An Evolutionary Model of Energy Transitions
With Interactive Innovation-Selection Dynamics

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Abstract
We develop a stylised application of an evolutionary approach to model substitution of energy technologies. The evolution of the energy system is modelled here with replicator dynamics extended by recombination and mutation, which gives rise to interactive innovation-selection dynamics. The framework describes a population of boundedly rational investors who decide each period on the allocation of investment capital among different energy technologies. Investors tend to invest in below-average cost technologies, just as under replicator dynamics. In addition, they devote a constant fraction of investments to alternative technological options and research on recombinant innovation.
We study the dynamics of shares of investments in energy technologies for three different selection environments: with selection operating on technologies characterised by constant costs, costs decreasing steadily and exogenously over time, and costs depending on the level of cumulative investments. For each, we assess conditions under which a new technology emerges, and the coexistence of technological options is feasible. We evaluate which solutions are optimal in terms of minimising the average and total costs of investments in different technologies at the end of the investment period.

Keywords: bounded rationality, energy transition, investment theory, learning curve, optimal diversity

JEL code: B52, C61, O32, O33, Q42
1. Introduction

A transition to sustainable development requires a substitution of high by low carbon intensive technologies. The latter, such as renewable energy technologies, are typically characterised by high unit costs of installation and exploitation. They are still in early phases of development. Their deployment involves vast investments in R&D activities and the supporting infrastructure. However, producers have little incentive to adopt more sustainable energy technologies before the currently used machinery and production techniques become obsolete. Similarly, investors may be reluctant to shift their finances from mature industries towards research on and investments in new energy sources, as long as there is potential to grasp some rents from investing in incremental improvements in incumbent technologies (Perez, 2007). This is also for a reason that there is much uncertainty associated with the technological progress of renewable energy technologies, their potential for cost reduction and the time required for investments to reach a break-even point. Notably, without costly investments in installed capacity and innovation research, renewable technologies have little chance to become cost effective and competitive. A critical mass of investments is likely to play an important role in inducing a transition to a more sustainable energy system. Moreover, investing solely in the most profitable technologies, currently based on fossil fuels, may imply a short-term solution because of their impact on the environment. The crucial question is how many scarce resources (investment capital) to divert from fossil fuel technologies towards renewable technologies, while ensuring security of energy supply.

Diversifying investments in energy projects is essential to the process of technological change. Maintaining a variety of technological options may improve ‘adaptability’ of the system, minimize risks associated with unforeseen contingencies, and prevent lock-in of a dominant technology. In general, firms investing in a number of research projects, thus diversifying their research portfolios, are capable of modifying existing technologies easier and of applying these technologies later across different products and markets at lower costs (Granstrand, 1998). By widening their knowledge base through portfolio diversification firms may increase their capacity to absorb new knowledge. Indeed, combining existing technologies and ideas is widely recognized as an important source of innovation (Weitzman 1998; Fleming and Sorenson, 2001; Olson and Frey, 2002; Tsur and Zemel, 2006). Similarly, experimenting with variations of existing technologies may contribute to knowledge creation. On the other hand, economists often emphasize the high costs involved in maintaining diversity, notably lost advantages of scale and specialization (increasing returns to scale, including scale economies), organizational costs associated with coordination and integration of multiple projects, and cost of carrying out multi-disciplinary R&D activities. A recent study examines the optimal trade-off between the benefits of diversity and specialization with a formal model (van den Bergh, 2008).

To better grasp feedback mechanisms between innovation and selection in the process of energy substitution, we propose an evolutionary-economic approach based on replicator dynamics.
extended with recombination and mutation rates. The model integrates selection and two types of innovation, namely through variation and recombination of existing technologies. It gives rise to a general model of interactive selection-innovation dynamics. The proposed framework builds upon three lines of modelling in theoretical biology: the quasispecies equation (Eigen, 1971; Eigen and Schuster, 1979; Hofbauer, 1985; Schuster and Swetina; 1988; Bull et al., 2005; Nowak, 2006), replicator-mutator dynamics (Haderer, 1981; Stadler and Schuster, 1992; Bomze and Burger, 1995; Nowak et al., 2001, 2002; Komarowa, 2004; Nowak, 2006) and ‘recombination’ dynamics (Feldman et al., 1980, Barton, 1995, Boerlijst et al., 1996, Jacobi and Nordahl, 2006). The approach has been developed in Safarzynska and van den Bergh (2008). Here, we propose its stylised application to model an energy transition. In particular, we analyze the process of substitution of fossil fuel technologies characterized by low unit costs but high social or environmental costs by a cleaner renewable technology with a currently high unit cost but a great potential for cost reduction.

