# PATHWAYS project

## D3.4: Learning in Integrated Assessment Models and Initiative Based Learning - An Interdisciplinary Approach

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# 1 Introduction

In the context of understanding societal transition pathways, the process of learning entailed by the use of new technologies and innovations plays an important role. However, in innovation research learning is understood differently across disciplines. Different learning mechanisms or drivers contribute to technology improvement and its diffusion (Kahouli-Brahmi, 2008). We can broadly distinguish between learning mechanisms involving the interaction among agents and actors – we refer to them as social learning – and learning mechanisms related to the process of production and use of specific technologies – we refer to them as technical learning.

As discussed in Turnheim et al. (2015), addressing the global environmental and sustainability transitions poses analytical challenges that require an integration across disciplines. Quantitative system models, such as Integrated Assessment Models (IAMs), inform about the technological requirements to achieve future goals, but they do not outline the enabling conditions concerning governance and actor dynamics that would support certain technological pathways. The Pathways project[1] represents an effort in this direction. It combines three different disciplines - IAMs, socio-technical transition analysis, and initiative-based learning (IBL) - to provide a broader view on sustainability transitions and to provide policy-relevant insights on the energy and land-use transitions in Europe.

In this paper we explore which opportunities of integration exist between IBL and IAMs to improve the understanding of learning in the context of transition towards cleaner energy technologies. Understanding the process of transition requires understanding the complexity of the technological, economic, social, and ecological changes involved. Sustainability transitions present a number of challenges (Turnheim et al. 2015) relating to the innovation process, its uncertain dynamics, the role of path dependency and inertia in socio-technical systems as well as the interaction between incumbent and new actors. IAMs and IBL conceptualize learning in very different ways, already suggesting how different approaches can offer different and perhaps complementary insights. Indeed, each method provides only a partial understanding of some of the abovementioned components, and a more comprehensive evaluation can be achieved by combining multiple methodologies.

IAMs are quantitative systems modelling tools providing a forward-looking perspective of transitions. They can project the changes over time required to achieve predefined goals under specific sets of economic and technological assumptions. IAMs focus on replicating historical energy statistics and mostly rely on learning curves to project future technology costs based on historically observed trends. IAMs focus on what we defined above as technical learning, a reduced form of learning driven by technical drivers, such as cumulative capacity installed (Learning-By-Doing) and R&D (Learning-By-Research).

IBL provides interesting insights on learning that remain unobservable in other approaches. IBL is a qualitative approach which uses case study analysis to examine the mechanisms and dynamics in concrete projects and local initiatives involving a wide range of societal actors, such as citizens, businesses, civil society organisations and (local) government. They reveal the emerging properties in system change processes ignored by approaches such as IAMs, and inform about the configuration of actors and motives that lead to successful innovation solutions (Turnheim et al. 2015). In the IBL approach, learning focuses on social learning defined above as the processes and interaction among actors that determine the success or the failure of a given initiative and it includes technical, organisational, and cultural aspects.

[1] http://www.pathways-project.eu

As discussed in (Turnheim et al. 2015), alternative integration strategies exist, ranging from more ambitious efforts integrating insights from one discipline into another, to more modest forms of integration where multiple approaches are used in parallel, engage with each other, and enrich each other. In this paper we explore the potential for integration between these two different analytical approaches used in the analysis of transition pathways, to evaluate whether the combination of these two methodologies can offer better insights in the role of learning in transition dynamics. As context, solar PV technologies are used.
First, we begin the analysis by describing the frameworks used by IAMs and IBL to conceptualize learning. Second, we review the empirical evidence in both fields of research. Third, we investigate whether the evidence emerging from the case studies can inform modelling in IAMs and whether the framework used in IAMs can open new perspectives, raise new questions that can inform IBL in the analysis of case studies.

Our analysis shows that IAMs and IBL conceptualize learning in a very different way, and the two approaches have major structural differences with respect to the geographical as well as temporal scale of analysis. This is also due to the different goals the two methodologies have. IAMs develop possible alternative energy and technology pathways for the next fifty to eighty years, whereas IBL deals with understanding the configuration of actors in specific institutional settings that legitimize and support specific technologies. We therefore conclude that ambitious forms of integration of IAMs and IBL are not feasible as of today. Yet, the two approaches can be used in parallel and lead to mutual enrichment.

When defining a common understanding of learning, both IBL and IAMs to some extent use s-shaped learning curves to describe the dynamics of learning. When describing the outcome of learning processes, both IAMs as well as the IBL cases indicate the adoption and diffusion of technology over time or effort, although the underlying drivers are different. IBL refer to the learning that results when people engage one another and consider the adoption and diffusion of a technology to be a function of social learning. IAMs refer to the learning that occurs when more technology capacity is installed, no matter what is the underlying reason (e.g. imitation, cost competitiveness). Moreover,  whereas IBL cases focus on how the dynamics of social interaction (e.g. social learning) influence technologuy diffusion, IAMs focuses more on the implications of technology adoption/use on technology performance measured in terms of unitary investment costs.

Therefore IBL tend to see technology adoption as a function of social learning over time, IAMs instead relate improvements in technology costs to cumulative deployment. Moreover, whereas IAMs tend to view learning as a monotonic process, because that pattern fits well to the empirical data at the national scale over a time horizon of a few decades, IBL's case studies point at a richer description of the possible learning dynamics. S-shaped or logarithmic learning is one possible outcome, though less linear dynamics can also be observed, especially in the short term. The very different time scale of IAMs and IBL explain why such differences can be observed. IBL could try to investigate inter-project learning in order to obtain some insights on the possible longer-term implications of social learning.

We conclude that a two-way collaboration between IAMs and IBL can lead to mutual enrichment. On the one hand, IAMs show the relevance the modeling of learning can have for future energy and technology pathways. On the other hand, IBL points out the importance of less tangible forms of learning, such as social learning, which can accelerate the speed of technical learning. In terms of future research directions, more research on inter-initiative learning cycles to grasp implications for long-term learning is needed within the IBL field of research. To be more relevant for future-oriented analyses IBL could also be used to frame the analysis of case studies such as those provided in IAMs. IAMs need to assess the sensitivity that learning dynamics have on energy and technology scenarios and interpret the results in light of the insights provided by other disciplines, such as IBL.

The rest of the paper is organized as follows. Section 2 describes different conceptual frameworks used to describe learning. Section 3 reviews the empirical evidence on learning from IBL case studies and IAMs. Section 4 explores integration opportunities between IBL and IAMs. Section 5 concludes with some remarks on the integration opportunities between initiative based learning and integrated assessment models.

## 2 Learning: conceptual frameworks

The idea of learning is very prominent and prevalent in innovation research. Different disciplines have formulated stylized representations of the learning process related to the process of technological innovation and diffusion. Despite the different conceptualizations, s-shaped curves tend to appear in different fields of research. For example, Rogers (2003) finds that studies on the diffusion of innovations usually resemble an s-shaped (or sigmoidal) adoption distribution path, depending on the innovation: *"The diffusion curve "takes off" at about 10 to 20% when interpersonal networks become activated so that a critical mass of adopters begin using an innovation"* (p. 34). Rogers describes an "epidemic" diffusion model (see also Geroski 2000, Stoneman 2010), where innovation spreads quite autonomously from a certain point in time, e.g. through word of mouth (endogenous). In "epidemic" diffusion models, the number of adopters increases over time as non-adopters get in contact with adopters. The process of (technology) diffusion relies very much on the model of the spreading of diseases. In epidemic models, diffusion relies on the spread of information among potential adopters. Alternatively, "probit models" (see Geroski 2000) consider adoption rather an individual choice (e.g. of firms), thus depending more on external driving factors such as the relative price of competing innovations, or the technological improvements of the innovations and developments in competing or complementing technologies respectively (exogenous). For instance, if the price (or investment cots) of the innovation falls over time, the threshold to adopt decreases and more adopters (e.g. firms) appear - thus describing a diffusion path.

Although often criticised due to its theoretically weak analogy of biological evolution and socio-technological change, Rogers diffusion of innovation is still a staple in diffusion research (Sarkar 1998). Rogers translates the diffusion of innovation into a model, in order to classify adopters. His criterion for adopter categorization is innovativeness. That is the degree to which an individual adopts new ideas earlier than others. Rogers demonstrates that s-shaped adopter distributions closely approach a normal distribution. By making use of the mean and the standard deviation as the defining parameters of a normal distribution, he suggests to differentiate between five categories. These generally vary from innovators to the early majority on the left side of the adoption mean time, and then from the late majority to laggards on the right side (see Fig. 1). The categorization is asymmetric. There are three categories left to the mean, but only two categories right to the mean. Rogers (2003) explains that "innovators" and "early adopters" are not combined due to quite different characteristics of both. Innovators are more adventurous and open for risks in contrast to early adopters who are rather role models the majority follows and seeks the approval of. Terms like "innovators" or "early adopters" are widely used and understood by the public nowadays. Unfolding the distribution into a diffusion path along time reveals the s-shaped diffusion of innovation, assuming complete adoption (100 Percent of Adoption). Rogers (2003, p. 304) admits that incomplete or non-adoption is difficult to explain with his model.

