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Technology adoption with limited foresight and uncertain technological learning

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ABSTRACT

Most previous optimization models on technology adoption assume perfect foresight over the long term. In reality, decision-makers do not have perfect foresight, and the endogenous driving force of technology adoption is uncertain. With a stylized optimization model, this paper explores the adoption of a new technology, its associated cost dynamics, and technological bifurcations with limited foresight and uncertain technological learning. The study shows that when modeling with limited foresight and technological learning, (1) the longer the length of the decision period, the earlier the adoption of a new technology, and the value of a foresight can be amplified with a high learning rate. However, when the decision period is beyond a certain length, further extending its length has little influence on adopting the new technology; (2) with limited foresight, decisions aiming at minimizing the total cost of each decision period will commonly result in a non-optimal solution from the perspective of the entire decision horizon; and (3) the range of technological bifurcation is much larger than that with perfect foresight, but uncertainty in technological learning tends to reduce the range by removing the early adoption paths of a new technology.

1. Introduction

Most of the literature on technology adoption is from the perspective of the psychology-based acceptance of new technologies by individual users or organizations. Well-known works from this perspective include the technology adoption lifecycle model (see Rogers, 1962), the Bass diffusion model (Bass, 1969), and the technology acceptance model (TAM) (see Bagozzi, Davis, & Warshaw, 1992; Davis, 1989). There are times when human society as a system needs to consider the adoption of new technologies for the sustainable development of the system, i.e., there are occasions when technology adoption needs to be studied from the perspective of social planning instead of from the perspective of individual users or organizational psychology. Technology adoption with social planning is not commonly appropriate for end-use technologies; instead, they are more applicable to infrastructures, such as power plants and railways.

Operational optimization models have been a major tool in the study of technology adoption from the perspective of social planners. The purpose of these models is mainly to determine the optimal technology adoption path that minimizes the total cost of the entire system, satisfying various constraints. Well-known examples of such models include the MESSAGE (Messner & Strubegger, 1994) and MARKAL (Seebregts, 2001) models. Historical observations show that the diffusion of new technologies commonly takes a long time (e.g., see Geroski, 2000), and the environmental impact of using some technologies could be longer; for example, CO_2 emitted by power-generating technologies may remain in the atmosphere for a very long time (IPCC, 2007). Thus, these models are developed with a long-term perspective.

Most works analyzing technology adoption with an operational optimization framework assume perfect foresight for a long period of time (e.g., see Azar, Lindgren, & Andersson, 2003; Barreto & Kypreos, 2002; Ma, 2010). That is, these models assume that there is a decision-maker who has complete information about the future. However, in fact, nobody can have such perfect foresight. There are always many unpredictable factors that may affect the future development of the system. These models usually address unpredictable factors by assuming different future scenarios. In the real world, decision-makers commonly adjust technology strategies, based on evaluations of the market and technologies at different stages. In short, decisions related to technology adoption are commonly made with limited foresight, but adaptively, in reality.

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In recent years, some researchers have begun to introduce limited foresight into operational optimization models of technological change. For example, Hedenus, Azar, and Lindgren (2006) introduced limited foresight into the Global Energy Transition (GET) model; Martinsen, Krey, and Markewitz (2007) developed a multi-period IKARUS optimization model in which optimal solutions for previous stages have effects on later ones; Keppo and Strubegger (2010) developed a multi-stage MESSAGE model to study the diffusion of new energy technologies and their impact on CO_2 emissions, and the decision periods and their overlaps in their model can be determined freely. These studies focused mainly on the application of limited foresight. Technological change in these studies was treated mainly as exogenous and deterministic.

Technological learning is considered to be the endogenous driving force of the adoption of new technologies (e.g., see Ma, Grubler, & Nakamori, 2009; Schwoon, 2008). This means that the cost of using new technologies tends to decrease as the experience of using them accumulates (Arrow, 1962; Arthur, 1989). Historical observations show that technological learning is quite uncertain (McDonald & Schrattenholzer, 2001). In optimization models with perfect foresight, the expected risk cost that results from overestimating technology learning is summed over the entire time horizon (e.g., see Grubler & Gritsevskyi, 1998; Ma, 2010). However, with limited foresight, decision-makers are expected to address the risk cost stage-by-stage separately and how this will influence the adoption of a new technology remains an unexplored question.

