

Modelling Wind Turbine Diffusion: A comparative study of California and Denmark 1980-1995

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Abstract

In order for policy makers to effectively manage the process of the diffusion of renewable energy technologies, it is important to understand the mechanisms behind the diffusion process of such technologies. Most of the literature on innovation diffusion focuses on static or relatively simple dynamic models of diffusion. Recently, researchers have argued that analyzing innovation diffusion needs new methods, allowing for a more comprehensive dynamic analysis. With this aim in view, this research used system dynamics modelling as a dynamic tool for modelling wind turbine diffusion. To be able to see to what extent system dynamics is able to capture the underlying mechanisms of diffusion processes, a known case of wind turbine diffusion in California and Denmark was chosen as a comparative case study. The results showed that Denmark was more successful due to various reasons: high oil prices, strong networks enabling knowledge sharing, and determination of the government. This research also showed that system dynamics is a promising approach for understanding innovation diffusion in a holistic manner.

1. Introduction

Understanding the diffusion of innovation is of crucial importance for researchers and policy makers. Once the details of the causes and their interactions are clearly identified, managing the direction and the rate of diffusion becomes easier. Managing the diffusion of renewable energy technologies has gained more importance, since the need for clean energy and sustainable technologies has become a must rather than a luxurious option. Both the development of the new technologies and the adoption of these technologies in society create a challenge for policy makers.

A variety of studies has been conducted on this issue. However, most of these studies focus on static or relatively simple dynamic models of diffusion. Recently, researchers have argued that analyzing innovation diffusion needs new methods allowing for a dynamic analysis (Jacobsson and Johnson, 2000; Hekkert et al., 2007). Static analyses of innovation diffusion remain inadequate for explaining the reasons for the behaviour of diffusion. This is caused by not being able to capture indirect effects and time dependent effects of policies. Instead, only the direct effects are captured in a black-box manner.

This research aims to explain the reasons for innovation diffusion by defining an innovation system using a transparent, dynamic methodology. To reach this aim, system dynamics modelling has been chosen to model the innovation diffusion principles using a case study. To be able to see what system dynamics can bring to our understanding, a well-known case of diffusion of wind turbines in California (US) and Denmark is taken. Reading the same story with different glasses could bring a new perspective on the story, thus this case is analyzed with system dynamics using the dynamic perspective suggested in the diffusion literature.

The next section introduces the dynamic understanding of innovation diffusion in the literature. Section 3 provides background information about the diffusion stories in California, US, and in Denmark. Section 4 puts the literature and the case stories into the same modelling framework and the transfers the conceptual model into a system dynamics model. The results of this model are shown in Section 5, and the final section concludes with the achievements and the limitations of the study.

2. Innovation Diffusion in the Literature

Diffusion of innovation is a field of study looking to explain how and at what rate innovations are adopted in or through cultures. The idea was introduced by Rogers in 1962 (Rogers and Everett, 1983), and a vast amount of studies have been built on this since. The theory suggests that there are four main factors driving the diffusion process: the innovation itself, communication channels, time, and the social system the innovation spreads through. Yet, since the theory has both social and technological parts and it occurs in a complex system which is society itself, exactly explaining why diffusion succeeds or fails is not possible. On the other hand, tracing the activities impacting diffusion could be invaluable information to policy makers. This would allow them to not only understand the diffusion in a deeper manner, but also how to manage it. With this aim, researchers have considered the process of diffusion from different perspectives. Authors who emphasize the importance of a dynamic analysis are Hekkert et al. (2007) who describe functions of innovation systems and Yücel (2010) who covers the mechanisms of transitional change.

The functions (Hekkert et al., 2007) and mechanisms (Yücel, 2010) will be introduced below, and will then be used to develop the conceptual framework for our model of wind turbine diffusion. However, before introducing the functions and mechanisms, it is important to note that the activity of learning is central to many studies of innovation systems (Hekkert et al., 2007), and different learning activities can be seen in the functions and mechanisms. We can distinguish learning by actors on the supply side and learning by actors on the demand side. Learning by actors on the supply side can influence the quality and cost of the technology, and learning by actors on the demand side can influence the perception of the technology. An example of learning on the supply side is the well-known learning-by-doing mechanism. Learning-by-doing implies that the cost of the technology decreases as the cumulative production increases, since more opportunities exist to improve the product, or production methods (Argote and Epplé 1990; Arrow 1962; Dosi 1988). In that sense, learning-by-doing represents the experience gained by the industry by the scale of production. Sagar and Zwaan (2006) indicate that further research is needed on exactly how this learning takes place and what it involves. Learning-by-searching is another example of learning related to the supply side and this represents the knowledge gathered from R&D activities related to the technology. Learning which can influence actors' perceptions on the demand side can take place via direct observation or experience with a technology, or through social interaction in a network of actors, for instance by means of word-of-mouth.

Below, the processes described by Hekkert et al. (2007) and Yücel (2010) will first be explained and compared, and will then be discussed in the light of the wind turbine diffusion case.

Hekkert et al. (2007) distinguish the following seven processes that are important for innovation systems that perform well. They call these processes Functions of Innovation Systems (FIS).

- Function 1 consists of entrepreneurial activities. 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 about the product and strengthens the learning-by-doing mechanism.

- Function 2 is knowledge development. Mechanisms of learning are central to innovation, and this function refers to learning-by-searching and learning-by-doing.
- Function 3 concerns knowledge diffusion through networks. Exchange of information through a network is important for innovation diffusion. The number of members in the network and the level of interaction among them are the two main drivers for information spread.
- Function 4 concerns guidance of the search. 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 the initiative for guiding the market towards a certain technology in such situations.
- Function 5, market formation, 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.
- Function 6 is resources mobilization, which includes both the allocation of human capital and financial resources.
- Function 7 consists of creation of legitimacy. The new technology will compete with the existing ones. For this reason it is likely to face 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.

Yücel (2010) introduces a number of processes as mechanisms of transitional change.

- Experience driven change in option properties, such as the price and quality of the wind turbine option, occurs when the experience with an option leads to the development of an option. This mechanism is equivalent to learning-by-doing.
- Resource driven change occurs because the properties can also be influenced by utilizing resources. These resources are not only financial, but they also include, for example, physical capital, manpower, and time (R&D, managerial, etc.). In general, resource-driven changes are induced by purposeful resource allocations of the actors who aim to alter the option properties. This mechanism is equivalent to learning-by-searching.
- Individual learning refers to the improvement of the precision of information an individual has about the option. This can be through direct observation or the experience of an individual.
- Social learning is about the diffusion of information among people or parties. Information flow via social interaction (e.g. word-of-mouth or information contagion) is a well-known process in innovation diffusion.
- Commitment formation refers to the fact that decisions are not always history-independent. Decisions can be very much influenced by the former courses of action that were taken.
- The preference structure of an individual or group of individuals indicates the important issues in assessing the available options, as well as the relative importance (e.g. weights) of this issue. In the short term, the preference structures of actors can be assumed to be stable. However, in the long term this may not be the case.

Table 1 shows the general correspondence between the processes mentioned as functions of innovation systems and as mechanisms of transitional change.

