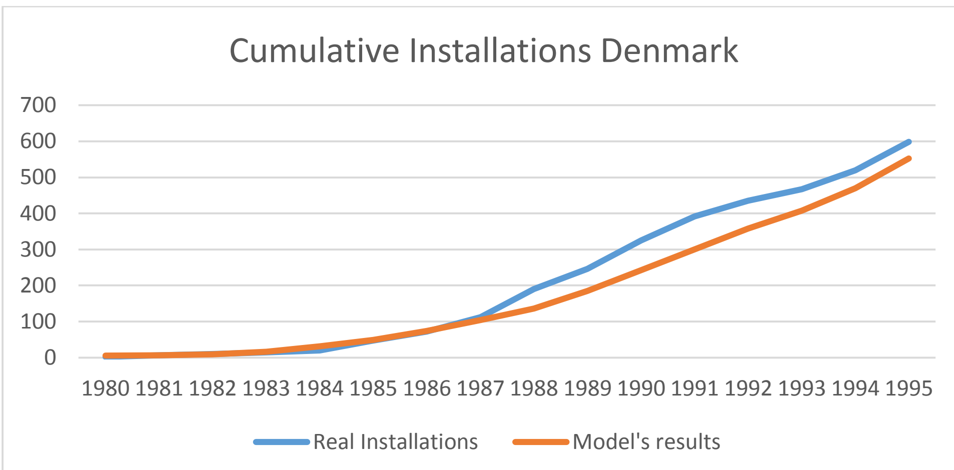
	investment cost		cumulative installations		yearly installations	
	real	model	real	model	real	model
1980	2500.00	2500.00	0	8.00	0	0.00
1981	2297.00	2189.47	10	7.87	0	0.00
1982	1847.19	1990.29	70	11.03	10	3.17
1983	1466.00	1792.83	240	22.77	60	11.74
1984	1404.00	1374.73	617	300.35	170	277.58
1985	1350.00	1063.98	911	682.08	377	381.72
1986	1044.07	906.82	1235	973.06	398	290.99
1987	750.00	813.02	1304	1192.55	275	219.48
1988	701.75	750.37	1202	1279.71	154	87.16
1989	698.50	707.12	1302	1291.80	59	12.09
1990	681.37	675.06	1454	1297.51	64	5.71
1991	618.11	649.39	1679	1369.92	161	72.41
1992	621.00	627.24	1655	1443.12	165	73.20
1993	632.00	607.96	1608	1481.98	17	38.86
1994	599.50	590.91	1609	1510.12	9	28.14
1995	567.00	575.53	1523	1527.64	54	17.52
R^2	0.96		0.96		0.82	
MAE/Mean	0.01%		1.87%		11.00%	

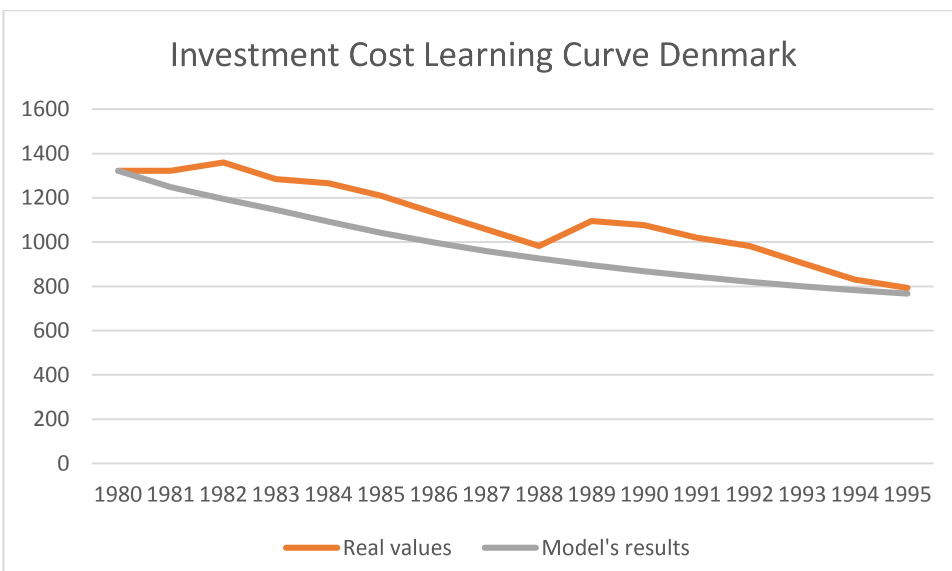

California cumulative installations
1800
1600
1400
1200
1000
800
600
400
200
0
1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995
Real cumulative installations
Cumulative installations in the model