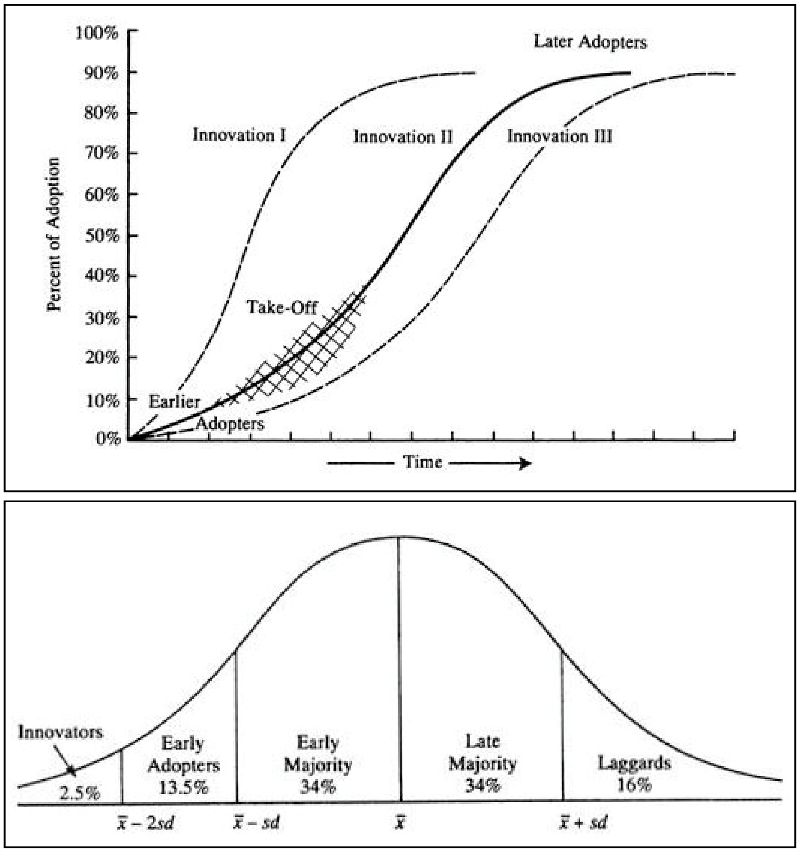


**Figure 1: Roger's diffusion process (above) and adopter categorization (below).**
Source: Rogers 2003, pp. 34 and 306.

However, Rogers' and many others, including Grubler et al. (1999), epidemic, s-shaped diffusion curve suggest an exclusively positive learning experience, in a monotonic fashion. The innovation's adoption rate "accumulate" over time, sometimes faster at the beginning, sometimes slower at the end. People adopt the innovation, sooner or later (or never) – but do not abandon it. In stark contrast to this, Fenn and Raskino (2008) and Beers et al. (2014) stress the idea of a "learning cycle" in transition research. Fenn and Raskino (2008) suggest a cycle to represent the adoption and social application of specific technologies (IT innovations) as well as business strategies. A technology triggers publicity until inflated expectations peak, following the s-shaped learning curve. However, in a "trough of disillusionment" (see Figure 2), also described as a "valley of death" in related theories (as such related to the idea of a creative destruction by Schumpeter (1939)) implementation fails and interest wanes. People seem to adopt new ideas and abandon them after some time, giving rise to a cyclical pattern. If technology providers survive and improve their products to the satisfaction of early adopters, second and third product generations may appear, where the technology is improved and more widely adopted. More funding opportunities emerge, the mainstream also adopts the innovation, and the diffusion takes off to broad market applicability, reaching a plateau of productivity again in a new s-shaped curve of learning, resembling more an asymmetric, slower Gompertz growth function.

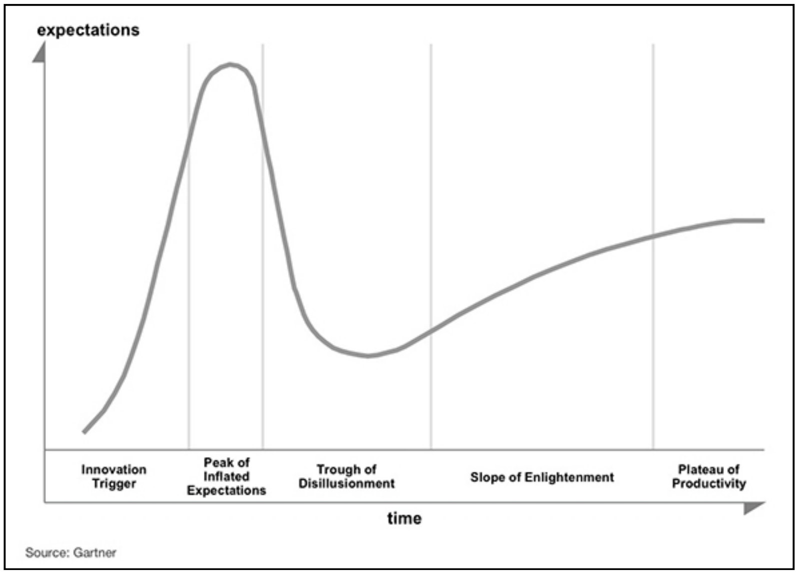


**Figure 2: Stylized form of the hype cycle.**
Source: Based on Fenn and Raskino 2008.

Schilling and Esmundo (2009) suggest that a s-shaped curve can also be observed if instead of lookin at adoption over time, we look at performance improvements in a given technology over the effort allocated to that specific technology. S-shaped curves have been empirically observed for a large number of energy. When performance is plotted against the amount of effort measured as cumulative R&D expenditure, several technologies show a slow improvement at the beginning followed by accelerated and diminished improvement, as characterised in Rogers's diffusion model (Figure 1). Generally the initial phase of technology diffusion is associated with the innovation phase, during which greater effort might be spent, especially in terms of R&D. Experience curves used in Integrated Assessment Models (IAMs), which generally measure effort in terms of cumulative installed capacity, tend to capture the second phase of the diffusion process after the take-off where the logarithmic shape prevails.

Different learning mechanisms or drivers contribute to the improvement of the technology and its diffusion during the different stages of the innovation and diffusion phase. Kahouli-Brahmi (2008) summarizes the main learning mechanisms that can be observed. The *Learning-By-Doing* (LBD) mechanism describes the improvement in the production process associated with experience, or the repetition of tasks, which can also involve changes in labour efficiency and administrative structure (Wright, 1936 in the aircraft industry, Arrow 1962 in the context of growth models). The Learning-By-Doing mechanism itself can be further decomposed into different kind of improvements, such as learning-by-manufacturing (e.g. in the fabrication process of PV modules), learning-by-copying (e.g. by imitating competitors such as in the PV cell development), learning-by-operating (e.g. the tacit skills gained by workers), and learning-by-implementing (e.g. learning about integrating PV modules into an efficient, well-functioning unit) (see Sagar and van der Zwaan 2006 for a review). *Learning-By-Researching* describes the learning effects due to R&D and the innovation processes (Cohen and Levinthal 1989). *Learning-By-Using* (Rosenberg 1982, Lee, 2012) refers to the positive feedback that can come from user experience to the producer, who can build on consumers' reaction to improve the product. *Learning-By-Interacting* (Lundvall, 1988, Habermeier 1990, Lee, 2012) refers to the interaction among various actors, such as laboratories, industries, end-users, political decision-makers, etc., which can enhance diffusion and ultimately facilitate cost reduction. In this context, network relationships play a crucial role. Other studies (see Baker et al. 2013 for a review) highlight the role of other factors such as economies of scale, knowledge spillovers, organizational forgetting, and employee turnover (Argote and Epple 1990). *Economies of scale* are associated with the decline in average cost of production in large-scale production activities characterized by high initial costs. Nemet (2006) finds that plant size accounted for 43% of the cost reduction in solar cells. Economies of scales are different from Learning-By-Doing effects because the former is driven by demand whereas the latter by cumulative capacity installed. Economies of scale are linked to the production process of typically capital-intensive industries, such as those in the energy sector. *Knowledge or experience spillovers* can occur across sectors, technologies, regions and countries, reinforcing the cost reduction due to the other forms of learning Kahouli-Brahmi (2008). An example of cross-sectoral spillovers is the cost reduction in solar cells driven by the events in the semiconductor market (e.g. decline in silicon costs, Nemet 2006). Learning can also lead to different or complementary outcomes than technology cost reductions, as emphasized by the quantitative systems modelling literature. There is also a broader societal and institutional transformation necessary to support the diffusion of the new technology, including systemic improvements and broader reductions in the cost of energy services (Sagar and van der Zwaan 2006).

The abovementioned learning mechanism can be broadly grouped into drivers involving the interaction among actors – we refer to them as social learning mechanisms – and drivers related to the process of production and technology deployment – we refer to them as technology drivers or technical learning (Table 1).

| **Social learning** | **Technical learning** |
|---|---|
| Learning-By-Using<br>(interaction between producer and end-users) | Learning-By-Doing - LBD<br>(cumulative production or cumulative capacity installed) |
| Learning-By-Interacting<br>(interaction between laboratories, industries, end-users, political decision-makers) | Learning-By-Researching - LBR<br>(R&D expenditure, knowledge stock) |
| Spillovers (interaction between sectors, countries, producers) | Economies of scales<br>(Production) |

**Table 1: Learning mechanisms. A summary.**

The remainder of the paper focuses on the two specific forms of learning that have become more prominent in the two analytical approaches examined, namely social learning in IBL and technical learning in IAMs. Section 2.1 presents the conceptual frameworks used by IBL, whereas Section 2.2 briefly summarizes the conceptual framework used in IAMs. The objective is to lay out common and/or contrasting concepts to first establish a common ground.

## *2.1 Social learning in Initiative Based Learning (IBL)*

Social learning can occur at two levels characterized by different time horizons (Pahl-Wostl, 2006). In the short- to medium-term social learning occurs at the level of processes and interactions between actors. In the medium- to long term it occurs at the level of structural change in the governance structure. Initiative-Based Learning (IBL) focuses *on agency and interactions at the level of individual initiatives and projects. Legitimation of novelty and public participation are seen as crucial for radically novel socio-technical configurations. These initiatives may be viewed as microcosms of future reconfigured systems. [...] Learning from initiatives on the ground is hence critical to the governance of transitions in the making, particularly effective forms of shaping and fostering transition efforts from the ground up* (Turnheim et al. 2015, p. 244).

Assuming IBL as "microcosms of future reconfigured systems", we focus on the first level of social learning that takes place between actors, and do not deal with structural changes steering learning at a larger scale. The literature on IBL in transition research defines and addresses social learning in numerous different ways and from various perspectives. In this paper we focus on social learning as "learning that occurs when people engage one another, sharing diverse perspectives and experiences to develop a common framework of understanding and basis for joint action“ (Schusler et al., 2003). The literature consistently describes individuals interacting in social groups, forming a "community" that mediates individual interests facing a changing institutional and organisational setting in favour of a shared interest. Social learning is "a learning process in which actors meet, discuss, and start to develop a shared meaning" (Nykvist, 2014; also Wenger, 2009).

Social learning is *an aspect of adaptive management approach* (Albert et al. 2012) in which skills are needed to adapt to changing planning and implementation strategies according to emerging knowledge. Axelsson et al. (2013) see stakeholders learning *how to steer the development towards sustainability* within a multi-level setting in social-ecological systems or landscapes. In addition to Albert et al. 2012, Axelsson et al. (2013) take note of issues such as trust and norms, which refer to an institutional setting rather than individuals´ and groups´ capacities to learn. Though IBL puts social learning into perspective "from the ground", it is acknowledged that social learning takes place in an institutional rather than individualistic or singular organisational setting, thus emphasising the multi-level notion of learning. We understand research on IBL to be an integral part of multi-level transition analysis (see Turnheim et al. 2015, and Liedtke et al. 2015 for IBL as real experiments or Living Labs in transition research).

