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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.

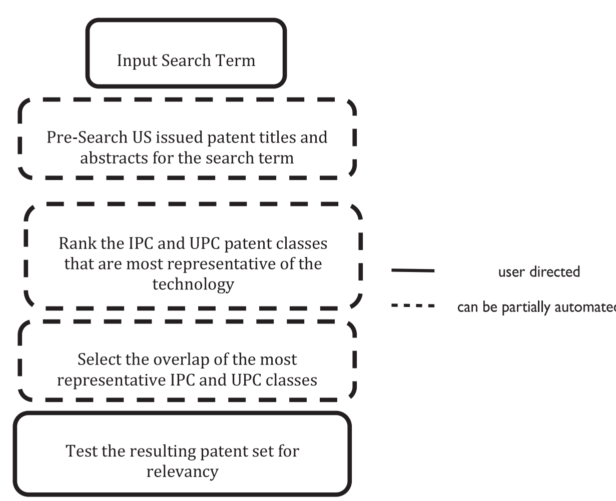

Fig. 1. Overview of the COM method (from Ref. [26]): most of the method can be automated via a computer, with only the selection of the search query and the testing of the final results left to the user.