Model dynamics can be interpreted as follows: in each period investors tend to invest in below-average cost technologies. In addition, they devote a certain (constant) fractions of investments, captured by mutation and recombination, to alternative technologies and research on recombinant innovation. Mutation and recombination determine the probability of the emergence of a new technology that is initially absent in the market. They are modelled here as conceptual variables with concrete behavioural interpretation, describing heuristic decision rules of boundedly rational investors. For instance, mutation can be seen as capturing the inability of investors to perfectly assess the profitability of different technologies, costly experimentation, deliberate portfolio diversification, and risky investments in new technologies. Recombination describes a fraction of investments devoted to research on recombinant innovation.

We study evolutionary dynamics for different model extensions, namely where selection operates on technologies characterised by constant costs, by costs that decrease steadily and exogenously over time, and by costs that change depending on the level of cumulative investments. The latter is consistent with and reflects learning-by-doing or learning-by-experience (Arrow, 1962). For each model version, we identify the conditions under which a new technology emerges and the coexistence of various technological options is feasible. In addition, we examine which decision rules, described by mutation and recombination rates, are optimal in terms of minimising the average and total costs of investments in alternative technologies and recombinant innovation at the end of investment period. The total cost is relevant to assess how costly it is to arrive at a certain mix of energy technologies at a certain time horizon, while the average cost at this time can be regarded as indicative of the cost of future (further) development or maintenance of the system. There is a trade-off between short-term and long-term benefits: investing in the currently cheapest technological option may be cost-effective in term of minimising immediate costs but in the long-term it can involve forgone benefits from recombinant innovation or from providing other technologies with good learning-by-doing and learning-from-experience opportunities. Under certain conditions, investments
in alternative (initially more expensive) technologies may contribute to a considerable reduction in their costs or render the emergence of a new technology with a great potential for cost reduction in the long-run.

The reminder of this paper is organized as follows. In Section 2, we review existing models of technological substitution in the energy sector. In Section 3, we present our model based on replicator dynamics extended with mutation and recombination. In Section 4, we present results of numerical analysis of the model for a stylised application to energy substitution. Section 5 concludes.

2. Change in energy technologies

In formal energy models, the process of technology substitution is typically conceptualised as following one of two simple patterns (Nakicenovic, 1997). According to the first pattern, a new technology becomes more attractive as the costs of the traditional technologies increase. Consistent with this view, renewable energy can substitute a traditional source of energy because of a rise in the price of the latter. Alternatively, the cost of new technologies is expected to decrease over time (e.g., because of R&D activities) causing renewable technologies to become competitive at one point along the learning curve. Under the assumption that the cost decreases at a constant rate over time it will be cost-effective to postpone investment in renewable technologies until they are cheaper and current vintages become obsolete. However, if technological change depends on learning due to R&D, costly investments are necessary to reduce the costs of renewable technologies. Moreover, postponing investment decisions is likely to result in a (reinforced) lock-in of energy systems to a fossil fuel intensive development path (Nakicenovic, 1997). Nevertheless, investors may prefer to delay investments if they expect that the costs of alternative technologies will decrease as a result of exogenous improvements in other supporting technologies (e.g. batteries) or due to investments undertaken by others (including the government and universities).

From another perspective, models of technology (energy) substitution are classified into bottom-up and top-down \(^1\) (Loschel, 2002). The bottom-up models rely on a detailed presentation of distinct technologies within the energy system (Mattsson and Wene, 1997; Messner, 1997; Seebregts et al., 1998; Gritsevskyi and Nakicenovic, 2000). Here, technological change relies on technological learning, i.e. technology cost reductions occurring along a learning curve. For instance, a one-factor learning curve expresses changes in technology costs as a function of cumulative installed capacity (Messner, 1997; Gritsevsky and Nakicovic, 2000):

\[
c_{it} = \alpha I_{it}^{1/\beta}
\]

where \(\alpha\) is the initial cost and \(\beta\) the learning elasticity (or learning index). The equation implies that with every doubling of total installed capacity \(I_t\) specific costs are reduced by a factor of \(2^{1/\beta}\), referred

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\(^1\) In addition, Loschel (2002) distinguishes integrated assessment models, developed to assess the effect of induced policy on climate change.
to as the progress rate. A number of models have endogenized the rate of cost reduction to capture technology learning due to learning-by-doing, investment in R&D, and spillover effects (e.g., Gritsevsky and Nakicovic, 2000). In addition, the learning curve can be extended to incorporate the learning-by-searching rate, resulting in a two-factor learning curve (Beglund, and Soderholm, 2006):

\[ c_{it} = \alpha I_{Kt} \beta K_{it} \]

\( K \) is cumulative knowledge through R&D investments up to time \( t \) and \( \tau \) is the learning-by-research or learning-by-searching coefficient characterising the rate of cost decline due to an increase in cumulative knowledge.

