Int. J. Production Economics 146 (2013) 386–391

Contents lists available at ScienceDirect

Int. J. Production Economics

journal homepage: www.elsevier.com/locate/ijpe

A hierarchical cost learning model for developing wind energy infrastructures

Amy J.C. Trappey [a,*], Charles V. Trappey [b], Penny H.Y. Liu [a], Lee-Cheng Lin [c], Jerry J.R. Ou [d]

[a] Department of Industrial Engineering and Engineering Management, National Tsing Hua University, Taiwan
[b] Department of Management Science, National Chiao Tung University, Taiwan
[c] Green Energy and Environment Research Laboratories, Industrial Technology Research Institute, Taiwan
[d] Bureau of Energy, Ministry of Economic Affairs & Department of Business Administration, Southern Taiwan University, Taiwan

ARTICLE INFO

Article history:
Received 2 July 2012
Accepted 11 March 2013
Available online 27 March 2013

Keywords:
Wind power
Learning curve
Hierarchical linear model

ABSTRACT

Renewable energy has been increasingly promoted and used to substitute non-renewable fossil-fuels, which cause negative effects on the environment. The Taiwan Statute for Renewable Energy Development has regulated and promoted renewable energy since 2009. A feed-in tariff (FIT) for renewable energy is one of the incentives that the government uses to promote the installation of green power generation facilities. The price of the electricity feed-in tariff is based on the current and future costs of renewable energy generation. When analyzing cost trends for renewable energy installation, many researchers use a single factor cost learning curve model. However, past studies indicate that there are multiple factors affecting the overall cost of installing renewable energy. Hence, this research develops a hierarchical installation cost learning model which considers multiple factors to accurately model and forecast wind energy development. This research uses wind power development data from Taiwan as a case study. We identify the cost factors, evaluate the learning effects, and compare the hierarchical learning curve model to the basic (non-hierarchical) learning curve model. The research results show an improved fit between the hierarchical model and the actual data when compared to the basic learning model. The study also provides new insights between the wind power learning progression of Taiwan and three countries in Europe.

1. Introduction

According to the International Energy Association report (IEA, 2008), the projected world demand for energy will increase 45% between 2006 and 2030 with an average annual growth rate of 1.6%. Oil remains the dominant fuel in the primary energy mix (IEA, 2008). Further, global climate change remains an important issue with global average sea levels increasing at an average rate of about 3.1 mm per year from 1993 to 2003 and the annual average Arctic sea ice shelf is shrinking 2.7% per decade since 1973 (IPCC, 2007). In order to help resolve the problem of energy demand and climate change, most of countries have increased their investment in renewable energy. Global investment in renewable energy in 2004 was $22 US billion dollars and reached to $211 US billion dollars in 2010 (REN21, 2011).

Renewable power generation policies have been implemented in 96 countries and represent the most common type of support policy. Two of the most popular policies for governments to stimulate the deployment of renewable energy are the implementation of Renewable Portfolio Standard (RPS) and Feed-in-Tariffs (FIT). RPS requires electricity supply companies to produce a specified fraction of their electricity from renewable energy sources and the renewable energy generators sell their electricity back to supply companies. RPS relies almost entirely on the private market for its implementation. Therefore, this approach helps deliver renewable energy at a lower cost, allowing renewable energy to compete with cheaper fossil fuel energy sources. Unlike RPS, FIT offers long-term contracts, which last 15 years to 25 years, where renewable energy producers guarantee to purchase all the generated renewable energy based on the cost of electricity generation. FIT is the most widely implemented policy with at least 61 countries and 26 states or provinces in the world implementing FIT. Ten countries and at least 50 other jurisdictions, including 30 U.S. states and British Columbia have implemented RPS (REN21, 2011). The Taiwan government passed the Statute

* Correspondence to: Department of Industrial Engineering and Engineering Management, National Tsing Hua University, Hsinchu, Taiwan 30013, R.O.C. Tel.: +88635742651; fax: +88535722204.

E-mail addresses: trappey@ie.nthu.edu.tw (A.J.C. Trappey), trappey@faculty.nctu.edu.tw (C.V. Trappey), s100034519@m100.nthu.edu.tw (P.H.Y. Liu), itriA00017@itri.org.tw (L.-C. Lin), jrou@moeaboe.gov.tw (J.J.R. Ou).

0925-5273/$ - see front matter
http://dx.doi.org/10.1016/j.ijpe.2013.03.017

for Renewable Energy Development in 2009 and used FIT as the incentive policy to promote investment in renewable energy. The goal of the statute is to increase the installed capacity of renewable energy to 8000 MW over the next 20 years.