Table 1. Correspondence between Functions of Innovation Systems and Mechanisms of Change

Functions of Innovations (Hekkert et al., 2007)	Mechanisms of Change (Yücel, 2010)
F1: Entrepreneurial activities	Experience driven change in option properties
F2: Knowledge development	Experience driven change in option properties Resource driven change in option properties
F3: Knowledge diffusion through networks	Individual and social learning (familiarity)
F4: Guidance of the research	Commitment Formation
F5: Market formation	<i>Not a mechanism but an activity affecting the purchasing decision</i>
F6: Resources mobilization	Resource driven change in option properties
F7: Creation of legitimacy	Preference structure change

- Function 1 says that entrepreneurial activities are the key drivers of experience for developing the technology, because the new entrants are more willing to take risks and innovative activities. Yücel also says that experience driven change in option properties helps diffusion by accumulation of actor's experiences leading to improvement in product properties (learning-by-doing is an example of experience driven change). The main source of the experience defined by Yücel is entrepreneurial activities as Hekkert describes.
- Function 2 refers to learning-by-searching and learning-by-doing coming from not only the entrepreneurs but from all actors, such as large firms and the research centers. Yücel'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 centers for a certain technology, and/or industry-government agreements.
- Function 3 is more about the demand side of the diffusion, mentioning the word-of-mouth coming from adopters and non-adopters. Individual and social learning from Yücel's mechanisms address the same concepts.
- 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. Yücel addresses this issue by explaining the effect of commitment formation to the technology.
- Function 5 covers the demand pull type of policies of a 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 this will trigger the individual and social learning mechanisms.
- Function 6 (resources mobilization) behaves as an input to Function 2 (knowledge development), where the resources are allocated to contribute knowledge development by the government. Therefore the correspondence to Yücel's mechanisms is the same as Function 2.
- Finally, function 7 concerns the demand for the new technology coming from the bottom, such as advocacy groups working for the legitimacy of the new technology. Yücel mentions this phenomenon by explaining the preference structure change of the actors where the conventional options are not satisfactory and they look for new options.

For the cases of wind turbine diffusion in California and Denmark, we will analyze whether the concepts mentioned in Table 1 exist or not, and then their interactions will be conceptualized. Below,

we first describe the development of wind turbines in California and Denmark, after which we relate both situations to the concepts discussed above.

3. Wind Turbines in California and Denmark

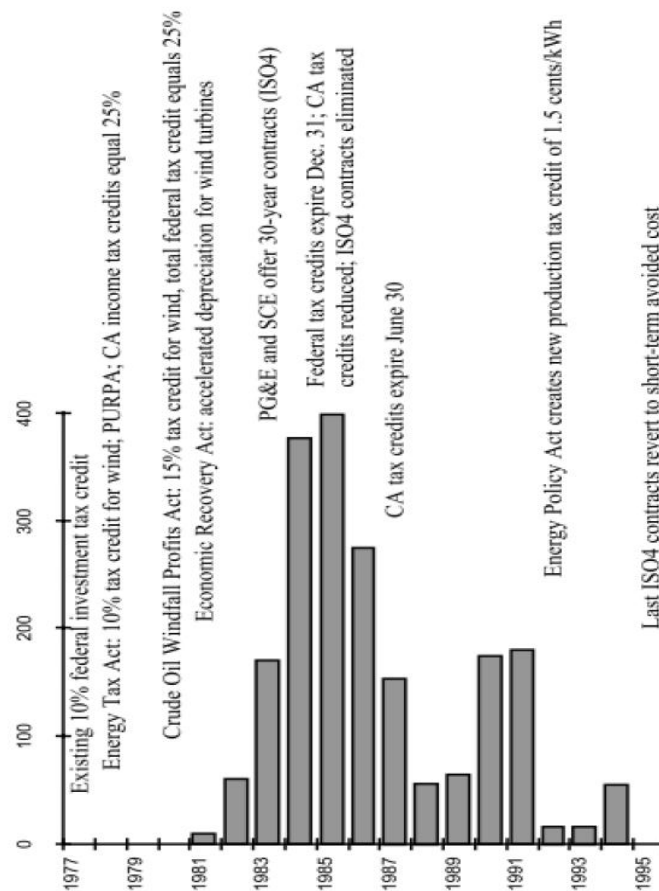
3.1 California

The diffusion story of California starts with the oil crises of the 1970s, when the U.S. government started to seek alternative solutions for energy, to reach a more secure energy supply. Electricity generation from wind turbines was one of the possibilities in this regard, because it was the only promising technology among renewables in terms of cost-competitiveness at that time (Menz and Vachon, 2006). Also, a secondary reason was important to policy-makers. Due to urban fog and acid rain during the 1970s, the environmental concerns had increased (Norberg-Bohm, 2000). Various gas emissions such as SO₂ (which leads to acid rain) concerned the policy makers about public health (Menz and Seip, 2004). With these concerns, there were several policy attempts to stimulate environmentally friendly energy generation, such as the Clean Air Act. Although these policies did not create a strong stimulus for wind turbines, it initiated the increased R&D investment growth of the late 1970s (Norberg-Bohm, 2000). Following R&D investments and additional federal and state policies creating incentives for wind turbines, about 95% of the wind turbines in the US are installed in California, where favorable weather conditions also played an important role (Sawin, 2001). It is possible to categorize these policies into supply-push and demand-pull policies, where supply-push policies aim to stimulate innovations, whereas demand-pull policies try to create a market for new technologies.

Supply-push technologies are easily visible from the 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 total, from 1975 to 1988, the US spent \$427.4 million on R&D only for wind technology (in real dollars).

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 et al., 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 the aim was to approximate the avoided costs of the utilities (Martinot et al., 2005). In 1980, California offered a 25% state tax credit for investments in wind power, where there was also a 25% federal tax credit. Federal tax credit 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 et al., 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. 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. The implementation of these policies and corresponding wind turbine installations can be seen in Figure 1.



PURPA = Public Utilities Regulatory Policy Act; CA = California; PG&E = Pacific Gas & Electric Company; SCE = Southern California Edison; ISO4 = Interim Standard Offer 4

Figure 1. Annual wind turbine installations (MW) and policies in California (Norberg-Bohm, 2000)

3.2 Denmark

In Denmark, the wind turbine energy topic was raised during the same time, where the main motive was the oil crises of the 1970s. Denmark had no energy source of its own, therefore the country was highly dependent on imports. 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 (Kamp, 2002). Environmental concerns were also on the rise, and it took a significant role in determining Danish energy policy for the following years. Society was strongly against nuclear energy, therefore Denmark had no other choice than wind turbines, since other renewables were far away from being cost competitive. Similar to the United States, Danish wind turbine policies followed two paths: supply-push and demand-pull.

Under the supply-push policies Risø National Laboratory and the Technical University of Denmark started a Wind Power Program, to develop knowledge about large wind turbines (Van Est, 1999). In the first phase of this program, 35 million DKK was spent on developing wind turbines, and 82% of this budget went to development of large wind turbines (Van Est, 1999).

