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Diffusion trajectory of self-propagating innovations interacting with institutions—incorporation of multi-factors learning function to model PV diffusion in Japan

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Abstract

This paper first proposes a modeling framework to study diffusion of innovations which exhibit strong interaction with the institution systems across which they diffuse. A unique character of such generic innovation is that specific applications are continually developed during its diffusion. This self-propagation in continual applications generation, which is dependent upon the cumulative installed base of the technological innovation, can be modeled to lead to a dynamic changing carrying capacity in an otherwise simple logistic diffusion curve. The cumulative installed base is dependent upon the price of technology and the cost learning dynamics. This paper utilizes a multi-factors learning function to represent such learning dynamics. Empirical estimates from our model are compared with those from other logistics curve formulations and are shown to better fit the annual PV production data during the past quarter century in the case of Japan.

The very fact that the potential of this class of innovation can be leveraged only if it interacts closely with the institution highlights the importance of institutional determinants of adoption and diffusion of such innovations like PV. We therefore attempt to put forward an institutional framework, based on viewing PV as a technology platform, to consider PV diffusion beyond mathematical and empirical modeling. Some future research directions are also proposed.

JEL classifications: O00; C51; O31; Q48

Keywords: Multi-factors learning function; Self-propagation; Institutions

1. Introduction

Despite its geographical disadvantages, Japan has taken a leading role in world's PV development. This is largely due to two categories of inter-related and reinforcing factors as summarized in Table 1.

First, as of to date, the dominant PV production technology is based upon crystalline silicon which can leverage upon the knowledge base of semiconductor-based electronics component industry. In addition, PV as a generic technology is central to a complex web of related technologies and the interdisciplinary nature of its development is subjected to the benefit of technology spillover learning which reinforces mutual interaction (Watanabe, 1999).

Second, due to the critical nature of PV as a generic technology, the PV development is targeted by explicit and exogenous government intervention such as joint R&D and subsidiary programs initiated by Japan's MITI (Ministry of International Trade and Industry). Most of these programs are long-run R&D programs. The most notable being the Sunshine Project; since its inauguration in 1974, industry's PV R&D has been largely induced by this Project (Watanabe, 1997). Other follow-on programs such as the newly established Subsidy Program initiated by the New Energy

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Table 1
Identical nature of PV and basic principle of MITI's PV initiative

(i) PV is categorically of the same nature as semiconductors, which is a generic technology
(ii) The "footloose" character of the technology which can maximize the benefit of learning effects and economies of scale
(iii) The interdisciplinary nature of its development, which can maximize the benefit of technology spill-over, and
(iv) Efficient learning is linked to technology spill-over and both have mutually stimulation interactions.

In light of these advantages, MITI initiated PV development by
(i) Encouraging the broad involvement of cross sectoral industry,
(ii) Stimulating inter-technology stimulating and cross sectoral technology spill-over,
(iii) Inducing vigorous industry investment in PV R&D leading to an increase in technology stock, and
(iv) Creating initial market by providing subsidy program, thereby expecting to trigger a virtuous cycle.

Foundation (NEF) in 1994 are aimed at triggering market acceptances of PV which will lead to acceleration of PV production (Watanabe et al., 2002). This is a two-pronged approach to accelerate the acceptance of PV as a viable source of renewable source in Japan.

Supported by these efforts, PV development trajectory sustains a virtuous cycle or positive feedback among R&D, market growth and cost reduction as illustrated in Fig. 1 in Japan. Market growth induces and is driven by the continual development of specific applications[1] of PV in different sectors and contexts. [2]PV can therefore be characterized as a self-propagating innovation as new applications are continually generated as it diffuses across the institution or potential user community. (Watanabe et al., 2000).

1.1. Some facts and figures

Driven by such virtuous cycle industry dynamics, Japan's PV (solar cell) production in 1996 amounted to 38.9 MW which accounted for 23.9% of the world's total production following the US (38.9 MW, 43.9%). However, Japan's production dramatically increased leading to 49.0 MW (32.0%) in 1998, 80.0 MW (39.7%) in 1999 and 128.6 MW (44.7%) in 2000, and ranked first in the world from 1999 on as illustrated in Fig. 2.

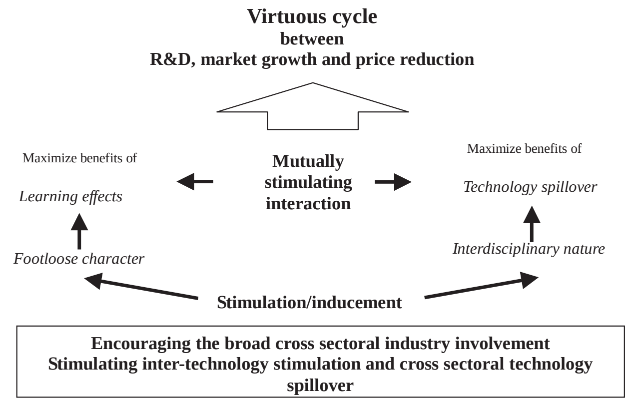

Fig. 1. Mechanism of Inducing System of PV Development. *Source*: Watanabe et al. (2002).

