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On improvement rates for renewable energy technologies: Solar PV, wind turbines, capacitors, and batteries

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ABSTRACT

An important issue in various domains of renewable energy is the use of technological improvement trends to project future capabilities of energy technologies. This paper analyzes two pairs of renewable energy technologies and finds that the annual improvement rate of cost/investment is quite different for the four technological domains: namely, solar photovoltaics (PV) (9.0% per year), wind turbines (2.9%), batteries (3.1%) and capacitors (21.1%). While these trends have been reasonably consistent over long time frames, projecting these trends into the future without a better understanding of the underlying causes of the improvements is not at all reliable. This paper establishes theoretical fundamentals for explaining the differences in such rates and a framework for empirically probing such explanations using patent data. Employing this framework, this study collects and analyzes a set of highly representative patents for each of the four domains, allowing measurement of: patenting rates, reliance on scientific literature and other characteristics of the different fields. Our study of the inventions, while not establishing an indisputable causal relationship for the differing rates, establishes a broader theoretical basis for why such rates differ so greatly and why they might be stable over time. Among many possible effects, this study indicates that the age of knowledge utilized in the patents and the percentage of very important inventions in the field are the most likely significant contributors to higher rates of advance.

1. Introduction

Technological forecasting to understand how each of the renewable energy domains will improve in the future is used to anticipate potential contribution to climate change, to guide policy and to guide private investment decisions. Such methods have been used to forecast decreases in cost for energy generation technologies such as solar PV [1] and wind turbines [2]. Although the improvement in many of these technologies has been shown to be exponential with time [3–5] and relatively stable over long periods [6] it is important to note that 'past performance does not indicate future returns'.

While examining these rates in individual domains is important, this paper addresses the relative rate of cost reduction in groups of competing technologies. Among competitive approaches, those improving faster than the alternatives that are available are likely to be most economically viable and thus most highly used in the longer term. However, projection without an adequate explanatory base is still not very reliable. Indeed, variability among components, natural resource depletion and other possible saturation effects have been pointed out as reasons for weak extrapolation [7]. Strong explanations in the form of predictive theories would be extremely valuable for technology developers, research policy (funding and other aspects) and energy policy (R&D vs. demand subsidies and how to deal with questions of technological choice [2]). Additionally, reliable explanations are useful to potential adopters of renewable energy technologies, as they help reduce the uncertainty of the correct timing to install a certain technology [8–10]. This paper provides a foundation for building such reliable explanations in the future.

There are two well-known ways of quantifying cost reductions and performance increases: 1) a generalization of Moore's law [11,12] which treats time as the independent variable, 2) generalizations of Wright's law [13–15] which treats cumulative production as the independent variable. A recent paper has shown that these different treatments are approximately equivalent (with a slight advantage to Wright's law) in the ability to predict future performance from existing data [16] and it is clear that both frameworks are independently describing the same phenomenon – namely an improvement in performance of a given technology

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over time or usage. In this paper, we choose to use the generalization of Moore's law partly because of data availability (lack of reliable production data for batteries and capacitors but it does exist for solar and wind), partly because of fundamental difficulties with decoupling changes in demand (and thus production) from changes in performance [17] and partly because the connections in either case may well be through other variables such as R&D spending [18]. The most important point is that our use of patent information for potential explanations of differences in rates apply in either formalism because of the almost full equivalence of the two frameworks – Moore based on annual improvement rate and Wright based upon learning rate [16].

This paper contributes to our understanding in two ways. First, we examine the literature on technological change and derive from it possible theoretical explanations for differences in rates of improvement for different technological domains. Secondly, we develop an approach to utilize patent information from groups of patents in the domains to examine aspects of the hypothesized explanations for rate differences. Similar to technological improvement trends, the sources of the change in technological capabilities have been studied for individual domains [19,20]. While these studies provide useful specific information on each domain, they do not attempt to explore why the rates of improvement differ between the domains. Thus, our study examines characteristics of the inventions in the different domains that may account for the important *differences* in rates of improvement. Our focus is on delineating possible explanations for differences in rates of advance of different renewable energy domains. Overall, our contribution is to call attention to the importance of differences in rates of improvement and to establish both a theoretical beginning to understanding the reasons for the difference and an empirical method of using patent data to probe the theoretical ideas.