Wind power has become the fastest growing source of renewable energy. According to the REN 21 Report (REN21, 2012), global wind capacity increased by 20% (from 198 GW in 2010 to 238 GW in 2011) which is more than any other renewable technology. Over 68 countries have added more than 10 MW of reported capacity, with 22 of these countries passing the 1 GW level during 2011. Taiwan is an island with an extensive coastal region. The Taiwan potential for wind energy can be developed by 3000 MW and is considered the most suitable for development than other renewable energies (Liou, 2010). The government regularly revises FIT prices for new installations in order to ensure economic efficiency and to minimize windfall profits for renewable energy installers. In other words, the government reduces FIT prices if renewable energies reach mature development and stable installation costs. Thus, for countries with the potential for developing wind energy and adopting FIT policies, understanding the trend between the relationships of wind energy costs and wind energy production and utilization is important. Learning curves offer important strategic implications for industrial production (Chand and Sethi, 1990). Product output are depicted by a production cost curve and its variation with output level. Previous studies (McDonald and Schrattenholzer, 2001; Ibenholt, 2002) utilized the learning curve to analyze the relationship between wind power generation cost and the accumulated wind power production. The empirical results help governments and power plant installers understand the installation cost changes and trends for wind-power electricity production. Nonetheless, these studies usually adopt a single factor learning curve model to describe the cost trend. Some researchers note that single factor learning curve models provide a weak explanation of the causal effects and may bias the estimation of cost trends (Nemet, 2006; Yu et al., 2011). Therefore, this study develops a hierarchical cost learning curve model to interpret the cost trends of a wind power facility. The purpose is to discover the multiple factors that significantly impact the relationship between wind cost and accumulated wind production. The results provide information for policy makers to improve the design of wind energy systems and to optimize wind energy development.

This research paper is organized as follows. Section 2 is a literature review which introduces learning curves and the hierarchical linear model. Sections 3 and 4 describe the methodology and present a case study, respectively. For the case study, the learning curve is used to compare the fitness of hierarchical model with general learning curve model. The progression rate is compared with similar studies conducted in Denmark, Germany and the United Kingdom. Section 5 provides a conclusion and overview of the research results and contribution.

2. Literature review

In this section, the concepts of basic and hierarchical linear curve models and the related research literatures are reviewed.

2.1. Basic learning curves and related literature

A learning curve offers a means of analyzing past cost development that had been adapted to analyze future cost development (Neij, 2008). The curve shows the relation between accumulated production quantity or experience and unit production time or cost for a given activity or product. The learning curve effect (Fig. 1) depicts that as the total production quantity (in units) doubles, the cost per unit declines by a constant percentage (Jaber and El Saadany, 2011). Wright (1936) was one of the first researchers to describe and apply the learning effect. By observing the aircraft industry, he proposed a mathematical model to describe the declining trend of required labor hours needed to produce one unit of product at a constant rate. Learning curves have been widely applied and each application typically has a unique learning rate. The usefulness of learning curves was demonstrated during World War II as a very effective means for predicting the cost and time for constructing ships and aircraft (Yelle, 1979).

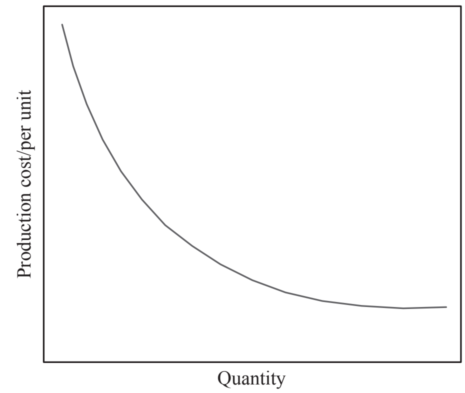

Fig. 1. A typical learning curve.

The learning curve can be applied to describe effects of groups as well as individual performance, e.g., a group comprising direct and indirect labor. Technological or skill progresses are considered types of learning. The industrial learning curve can be used to model the improved skill of an individual by repetition of simple operations. It can also be used to describe more complex systems, such as group efforts of people on production lines and others in supportive positions, all working to progressively improve a common task (Jaber and Bonney, 1999). Learning curves are described by the following equation (Berndt, 1991):

$$C_t = C_1 n_t{}^{\alpha} e^{u_t}$$

where C_t represents the unit production cost at time t and C_1 is the first unit production cost. n_t Is the production quantities accumulated to time t, α is the learning index, u_t is the stochastic term, and e^{u_t} is the error term following a normal distribution.

A reliable learning curve model is a useful tool for the planning and control of operations. The predictions of future performance are more reliable, the use of resources are better planned, the sequencing of operations are more precise, and the cost of future production are more accurately estimated when learning effects are taken into consideration (Andrade et al., 1999). Plaza and Rohlf (2008) focused on the relationship between the capabilities of a project team and consulting-cost management. They proposed a model based on learning curves to study the impact of training on project cost and duration. In order to further define production ramp-up, Terwiesch and Bohn (2001) modeled the complex dynamics of a new product's ramp-up by providing concrete values for the cost and benefits of learning efforts. Specifically relevant to this research, there are research papers which apply learning curves to renewable energy production. Wang et al. (2011) simulated wind energy industry development in China using a logistic learning curve model. Ibenholt (2002) constructed learning curves of wind power production costs in three countries, i.e., Denmark, Germany and United Kingdom. He compared the aerodynamic conditions and renewable energy policies which affect the costs and utilizations of wind power in these countries. Neij (2008) presented an analytical framework, which was based on an assessment of available experience curves. The analysis was complemented with a bottom-up analysis of sources of cost reductions and expert assessments of long-term