Modeling Technological Change in Energy Systems
-- from optimization to agent-based simulation

Tieju Ma†* **Yoshiteru Nakamori***

*School of Knowledge Science, Japan Advanced Institute for Science and Technology
†Transition to New Technology Program, International Institute for Applied Systems Analysis
{tieju, nakamori}@jaist.ac.jp

Abstract

Operational optimization models are one of the main streams in modeling practices on energy systems. Agent-based modeling and simulations seems to be another rising stream in the field of modeling energy systems. In either optimization or agent-based modeling practices, technological change in energy systems is a very important and inevitable factor that modelers need to deal with. By introducing three modeling practices with a deliberately simplified energy system, this paper tries to explain how traditional optimization model, endogenous technological change optimization model, and agent-based model treat technological change differently and compares different philosophy underlying the three modeling practices and their advantages and disadvantages.

Keywords: Technological change, energy systems, agent-based modeling

1 Introduction

In most traditional optimization energy models, technological change has been largely treated as exogenous. Technological change is either reduced to an aggregate exogenous trend parameter (the "residual" of the growth accounts) or introduced in the form of numerous (exogenous) assumptions on the costs and performance of future technologies. In such models, for triggering both adoption and penetration of otherwise uneconomic technologies, most of time it is inevitable to include additional (e.g., environmental or capacity) constraints. Most traditional optimization models are linear optimization models, thus it is easy to get global optimal solutions, even energy systems modeled are quite large and complex, e.g., with hundreds of energy technologies and thousands of parameters.

From the middle of 1990s, researchers started to develop optimization models of energy systems with endogenous technological change, e.g., see [7-9, 11]. The most important feature of endogenous technological models is that, as experience in new technologies accumulates, the cost of using them tends to decrease—so-called technological learning which is a classical example of increasing returns [2]. Endogenous technological change models are also called induced technological change models [6], or LBD (learning by doing) models [1]. With endogenous technological change, it is not necessary to include additional (e.g., environmental or capacity) constraints which are actually at odds with historical experience [4] for triggering the penetration of advanced but currently uneconomic new technologies. The resultant mathematical problems of endogenous technological change models are non-convex optimization problems. Some endogenous technological change models also consider uncertainties in technological learning, e.g. see [7], thus the resultant optimization problems are not only non-convex but also stochastic. Comparing to the traditional optimization models, it is much more difficult to find (especially global) solutions for endogenous technological change models, especially those considering uncertainties. It is necessary to apply some very specific searching techniques, e.g., see [1], for finding solutions.

In recent years, agent-based modeling (ABM) and simulations have got increasing concerns by many researchers in the field of modeling energy systems. Agents in ABM can be simply defined as autonomous decision-making entities. ABM is thought as a powerful tool for studying complex adaptive systems which are systems with multiple elements/entities adapting or reacting to the pattern these elements create together [3]. In real world energy systems, there are many heterogeneous participating entities involved, and those entities not only interact with each other but also adapt or react to the pattern they create. It is difficult to catch those features related to heterogeneous entities and their interaction and adaptive behaviors with conventional optimization approaches, equilibrium analysis, and other analytical techniques. ABM is not only a good tool for dealing with those features, but also provides a way for rethinking the dynamics of energy systems. Examples of the applications of agent-based modeling in energy systems include: Bunn and Oliveira [5] used agent-based simulation to develop detailed insights into potential electricity market ahead of the introduction of new electricity trading arrangements of England and Wales, and Stephan and Sullivan [13] put forward an agent-based model to study the transition of a personal transportation system based on conventional fuels to one based on alternative fuel, such as hydrogen. Technological change in ABM can be in various forms. Comparing to optimization approaches, technological change in ABM is not any more the result of a long-term strategic planning, but the result of agent's reacting and adaptive behaviors.