Sol et al. (2013) observed that learning is a "dynamic process" where knowledge is created in an on-going fashion. The term "dynamic" incorporates the possibility that changing internal interaction between actors may affect the quality and effectiveness of learning. In addition to internal dynamics, external dynamics such as trends, hierarchy or money also play a crucial role and influence internal learning dynamics between actors. Internally and externally driven dynamics may cause learning patterns which face struggles hindering, stopping or even destroying learning efforts. On the one hand, social learning can be understood as a part of our daily life occurring through social interactions and processes within a closer social network. On the other hand, social learning can become deeper learning in the sense of transformative learning, i.e. in the form of double-and triple loop learning. Learning in loops is able to transform the frame of reference and calling into question guiding assumptions (Nykvist, 2014), effectively destroying common knowledge if successful. Whereas single-loop learning refers to the simple adaptation of new knowledge, double-loop (or deutero-) learning hence considers the ability to learn itself (Albert et al., 2012). In this respect Kemp et al. (1998) evaluate learning processes as most effective when they contribute not only to everyday knowledge but also to "second-order learning" where people question the assumptions and constraints of regime systems. Second-order learning emerges when basic assumptions, and values are questioned and become the subject of learning. More recently, van Mierlo (2012) takes up Kemps and colleagues different orders of learning where first-order learning includes gaining experience about how to do things better within the framework of pre-existing goals and assumptions. In this view first-order learning alone would not contribute to regime change and second order learning is assumed to be essential for regime change (van Mierlo 2012).
Van Mierlo (2012) further differentiates between the concept of convergent and divergent learning. Convergent learning occurs when "diverse actors develop visions on solutions and problems that complement one another, and change their roles and goals in close association with each other". It highlights the "complementarity among the fundamentally different assumptions and values of the various project participants. They do not necessarily come to share a completely common view during the learning process; it suffices if their perspectives overlap partially or are mutually supportive". Challenging a regime may require this type of learning. Convergent learning takes place when visions and actions align because of experiences in the pilot project. In contrast, divergent learning occurs in the individual participants' thinking, such that it is purely actor bound. The individual learning experiences may deviate from each other and may be contradictory to each other. However, divergence can be seen as a learning process as well (van Mierlo, 2012).

## 2.2 Technical learning and experience curves in quantitiative systems models

Technical learning in quantitiative systems models has been mostly conceptualized through experience curves. Experience curves focusing on *Learning-by-Doing* (LBD) and *Learning-by-Researching* (LBR) are used by quantitiative systems models, including IAMs and energy system models, to describe the observed technology cost reduction occurring with increased experience documented for several energy technologies. Differently from the literature that has examined social learning, which is much more oriented at understanding the underlying processes and the role of governance and institutional factors, the approaches using experience curves focus on the drivers that are 1) easy to quantify (e.g. LBD and LBR) and 2) simple to represent in the models by reduced-form equations to project future technology costs.

The Learning-By-Doing hypothesis describes the improvement in a technology performance occurring with the growing effort dedicated to that technology. Performance is generally measured using indicators such as capital costs or unitary investment costs. Effort is generally measured in terms of cumulative installed capacity. Specifically, a power function is used to describe a negative relationship between the cumulative capacity $K_{t,i}$, installed at time $t$ in country $i$, and installation capital costs, $CC_{t,i}$, where $CC_{0,i}$ is the cumulative installed capacity at the beginning of the period:

$$CC_{t,i} = CC_{0,i}\left(\frac{K_{t,i}}{K_{0,i}}\right)^{-b} \qquad \text{Eq. [1]}$$

where the parameter $b$ measures the strength of the learning effect. It relates to the learning rate, $LR$, which measures the rate at which unit costs decrease for each doubling of the cumulative capacity, through the following relationship, $LR= 1- 2^{-b}$. A 20% learning rate means that when the cumulative installed capacity doubles compared to the initial level, technology costs fall by 20%. Some models include a floor cost to set a minimum price below which investment costs cannot fall:

$$CC_{t,i} = max\left\{\overline{\overline{CC_{t,\iota}}}, CC_{0,i}\left(\frac{K_{t,i}}{K_{0,i}}\right)^{-b}\right\} \qquad \text{Eq. [2]}$$

Learning-By-Researching describes the improvement in technology performance occurring with growing effort dedicated to R&D, measured in terms of either R&D expenditure or R&D knowledge stock. The models representing both LBD and LBR adopt two-factor learning curves, which separate the effect of experience from that of R&D:

$$CC_{t,i} = CC_0\left(\frac{K_{t,i}}{K_{0,i}}\right)^{-b}\left(\frac{R\&D_{t,i}}{R\&D_{0,i}}\right)^{-c} \qquad \text{Eq. [3]}$$

The power function form is the most commonly used because it generally represents a good fit to the data (Baker et al. 2013). When plotting an indicator of performance, such as unitary investment costs, versus cumulative capacity installed as an indicator of effort, this functional form results in a logarithmic relationship, which can be seen as the second part of a s-shaped curve after technology take-off (see Figure 1). This is a good approximation when the focus is on Learning-By-Doing. In the case of Learning-By-Researching, where R&D investments are used as an indicator of effort, an s-shaped relationship seems to be a better fit to the data (Schilling and Esmundo 2009). Several models (e.g. WITCH, Bosetti et al. 2016 IMAGE, Stehfest et al. 2014) do account for knowledge and experience spillovers, and assume that the cumulative capacity installed in any world region reduces technology cost everywhere. Regarding knowledge spillovers, models (e.g. WITCH) often assume only a limited degree of international spillovers.

The purpose of the learning curves in models is *not to explain* the complexity of the underlying processes (e.g. what are the drivers), as in IBL, but rather to *project* long-term installation costs, considering historically observed patterns (Wiesenthal et a. 2012). The simplicity of reduced-form approaches offers tractability within the context of complex IAMs. Simplicity, however, comes at the cost of not explaining what are the "true" drivers explaining the observed reduction and potentially omitting some important variables (Nemet, 2006; Nordhaus, 2009). Models generally rely on empirical evidence based on history for the calibration of the learning rate parameters. Understanding how the observed trends can be used in models for future scenarios is important because assumptions about the functional form, the learning rates, and the floor cost crucially affect models' results and influence the future energy mix, as discussed in Section 4.

## 3 Learning: the empirical evidence

Theoretical approaches from different disciplines seem to converge on a vision of the learning process associated with technology diffusion as having a sigmoidal, s-shaped form, or as a sequence of s-shaped alternating processes. This section summarises the empirical evidence on learning emerging from the case studies examined by the IBL approach and from Integrated Assessment Models (IAMs).

### *3.1 Social learning – Evidence from case studies*

Within the Pathways project, 208 studies addressing social learning were screened through Google scholar. The whole sample of studies consisted of case studies as well as of studies providing more conceptual and theoretical insights. In a subsequent step, we selected a subsample of studies fulfilling three major requirements at the same time: 1) they deal with social learning, 2) they address one of the PATHWAYS domains, mobility, energy( consisting of electricity and heating), or agri-food/land use, 3) they focus on either the UK, Germany, Sweden or the Netherlands (countries in which PATHWAYS conduct case studies). We ended up with a detailed review of 17 IBL cases systematically reviewing the main actors involved in the cases, how they learn, and which forms, dynamics, drivers and barriers they encounter throughout their learning process.[2]

Convergent learning, that is the idea of a common vision fostering social learning, is typically prevalent throughout the studies. In the studies analysed, a common idea/vision of the project seems to be central to social learning processes. Some studies stress the importance of the multi-actor framework and stakeholders involvement in learning processes. In all cases, multi-actors and stakeholders from different social classes engage in a collaborative learning process. In this respect, hierarchical internal social networks as well as external hierarchies determined by power, money and time affect the individual's behaviour and the social learning progress as a whole. Social learning involves the management of differing interests, understanding and skills in order to anticipate and adapt to possible actions and consequences resulting from internal and external hierarchies. The cases commonly stress that learning is highly affected by trust among the members within the learning network. As such, the social capital accumulated by the members of the network very much predicts the learning outcome. Equally important are more tangible characteristics of the members of the social network, such as expertise and skills that members can contribute to solve the issues at stake and leaders can provide to organise the learning process and bind learning ties among members. In addition, a beneficial management of learning depends on leadership of change-oriented agents with convincing visions and the capacity to bring up and communicate innovative solutions. A successful learning management needs to diffuse information that raises awareness and requires involvement of group members to motivate them to participate in learning processes. In this regard, small learning networks are more likely to show social cohesion and group affinity in personal contacts, which seems beneficial for social learning in the cases

[2] Please see annex for the detailed summary of the main actors and how they learn in the cases as well as the respective conclusions on forms, dynamics, drivers and barriers of social learning.

analysed. Although small in size, a heterogeneous composition of the learning network including actors across sectors and levels seemed to be helpful for social learning. In a nutshell, social learning in heterogeneous groups depends on the power structure of the network and trust-relationships.

In order to foster inter-group learning between small, but effective learning networks, personal contacts need to be tied across the network's boundaries. It is straightforward that in turn, a beneficial internal and external communication within and between social network depends on communication skills of the learning leaders. Typically, the key dimensions and variables that determine social learning in IBL studies interrelate to each other. The management of trust, social capital, expertise and skills among the members of the learning network depends on the size and composition of the network and vice versa. We identified multi-actors in heterogeneous networks that are characterised by personal, small and socially cohesive networks, managed by skilled leadership and bounded by social capital.

Case studies also inform on how social learning proceeds. Some of the cases deal with forms and levels of learning occurring in initiatives and projects. We find that social learning takes time and is a dynamic process in which past learning experiences shape future learning processes (intertemporal dynamics). Within those dynamic forms, learning faces drawbacks, setbacks, radical processes and peaks, and may end on learning plateaus and thus show diverse and non-linear forms of learning. Also, destructive learning and conflicts are described in some cases. External and contextual factors like changes in financial schemes or legislation may trigger a learning crisis and thus intervene in social learning processes.

The importance of the local context (i.e. actors and networks from varying cultural, institutional, geographical and even climatic conditions) clearly emerges in the cases analysed. The cases show a great diversity by nature, and initiatives in the same domain or pursuing the same or similar goals can end up learning differently, because of the different contexts (involving also different potential unexpected events/external influencing factors) in which they are carried out. Indeed, projects might be understood as *local reinterpretations and reinventions of a more generic, mobile concept of an emerging niche trajectory* (Raven et al., 2008). The results of learning processes depend on the kind of knowledge involved and on how social relations and communication are performed which, in turn, depends on the kinds of social relations and knowledge people have (Lahtinen, 2013).