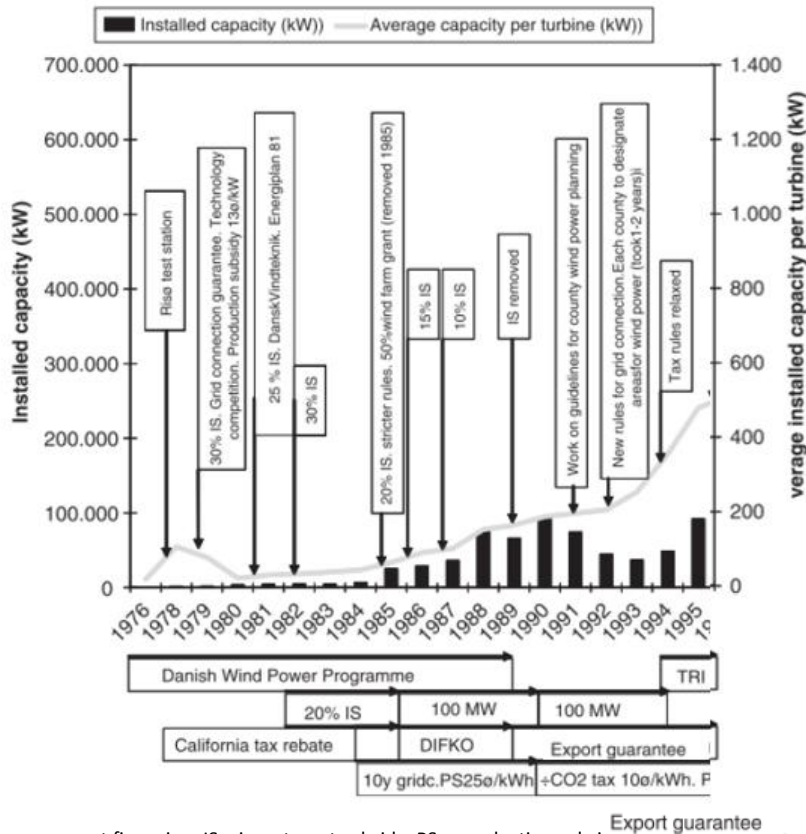
Apart from putting R&D efforts into wind energy, the Wind Power Program directly involved the utilities in the program, since they would be the potential buyers of the technology. This involvement helped utilities to become more familiar with the technology from the development phase, which could be also interpreted as a demand-pull policy (Kamp, 2002).

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 favor of small, locally owned power plants instead of centralized power plants. Besides, the society was environmentally conscious, therefore their mind-set was highly in favor of renewables instead of nuclear energy (Sawin, 2001). Therefore the Danish government provided clear aims to the producers by stating that they wanted to reach a 10% wind share in electricity generation by 2000 which is named the EnergiPlan Act (Olume and 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% 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% of its price. This policy resulted in an increase in wind turbine installations.

In 1986-87 investment subsidy was reduced to 20% and 10% respectively. And this subsidy was removed totally in 1989 (Kamp, 2002). In addition, 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 by the end of 1990. However, this agreement was only totally realized at the end of 1992 (Buen, 2006).

Figure 2 shows an overview of policies over time and the wind turbine installations per year in Denmark during 1976-2002. The figure can be interpreted as the visual representation of the policy procedures and their effects on wind turbine installations. Note that the California tax rebate became an advantage for the Danish producers, since they export wind turbines to the U.S. This advantage contributed to their knowledge of building better wind turbines.



DIFKO = Joint company export financing; IS = investment subsidy; PS = production subsidy; TRI = turbine replacement incentive; GCS = green certificate scheme.

Figure 2. Annual wind turbine installations in Denmark and related policies (Buen, 2006)

4. Model structure

After describing the concepts for analyzing innovation diffusion and introducing the stories of California and Denmark, this section aims to bring them together into one modeling framework. The presence of the change processes and how they are shaped are explained in the following paragraphs.

4.1 Case studies and their relationship with the theory

The main similarities among these two cases in terms of the functions introduced in Table 1 are the following. Entrepreneurial activities (F1) were existent in both cases resulting in reduction in investment costs and improvement in the capacity factor of wind turbines by means of the learning-by-doing mechanism (Sawin, 2001; Kamp, 2002). The knowledge development function (F2) was also active in both cases, which is triggered by R&D investments of the governments. Knowledge diffusion through networks (F3) is also active in both cases, because this function implies individual and social learning about the new technology via direct experience of the adopter, or hearing, seeing or talking about the new technology. For the wind turbine installers, the individual learning mechanism was active, whereas for the other utilities which are considered as potential adopters, the social learning mechanism was active. Market formation (F5) was provided in a similar manner in both cases with the provision of subsidies, instead of creating a niche market or making a pilot program. Since there was no competitive environment among the renewable technologies, and the wind turbine was the only alternative to the conventional technologies, resource mobilization (F6) is not affected by other technologies, the only key-point was the governmental mind-set and the budget (nuclear energy was

on the agenda of the government, but it was excluded from comparison, due to its negative environmental perception).

There was no other alternative which could make commitment formation necessary (F4) since wind turbines were the only alternative in terms of cost competitiveness. Also, creating of legitimacy (F7) was not necessary, since the government itself wanted to have cleaner energy. This means that these two functions were not active in these cases.

The main mechanisms that were active can thus be summarized as learning-by-doing (F1, F2), learning-by-searching (F2, F6) and knowledge diffusion through networks/familiarity (F3). F5 consists of the policies that were implemented by the government.

These similarities show that both cases have the same diffusion structure with the same active and inactive mechanisms. Yet, the way in which these mechanisms work, created the differences between the two cases. For instance, the knowledge diffusion through the network was stronger in Denmark compared to California, because the government involved the utilities in the development of wind turbines from the beginning. The Danish Windmill Owners Association published a monthly magazine and brought wind turbine owners and potential adopters together with conferences from the early phases of wind turbine development (Kamp, 2002). Another difference between California and Denmark came from the determination of the Danish government and the Danish society on adopting wind turbines as an energy source from the beginning. They saw wind turbines as an only alternative, because they did not have any resources for fuel for conventional technologies, and they did not want nuclear energy with the security and environmental concerns. Last but not the least, even though the oil crises affected both countries, Denmark was affected more by this, because the average cost of producing energy from conventional sources was nearly three times more than the United States, which made an expensive option like wind turbines more affordable.

4.2 General model description

The active mechanisms mentioned above were used to model wind turbine diffusion with system dynamics. Since both cases have the same active mechanisms, the structure of the model is the same for both cases. The main mechanisms that were identified in the previous section, i.e. learning-by-doing (green-red loops R1 and R2), learning-by-searching (blue), and familiarity (orange-red loop R3) are shown in Figure 3. Although all mechanisms seem positive, the LCOE's of conventional technologies have to be considered as well, since the adoption decision is based on comparing LCOE of wind turbines with LCOE of conventional technologies.

