European Journal of Operational Research 000 (2016) 1–10

Contents lists available at ScienceDirect

European Journal of Operational Research

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

Innovative Applications of O.R.

Optimizing systematic technology adoption with heterogeneous agents

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ARTICLE INFO

Article history:
Received 25 May 2015
Accepted 7 July 2016
Available online xxx

Keywords:
OR in societal problem analysis
Systematic technology adoption
Optimization
Heterogeneous agents
Uncertain technological learning

ABSTRACT

The traditional operational optimization models of systematic technology adoption commonly assume the existence of a global social planner and ignore the existence of heterogeneous decision makers who interact with each other. This paper develops a stylized (or conceptual) optimization model of systematic technology adoption with heterogeneous agents (i.e., decision makers) and uncertain technological learning. Each agent attempts to identify optimal solutions to adopting technologies for a portion of the entire system. The agents in the model have different foresight and different risk attitudes and interact with one another in terms of technological spillover.

This paper first illustrates that although a well recalibrated representative model can perform well enough when the interest is placed on aggregate variables, it could react to a policy (a carbon tax in this paper) differently from the multi-agent model. Then this paper explores how the agents' heterogeneities and interactions affect the optimal solutions of systematic technology adoption. The main findings of the study are that (1) the existence of multiple agents implies a slower adoption of advanced technologies in the entire system than assuming the existence of a global social planner, (2) with homogeneous agents, technological spillover tends to enhance the lock-in effect on previous technologies, and (3) with heterogeneous agents, even a small technological spillover rate can significantly accelerate the adoption of the advanced technology.

1. Introduction

The adoption of new technologies has long been believed and shown to be one of the most important sources of economic growth, long-run productivity and sustainable development (e.g., Freeman, 1994; Metcalfe, 1987; Mokyr, 1990; World Bank, 2000). Studies on technology adoption can be grouped into one of two streams. The first stream addresses the psychology-based acceptance of new technologies by individual users or organizations. The well-known models in this stream 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). The second stream analyzes technology adoption from the perspective of social planning instead of from the perspective of individuals. In this manuscript, systematic technology adoption refers to the second stream, and such technology adoption is planned by social planners on a system level to meet a certain system objective, e.g., to satisfy a country's demand for electricity at a minimum total cost and with acceptable environmental effects.

Significant effort has been devoted to the development of operational optimization models of systematic technology adoption. Well-known examples of such models include MESSAGE (Messner & Strubegger, 1994) and MARKAL (Seebregts, 2001). The purpose of these models is usually to determine the optimal systematic technology adoption to minimize the total cost of the entire system subject to various constraints. To date, most of these models assume the existence of a global social planner and ignore the existence of heterogeneous decision makers who interact with one another in the system under study. Although certain optimization models involve different regions (e.g., Messner & Strubegger, 1994) and quite a few of such models introduce elements such as different hurdle rates for different sectors (e.g. Dodds, 2014) that imitate differences in the preferences of specific representative agents, existing models commonly ignore uncertain technological learning, the heterogeneity of agents in terms of their limited foresight and risk attitudes, and especially the interactions among agents.

This study develops a stylized (or conceptual) optimization model of systematic technology adoption with heterogeneous agents (i.e., decision makers) and uncertain technological

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http://dx.doi.org/10.1016/j.ejor.2016.07.007

learning. Technological learning denotes the cost reduction of new technologies while experience with them accumulates (Arrow, 1962); this reduction is a classic example of increasing returns (Arthur, 1989), which has been ignored in most existing operational optimization models. In the model presented in this manuscript, systematic technology adoption is no longer decided by a global social planner. Instead, there are many agents in the system, and each of them attempts to optimize technology adoption for part of the entire system. The agents are heterogeneous in terms of their foresights and attitudes toward the risk resulted from overestimating technological learning. And there is technological spillover among agents, which means that the technology experience one agent gains can somehow benefit other agents. Using this model, we explore how the agents' heterogeneities (in foresights and risk attitudes) and technological spillover affect the optimal solutions of systematic technology adoption.

Some researchers (e.g. Krusell & Smith, 2010) have argued that a well calibrated representative model (i.e., a global-social-planner model) can perform well enough when the interest is placed on aggregate variables such as the overall adoption of a new technology. In our research, we show that it is possible that a representative model can be recalibrated to result in the same adoption rate of a new technology as that resulted from a multi-agent model. But when implementing a carbon tax in the system, it is possible that the representative model fails to adjust, i.e., the adoption rate is different from that with the multi-agent model. This experiment enhances the idea that it makes sense to do modeling considering heterogeneous agents.