California yearly installations
450
400
350
300
250
200
150
100
50
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
real yearly installations
yearly installations in the model


Investment Cost Learning Curve California
3000
2500
2000
1500
1000
500
0
1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995
Real Cost Decrease
Model's results


Yearly installations in Denmark
100
80
60
40
20
0
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
Real Yearly Installations
Model's Results


Cumulative Installations Denmark
700
600
500
400
300
200
100
0
1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995
Real Installations
Model's results


Investment Cost Learning Curve Denmark
1600
1400
1200
1000
800
600
400
200
0
1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995
Real values
Model's results

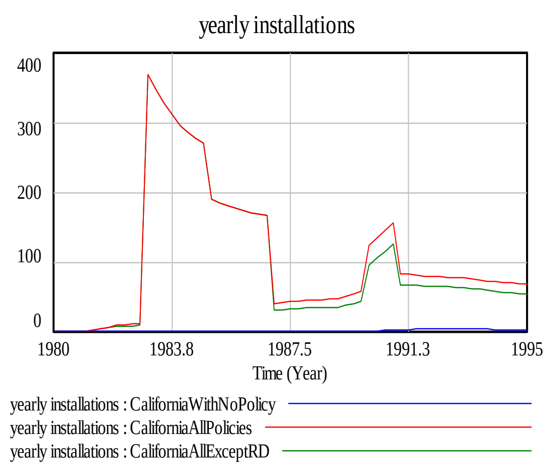
Appendix H- Testing the combined effects of policies

This appendix looks for the possible effect of combined policies which might result in worse results in wind turbine diffusion compared to sum of all policies. To test this, the policies were removed from the model one by one and their results are compared with the full model. This method is repeated both for California and Denmark cases.

Appendix H.1. Testing the combined effects of policies in California

Below the results of removing one policy in California model is shown, by showing the yearly installations and cumulative installations.

Appendix H.1.1. All Policies except R&D investments



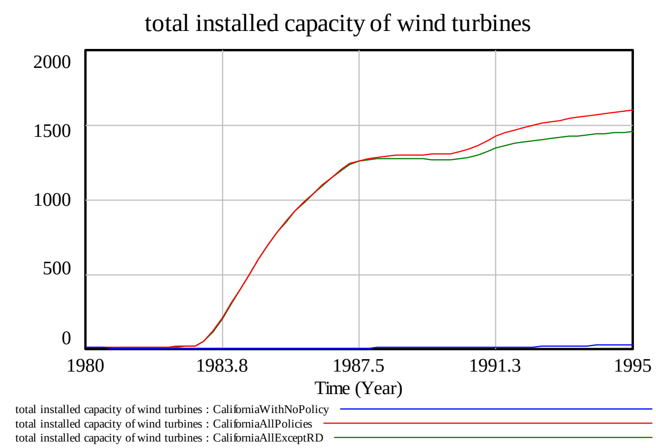


Figure H.1 Effect of all policies except R&D installations

As the Figure shows, when the R&D investments are cut, the wind turbine installations are decreased a little, showing that R&D investments have a positive effect in combination to all other policies. This variable triggers the learning by searching mechanism which helps to cost reduction by improving capacity factor of wind turbines and decreasing the investment cost, and as a result less costly wind turbines result in more installations.