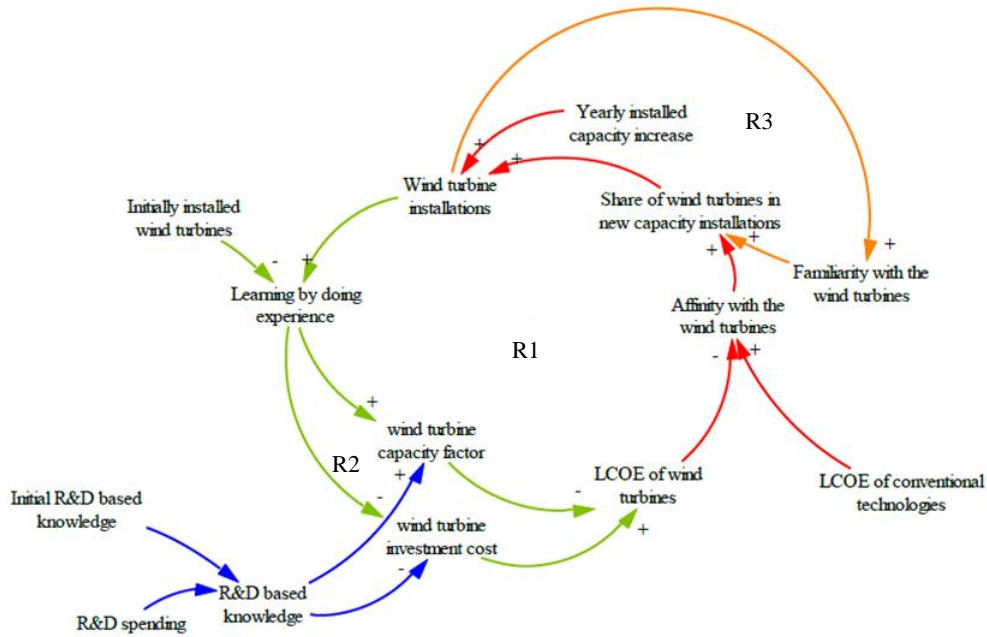


Figure 3. Causal loop diagram of the main mechanisms in the model

At an aggregated level there are two main influences on wind turbine installations, the familiarity with wind turbines and affinity with wind turbines. Familiarity increases with installations, and decreases with time. Affinity is a way of comparing wind turbines with other technologies and determining the share of wind turbines in new capacity installation. This comparison is based on the levelized cost of energy (LCOE). The LCOE represents the price of electricity at which electricity should be generated from a power source to break even over the lifetime of a power plant (NREL, 2013). It is a calculation method including both performance and cost related factors, such as capacity factor and investments costs, which improve over time by the learning-by-doing and learning-by-searching mechanisms. Appendix A contains a more detailed model description.

This diffusion structure (i.e. model structure) is the same for California and Denmark. The difference between the cases lies in the quantification of the model. The initial values and parameter values differ between the cases, and the policies that have been implemented also differ between the cases. The model has been represented in Vensim.

Before going through the model results, a brief explanation about the validation work should be given. With regard to model structure, a parameter confirmation test and dimensional consistency test were conducted. Following this, extreme conditions were applied to LCOE, familiarity and learning parameters and the results showed that the model behaves as expected under these extreme conditions. For the sensitivity analysis, the parameters were altered with a 10% increase and decrease. Univariate analysis was conducted using all parameters, and multi-variate analysis was conducted on parameters related with familiarity, on parameters related with learning curves, and on parameters related with affinity. The results showed that the model is numerically sensitive to the parameter value changes, as expected. The sensitivity to the alpha values which influence learning-by-doing is largest. The alpha values in the model were chosen so that the same cost and performance improvement would be achieved in the model from 1980 to 1995 as in the available data from these two years. A comparison with historical data (Figure 4 below and Appendix C) shows that the model is able to capture the main dynamics of the diffusion stories in California and Denmark. Although the actual data points show significant differences, the behavior is representative considering the high R^2 values.

5. Model Results

5.1 Base results

The initial results of the model for yearly installations of wind turbines are shown in Figure 4, with their fit to the real wind turbine installations. As the base results in Figure 4 show, the model is able to capture the stories of innovation diffusion. However, it should be noted that the initial settings are quite important to reach real world imitating results. Therefore, we have tried to set the initial values of variables in an explainable manner as much as possible (see Appendix B).

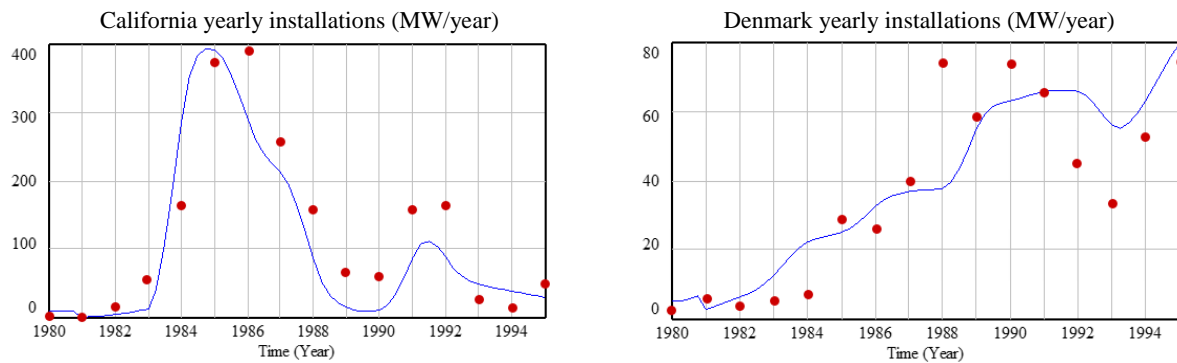


Figure 4. Comparison of model results and actual yearly wind turbine installations (red dots represent the real values whereas blue lines are the model results)

The blue lines in Figure 5 show the model results for the total installed capacity of wind turbines over the years. The behavior of the model without any policy interventions is also shown in Figure 5 (red lines), indicating the results of different initial conditions and parameters of these cases.

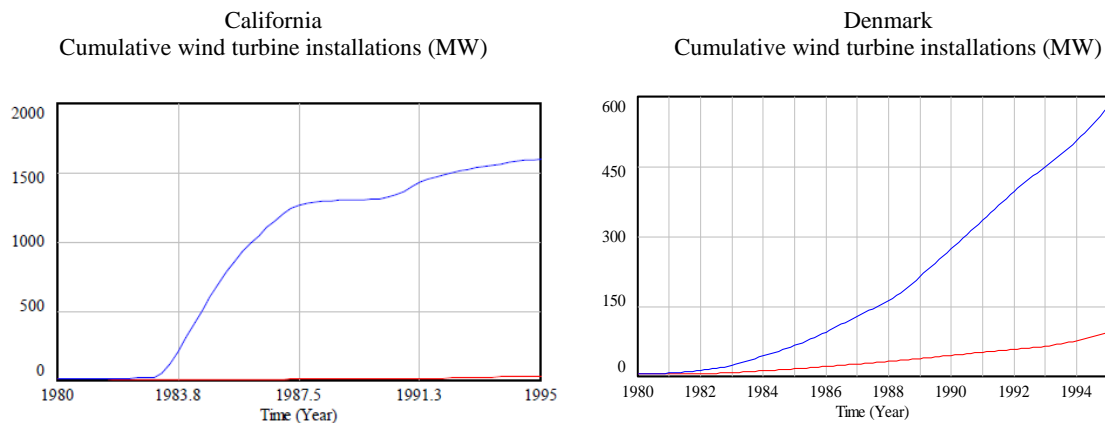


Figure 5. Cumulative wind turbine installations with (blue) and without policies (red)

As is clear from Figure 5 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 the following combined effects:

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 is 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 effect was coming from the bottom, where the investors and entrepreneurs worked together for effective communication. Such a movement was not observed in the 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 the demand share of wind turbines.