It is possible to translate a generic concept into a local project, as well as to transfer local lessons into general rules, but these processes are difficult and require careful analysis (Raven et al., 2008)[3]. Indeed, as the practical experiences are so variable and diverse, drawing general conclusions beyond a certain level of abstraction might be particularly challenging. According to Axelsson and colleagues (2013), *a key challenge in social learning for sustainable landscapes is to move from local experiences and results to local tacit knowledge, and from tacit to explicit knowledge*. Niche innovation occurs in relation to a particular local context; consequently, socio-technical innovation and the particular context within which it takes place are mutually shaping (Hodson & Marvin, 2007; Raven et al., 2008). Raven and colleagues found e.g. that the sensitivity to local context and the local nature of the project were key factors determining the success of the project. Local communication and participation are particularly significant, and *ready-made solutions cannot be dropped into a context without local negotiations* (Raven et al., 2008).

The analysis of the IBL cases point at a number of characteristics with respect to four main dimensions of social learning, summarized in Table 2, namely management, size and composition of networks, length and timing of learning, and local context. The management of learning depends on trust, social capital, expertise and skills among members of the network and its leaders. The size and composition of successful learning

[3] For further reading on generalising case study research, we refer to Flyvberg (2006) and Yin (2013).

networks is typically small, heterogeneous, but socially cohesive and characterised by personal contacts. The length of learning is typically extensive along the duration of the initiative or project only (short time scale). This means, social learning takes place throughout the whole project time (within the project), but not between projects (e.g. follow-up projects on a medium to long-term time scale). Learning between projects is typically not observed. The timing of learning is dynamic and non-linear. Social learning typically passes different phases and speeds of learning. Apart from typical variables and identified key dimensions of social learning, the cases emphasize the role of the local context. Depending on the context of the initiative, network members bring in and consent on respective tacit knowledge. The cases are embedded in specific regional or national institutional contexts (politics and policies). Thus, external factors may cause intra-project crises and conflicts depending on changing contextual circumstances.

| **Management of Learning** | **Size and composition of network** | **Length and timing of learning** | **Local context** |
| --- | --- | --- | --- |
| Trust<br>Social Capital<br>Leadership<br>Expertise<br>Skills | Small<br>Heterogeneous<br>Personal<br>Socially cohesive | Extensive (within project, short-term)<br>Dynamic<br>Non-linear (drawbacks, setbacks, conflicts radical, peaks, plateaus) | Tacit knowledge<br>Local reinterpretation<br>Institutional embedment<br>External factors (crisis) |

**Table 2: Summary of key dimensions of social learning in Initiative Based Learning (IBL).**

Two of the case studies focus on social learning in the adoption of solar PV. Van Mierlo (2012) analysed multiple stakeholders (companies, local governments, private households) in four different photovoltaic energy pilot projects in the Netherlands and identified very diverse learning experiences. The observed diversity stems from different levels of ambition of the projects, different negotiating processes, different kinds of network management of different heterogeneous networks. Both convergent and divergent learning were observed in the case studies. Convergent learning was characterized by shared learning experiences throughout the projects. In the cases characterized by divergent learning, participants learned from diverse subjects with some contradictory learning experiences (see table below). Barely any management of the network nor learning management have been observed in the case studies. The cases analysed suggest that convergent learning challenging regime rules benefits from creative negotiation processes and network management.

Van Mierlo´s (2012) inquiries on four cases on PV are the most elaborate and extensive ones found in the literature. However, as seen in Table 3, the results are still inconclusive. The author found convergent learning in three cases, whereas in one other no shared vision was observed. At the same time, divergent learning revealed non-contradictory learning experiences in one case to several contradictory learning experiences in another. When it comes to learning beyond projects analysed, in three cases, almost all participants were involved in new projects in the same market segment, whereas in one case, only the architect was involved in a new project. When it comes to exploring new market segments, again, in three cases new potential was explored, in one case no repeated use has been observed. In the end, the author calls for further inquiry into relationships between divergent, convergent and second-order learning.

| Learning Mode | Amsterdam | Apeldoorn | Amersfoort | AC project |
|---|---|---|---|---|
| **CONTRIBUTING TO REPLICATION IN THE NICHE** | | | | |
| **Convergent learning** | *No shared vision about the future. No shared learning experiences.* | Shared, rather global future vision. Some shared learning experiences. | Shared, specified future vision. Many shared learning experiences. | Shared future vision. Some shared learning experiences. |
| **Organizational adjustments** | *Adjustments conducted by only two PV parties.* | Adjustments conducted by five participants. | Adjustments conducted by five participants. | Adjustments conducted by two actors from the existing regimes. |
| **Repeated use in same market segment** | *Architect only building party that became involved in new pilot project.* | Almost all participants undertook new projects. | Almost all participants unertook follow-up projects. | Almost all participants involved in new projects. |
| **CONTRIBUTING TO NICHE SPLITTING** | | | | |
| **Divergent learning** | Participants learned much about diverse subjects with several contradictory learning experiences. | Participants learned much about diverse subjects with some contradictory conclusions. | Many actor-specific learning experiences, one contradictory. | *Some actor-specific learning experiences, none contradictory.* |
| **Exploration of different market segments** | Test in new potential market segment: existing houses by energy company. | Use in office sector, existing houses, and others. | Use in office sector and other ownership relations. | *No repeated use or tests in different market segment.* |

**Table 3: Summary of learning modes observed in PV cases in NL.**
Source: Van Mierlo (2012), p. 15

A case study within the PATHWAYS project focused on local community renewable energy in the UK – specifically on an innovative, individual initiative named Brixton Energy (Repowering London). This initiative has been creating and managing "cooperatively owned renewable energy projects", including the UK's first *inner-city* renewable energy co-operatives. To date, it has completed three community rooftop-installation projects in Brixton, South London. With regard to learning as mentioned above, it occurred in an iterative manner with individual projects building on and profiting from their forerunners' experiences and lessons. In the beginning, learning followed a peer to peer (P2P) model along personal contacts among participants rather than being steered and organised via intermediary organisations. Later on, learning occurred in an upstream manner with Repowering "pulling" information from the individual projects rather than "pushing" what is deemed important for the field (Håkansson & KCL  2015).

The evidence from the case studies, including the two focusing on solar PV, highlight the importance of internal and external factors that shape and influence the learning process, such as the role of network size and composition and the importance of local context. Yet, the thin empirical evidence on social learning in the PV cases does not allow to draw general conclusions on social learning in PV. Rather it highlights the diversity of learning experiences encountered in all of the cases. However, the exemplifying cases mirror some of the identified key dimensions and variables found in the broader analysis of case studies, and are summarized in Table 2. These are the characteristics of the composition and size of network and more important timing and forms of learning. Learning occurs convergently and divergently, opening up to the possibility of "contradictory" (van Mierlo 2012) or "iterative" (Turnheim 2015) and potentially non-linear learning experiences. An interesting result is the presence of learning across projects, which seems to characterize PV as opposed to other domains examined in the PATHWAYS project. In contrast to other case studies, social learning in PV took place between projects, that is between former and following projects. The cases analysed by van Mierlo (2012) social learning took place between timely overlapping projects, initiated between 1991 and 1994 and completed between 1995 and 1998.

Continuity in learning is an assumption that characterizes the modelling of technical learning in models as well, and which is supported by historical data when statistics over longer time periods (e.g. annual time series) are considered. The next section briefly summarizes the empirical evidence on technical learning.

### *3.2 Technical learning – Evidence from the existing literature*

The simplicity of the reduced-form approach used by IAMs offers tractability in the context of models that integrate climate, energy, and economic systems, and aims at developing future transition technology scenarios where technology deployment takes into account forms of technological change.

Models generally rely on empirical evidence for the calibration of learning rate parameters. Empirical studies on experience curves have generally focused on LBD and LBR. Several reviews of the existing empirical literature on historical LBD and LBR learning rates already exist and Table 4 summarizes the estimates reported in the most recent reviews (Rubin et al., 2015, La Tour et al. 2013, Baker et al. 2013, Neij, 2008, Junginger et al. 2008, Kahouli-Brahmi 2008), together with some new econometric analysis (Witajewski-Baltvilks et al. 2015, Lee 2012). Given the focus of the paper is on solar PV, Table 4 reports the estimated learning rates for this technology. LBD estimates a cluster around 20% of cost reduction for each doubling in the cumulative installed capacity, with a range from 9 to 47%. A learning rate of 20% means that, when the cumulative installed capacity doubles, unitary investment costs decline by 20%.

The reasons for the width of the range include the temporal and geographic characteristics of the dataset used in the estimation (Soderholm and Sundqvist 2007), the empirical specification, and the extent to which endogeneity issues are addressed (Soderholm and Sundqvist 2007, Nordhaus, 2009, Witajewski-Baltvilks et al. 2015). For example, Witajewski-Baltvilks et al. (2015) show how LBD rates can vary when statistical uncertainty is considered and when some of the variables that are generally omitted from experience curves, such as policies and energy prices, are included. Soderholm and Sundqvist (2007) show that explicitly accounting for economies of scales reduces LBD rates, suggesting that if this driver is not modelled, LBD rates are upward biased. Soderholm and Sundqvist (2007) show that including a time trend so as to capture any underlying change in trend other than R&D knowledge stock or installed capacity absorbs all variation otherwise captured by the R&D stock, whereas LBD are quite stable, especially when endogeneity issues are taken into account.

| **Source** | **Rate** | **min** | **max** | **mean** | **Timeframe** | **Method** |
|---|---|---|---|---|---|---|
| Baker et al. (2013) | LBD | 17 | 35 | 20 | na | Review |
| Junginger et al. (2008) | LBD | 10 | 47 | 22 | 1957-2006 | Review |
| Kahouli-Brahmi (2008) | LBD | 18 | 35 | 23 | 1959-1998 | Review |
| La Tour et al. (2013) | LBD | 10 | 30 | 21 | 1965-2005 | Review |
| Lee, conference proceeding (2012) | LBR | 9 | 15 | 11 | 2001-2010 | Regression analysis |
| Lee, conference proceeding (2012) | LBD | 10 | 10 | 10 | 2001-2010 | Regression analysis |
| Neij (2008) | LBD | 10 | 47 | 20 | 1976-2001 | Review |
| Rubin et al. (2015) | LBD | 10 | 47 | 23 | 1959-2011 | Review |
| Rubin et al. (2015) | LBR | 10 | 14 | 12 | 1971-2001 | Review |
| Rubin et al. (2015) | LBD | 14 | 32 | 18 | 1971-2000 | Review |
| Witajewski-Baltvilks et al. 2015, Mod 1 | LBD | 9 | 33 | 20 | 1990-2012 | Regression analysis |
| Witajewski-Baltvilks et al. 2015, Mod 2 | LBD | 10 | 46 | 27 | 1990-2012 | Regression analysis |
| Witajewski-Baltvilks et al. 2015, Mod 3 | LBD | 10 | 29 | 19 | 1990-2012 | Regression analysis |
| Witajewski-Baltvilks et al. 2015, OLS | LBD | 10 | 14 | 12 | 1990-2012 | Regression analysis |