2. Research framework and methods

2.1. Domains, performance and patents

The first step in our research was to select four renewable energy domains for comparative analysis. We selected two leading energy generation domains (solar PVs and wind turbines) and because of growing evidence for the need to consider electrical storage in renewable energy systems [21], we also chose batteries (the leading candidate) and electrical capacitors – some see the latter as an important emerging storage technology [22].

The second step in our research was to examine the historical performance of these four technological domains. This involves careful analysis of various data sources resulting in a time dependent set of performance parameters. In the cases studied here, we examined only the most economically significant performance metric-energy produced per unit cost. It is problematic to estimate the overall costs of electrical energy generation [23], therefore we measured device peak watts per dollar as it is the 'most fundamental metric for considering the costs of PV' [24] and we used the same metric for wind. We note that these metrics do not reflect important costs for these two technologies such as maintenance, installation, and operation (load factors) so cannot be considered total economic metrics. The metric we used for energy storage is similar watt-hours per dollar. We chose the storage metrics for consistency with the generation technologies where the only available performance data are cost based. In energy storage, similar improvement rates are found with watt-hours per kg or watt-hours per liter as for watt-hours per dollar [4]. The data was collected from a variety of sources that we judged reliable enough to use and can be found in Appendix A.

The next step in our research was to obtain a relevant and nearly complete set of patents from 1971 to the present (retrieved on 5.15.12) for each technological domain. Patents were selected as the means for the comparative invention study because 'Patent Data is the single most dominant indicator in invention studies' [25]. The method we used to select the patent set and the makeup of the patent sets used for analysis in this paper has been described in a recent paper by the authors [26]. Indeed, the study reported here could not have been done reliably without the search method developed in that earlier work.

In this method we use a keyword search of the domain (ex: solar PV) to find a pre-search set of U. S. patents. The pre-search set is then analyzed for the most representative United States and international patent classes for the desired set of patents, this is done using a measure of precision and recall of the patent classes within the pre-search set of patents. Finally, the individual patents that are classified in *both* the most representative U.S. and international patent classes are used as the data set for the study. The classification overlap is the key conceptual difference between this method and others so now we refer to it as the classification overlap method (COM). Fig. 1 (modified from Ref. [26]) shows the method in a process flow. The last step shown is important for the current study. A sample of 300 patents from each of the data sets is then read to estimate the relevance of the final data set as representative of the technological domain. A judgment is made for each patent read whether the knowledge embedded in the patent is in fact knowledge directly related to the domain (for example, solar–thermal patents are not judged relevant for the solar PV class).

The COM is superior to other Boolean or classification techniques used previously for a variety of domains; it is repeatable by different researchers and is generalizable across domains [26]. When performing a search for organic solar PV patents, Lizin et al. [5] selected the international patent class H01L-031; H01L is the same high-level international patent class that the COM method uses (H01L), but the COM removes many imaging sensor (camera) patents present in the H01L-031 IPC and allows us to focus on other types of solar PV that are not organic solar PV. Table 1 shows the specific patent classes used to define each domain as well as the size and relevancy of each patent set. Please note that the wind turbine and battery patent sets used emendations [26] to the standard classification-overlap methodology to increase the relevancy and completeness of the patent sets.

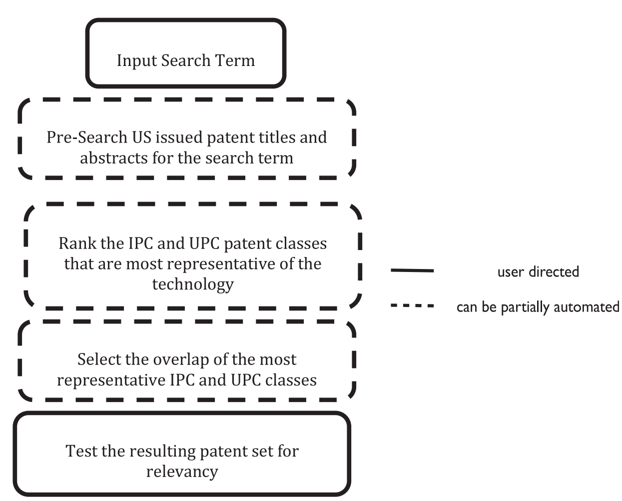

Fig. 1. Overview of the COM method (from Ref. [26]): most of the method can be automated via a computer, with only the selection of the search query and the testing of the final results left to the user.