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 (note that Denmark also gained advantage from the California tax rebate, which was modelled implicitly by calibrating the learning-by-doing factor). 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. However, without any policy intervention, the rate of innovation diffusion would still be low in Denmark. Thus, it would be wrong to conclude that the policies were not the real reasons for fostering wind turbine diffusion. For this reason, policy tests were conducted to see the effects of policies in fostering wind turbine diffusion.

5.2 Policy tests

All policies were implemented in isolation to observe the sole effects on the diffusion, and also all-but-one type of policy tests were conducted by removing a policy from the full model to see whether there is a policy that hinders the installation rate. Additionally, the policies existing in one of the cases but not in the other one were also added to the other model to see what would be the possible consequences of that policy. For example a PURPA act type of policy did not exist in Denmark, but for a what-if analysis it was put into the Danish model. The results for each policy are explained briefly below. The graphs are mainly shown in total installed capacity, since it is the main variable representing adoption, however graphs of yearly installations are also shown if there is interesting behavior.

Effect of R&D efforts

The effect of R&D investments on wind turbine installations triggers the learning-by-searching mechanism, leading to a decrease in LCOE of wind turbines and making it a more attractive option for the utilities. However, the results show that this effect is quite small for fostering wind turbine installations (Figure 6).

California(MW)

Denmark(MW)

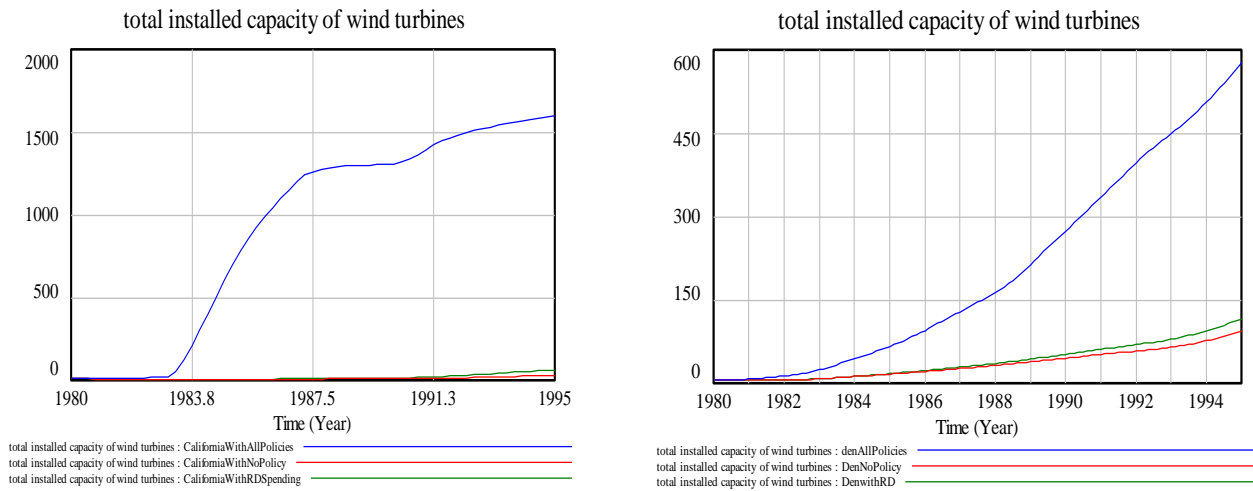


Figure 6. Effect of R&D investments on cumulative wind turbine installations

It is important to note that, in total the United States spent 538.5 million (in 1980 \$) from 1980 to 1995, 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(in 1980\$ value), and they spent 12.5 million from 1970 to 1980 which was treated as an initial value (Norberg-Bohm, 2000; Sawin, 2001). These results show that, in the model learning-by-searching mechanisms are not enough for effective diffusion, because it takes time to reach a cost competitive result 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.

Effect of subsidies

The effect of subsidies on wind turbine installations aims at the demand for wind turbines by directly influencing the LCOE. The subsidies in general are more effective than R&D efforts (Figure 6), but they do not contribute to the diffusion significantly (Figure 7).

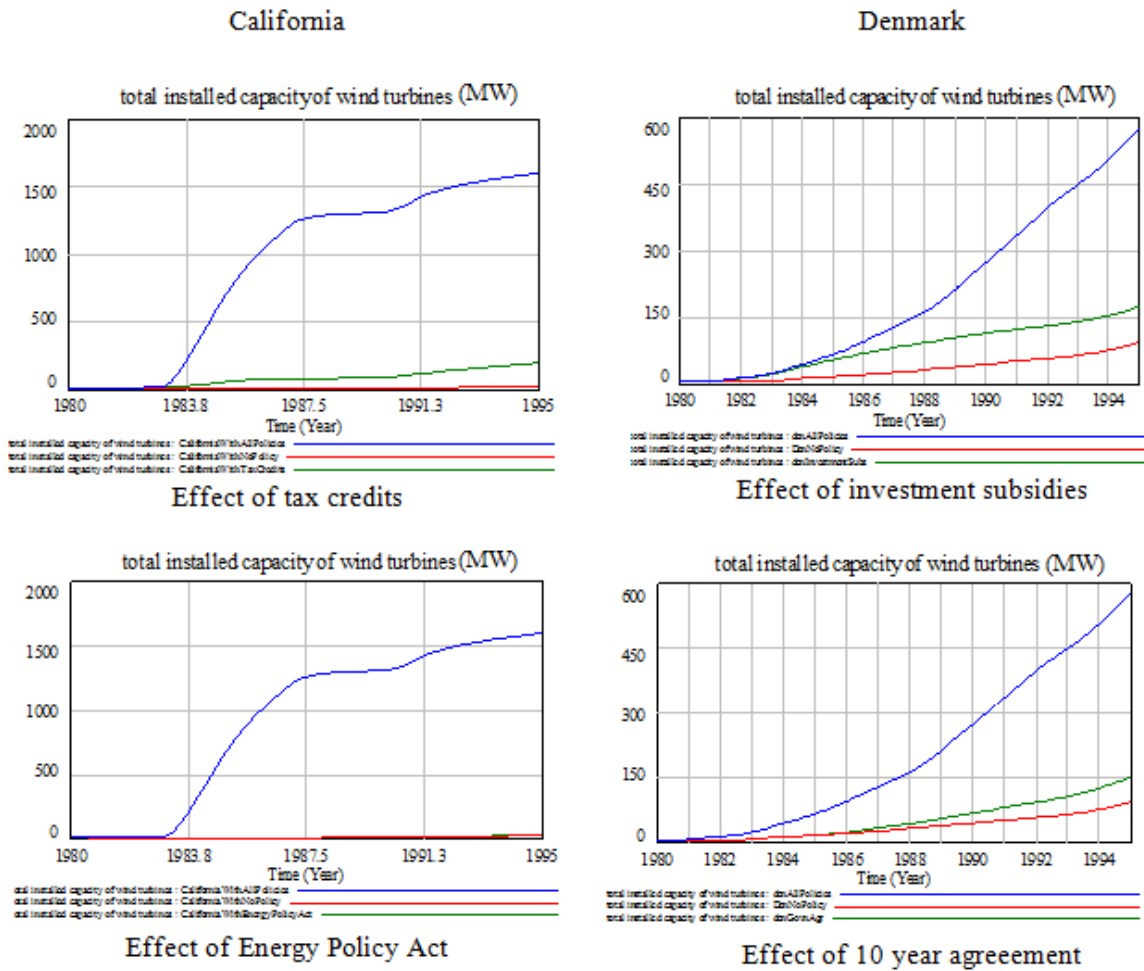


Figure 7. Effect of subsidies on wind turbine installations

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 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.