Appendix H.1.2. All Policies except PURPA Act

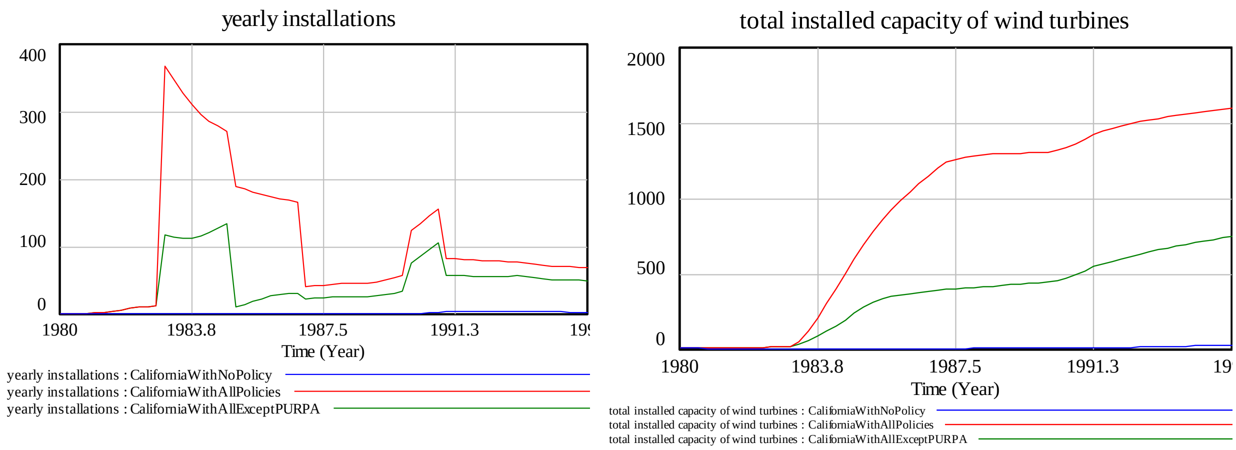


Figure H.2 Effect of all policies except PURPA act

As expected, PURPA act has a significant impact on wind turbine installations in California, but it has no negative effects in combination with the other policies, since the green line is lower than the full model's result. This act directly intervenes to the LCOE of wind turbines and makes it a cost competitive option. Even when the act is removed, due to learning by doing mechanism, the costs were reduced therefore there is more preference on installations.

Appendix H.1.3. All policies except long term contracts

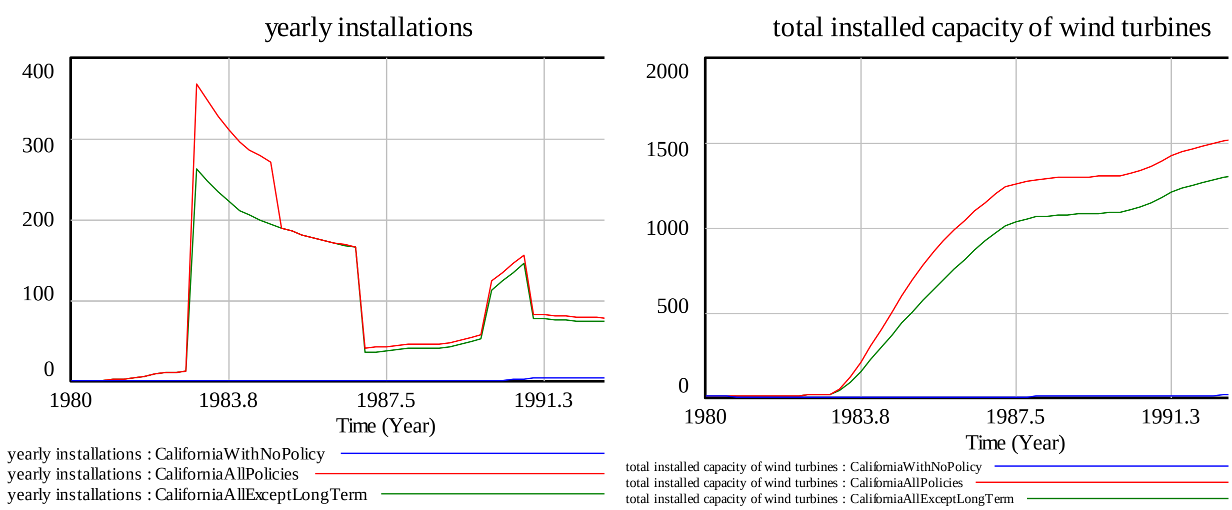


Figure H.3 Effect of all policies except long term contracts

The Figure shows that long term contracts result in additional installations during the period of 1983 -1985. Since the installations with all policies (red line) is higher than the installations with all policies except long term contracts (green line), it can be concluded that long term contracts do not interfere with the other policies negatively.