In bottom-up models, the objective function typically minimizes the total cost of the energy system, i.e. the sum of costs of investments and operating technologies, under system constraints. For instance, Messner (1997) analyzes the dynamics of investment paths of various energy technologies within the Message model, where the objective function minimizes the sum of the discounted costs of the overall energy system under a number of constraints: acquiring sufficient supplies of exogenous demands, balancing quantities for all energy carriers and periods, satisfying resource availability, and ensuring a sufficient capacity of installed technologies. The process of technological learning is formalised here with the one factor learning curve, i.e. as a function of cumulative investments in installed capacities. Subsequently, three alternative scenarios for different learning effects are compared: static, dynamic with exogenous cost reductions, and dynamic with endogenous cost reductions depending on R&D investments. The results support the importance of early investments in development of new technologies in the model version with endogenous cost trajectories. Here, the cost reduction is achieved earlier than in the model with the constant exogenous rate of learning, and required the lowest level of cumulative investments (Messner, 1997).

Bottom-up models can generate numerous pathways of how the energy system can evolve in the future. For instance, Gritsevsky and Nakicovic (2000) simulated 520 alternative technology dynamics, within which they identified 53 optimal, feasible (given various constraints) technological development paths. However, it is difficult to assess the likelihood of the occurrence of alternative scenarios. The reason is that the bottom-up analysis neglects the effects of interactions of the energy sector with other economic sectors. Alternatively, a top-down approach relies on an aggregated production function for the entire economy. It captures the possibility of substitution of different energy technologies through substitution elasticities in the production function. Technologies are typically not described in detail but by an input-output matrix at the industry level. Changes in the input-output coefficients capture other than cost/price driven improvements in technology that affect energy intensity in a given industry sector (Begdun and Soderholm, 2006). The coefficients are updated each period. For instance, for the model with \( n \) sectors, the entrances at the input coefficient matrix \( A(t) \) change according to (Pan, 2006):

\[ A(t) = A(t-1)S^O(t) + A^N(t)(1-S^O(t)) \]
where $S_j^O(t)$ are the shares of the old process in the sector $j$. The elements $a_{ij}^O$ and $a_{ij}^N$ are technological coefficients for old $O$ and new $N$ technological processes, respectively. Recent models endogenize the rate of change in technological coefficients (Goulder and Schneider, 1999; Pan, 2006). For instance, in Pan’s (2006) model the technical coefficients change along the generalised logistic curve:

$$a_{ij}^O = a_{ij}^0 + \frac{a_{ij}^N}{1 + e^{-(\ln(M/IRD(t)))}}$$

with $a_{ij}^0$ an initial level, and $a_{ij}^N$ a saturation level of the coefficient, $\alpha$ the average growth rate, $IRD$ the index of investment in R&D in new technology, and $M$ the maximum growth. Here, R&D activities shift relative weights of technologies in the production process.

Top-down models focus on technological change at the aggregate level, and thus do not account for how different energy technologies may evolve in the future. Some attempts have been undertaken to combine bottom-up with top-down type of approaches (e.g., Rutherford, 1995; Bohringer and Rutherford, 2006). However, no hybrid model is capable to incorporate all of the relevant factors at the micro and macro level, including energy prices, availability, different aspects of market behaviour and characteristics of supply and demand at the level of industries (Wilson and Swisher, 1993). The technological and economic complexity and multidimensionality of objectives involved in such models makes it difficult to derive concrete policy implications from their analysis.

In the next section, we propose a novel approach to model dynamics of economic-energy system. The model can be considered to represent a bottom-up framework. However, it differs from existing models in that it relies on a simplified representation of the energy system and assumes myopic behavior of investors and costly experimentation instead of perfect cost-minimising. The analysis of this system may contribute to better understanding of the mechanisms behind the substitution process of energy technologies.

3. An evolutionary model of selection, mutation and recombinant innovation

In this section, we propose a formal model of technological substitution. The evolution of investment shares in various technologies is modelled with replicator dynamics extended by mutation and recombination, which we refer to as interactive innovation-selection dynamics. We do not discuss here general properties of the system, i.e. equilibrium and stability conditions, as these have been derived elsewhere (Safarzynska and van den Bergh, 2008). Here, we present the general framework, while in Section 4 we discuss results from its stylised application to model the process of technology substitution in the energy sector.

The framework describes the dynamics of $n$ technologies competing for adoption. We assume a very large population, in which investors allocate capital between a number of technologies, based on their relative unit cost. In particular, they tend to invest in below-average cost technologies. Thus, the share of investments in the cheapest technology is expected to increase over time. In addition, investors may devote a certain percentage of investments, described by a mutation rate $\mu$, to alternative
technologies. The mutation rate can be seen to capture the imperfect, myopic or local nature of search for returns on investment. It describes a ‘rule of thumb’ so as to devote a certain fraction of investments for the purpose of diversification and experimentation with new variations.