Effect of the PURPA act

The PURPA act, which was explained in section 3.1, required utilities to purchase power from qualifying facilities. The effect of the PURPA act on wind turbine installations shows that this policy is quite effective in California, making the cost effectiveness of the wind turbines closer to the conventional technologies (Figure 8).

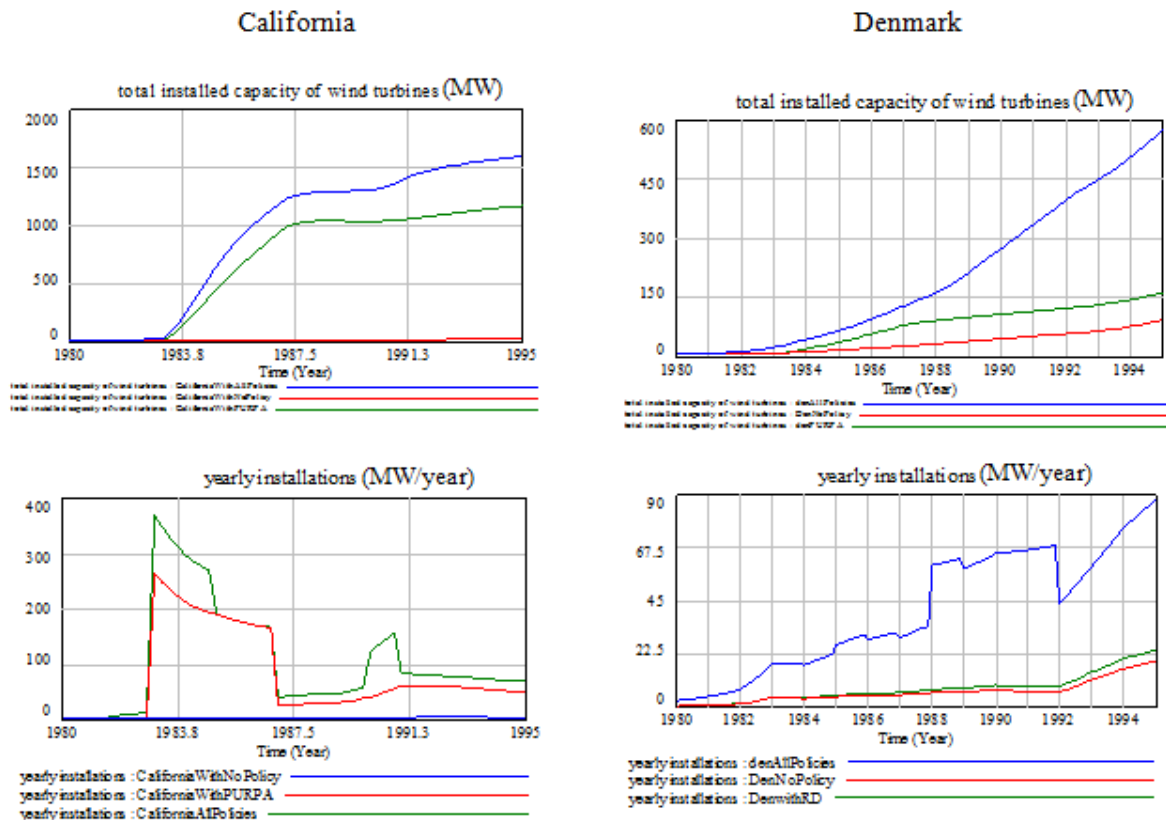


Figure 8. Effect of the PURPA act on wind turbine installations

In Denmark, the cost of conventional technologies is 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 (meaning that they still thought it was expensive). The level of affinity is not that strong in Denmark with the 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.

Effect of the EnergiPlan act

The EnergiPlan act policy, which aims for a %10 energy share of wind turbines by 2000, represents the determination of the Danish government in setting wind turbines as the only energy alternative and determining persistent goals for the wind turbine share in energy generation. This policy has a soft effect similar to marketing, making the option visible to consumers. 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 (Figure 9).