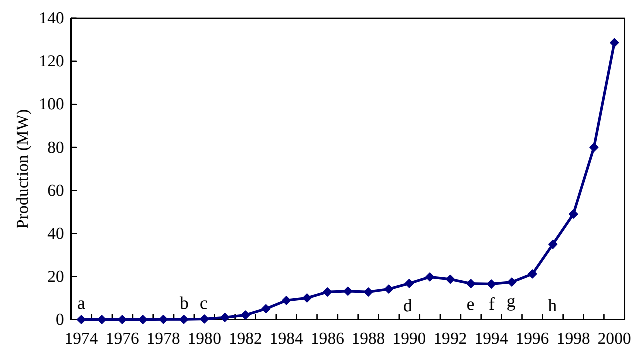

Fig. 2. Trends in PV production (1974–2000). a—1974: Inauguration of the Sunshine Project. b—1979: Strategy to Accelerate the Sunshine Project. c—1980: Establishment of NEDO (New Energy Development Organization). d—1990: Establishment of PVTEC (Photovoltaic Power Generation Technology Research Association). e—1993: Inauguration of the New Sunshine Program. f—1994: Start of the NEF Subsidy Program. g—1995: Deregulation of the Law of Electric Power Industry. h—1997: New Energy Utilization Act.

Taking Japan's PV development and diffusion trajectory over the last quarter century, in order to better understand existing[3] and predict future trajectory of PV development in Japan, we attempt to postulate a framework to model diffusion of PV. Our objective in this paper is to model the diffusion dynamics and also to suggest a broader institutional framework that facilitates diffusion of self-propagating innovations.

The next section reviews received theories of production learning and technology diffusion. Section 3 details the construction of a model of diffusion for PV and corresponding empirical analysis of actual PV production data. Section 4 outlines an institutional framework for diffusion of PV. Section 5 concludes with some directions for future research.

[1]There are four primary types of applications for PV power systems: off-grid domestic, off-grid non-domestic, grid-connected distributed and grid-connected centralized.

[2]Japan continues to make dramatic progress in implementing significant PV capacity through a range of research demonstration and market measures. The main programs implemented in 2000 were: PV field test project for public facilities; residential PV system dissemination program; PV field test project for industrial use; introduction and promotion of new energy at regional level; financial support project for entrepreneurs introducing new energy *business models*; support projects of local efforts to introduce energy and PV applications in the educational sector such as the Eco-school promotion pilot model project. (*source*: NEDO, 2001).

[3]For example, as is evident in Fig. 2, there is a conspicuous jump, particularly from 1997, in the diffusion trajectory. It is essential to understand if this jump is due to exogenous policy intervention or endogenous learning.

2. Towards a modeling framework of PV diffusion

In order to better understand existing[4] and predict future trajectory of PV development in Japan, we attempt to postulate a framework to model diffusion of PV. Utilizing the logistic curve formulation, we are interested to incorporate different modes of learning in the supplier and user sides which drives the PV diffusion. Production learning, however, stems not only from cumulative production but is also due to knowledge stock built-up due to exogenous government initiated R&D and subsidiary programs. User learning, which is proportional to the existing cumulative installed base of PV, has a direct impact upon the carrying capacity or potential adopter population size in the logistic curve. The dynamic capacity of the diffusion trajectory of PV is therefore postulated as a function of the cumulative production (installed base) of PV. We next provide a review of received theories of production learning and technology diffusion to pave the way for formulation of PV diffusion model.

2.1. Production learning

Beginning with Wright (1936) a number of studies have demonstrated that the unit cost of producing manufactured goods tends to decline significantly as more are produced. It has been argued that this effect is the result of the development of increasing skill in production attained by what Arrow (1962) has termed "learning-by-doing." More recently, Rosenberg (1982) has demonstrated that similar gains can accrue to the end users of a product as their skill or understanding grow through "learning-by-using."

Arrow (1962) drew the economic implications of learning-by-doing. He generalized the learning effects and proposed a hypothesis for economic studies that "technical change in general can be ascribed to experience, and it is the very activity of production which gives rise to problems for which favorable responses are selected over time." An important empirical question concerning learning in the economics, industrial engineering and management science literature is which index or proxy of experience is the best and under what conditions. While in Arrow's model, he used cumulative investment as embodiment of experience, some authors have used cumulative output or production as a proxy of experience. An innovative empirical study by Lieberman (1984) used both cumulative output and cumulative investment as index of experience. The significance of this is that he tried to distinguish learning into cumulative production output driven autonomous learning and R&D driven induced learning as cumulative investment is closely related to R&D spending. Solow (1997) also suggested that long term productivity will not be sustained by continual cumulative production alone but must be complemented by discrete technological innovations obtained by R&D. Continuous improvement is not the appropriate foundation for unbounded growth. The number of man-hours needed to fabricate the airframe for a B-17 could not have been diminished to negligibility without some technological breakthrough. A major theme is therefore to combine innovation and continuous improvement (learning by doing).