Next, a fraction \( r \) of investments, described by the recombination rate, is devoted towards fundamental research on recombinant innovation. This process may lead to the emergence of a new technological option that is initially absent in the population.

Formally, changes in the market shares of the already existing technologies \( x_i \) follow:

\[
\dot{x}_i = \sum_j x_i f_{ij} - x_i \Phi_t - r \sum_k \alpha_{kj} \gamma_{kj} x_k x_i \quad \text{for } i=1,...,m \text{ existing technologies (1)}
\]

and for a new emerging technology \( e \), which is initially absent on the market:

\[
\dot{x}_{et} = \sum_j x_i f_{ej} - x_{et} \Phi_t + r \sum_k \gamma_{kj} x_k x_{et} \quad \text{for } e=m+1,...,n \quad (2)
\]

Here \( x_0 \) is the share of investments going to technology \( i \), \( f_i \) is fitness of technology \( i \) at time \( t \) (defined below), \( \Phi_t \) represents average fitness, defined as \( \Phi_t = \sum_i f_i x_i \); the matrix \( Q=q_{ij} \) describes the fractions (probabilities) of investments in \( i \) being directed towards technology \( j \) (\( \sum_j q_{ij} = 1 \)); and \( \gamma_{ij} (\= \gamma_{ji}) \) is a binary variable that takes a value 1 if \( i \) and \( j \) can be recombined into \( e \) and 0 otherwise; this reflects that not all technologies can be recombined. In the next section, we apply the framework to three technology context and set \( \gamma_{12}=1, \gamma_{23}=0, \) and \( \gamma_{21}=0 \) assuming that incumbent technologies 1 and 2 may be recombinated to give rise to a novel technology 3.

The parameter \( r \) is the recombination rate, while \( \alpha_{kj} \) and \( \alpha_{jk} \) are weights at which technology \( k \) and \( j \) are being combined to give rise to \( e \). These weights depend on the relative cost of technologies:

\[
\alpha_{ej} = \frac{c_{i0}}{c_{i0} + c_{j0}}
\]

\[
\alpha_{ji} = 1 - \alpha_{ej}
\]

The latter follow from the assumption that \( \sum_k \alpha_{ek} = 1 \). This way we ensure that investments in more profitable technology lose fewer shares over time.

Formally, we define:

\[
r_{kj}^e = r \gamma_{kj} x_k x_i
\]

as the probability that investments in research on recombination of technologies \( j \) and \( k \) give rise to the technology \( e \). If one of the parent technologies is absent in the population technology \( e \) will not emerge (especially in the absence of mutation). In this case, the probability of recombination is zero. If both parent technologies are present in the population but technology \( e \) is unable to take-off, there will be a constant flow of investments into research on recombinant innovation that lasts for as long as both parent technologies exist on the market.

The mutation probability is described as:

\[
q_{ii} = 1 - \mu
\]
Here, mutation $q_{ik}$ captures the fraction of investments in innovation research if technology $k$ is a new emerging technology; otherwise, if $k$ is an incumbent technology, mutation describes the fraction of investments (devoted towards alternative technologies) with the purpose of diversification. We assume that investors tend to diversify the investment portfolio by allocating fraction $\mu$ of capital equally among $n-1$ technologies alternative to technology $i$.

Selection dynamics depend on the relative fitness of technologies. We define the fitness of a technology as:

$$f_i = a - c_{it}.$$  \hfill (6)

This way technologies characterised by a lower costs have a higher fitness. The parameter $a$ does not vary between technologies, and $a \geq 1$.

We consider three alternative cost functions, namely constant costs, costs decreasing steadily and exogenously over time, and dynamics with cost reductions occurring along the learning curve. In case selection operates on constant unit costs:

$$c_{it} = c_{i0},$$  \hfill (6a)

with $c_{i0} \in (0,1)$.

Alternatively, unit costs decrease over time according to:

$$c_{it} = \frac{c_{i0}}{gt + b}$$  \hfill (6b)

with $a, b, c, g$ constants.

Here, the unit cost decreases automatically over time regardless of investments in technology $i$.

