



# A hierarchical cost learning model for developing wind energy infrastructures

Amy J.C. Trappey<sup>a,\*</sup>, Charles V. Trappey<sup>b</sup>, Penny H.Y. Liu<sup>a</sup>, Lee-Cheng Lin<sup>c</sup>, Jerry J.R. Ou<sup>d</sup>

<sup>a</sup> Department of Industrial Engineering and Engineering Management, National Tsing Hua University, Taiwan

<sup>b</sup> Department of Management Science, National Chiao Tung University, Taiwan

<sup>c</sup> Green Energy and Environment Research Laboratories, Industrial Technology Research Institute, Taiwan

<sup>d</sup> 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.

© 2013 Elsevier B.V. All rights reserved.

## 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](mailto:trappey@ie.nthu.edu.tw) (A.J.C. Trappey), [trappey@faculty.nctu.edu.tw](mailto:trappey@faculty.nctu.edu.tw) (C.V. Trappey), [s100034519@m100.nthu.edu.tw](mailto:s100034519@m100.nthu.edu.tw) (P.H.Y. Liu), [itria00017@itri.org.tw](mailto:itria00017@itri.org.tw) (L.-C. Lin), [jrou@moeaboe.gov.tw](mailto:jrou@moeaboe.gov.tw) (J.J.R. Ou).

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 Schratzenholzer, 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

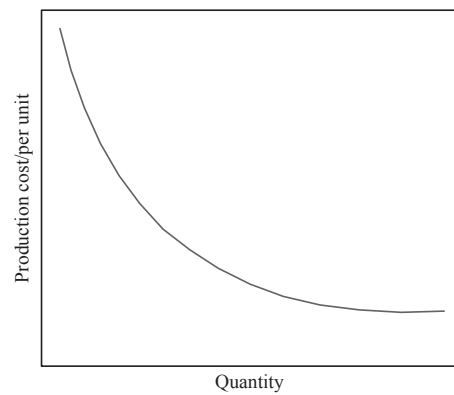


Fig. 1. A typical learning curve.

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).

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  $t$ ,  $\alpha$  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

analysis of future costs for developing new technologies of green electricity generation. Qiu and Anadon (2012) used bidding data for wind power projects from 2003 to 2007 in China and applied learning curve models to predict development costs.

For most studies related to energy production learning curves, a one-factor learning curve model was applied. Thus, only the relation between the production cost and the production quantity (the accumulated capacity when used in renewable energy) was modeled. In addition to the learning effect generated from experience, Nemet (2006) considered that other observable factors played important roles in decreasing production costs. He identified seven factors that affect photovoltaic module costs and found that plant size, module efficiency, and the cost of silicon are critical factors that impact the production cost of solar power. More importantly, the accumulated production quantity, which is usually represented by the learning experience curve, weakly explains decreasing costs. Yu et al. (2011) also noted that the one factor learning curve model only explains cost declines in the initial development stage of a new technology and cannot fully describe the cost changes caused by other factors such as key material (input) prices. Ibenholt (2002) also indicated that the connection between wind power electricity production cost and accumulated production quantity may be influenced by factors such as R&D investment, policy measures, changes in input material prices (e.g., steel), competition in the market, economies of scale, and other technology specific variables. The relationship among these factors and wind power production quantity and cost are often discussed and planned in a nested and hierarchical fashion. Thus, this paper incorporates the hierarchical linear model concept as a cost learning curve model to include multiple factors that significantly influence cost changes.