This paper uses three models as examples to explain how technological change could be treated differently in optimization and agent-based modeling practices and compare advantages/disadvantages of and different philosophy underlying different modeling practices. The three models are namely traditional optimization model, endogenous technological change model, and agent-based model. For simplicity and comparable, all the three models are based on the same deliberately simplified energy system which is composed of three energy technologies. Each of the three models can be looked as an example of a stream in modeling energy systems.

This paper neither aims to summarize or cover all modeling practices in energy systems, nor does it study the detailed behaviors of the three models. Instead, the main purpose is to explain how technological change is treated differently in different modeling practices.

The rest of the paper is organized as follows. Section 2 describes the deliberately simplified energy system and introduces the three different models. Section 3 introduces initializations and analyzes results of the three models, and then compares different philosophy underlying the three modeling practices and their advantage/disadvantages. Section 4 gives concluding remarks.

2. The 3-Technology Energy System and the three Models

2.1 The 3-technology energy system

The deliberately simplified energy system assumes the economy demands one kind of homogeneous goods (e.g., electricity) and the exogenous demand increases over time. There are three technologies, namely, existing technology—T1, incremental technology—T2, and revolutionary technology—T3, that can be used to produce the goods. The existing technology has a low efficiency with a low initial investment cost, e.g., coal power plants; the incremental technology has a higher efficiency with a higher initial investment cost, e.g., gas turbines; and the revolutionary technology has a much higher efficiency with a much higher initial investment cost, e.g., photovoltaic cells. The incremental and revolutionary technologies have learning potential, which means their initial investment cost could decrease in the future.

2.2 The traditional optimization model

The story of the traditional optimization model is: there is a global social planner who makes a long-term strategic (e.g., 100-year) plan for the energy system thus the discounted total cost is minimized for satisfying the given demand; the driving forces for the adoptions of "incremental" and "revolutionary" technologies could include: capacity constrains of the "existing" technology, environmental constrains, resource depletion, and gradually (exogenously) decreasing cost of "incremental" and "revolutionary" technologies.
The demand is exogenous and increases over time as shown in Equation (1).

$$D^t = 100(1+\alpha)^t, \qquad (1)$$

where t denotes time (year), D^t denotes the demand at t, and α is the exogenous annual increasing rate of demand.
Let x_i^t ($i = 1,2,3$) denote the annual production of technology i at time t, and let η_i denote the efficiency of technology i; then the annual ex-

traction R^t is the sum of resources consumed by all technologies, as shown in Equation (2)

$$R^t = \sum_{i=1}^{3} \frac{1}{\eta_i} x_i^t. \qquad (2)$$

Let y_i^t ($i = 1,2,3$) denote the annual new installation of technology i at time t; then the total installed capacity of technology i at time t, denoted by C_i^t ($i = 1,2,3$) can be calculated according to Equation (3).

$$C_i^t = \sum_{j=t-\tau_i}^{t} y_i^j, \qquad (3)$$

where τ_i denotes the plant life of technology i. The following intertemporal optimization will be used to minimize the total discounted cost.

$$\min \sum_{i=1}^{3}\sum_{t=1}^{T}(1-\delta)^t c_{Fi}^t y_i^t + \sum_{t=1}^{T}(1-\delta)^t c_E^t R^t + \sum_{i=1}^{3}\sum_{t=1}^{T}(1-\delta)^t c_{OMi}^t x_i^t \qquad (4)$$

subject to

$$\begin{cases} D^t \le \sum_{i=1}^{3} x_i^t & (t=1,\cdots T) & & (5) \\ x_i^t \le C_i^t & (t=1,\cdots T) & (i=1,\cdots 3) & (6) \\ x_i^t \ge 0 & (t=1,\cdots T) & (i=1,\cdots 3) & (7) \\ y_i^t \ge 0 & (t=1,\cdots T) & (i=1,\cdots 3) & (8) \end{cases}$$

where:

T denotes the scale of the problem;

δ denotes the discount rate;

c_{OMi}^t denotes the operating and maintenance (O+M) cost of technology i at time t;

c_{Fi}^t denotes the cost of building unit capacity (or investment cost) of technology i at time t;

c_E^t denotes the cost of extracting each unit resource at time t;

The constraint function Eq. (5) denotes that the total annual production of all three technologies must satisfy the given demand; the constraint function Eq. (6) denotes that annual production for each technology does not exceed its total installed capacity; the constraint functions Eq. (7) and Eq. (8) denote that decision variables cannot be negative.