Finally, according to a third cost specification unit costs fall over time in proportion to the level of cumulative investment in installed capacity of technology $i$, that is along a learning curve (Arrow, 1962):

$$c_{it} = c_{i0} I_{it}^{-\beta_i}$$  \hfill (6c)

Here, $c_{i0}$ the initial cost, $\beta_i \in (0,1)$ the learning rate, and $I_{it}$ cumulative investment up to date $t$. The equation implies that with every doubling of total installed capacity specific costs are reduced by a progress rate of $2^{-\beta_i}$. Given that we are working in an infinite population framework (due to replicator dynamics), cumulative investments in technology $i$ are defined as being equal to the cumulative shares of investments in this technology:

$$I_{it} = \int_0^t x_{it} \, dt$$  \hfill (7)
4. Model dynamics

In this section, we present numerical and statistical analysis from the model as described by equations 1-6 but for three technologies. We perform three types of analysis. First, in Section 4.1, we examine the evolution of shares of investments in a new emerging technology for different recombination and mutation rates. In Section 4.2, we look at the average cost of investments in different technologies achieved at the end of investment period. Finally, a third type of analysis conducted in Section 4.3 examines the impact of mutation and recombination on diversity.

4.1 Parameter values

Initially, we generate a market with 3 technologies: 2 exist and 1 emerges. In the beginning of the simulation run investment capital is allocated equally between two incumbent technologies, while no investments are being made in a new emerging technology \((x_{1,0}=x_{2,0}=0.5\) and \(x_{3,0}=0\)). The motivation for this is that latter technology either is not invented yet or it exists (as a blueprint) but because of its high cost has not attracted capital thus far.

We analyse market dynamics for \(T=500\) time steps, referred to as the investment period (\(T\) is the time horizon). For simplicity, we set \(a, g\) and \(b\) to 1. Other parameter values are: \(c_1=0.1\), \(c_2=0.2\), \(c_3=0.4\), \(\beta_1=0.05\), \(\beta_2=0.05\), \(\beta_3=0.35\). These values imply that technologies 1 and 2 are mature and characterised by a low potential for cost reduction, whereas technology 3 has a high (the highest) unit cost as well as a high potential for cost reduction. We set relative values of learning rates and costs for incumbent technologies to approximate the characteristics of fossil fuel technologies, and for a new emerging technology to reflect the features of renewable energy technologies, as documented in the literature. Note that estimates associated with different energy technologies and time spans vary over a wider range, e.g. for electricity generation technologies learning rates range from 0.03 to 0.35 as shown in Figure 1. We set the parameters of the learning rates within this range.

Source: Kohler et al. 2006.

Figure 1. Learning rates in electricity production technologies
4.2 Dynamics of new technology shares

Figures 2-4 show shares of investments in technology 3 observed at the end of investment period for different cost specifications. Figures 2a-4a depict 1000 points obtained from (different) simulations with mutation and recombination rates randomly generated within a range (0,1). Histograms in Figures 2b-4b summarize how many times out of 1000 cases a particular level of shares of investments in technology 3 in the investment portfolio has been observed at the end of investment period ($T=500$).

Figure 2 depicts shares of investments in technology 3 in the model version with constant unit costs. Here, changes in the recombination rate have a negligible effect on the share of technology 3 in total investments. On the other hand, a higher mutation rate increases the share of investments from a low value (for 0 mutation rate) to its maximum value, here 0.45 (for mutation rate equal 1).

For the model version with cost decreasing steadily and exogenously time, shares of investments in technology 3 converge to a value between 0.3 and 0.8, the precise value depends on the mutation and recombination rates (Figure 3a). Figure 4a shows similar results for the model version with costs decreasing along the learning curve. In both cases, investments in technology 3 never take over the entire investment portfolio (i.e. never converge to 1) regardless of the heuristic decisions of investors. In fact, mutation gives rise to the coexistence of two or three technologies in the investments portfolio for a wide range of initial parameter settings, as shown in Safarzynska and van den Bergh (2008).
The frequency distributions of shares of investment in technology 3 in the investment portfolio vary between alternative selection environments, as is shown in the histograms depicted in Figure 2b-4b. For the selection environment with constant unit cost, the frequency distribution is skewed to the left, which means that lower concentrations of technology 3 are expected here than in selection environments with unit costs subject to dynamic cost reductions (exogenous or endogenous), since here the frequency distribution is skewed to the right.

Table 1 summarises the results from regression analyses of mutation and recombination rates on the share of technology 3, corresponding to data obtained from model simulations for randomly generated mutation and recombination at the end of the investment period $t=500$. Formally, we estimate coefficients of the function:

$$x_3 = \alpha_0 c + \alpha_1 \mu + \alpha_2 \mu^2 + \alpha_3 r + \alpha_4 r^2 + \epsilon$$

where $c$ is a constant and $\epsilon$ is an error term. We include squared mutation and recombination rates to evaluate the nonlinear impacts of these variables on the dependent variable (as suggested by patterns...
depicted in Figures 2a to 4a). The results confirm the positive and statistically significant impact of mutation on the levels of shares of technology 3 in the model version with constant unit costs, and its negative impact on the level of technology shares in the model with dynamic cost reductions (endogenous or exogenous). The reason behind this discrepancy is that in the former model version, constant fractions of technology 1 and 2 are directed towards technology 3, while in the latter model versions these fractions decrease over time as these technologies become cheaper. For each selection environment, the impact of recombination on the share of technology 3 is positive.