As suggested by the various learning paradigms above, the claim that cost reduction or productivity improvement can be attributed solely to increase in (passive) cumulative production independent from any other factors needs revision; another factor that may account (also) for productivity improvement is technological progress. A possible proxy or index for technological progress is technology knowledge stock. In this vein, Kouvaritakis et al. (2000) proposed a *two factors learning curve* (2FLC) model which incorporated both cumulative production and R&D expenditure indexed by cumulative technology stock[5] as follows:

$$C = AK^{-a}T^{-b},$$

where C is the unit cost of production; A the original specific cost at unit cumulative capacity and unit technology stock; K the cumulative production; T the cumulative technology stock; $-a$ the learning-by-doing rate; and $-b$ the learning-by-searching rate. It is interesting to note that this functional form can be interpreted as the classical Arrow form[6] augmented with technology progress. We can assume in the 2FLC learning model that the effect of cumulative production on cost reduction is due to autonomous learning while the effect of cumulative technology stock on cost is due to induced learning or R&D investment such as due to exogenous governmental subsidiary programs.

2.2. Technology diffusion

In his work, "Diffusion of Innovation," Rogers (1983) defined diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system." Existing literature on innovation or technology diffusion can be roughly classified into three strands: (1) modeling

[4]For example, as is evident in Fig. 2, there is a conspicuous jump, particularly from 1997, in the diffusion trajectory. It is essential to understand if this jump is due to exogenous policy intervention or endogenous learning.

[5]A dynamic version of the model will need to include the time lag from R&D effort to actual technology knowledge generation and its subsequent depreciation.

[6]The Arrow classical learning by doing functional form can be summarized as: $C = AK^{-a}$.

the successive generations of a technology, (2) modeling the technology substitution where a superior technology replaces an existing technology and (3) modeling the diffusion of a novel generic innovation. The modeling interests range *from* delineating and incorporating explanatory market variables such as price to account for diffusion *to* a more microscopic account of the rational to adopt a technology such as whether it is innovation driven or imitation driven. There are also emerging interests concerning how institutional factors and the characteristics of the innovations, in terms of their radical-ity and scope (Lee et al., 2003) will determine their diffusion.

The diffusion process is actually similar to the contagion process of an epidemic disease (Griliches, 1957) and exhibits S-shaped growth. This process is well modeled by the *simple logistic growth* function, [7]an epidemic function which was first introduced by Vehrlust in 1845 (Meyer, 1994). While this simple logistic growth function displays diffusion symmetric with respect to the deflection point, observed diffusion patterns are not necessarily so. From a modeling perspective, Dixon (1980) postulated the *Gompertz curve* that is more general and can admit non-symmetrical diffusion trajectories.

Meyer extended the analysis of logistic functions to cases in which dual growth processes operate such as when cars first replaced the population of horses but then took on a further growth trajectory of their own. Aiming at modeling such diffusion processes that contain complex sub-growth processes that cannot be well modeled by the single logistic, Meyer (1994) introduced the *bi-logistic growth function*.[8]

In addition to single and bi-logistic growth to model diffusion of innovations, some innovations interact with institutions and display systematic changes in their process of growth and maturity (Watanabe et al., 2002). One such example is network externality (Oster, 1994) observed in the case of the diffusion process of Information Technology or other network-dependent products. The usefulness of such networking products depends upon the number of users within the same compatible network, the rate of adoption will therefore increase as the cumulated installed base or network size rises, usually exponentially until physical or other limits slow the adoption. Meyer and Ausbel (1999) introduced an extension of the simple logistic model of growth by allowing a sigmoid increasing carrying capacity. This approach admits innovation diffusion trajectories with steadily increasing carrying capacity due to innovations interacting and altering the institution (Watanabe et al., 2002). This *logistic growth with a dynamic carrying capacity* approach will be utilized and adapted in this study of PV diffusion in Japan.

[7]A general formulation is the Bass model of which the simple logistic curve is a special case.

[8]The bi-logistic growth function can further be refined into four categories: sequential, superposed, converging and diverging.

3. Diffusion trajectory of PV as a self-propagating innovation

3.1. Carrying capacity of self-propagating innovation process

In the diffusion process of self-propagating innovations typically observed in innovation process of IT and PV, the following mechanism can be identified (Watanabe et al., 2002).

Demand (D) increase leads to increase in production (y) resulting in increasing cumulative production (Y) which in turn activates and maximizes interaction (IA) with institutions leading to an increase in potential customers (carrying capacity, N) (Watanabe et al., 2002) as illustrated in Fig. 3. The essence being which the carrying capacity, which is the potential adopter population, is dependent upon the effect of the innovation's interaction with the institution.

$$N = N(\text{effects of interaction with institutions}). \tag{1}$$

As explained, the effect of a self-propagating innovation interacting with the institution is dependent upon the magnitude of the cumulative installed base of the innovation which is directly a function of the price of the technology. The price is driven by cost of production which is subjected to the general learning by doing LE effects (Arrow, 1962). The dynamic carrying capacity is in turn subjected to the instantaneous cumulative installed base, due to the effect of network externality. Thus, dynamic carrying capacity at time $t,N(t)$, can be enumerated by the following equation:

$$N(t) = N_0\, LE^{-\alpha}, \tag{2}$$

where N_0 is the initial carrying capacity; and α the elasticity of learning to carrying capacity. Given the prices of technology at time t to be $p(t)$, the learning process (LE) leads to production cost reduction which will lead to a price drop as represented by the following function:

$$p(t) = p_0(Y(t))^{-\lambda} = LE, \tag{3}$$

where p_0 is the initial price; $Y(t)$ the cumulative production at time t; and λ the learning coefficient.