**Table 4: Learning rate estimates based on the empirical evidence.**

Most models use an approach based on endogenous technological change modelled through a one-factor learning curve (LBD) as described in Eq. [1]. This is the case for REMIND, IMAGE-TIMER, IMACLIM, E3MG and WITCH. A few models use a two-factor learning curve for endogenous technological change, considering both the effects of learning-by-doing and learning-by-researching, whereas some other models use an exogenous technical change by defining different investment costs for future periods (which varies according to reference/policy scenarios). Table 5 summarizes the learning rates used by selected IAM models, REMIND, IMAGE-TIMER, IMACLIM, E3MG, POLES, MERGE-ETL. Since models rely on empirical literature, it is not surprising that the range of LBD rates in terms of minimum, maximum, and mean values among the studies founs in the literature is very similar (9-45%, average value 20%) to the range emerging from the empirical literature in Table 4. What has not been fully explored is how different learning rates interact with floor cost used by some models (Eq. [2]) to determine technology penetration.

| Source | Type | min | max | mean | Timeframe | Floor cost |
|---|---|---|---|---|---|---|
| E3MG (Edenhofer et al. 2010) | LBD | na | na | 30 | Constant | 1250 |
| IMACLIM (Bibas et al. 2012) | | | | | | |
| central station PV | LBD | 15 | 25 | na | Constant | 982 |
| rooftop PV | LBD | 15 | 25 | na | Constant | 1715 |
| IMAGE-TIMER (Baker et al. 2013) | LBD | na | na | 35 | 2000 | 0 |
| | LBD | na | na | 9 | 2100 | 0 |
| MERGE-ETL (Magné et al. 2010) | LBD | na | na | 10 | Constant | 0 |
| | LBR | na | na | 10 | Constant | 0 |
| POLES (Criqui et al. 2015) | LBD | na | na | 20 | Base year | 1100 |
| | LBR | na | na | 45 | Base year | 1100 |
| REMIND (Luderer et al. 2015) | LBD | na | na | 20 | Constant | 500 |
| WITCH (http://doc.witchmodel.org/) | LBD | na | na | 16.5 | Constant | 500 |

**Table 5: Learning rate in IAMs. Miminum, maximum, and mean values resulting from the survey of existing models with learning. Constant means that the LR is constant over time, whereas in the other cases LR is varying over time and values for 2000/base year/2100 are provided**

As discussed in Sagar and van der Zwaan (2006), it is not clear how learning rates should be extrapolated when moving into the future. Soderholm and Sundqvist (2007) find that learning rate estimates over more recent periods are larger than those estimated on the full sample because of the market power that characterizes the initial diffusion of the technology, whereas the increased competition that emerged during the diffusion stage, led to a faster decline in technology costs. However, bias could also go in the other direction because of diminishing returns and the difficulty to further reduce costs beyond certain levels. Only a few estimates are available in the literature for future periods. OECD/IEA (2014) and Neij (2008) provide an estimate for LBD rates up to 2035 and 2050 respectively, whereas Bosetti et al. (2016) present a review on recent expert elicitation exercises about future cost reduction due to different levels of R&D expenditures, see Table 6. Whereas LBR estimates tend to be lower than the few estimates reported in the empirical literature, LBD rates are not much different from the ones estimated from historical data.

| Source | Rate | R&D Level | min | max | mean | Timeframe | Method |
|---|---|---|---|---|---|---|---|
| Bosetti et al. (2016) CMU | LBR | High | -1 | 13 | 6 | Future: 2030 | Expert elicitation |
| Bosetti et al. (2016) FEEM | LBR | High | 4 | 12 | 7 | Future: 2030 | Expert elicitation |
| Bosetti et al. (2016) Harvard | LBR | High | -3 | 11 | 3 | Future: 2030 | Expert elicitation |
| Bosetti et al. (2016) CMU | LBR | Low | -2 | 13 | 5 | Future: 2030 | Expert elicitation |
| Bosetti et al. (2016) FEEM | LBR | Low | 1 | 10 | 6 | Future: 2030 | Expert elicitation |
| Bosetti et al. (2016) Harvard | LBR | Low | -2 | 8 | 2 | Future: 2030 | Expert elicitation |
| Bosetti et al. (2016) UMass | LBR | Low | -1 | 7 | 4 | Future: 2030 | Expert elicitation |
| Bosetti et al. (2016) FEEM | LBR | Mid | 2 | 11 | 6 | Future: 2030 | Expert elicitation |
| Bosetti et al. (2016) Harvard | LBR | Mid | -1 | 10 | 3 | Future: 2030 | Expert elicitation |
| Bosetti et al. (2016) UMass | LBR | Mid | -1 | 7 | 5 | Future: 2030 | Expert elicitation |
| Neij (2008) | LBD | - | 15 | 25 | 20 | Future: 2050 | Expert elicitation |
| OECD/IEA (2014) | LBD | - | 20 | 20 | 20 | Future: 2035 | Expert elicitation |

**Table 6: Learning rate estimates based on expert elicitation**

## 4 Exploring integration opportunities between IBL and IAMs approaches

Turnheim et al. (2015) set out alternative integration strategies that could be used to connect findings and hypotheses from different disciplines, including quantitative systems modelling (like IAMs) and initiative-based learning (IBL). Integration strategies can take different forms and be based on alignment or bridging, and interaction between the two. This section explores which form of integration strategy could be used to connect IBL and IAMs to improve the understanding of learning in the context of energy transition.

As highlighted in Section 3, structural differences between IBL and IAM approaches make ambitious forms of integration between IBL and IAMs not feasible. IAMs have been developed with the goal of integrating global climate, biophysical, and socioeconomic dynamics in a consistent framework and in a quantitative way. IAMs adopt parsimonious representations of the human system and do not describe societal dynamics and interactions because human behaviour such as power, agency, and social learning are difficult to capture in mathematical equations (van Vuuren and Kok, 2012). IAMs are outcome-oriented and focus on the consequences of exogenously specified policies, with very limited attention to the processes leading to those outcomes. IBL, on the contrary, engages with concrete projects, where it is examined how actors with different views and motivations align with technological opportunities, consumer preferences, infrastructure requirements, and policy frameworks into working configurations. IBL studies reveal the complexity and uncertainty of transitions in the making, but cannot capture the broader understanding of macroeconomic, systemic consequences as provided by IAMs. These differences reflect the different purposes of the two approaches which is developing future scenarios to understand technical requirements necessary to achieve predefined future goals in IAMs, and understanding real-world complexities blocking and facilitating conditions in the concrete implementation of projects in IBL.

Having explored how learning is conceptualized in IBL and IAMs, it seems that the most viable method of integration is a “two-way recursive collaboration” (Turnheim et al. 2015) where two methodologically distinct approaches are used to mutually inform each other (“dialogue”). The in-depth analysis of social learning carried out by IBL through case studies has highlighted a set of important drivers of learning that are not represented in IAMs. IAMs can address drivers of social learning in the interpretation of their quantitative results and assumptions. We can consider the form of integration observed different from “one-off methodological enrichment” because the IBL practitioners were asked to interpret and communicate their results in a way that can be informative to IAMs. On the one hand, IAMs rely on mathematical equations to describe the various components of the energy, economic, and climate systems, including learning, as described in Section 2.3. On the other hand, IBL are mainly descriptive, and results from case studies can be difficult to generalize. In this work, a thought experiment was carried out where IBL practitioners have made an effort to draw stylized shapes of learning that could be translated into functional forms in IAMs from the theoretical frameworks and empirical evidence.

Section 4.1 describes "two-way recursive collaboration" between IAMs and IBL approaches where 1) IBL results are first generalized using a conceptual framework that can be utilized by IAMs and 2) IAMs use IBL results to interpret the cases of sensitivity analysis of learning curves. Although learning in models is driven by physical variables, such as capacity installed, the learning rates are used to described the relationship between capacity and costs. As discussed in Section 3, the actual value of learning rates is the result of the interaction between observed measurable trends (e.g. the relationship between costs and capacity) and non-observable factors, which are not explicitly included in the analysis because not measurable. Issues such as trust, network structure, values, and norms are unobservable (from a quantitative point of view) but they do influence the empirical value of learning rates. In a collaborative effort described below, we have tried to conceptualize learning in a similar way between the two approaches by looking at the relationship between a performance indicator (the reciprocal of the investment cost, how many watts can be generated for each dollar invested) and effort or time. Although we can say that with time effort accumulates, having effort or time on the horizontal axis can lead to different shapes in learning. As discussed in Schilling and Esmundo (2009), if effort is relatively constant over time, plotting performance against time or effort would not make too much difference.

## *4.1 Generalizing learning dynamics from IBL case studies*

As discussed in Section 3.1, case studies provide insights on the process of social learning in terms of interactions among actors. One of the results emerging from IBL case studies is the existence of non-linear social learning in the form of either *rapid learning* or *destructive learning.* Rapid social learning can be operationalized through three alternative functional forms:

1) An exponential function describing rapid learning processes at the early stage of the project or initiative. This may be the case when members join the social learning network, the more members learn from one another, the faster learning accumulates. Indeed, the learning process is stimulated by increasing skill and competence of its participants, and by an effective implementation of social learning management;
2) A logarithmic function describing radical learning progress at the beginning of the initiative or project, followed by a flatter, still positive learning experience, that decreases over time and at some point only reveals marginal learning progress and approximates a learning plateau;
3) A s-shaped function as proposed by Rogers (2005) and as also found by the empirical literature on learning curves (Section 3.2). Here, learning progresses slowly at the beginning and accelerates half way, reaching a learning plateau. This curve can be interpreted as the combination of the exponential (early stage) and the logarithmic (late stage) functions.