2.3 An endogenous technological change model

The endogenous technological change model shares almost the same story of the traditional optimization model except that the investment costs of the incremental and the revolutionary technologies are now a function of the cumulative experience in using them.

The endogenous technological change model is still intertemporal optimization, with Eq. (4) as the objective functions and Eq. (5) ~ (8) as constrains. But now the investment costs of technologies (c_{Fi}^t) neither keep constant nor change with exogenous decreasing rates. Instead, c_{Fi}^t will decrease with the increase of cumulative installed capacity of the corresponding technology, which can be looked as cumulated experience in it, as denoted by Eq. (9).

$$c_{Fi}^{\ t} = c_{Fi}^{\ 0} \times (\bar{C}_i^t)^{-b_i}, \qquad (9)$$

where 2^{-b_i} is the progress ratio ($1-2^{-b_i}$ is the learning rate) of technology *i*, and c_{Fi}^0 is the initial investment cost of technology i, $\bar{C}_i^t$ is the cumulative installed capacity of technology i by time t and

$$\bar{C}_i^t = \sum_{j=-\infty}^{t} C_i^j = \sum_{j=1}^{t} C_i^j + \bar{C}_i^0. \qquad (10)$$

Such endogenous mechanism can also be applied to resource depletion, which means the extraction cost c_E^t in Eq. (4) is neither constant nor determined by an exogenous parameter; instead it depends on the accumulated extraction by time t. Suppose cumulative extraction by time t is

$$\bar{R}^t = \sum_{j=1}^{t} R^j, \qquad (11)$$

the extraction cost of the resource is assumed increases over time as a linear function of resource depletion, as shown in Equation (12):

$$c_E^t = c_E^0 + k_E \bar{R}^t. \qquad (12)$$

2.4. The agent-based model

Various agent-based models could be developed with different understandings of decision makers and their behaviors. Researchers commonly use agent-based models to study interactions among multi-decision entities, e.g., see [9], but for comparing with the two models introduced above, the story of the agent-based model introduced here is very simple: the same as above, there is only one decision maker (or we call it an agent), but now this agent is not so smart to minimize the total cost of a long-term, or we can say it is myopic, and its decisions are made for a short term, e.g., one-year; the agent is not clear about the future demand thus it could not be completely rational, i.e., it is possible that the agent would build more or less capacity than really needed; although the agent is myopic and not full-rational, it is adaptive, it will adjust its decision according to the pattern – resource depletion and demand dynamics – somehow created by itself; and the demand is not exogenous as that in the models introduced above, it is somehow influenced by the agent's previous decisions. The following are more details of the agent-based model.

At each year, the decision agent calculates the average annual growth rate of extraction cost for the last three years, and then uses this growth rate to forecast the extraction cost for the next year. The agent uses each technology's current cost – without considering the potential of technological learning effect-- to evaluate which technology is cheapest for the next year. The agent's expectation on demand is also based on the last three years' data, it calculates the average annual growth rate of demand for the last three years, and then uses this growth rate to forecast the demand rate for the next year. If the agent's expected demand for the following year is higher than available capacity, it will build new capacity of the cheapest technology to fill the gap; otherwise it will not build any new capacity.

