Dynamics of Innovation and Diffusion in Large-Scale Complex Technical Systems: the Case of Wind Energy

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"The World Market [for new wind plant capacity] is 55 GW and the US market is X."
CEO of a large wind turbine OEM's at a recent US Windpower conference

The quote above illustrates the instability in the US market over the years. Inconsistent policy, such as the on-again, off-again production-tax credit scheme in the US, is as a key source for boom and bust cycles in the country's wind energy industry (U.S. Department of Energy, 2015). Over the last several decades, various incentive systems governments have implemented and removed in a number of nations and states across the globe. The stops and starts of policy supports in key markets (such as the US in the 1980s) have brought about rapid growth and subsequent collapse of the local industry only to be restarted again by new policy incentives in later years (van Est, 1999). The quote above also highlights that regardless of instability in one wind energy market, in this case the US, the industry expects relatively stable global demand. Policies across several nations since the mid-1980s have led to a relatively stable and growing global market for wind energy that has enabled significant innovation in wind energy technology to the present day. This paper examines the interplay of technology innovation and diffusion dynamics where markets for the technology are local but innovation is global. The author develops a system dynamics model through the combined use of theory and data calibration for wind energy innovation (global) and diffusion (local). The model captures the effects of inconsistent policy for different nations and states while demonstrating that the global aggregation of market demand has enabled continuous technical innovation, which then feeds back to condition local conditions. The result of this turbulent process has enabled wind energy to become a significant component of the global electricity generation portfolio.

Keywords: Wind Energy, Diffusion, Renewable Energy, Technology Policy, Policy Incentives, System Dynamics

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Introduction

By the time that the 1973 oil crisis occurred, large-scale dependency on fossil fuels for electricity generation existed across the world. For Denmark and the US, the key players for large-scale wind energy deployment in the early 1980s, where there was past concern for coal shortages, the oil-based electricity generation that had replaced coal in each system was now problematic.

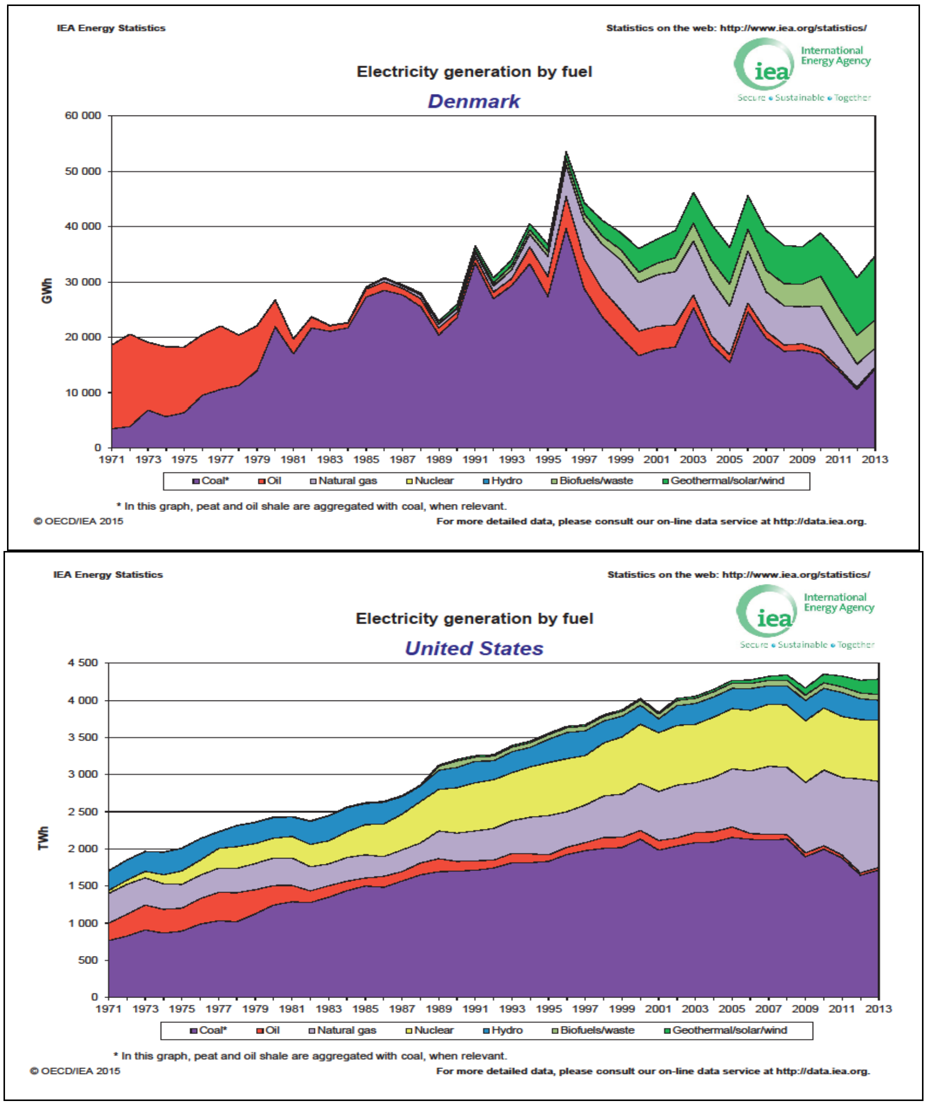


Figure 1: Electricity Generation by energy source for Denmark and the US from 1971 to 2013 (International Energy Agency, 2016).

As noted above, both the US and Denmark reduced the use of oil for electricity generation from the late 1970s onward because of the oil crisis. The oil crisis thus directly created an époque of innovation and diffusion of the wind energy technology. However, a stable and sustainable wind industry did not blossom immediately. Resistance from established vertically integrated utilities as well as high costs of wind energy was both impediments to growth of the sector. Governments enacted wide variety of national policies and laws to invoke change in the electric utility sectors across Europe and the US in order to allow for the development of wind energy and other non-oil electricity generation technologies. Certain countries, such as the US, sought to create a more competitive electricity market for energy. The *Public Utility Regulatory Policies Act* of 1978 was the first in a wave of federal legislation seeking to deregulate the electricity market and to incentivize non-oil based forms of electricity production (Gipe, 1995). On the other hand, many European countries with more centralized governmental control over their electric sectors introduced mandates for change. As discussed, Denmark initially promoted nuclear power but found strong resistance from the public. This led them to negotiate a path for reform directly with their utilities and this resulted in investment subsidies and brokered power purchase deals for wind energy (van Est, 1999).

Despite these bold historical initiatives, changing policy landscapes for wind energy have been in general been unstable. In the mid-1980's, the oil-crisis subsided and the Reagan administration removed the policy support for wind energy that had fueled the "wind rush" (Gipe, 1995). Industry as a result experienced cases of widespread bankruptcy both in the US and Europe. Few companies survived during this period and those that did, predominantly in Denmark, relied on substantial government support for continued operation (van Est, 1999). In the subsequent decade, due once again to renewed policy support for wind energy first in Europe, development rebounded. Eventually in 2000 and after, the US and other global markets adopted policy support for wind energy once again spurring a decade and a half of exponential growth. Below is a chart of global wind installations from 1981 to 2000.

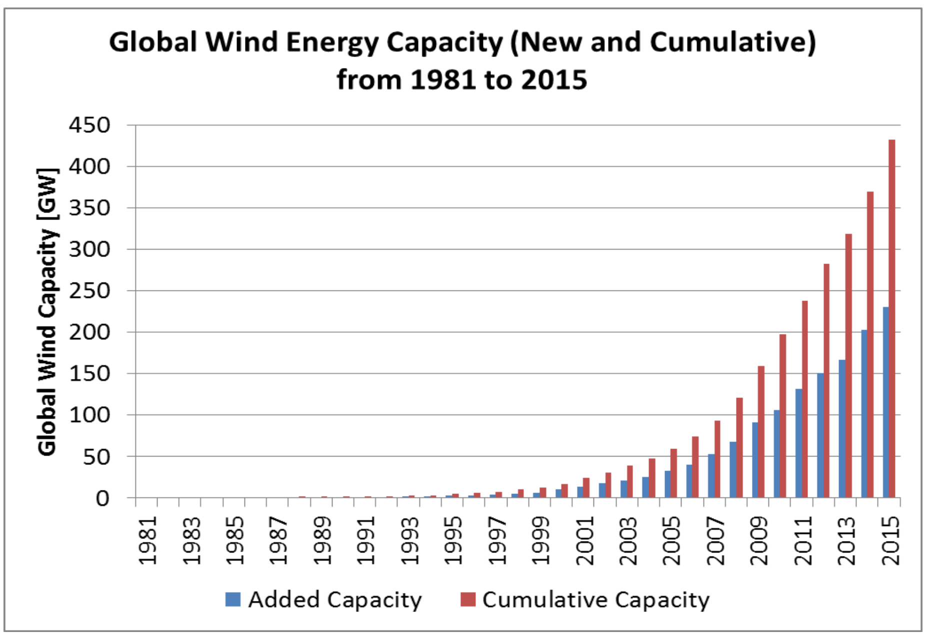


Figure 2: Global and National Wind Diffusion Levels (the Wind Power Net 2015, Eco Indicators 2009, GWEC, 2014)

The next graphic shows that despite the smooth growth profile for the industry in terms of installed capacity, the trend in individual countries has been far less consistent. The dramatic rise and crash of the US market in the 1980's was followed by a period in which favorable German then Danish and Spanish subsidies drove the market in the 1990's till the US again adopted favorable (though inconsistent) policy to promote wind after 2000. In addition, after 2000, non-European countries began looking to wind energy for electricity generation. Led by India and then China, the rest of the world became a more prominent adopter of the technology to the point where Europe and the US constitute a little over a third of the global market for wind energy. Thus, the remarks of the CEO reflect the current and historic wind energy climate – sustained growth globally, volatile markets locally.