Table 1. Regression coefficients for the share of technology 3 in the investment portfolio

<table>
<thead>
<tr>
<th>Selection environment</th>
<th>Constant unit cost</th>
<th>Cost decreasing steadily over time</th>
<th>Cost changing along a learning curve</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>0.05*</td>
<td>0.46*</td>
<td>0.43*</td>
</tr>
<tr>
<td>µ</td>
<td>0.85*</td>
<td>-0.48*</td>
<td>-0.28*</td>
</tr>
<tr>
<td>µ²</td>
<td>-0.63*</td>
<td>0.31*</td>
<td>0.13</td>
</tr>
<tr>
<td>µ</td>
<td>0.19*</td>
<td>0.27*</td>
<td>0.28*</td>
</tr>
<tr>
<td>µ²</td>
<td>-0.08*</td>
<td>-0.15*</td>
<td>-0.15*</td>
</tr>
<tr>
<td>number of observations</td>
<td>255</td>
<td>255</td>
<td>255</td>
</tr>
<tr>
<td>R²</td>
<td>0.87</td>
<td>0.68</td>
<td>0.41</td>
</tr>
</tbody>
</table>

* variables significant at 1 percent level.

The allocation of investment capital among different technologies undertaken at the beginning of the investment period (t=0) affects the average cost of investments achieved at the end (t=T). The allocation of investment capital among different technologies undertaken at the beginning of the investment period (t=0) affects the average cost of investments achieved at the end (t=T), and thus the total cost of investments in different technologies over the investment horizon. The average and total costs are important indicators to evaluate the attractiveness of different investment heuristics. The average cost achieved at the end of the investment period (t=T) may be indicative of the
future average cost of the energy system (for $t>T$), while the total costs to that date approximates expenses required to arrive at a certain technology mix in the investment portfolio. The difference in the relative levels of the average and total costs for different investment heuristics capture the trade-off between short-term and long-term benefits. Investors concern about immediate profits will prefer to invest in cheapest technological options. In the long run, this may not be the optimal strategy in terms of providing technologies with learning opportunities to reduce their unit costs.

Figures 5 to 7 present simulation results. Figures 5a-7a show the average and Figures 5c-7c the total costs of investments as functions of mutation for three alternative model versions. Each figure presents 5000 points obtained from different simulations with a randomly generated mutation rate within the range (0,1), and for the recombination rate set to: $r=0$, $r=0.25$, $r=0.5$, $r=0.75$, or $r=1$ with equal probability. Analogously, Figures 5b to 7b show changes in the average and Figures 7d-7d in the total cost of investments as a function of recombination. Here, a recombination rate is drawn randomly from the (0,1) range before each simulation, and simulations are repeated 1000 times for different mutation rates, namely: $\mu=0$, $\mu=0.01$, $\mu=0.025$, $\mu=0.05$, $\mu=0.075$, $\mu=0.25$, $\mu=0.5$, $\mu=0.75$, $\mu=1$. As a result each figure (5b to 7b and 5d to 7d) depicts 9000 points obtained from distinct simulation runs.

The simulation results support that in the model version with constant unit costs, an increase in the mutation or recombination rate contributes to higher average and total cost of investments (Figure 5a-5d). Here, an optimal (obvious) solution in terms of minimising these costs is to invest solely in the cheapest technological option.

In the model version with costs decreasing steadily and exogenously over time, unit costs fall automatically regardless of the level of investments. Theoretically, both costs of investments would be minimized if each period investors shift (all) investment capital towards the cheapest available option. However, this assumption is unrealistic; investments in technologies are not perfectly mobile; there are constraints to re-allocate capital. In addition, investors may be incapable to compute the optimal strategy every time period. Thus, we evaluate an impact of various heuristics, i.e. how to allocate constant fractions of capital among different technologies, on the average and total costs of investments at time $t=T$. The results from model simulations suggest that for a given recombination rate, an increase in the mutation rate tends to lower the average and totals cost of investments (Figure 6a and 6c), except for very low values of the mutation rate. These results are counterintuitive. Mutation describes a heuristic rule to detract capital away from the cheapest options; consequently it is expected to increase the average cost of investments, which indeed occurs in the alternative model versions. On the other hand, mutation ensures that some of investments in a new (initially expensive) technology are redirected to incumbent (cheaper) technologies. Here, such “back mutations” tend to lower the average cost of investments in different technological options (achieved at the end of investment period). This supports to some extent that if costs decrease steadily and exogenously over time, it is beneficial to postpone investments in new technologies until they become cheaper. In addition, in the discussed model version, a higher recombination rate increases the average and total
costs of investments (Figure 6b and 6d). The impact of changes in the recombination rate on the total cost of investments is stronger for lower values of mutation (Figure 6d).