The exogenous increasing demand is influenced by price for satisfying it which is decided by weighted average cost of technologies. Eq. (13) describes the dynamics of the demand.

$$d^{t+1} = (1+\alpha) d^t \frac{\left(1-e^p\right) p^{t+1} + \left(1+e^p\right) p^t}{\left(1+e^p\right) p^{t+1} + \left(1-e^p\right) p^t}, \quad (13)$$

where d^t and d^{t+1} denote the demand at time t and $t+1$, respectively; α is the exogenous annual increasing rate; e^p is the price elasticity of demand; p^t and p^{t+1} are the price of the goods at t and $t+1$, which is decided by weighted average cost of technologies at corresponding step, as denoted in Eq. (14).

$$p^t = \sum_{i=1}^{3} w_i \tilde{C}_i^t , \quad (14)$$

where w_i denotes the share of technology i, and $\tilde{C}_i^t$ denotes the cost[1] of producing one unit goods with technology i at time step t, which can be obtained according to Eq. (15)

$$\tilde{C}_i^t = \frac{c_{Fi}^t}{\tau_i} + c_{OMi}^t + \frac{1}{\eta_i} c_E^t . \quad (15)$$

3. Initializations and Results of the three Models

Table 1 shows initial values of common parameters in the three models.

3.1 Results of the traditional optimization model

As a simplest case of the traditional optimization model, we assume that extraction cost c_E^t and investment cost for each technology $c_{Fi}^t (i = 1,2,3)$ does not change over time. With these assumptions, the problem denoted by Eq. 4 ~ Eq. 8 is a linear optimization model. And it is not surprising that the "incremental" and "revolutionary" technology do not appear in the optimal solution, which does not accords with historical observations that new technologies would replace old ones little by little, especially for a long-term. There are quite a lot of things we can do to force the adoption of the "incremental" and "revolutionary" technologies in the optimal solution, such as, adding capacity constrains, adding environmental constrains, assuming resource depletion, assuming exogenous technological change, and so on.

Fig. 1 shows a result of the traditional optimization model, with the assumption of an exogenous annual decreasing rate of 5% for the incremental technology, and an exogenous annual decreasing rate of 10% for the revolutionary technology, and an exogenous annual increasing rate of 1% for the resource extraction cost. In Fig. 1, the horizontal dimension denotes time, and the vertical dimension denotes the share of each technology's installed capacity. From 1990 to 2030 the share of the existing technology de-

[1] For a technology, its current initial cost for building unit capacity is used for all existing capacities.

creases while that of the incremental technology increases. From 2030 to 2060, the incremental technology is the only technology in application. And from 2060, the share of the revolutionary technology increases, but then it starts decreasing from 2070. This is a result of exogenous technological learning, by which technological learning is treated outside the economy, which means decision makers do not need to consider investment on technological learning. They just fetch a new technology outside the "economy box" when they find the new technology is cheap (considering environmental cost) enough, and give it away when they see other technologies are cheaper. As shown in Fig. 1, the decision maker fetches the revolutionary technology at 2060 then his/her attention switch back to the incremental one.

Table 1. Initial values of parameters

Parameters related to the three technologies			
	Existing Tech.	Incremental Tech.	Revolutionary Tech.
Initial cost (US$/kW)	$c_{F1}^{0} = 1000$	$c_{F2}^{0} = 2000$	$c_{F3}^{0} = 40000$
Efficiency	$\eta_1 = 30\%$	$\eta_2 = 40\%$	$\eta_3 = 90\%$
Plant life (year)	$\tau_1 = 30$	$\tau_2 = 30$	$\tau_3 = 30$
Initial Total Installed Capacity (kW)	$C_1^0 = 100$	$C_2^0 = 0$	$C_3^0 = 0$
Initial Cumulative Installed Capacity (kW)	$\overline{C}_1^0 = 1000$	$\overline{C}_2^0 = 1$	$\overline{C}_3^0 = 1$
O+M cost (US$/kW)	$c_{OM1} = 30$	$c_{OM2} = 50$	$c_{OM3} = 50$

Other parameters			
Increasing rate of annual demand		$\alpha = 2.6\%$	
Initial extraction cost (US$/kW)	$c_E^0 = 200$	Extraction cost coefficient (for the second and third models)	$K_E^0 = 0.01$
Scale of the problem		$T = 100$, decision interval is 10 years	
Discount rate		$\delta = 5\%$	