Following Kouvaritakis's (2000) postulate on 2FLC, if we express learning effect process by multi-factors function incorporating internal factors such as cumulative production and economies of scale, and external factors such as technology stock, the following

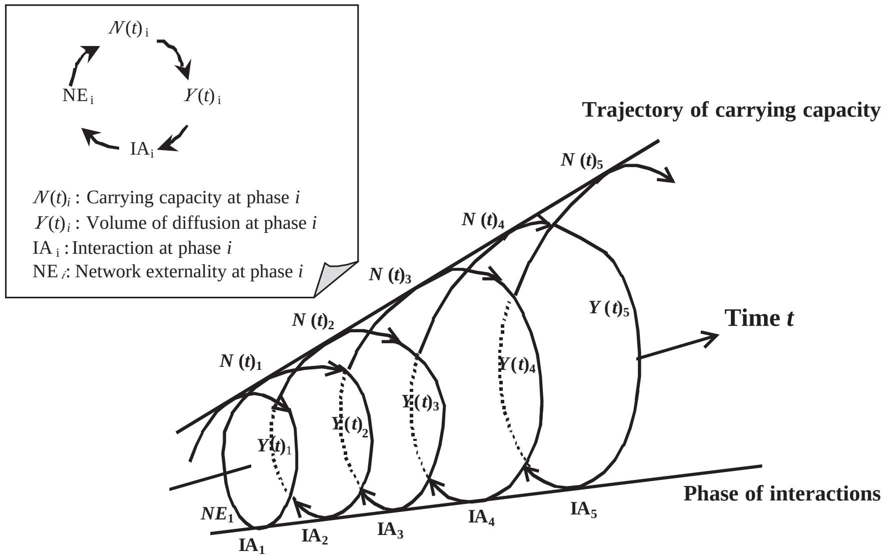

Fig. 3. Trajectory of carrying capacity of self-propagating innovations. *Source*: Watanabe et al. (2003a,b).

multi-factors learning function can be developed:

$$LE = p_0 e^{-\lambda_1 t} Y_{\#}(t)^{-\lambda_2} T(t)^{-\lambda_3}, \tag{4}$$

where λ_1 is the time effect on cost due to economy of scale; $Y_{\#}(t)$ the cumulative production[9] avoiding duplication of technology stock (T); and λ_2 *and* λ_3 the learning coefficients of cumulative production and technology stock, respectively.

Therefore, carrying capacity can be enumerated by the following equation:

$$N(t) = N_0 LE^{-\alpha} = N_0 \left(p_0 e^{-\lambda_1 t} Y_{\#}(t)^{-\lambda_2} T(t)^{-\lambda_3}\right)^{-\alpha}. \tag{5}$$

As is evident in Eq. (5), we have explicitly modeled the dynamic capacity, which is a parameter of the diffusion curve, in terms of both production side learning parameters and exogenous technology stocks. Therefore, we attempt to model the unique property of self propagation of an innovation, via a changing dynamic capacity, in terms of its production-based and institutional[10] (policy-initiated) underpinnings. This is a novel approach in this paper.

3.2. Diffusion process of self-propagating innovations

As reviewed in Section 3.1, since diffusion process of self-propagating innovations will accompany with dynamic carrying capacity and that its diffusion of innovation is not necessarily symmetric with respect to deflection point, the diffusion process can in general be traced by Gompertz function (Dixon, 1980):

$$\frac{d}{dt} \ln Y(t) = \beta(\ln N(t) - \ln Y(t)), \tag{6}$$

where β indicates coefficient of diffusion velocity (Metcalfe, 1981).

Making provision for a dynamic changing capacity for self-propagating diffusion, substituting Eq. (5) for $N(t)$ in Eq. (6), the following equation can be obtained:

$$\frac{d}{dt} \ln Y(t) = \beta\big(\ln N_0 - \alpha \ln p_0 + \alpha\lambda_1 t + \alpha\lambda_2 \ln Y_{\#} + \alpha\lambda_3 \ln T - \ln Y(t)\big). \tag{7}$$

With the establishing of (7) and based upon the observed cumulative PV production Y, the dynamic changing capacity $N(t)$ of the self-propagating PV innovation can therefore be estimated.

4. Empirical analysis of production and diffusion trajectory of PV in Japan

4.1. Development of multifactor learning function

We now develop a production function for the PV technology. We assume a standard Cobb–Douglas type for tractability. The factors of production are labor, capital and knowledge stocks. Labor and capital are appropriated on a priority basis in accordance with trends in relative energy prices (Pey)[11] (Watanabe, 1997,

[9]Note that the cumulative production without duplication of technology stocks prevents double counting of technology's effect on cost reduction. It must also be stressed that the effect of cumulative production on cost is due to learning by doing or *dynamic economy of scale*. The effect of static economy of scale is assumed by a time effect on cost. See e.g. Shum and Watanabe (2004, [19]) for their categorization of different types of production economies such as static economy of scale, dynamic economy of scale, static economy of scope and dynamic economy of scope.

[10]Here, institutional refers to general non-market based factors.

[11]Number of labor involved in PV production is generally proportional to number of researchers responsible for PV R&D which

1999), its production (y) can be depicted by the following function:

$$y = f(L, K, T) = f(L(Pey), K(Pey), T) \approx f(Pey, T). \quad (8)$$

This can be further simplified as follow according to the Cobb–Douglas functional form

$$y = APey^{b_1}T^{b_2}, \quad (9)$$

where A is the scale factor; and $b_1$and b_2 the elasticity of relative energy prices and technology stock to production, respectively.