## 2.2. Hierarchical linear model (HLM) and related literature

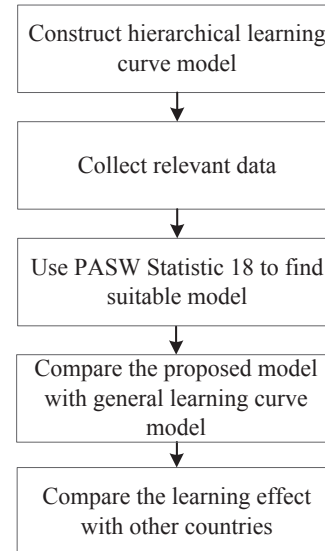
Hierarchical linear models are a statistical model of parameters that vary at more than one level. These models are generalizations of linear models, which can be extended to non-linear models. HLM is appropriate for research where the data are described in a nested structure, such as students in a class where within a cohort there may be many varying factors such as weight, sex, and height. HLM is applied frequently in the educational domain, since it fits the classical nested structure of student and faculty populations (Wen and Chiou, 2011). To estimate the likelihood of success of students, Cyrenne and Chan (2012) track the performance of university students and analyze with a least squares dummy variable model and a hierarchical linear model. Perry et al. (2007) applied HLM and regression techniques to explore the effects of teacher practices in promoting student academic achievement, behavioral adjustment, and feelings of competence. Other areas such as sociology and consumer science have also applied HLM as a method to understand attitudes, motivations, and behaviors. Gentry and Martineau (2010) describe HLM as an example of a multilevel methodological approach to examine changes over time in the evaluation of human resource team leadership development. Addressing the multilevel relation among time variance, disposable income, and U.S. entertainment consumption, Chen (2012) adopted a hierarchical linear model to determine that time variance and disposable income are positively related to entertainment expenditures over different entertainment categories. As reported by Wen (2006), HLM applications have also been used in biostatistics and economics.

HLM was first developed by Lindley and Smith (1972). In general, the model of HLM can be classified as the full model, the intercept model, and the coefficient model (Table 1).

For the full model, level 1 is the basic structure of HLM, which denotes the relation between the dependent variable  $Y_{ij}$  and the explanatory variable  $X_{ij}$ . In level 2, two dependent variables are derived as the intercept ( $\beta_{0j}$ ) and coefficient ( $\beta_{1j}$ ) of the linear

**Table 1**  
HLM model types.

Type	Level 1	Level 2
Full model	$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \varepsilon_{ij}$	$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j}$ $\beta_{1j} = \gamma_{10} + \gamma_{11}Z_j + u_{1j}$
Intercept model	$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \varepsilon_{ij}$	$\beta_{0j} = \gamma_{00} + \gamma_{01}Z_j + u_{0j}$
Coefficient model	$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \varepsilon_{ij}$	$\beta_{1j} = \gamma_{10} + \gamma_{11}Z_j + u_{1j}$



**Fig. 2.** Constructing a hierarchical learning curve of wind power installation in Taiwan.

model in level 1. Both are influenced by the explanatory variable  $Z_j$ . By the values of parameters  $\gamma_{00}$ ,  $\gamma_{01}$ ,  $\gamma_{10}$  and  $\gamma_{11}$  in level 2 equations indicate the degree that  $Z_j$  interacts with the variables  $\beta_{0j}$  and  $\beta_{1j}$  can be determined.  $\varepsilon_{ij}$ ,  $u_{0j}$  and  $u_{1j}$  are the error terms for both models in level 1 and level 2. For the intercept model,  $Z_j$  determines  $\beta_{0j}$  which is the intercept in level 1. While in the coefficient model, the coefficient  $\beta_{1j}$  of level 1 is estimated by  $Z_j$  in level 2.

Gill (2005) explains that HLM has several advantages over standard linear models. Their arguments include that hierarchical models are ideal tools for identifying and measuring structural relationships that fall at different levels of the data generating procedure with virtually no limit to the dimension of their hierarchy. Hierarchical models also directly express the exchangeability of units, whereas nonhierarchical models applied to multilevel data typically underestimates the variance. Finally, hierarchical models facilitate the testing of hypotheses across different levels of analysis, whereas nonhierarchical models can be nested within hierarchical models, allowing a likelihood or Bayes factor test of the validity of the proposed hierarchical structure.

## 3. Methodology

In order to build a hierarchical learning curve of the cost of installing wind power in Taiwan, we collect relevant data and use statistic software to fit the model (Fig. 2). Residual analysis is used to confirm the fitness of the hierarchical learning curve model and compare the model to the basic learning curve model. Finally, the study compares the learning effect of Taiwan wind power installation with the cases of Denmark, Germany and the United Kingdom described by Ibenholt (2002).