Appendix H.1.4. All policies except subsidies

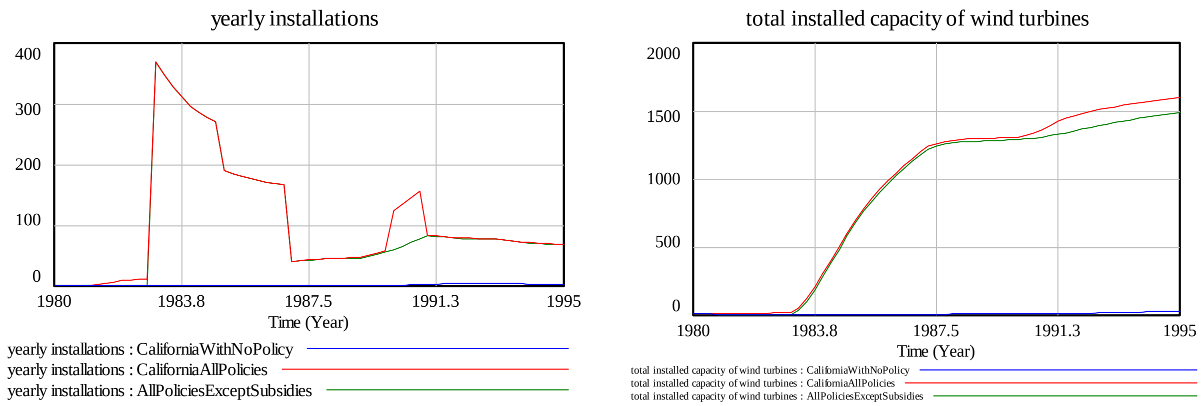


Figure H.4 Effect of all policies except subsidies

This Figure shows that there is al little effect of subsidies on wind turbine installation. The first part of the installation only shows its effect during 1981-1983, because after 1983 PURPA act starts and its effect overrules the effect of subsidies, since LCOE decreases more with PURPA act. During 1990-1991, another subsidy of Energy Policy Act Credit shows its effect by offering 15 $/mWh subsidy. These results imply that the effect of federal and state tax credits becomes redundant when PURPA act is active, because they both target the same value. However, these policies have no negative effect on the model when combined with the other policies.

Appendix H.2. Testing the combined effects of policies in Denmark

Below the results of removing one policy in California model is shown, by showing the yearly installations and cumulative installations.

Appendix H.2.1. All Policies Except R&D investments

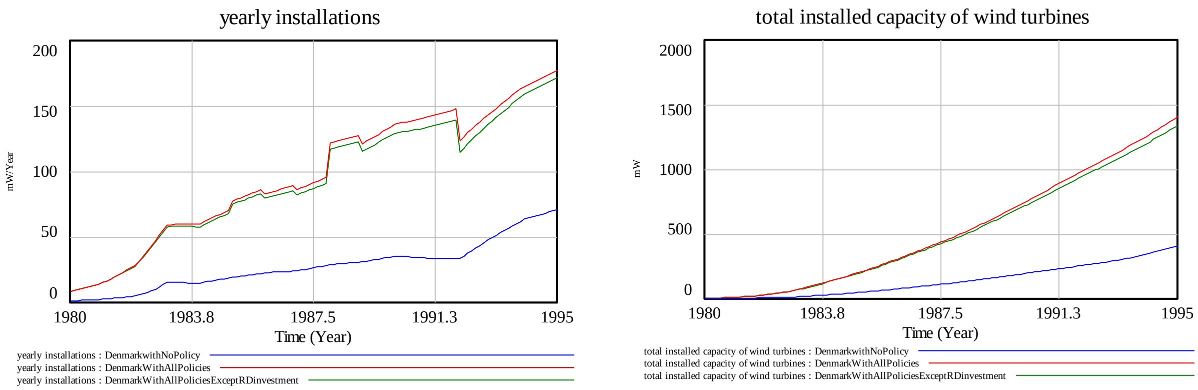


Figure H.5 Effect of all policies except R&D installations in Denmark

Similar to California case, the effect of R&D installations are visible but not that strong. There is no combined effect of this policy hindering the other policies.