Conducting correlation analysis of Eq. (9) by taking logarithm over the period 1975–1996, the following results with high statistical significance are obtained:

$$\begin{array}{llllll} \ln y = -8.575 + 5.565 \ln Pey + 2.213 \ln T & & & adj.R^2 & DW \\ \quad (-25.14) \quad (11.64) \qquad\quad (31.67) & & & 0.980 & 1.65 \end{array}. \quad (10)$$

From Eq. (10) technology elasticity to production b_2 can be identified as 2.213 with extremely high statistical significance.

From Eq. (9) PV production avoiding duplication with technology stock (T) can be obtained as follows:

$$y_{\#} = \frac{y}{T^{b_2}}. \quad (11)$$

Therefore, the cumulative production avoiding duplication with technology stock can be depicted as follows:

$$Y_{\#} = \sum \frac{y}{T^{b_2}}. \quad (12)$$

Substituting Eq. (12) for $Y_{\#}$ in Eqs. (3) and (4), the following equation is obtained:

$$p(t) = p_0 e^{-\lambda_1 t} \left(\sum \frac{y}{T^{b_2}} \right)^{-\lambda_2} T^{-\lambda_3}. \quad (13)$$

Applying technology elasticity to production, $b_2 =$ 2.213 identified by Eq. (10) and conducting regression analysis of Eq. (13) by taking logarithm over the period 1975–1996, the following multifactor learning function consisting of effects of static economy of scale, cumulative production and technology stock can be obtained with high statistical significance:

$$\begin{array}{l} \ln p = 5.396 - 0.034t - 0.484 \ln\left(\sum \frac{y}{T^{2.213}} \right) - 0.207 \\ \qquad (16.48)\,(-3.60)\,(-20.73) \qquad\qquad\qquad (-3.74) \\ \ln T \quad adj.\ R^2 \ DW \\ \qquad 0.996 \quad 1.26 \end{array}. \quad (14)$$

From Eq. (14) learning coefficients of three factors, coefficients of economy of scale, elasticity of cumulative production to price, and technology stock to price can be identified as –0.034, –0.484 and –0.207, respectively; thus multifactor learning function can be developed accordingly. Learning rate of cumulative production is $1\text{-}2^{-0.484} = 0.285$, while learning rate of technology stock is $1\text{-}2^{-0.207} = 0.134$.

4.2. Diffusion process of self-propagating innovations

In order to demonstrate the hypothesis that a signature characteristic of self propagation innovation is that the dynamic carrying capacity of the diffusion trajectory is subjected to effects of the innovation's interaction with institutions through learning, correlation analysis of Eq. (7) is conducted using Japan's PV data from 1975–1996. The following results with high statistical significance are obtained:

$$\begin{aligned} \frac{dY(t)}{dt} &= Y(t+1) - Y(t) = Y(t+1) & adj.\ R^2 \quad DW \\ &= \beta Y(t)(\ln N(t) - \ln Y(t)) & 0.989 \quad 1.14 \\ &= \beta Y(t)\left[\ln N_0 - \alpha\left(\ln p_0 - \lambda_1 t - \lambda_2 \ln Y_{\#} - \lambda_3 \ln T\right) - \ln Y(t)\right] \\ &= (0.798Pey + 0.473D)\ Y(t)\Big(21.381 - 2.480 \\ &\quad (8.70) \qquad\quad (4.24) \qquad\qquad (47.87)(-34.30) \\ &\quad \times \left(5.396 - 0.034t - 0.484 \ln \sum \tfrac{Y}{T^{2.213}} - 0.207 \ln T\right) - \ln Y(t)\Big). \end{aligned} \quad (15)$$

In this analysis, following Metcalfe (1981) [7] coefficient of diffusion velocity,[12] β is assumed to be subject to

(*footnote continued*)
are strongly correlated with trends in relative energy prices as follows (1976–1996):

$$\begin{array}{lll} \ln(Researchers) = 7.053 + 0.868 \ln Pey - 1.025D_{1975,76} & adj.R^2 & DW \\ \qquad\qquad (121.65) \quad (4.63) \qquad\quad (-8.60) & 0.845 & 0.59 \end{array}.$$

[12] Metcalfe, in his "Impulse and Diffusion in the Study of Technical Change," (1981) postulates the diffusion equilibrium of a new industrial material (e.g. rayon) as a function of its technical properties and price relative to those of competing materials as follows: $g_d(t) = b[m(p) - y(t)]$ where $g_d(t)$: proportionate rate of growth of demand at t, $m(p)$: equilibrium market demand depending on price p, $y(t)$: the rate of demand at t, and b: adoption coefficient. Adoption coefficient b implies diffusion velocity and the above equation can be reformulated to b as a function of relative price with competing materials.