Table 1
Summary of patent data sets for renewable energy (adapted from Ref. [23]).

Field of interest	UPC/IPC classification codes	Size of patent set	Percent relevant patents
Photovoltaic electricity	136/H01L	5101	85%
Wind turbine	(416 or 290)/F03D	2078	94%
Electric capacitor	361/H01G	6173	84%
Electrochemical battery	429/H01M not 'fuel cell'	16,466	83%

We analyzed these four sets of patents by a number of quantitative and qualitative approaches in order to test for possible causal factors as suggested by a review of the technical change literature (see Section 2.2). Since we only tested four domains there is not a focus on statistical tests but rather whether given concepts appeared from these four domains to be capable of an explanation for the differences.

2.2. Theories of technological change

Although there is no existing theory to explain performance improvement (or cost reduction) rate differences between technological domains, there are a large number of useful theoretical writings on technological change. This section of the paper uses this prior work to establish a foundation for explaining improvement rate differences as well as to develop some preliminary hypotheses that are testable from the patent data. To organize this analysis, we first look at larger socio-technical aspects of technological change and then at more specific technical aspects of the inventions that underlie technological change. We note the general consensus that innovation refers to the economic and business aspects of the technical change whereas invention is – as the patent database confirms – limited to improved technical characteristics [27].

2.2.1. Innovation, socio-technical aspects and resulting hypotheses

The scholarly debate in the 1970s and early 1980s on the relative importance of two broad sources of innovation – technology push vs. demand pull – settled into a general consensus that both were important. In particular, the agreement was that most technical innovations were driven by science and technology but that the role of demand and more broadly market and social forces were complementary. Dosi's important paper [28], while agreeing with Mowery and Rosenberg [29] that the demand-pull researchers had failed "to provide evidence that needs expressed through market signaling (a claim of proponents) are the prime movers of innovative activity", also noted that in selecting a specific technological trajectory, "the role of economic, institutional and social factors must be considered in greater detail". In this regard, the relative performance of specific technical approaches (our concern in this paper) might be assumed to depend more upon the invention characteristics discussed in the following sub-section of the paper. However, there are several aspects where the demand or usage could play an important role in the relative rate of improvement in a technological domain. More highly used technologies would potentially benefit from more user input whose value in improvement has been shown [30], would enable more opportunity to learn by doing in production [31] and as shown in the detailed case by Sinclair et al. [18], directly benefit from more R&D because of a profit motive of a private firm. Our study using patents can possibly test this final possibility since the number of patents accruing in a field should relate fairly well to the amount of R&D spending [32]. Thus, our first hypothesis is:

Hypothesis 1. The performance improvement or cost reduction rate in a technological domain should increase with the average annual rate of patenting in that domain (simply calculated by dividing the total number of patents in the set by the number of years over which the particular patent set was issued). The total number of years was 41 for each of the domains as the searches were performed from 1970–2011.

2.2.2. Invention characteristics and resulting hypotheses

The importance of radical or breakthrough inventions to technological progress has been widely discussed [33–36]. Thus, it might be reasonable to suspect that technological domains with enhanced radical invention would improve in performance faster than those with less of such breakthroughs. Despite the extensive conjectures about the role of radical inventions, only little has been done to objectively characterize such inventions. However a recent paper [25] has performed a study using patents to try to objectively identify the characteristics of radical inventions. Their research was carried out on a random sample of 150,000 European patents from 1989 to 1993, taking those with greater than 20 citations in the first five years after their issuance as radical and then comparing these 96 patents to a control set of 96 with less than 20 citations. While one may legitimately argue that patent citations is only one aspect of an invention and may not fully capture the concept of radical, it has been fairly clearly established that citation counts of patents do reflect technical importance [37] and at least in one case also correlate with economic significance [38]. Thus, this prior research suggests that domains with more patents of higher citations will progress more rapidly; specifically.

Hypothesis 2. Technological domains with a greater percentage of patents with citations >20 should have higher rates of improvement of performance or cost reduction.