The third model version introduces technological learning, meaning that unit costs fall as function of cumulative investments (cumulative knowledge). Here, costly investments are necessary to induce technological change. Without them new technologies will remain expensive. Certain combinations of mutation and recombination rates render the average cost of investments to be lower than other combinations as unit costs depend directly on mutation and recombination rates. The results suggest that an increase in recombination typically reduces the average and total costs of investments (Figure 7b and 7d). On the other hand, a higher mutation rate increases the total cost of investments (Figure 7d), while the impact of mutation on the average cost is nonlinear (Figure 7a). For a given recombination rate (but different from zero), an increase in mutation above a certain threshold level $\mu_l^2$ tends to increase the average cost of investments, while below this threshold an increase in the mutation rate decreases it. A high recombination rate implies that much investment is undertaken in technology 3, which is assumed here to have the highest potential for cost reduction. Provided with sufficient learning opportunities, technology 3 may achieve a very low unit cost. As a result the average cost of investments in different technologies at the end of investment period will be lower. Here, “back mutations” causing a high fraction of investments being diverted from the emerging technology 3 to incumbent technologies has the effect of slowing down cost reduction of the former.

In all reported cases (i.e. the three different selection environments), the total cost of investments has been minimised in the absence of investments in alternative technologies and research on recombinant innovation. Interestingly, in the model with costs decreasing along the learning curve, a combination of a low (but positive) mutation rate and a high recombination rate ensures the lowest possible average cost of investments achieved at the end of investment period (a point corresponding to mutation being equal to $\mu_l$ in Figure 7a). Here, a positive value of investments in alternative technologies and in research on recombinant innovation may contribute to high reductions in the unit cost of an emerging technology. This contrasts with the results obtained for alternative cost specifications, where the lowest possible average cost of investments was achieved for zero mutation and zero recombination rates. Consequently, if a policy objective is to promote development of cheap technologies, e.g. to secure future energy supply, little investments in diversification and more in recombinant innovation are to be recommended if technologies are characterised by unit costs decreasing along a learning curve. This case may be most relevant as empirical evidence indicates that over time the costs of energy-related technologies are well described by learning curves (see Kohler et al., 2006).

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2 The threshold level differs for different combinations of mutation and recombination.
Figure 5. Average costs of investments, recombination and mutation for constant units cost
**Figure 6.** Average costs of investments, recombination and mutation for costs decreasing steadily over time

**Figure 7.** Average costs of investments, recombination and mutation for costs decreasing along a learning curve
4.4 Optimal diversity

Maintaining diversity is important for an economic system, as it may improve system adaptability to unforeseen contingencies or prevent lock-in to a single technology. Here, we examine technological diversity achieved at the end of simulation run as a function of mutation and recombination rates. Diversity is measured with the Simpson index, defined as the squared sum of shares of each technology \( D = \sum x_i^2 \), leading to \( D \in (0,1) \). This captures two aspects of diversity, namely variety and balance. The former measures the number of options and the latter the distribution of shares of each category in a population.\(^3\) Low values of the index reflect a situation of high diversity where two or more technologies coexist on the market (i.e., enter the investment portfolio). A high value of the index implies low diversity, while a maximum value of 1 indicates that a market is locked into a single technology.

Figures 8a, 9a, and 10a present diversity as a function of the mutation rate and 8b, 9b, 10b as a function of the recombination rate for the three model versions. Here, we are interested in understanding under which conditions, i.e. mutation and recombination rates, a higher diversity can be achieved. The results suggest that mutation generally enhances diversity (Figures 8a, 9a and 10a), while recombination typically decreases it (Figures 8b, 9b and 10b). The former result is consistent with our expectations; as mutation describes the fraction of investment devoted towards alternative technologies. On the other hand, a higher recombination rate implies that larger shares of two incumbent technologies are devoted towards a new technology. This may increase significantly the share of investments in the new emerging technology, lowering diversity of the investment portfolio. For model versions with dynamic costs reductions (where costs decrease either exogenously and steadily over time or along a learning curve) recombination enhances diversity for low values of mutation rates.

Notably, in the model version with constant unit costs, recombination does not affect diversity (Figure 8b).\(^4\) This suggests that for a given mutation rate, a unique distribution of technological shares can be identified at which the system stabilizes, for any value of the recombination rate. In addition, in model versions with constant costs and cost reductions occurring along the learning curve, in the absence of mutation, the system gets locked into a single technological standard (Figures 8b and 9b). Here, regardless of the value of the recombination rate, the diversity index is equal to 1 (corresponding to the minimum diversity).