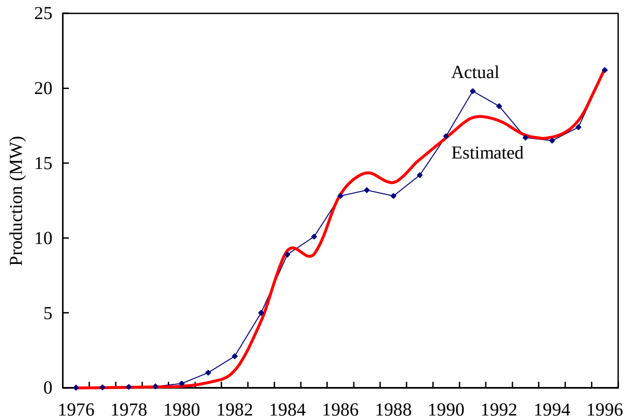

Fig. 4. Trends in PV Production in Japan (1975–1996)—Actual and estimated, $y(t)$.

energy prices and depicted as follows:[13]

$$\beta = \beta_0 + \beta_1 Pey + \beta_2 D, \tag{16}$$

where D indicates dummy variables corresponding to a turning point of international oil prices from increasing trend lasting up until 1982 to declining trend starting from 1983. Therefore, $D = 1$ for 1982 and 1983, and $D = 0$ for other years.

Fig. 4 illustrates trends in PV yearly production over the period 1975-1996 by comparing actual trajectory and estimated trajectory derived from Eq. (15).

Note that the estimated trajectory reflects the actual behavior of PV production in Japan with a highly representative fit-ability. This trajectory demonstrates an indication of sharp increase after 1995. This is considered due primarily to the inauguration of the New Sunshine Program in 1993 and also the Subsidy Program for residential PV systems initiated by the New Energy Foundation (NEF) starting from 1994 (Watanabe et al., 2003a, b). This suggests the multi-factors learning approach does account for effects on diffusion due to exogenous policy stimulation.

Fig. 5 compares the projected carrying capacity generated by our approach the Multi-factors learning function (MFLF) and those generated by, say, an epidemic function with dynamic carrying capacity

[13]The results of the correlation analysis by applying Eq. (12) to Eq. (7) is as follows which demonstrates β_0 is statistically insignificant suggesting β_0 in Eq. (16) should be treated as $\beta_0 = 0$

$$\frac{\mathrm{d}Y(t)}{\mathrm{d}t} = \underset{(0.02)}{(0.003} + \underset{(4.12)}{0.795Pey} + \underset{(4.26)}{0.473D)}\, Y(t)\Bigg(\underset{(40.96)}{21.375} - \underset{(-2.48)}{2.479}$$

$$\left(5.396 - 0.034t - 0.484 \ln \sum \frac{y}{T^{2.213}} - 0.207 \ln T\right)$$

$$- \ln Y(t)\Bigg) \quad \underset{0.987}{adj.\,R^2} \quad \underset{1.61}{DW}.$$

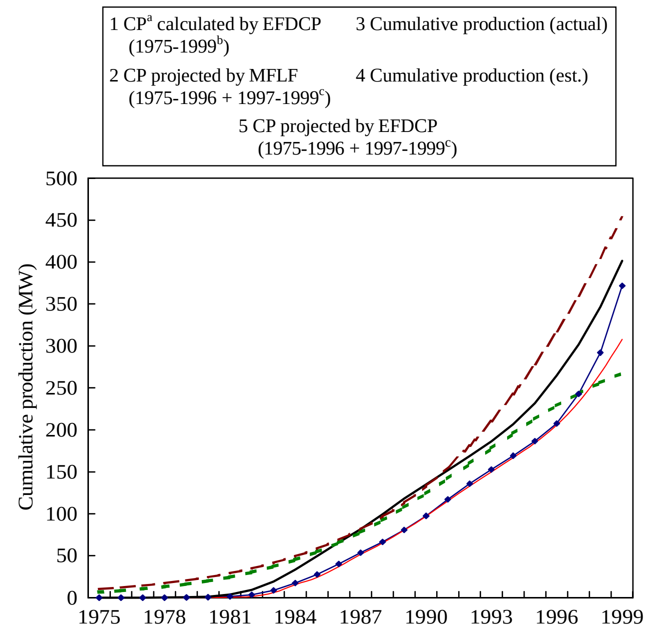

Fig. 5. Comparison of trajectories of carrying capacities derived by two methods. [a]CP: carrying capacity; EFDCP: epidemic function within dynamic carrying capacity; MFLF: multifactor learning function. [b]Directly estimated over the period (1975–1999). [c]Estimated over the period (1975–1996) and projected up to 1999.

(EFDCP) shown in (17)

$$Y(t) = \frac{N_N}{1 + a\,\exp(-bt) + \frac{ba_N}{b - b_N}\exp(-b_N t)}, \tag{17}$$

where a, b, a_N, and b_N are the coefficients; and N_N the carrying capacity.

We also included the cumulative production as is generated by our approach and the actual cumulative production data as comparison. The followings are observed: the carrying capacity as generated by the MFLF 8, we note that contrary to the gap in cumulative production trajectory, the projected carrying capacity maintains its smooth behavior enveloping the cumulative production. It seems therefore that the estimate of dynamic carrying capacity is more reliable than the estimates of the cumulative production due to that we explicitly model.

In general, we have found that the MFLF approach yields the best estimate of carrying capacity of PV diffusion due to that it nicely envelopes the actual PV cumulative production data. On the other hand, the other carrying capacity estimates (the two dashed lines in Fig. 6) by EFDCP either overestimate or underestimate the carrying capacity. The latter being that (the lower dashed trajectory) however crosses from below the actual cumulative production in 1997, 1998 and 1999 which is implausible since actual cumulative production should not be larger than carrying capacity.