Van Mierlo (2012) characterises learning outcomes in her case studies in terms of number of houses equipped with PV technology, completed between 1995 and 1998 (though the projects were initiated in 1991 and ended around 2000) and the total power in terms of kilowatt peak (kWp) generated. A major issue highlighted in the case study at the time of the initiating project has been the high costs per kWh for PV. As a consequence large subsidies have been paid in order to foster learning about the technical and social bottlenecks and possibilities of PV. Based on the van Mierlo (2012)'s PV case studies, we decided to use performance measured in watt-peak per dollar (Wp/$) as a bridging device to operationalize learning in terms of the learning outcome. The use of this concept makes it possible to integrate the more qualitative findings from case studies into dynamics and forms of learning used by IAMs, so that a more direct operationalization through learning curves can be pursued. [4]

Learning may proceed rapidly, destructively, with peaks, plateaus or loops that may cause rapid performance gains with peaks and plateaus (stagnation), which in turn may slip in loss of performance due to destructive learning or regain performance in loop learning. Data, Indicators and Operationalization can take several forms here and depend on the interest and level of analysis; Table 7 provides a non-exhaustive example.

| | Individual-centric | Network-centric | Systems-centric |
|---|---|---|---|
| **Characterizing features** | | | |
| Learning process | Transformative: learning as a transformative process that occurs during a participatory activity and involves the individual | Experiential: learning as a process embedded in past experience and/or observation of other practitioners | Emergent: learning as an emergent property of the social-ecological system |
| Learning outcomes | A change of participants' internal-reflective processes; a change of participants' behavior | A change in established resource use or management practices | Shift of the social-ecological system on a more sustainable path |
| **Level of analysis** | | | |
| Unit of observation | The individual | The individual, network, multi-stakeholder platform | The individual, ecosystems, institutions |
| Unit of analysis | The participant | Networks<br>Multi-stakeholder platforms | The social-ecological system |
| Learning agent of interest | The individual who participates in a participatory workshop | The practitioner, member of a community of practice, and/or network of practitioners | The stakeholder, community member, or practitioner who is involved in resource management |
| **Operationalization** | | | |
| Operational measures | Moral dimension (civil virtues), cognitive dimension (improved understanding of problem domain), relational dimension (relational base), trust (trust toward participants, process) | Change in how things are done; improved relationships | Change of institutions and management practices at higher levels (e.g., policy), with interest for ecosystem responses |

**Table 7: Three research approaches in social learning. Rodela 2011, 3.**

Based on the evidence from the case studies, a linear pattern is less likely, as it implies constant learning over time (Figure 3). With time passing by, effort accumulates to realize the target of the projects, and also across projects, as described by van Mierlo (2012), giving rise to monotonic learning in the effort level. As the performance gained from effort invested may peak, plateau or reduce, the accumulated effort is always positive with respect to the duration of the projects.

[4] However, it is crucial to note that none of the case studies operationalize or quantify any "amount" of social learning over time, but focus on how social learning may proceed over time and why. The graphical depictions on forms of learning thus are to some extent hypothetical and stylized. They exclusively serve to illustrate social learning as described in the cases and translate them into potential functional forms of social learning. This is partly due to the fact that different forms of social learning may occur on different level of analysis for example in terms of joint problem solving, acquired knowledge, etc. An overview on this can be fond in Rodela (2011) as well as Schol et al. 2013.

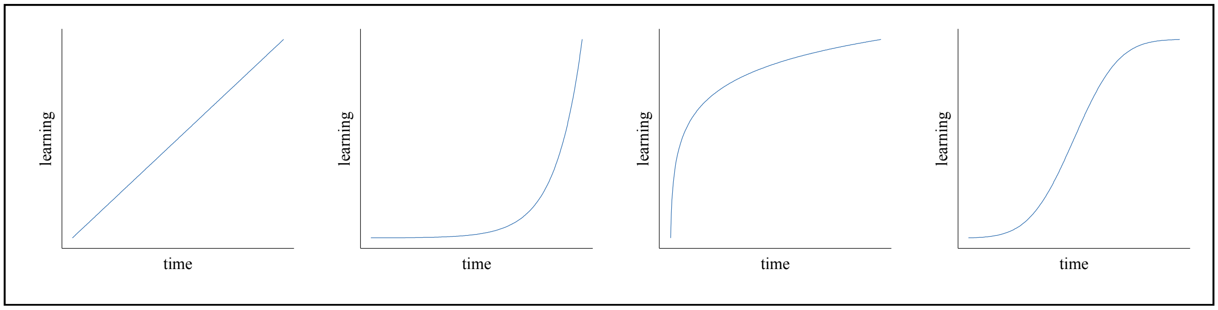


**Figure 3: Constant and "rapid" learning – linear, exponential, logarithmic and logistic learning**

Destructive learning occurs when there is a loss of learning performance during the project and initiative, see Figure 4. This learning curve suggests steep learning at the beginning, leading to a peak from which learning may decrease (destructive learning) e.g. due to conflicts, crises or external shocks. Falling slopes indicate a loss of knowledge and a loss of performance eventually. This may be the case when initiatives end and no inter-project learning is observed afterwards. That is, the project missed to implement a management that ensures that learning survives or even continues after the end of the project. This is neither implausible nor very likely in the short run (Albert et al. 2012).

Still, more likely to be observed is some sort of "creative destruction", when destructive learning paves the way for new learning and social learning occurs in learning cycles in which peaks, valleys and drawbacks take turns. Conflicts may be solved and external shocks may be adapted to (Feola and Nunes 2014). This stylized form of social learning is probably the most likely path observed in local initiatives. However, this applies to local initiatives with a short-run time horizon, which typically last between five and seven years, whereas in the long-run the local initiatives may last multiple generations or spread on to inter-project learning lasting for more than ten years. The longest period covered in the analysed case studies was 13 years (see Ornetzedera and Rohracher 2006 on Sustainable Buildings in Vauban, Freiburg). Analytically, at some point, IBL research is unlikely to grasp inter-project learning or learning in cycles in multi-generation projects since those would require extensive qualitative historical research.

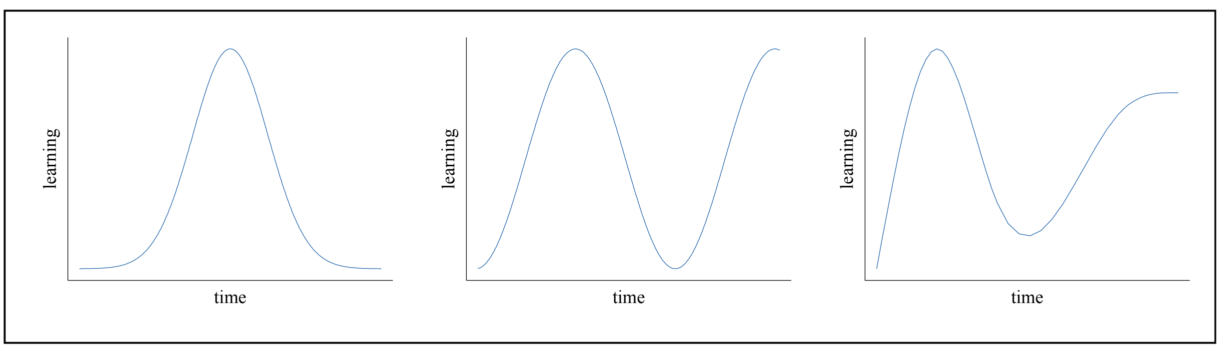


**Figure 4: "Destructive" learning – normal, sinus and "hype" learning (learning cycles)**

## 4.2 *Exploring learning dynamics in IAMs. Evidence from the WITCH model*

IAMs generally represent learning using s-shaped or logarithmic functions, therefore assuming positive and monotone learning. Destructive learning, which has emerged as a possible pattern from the case studies, especially in the short run, can hardly be applied in models as IAMs have much longer time scaleswith time steps of at least one year. As previously discussed, whereas destructive learning is possible over the time horizon of individual initiatives, it becomes more unlikely over a longer time horizon and at broader geographic scales (country or regions).

We use the WITCH model[5] to examine the learning dynamics of solar PV resulting from the LBD approach used in the model and to understand its sensitivity to key learning parameters. The WITCH model uses a one-factor learning curve with a floor cost, as described in Eq. [2]. The default values for the learning rate and the floor cost are 16.5% and 500$/kW.

Using the reciprocal of the investment cost as performance indicator (y-axis) and cumulative capacity as effort indicator (x-axis), the resulting learning curve for a baseline case is a logarithmic relationship between capacity and performance (see Figure 5). The time horizon is 2005 to 2100 and the model represents the massive deployment in solar PV observed over the last decade. Learning is very fast at the beginning but it decreases over time and at some point only reveals marginal learning progress and approximates a learning plateau. An s-shaped relationship tends to prevail when the role of R&D during the early stages of innovations are considered. Since the time horizon of the analysis here starts in 2005, we are already in the deployment stage of the technology, or in the late stage of the s-shaped curve, which is why a logarithmic behavior appears. Figure 5 shows that climate policy stimulates the installation of solar capacity, which drives investment costs further down to achieve the floor cost[6].

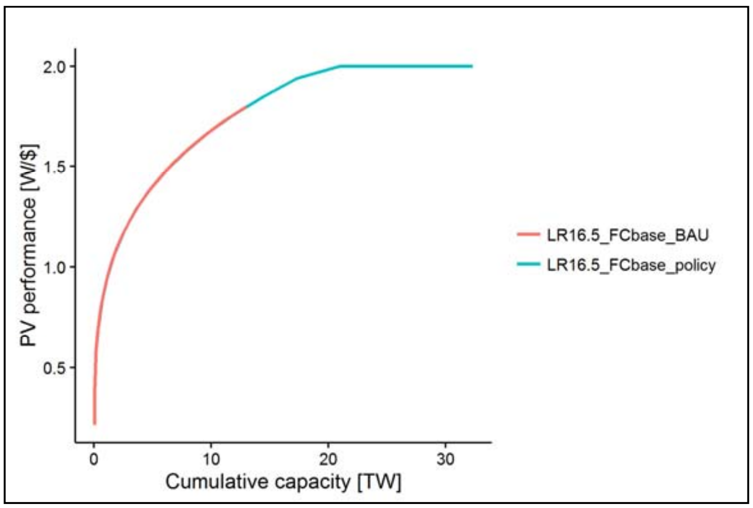


**Figure 5: Performance of solar PV as a function of cumulative capacity to 2100, policy scenario, LR=16.5%, floor cost = 500 $/kW**

The default learning value (16.5%) means that, when the cumulative installed capacity doubles, unitary investment costs decline by 16.5%. The value is close to the mean value estimates found across studies (see Tables 4-6), and it has also been chosen to largely reproduce the actual cost path that took place over the decade of 2005 to 2015. However, as discussed in Section 3, a broad range of values (9 to 47%) results from the review of the existing empirical literature. One of the arguments behind these different values is the presence of omitted variables. As discussed in Section 2, there are indeed other forms of learning, beside LBD, which could accelerate and reinforce the impact of cumulative capacity installed on cost reduction or

[5] http://doc.witchmodel.org/

[6] In the Pathways project two alternative decarbonization scenarios, Pathway A and Pathway B, have been considered. The two scenarios share the same mitigation policy targets, an 80% reduction in GHG emissions in 2050 compared to 1990 levels in the European Union and an increase in global temperature in 2100 less than 2°C relative to pre-industrial levels with a likely chance. Pathway A focuses on technological substitution in the form of efficiency improvement and fuel switching as the main mitigation strategy. Figure 7 shows results for Pathway A (base policy) and for a Business-as-Usual (BAU) scenario, where no policies or specific technological assumptions are implemented.

in other words, which could influence the learning rate. Elements such as social learning can be addressed in IAMs by varying the exogenous value assigned to the learning rate. The floor costs is another important parameter that affects the extent and the speed of technology penetration.