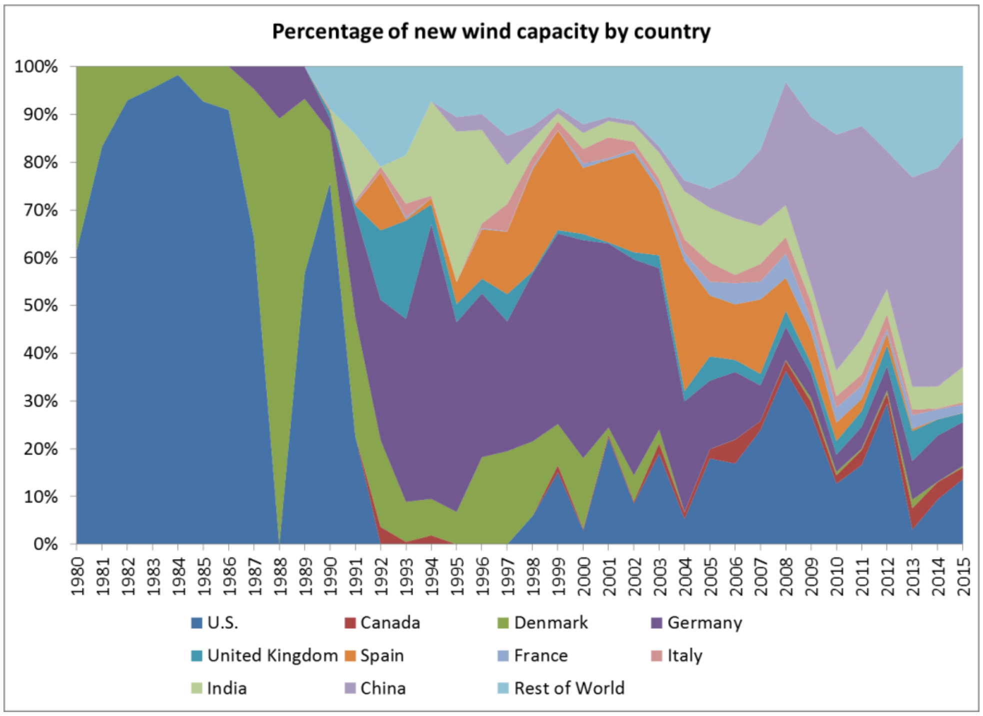


Figure 3: Percent of new global wind energy installed capacity by country (the Wind Power Net 2015, Eco Indicators 2009, and GWEC, 2014)

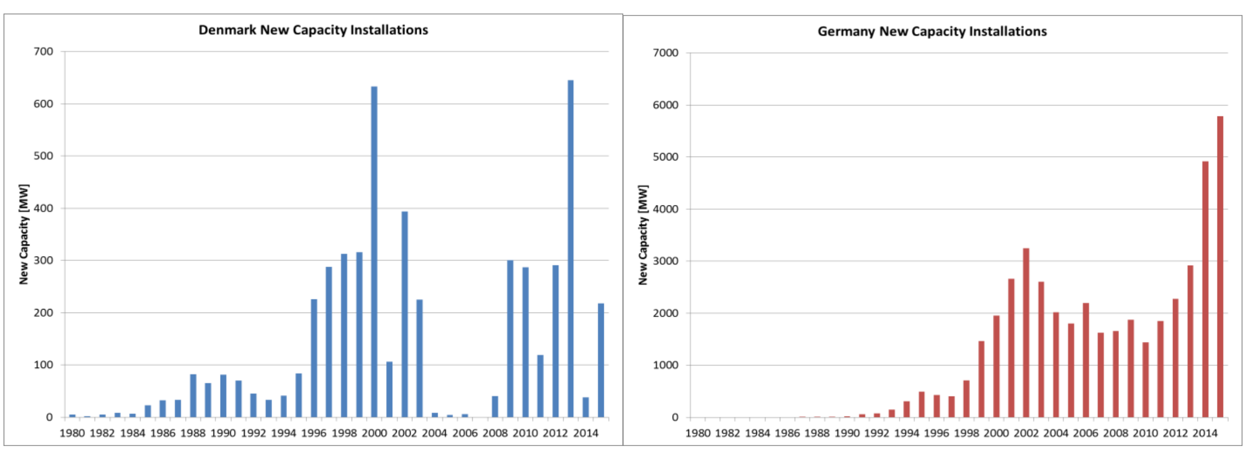


Figure 4: Capacity Installations for Select Countries by Year.

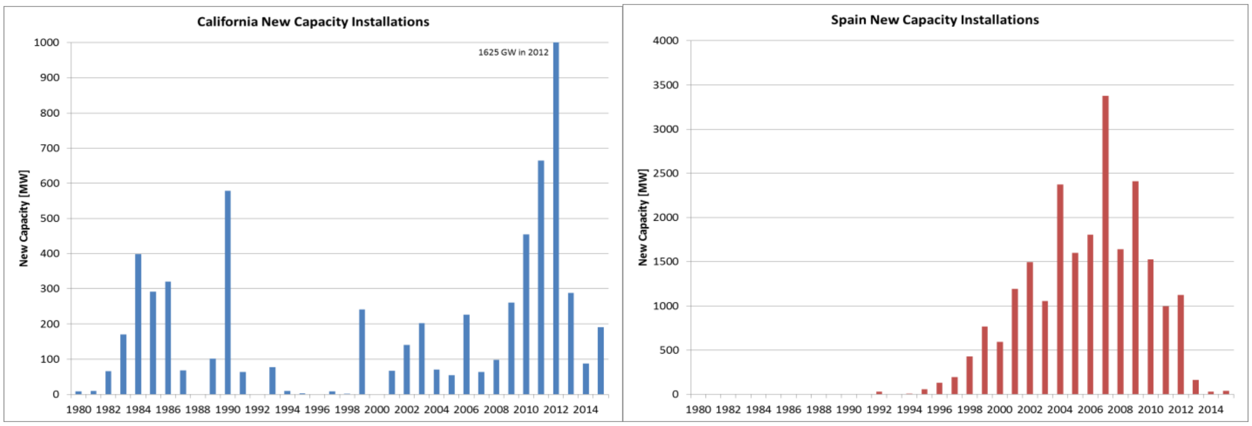
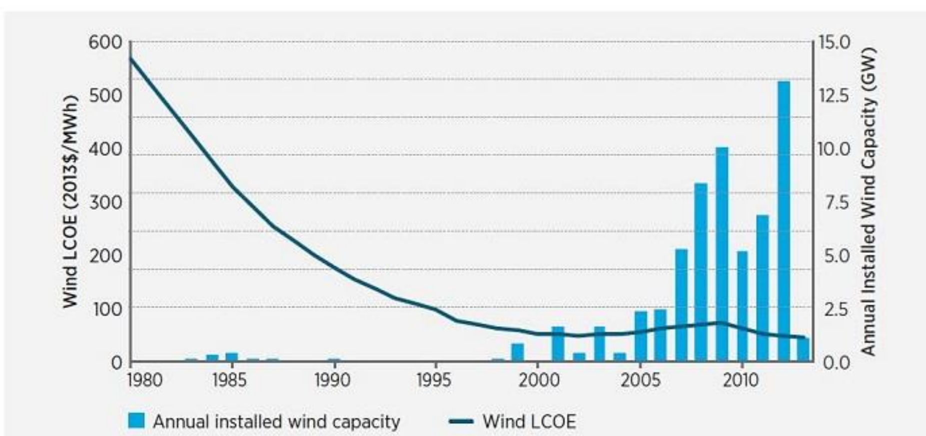


Figure 5: Capacity Installations for Select Countries by Year.

Some would argue that the industry today with a relatively consistently growing global demand has finally become self-sustaining. The current action of the US government to phase out the main federal policy support for wind, the production tax credit (U.S. Energy Information Adminstration, 2016), is indicative of this perspective that wind energy is moving towards parity with other energy technologies and should no longer need policy support to remain competitive. At the same time, the wind energy sector, in all countries where it is currently active, relies upon considerable government support. A metric often used to characterize the relative competitiveness of energy technologies is the levelized cost of energy (LCOE), which includes all capital and operating costs normalized to the current year divided by the expected annual energy production. As seen in the graphic, wind energy LCOE for US projects has decreased continuously since the early 1980's with the exception of the period around year 2010 when supply constraints and high commodity prices led to increasing wind turbine costs and pricing (U.S. Department of Energy, 2015). Current LCOE estimates for a US site with good wind resource are \$0.045/kWh and lower versus upwards of \$0.50/kWh in the early 1980's.



Note: In the *Wind Vision*, 'good to excellent sites' are those with average wind speeds of 7.5 meters per second (m/s) or higher at hub height. LCOE estimates exclude the PTC.

Source: Adapted from Lawrence Berkeley National Laboratory 2014 data [23]

Figure 6: US DOE *Wind Vision* LCOE estimates for US based projects from the early 1980's through 2013. The LCOE for early projects are higher than those estimated by other sources including early Danish projects (Lantz, Wiser and Hand, 2012) but decreasing trend is present regardless of the source.

Across electricity generation technology, wind energy does indeed compare well on an unsubsidized basis in the US. The Energy Information Administration estimates that for plants installed in the next several years, unsubsidized LCOE for a typical wind plant will be about $0.059/kWh that is higher than the Wind Vision estimate by about $0.015/kWh (U.S. Energy Information Administration, 2016). However, analyses estimated that advanced combined-cycle natural gas plants have an LCOE for the same period of $0.056/kWh – only $0.003/kWh lower than wind energy. Thus, plans to remove subsidies in the US for wind energy by the early 2020's could still be compatible with continuing growth for wind in that country. On the other hand, discussion of the production tax credit "cliff" is common among industry representatives with many forecasting a rush of installations in the next few years before the federal government removes policy support and an abrupt cessation of development thereafter.

Analysts have made a wide variety of arguments regarding the influence of policy support for wind energy on technology development, adoption trends and firm behavior. This paper presents a system dynamics model that reflects the historic performance of different countries' wind energy markets. In so doing, we investigate the impact of policy on the respective development of different national markets for wind energy along with the development impacts on the industrial base and the technology innovation. The results provide insight into the dynamic relationships between policy, technology adoption, and industry development in order to guide national policy-making strategy for future development of the wind energy sector.

Modeling Wind Energy Diffusion

Before formulating the model, a theoretical understanding of technology diffusion is critical. As discussed, there are two basic types of technology diffusion models. The first is a "threshold model" that focuses on economic factors as the main determinants for the adoption of a product or technology (Griliches, 1957). The second are "social models" of diffusion relied on social contagion as the main factor influencing adoption (Bass, 1969; Rogers, 1995; Ryan and Gross, 1943; Mahajan and Peterson, 1985; Mahajan, 1990). The basic "Bass model" of diffusion has become especially prominent and well known in marketing and has been used substantially in prior System Dynamics studies (Homer, 1987; Sterman, 2000; Milling and Maier, 2001). In contrast to the aggregated form of the system dynamic / Bass model of diffusion, "network models" of diffusion have also been developed which attempt to capture how complexity within the social networks affect product and technology adoption. Aspects related to network structure, the heterogeneity of network agents and relationships, and sequence or timing have all been shown to influence the adoption process (Valente 1995). Finally, a last main category of diffusion models brings together the economic aspects of threshold models and the social aspects of the Bass diffusion models. These "mixed-influence models" are particularly well-suited for analysis using system dynamics since the combination of economic and social effects can be well-modeled using additional feedback relationships affecting adoption behavior (Sterman, 2000; Milling and Maier, 2001; Granovetter, 1985; Weil, 1998).

For wind energy adoption, a mixed-influence model is useful to describe both the economic and social aspects affecting diffusion. In fact, a few such models have previously been developed specifically to look at wind energy adoption (Pruyt, 2004; Dyner, 2006). The first model by Pruyt was designed in order to critique a spreadsheet model of diffusion that was created outside of the system dynamics framework and thus ignored key feedback relationships in the system. In particular, he critiques the model for ignoring the development of wind energy sector capacity which is believed to be a critical oversight of the original model. Secondly, he relaxes various assumptions of the original model regarding learning processes for the technology that affect turbine performance and cost overtime. He compares the results of the new model behavior with those projected by the original model in terms of industry performance, installed capacity of WECS and the consequences for greenhouse gas emissions. The model does a good job of identifying the weaknesses associated with lack of feedbacks in the original model and adds critical endogenous relationships. However, the model was designed specifically to be aligned with the GWEC Windforce12 model and thus does not get into the comparative policy evaluation as is proposed in this study. In addition, there are no aspects related to wind resource availability (carrying capacity) and its effects on profitability nor the social dynamics previously discussed including utility and/or public resistance or support.