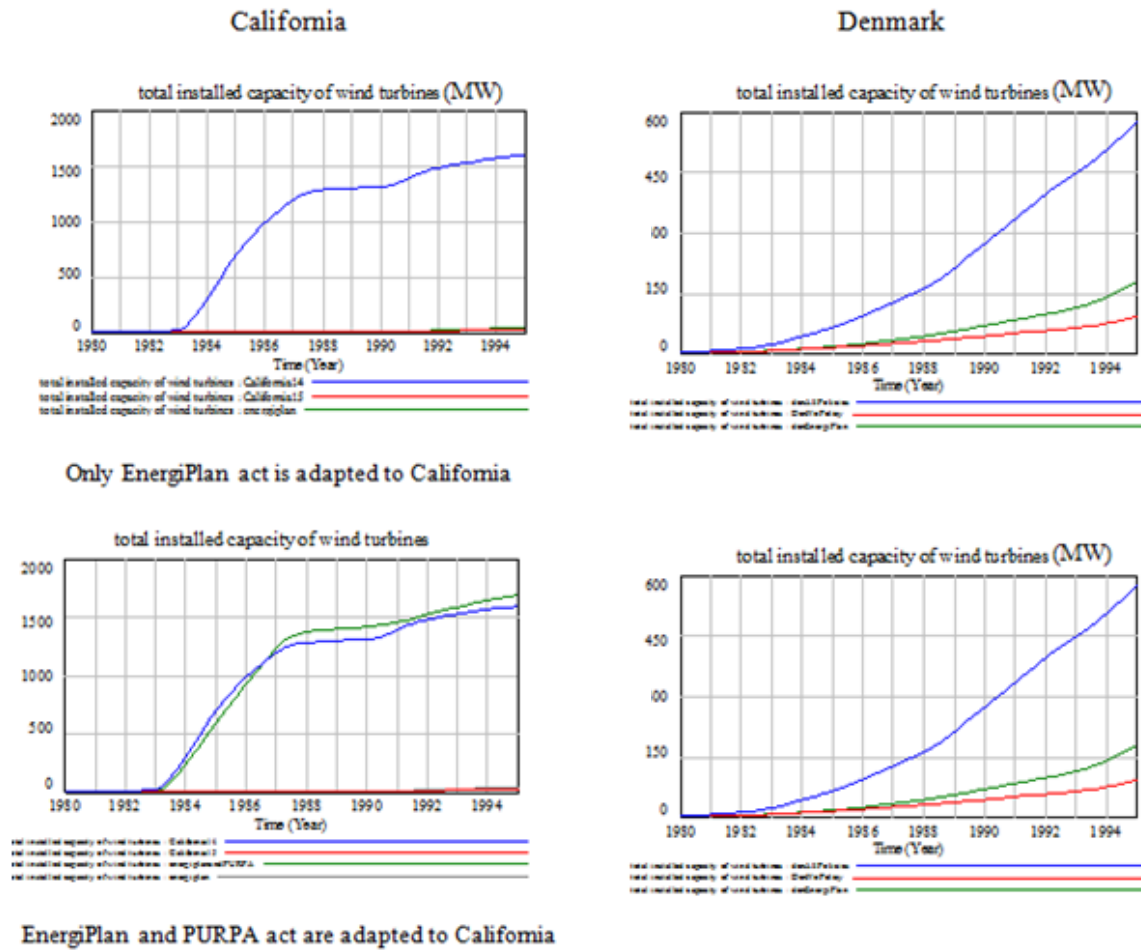


Figure 9. Effect of the EnergiPlan act on wind turbine installations

The results show that in isolation the EnergiPlan act also does not have a significant effect, because even though the familiarity plays a significant role in adoption, it is not sufficient by itself, because if the option remains expensive, people would not purchase it. Therefore, the effect of this policy is also tested with the PURPA act and the results showed that awareness campaigns in addition to demand-pull policies have significant effects in fostering diffusion.

Effect of long-term contracts

As an extension of the PURPA act, California offered long-term contracts for installing wind turbines. There was no such offer in Denmark, therefore this policy is implemented in the Denmark model to see the possible effects (Figure 10). This policy creates a temporary demand for installing wind turbines, but the effects are not as strong as the PURPA act. The results of the Danish case also shows similar results.

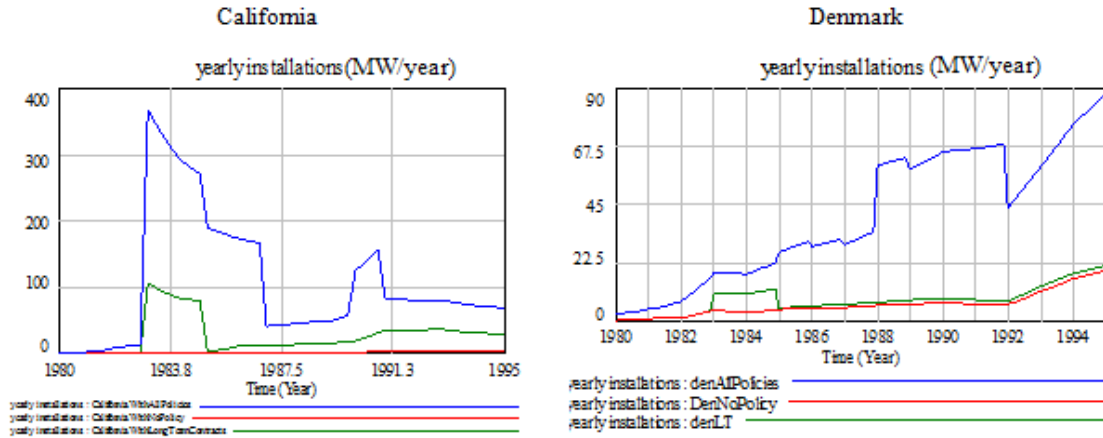


Figure 10. Effects of long-term contracts on wind turbine installations

Effect of government installing wind turbines

Denmark decided to install 100 MW of wind turbines with government funding with an agreement with the utilities from 1988 to 1992. There was no such attempt in California, therefore to show the possible results this addition is modelled (Figure 11).

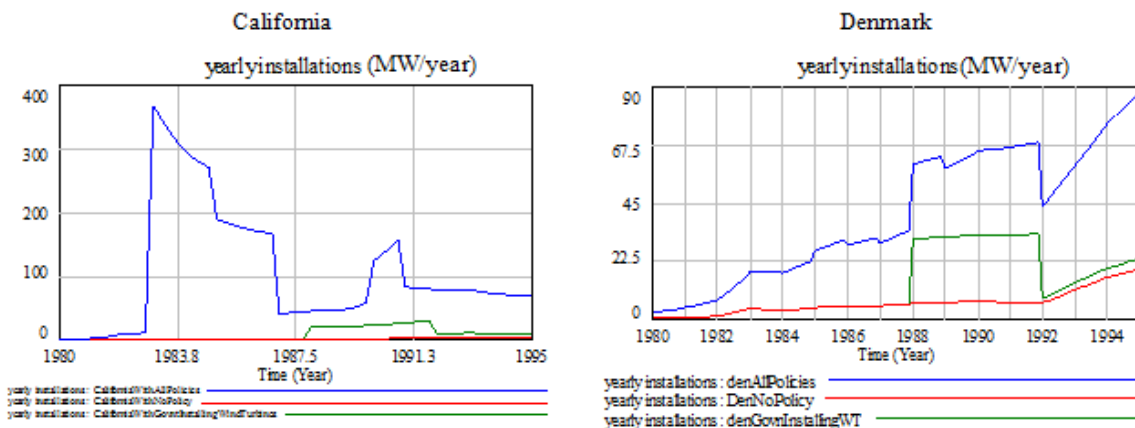


Figure 11. Effect of government installing wind turbines on diffusion

The results show that the effect of governmental installing wind turbines has a temporary boost in the installations. Also, the familiarity changes were checked for these external installations and the model shows almost no change in familiarity. The reason for this is because these installations are added from outside the system, and it does not affect the yearly installations done by utilities or cooperatives.

Therefore, the affinity to wind turbine installations does not change, leading to no change in familiarity. 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.

5.3 Summary of model results

The model shows that the differences between the 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 had no interest in building networks regarding wind turbines, which also resulted in decreasing familiarity with 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 to 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, policy interventions exist to counteract the disadvantageous situation of California. From a policy making perspective, we see that the most effective policies in both cases are 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 model results also show that the direct interventions on installing wind turbines such as long term contracts in California and government installing wind turbines in Denmark have temporary effects on diffusion, whereas the effects of stimulating markets also impacts the adoption in the future due to increased familiarity and triggered a 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 according to the results of the model.

6. Discussion and Conclusions

This research is an attempt to explain innovation diffusion with a more comprehensive dynamic approach. The study showed promising results in behaviour for modelling innovation diffusion, by looking at diffusion stories which occurred in the past. Even though the data points showed significant differences, the behavior was representative, making it useful for analyzing the behavior of the diffusion. This way it was possible to observe the ability of the system dynamics method to capture the different diffusion paths. This could be an indication for future studies, with the suggestion of forecasting the direction of a certain technology in society with planned policies.

Developing a system dynamics model for a historical case is not often done in the system dynamics literature. This case has shown that this can also be an interesting contribution to the knowledge about a case, as it allows for a coherent and integrated dynamic explanation of the development of the case over time.

System dynamics also brought a new ability to test the non-existent policies which could be considered as a what-if analysis. With the common methods, such as regression analysis, such a transparent what-if analysis is not possible. Therefore for understanding the possible effects of a policy, system dynamics may be used. Additionally, this study also showed that the supply side of the innovation of diffusion is worth considering, since it has important effects on creating the demand.

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 have remained theoretical so far (Hekkert's FIS has not been implemented in a quantified manner to the authors' knowledge). This study was also an attempt to apply these theoretical suggestions to case studies. To test the validity of these theories, more case studies should be conducted with other well-known diffusion stories. This way, the strength of these theories can be supported.