Here we examine the sensitivity of model's results to the range of learning rate values identified by the empirical literature and examine twelve combinations of learning rates (9, 21, 35, 47%) and floor costs (0, 587, 1349$/kW) values for the solar PV technology applied to the Pathway A storyline, i.e. considering a modeling framework which substantially replicates the present technological patterns. The values chosen for learning rates correspond to the minimum, mean and maximum values from literature (9, 21 and 47 respectively, see Table 4, 5, 6), whereas the 35% was selected as a comparison value to investigate the influence of learning rate on investment cost. Values for floor cost correspond to the minimum, mean and maximum values from the ones used in the IA models (see Table 4). The analysis reveals that at increasing levels of learning rates, the curvature tends to progressively decrease, and the shape of the curve tends to converge to a linear learning (Figure 6).

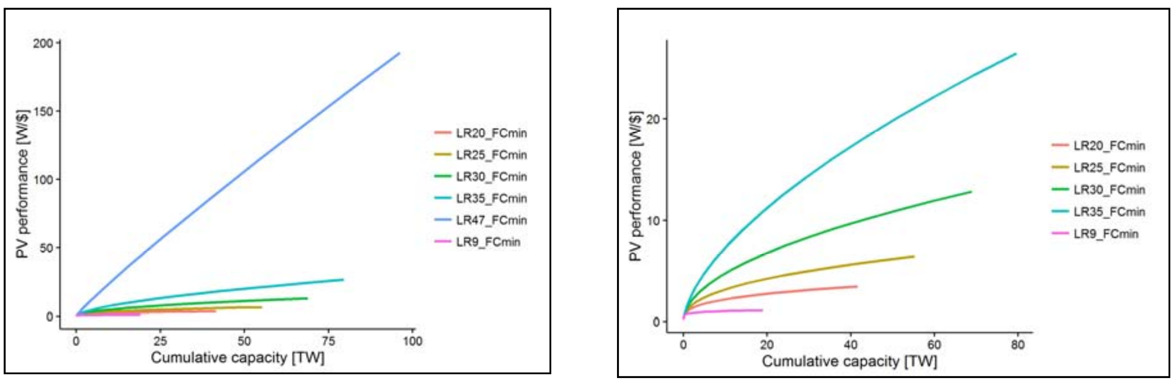


**Figure 6: Performance of solar PV as a function of cumulative capacity to 2100, policy scenarios, detail on minimum floor cost scenarios.**
Note: The right panel excludes the maximum LR scenario

Figure 6 and 7 show that:

- when learning rates are low, the cost reduction is so slow that the floor cost threshold is hardly reached by 2050: different floor cost values have barely any impact on PV penetration;
- when learning rates are high, the cost decrease is so fast that the floor cost threshold is reached very soon: in these cases, the floor cost represents the actual investment cost for a considerable part of the century and different floor cost values significantly influence PV penetration.

More in detail, the high floor cost is reached in 2020 under all values of learning rates except for LR9, where it is reached in 2030. In all these scenarios, world PV penetration tends to stabilize at about 3% of the electricity mix (Figure 8). The medium floor cost is reached in the three highest learning rates scenarios (2025 for LR47, 2030 for LR35, 2050 for LR20). When such value is reached, PV penetration sets at about 8% and remains stable over time. The minimum floor cost hypothesis is relevant for the two high learning rate scenarios, where the PV penetration can increase beyond the aforementioned 8% threshold. However, an analysis of the results after 2050 would show that, in any case, PV penetration would not exceed 25% even with investment costs close to zero. This is due to essentially two main factors. The first one is related to the equations which model the system integration constraints of wind and PV in the electricity mix and which do not allow an indefinite penetration of those technologies. The second and main factor is related to the WITCH modeling structure, which is based on a Constant Elasticity of Substitution (CES) framework. According to the CES structure, the competition between technologies is not based on pure economic considerations only (but is complemented with additional constraints like the system integration equations)

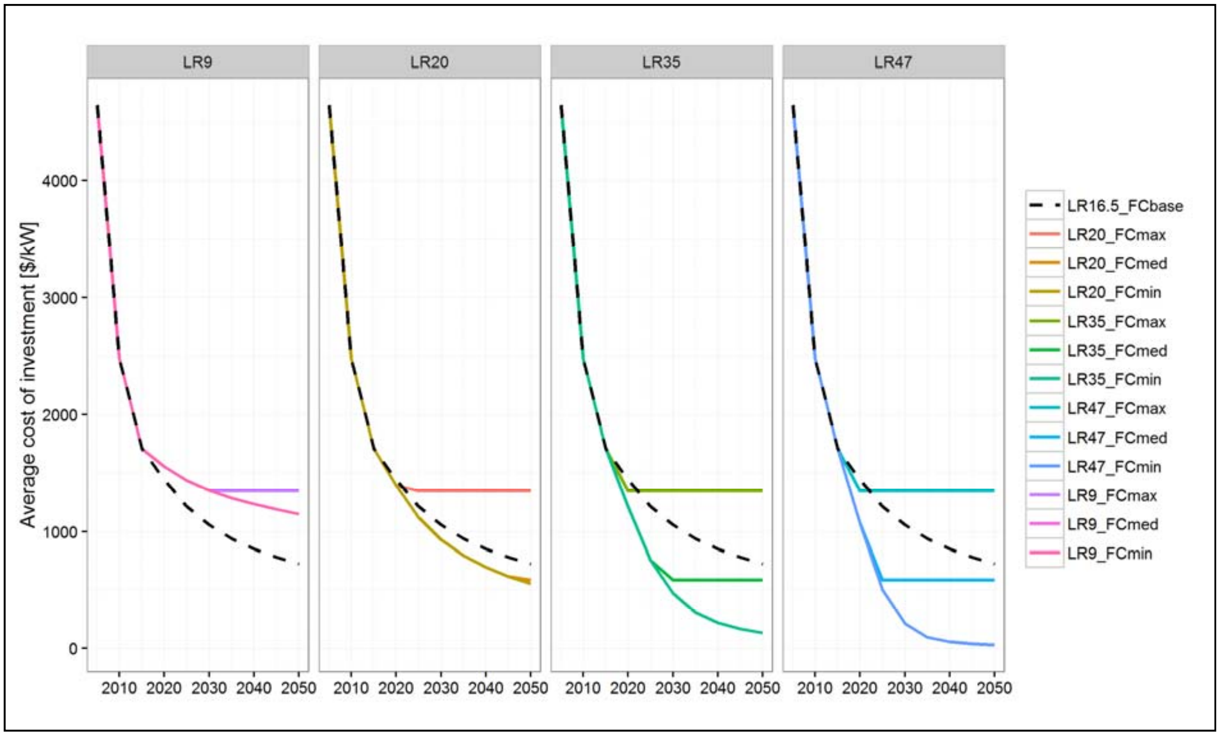


**Figure 7: Average cost of investment for PV to 2050**

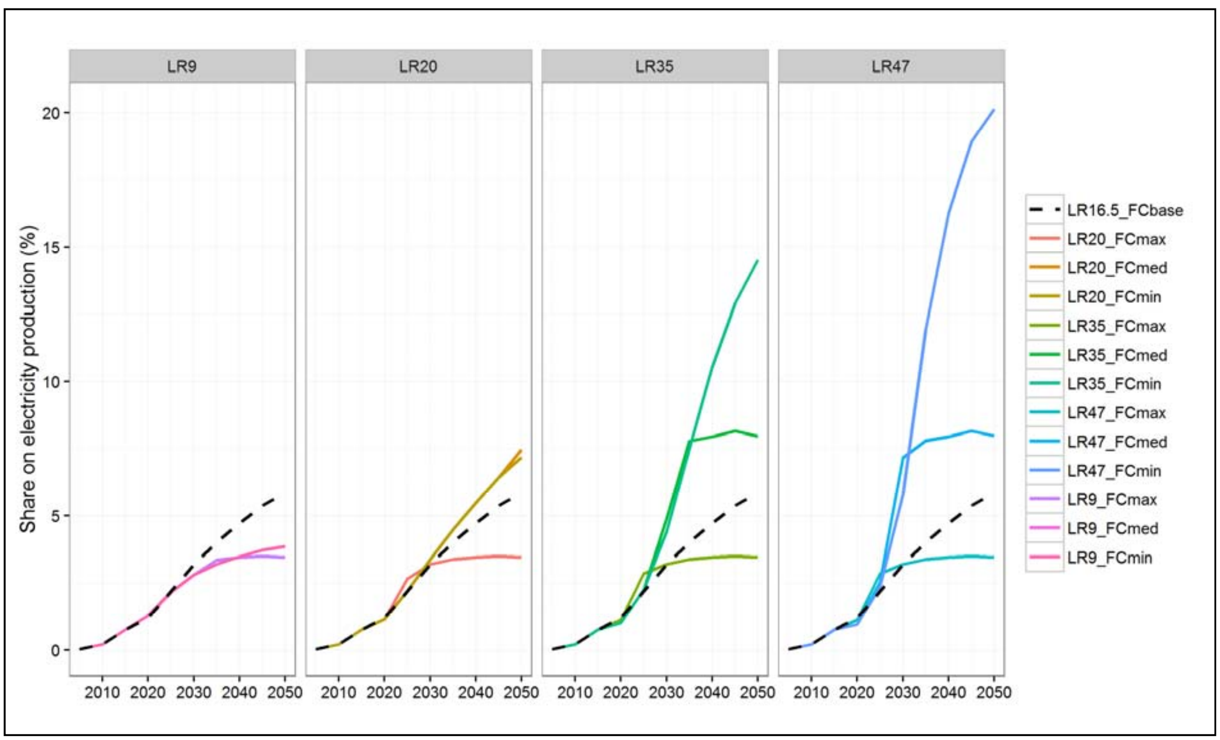


**Figure 8: World penetration rate for PV in the electricity mix to 2050**

and does not take place indistinctly across all technologies, but follows a strict hierarchical sequence: PV competes with wind and CSP, then the renewables compete with fossils, and so on. Since this competition is not fully flexible (i.e. the substitutability across technologies is not infinite, in order to model what in reality is experienced as a preference for heterogeneity), there is ultimately an implicit threshold to the penetration of each technology even if it is installed for free, as it would happen in the considered case (see Carrara and Marangoni, 2016 for more details).