The second model by Dyner (2006) is a diffusion model for wind energy but takes into account a much more brought set of relationships related to the overall electricity market at the expense of detailed modeling for the wind industry in particular. For instance, the Dyner model does not address aspects related to job creation or industry capacity which are key features of the GWEC Windforce 12 / Pruyt 2004 model. Advantages of the Dyner model are the added endogenous relationships regarding expansion of wind and the overall electricity market supply, demand and price as well as a more detailed financial model of the wind industry including income, cash flow, debt and financial indicators. Thus, the decision to invest is more nuanced in terms of its dependence on the endogenous price of electricity and the influence of financial factors on expected profitability. The importance of the combination of the industry capacity aspects of the Pruyt 2004 model, the endogenous electricity aspects of the Dyner 2006 model, and the learning curve effects in both models will be discussed in more detail in the model formulation section of this paper.

It is worth noting that there is another model paradigm that has been used to explore the adoption of wind energy: capacity expansion. Capacity expansion models, both using system dynamics or more traditional economic optimization models, reflect the overall development of an entire regional electricity system (Vogstad, 2002). Such models can either focus exclusively on generation or also incorporate aspects of transmission as well. Similarly Dyner 2006, these models incorporate an endogenous relationship between market supply, demand and price of different generation sources. Various applications of capacity expansion models using system dynamics have looked at wind energy development in addition to suite of different electricity generation options (Ozdemeir, 2002; Ford, 1996, 1999; Pruyt, 2004; Vogstad, 2002; Karstad, 2009). Indeed, the diffusion model developed in this paper could be adapted for incorporation into a capacity expansion model. However, two reasons led to the decision to implement a diffusion model for this specific research project. The first reason was desire to isolate wind energy adoption as the unit of analysis for this work and detailed modeling such a focus required. Secondly, the desire to do broad comparison of different national cases in terms of both calibrating and performing model analysis meant that a diffusion model was more appropriate for tractability. Thus, the model discussed in the subsequent sections falls into the category of an aggregate mixed-influence diffusion model for technology adoption.

Integrating Innovation and Diffusion Dynamics

While learning curves are simplistic representations of technology innovation, they do embody the important phenomena that there is interplay between technology innovation and diffusion. While a "market push" model of innovation suggests that innovation is possible in isolation, "demand pull", "user innovation" and most other theories of the subject rely on adoption of the technology in order to push forward its development. There is an explicit link between the innovation of a technology and its adoption. As a market adopts a technology, there is learning at many levels including the design, manufacturing, deployment, use and operation. This learning leads to innovation that in turn improves the desirability of the technology for one or potentially several metrics such as cost, improved performance, increased functionality, etc. The desirability influences additional adoption and a positive feedback process is established.

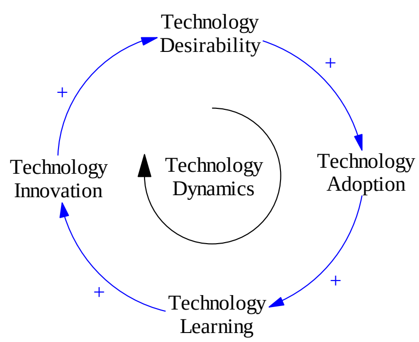


Figure 7: Illustration of the basic dynamics of innovation and diffusion.

While seemingly obvious, this basic feedback is critical in particular to technologies of large-scale complex socio-technical systems. Complex systems have many interlinked components and subsystems—they may even involve systems of systems—where the "whole is more than the sum of the parts" and significant physical coupling is present throughout. Secondly, these systems tend to have a large degree of heterogeneity with respect to design conditions. Finally, uncertainty means that these systems face significant sources of uncertainty throughout their design, development and deployment. In order to innovate, it is necessary to develop more understanding of the complexity, heterogeneity and uncertainty that these systems face. Through diffusion, learning takes place around the system complexity in terms of a better understanding of the coupling, reducing the uncertainty and experience with various heterogeneous external conditions. This drives further innovation and the positive feedback loop of innovation and diffusion dynamics. Wind energy is a large-scale complex socio-technical system that embodies all of these attributes (Dykes 2011). Thus, modeling the diffusion of wind energy needs to account for not just the market dynamics, but the dynamics of innovation as well.

A System Dynamics Model of Wind Energy Innovation and Diffusion: Model Formulation

Even in 2016, the complex, uncertain and heterogeneous nature of wind energy technology means that innovation depends on deployment. Diffusion drives technical learning that leads to improved system performance and reduced costs which leads to further adoption of the technology. As discussed, the diffusion of wind energy over the last several decades has taken place in one market continuously but instead has been supported by the aggregation of demand across several markets which themselves have each at times been volatile. This system dynamics model for wind deployment and technological innovation depends addresses these interactive global and local dynamics.

Theoretical Derivation –Causal Loop Diagram and Key Assumptions

The basic theoretical framework used in this study is a threshold model of diffusion with additional dynamics for industry development and endogenous technological innovation or learning. In order to reduce the scope of the study and keep the model tractable, we allow a few important simplifying assumptions:

1. Technology evolution / innovation are global phenomena independent of any individual state activity. Wind turbine OEMs have traditionally operated in many national markets with the top global firms competing for market share in every active market. Increasingly, OEM's tailor their product platforms for different market segments with different needs; however, the technology deployed globally is similar. The main caveat to this is the recent rise of Chinese OEM's. These OEM's were initially only active in Chinese and east Asian markets, but they too are now competing in global markets and have similar product offerings to those of other global OEM's. This also neglects the offshore market where wind turbine innovation has diverged from the land-based markets with turbine sizes much larger than their land-based counterparts do. Future work will need to explore heterogeneity in turbine product lines and their evolution and dynamics over time.
2. The overall wind energy installed capacity and generation is low such that cost impacts to traditional electric grid operation are negligible relative to overall electricity costs. This is important since many studies looking at high levels of renewables on the grid do estimate that there may be additional cost impacts to the overall system in terms of system operation costs and the need for additional new transmission and/or storage (U.S. Department of Energy, 2015). Here, we assume we haven't reached a critical level of renewables generation to affect any of these costs, or equally, we assume that those issues are resolved through innovation so that the grid itself changes and is able to accommodate increasing levels of wind energy without significant cost increases to operation, transmission or storage. In addition, this means that relative to natural growth of electricity generation and additional capacity, the wind contribution is small and thus unconstrained by "queuing" effects of having to enter into a capacity market pipeline (interview with a wind energy developer 2016). Finally, as levels of wind energy in an electric grid system grow, there can even be concerns over system reliability and stability. While these factor into costs, they are important in and of themselves. In future work, it will be important to address the additional dynamics of grid integration since both

effects of saturation of the forward capacity markets and potentially increased electricity costs are relevant to the current and future wind industry. Several countries do indeed already have levels of wind energy generation above 10% of overall annual generation.

3. Several local factors can limit wind energy development. NIMBY-ism (Not-in-my-backyard-ism) has remained relatively consistent over time such that the percentage of projects fail due to NIMBY issues has not changed over time and we can exclude the dynamics associated with NIMBYism. Similar constraints that limit wind project feasibility are environmental issues, affecting local habitats, species, migration corridors, and national security issues, such as radar interference near military installations. For the purposes of the study, we assume that land that would be affected by NIMBY-ism, environmental or security concerns is already removed from the potential land area available for wind development. Future work will consider dynamics associated with these local factors and NIMBY-ism in particular since in actuality an important feedback between increasing levels of wind energy development and local resistance.

While these assumptions break down for certain cases and under certain conditions, they are generally reasonable for the historical development of the industry with relatively low penetrations of wind energy in the electric grid system. Having defined the scope of the model, we next develop the general dynamics of interest. The core model structure and feedback loops are shown in the below figure.

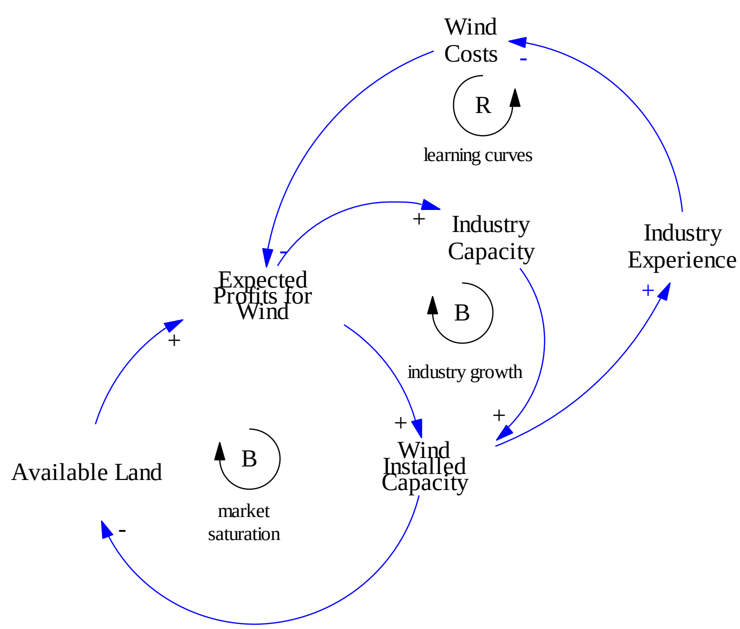


Figure 8: Core Causal Loop Diagram for Wind Diffusion

The core of the model is a threshold model where markets adopt wind based on expected profits and low costs. In other words, adoption of wind energy happens when its LCOE is lower than other forms of energy. The initial adoption of the technology, enabled in this case through policy support, kicks off the technology innovation and learning curve dynamics that further reduce the LCOE and create a positive feedback to adoption. The industry capacity limits the speed of adoption. As adoption grows, forecasts for future sales of the technology grow and so does the industry capacity along the value chain. However, the growth of the market in terms of industry build-up and deployment creates a balancing loop where the increased adoption decreases the available good land for projects (i.e. those sites with good wind resource and other criteria to help keep LCOE low) and eventually the market becomes saturated. These are the core dynamics of the model and, as mentioned, the industry and technology dynamics are global while the market dynamics are local: the model disaggregates market dynamics across markets in different countries and states.

As previously mentioned, two key additional sub-models are not included in the core model above. The figure below shows the additional feedbacks.