The data was checked to determine whether the learning curve factors would interfere with the relationship between accumulated wind energy capacity and wind power installation costs. This study utilizes the coefficient models to construct the hierarchical learning curve model of installing wind power in Taiwan and the detailed data analysis is presented in Section 4. The model, as shown in Eqs. (1) and (2), assumes that  $\beta_0$  and  $\beta_1$  have fixed effects.

$$\text{Level 1 : } C = \beta_0 X^{\beta_1} \epsilon \tag{1}$$

$$\text{Level 2 : } \beta_1 = \gamma_0 + \gamma_1 Z_1 + \gamma_2 Z_2 + \dots + \gamma_m Z_m + \delta \tag{2}$$

natural logarithms are used to estimate parameters and Eqs. (1) and (2) are combined into Eq. (3).

$$\ln C = \ln \beta_0 + \gamma_0 \ln X + \gamma_1 Z_1 \ln X + \dots + \gamma_n Z_n \ln X + \ln \epsilon \tag{3}$$

where  $C$  and  $X$  separately denote the wind power installation costs and accumulated installed wind power capacity, respectively.  $Z_1, Z_2, \dots, Z_n$  are considered as the variables that may interfere with the relationship between the cost and the accumulated installed wind-power capacity. The estimated parameters contain the intercept ( $\ln \beta_0$ ), the learning index  $\gamma_0$ , and the interference coefficients  $\gamma_1, \dots, \gamma_n$ .

#### 4. The cost learning curve of installing wind power

In order to reduce emission of carbon dioxide and promote development of renewable energy, Taiwan passed the Statute for Renewable Energy Development in 2009. The electricity purchase program, which is related to the installation cost, is a critical incentive encouraging people to install renewable energy. This research used wind power installation in Taiwan as a case study to collect data and demonstrate the building of hierarchical cost learning curve model.

##### 4.1. Hierarchical learning curve cost model—the Taiwan wind power sector case

For the Taiwan learning curve cost model for installing wind power, we consider the relation between cumulative capacity, the installation costs and other variables which may impact costs. The above-mentioned factors, except changes in input prices, are not easily quantified. Steel cost plays a key role on the increase or decrease in wind power installation costs. International oil prices also drive renewable energy demand. Thus, the global steel price index and the oil price are used as variables  $Z_1$  and  $Z_2$  in our model. The reference installation cost ( $C$ , in the unit of €/kW) used in the research is based on the report published by the European Wind Energy Association (2009). Since offshore wind power has not yet developed in Taiwan, we only use the historical data of onshore installation costs in the case study. The cumulative capacity and oil price from 2000 to 2010 was collected from the Taiwan Bureau of Energy (Bureau of Energy, 2011, 2012). The global steel index was sourced from the CRU (2012), which publishes annual data in mining, metals, and fertilizers. The global steel price index ( $Z_1$ ) and the oil price ( $Z_2$ ) are the inputs of level 2 model and Eq. (3) is expressed as follows:

$$\ln C = \ln \beta_0 + \gamma_0 \ln X + \gamma_1 Z_1 \ln X + \gamma_2 Z_2 \ln X + \ln \epsilon \tag{4}$$

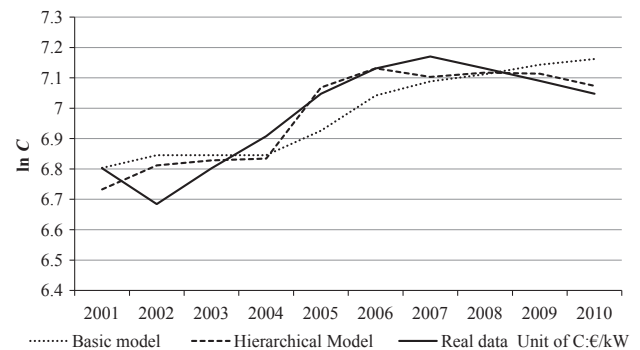
we use PASW Statistic 18 (IBM, 2012) to estimate the parameters and the statistical report is shown in Table 2.

Table 2 shows that the relationship between wind power installation costs and the accumulated wind power installed capacity is significant and positive. The steel price has a significant and positive effect, which interferes with the relationship between the cost of installing wind power and the accumulated installed

**Table 2**  
The output table generated by PASW Statistic 18.

Model	Coefficient	Standard error	t
Intercept	6.475*	0.104	62.461
Cumulative capacity	0.156*	0.049	3.167
Steel price × cumulative capacity	0.001**	0.000	2.446
Oil price × cumulative capacity	-0.003**	0.001	-2.805

\*  $p < 0.001$ .  
\*\*  $p < 0.05$ .