As an example, Fig. 2 shows a log–log plot of the citations for the capacitor domain and indicates that patent citations roughly follow the well established power law for scientific paper citations [39,40]. The vertical axis of Fig. 2 shows the number of citations that each particular patent received, and the horizontal axis shows the ranking of that patent within all of the patents within that domain for number of citations, for example the most cited patent in the capacitor data set was cited 361 times and is ranked first in the 6173 patents. The 987 patents that are cited at least 20 times for the capacitor patents are also highlighted on this log–log plot. It is important to note that there were 6173 patents in the capacitor set, with 1242 patents being cited zero times and therefore not shown on the logarithmic scale.

There have been several suggestions [41–43] that inventions that are more important (or radical/breakthrough) are more reliant

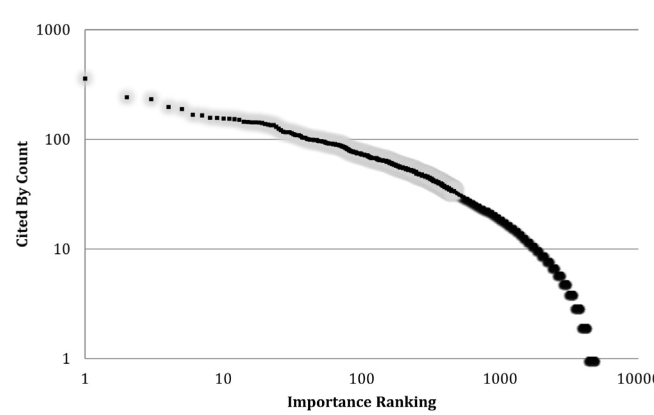

Fig. 2. A log–log plot of the importance distribution of capacitor patents with the patents that received more than 20 citations highlighted. These are 16% of the total patents in the domain.

on recent science than less important inventions. For this reason and from the general possibility that greater progress is possible in domains more solidly connected to recent science, there appears good justification for presuming domains that are more closely connected to science will progress more rapidly. Since the use of the citations in a patent that are to non-patent literature (NPL) – usually scientific journals – are available, the NPL citation fraction has been used to ascertain the scientific connection of specific patents [44]. For understanding differences in rates between domains, this theory suggests that domains whose patents cite more scientific articles will improve more rapidly than those who cite less such articles; the resulting hypothesis is:

Hypothesis 3. Technological domains with a higher frequency of citations to the scientific literature should have higher rates of improvement in performance or cost.

The non-patent literature citation rate for a single patent is simply the number of non-patent citations divided by the total citations and is averaged over all of the patents in a particular technological domain in order to test hypothesis 3.

The literature on the nature of breakthrough inventions has conjectured that breakthrough patents rely more on recent (or emerging) inventions [44,45]. The logic of this conjecture is that if more recent patents are the most important ones to current patents, acceleration of performance is more likely than for a field that is still relying on older foundations; the resulting hypothesis is:

Hypothesis 4. Technological domains whose patents cite more recent patents should have higher rates of improvement in performance or cost.

In order to test hypothesis 4, we created a distribution of the patents that were cited by a particular domain over the last several hundred years. The results for each domain are similar to the capacitor example shown in Fig. 3 with a long 'tail' of years with few patents that are cited by the domain followed by a 'peak' set of years when most of the cited patents were published.

Using this distribution we can find the average date of publication of the patents cited by a particular domain and subtract it from the average date of issuance of the patents within the same technical domain. This particular metric is similar to the 'citation lag' metric introduced by Nemet and Johnson [46] and to the price index introduced much earlier [39]. For the case of capacitors, the average date was 1990.1, and the average date of publication for patents within that domain was 1996.4, making the average age of a cited patent 6.3 years.