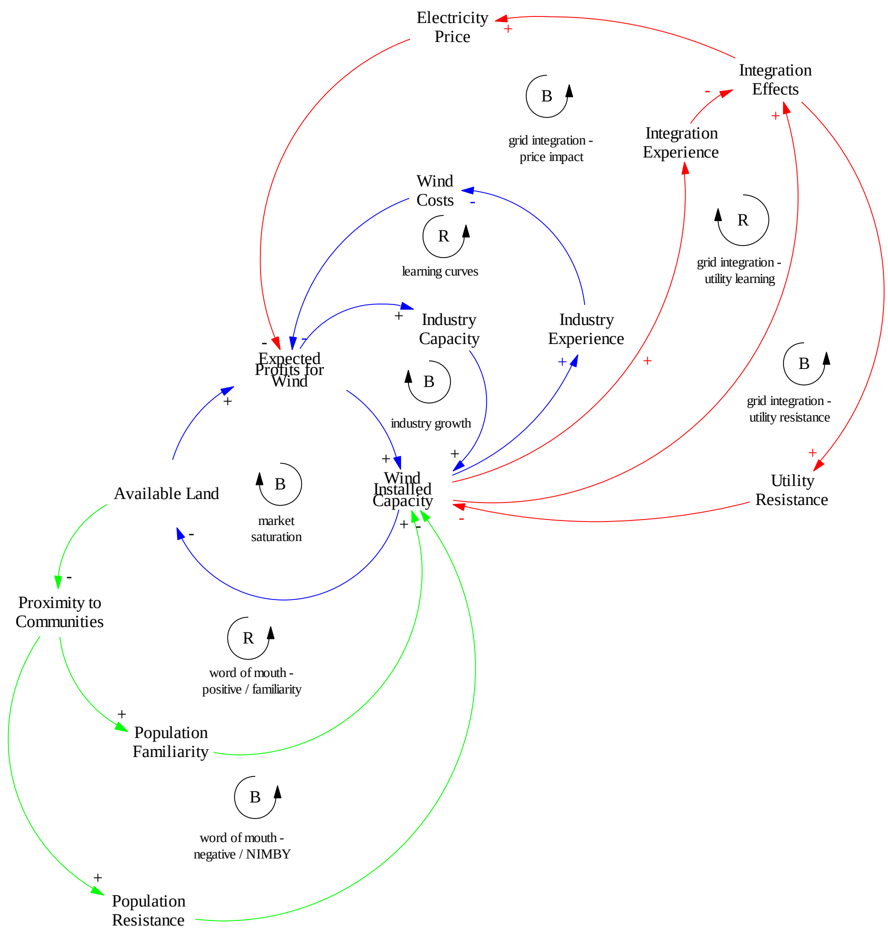


Figure 9: Additional wind industry dynamics for grid integration and NIMBY-ism

These include local resistance primarily from NIMBY-ism and grid integration (including cost issues and system stability). These dynamics are important as the market grows. The primary social or Bass dynamics of the model include the population familiarity and population resistance (NIMBY-ism). Before any wind farms exist, there is an intrinsic resistance to the unknown but as industry builds more and more successfully operating wind farms, positive word of mouth concerning the technology's viability spreads. However, there is a secondary social loop around the encroachment of wind farms on nearby population dense areas and NIMBY resistance / negative word of mouth develops. In addition, this larger system diagram includes endogenous relationships between wind energy deployment and electricity price. The more wind capacity on the system, the higher the electricity price due to the system costs associated with the intermittent resource. There is also a build-up of resistance by utilities or system operators who have to manage the system integration issues and from the public if the installed capacity is high enough to affect overall system performance.

While these additional feedback loops are important, especially for high levels of wind in the system, they are much more uncertain and beyond the scope of the current model. In addition to the exclusion of these dynamics associated with local resistance and grid integration, we are also excluding the offshore market as well. The offshore market essentially adds a duplicate of the original model since the technology, resource and even policy supports can be fundamentally different from for land-based systems. There are even interactive dynamics between local resistance and the move to offshore wind in population dense regions. Future work will add this co-flow structure to the model since offshore wind development is already important in many European countries.

Even in the simplified form, the core model already involves a number of complexities including various nonlinear relationships and feedback delays. The next section describes the formal model and important functional relationships.

Model Formulation

The core model consists of three sub-models: (1) the wind resource, associated land and LCOE for a given project based on the wind resource, (2) technology learning include scaling of the technology, improved performance and reduced cost, and (3) the wind project development pipeline (with co-flows for turbines, capacity and generation) and the industry value chain (turbine suppliers and project developers). We describe each of these model formulations and then in the next section, we demonstrate how we select the cases for analysis including the disaggregation into regional markets that feed the global dynamics of technology development. The model is built in Vensim® DSS for Windows Version 6.4c (x32) from Ventana Systems, Inc. Vensim is a system dynamics modeling software tool that allows a user to visually build up a system dynamics simulation by adding variables to a graphical template and then interlinking them and defining functional relationships. Details of the model can be found in the model attachment for this paper.

Model Input Specifications

This section describes how we select the cases for analysis and the estimation of several model inputs and outputs from available data.

Case Selection

While the wind turbine market is relatively global, the markets for wind power plants are local and depend significantly on local conditions including many factors such as the strength of the wind resource, the overall cost of electricity due to the local make-up of the electricity generation portfolio, transmission, market type and other factors, the availability of undeveloped land and population density, and more. In addition, over time, local market conditions can change due primarily to the influence of regional and national policies that affect the viability of wind energy. On a national level, the states with significant levels of installed wind capacity are those that at some point over the last few decades have put policy in place to support wind energy. The table below shows the total global wind capacity along with the installed capacity in nations with greater than 5 GW of installations.

Table 0-1: Installed Wind Capacity (in MW) since 1980 for the world and nations with over 5 GW of capacity in 2015 (Eco-Indicators 2010, GWEC, 2014).

	China	U.S.	Germany	India	Spain	United Kingdom	Canada	France	Italy	Brazil	Sweden	Poland	Denmark	Portugal	World
1980	0	8	0	0	0	0	0	0	0	0	0	0	5	0	**10**
1981	0	18	0	0	0	0	0	0	0	0	0	0	7	0	**25**
1982	0	84	0	0	0	0	0	0	0	0	0	0	12	0	**90**
1983	0	254	0	0	0	0	0	0	0	0	0	0	20	0	**210**
1984	0	653	0	0	0	0	0	0	0	0	0	0	27	0	**600**
1985	0	945	0	0	0	0	0	0	0	0	0	0	50	0	**1,020**
1986	0	1,265	0	0	0	0	0	0	0	0	0	0	82	0	**1,270**
1987	0	1,333	5	0	0	0	0	0	0	0	0	0	115	0	**1,450**
1988	0	1,231	15	0	0	0	0	0	0	0	0	0	197	0	**1,580**
1989	0	1,332	27	0	0	0	0	0	0	0	0	0	262	0	**1,730**
1990	0	1911	48	0	2	10	1	0	3	0	8	0	343	1	**1,930**
1991	0	1975	110	39	3	14	1	1	4	0	12	0	413	1	**2,170**
1992	0	1823	183	39	33	50	10	1	7	0	20	0	458	3	**2,510**
1993	0	1813	334	79	34	131	12	3	18	0	29	0	491	8	**2,990**
1994	0	1745	643	185	41	153	22	3	21	0	40	0	532	8	**3,490**
1995	38	1731	1137	576	98	200	22	3	22	0	67	0	616	8	**4,780**
1996	79	1678	1564	820	227	238	23	6	34	0	105	0	842	18	**6,100**
1997	170	1579	1966	940	420	322	23	7	119	0	123	0	1130	29	**7,600**
1998	224	1698	2672	1015	848	331	23	15	164	0	174	2	1443	48	**10,200**
1999	268	2251	4138	1077	1613	357	78	18	232	0	196	3	1759	57	**13,600**
2000	346	2377	6095	1220	2206	412	92	57	363	0	209	4	2392	83	**17,400**
2001	402	3918	8754	1456	3397	427	131	83	664	0	295	19	2498	125	**23,900**
2002	469	4531	12001	1702	4891	534	161	133	780	0	357	32	2892	190	**31,100**
2003	567	5995	14609	2125	5945	742	327	222	874	0	399	35	3117	268	**39,431**
2004	764	6456	16629	3000	8317	933	444	363	1127	0	452	40	3125	553	**47,620**
2005	1260	8706	18428	4430	9918	1565	684	723	1635	0	493	121	3129	1064	**59,091**
2006	2604	11329	20622	6270	11722	1955	1460	1412	1902	237	516	172	3135	1681	**74,133**
2007	6050	16515	22247	8000	15097	2477	1855	2220	2702	247	710	306	3124	2201	**94,122**
2008	12,210	25,170	23,903	9,587	16,740	3,288	2,369	3,426	3,537	339	1,067	472	3,164	2,862	**121,188**
2009	25,104	35,159	25,777	10,925	19,149	4,070	3,319	4,410	4,850	606	1,560	725	3,465	3,535	**157,899**
2010	44,733	40,200	27,214	13,064	20,676	5,203	4,008	5,660	5,797	932	2,163	1,107	3,752	3,702	**197,637**
2011	62,733	46,919	29,060	16,084	21,674	6,540	5,265	6,800	6,747	1,509	2,970	1,616	3,871	4,083	**238,035**
2012	75,564	60,007	31,332	18,421	22,796	8,445	6,200	7,196	8,144	2,508	3,745	2,497	4,162	4,525	**282,482**
2013	91,412	61,110	34,250	20,150	22,959	10,711	7,823	8,243	8,558	3,466	4,382	3,390	4,807	4,730	**318,596**
2014	114,763	65,879	39,165	22,465	22,987	12,440	9,694	9,285	8,663	5,939	5,425	3,834	4,845	4,914	**369,553**
2015	**145,104**	**74,472**	**44,947**	**27,151**	**23,025**	**13,603**	**11,205**	**10,358**	**8,958**	**8,715**	**6,025**	**5,100**	**5,063**	**5,079**	**432,419**

In addition to those listed above, many countries have between 500 MW and 5 GW of installed wind capacity including Turkey (4.7 GW), Australia (4.2 GW), Netherlands, (3.4 GW), Mexico (3.0 GW), Japan (3.0 GW), Romania (3.0 GW), Austria, (2.4 GW), Ireland, (2.5 GW), Belgium (2.2 GW), Greece (2.2 GW), Finland (1.0 GW), Norway (0.8 GW), Korea (0.8 GW), New Zealand (0.6 GW), Czech Republic (0.3 GW), Hungary (0.3 GW). All of these nations have employed policies to support wind energy development at a national level and thus serve as candidates for analysis.

In addition to national level policies, however, certain countries have significant heterogeneity in regional electricity markets and policies. The most prominent examples of this are the United States and Canada. In each of these cases, important state- or province-level policies have enabled the deployment of wind energy over the last several years.

Table 0-2: Installed Wind Capacity (in MW) since 1999 for the United States and states with over 2 GW of capacity in 2015 (WindExchange 2015).