**Fig. 3.** The costs estimated by the hierarchical and basic models, compared to historical costs.

capacity. The oil price has a significant but negative effect. Thus, decreasing oil prices strongly affects the relationship between the installation costs and the accumulated installed wind power capacities.

Progression rate (PR) explains the rate of the increase or decline in cost, determining the percentage of cost that will likely occur when cumulative capacity is doubled (Ibenholt, 2002). The PR is calculated using Eq. (5).

$$PR = 2^\alpha \tag{5}$$

where  $\alpha$  represents the learning index ( $\alpha$  is equal to  $\gamma_0$  in this study). Therefore, the learning index of Taiwan is 0.156 and PR is 111.4%. The value PR (= 111.4%) shows that the cost of installing wind power in Taiwan will increase 111.4% from the former level when the cumulative installed wind power capacity is doubled.

##### 4.2. Comparison of learning curve models

The traditional basic model is compared with the hierarchical model since the basic learning curve model does not contain interfering and nesting effects. The basic learning curve only considers cumulative capacity  $X$ , which may influence the estimated learning index. The estimated basic cost learning curve is shown in Eq. (6).

$$\ln C = 6.677 + (0.079) \ln X \tag{6}$$

by comparing the costs estimated by the two models in a period of 10 years (2001–2010) with the actual installation costs, the results show that the hierarchical learning curve better describes the fluctuation of costs. Fig. 3 depicts the log values of costs (in €/kW) from 2001 to 2010 estimated by the basic model and the hierarchical model, with the corresponding real data as reference. Table 3 indicates that the hierarchical model is a better fit with much higher values on both  $R^2$  and adjusted  $R^2$ . The learning index for the basic model is 0.079 and the resulting PR is 105.6%. Table 4 shows the different learning indexes and PR values when using the hierarchical and basic learning curve models. The PR calculated using the hierarchical learning curve is higher than the basic

**Table 3**  
R<sup>2</sup> and adjusted R<sup>2</sup> of the hierarchical and basic models.

	Hierarchical learning curve (%)	Basic learning curve (%)
R <sup>2</sup>	87.1	70.1
Adj. R <sup>2</sup>	80.6	64.4

**Table 4**  
The learning index and PR estimated by the hierarchical and basic models.

	Hierarchical learning curve	Basic learning curve
Learning index ( $\gamma_0$ )	0.156	0.079
Progression rate (PR) (%)	111.4	105.6

learning curve. If the basic cost learning curve is applied which considers the cumulative capacity as the only influencing factor, then the future wind power installation costs in Taiwan will likely be over projected.

#### 4.3. Comparing the learning index and PR with other countries

According to the research reports published by [Ibenholt \(2002\)](#) and [ISET \(2000\)](#), the progression rates (PRs) of the wind power installations in Denmark, Germany and the United Kingdom are 92–93% (1984–1999), 92% (1990–1998), and 75% (1991–1999) respectively. A lower PR shows that doubling the cumulative capacity will decrease cost faster. The PR value of UK is the lowest among three countries, yet Denmark and Germany have no significant difference in the same period of time. For the renewable energy development, the United Kingdom has adopted RPS as its policy. The tender system, which is used to set the price, enhances the competition between wind power generators and leads to installation cost reductions. However, according to some reports ([Ibenholt, 2002](#)), a lower PR value may also reflect the hampering of diffusion because of a competitive and fierce market. Unlike the United Kingdom, Denmark and Germany both use FIT as the renewable energy development policy which creates stable conditions for installing wind power generators and increases the cumulative capacity ([Ibenholt, 2002](#)). Taiwan's development of renewable energy has occurred much later in comparison to these three countries. Taiwan's government did not pass the Statute for Renewable Energy Development until 2009 and has only recently implemented FIT as its renewable energy development approach. With a less matured wind power market and a lower level of accumulated wind power capacity, Taiwan's PR (= 111.4%) represents that the installation costs will increase to 111.4% of the previous costs if installation capacity is doubled. Taiwan has the highest PR comparing to the three countries since the market has not reached an equivalent scale of economy where the learning effect can impact the installation costs. In addition, due to an oligopoly in the Taiwan power generation market, the market is dominated by a small number of firms that cannot efficiently develop wind power and benefit fully from the learning effect.