Theories of technological progress have also been advanced that emphasize the importance of the breadth of knowledge utilized in developing a given invention [47–50]. Studies have been made of the ratio of citations made by a patent to fields outside of the domain of interest expecting to find more highly cited patents

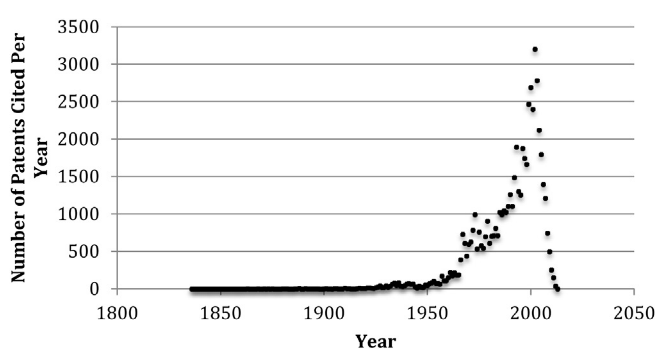

Fig. 3. Temporal distribution of patents that are cited by the set of capacitor patents from 1970 to 2011 (the foundation of knowledge for the domain).

having more citations outside of their primary domain [46]. However, results indicate that more important patents tend to cite more often within their field than outside it [46,51]. Thus our final hypothesis is:

Hypothesis 5. Technological domains that cite higher internal fractions of patents from their domain will have higher rates of improvement.

Hypothesis 5 can be tested using the inter-field citation rate. This metric is a ratio of the number of patents that are cited outside of the domain of interest to the total number of cited patents. Thus we would expect a lower interfield citation rate to correlate with high improvement rates.

The preceding hypotheses in this sub-section all arise from work done on the idea of important, breakthrough or radical patents. There are several other concepts in the literature that might be part of a more general theoretical foundation for explaining differences in improvement rates. One idea – that domains that are more decomposable or where elements of the technological artifact do not interact as strongly with one another will improve more rapidly than domains whose elements do interact strongly – was first conjectured to explain large differences in rates of improvements between performance in energy and information technologies [4]. A model has been developed [52] that in fact shows a higher rate of learning and cost reduction (Wright formulation but applicable to a Moore framework) for technologies with fewer interactions among components of the technologies. As of yet, there has not been found a way to quantitatively test this theory. Other ideas such as that scale effects are important [53] or materials innovations are important [54] have also not been tested. We do not yet have a way to test these potentially important hypotheses objectively with patent data. However, we pursue a qualitative study of the most important patents in each of our four domains to explore these ideas.

3. Results

In Section 3.1 we present the different rates of improvement between the four renewable energy domains. In Section 3.2 we discuss the quantitative measures that we tested and how they relate to the improvement rates. Finally, in Section 3.3 we will examine 12 of the most highly cited patents within each domain and discuss some qualitative differences between the domains of interest.

3.1. Rates of improvement

We constructed performance/cost improvement curves for each of the four domains of interest. We used semi-log plots of performance with time (similar to Moore's law) for the reasons given in Section 1. In this section we will compare the technological improvement rates between the two dominant energy generation technologies (solar PV and wind turbines), as well as two energy storage technologies (batteries and capacitors).

As mentioned in Section 2, the fundamental unit of measurement for the energy generation technologies is peak watts per dollar. Fig. 4 shows the results as a function of time for solar PV and wind turbine technologies.

Along with the plotted data points for each of the domains, we fitted each domain with an exponential regression to estimate a continuous exponential improvement rate. The domains that perform similar functions were grouped together for comparison (i.e. solar PV and wind turbines for energy generation). For solar PV, the exponential fit gives an improvement rate of 9.0% per year, with an R^2 value of 0.93 using 35 data points. The improvement rate for wind turbines is only 2.9% with an R^2 of 0.66 using 23 data points.

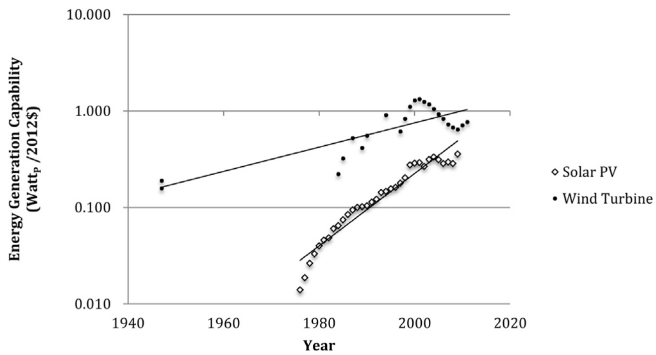

Fig. 4. Output per unit cost (in constant 2012$ adjusted by the consumer price deflator). Improvement of solar PV and wind turbines (1947–2011).