Concluding, to stimulate the coexistence of technological options in the long run, investments in different technologies are to be recommended. Conversely, investments in recombinant innovation typically reduce diversity as they lead to a high concentration of investments in a single technology. This has the disadvantage of decreasing technological diversity in the overall system. On the other

\(^3\) In general, the concept of diversity can be elaborated as having three properties: variety, balance, and disparity (Stirling, 2007).
\(^4\) Only for high values of mutation rates, an increase in recombination slightly decreases diversity.
hand, if a new emerging technology ultimately dominates the investment portfolio (see, Section 4.1), this can be considered as a successful case of technological substitution, i.e. a replacement of a socially or environmentally unattractive technologies by a much more attractive one, e.g. fossil fuel by a renewable energy technology.

(a) Diversity versus mutation

Figure 8. Diversity, recombination and mutation for constant unit costs

(a) Diversity versus mutation

(b) Diversity versus recombination

Figure 9. Diversity, recombination and mutation for costs decreasing steadily over time

(a) Diversity versus mutation

(b) Diversity versus recombination

Figure 10. Diversity, recombination and mutation for costs decreasing along the learning curve
5. Conclusions

In this paper, we developed a stylised application of an evolutionary model of technological substitution to study the replacement of fossil fuel technologies by a renewable energy technology. The framework describes a population of boundedly rational investors. In each period, investors decide on the allocation of investment capital among different technological options. They tend to invest in below-average cost technologies. In addition, they devote a certain fraction of investments, captured by mutation and recombination, to alternative technologies and research on recombinant innovation. Here, mutation and recombination are conceptual variables with concrete behavioural interpretations, describing heuristic rules of investors. Mutation can capture a number of potential behaviors, namely the inability of investors to perfectly assess the profitability of different technologies, costly experimentation, deliberate portfolio diversification, and risky investments in new technologies. In addition, investments in recombinant innovation may stimulate the emergence of a new technological option initially absent on the market.

We examined the evolution of the energy system in the context of two incumbent energy technologies and an emerging one. The incumbent fossil fuel technologies are mature and characterised by a low potential for cost reduction, while the new emerging renewable technology has a high unit costs but also a high potential for cost reduction. We studied evolutionary dynamics for three different model versions, namely where selection operates on technologies characterised by constant costs, by costs that decrease steadily and exogenously over time, and by costs that change depending on the level of cumulative investments.

The analysis shows that different heuristics of investors yield different qualitatively outcomes in terms of the structure of the investment portfolio. For each model version (or selection environment), a new renewable technology has attracted some investment capital, but it was never able to take over the entire investment portfolio. For the constant selection environment, investments in diversification increase, while in the alterative model versions with dynamic (endogenous or exogenous) cost reductions, such investments reduce shares of the technology 3 ultimately achieved in the investment portfolio. In addition, for each model version more investments in recombinant innovation increases the share of technology 3 achieved at the end of investment period.

We examined which heuristic decision rules of investors, regarding the allocation of capital among different technological options, are optimal in term of minimising the average and total costs of investments at the end of investment period. The simulation results suggest that in all model versions the total and average costs of investments in different technologies are minimized in the absence of investments in alternative technologies or research on recombinant innovation. The only exception is in the model version where the cost falls along a learning curve. Here, the optimal investment rule with respect to minimizing the average cost involves investing a small amount of capital in alternative technologies and a larger fraction of investment capital in research on recombinant innovation. Thus, where costs decrease along a learning curve and the policy objective is to provide technologies with
learning opportunities to achieve the cheapest possible mix of technologies in the long run, investments in recombinant innovation and diversification are to be recommended. In fact, costs decreasing along learning curves reflect a stylized fact as established in the energy literature.

In addition, it was shown for each model version that investments in alternative technologies enhance diversity over time, whereas investments in recombinant innovation reduce it. In particular, directing more investment to recombinant innovation typically causes a new technology to capture a large share of investments, thus decreasing diversity of technological portfolio (by reducing its balance). Notably, the successful substitution of energy technologies requires that investments in a new emerging technology start dominating the investment portfolio, which was more likely to occur for model versions with dynamic (exogenous or endogenous) cost reductions.

The analysis of the properties of the proposed model provides insight into the process of induced technological change. The benefits of increasing returns (due to specialisation) and of diversity (due to “keeping options open”) depend on the specific features of the system, such as the type of selection environment, opportunities for cost reductions, and the length of investment horizon. The question arises how many scarce resources to divert from these technologies towards alternative solutions and innovation research. The model offers an analytical tool to address this issue, which we illustrated with an application to substitution of energy technologies.

References