Appendix H.2.2. All policies except Investment Subsidies

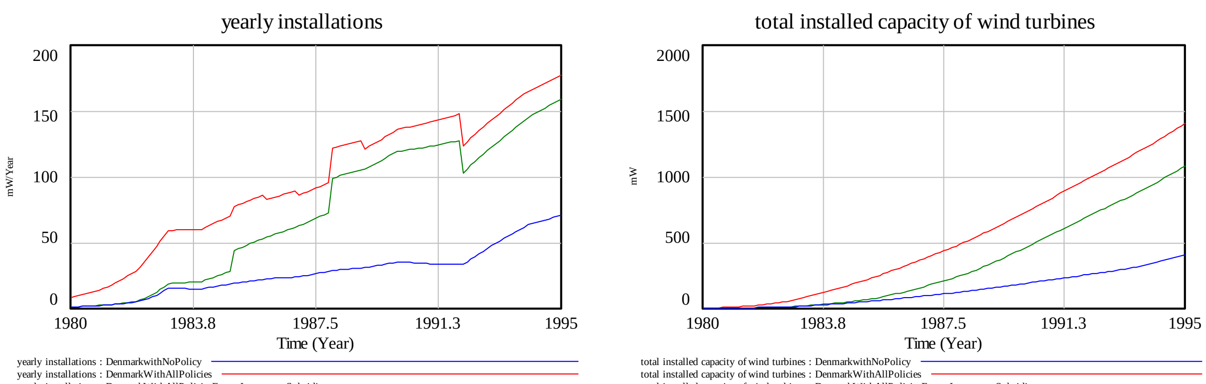


Figure H.6 Effect of all policies except investment subsidies in Denmark

Unlike California, subsidies directly or indirectly affecting LCOE of wind turbines are effective in Denmark. The main reason is the lack of feed in tariff in the policies of Danish goverment. These subsidies are the main ones helping the utilities to install wind turbines in a cost competitive manner whereas that was provided by PURPA act in California. Besides, as the Figure suggests, there is no combined effect of this policy on the model.

Appendix H.2.3. All Policies except 10 year agreement between the Goverment and the Utilities

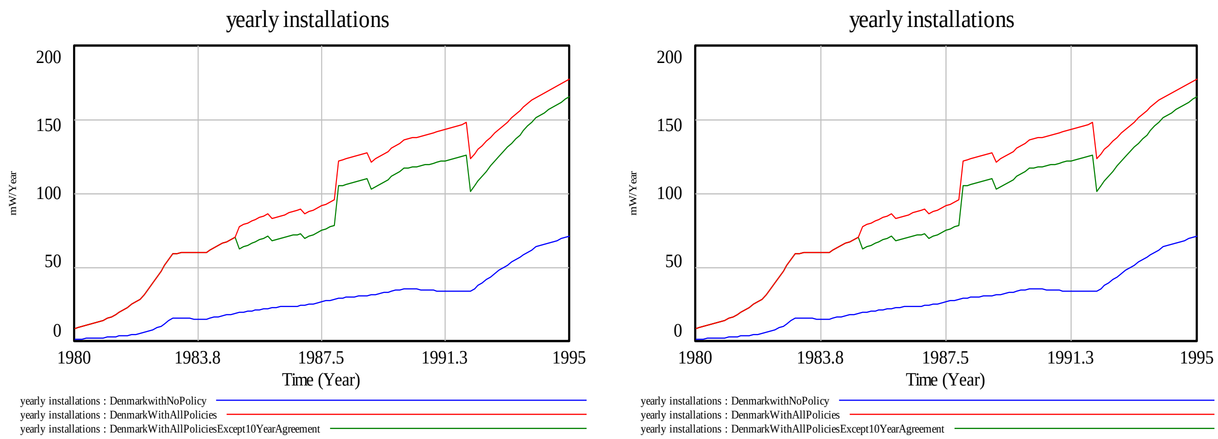


Figure H.7 Effect of all policies except 10 year agreement between the government and the utilities in Denmark

Similar to investment subsidies, this 10 year agreement is a reduction on LCOE starting from 1985 and it helps the utilities to install wind turbines by making it a more cost competitive option. It is observed that there is no negative effect of this policy when it is combined with the other policies.