## 5. Conclusions

Countries are actively developing renewable energy and wind power is one of the most potential sources of renewable energy. Previous studies constructed the level-1 basic (general) wind learning curve model, which biases the estimated learning index. This paper proposes a hierarchical cost learning curve model for wind power and uses the accumulated wind power installation in Taiwan as a case study. This study includes two price variables, the

steel price index and the oil price, to construct a hierarchical cost learning curve model for wind power. The research shows that both the steel price index and the oil price have significant effects on the relationship between the wind power installation costs and accumulated wind power installation capacity. When the steel price index increases and the oil price decreases, then wind energy development is obstructed and policy makers must provide subsidies or raise wind tariffs to stimulate wind energy investment. In addition, by comparing the basic learning curve model, the cost estimated by the hierarchical model provides a better R<sup>2</sup> and adjusted R<sup>2</sup> and shows that the fitness of hierarchical learning curve is superior to the basic learning curve.

The present research uses the hierarchical cost learning curve model to explore the effects of steel and oil prices on the relationship between the installation costs of wind power facilities and accumulated wind power production. The research provides opportunities for researchers and policy makers to apply the advanced learning curve modeling techniques to the new areas of renewable energy sector, e.g., offshore wind, solar, geothermal heat, ocean tides, to provide reliable and effective strategic development and incentive plans.

## Acknowledgments

This research is partially supported by the National Science Council and the Industrial Technology Research Institute in Taiwan.

## References

- Andrade, M.C., Pessanha Filho, R.C., Espozel, A.M., Maia, L.O.A., Qassim, R.Y., 1999. Activity-based costing for production learning. *International Journal of Production Economics* 62 (3), 175–180.
- Berndt, E.R., 1991. *The Practice of Econometrics: Classic and Contemporary*. Addison-Wesley, Reading, MA.
- Bureau of Energy, 2011. *Energy Statistical Hand Book 2010*. Bureau of Energy, Taipei, Taiwan. Available from: <http://www.moeaboe.gov.tw/English/Statistics/EnStatistics.aspx>. (accessed 5.10.12).
- Bureau of Energy, 2012. *The Information System of Management and Analysis of Oil Price*. Available: <http://210.69.152.10/oil102> (accessed 5.10.12) online.
- Chen, C.K., 2012. Hierarchical linear relationship between the U.S. leisure and entertainment consumption. *Technology in Society* 34 (1), 44–54.
- CRU, 2012. *Global Steel Price Index*. Available: <http://cruonline.crugroup.com/SteelFerroAlloys/PriceIndex/tabid/143/Default.aspx> (accessed 5.10.12) online.
- Chand, S., Sethi, S.P., 1990. A dynamic lot sizing model with learning in setups. *Operations Research* 38 (4), 644–655.
- Cyrenne, P., Chan, A., 2012. High school grades and university performance: a case study. *Economics of Education Review* 31, 524–542.
- EWEA, 2009. *Pure Power Wind Energy Targets for 2020 and 2030*. Available: [http://www.ewea.org/fileadmin/ewea\\_documents/documents/publications/reports/Pure\\_Power\\_Full\\_Report.pdf](http://www.ewea.org/fileadmin/ewea_documents/documents/publications/reports/Pure_Power_Full_Report.pdf) (accessed 5.10.12) online.
- Gentry, W.A., Martineau, J.W., 2010. Hierarchical linear modeling as an example for measuring change over time in a leadership development evaluation context. *Leadership Quarterly* 21 (4), 645–656.
- Gill, J., 2005. Hierarchical linear models. *Encyclopedia of Social Measurement* 2, 209–214.
- Ibenholt, K., 2002. Explaining learning curves for wind power. *Energy Policy* 30 (13), 1181–1189.
- IBM, 2012. *IBM SPSS Software*. Available: <http://www-01.ibm.com/software/analytics/spss> (accessed 5.12.12) online.
- IEA, 2008. *World Energy Outlook 2008*. International Energy Association, Paris, France. Available: <http://www.iea.org/textbase/nppdf/free/2008/weo2008.pdf> (accessed 5.12.12) online.
- ISET, 2000. *Cost tendencies in the German wind energy market 1998*. Fraunhofer Institute for Wind Energy and Energy System Technology, Kassel, Germany. Available from: [www.iset.uni-kassel.de](http://www.iset.uni-kassel.de). (accessed 5.10.12).
- IPCC, 2007. *Climate Change 2007: synthesis report*. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. In: Core Writing Team, Pachauri, R.K., Reisinger, A. (Eds.), IPCC, Geneva, Switzerland, Available from: [http://www.ipcc.ch/publications\\_and\\_data/ar4/syr/en/mains1.html#1-1](http://www.ipcc.ch/publications_and_data/ar4/syr/en/mains1.html#1-1). (accessed 5.10.12).
- Jaber, M.Y., El Saadany, A.M.A., 2011. An economic production and remanufacturing model with learning effects. *International Journal of Production Economics* 131 (1), 115–127.
- Jaber, M.Y., Bonney, M., 1999. The economic manufacture/order quantity (EMOQ/EOQ) and the learning curve: past, present, and future. *International Journal of Production Economics* 59 (1–3), 93–102.