With technological learning, optimization models will be nonlinear and non-convex, and thus, there could be more than one local optimal solution with very similar total costs but different technology adoption paths and thus different environmental impact, which has been called technological bifurcation (Chi, Ma, & Zhu, 2012; Ma, 2010). Studies on technological bifurcations can help decision-makers understand how to lead the adoption of advanced and environmentally friendly technology without incurring extreme costs. With limited foresight, technology adoptions will be decided by a series of sequential decisions instead of by a one-time decision with perfect foresight, and how this will influence technological bifurcations constitutes another unexplored question.

With a stylized techno-economic system, we explore in this paper the adoption of a new technology, its associated cost dynamics, and technological bifurcations with two types of limited foresight schemes and uncertain technological learning. The model and study presented in this paper are not intended by any means to be "realistic" in the sense of showing technological or sectoral detail. Rather, the model is intended to be used primarily for exploratory modeling purposes and as a heuristic research device to examine in depth the impacts of alternative model formulations of the dynamics of technology adoption.

The rest of the paper is organized as follows. Section 2 introduces an optimization framework for technology adoption and two types of limited foresight schemes. Section 3 introduces a simplified techno-economic system model based on the optimization framework introduced in Section 2. With the stylized model introduced in Section 3, Section 4 analyzes how different limited foresight and uncertain learning influence the adoption of a new technology and its associated cost dynamics. Section 5 analyzes technological bifurcations with the two limited foresight schemes. Section 6 provides concluding remarks.

2. Modeling framework with perfect and limited foresight

2.1. Optimization modeling framework for technology adoption

Fig. 1 is an illustration of the modeling framework used in this paper. The left side of the figure lists natural resources, such as coal, crude oil, and gas; the right side lists human demands, such as transportation and heating, and, in the middle, there are various types of technologies (denoted as Tech 1,Tech 2,...,Tech N) that link human demands to natural resources. For example, Resource 1 is coal, Tech 1 is a technology to extract coal from nature, and Tech 2 is a coal power plant that can generate electricity with coal. Thus, Tech 1's output can be Tech 2's input, and Tech 2's output – electricity – can be used as an input for other technologies to provide services such as heating and transportation. Many large-scale models in use, such as the MESSAGE (Messner & Strubegger, 1994) model and the MARKAL (Seebregts, 2001) model, have essentially the same structure as that shown in Fig. 1.

With the structure shown in Fig. 1, suppose there are N technologies available in the economic system under study, the technology strategy at time t can be denoted as $X^t = \begin{pmatrix} x_1^t \\ \vdots \\ x_N^t \end{pmatrix}$, and the cost vector for strategy X^t can be denoted as $C^t = (c_1^t, \ldots, c_N^t)$. Here, the strategy of using a technology is expressed numerically, it is quantified by the new installed capacity and production of the technology, i.e., $x_i^t = \{s_i^t, p_i^t\}$, where s_i^t denotes the volume of technology i's capacity installed at time t, and p_i^t denotes the production of technology i at time t. The simplified objective function (see Messner, Golodnikov, & Gritsevskyi, 1996) of a deterministic (endogenous/exogenous) technological change model can be written as:

$$\min \sum_{t=1}^{T} C^t X^t, \tag{1}$$

where T denotes the time scale of the problem. The above objective function will be subject to various constraints related to demands, resources, and relationships among technologies (one technology's output may be another's input). With technological learning, C^t is a function of initial status and decisions at previous strategies; that is,

$$C^t = f(X^0, X^1, \ldots, X^{t-1}, B), \tag{2}$$

where B is a vector containing technology learning rates and X^0 denotes the initial status of technologies. Note that the initial status plays an important role in technological learning models. Combining Eq. (2) with Eq. (1), the objective function can be written as

$$\min \sum_{t=1}^{T} f(X^0, X^1, \ldots, X^{t-1}, B) X^t. \tag{3}$$

Using $\overline{X}^{t-1}$ to denote $(X^0, X^1, \ldots, X^{t-1})$, Eq. (3) can be simplified to

$$\min \sum_{t=1}^{T} f(\overline{X}^{t-1}, B) X^t. \tag{4}$$

With technological learning, the objective function in Eq. (4) is a non-linear non-convex function.When incorporating the uncertainty of technological learning into the model, the elements in vector B in Eq. (4) are treated as random values.[1] We define the vector of uncertain technological learning rates as $B(W)$, where W denotes the vector of elements from probability spaces that are commonly characterized by lognormal distributions (McDonald & Schrattenholzer, 2001). For a given strategy along the entire time scale, $X = \{X^1, \ldots, X^T\}$, and an observed scenario W of the cost path

[1] In real applications, we can assume that some technologies have no learning effect, and their learning rates can be viewed as deterministic and equal to 0. For example, see the introduction to "existing" technology in Section 3.