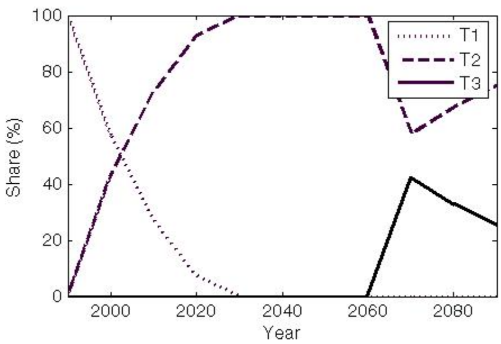

Figure 1 The result of the first model

Assuming an exogenous decreasing rate of investment cost of new technologies will result in the adoption of new technologies. But in reality, technological change – decreasing cost here -- does not fall like "manna from heaven", and it is the result of accumulated experience/practice in new technologies. By assuming an exogenous decreasing rate of investment cost, we allow such a situation to happen in the model: even there is no experience/practice at all in a new technology before a certain time, e.g. 2000, the investment cost of it still decrease, which means the technological change is treated as outside the economy or the energy system we are modeling, or we can say it is treated as "manna from heaven". The model introduced in the following subsection treats technological change and also resource depletion as inside the economy or the energy system we are modeling.

3.2 Results of the endogenous technological change model

With the endogenous technological change model, we assume the learning rate of the incremental technology is 10%, i.e., $b_2 = 0.1520$ and $1 - 2^{-b_2} = 10\%$, and that of the revolutionary technology is 30%, i.e., $b_3 = 0.5146$ and $1-2^{-b_3} = 30\%$. Figure 2 shows a result of the model in which adoption of new technologies is the result of technological learning and resource depletion. With technological learning, the decision maker has to consider the cost of technological change, thus when a decision is made to investment on a new technology, it is expected that this new technology will get continuous application in the future. Temporary technology adoption happened in Fig. 1 from 2060 is not expected to happen in this case.

In order to see whether endogenous technological change itself can be a mechanism for the adoption of new technologies, we then assumed there is no resource depletion, i.e., the resource extraction cost keeps constant, and the result is that the incremental technology takes over the existing technology at 2030, while the revolutionary technology does not appear by 2090. This result proves that technological learning itself can be a mechanism for the adoption of new technologies, without any additional constrains, but of course adoption of new technologies can be enhanced by other factors such as resource depletion. Endogenous technological change models improve traditional optimization models with the cost of increasing computing complexity. Running the two models on the same platform – Matlab7.0 -- with the same optimizer, and on the same computer with a Pentium 4 CPU 3.00Ghz, it takes around 2.5 seconds for getting the result shown in Fig. 1, while it takes around 87 seconds for getting the result shown in Fig. 2.

It is also widely accepted that technological learning is highly uncertain, as evidenced by investment cost distributions for biomass, nuclear and solar electricity generation in numerous engineering studies, e.g., see [12]. A common way to modeling uncertainty in endogenous technological learning is to let learning rates or progress ratios in Eq. (9) be random values, and adding the cost of overestimating it to the objective function with a risk factor [7, 10]. Following historical studies, random values of learning rates are commonly characterized by lognormal distributions based on empirical analysis of technological characteristics using the IIASA technology inventory [14]. The risk factor denotes decision maker's risk attitude which is a subjective parameters. There will be different optimal solutions with different values of the risk factor. The story of the endogenous technological change model with uncertainties is: the decision maker wants to find the hedging strategy depending on his/her risk attitude. With different risk attitudes, we somehow moved from optimization to simulations, or we could say "simulations with optimization model". Optimization models of endogenous technological change under uncertainties result in non-convex stochastic optimization problems. Comparing to the traditional optimization models, it is much more difficult to find (especially global) solutions. It is necessary, especially when the number of parameters is large, to apply some very specific searching techniques for finding solutions.