The upper trajectory is, while looks more promising, much higher than the carrying capacity estimated by

Table 2
Comparison of carrying capacity estimation approaches

Traditional (EFWDCC)	$N = N(t)$	Estimated by general specification of how carrying capacity will vary
Incorporation (DTMFLF)	$N = N(t, Y_{\#}(t), T(t))$	Estimated by specifying how carrying capacity is driven by multi-factors learning, capturing effects of cumulative production and technology stock built-up due to exogenous policies

multifactor learning function and discrepancy between dashed lines (lower line and upper line) is too big to rely on these estimations. A possible source of inaccuracy in these two epidemic functions with dynamic capacity is that its formulation is general without provision for interaction of the diffusing innovation and institution. Meyer and Ausubel (1999) proposed logistic models with logistically varying dynamic carrying capacity or the so-called logistic inside a logistic. Others (Banks 1994) describe models where the dynamic carrying capacity varied sinusoid-ally, exponentially and linearly. These formulations are deemed to be lacking a physical meaning as of why the capacity is changing in a particular fashion.

On the other hand, our contribution in this model is that we explicitly model the dynamic capacity as a function of the price of technology subjected to production cost learning by doing and technology stock, thus influencing the installed base upon which the interaction between the innovation and the institution in the sequel depends. By incorporating this more refined self-propagating characteristic of PV into the representation of the dynamic capacity, our trajectory neither overestimates nor underestimates and demonstrates a very steady trajectory keeping a reasonable margin with the cumulative production trajectory compared to that derived from a "general" epidemic function with dynamic changing capacity. These two different approaches to estimate carrying capacity for self-propagating innovations are compared in Table 2.

5. Institutional framework for diffusion of PV

There is no doubt that the presented modeling exercise above demonstrates the importance of accounting for an economic mechanism which makes provision for a changing carrying capacity of an innovation or a technology during its diffusion. Carrying capacity is changing due to that new applications in the user community are continually discovered. PV as a generic renewable energy technology (RET) will be increasingly applied to newer energy problems and applications in future. This constitutes the self-propagation nature of the technology. This is a practical characterization of the technology with a key implication being that if PV is to be diffused widely, an institutional environment that facilitates the engagement of PV technology development and end user applications engineering must be established. A sense of local adaptation of a generic technology is called for.

This is very different from the existing *production paradigm* of fossil-based energy technology which emphasizes generation, distribution and consumption scaling. Efficiency counts in the existing system. For renewable energy like PV, customization to local condition is more important in order that it would at all be accepted. Tsoutsos and Stamboulis (2004) suggested that a *user-oriented* policy, which requires the development of concrete adapted solutions, is considered instrumental to the successful diffusion of renewable energy technologies like PV.

In this vein, the generic PV technology can be considered as a *technology platform* which is to be customized to different local application contexts. This is very similar to the principle of product platform in which a similar architecture of an engineering solution is reused across different applications with differentiation. However, an important principle is that there must be a proper mechanism to transfer the competence and knowledge *across* different derivative development projects in order that the platform or the technology will get adopted. PV technology suppliers must make provision for such an infrastructure or institution so that cross-learning (Shum, 2003) among different projects developers or intermediate systems integrators across time and space is possible. This is a cornerstone of this user-oriented policy.

Another key aspect of this user-oriented policy is that it will have externality effects beyond the technology supplier and the end users. This creates and sustains a local eco-system of *complementary* technologies and services suppliers such as software, design and engineering services, materials, construction and mechanical engineering. The type of interactive, collocated product development and learning achieved not only lead to the performance improvement of the local renewable technological system but also exhibits export dynamism and is an important mechanism for the diffusion of the RET under consideration. Such local collaborative enterprises contribute to mobilization of public opinions and local resources and creates the basic fabrics of a new socio-economic landscape for the diffusion of the RET under consideration. Suitable institution to finance, coordinate and sustain such a local cluster of players must be established.

While the above concerns about the downstream applications development for the PV technology, another important consideration is the development of the technology *itself* during its diffusion. A rather unexplored area of study in technology diffusion is the continual interaction between the technological innovation and its diffusion; specifically, when an innovation is diffusing, users will have opinions as of how to improve the innovation. The continual improvement of the original innovation may facilitate its further diffusion.

In the case of diffusion of PV, apart from generation of local and specific applications, the continual development of the technology strives to improve the performance and reduce production costs of the PV cells. As a result, over a period of 20 years, the average efficiency of the modules has improved from about 7–8% at the end of the 1970s to between 13–15% at present. Even higher efficiency has been achieved for prototypical cell in experimental settings using the best processes (Menanteau, 2000). Although cost has fallen considerably since the first terrestrial applications [$300/Wp] and are now around $3–4/Wp, they are still significantly higher than the objective of ~$0.5/Wp. There are several factors of this difficulty due to still small production scale and the lack of any radical innovation in the production process.

A more fundamental concern is the choice of production process for PV manufacturing. This will determine the extent of cost reduction achievable by learning by doing. In the 1980, mono-crystalline silicon represented 90% of the commercial production of the PV cells, but since then its relative importance has gradually declined in favor of polycrystalline silicon. These two technologies, however, together still hold a market share of 80% of PV sales (1995). Crystalline silicon-based production process can be regarded as a dominant technology in PV production.