The wind turbine data is noisy due to the price fluctuations within the wind turbine market over the decade spanning 2000–2010, as is described in detail by Bolinger and Wiser [20]. In fact, if we had to rely only on recent data, the reliability of wind turbine performance trends would be very low. However, we were able to find data from two early commercial wind turbines that were used to produce electricity (as opposed to directly powering machinery). Without the two earlier points included, the improvement rate only changes slightly to 3.4%, which is still significantly lower than that of the solar PV domain. It appears that wind turbine and solar PV data may be distorted by recent data perhaps related to demand subsidies in these markets. Due to these factors and also due to unreliability in extrapolation without adequate theory, extrapolations of the curves is only of nominal interest; nonetheless the intersection of the two fitted curves is in 2021.

Similar to the energy generating technologies shown in Fig. 4, Fig. 5 shows the technological improvement with time in the two energy storage domains. The differences in improvement rates between batteries and capacitors are even more striking than that between solar PV and wind turbines. The improvement rate for batteries is 3.1% ($R^2 = 0.77$, $n = 9$), and the improvement rate of capacitors is 21.1% ($R^2 = 0.97$, $n = 6$). With the caveats expressed above, we note that the two fitted curves in this case intersect in 2034.

There are significant differences in rates between the selected sets of technologies, and if indicative of the future could determine which domains end up dominating their respective function (energy generation, energy storage). For the chief purpose of this paper, the large differences between the improvement rates sufficiently differentiate the domains to empirically examine the hypotheses that were discussed in Section 2.2 of this paper.

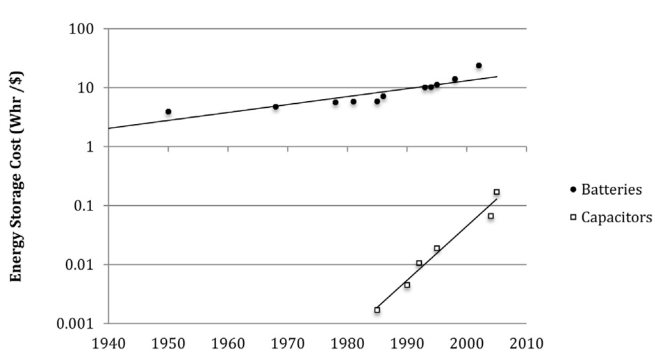

Fig. 5. Energy storage per unit cost (in constant 2012$ adjusted by the consumer price deflator). Improvement of batteries and capacitors (1950–2005).

3.2. Quantitative patent results

In this sub-section, we explore the five hypotheses derived from theories of technological change in Section 2.2 for the four renewable energy domains whose rate of progress was given in Section 3.1. Table 2 shows the summary of the results for the applicable measure for each hypothesis.

It is informative to compare the results by looking at the four domains as two independent sets (one for energy generation and one for energy storage). There are only two hypotheses that are consistent with the empirical results for both pairs in this type of comparison. The proportion of highly cited patents is higher for the two technologies with higher improvement rates (solar PV and capacitors) in accord with hypothesis 2. This may lend credence to the idea that radical or breakthrough inventions tend to move technologies forward, although the difference between batteries and capacitors is very small for this metric, which weakens the argument since the battery domain progresses much more slowly than the capacitor domain. Perhaps the strongest signal in this comparison is that from the average ages of cited patents which is significantly smaller for solar and capacitors as suggested by hypothesis 4. Wind turbine patents cite patents over twice the age of those cited by solar PV, and batteries cite patents 1.5 times older on average than those of capacitors. These results support the idea that domains that rely on more recent technology tend to develop more quickly.

In order to analyze the four data points as a whole, we performed a correlation analysis on this data, as has been done by similar studies in the past [55]. Not surprisingly, the limited number of data points in the study (four) assures that there were no statistically significant correlations (see Appendix B). In fact, the qualitative review agrees with the statistical test in showing no reliable explanation for the difference in rates; the strongest hypothesis after this review remains the age of patents cited in the domain.

3.3. Qualitative patent results

While the quantitative data can bring objectivity to the comparison between domains, we also performed a thorough reading of some of the most important patents in each of the domains. In order to select these patents, we picked the three most cited patents from each of the four decades that were represented (1970s, 1980s, 1990s, 2000+). A list of the titles of all 48 patents is given in Appendix C along with their dates of issue.