	Texas	Iowa	California	Oklahoma	Illinois	Kansas	Minnesota	Oregon	Washington	Colorado	North Dakota	Grand Total
1999	184	242	1,616	0	0	2	273	25	0	22	0	**2,472**
2000	184	242	1,616	0	0	2	291	25	0	22	0	**2,539**
2001	1,096	324	1,683	0	0	114	320	157	180	61	0	**4,232**
2002	1,096	423	1,823	0	0	114	338	218	228	61	5	**4,687**
2003	1,290	472	2,025	176	50	114	558	259	244	223	66	**6,350**
2004	1,290	634	2,095	176	51	114	600	263	241	231	66	**6,723**
2005	1,992	836	2,149	475	107	264	745	338	390	231	98	**9,147**
2006	2,736	932	2,376	535	107	364	896	438	818	291	178	**11,575**
2007	4,353	1,273	2,439	689	699	364	1,300	885	1,163	1,067	345	**16,907**
2008	7,113	2,791	2,537	708	915	921	1,753	1,067	1,375	1,068	714	**25,410**
2009	9,403	3,604	2,798	1,031	1,547	1,021	1,810	1,758	1,849	1,244	1,203	**34,863**
2010	10,089	3,675	3,253	1,482	2,045	1,074	2,205	2,104	2,104	1,299	1,424	**40,267**
2011	10,394	4,322	3,917	2,007	2,742	1,274	2,718	2,513	2,573	1,805	1,445	**46,916**
2012	12,214	5,133	5,542	3,134	3,568	2,713	2,987	3,153	2,808	2,301	1,680	**60,005**
2013	12,355	5,178	5,830	3,134	3,568	2,967	2,987	3,153	2,808	2,332	1,681	**61,108**
2014	14,098	5,688	5,917	3,782	3,568	2,967	3,035	3,153	3,075	2,593	1,886	**65,877**
2015	**17,713**	**6,212**	**6,108**	**5,184**	**3,842**	**3,766**	**3,235**	**3,153**	**3,075**	**2,992**	**2,143**	**74,472**

In addition to the above states, many others have as much installed capacity or more than many of the nations listed above: Indiana (1.9 GW), New York (1.7 GW), Michigan (1.5 GW), Wyoming (1.4 GW), Pennsylvania (1.3 GW), New Mexico (1.1 GW), South Dakota (1.0 GW), Idaho (1.0 GW), Nebraska (0.9 GW), Montana (0.7 GW), Wisconsin (0.6 GW), Maine (0.6 GW), West Virginia (0.6 GW), Missouri (0.5 GW) and several others have at least 100 MW installed. In Canada, both Alberta (>1 GW) and Ontario (>3 GW) have significant installations. While national policies are important to wind development, the federal policies have often not been sufficient by themselves and the state- and province-level policies in these nations have played a key role in catalyzing wind energy deployment.

Therefore, the approach for case selection involves a mixture of nations and states/provinces where appropriate. The list above of nations and states includes then 45 jurisdictions that can be included in the analysis. This is a large number of countries and we reduce the number to those who have made the most significant contribution to global wind capacity. However, the model is flexible to accommodate any combination of jurisdictions that the user would like to analyze. To do this, we created a Python script to sort the input and output data according to a user-defined grouping of the nations and states. For instance, one potential grouping is every nation, US state, and Canadian province in the world. This would give 312 separate jurisdictions for the model. A more historic analysis may consider only those jurisdictions with significant installed capacity prior to 2001 (after which the number of nations and states that had policies to support wind energy development grew substantially). Such a historical selection would include (according to the tables above), Denmark, Germany, Spain, India, and the US state of California. An analysis focused more on the present day might include the 45 jurisdictions above. The subsequent case studies and scenarios will use a select set of nations and states from the 45. We will provide additional details about these cases in the simulation section. The next sections describe data collection for each nation and state/province as well as global data about technology trends.

Data Collection

The data collection for each of the sub-models described in the model formulation includes data for wind resource, LCOE, technology innovation and cost trends, and wind projects. Details of the data collection are omitted for length but can be found in detail in the PhD thesis manuscript from which this conference paper is developed. The data collected included disaggregate wind resource data for each state and nation, electricity costs and renewable policy incentives by nation and state, and historical data on turbine technology performance and cost trends.

Case Study Simulation

We present two sets of simulation for the cases identified in the previous section. Firstly, we simulate the four countries who were the earliest adopters of wind energy to calibrate a few key model parameters around the developer capacity and turbine supply chain. Then, we run a second simulation involving the largest wind markets in the world including several US states. As will be discussed, we exclude a few large wind energy-adopting nations due to lack of available data for key input parameters like electricity prices and policies.

Historically dominant wind markets

The first nations and states to begin to adopt wind energy in significant quantities were respectively: Denmark, California in the United States, Germany and then Spain. We will refer to all of these jurisdictions as states for the remainder of this section. These states all have regions with strong wind resources. Like much of the world, all of these countries felt the effects of the oil crisis and began to look at renewable energy to replace fossil-fuel based generation sources. In the historical case study, we took an in-depth look at the situations in Denmark and California. These states were the first to put in place policies that would allow wind to be competitive with other wind energy sources. Denmark used investment subsidies and loan guarantees while California, in addition to taking advantage of federal ITCs of 25%, used an in-state program offered an additional ITC of 25% and an accelerated depreciation tax incentive amounted to nearly another 50% investment tax credit (Folkecenter, 1985). Essentially, California was giving away money to anyone who would invest in wind projects. These had some negative unintended consequences, but it was effective in enabling the “wind rush” of massive deployment (relative to the period).

The change of administrations in 1984 in both California and in the federal government then led to a hasty removal of the proactive renewable energy policies and by the start of 1986, the government had fully removed all of the key policy incentives for wind energy. While Denmark continued to reinforce its own market and keep the tiny industry alive, the global market stagnated until 1989 when Germany enacted the first ever feed-in-tariff for renewables that benefited wind energy. Germany became the next hot spot for wind energy deployment until the year 2000 when additional nations, first Spain then others, followed suite with their own FIT or alternative incentive programs. Thus, we are looking for a few key dynamics from our initial simulation case:

- The boom-and-bust of the California market and phased continuous growth of the Danish, then German, and finally Spanish markets

- The feedback between the aggregation of market development across the cases along with the rest of world growth (as an input) leading to technology learning in terms of technology scaling and cost reductions per unit power

The following graph shows the resulting simulation of cumulative installed wind energy capacity for the simulated and actual data.

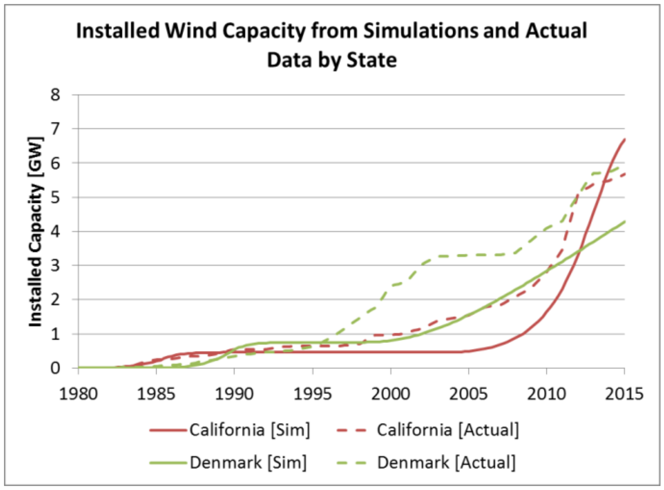


Figure 10: The above figure shows the actual and simulated trends in installed capacity for Denmark and California.

Immediately, differences between the simulated and actual data are apparent. The simulation for California shows more significant growth in the early 1980s and less aggressive (but more continuous growth) since 2010. For Denmark, the simulation does not quite keep up with the actual growth since 2000. This could be for two reasons: firstly, the policy data may not adequately represent the full suite of incentives over the past several years for projects in Denmark; a second likely factor is the lack of modeling the offshore wind market as its own entity. Denmark has aggressively pursued offshore wind for the bulk of its recent capacity additions and nor the technology nor the resource are modeled in the current framework.

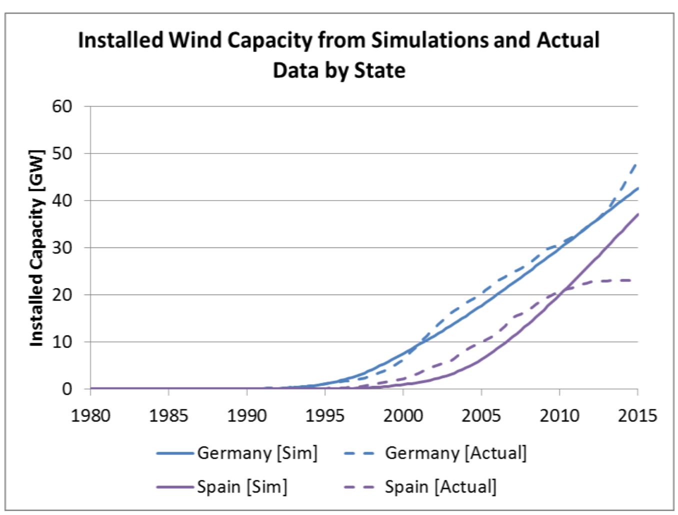


Figure 11: The above figure shows the actual and simulated trends in installed capacity for Germany and Spain.

For Spain and Germany, the main difference is that there seems to be a phase shift between the actual growth curve and the simulated growth curve. Thus, the simulated installed capacity lags the actual capacity in both cases. A key sensitivity of the model is the developer capacity model that limits the growth of the market to a reasonable level (otherwise, there would be an immediate massive increase in development once the government puts incentives in place in a given state). Allowing developer capacity to scale up more quickly allows the German and Spanish markets to grow much faster but the California market as well. A potential remedy would be to have the maximum developer capacity growth be a function over time that in the early days of the industry would be limited while it could accelerate as the industry matures. Right now, the average maximum growth rate for global historic data of 40% is used; this variable could be both time and geographically dependent. However, despite the discrepancies between the actual and simulated data, the model captures the basic trends of the growth dynamics. Statistics comparing the two data streams support this finding.

Table 0-1: Statistics of Model Fit to Actual Data for Installed Capacity; Statistics are for the full simulation set from 1980 through 2014 inclusive

	California	Denmark	Germany	Spain
Actual Installed Capacity 2014 (GW)	5.7 GW	5.9 GW	48 GW	23 GW
Simulated Installed Capacity 2014 (GW)	6.7 GW	4.3 GW	43 GW	37 GW
R-squared	0.8769	0.8850	0.9944	0.9252
MAE / Mean	0.3716	0.4270	0.0751	0.2597
Theil Bias Fraction (Um)	0.4350	0.4424	0.1567	0.0084
Theil Unequal Variance Fraction (Us)	0.09402	0.3605	0.2735	0.2107
Theil Unequal Covariance Fraction (Uc)	0.4710	0.1971	0.5698	0.7809

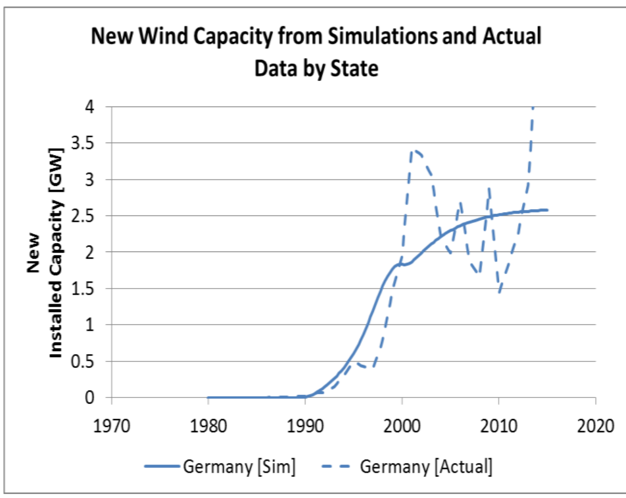
The statistics show that the R-squared value is relatively high for all the cases meaning that the model explains the variance relatively low. However, the mean absolute error over the mean (MAE/mean) are relatively high.[3] There are issues in capturing the growth dynamics of each case as we can see a phase shift where the model either is ahead of (as in the case of Germany) or lags (as in the case of Spain, Denmark and California) the actual data. The Theil statistics show some evidence of this bias (Um) and phasing issues (Uc). This is most prevalent for Germany and Spain where it is clear that both the slopes and phasing of the simulated versus actual data are different. Better quality and more disaggregation of data on many of the model inputs (electricity prices, policy, land-based and offshore technology) would allow a better calibration of the model and fit to the data on market growth. In addition, there are some assumptions based on a few data sources around the growth of the industry, supply chain and developer capacity that may be more complex than currently represented in the model. Future work may involve a data gathering effort focused specifically on the industry supply chain dynamics to inform

[3] MAE/Mean is used here rather than root mean squared error or relatied statistics because it weights errors linearly. Since this is a growth model where the market is expected (and does) grow exponentially, RMSE or other metrics would give more weight to the larger absolute errors that occur later in time. In addition, because the market begins with no capacity, MAE/Mean is used instead of the mean absolute percentage error.

the structure of these sub-models and input and calibration of the supply chain models rather than using simple data sources. In addition to installed capacity, it is important to look at the year-to-year industry growth and the dynamics of how the simulation captures the stop-and-start of various state policies affecting the market. The graphs below show the year-to-year growth of capacity by state along with a table of statistics for the fit of simulated to actual data.