It should be noted that the conditions and the mind-sets of the actors have changed in wind turbine diffusion since the 1980s. At that time, the knowledge about environmental hazards coming from 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 today, the number of environmentally friendly consumers has increased, demanding green energy from the utilities even at a higher price. The change of this mind-set offers a new research focus, to understand the change in people's minds and the factors affecting this change.

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Appendix A Model description

This appendix contains more details about the implementation of the model structure, which was shown at an aggregated level in Figure 3.

The learning-by-searching and learning-by-doing mechanisms are modelled with the two factor learning curve formula (Kouvaritakis et al., 2000).

The formula for cost improvement is as follows:

$$SPC = A \cdot \left(\frac{CC}{CC_0}\right)^{-\alpha} \cdot \left(\frac{KS}{KS_0}\right)^{-\beta} \quad (1)$$

In equation (1), SPC stands for the investment cost per unit for the technology (specific cost) and CC is the cumulative installed capacity at a given time, which is divided by the cumulative capacity at time 0 (CC_0). $-\alpha$ is the learning factor, and A is the specific cost at time 0. KS stands for the knowledge stock at a given time, measured by the R&D investments of that year. KS_0 is the initial knowledge stock and β represents the learning by searching factor, which is the representation of the percentage improvement on the investment cost coming from the learning-by-searching process, similar to $-\alpha$ representing the percentage improvement of learning-by-doing process. This formula is also adopted for performance improvement of the capacity factor, with positive α and β values.

Affinity with wind turbines represents the probability of an actor to purchase wind turbines by comparing it with the conventional technologies. Modelling affinity and familiarity is adopted from Struben and Sterman's (2008) work on electric vehicle adoption. The formula of affinity is based on standard multinomial logit choice models, which is a commonly used framework in modelling consumer choice among the different options in the consideration set. In this case, the consideration set consists of wind turbine vs. conventional technologies:

$$a_j = a^* \exp\left(-\delta \left[\frac{LCOE_j}{LCOE^*} - 1\right]\right) \quad (2)$$

Equation (2) represents the affinity of wind turbines based on LCOE. a_j is the affinity towards wind turbines at a given time, where a^* represents the reference affinity for the reference $LCOE$ value $LCOE^*$. The reference value stands for a normal value that the adopter has an idea about. For example, an actor decides whether the given $LCOE$ of the available options is 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, on the 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 a 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. The formulation of $LCOE$ is given in (3):

$$LCOE_t = \frac{EAC}{E_t} + M_t + F_t \quad (3)$$

where

$$EAC = \frac{I_0 \cdot r \cdot (1+r)^n}{(1+r)^{n+1}} \quad (4)$$

EAC stands for equivalent annual cost representing the cost per year of owning and operating an asset over its lifetime (Short et al., 1995). I_0 represents the overnight cost of the project meaning if the project was completed overnight (no interest rate was taken into account). E_t stands for the electricity generation in the year t , r stands for discount rate, n represents the lifetime of the project (which is 20 years for wind turbines), M_t represents the operation and maintenance cost in year t and F_t represents the fuel cost in year t . Utilities make their decision based on this LCOE in the model with the corresponding affinity to the LCOE of that year.

However, to be able to consider wind turbines as an option of energy generation, the actor should be familiar with it. Knowledge diffusion through networks is another important part of the diffusion process, therefore familiarity should also be modelled. Modelling familiarity is also adopted from Struben & Sterman's (2008) study. The causal loops are shown in Figure A1.

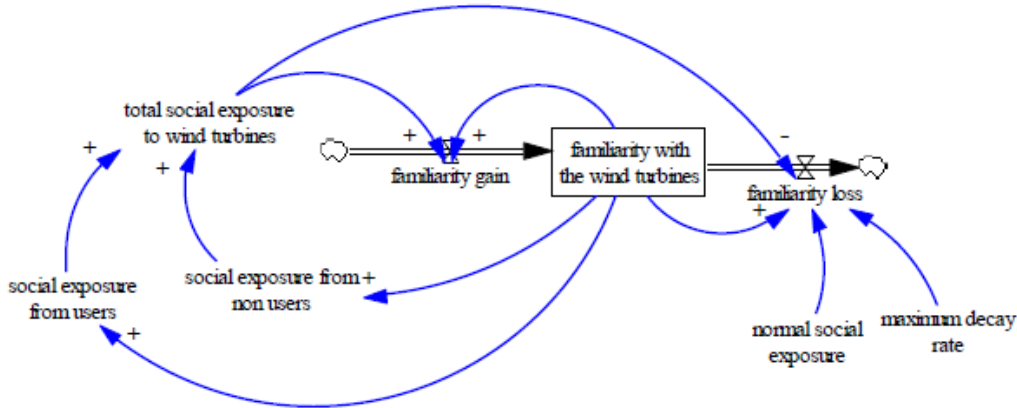


Figure A1. Stock-flow diagram for modelling Familiarity

Familiarity is a stock variable between 0 and 1, where 0 represents no familiarity with the technology and 1 represents that all adopters and potential adopters are familiar with the new technology. Familiarity gain is determined by the social exposure coming from marketing campaigns, individual learning and social exposure coming from the users, and finally the social learning standing for the social exposure coming from non-users, which is word-of-mouth. The equation is shown below:

$$n_t = a + c_i F \left(\frac{W}{N} \right) + c_j F \left(1 - \frac{W}{N} \right) \quad (5)$$

In the familiarity gain equation which is illustrated in (5), a represents the social exposure gained by marketing/awareness programmes c_i represents the effectiveness ratio of the users, F represents the 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 also decays over time, when there is not enough social exposure. This decay occurs in a non-linear way, because if the level of social exposure is low, familiarity decays very fast, but if the

level of social exposure is high it does not. This is modelled with the following exponential function (Struben and Sterman, 2008):

$$\phi_t = \phi_0 \frac{\exp(-4\varepsilon(n_t - n^*))}{1 + \exp(-4\varepsilon(n_t - n^*))} \quad (6)$$

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 the decay. ϕ_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.

Appendix B- Initial Settings for the Model

Although the active mechanisms for California and Denmark are the same in the model, 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 values of these variables and the reasoning behind those values are shown in the Table below.

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 a more 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). 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 based on available data. Note that these beta values are also less effective compared to alpha values which are 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 increase the knowledge of nonusers. For this reason, the effectiveness of contacts of non-users is assumed to be 7% 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 12% less in CA.
Initial familiarity	0.25	0.25	Initial familiarity with the wind turbines was low but not zero for both cases. Both CA and DK had historical experiences with wind turbines (see Section 3) and they were familiar with the windmills. There was 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 (in MW).
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) 0.0265 (stdev)	0.77 (mean) 0.0172 (stdev)	The interest rates are also taken from the literature (Sawin, 2001).
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%	These 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 weighted 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 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.

Appendix C – R2 and MAE/Mean Tests Results

The tables below show the real data, model data and the results of these tests.

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
R2	0.87		0.98		0.76	
MAE/Mean	10.95%		15.09%		27.56%	

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
R2	0.96		0.96		0.83	
MAE/Mean	7%		13%		39%	