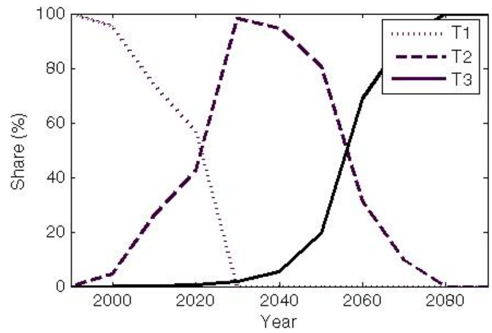

Figure 2 The result of the second model

With the endogenous technological change model, we further assume the learning rate of the incremental technology is a random value characterized by a lognormal distribution with mean as 10%, and standard deviation as 0.01, and the learning rate of the revolutionary technology is a random value characterized by a lognormal distribution with mean as 30%, and standard deviation as 0.03. By considering the cost resulting from overestimating technological learning as an additional cost in the objective function, we found the adoption of new technology will be delayed to some extent, depending on the decision maker's risk attitude.

3.3 Results of the agent-based model

With the agent-based model, we assume the price elasticity is 0.5, i.e, $e^p = 0.5$. Fig. 3 shows a result of the agent-based model in which the decision maker is myopic, technological leaning and the demand are treated as endogenous, the same as in the second model. In this modeling practice, decisions are not made only once at the beginning year as in the first and the second model, instead decisions are made every short period based on the decision maker's knowledge about the past and his/her expectation (which is also based on his/her knowledge about the past and his/her expectation model). The decision maker's knowledge about the past and his/her expectations about the future are updated every step, so we could say the decision maker denoted in this model are adaptive agents. Figure 3 shows that with myopic and adaptive agent, technological change could also happen, but the revolutionary technology are not adopted, partly resulting from the decision maker's myopia, and partly resulting from the revised (actual) demand which is lower than the exogenous demand projection used in the first and second models, as shown in Figure 4. Figure 4 shows the exogenous demand versus the endogenous (or revised) demand. The endogenous demand increases more slowly than that of the exogenous demand, which means, the high cost of satisfying demand cuts down expected demand.

4. Concluding Remarks

The optimization models can tell us "what should be" in terms of reaching some objectives, e.g., to minimize the total cost of energy systems meanwhile satisfying (exogenously) given demands and environmental and economic constrains. While the agent-based models can tell us "what could be" under various assumptions. Unlike optimization models, agent-based simulations can not give us solutions for strategic planning, while it can aid intuitions.

Table 2 summarizes different philosophy underlying the three modeling practices and their advantages and disadvantages

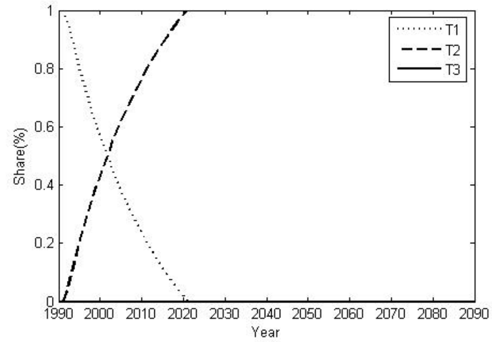

Figure 3 The result of the third model

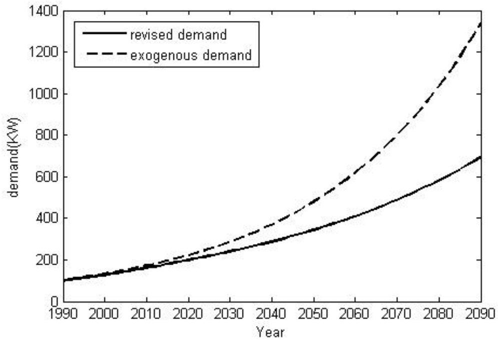

Figure 4 The exogenous demand and the revised demand.