Appendix H.2.4. All Policies except Government Agreement for installing wind turbines

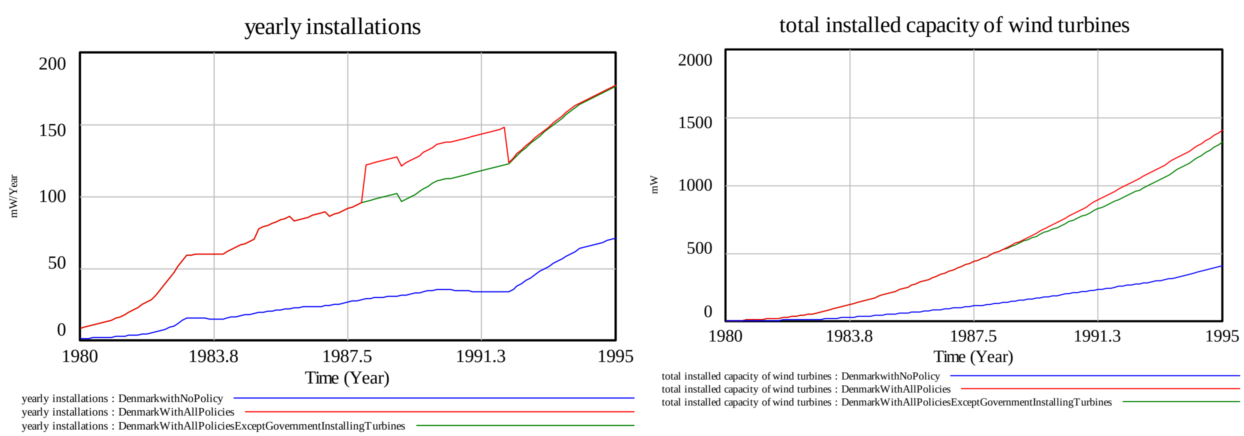


Figure H.8 Effect of all policies except Government installing wind turbines in Denmark

This policy only contributes to the result by not interfering with the any feedback loops. Therefore it has no negative effect on the model when it is run with the other policies.

Appendix H.2.5. All Policies except EnergiPlan Act

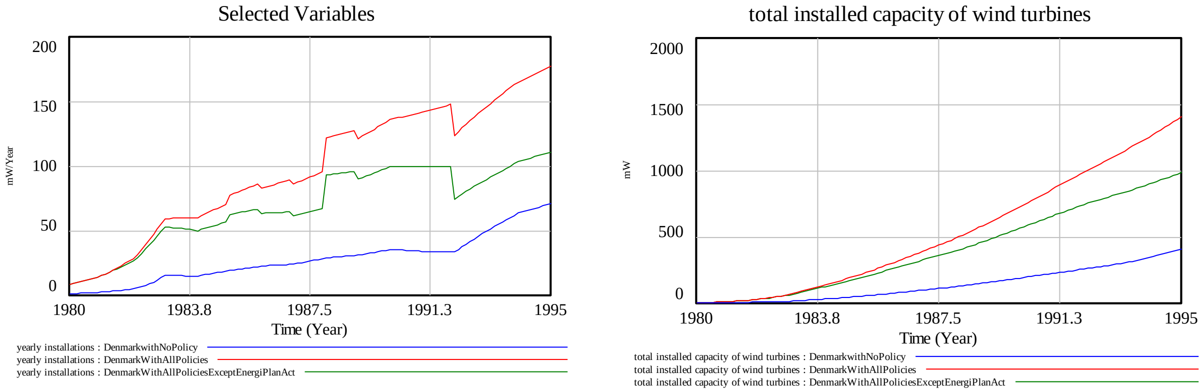


Figure H.9 Effect of all policies except EnergiPlan Act in Denmark

This Figure shows that EnergiPlan was one of the significant policies stimulating wind turbine installations in Denmark. Yet, it has no counter effect on the other policies.