The model presented in this manuscript is not intended by any means to be a "realistic" model in the sense of showing technological or sectoral detail. Rather, the model is primarily intended to be used for exploratory modeling purposes and as a heuristic research device for the in-depth examination of the effects of alternative model formulations on the dynamics of endogenous technology transitions.

The rest of the manuscript is organized as follows. Section 2 introduces the framework of operational optimization models of systematic technology adoption and the heterogeneous agents in our model. Section 3 presents the stylized optimization model of systematic technology adoption with heterogeneous agents and uncertain technological learning. Section 4 presents the experiment which shows that a recalibrated representative model reacts differently from the multi-agent model when a carbon tax is implemented in the system. Section 5 explores how the agents' heterogeneities and interactions affect systematic technology adoption. Section 6 presents the conclusions.

2. Modeling framework with heterogeneous agents

2.1. Framework of optimization models of systematic technology adoption

Fig. 1 presents an illustration of optimization models of systematic technology adoption (Ma, 2010). The right side of Fig. 1 is the list of human demands, such as heating and transportation. The left side is the list of natural resources, such as coal and gas. In the middle, there are chains of technologies that link natural resources to human demands. For example, Tech 1 is coal mining, Tech 2 is a coal power plant, which can generate electricity with the output of Tech 1, and the output of Tech 2 can subsequently be used as the input for other technologies to satisfy human demands.

Technologies in Fig. 1 include both mature existing technologies such as traditional coal power plants and new technologies such as photovoltaic power plants. With the system structure presented in Fig. 1, the objective of optimization models of systematic technology adoption is to find the optimal combinations of technologies along the time dimension so that the total cost of the system is minimized with various constraints (e.g., demands should be satisfied).

2.2. Heterogeneous agents and technological spillover effect

Most existing optimization models of systematic technology adoption assume the existence of a global social planner, who decides the technology adoption for the entire system, as illustrated on the left side of Fig. 2. The stylized model that will be presented in Section 3 assumes that the entire system is managed by a number of agents, abbreviated as A1, A2, etc., as shown on the right side of Fig. 2. Each agent makes decisions for a portion of the entire system. These agents are heterogeneous in terms of their lengths of foresight and attitudes toward the risk that results from the uncertainty of technological learning, and there are interactions among agents in terms of technological spillover. We provide more explanations on the notions of foresight of agents, uncertain technological learning, and technological spillover in the following.

2.2.1. Foresight of agents

Traditional optimization models of systematic technology adoption usually assume a decision maker who has complete information about the future, i.e., with a perfect foresight for a long period of time (e.g., see Azar, Lindgren, & Andersson, 2003; Barreto & Kypreos, 2002). In reality, decision makers commonly do not have perfect foresight and need to adjust decisions from time to time. In recent years, researchers have begun to introduce limited foresight into optimization models of systematic technology adoption (e.g., Hedenus, Azar, & Lindgren, 2006; Keppo & Strubegger, 2010; Martinsen, Krey, & Markewitz, 2007; Chen & Ma, 2014).

Fig. 3 illustrates perfect foresight and two types of limited foresight schemes (Keppo & Strubegger, 2010). From Fig. 3, we can see that the entire time horizon is composed of only one decision period with perfect foresight, while it is divided into several connecting decision periods with limited foresight. With the first type of limited foresight, there is no overlap between two connecting periods, which means a decision maker will adjust his/her decisions at the end of a decision period; and with the second type of limited foresight, there is an overlap between two connecting decision periods, which means that a decision maker will adjust his/her decisions before the end of a decision period. In Fig. 3, a decision interval is a basic time unit for installing new technological capacities, and each decision period is composed of several decision intervals.

The stylized model that will be presented in Section 3 assume that agents have different lengths of (limited) foresight, and the model adopts the second type of limited foresight (i.e., the LF2 in Fig. 3). Each agent makes decisions every 10 years, there are overlaps between connecting decision periods, and the longer the agent's foresight is, the longer the overlap is.

With technological learning, the optimization model will be non-linear and non-convex. With limited foresight, a decision maker is myopic, which means he/she focuses only on minimizing the cost in the current decision period. At each decision period, there could be more than one local optimal solution to technology adoption with highly similar total costs but different technology adoption paths (Chi, Ma, & Zhu, 2012; Ma, 2010). In this manuscript, for the sake of simplification, each agent selects the local optimal solution with the minimal cost at each decision period.

2.2.2. Uncertain technological learning and agents' risk attitudes

Technological learning denotes the cost reduction of new technologies while experience with them accumulates (Arrow, 1962).