Table 0-2: Statistics for actual to simulated data on new capacity installations; Statistics are for the full simulation set from 1980 through 2014 inclusive

	California	Denmark	Germany	Spain
R-squared	0.3015	0.0804	0.7479	0.4022
MAE over Mean	1.0	0.8931	0.325	0.8715
Theil Bias Fraction (Um)	0.0227	0.0482	0.0022	0.1154
Theil Unequal Variance Fraction (Us)	0.1735	0.1850	0.1492	0.1770
Theil Unequal Covariance Fraction (Uc)	0.8038	0.7669	0.8486	0.7076



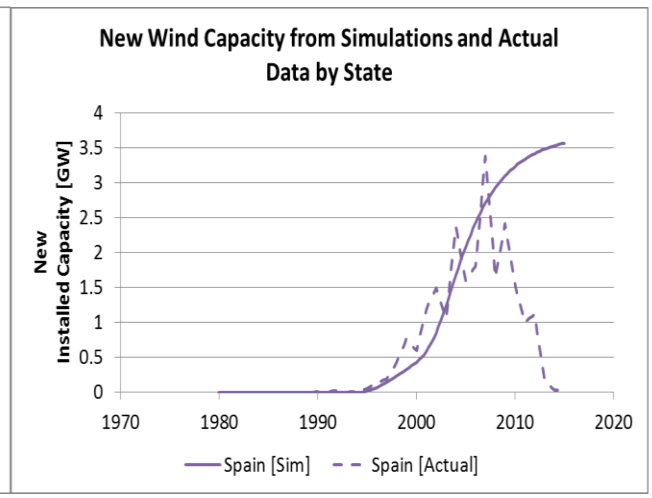
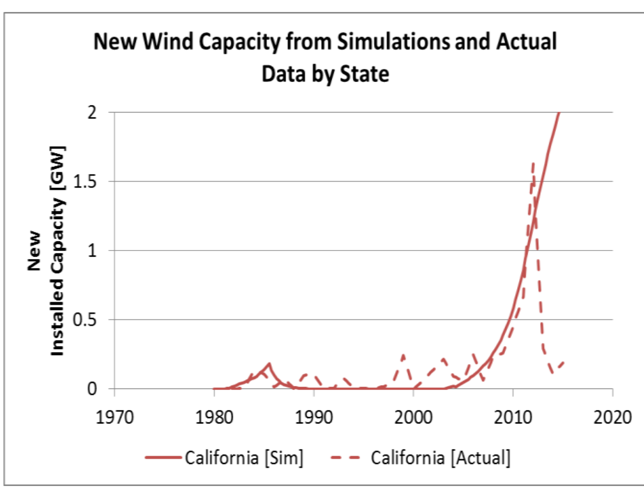


Figure 12: Graph of simulated and actual new wind energy capacity additions for Germany and Spain



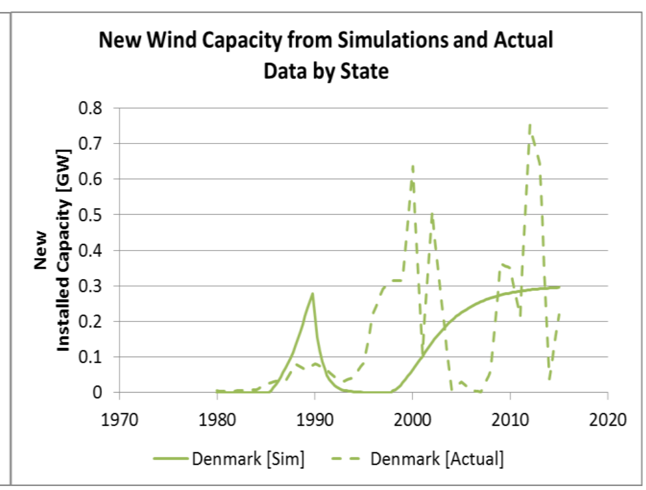


Figure 13: Graph of simulated and actual new wind energy capacity additions for California and Denmark

Firstly, we note that the market for wind energy is much more volatile than the simulation can capture. The model captures certain important market instabilities: the boom-and-bust of the early 1980's California market, the periodic cancellation of the US PTC incentive in 2000, 2002 and 2004 and some fluctuation of policy support in Denmark in the late 1990's. However, the model does not capture a significant amount of volatility in the more recent years in Denmark, Spain and Germany. Further work to characterize the impact of policy on those respective markets and adjusting the policy inputs may help capture some of the variance that is not currently simulated. Notably, in the past few years the market in Spain has stagnated – the government removed the FIT program that had promoted most of the growth over the past decade and replaced it with a remuneration system (IEA Spain 2015). However, Spain also has very high electricity prices and thus the removal of the FIT does not affect the simulation in the last few years. An important feedback missing from the model is the relationship between the amount of wind electricity in a system and the electricity price due to costs of integration. As previously mentioned, the model does not contain this structure, but Spain happens to be uniquely vulnerable to this dynamic because its system is relatively isolated (with only a few points of interconnection to France) and the level of wind energy generation in the system has been quite high (upwards of 10% and more). Future work will address this grid integration causal loop since it is increasingly important with the growth of wind energy in electric grid systems.

The differences between the simulated and actual data also appear in the statistics in Table 9 where you can see that the R-squared value for these simulations is quite low except for Germany (at 0.75) and the MAE/mean are quite high (again excepting Germany at 0.35). However, the Theil statistics show less systematic error than was present for the cumulative capacity simulations. Having the most of the error categorized as unequal covariation or unequal variation and covariation indicates that there are some systematic phasing issues (for instance the cycles in the California market or the lag in growth of the Spanish market) but generally, the trends and means are agreeing across the cases. While it would be ideal to have a perfect fit of the actual and simulated data, the system this model addresses has a very large scope with many important dynamics that are difficult to capture in a simplified way. The ability to capture the basic trends in growth and cyclic market behavior give sufficient confidence to move forward with additional analysis.

Before that, however, the other key area for the model fit is on the technology scaling and cost trends. The figures below show the actual versus simulation data on key turbine and plant attributes.

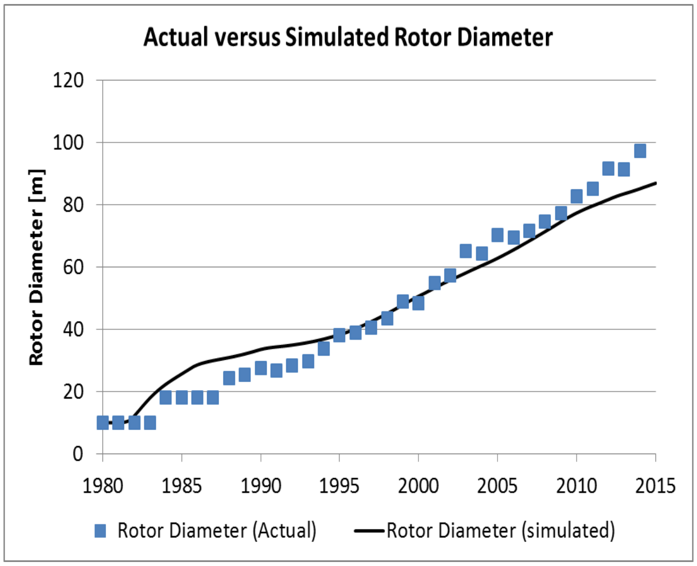


Figure 14: Actual versus simulated rotor diameter

The model learning curves fit to technology trends data as we discussed earlier. Here, the technology trend fits are evidence of the model's ability to capture the dynamics between the technology development and the capacity growth where the technology scaling helps to improve the breakeven expected annual energy generation and market growth in turn promotes further learning. Looking at the above and below graphs shows slightly faster than expected growth in the early years and slower growth in the more recent past. The statistics show good agreement with high R-squared and low MAE/mean and the different slopes in the rotor diameter and rated power graphs explain the high unequal variance fraction of the Theil statistics. For hub height, on the other hand, there is evidence of bias though overall there is good agreement in the trends.