Adoption of the crystalline silicon technology for PV production had the benefit to draw upon the learning process already underway in the electronics sector which is also silicon-based. However, the current PV cell production processes today differs very little from those initially used in the electronics industry and developed for producing cells for space applications. Cost was of secondary importance in the space applications since PV cells represented a very small portion of the total cost of building and launching a satellite. In essence, existing processes are better adapted to small-scale production of high efficiency and top quality PV cells (Menanteau, 2000).

This historical analysis of the emergence of production technologies for PV cells makes it clear that the initial application *niche* (Weber and Dorda, 1999) and the associated production processes will have long term effects on the subsequent development trajectory of the industry. The adoption of silicon-based production technology for PV is due not only to its being used by the electronics component sector but also is restrained by the choice of initial niche applications requirements. To revisit a [new] diffusion strategy for the PV technology in the future, we need to appraise different technology options.

While cost reduction can be expected with incremental progress on crystalline and polycrystalline silicon-based cells, experts believe that only thin-film technologies have the potential to reach module prices of $1/Wp ((Menanteau, 2000). Thin-film technologies use radically different manufacturing processes and are particularly suited to large-scale industrial production because the active material can be deposited on large glass or metal substrates. Thin-film technologies seem potentially more promising given the possibility for much greater cost reductions than in the case of crystalline silicon technologies. A hybrid technology known as thin-film silicon has the potential to benefit from an existing knowledge base as well as the likelihood of cost reduction in thin-film technologies.

All these existing and new technologies, crystalline-silicon based, hybrid or thin-film and its variants, in their vying for as a dominant production technology for PV in the future, will be judged in terms of the following: *the potential for performance improvement*, the feasibility of introducing industrial-scale manufacturing processes, the extent of savings to be expected from larger production batch, the possibility of benefiting simultaneously from scale effects and exogenous policy initiatives, feedstock cost structure etc. From a diffusion standpoint, the dominant technology must be able to fully benefit from the repeated iterations of innovation and re-innovation (improvement) during its diffusion. If a technology "run out of room for improvement" too soon, it may not be a viable candidate from the standpoint of sustained and interactive development among suppliers and users. On the other hand, the technology must also be able to leverage existing experience. Exogenous policy initiatives to invest upon and increase knowledge stock of a given PV production technology, thus expediting the diffusion of PV, must be based on an explicit understanding of this trade-off.

6. Conclusion

PV as a sustainable energy technology is categorically of the same nature as semiconductors or other silicon-based technologies as it is a generic technology exhibiting a "footloose" character. This makes the PV industry highly subjected to interdisciplinary development and spillover learning in development. Furthermore, applications of PV are continually developed during its diffusion across user community and institutions. Exogenous governmental supports and policies targeted to develop PV further reinforce this critical nature of PV. The result is a dramatic increase in Japan's PV development in the very recent years of the 1990s.

We attempted to develop a novel model to address development and diffusion of such so-called self-propagating innovations under exogenous policy initiative. The most important aspect our approach captures is a formulation of the interaction of the innovation with the institution in terms of a dynamically changing carrying capacity of a suitable diffusion curve. The carrying capacity or the potential adopter population of PV energy technology is directly dependent upon the cost learning in the supply side. Cost learning is also due to induced technology stocks driven by exogenous governmental R&D policy initiative. These two categories of cost reduction sources are summarized in a multi-factors (cumulative production and technology stocks) learning function in order to explain observed diffusion trajectory of PV in Japan. Our contribution in this paper is that we have specified a policy driven economic mechanism which attempts to explain how the carrying capacity of an innovation may be changed during its diffusion instead of an assumed or general functional as is prevailing in the existing literature.

Taking Japan's PV development and diffusion trajectory over the last quarter century, our approach is able to reflect the actual behavior of Japan's PV production under exogenous policy initiatives with extremely high representative fit-ability. We also showed that our approach provides reliable trajectory of carrying capacity suggesting trustworthy forecast of PV development in the future. Our model can therefore serve as a useful policy analysis tool to predict effects of, for example, new potential policy initiatives which will have strong influence upon the economics of production and diffusion of PV as a sustainable energy technology.

Beyond modeling and empirical analysis and unique context of Japan, in general, it is important to highlight that PV or other RET represent new production paradigm in energy sector and are made up of multiple discrete and associated linkage mechanisms. These complex systemic technologies are delivered by communities of organization and their diffusion are especially subjected to institutional determinants. We have touched upon several dimensions of this institution such as customization to local applications, collocated applications development and cross-learning among applications. These various aspects can be summarized by a user-oriented policy that facilitates applications generation. We also highlight the importance of the choice of a production technology from the standpoint of its potential to be improved upon driven by learning by using and exogenous policy stimulation. A two-pronged comprehensive approach in both supply and demand sides is necessary.

Further works on diffusion of PV can be targeted towards delineating and analyzing the significance of the respective constituent factors in the multi-factors learning function in their contribution to self-propagation in the supply side. In the demand side, we need to explore new modeling capability to capture applications generation in the logistic curve formalism. Overall, newer diffusion frameworks must address both the effects of continual improvement of the innovation and the creation of new applications for the innovation. Both of these are essential determinants of the diffusion of generic or self-propagating innovations like PV or other types of RET.

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