After reading the sets of patents, an apparent distinction can be drawn between the more rapidly improving domains of solar PV and capacitors and the slower domains of wind turbines and batteries. An in depth look at the 12 most cited wind patents shows that most of the inventions tend to be at the macrolevel, of a higher technological hierarchy [54]. Titles such as ‘Wind Turbine’ and ‘Horizontal Windmill’ indicate the fact that the more in-depth

Table 2
Summary of quantitative hypotheses results.

Domain	Solar PV	Wind	Capacitors	Batteries
Improvement rate	9.0%	2.9%	21.1%	3.1%
H1 – patenting rate	124.4	32.8	150.6	401.6
H2 – % of patents cited over 20 times	21%	15%	16%	14%
H3 – NPL citation %	28%	9%	11%	21%
H4 – average age of cited patents (years)	12.2	26.6	6.3	9.2
H5 – % of cites to other domains	69%	80%	71%	67%

review confirms: in this domain, a many inventions represent the changing of the system as a whole – rather than a single component.

The opposite case can be made for batteries, with many of the improvements in the battery patents being mostly at the material level, with very few changing the entire system. This is indicated in titles such as 'Ion Conductor Material' and 'Protective Coatings for negative electrodes'.

The two domains with higher technological improvement rates show patents from both high and low level technical hierarchy levels in their set of top patents. The solar PV list includes 'Amorphous Silicon as a UV filter', as well as 'Photoelectric Conversion Device and photocell'. Patents that top the capacitor domain include patents like 'Columbium powder and method of making the same' as well as 'Supercapacitor structure': in-depth review confirms the mixed hierarchy in this patent set.

While these qualitative results are only suggestive, they indicate that technologies may improve more rapidly when there are *both* important system level and important component level improvements being developed in the domain.

4. Discussion and conclusions

This paper examines quantitative technology improvement rates in the form of cost and investment in four important renewable energy domains. Technological improvement rates, learning rates, and other frameworks are commonly used in single domains throughout the research community but are not often used to compare different domains against each other. In addition, predictive uses of these tools should and will continue to be questioned until further understanding is available of the underlying factors that cause these improvements. This paper developed a theoretical basis for an approach that compares domains and derived possible reasons for different rates of advance. This is complementary to frameworks that view technological progress one domain at a time.

Significant and sizeable differences between the improvement rates of solar PV, wind turbines, capacitors and batteries were found in this study. A framework for empirically studying the factors that can cause such substantial differences between these rates was developed based upon a new method for obtaining patent sets differentiated by domain. Our empirical study of the four renewable energy domains led to some findings that are consistent with prior theories of technological change. Most notably, we found that patents from the domains with higher improvement rates cited more recent patents and had a higher percentage of important patents with over 20 citations. While these findings are potentially important, the limitations inherent with only having results for four domains should not be forgotten. In the same way, the interesting indications that neither the number of patents in a domain nor the scientific connections are important in rate differences – while potentially significant from a policy perspective – must be tempered by the same caution.

As with all studies using patents as a data source, there are limitations to the data source. Of potential relevance to this study are the differences in patenting strategies between domains, and between geographic areas [56]. Most significant is that some contributions to cost reduction such as production worker learning and production capacity effects may well not be reflected in the patent database. This could introduce some systematic bias to any correlation between improvement rate (especially of cost) and patent characteristics. Additionally, while our patent selection method has proven to be superior to previous methods, there is no way to ensure that we were able to select all of the patents that represent a field, and there are a number of patents within each data set that may not properly belong to that domain – see Table 1 and [26]. Nevertheless, the patent data provides the most detailed, objective, and accessible information on technical inventions and the most viable way to empirically examine theories related to differences in rates of improvement in different domains.

Further studies should look to other technical domains that possess differing rates of progress while attempting to test the full range of theories for the difference in improvement rates that were derived in this paper from broader theories of technological change. At the completion of those two objectives, it will be possible to more fully develop a predictive understanding of the improvement rate differences and to complete a robust statistical analysis of these theories. Communicating the importance of reliable theory for rate of advance differences and a way forward to such a theory is the end objective of this paper.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.renene.2014.03.002.

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