Table 0-3: Statistics on technology parameter fits; Statistics are for the full simulation set from 1980 through 2014 inclusive

	Rotor Diameter	Rated Power	Hub Height
R-squared	0.9840	0.9689	0.9578
MAE over Mean	0.1063	0.2114	0.1803
Theil Bias Fraction (Um)	0.0087	0.0857	0.7133
Theil Unequal Variance Fraction (Us)	0.7423	0.6229	0.0547
Theil Unequal Covariance Fraction (Uc)	0.2490	0.2914	0.2319

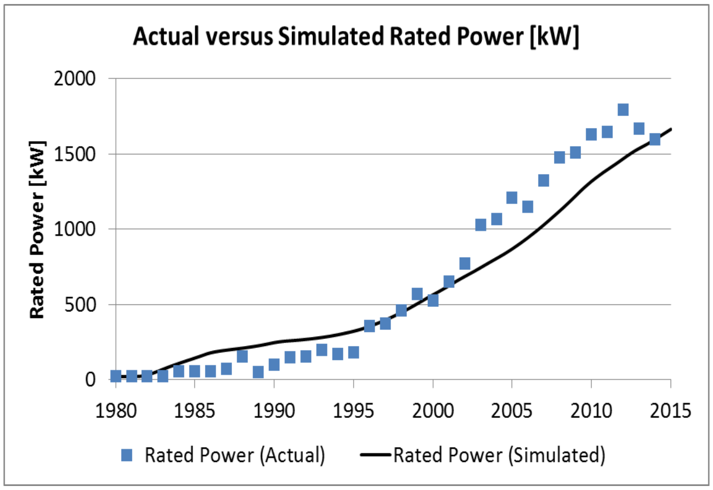


Figure 15: Actual versus simulated rated power

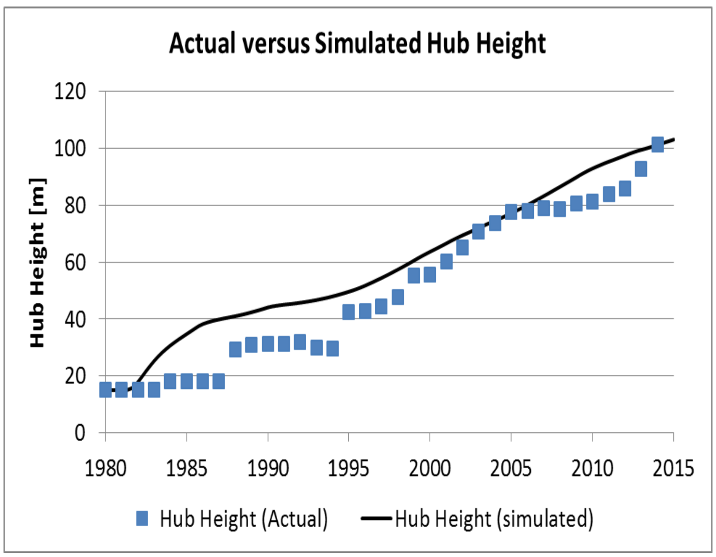


Figure 16: Actual versus Simulated Hub Height

Less favorable statistics result for the turbine and project cost trends. The R-squared values are weak though the MAE/mean values are not still low. The Theil statistics show some evidence of bias and different trends. As discussed earlier, the turbine cost data shows a bump in data around 2005 due to a variety of factors. The cost reduction learning curve excludes these effects so we do not expect as good a fit as for the technology that has scaled relatively smoothly over time. There is a markup function in the model for turbine cost due to supply constraints.

Table 0-4: Statistics on technology parameter fits; Statistics are for the full simulation set from 1980 through 2014 inclusive

	Turbine Cost	Balance of Station Cost
R-squared	0.4932	0.0459
MAE over Mean	0.2063	0.2882
Theil Bias Fraction (Um)	0.5016	0.3526
Theil Unequal Variance Fraction (Us)	0.0822	0.1525
Theil Unequal Covariance Fraction (Uc)	0.4162	0.4949

Having shown the model is capable of capturing the basic market dynamics of feedback in technology learning and market growth and the influence of policy measures on market growth, the next simulation set expands from our four historical cases of interest to a large set of states that make-up the dominant wind energy generating nations and states today.

Largest wind markets in 2015

From the largest model, we select a subset including Denmark, France, Germany, Italy, the Netherlands, Poland, Portugal, Spain, Sweden, Turkey, and the United Kingdom, and in the USA: California, Illinois, Iowa, Kansas, Minnesota, Oklahoma, Oregon, Texas, and Washington. Excluded from the set are India, China, Brazil and Mexico for which there is a lack of quantitative information around electricity prices and policy value. Also excluded are Australia and Canada for similar reasons since there is significant heterogeneity in across the states and provinces. Further work will look at gathering data on these and other countries so that they can be included in the model. Below is a graph of the simulated market growth for wind energy. The following series of graphs shows the results compared to actual data for the modeled cases.

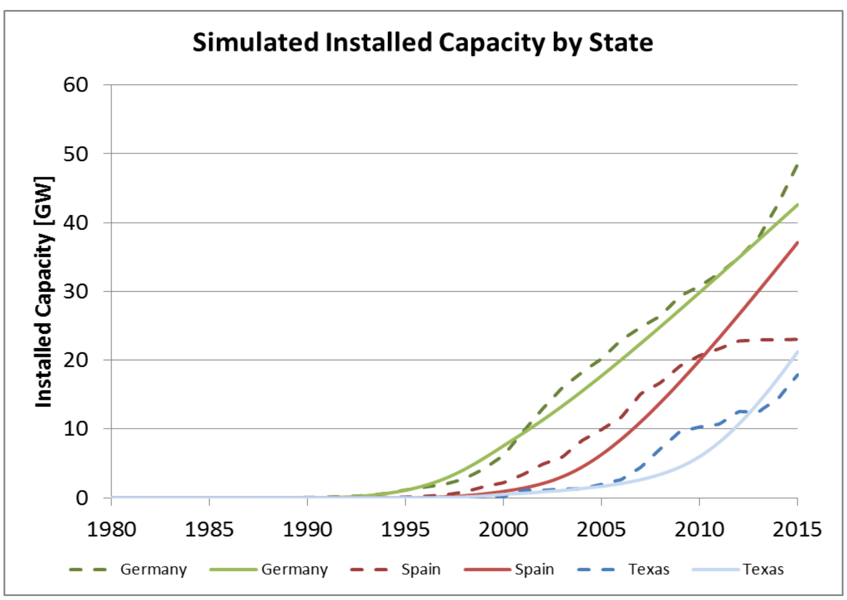


Figure 17: Installed capacity for three of the largest installed capacity cases: Germany, Spain and Texas. Note that dashed lines are actual capacity while smooth lines are simulated capacity.

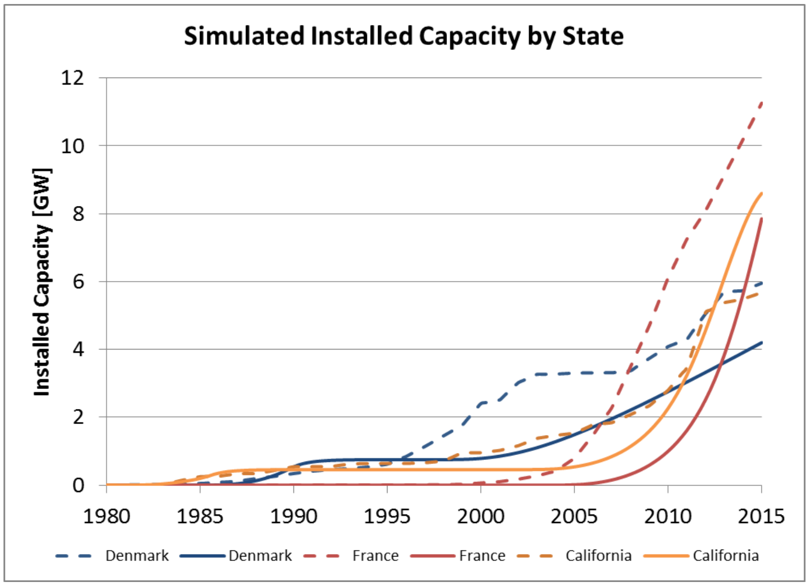


Figure 18: Simulated and actual capacity for additional cases with large installed capacity: Denmark, France, and California. Note that dashed lines are actual capacity while smooth lines are simulated capacity.

As we can see in the above graph, the trends from the previous simulations including Denmark, California, Germany and Spain are still present. There is somewhat early development of both the California and Danish markets that taper off and Germany dominates the market growth through the early 2000s followed by Spain and then a number of other countries. Significantly, the market for wind energy in Texas starts to develop and experiences exponential growth. The model overshoots the actual growth by a significant amount that may be an issue with the implementation of electricity prices or policy incentives. A host of other states follow suits and we see the strong exponential growth in several countries after the early 2000s that led to the global boom in wind energy and also the “seller’s market” for wind turbines from the mid-2000s onward (Bolinger and Wiser, 2011).

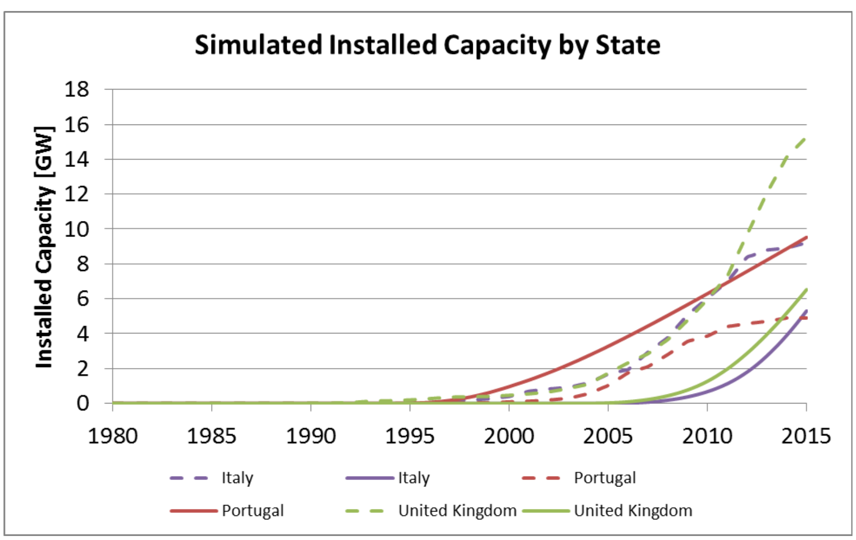


Figure 19: Installed capacity for other European nations in the simulation: Italy, Portugal, and the United Kingdom. Note that dashed lines are actual capacity while smooth lines are simulated capacity.

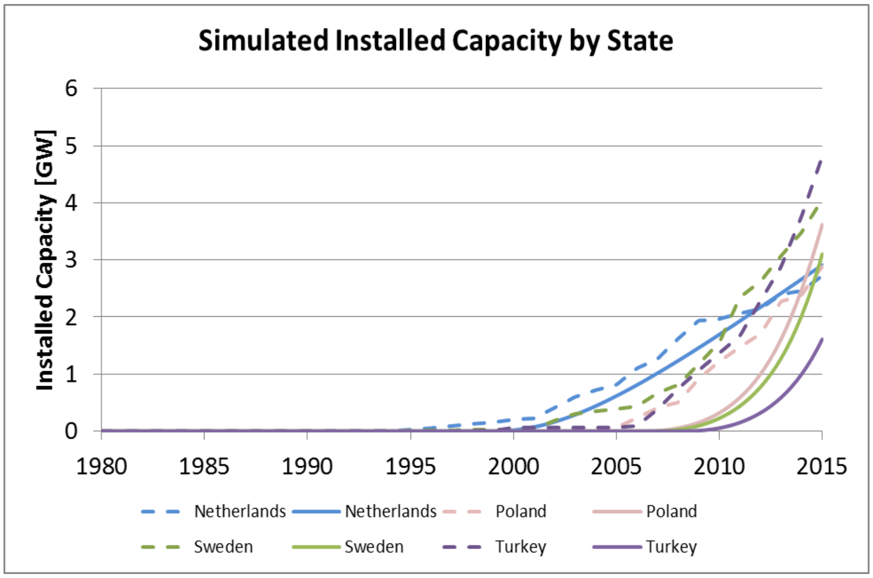


Figure 20: Installed capacity for other European nations in the simulation: the Netherlands, Poland, Sweden and Turkey. Note that dashed lines are actual capacity while smooth lines are simulated capacity.