- Liou, H.M., 2010. Policies and legislation driving Taiwan's development of renewable energy. *Renewable and Sustainable Energy Reviews* 14, 1763–1781.
- Lindley, D.V., Smith, A.F.M., 1972. Bayes estimates for the linear model. *Journal of Royal Statistical Society. Series B (Methodology)* 34 (1), 1–41.
- McDonald, A., Schrattenholzer, L., 2001. Learning rates for energy technologies. *Energy Policy* 29, 255–261.
- Neij, L., 2008. Cost development of future technologies for power generation—a study based on experience curves and complementary bottom-up assessments. *Energy Policy* 36 (6), 2200–2211.
- Nemet, G.F., 2006. Beyond the learning curve: factors influencing cost reductions in photovoltaics. *Energy Policy* 34, 3218–3232.
- Perry, K.E., Donohue, K.M., Weinstein, R.S., 2007. Teaching practices and the promotion of achievement and adjustment in first grade. *Journal of School Psychology* 45 (3), 269–292.
- Plaza, M., Rohlf, K., 2008. Learning and performance in ERP implementation projects: a learning-curve model for analyzing and managing consulting costs. *International Journal of Production Economics* 115 (1), 72–85.
- Qiu, Y., Anadon, L.D., 2012. The price of wind power in China during its expansion: technology adoption, learning-by-doing, economies of scale, and manufacturing localization. *Energy Economics* 34 (3), 772–785.
- REN21, 2011. 2011 Renewables Global Status Report. Renewable Energy Policy Network for the 21st Century, Paris, France. Available: [http://www.ren21.net/Portals/97/documents/GSR/REN21\\_GSR2011.pdf](http://www.ren21.net/Portals/97/documents/GSR/REN21_GSR2011.pdf) (accessed 5.10.12) (online).
- REN21, 2012. 2012 Renewables Global Status Report. Renewable Energy Policy Network for the 21st Century, Paris, France. Available: <http://www.map.ren21.net/GSR/GSR2012.pdf> (accessed 5.10.12) (online).
- Terwiesch, C., Bohn, R.E., 2001. Learning and process improvement during production ramp-up. *International Journal of Production Economics* 70 (1), 1–19.
- Wright, T.P., 1936. Factors affecting the cost of airplanes. *Journal of the Aeronautical Sciences* 3 (4), 122–128.
- Wang, Z., Wang, F., Lu, Z., 2011. Evolution analysis of wind power industry in China based on logistic model. In: *Proceedings of the Computer Distributed Control and Intelligent Environmental Monitoring*. February 19–20, 2011, Changsha, China, pp. 1515–1518.
- Wen, F.H., 2006. *Hierarchical Linear Modeling: Theory, Method and Application*. Yeh Yeh Book Gallery, Taipei, ISBN: 978-92-64-04560-6.
- Wen, F.H., Chiou, H.J., 2011. *Methodology of Multilevel Modeling: The Key Issues and Their Solutions of Hierarchical Linear Modeling*. New Asia Institute, Taipei, Taiwan, Available: <http://140.136.247.242/~nutr2027/trail.pdf> (accessed 5.10.12) (online).
- Yelle, L.E., 1979. The learning curve: historical review and comprehensive survey. *Decision Science* 10 (2), 302–328.
- Yu, C.F., van Sark, W.G.J.H.M., Alsema, E.A., 2011. Unraveling the photovoltaic technology learning curve by incorporation of input price changes and scale effects. *Renewable and Sustainable Energy Reviews* 15 (1), 324–337.