References

[1]. Alan S. Manne and Leonardo Barreto, 2004 Learn-by-doing and carbon dioxide abatement, Energy Economics, vol. 26 pp. 621– 633

[2]. Arthur, W.B., 1989, "Competing Technologies, Increasing Returns, and Lock-in by Historical Events," *The Economic Journal* 99: 116–131.

[3]. Arthur, W.B., 1999, Complexity and the Economy. *Science*, **284**(5411), pp. 107-109.

[4]. Barnett, H.J. and Morse, C., 1967, *The Economics of Natural Resource Availability*, John Hopkins University Press, Baltimore, MA, USA.

[5]. Bunn W.E. and Oliveira F.S., 2001, Agent-based simulation—an application to the new electricity trading arrangements of England and Wales, IEEE Transactions on Evolutionary Computation, Vol. 5, No. 5. pp. 493~503.

[6]. Gritsevskyi, A., Nakicenovic, N., 2000. Modelling uncertainty of induced technological change. Energy Policy 28, 907–921.

[7]. Grübler, A. and Gritsevskyi, A., 2002, "A Model of Endogeneous Technological Change through Uncertain Returns on Innovation," in A. Grübler, N. Nakicenovic, and W.D. Nordhaus (eds.) *Technological Change and the Environment*, RFF Press, Washington DC, USA, pp. 280–319.

[8]. Kypreos, S., Barreto, L., Capros, P., Messner, S., 2000. ERIS: A model prototype with endogenous technological change. International Journal of Global Energy Issues 14. (1/2/3/4), 374– 397.

[9]. Ma, T. and Nakamori, Y., 2005, Agent-Based Modeling on Technological Innovation as an Evolutionary Process, *European Journal of Operational Research* 166(3): 741–755.

[10]. Ma, T. 2006, An Agent-Based Model of Endogenous Technological Change -- An Extension to the Grubler-Gritsvskyi Model, IIASA, Interim report, IR-06-044.

[11]. Messner, S., 1997. Endogenised technological learning in an energy systems model. Journal of Evolutionary Economics 7, 291– 313.

[12]. Nakicenovic, N., Grübler, A., and McDonald, A., (eds.), 1998, *Global Energy Perspectives*, Cambridge University Press, Cambridge, UK.

[13]. Stephan C. and Sullivan J., 2004. An Agent-Based Hydrogen Vehicle/Infrastructure Model, Proceedings of the 2004 congress on evolutionary computation, ©IEEE, New York, pp. 1774-1779.

[14]. Strubegger,M., and Reitgruber, I., 1995, Statistical Analysis of InvestmentCosts for Power Generation Technologies, WP-95-109, International Institute for Applied Systems Analysis, Laxenburg, Austria.

Table 2 Philosophies underlying the three modeling practices and their advantages and disadvantages

Modeling pratices		Philosophy	Advantages	Disadvantages
Traditional (linear) optimization models		A decision maker makes a long-term strategic plan under perfect foresight without considering the cost of technological change	Easy to get optimal solution and comparatively small computing complexity	Technological change is treated as outside the “economy box” -- the economic energy system being modeled.
Endogenous technological change models	With deterministic technological learning	A decision maker makes a long-term strategic plan under perfect foresight considering the cost of technological change	The model includes technological learning as a mechanism for the adoption of new technologies.	Nonlinear, non-convex (and stochastic with uncertain learnings) optimization problems, thus high computing complexity and difficult to get optimal (especially global) solutions.
	With uncertain technological learning	A decision maker makes a long-term hedging strategic plan (according to his/her risk attitude) considering uncertain cost of technological change	Decision makers’ risk attitudes are introduced into models	
Agent-based models		A decision maker makes adaptive plans based on the situation created by he/she (or with other decision makers), and technological change is the result of decision makers’ adaptive behaviors.	It is very natural to model adaptive behaviors and interactions among decision agents, technological learning and uncertainties can easily be introduced in the model.	Results are not optimal solutions but scenarios with various assumptions.