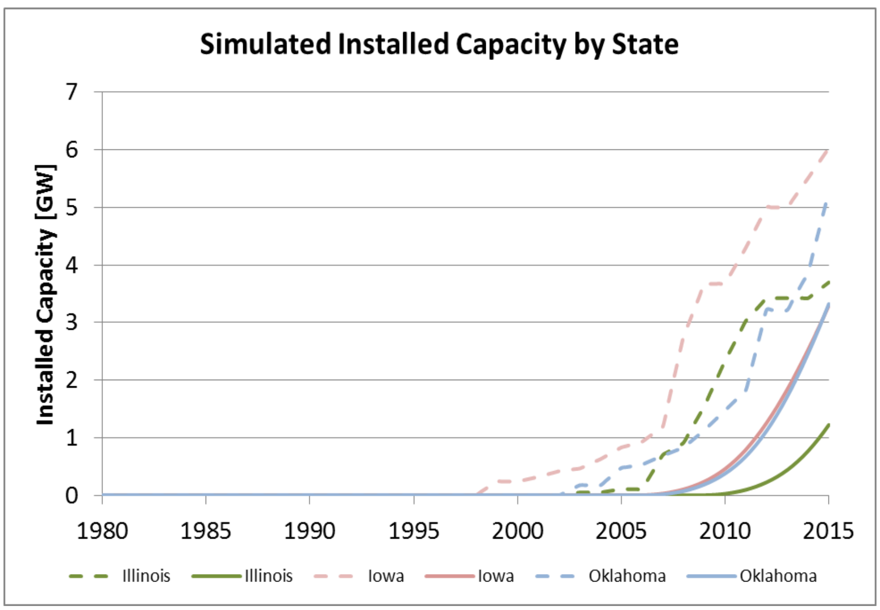


Figure 21: Installed capacity for other US states in the simulation: Illinois, Iowa, and Oklahoma. Note that dashed lines are actual capacity while smooth lines are simulated capacity.

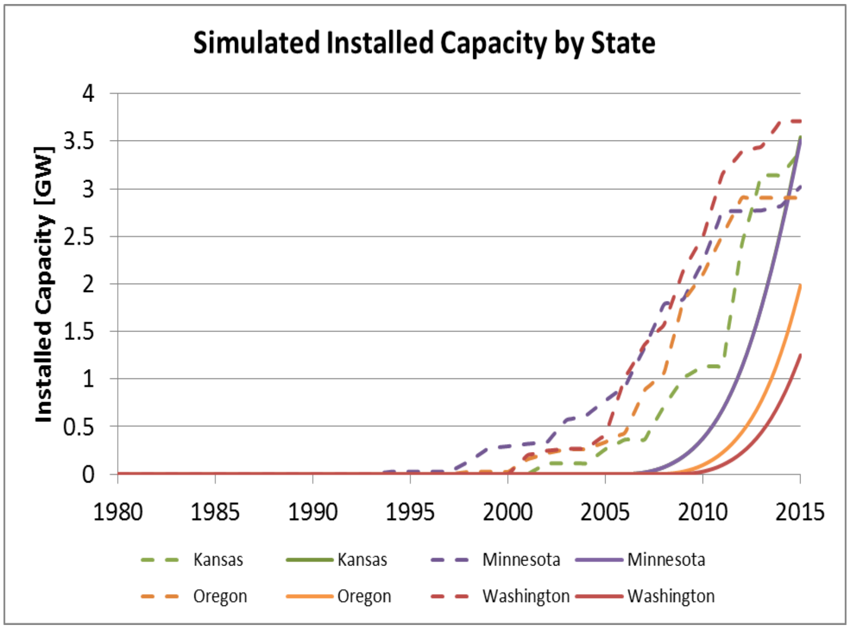


Figure 22: Installed capacity for other US states in the simulation: Kansas, Minnesota, Oregon and Washington. Note that dashed lines are actual capacity while smooth lines are simulated capacity.

The above graphs show that the simulation lags the actual data (i.e. there is a systematic presence of a phase shift between the two curves for most cases. There could be various factors accounting for this phase shift including industry build-up in anticipation of policy implementation, where developers recognize that legislation to promote wind development in a state is forthcoming so they begin prospecting in advance of the actual policies put in place. Another reason could be that the developer capacity builds-up much quicker than expected. This may be true especially for recent years where the global wind industry has grown substantially so that when new markets become attractive, developers can more quickly ramp up development in those regions. Future versions of the model may allow this by including the expectation of future development to drive prospecting ahead of policy implementation as well as allowing developer capacity to ramp up more quickly in particular regions as the overall industry grows. Below are the statistics from the analysis for the installed base:

Table 0-5: Statistics for fit of actual to simulated data for international states; Statistics are for the full simulation set from 1980 through 2014 inclusive

	DK	FR	DE	IT	NL	PL	PT	ES	SE	TR	GB
Actual Cap. 2014 [GW]	5.1	10.4	44.9	8.9	3.4	5.1	5.1	23.0	6.0	4.7	13.6
Simulated Cap. 2014 [GW]	4.2	7.9	42.6	5.3	2.9	3.6	9.5	37.1	3.1	1.6	6.5
% Diff.	-17%	-24%	-5%	-40%	-15%	-29%	86%	61%	-48%	-66%	-52%
R-squared	0.88	0.82	0.99	0.74	0.97	0.83	0.96	0.93	0.81	0.84	0.94
MAE/Mean	0.44	0.71	0.08	0.82	0.19	0.47	1.01	0.26	0.72	0.85	0.76

Table 0-6: Statistics for fit of actual to simulated data for US states; Statistics are for the full simulation set from 1980 through 2014 inclusive

	CA	IL	IA	KS	MN	OK	OR	TX	WA
Actual Cap. 2014 [GW]	5.1	3.8	6.2	3.8	3.2	5.2	3.1	17.8	3.1
Simulated Cap. 2014 [GW]	8.6	1.2	3.3	3.5	3.5	3.3	2.0	21.2	1.3
% Diff.	69%	-68%	-47%	-8%	9%	-37%	-35%	19%	-58%
R-squared	0.89	0.58	0.74	0.90	0.60	0.89	0.60	0.89	0.54
MAE/Mean	0.32	0.92	0.79	0.52	0.70	0.62	0.85	0.29	0.93

Here again the statistics reinforce that the model performs well for the four cases used in the previous simulation. Each of Denmark, Spain and Germany has high R-squared values and relatively low MAE/mean values. The additional states also tend to have high R-squared values for the cumulative installed base that is the main metric of interest for the model. The US states generally have lower R-squared and higher MAE/Mean values than the four historic cases with the exception of Texas that, along with California, was an early adopter of wind energy in the United States. This reinforces the fact that for cases where the growth is more recent, the model is not capturing the speed at which these markets start to develop wind and the lag that is present in the graphs. This is true as well for countries in Europe who are more recent entrants to the market. For all of these more recent cases, there is an under-prediction of the capacity in 2014 due to the growth lag. For certain European nations with significant offshore wind development, such as Denmark and the United Kingdom, the use of only a single technology type in the model (land-based turbines) and excluding the offshore wind resources of those nations also exacerbates the shortfall of simulated to actual installed capacity. Ignoring grid integration issues potentially also affects two of the few cases where there is an over prediction of capacity. Both Texas and Spain have experiences issues with grid integration of wind-generated electricity, as both of these systems are relatively isolated. Adding dynamics for grid integration would be necessary to accurately capture the growth dynamics for these cases and this will become true for other cases as well as wind energy becomes a more significant portion of the overall electricity generation portfolio in a given state.

In addition to evaluating the model on the resulting installed capacity for each nation, the global technology trends results in the table below show a good fit for the technology scaling and an adequate fit for the balance of station costs since the actual costs include the increase in costs in the early 2000's.

Table 0-7: Technology and Cost Trend Statistics; Statistics are for the full simulation set from 1980 through 2014 inclusive

	Rotor Diameter	Rated Power	Hub Height	Turbine Costs	BOS Costs
R-squared	0.985	0.963	0.961	0.499	0.046
MAE/Mean	0.102	0.210	0.183	0.206	0.288

The ability of the model to capture the growth of various global wind markets over time gives us the confidence to consider scenario analysis where the policy environment differs from reality. The next section will look at future growth and technology trends considering presence or lack of policy support for wind energy development.

Summary and Conclusions

This work explored the dynamics of diffusion and innovation around an inherently complex technology: wind energy. In particular, the study looked at how both the technology and markets for the technology have evolved since the oil crisis of the 1970s catalyzed their development. Looking at the available data on the development of the industry, it is readily apparent that there has been a relatively smooth exponential growth of global wind capacity while at the same time the growth of individual local markets has been extremely volatile. This is primarily due to the start-and-stop of government policy support for wind in the form of various incentive programs. One country or state may be the dominant market for wind for a period of a number of years only then to remove policy support altogether. Figures 2 and 3 tell the story well by showing the nice smooth growth curve for global installations over time and an extremely abrupt and choppy graph of the percentage of installations coming from a given country at a given time. Even though the local markets have been volatile, wind energy technology and cost learning curves have shown relatively continuous improvements over time. Thus, while local markets and policies affect the installed capacity in their jurisdictions, wind energy technology overall has steadily improved performance and reduced costs over the years.

This interplay of a regional markets, global markets, and technology learning are the core of a system dynamics for “technology dynamics” which embody the idea that “demand pull” type of policies promote technology innovation and this in turn increases the attractiveness and the likely adoption of the technology. There are many other important dynamics to wind energy development and this model also included key feedback loops around resource use (in this case wind resource / land available in a region) and the supply chain for wind project development and turbine manufacturing. The model required large amount of data as input for each of these sub-models including wind resource data, available land area for different regions, and electricity prices and policy incentives for each region or state of interest. On top of this, we calibrated model parameters for technology scaling and cost learning based on historical data. We also collected data for comparison to model outputs of turbines installed and overall electricity generation capacity from wind by state. Data for many states were very sparse and ultimately limited modeling of some cases of interest (such as China, India and Brazil) while at the same time there was a wealth of data available for US and European states.

Once formulated, the first analysis was a historic analysis of four historic cases of interest: California, Denmark, Germany and Spain. This countries and states were the earliest adopters of large-scale wind energy generation and we calibrated the sub-model for developer capacity for good agreement with these cases. The final model showed a relatively good fit between the actual and simulation data for both the capacity installed for each country and the technology trends over time. Once completed, we modeled a larger set of cases, those most prominent in the wind industry today, and the overall statistics for the analysis agreed well with actual data in terms of the general dynamics.

There are many caveats to the current results, however, since the model does not consider NIMBY issues, offshore markets and grid integration. These areas represent two key topics for future research. Grid integration has been its own topic of research for some time, and there is significant work around the costs that wind energy and other variable resources impose in the grid, as they become a larger percentage of generation. The dynamics of grid integration are critical in particular to looking at future policy scenarios for wind energy. In addition, the model does not consider dynamic land constraint and NIMBY issues. Population density and NIMBY issues drastically limit further development of land-based wind projects in many places, such as Europe. Offshore wind plants are a solution to NIMBY limitations on wind energy development. These can have their own NIMBY issues, but they tend to be less significant and several European nations are aggressively pursuing offshore wind energy. Having addressed these concerns, the model will be applied to policy scenarios to assess the impact for potential policies on the future development of the wind industry by region as well as global trends in wind technology innovation.

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