The impact of learning on PV penetration holds across regions, though actual PV penetration exhibits regional heterogeneity. In 2030, a smaller range and values (less than 3%) are observed in developing countries, whereas a higher range and values are found in in fast growing economies (3-10%) and in OECD countries (4-9%). In 2050 the share can reach almost 30% in fast growing countries, whereas it remains below 20% in OECD, and below 5% in developing countries (Figure 9.)

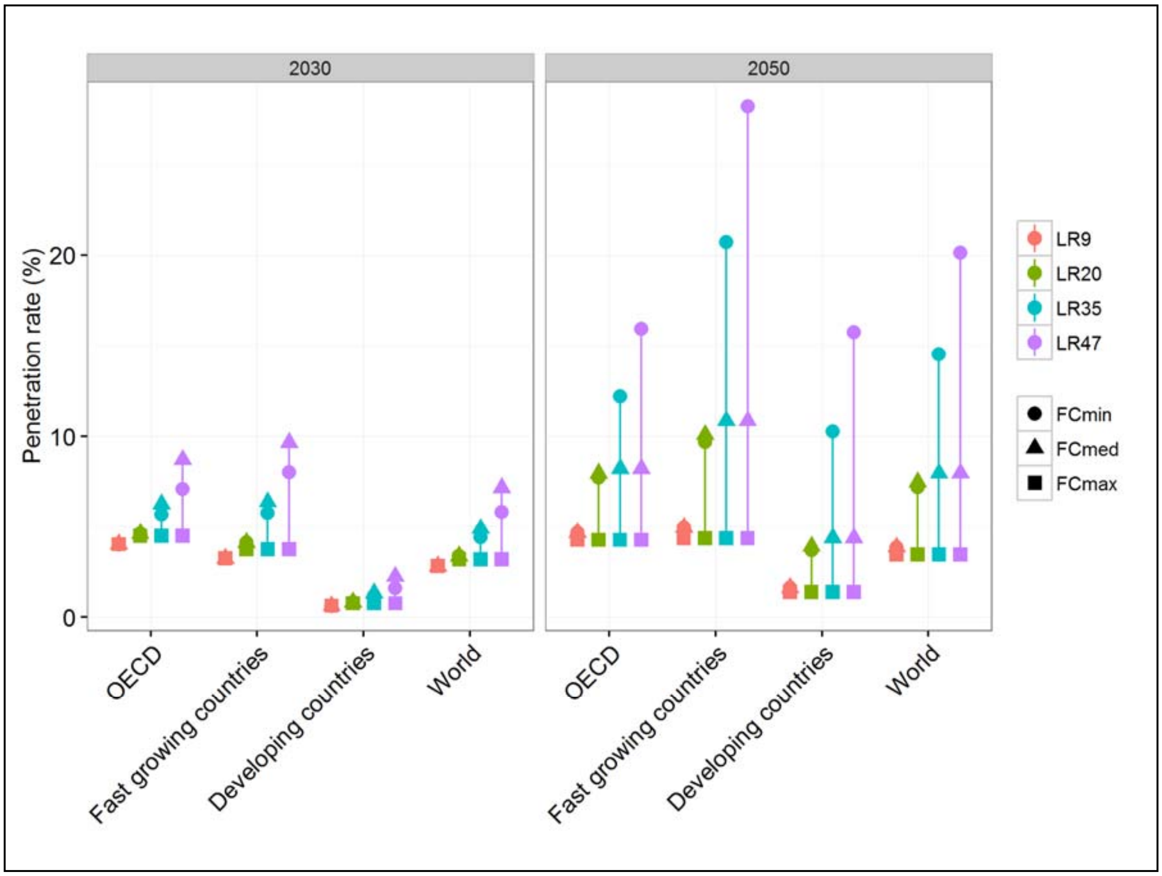


**Figure 9: Penetration rate for solar PV in the electricity mix to 2030 and 2050**

LCOE mainly depends on the investment costs, and thus it is strongly influenced by the values of learning rates and floor costs (Figure 10). Average LCOE values range between 6 and 10 c$/kWh in 2030 at global level. The range reported by the IPCC report (2011) is also (7.5-14.5 c$/kWh).

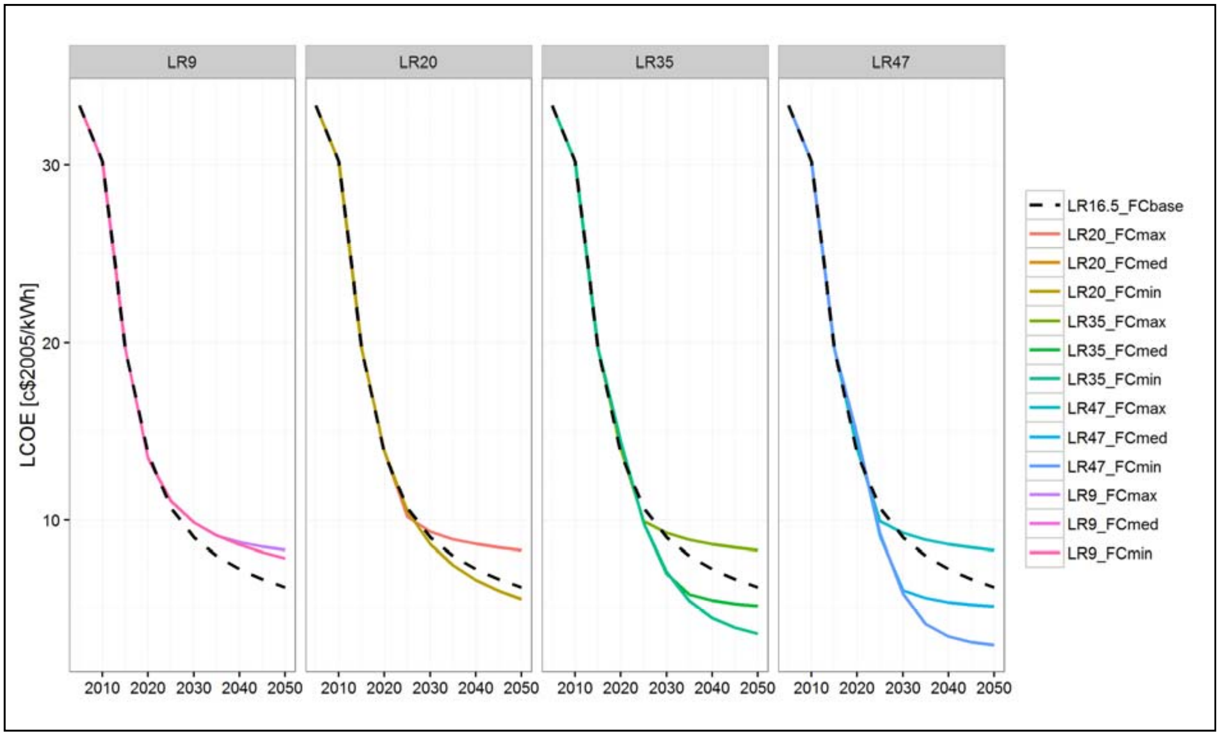


**Figure 10: World levelized cost of electricity from PV to 2050**

## 5 Conclusions

In this paper we explore opportunities of integration between two different analytical approaches used in the analysis of transition pathways, integrated assessment models (IAMs) and Initiative Based Learning (IBL). IAMs are quantitative systems modelling tools providing a forward-looking perspective of transitions. They can project the changes over time required to achieve predefined goals under specific sets of economic and technological assumptions. IBL are qualitative approaches where transition pathways are seen as the upscaling of successful solutions. They reveal the emerging properties in system changes processes ignored by other approaches such as IAMs (Turnheim et al. 2015) .

IBL provide interesting insights on learning that remain unobservable in other approaches. Learning goes beyond the notion of Learning-By-Doing used in IAMs, and it includes technical, organisational, and cultural aspects.

Given the novel perspective on learning provided by IBL, and in light of the lively debate on the use of learning curves in IAMs, this paper examines the potential for integration with respect to the representation of learning in the context of energy transition for the solar PV technology.

IAMs and IBL differ in scope and structure. In the two analytical approaches, learning is conceptualized in a very different way. IAMs focus on replicating historical energy statistics and use learning curves to project future technology costs based on historically observed trends, assuming those patterns will continue in the future. IAMs focus on what we here define as technical learning, namely a reduced-form of learning driven by technical drivers, such as cumulative capacity installed (Learning-By-Doing) and R&D (Learning-By-Research). Elements of social learning are implicit in the choice of the parameter value that characterizes the speed of learning. The empirical evidence summarized in this paper reveal a large range for the actual values of LBD rates that could be possibly used in learning in IAMs. The uncertainty in the learning rates is due to several reasons discussed in literature. One important reason is the impossibility to observe and measure less tangible forms of learning, such as social learning. Learning rates are generally estimated by fitting the observed data of investments costs and cumulative installed capacity or R&D expenditure. Factors such as spillovers, or contextual factors such as policies, institutional frameworks, governance structure, etc. are generally not included. The omission of variables that reinforce or undermine learning lead to biased estimates. This is why learning rate estimates vary with the sample used (e.g. country and time period) and with the explanatory factors included. The IAM-based empirical evidence shows that learning assumptions in models are important and can lead to different views about the role of solar PV in the future, long-term energy system.

The IBL-based empirical evidence highlights the diversity of learning experiences and the importance of key factors such as the composition and size of network, the timing, and the non-linearity in learning experiences. The case studies on initiatives suggest that a small, heterogonous, but cohesive social network, in which expertise is gathered and trust is built fosters social learning. A skilful project management that organises and maintains engagement of its network members is crucial to successful learning. However, social learning remains highly dynamic and non-linear. Learning may be progressive at some point of the initiative; at the same time, it may face drawbacks and setbacks that may even "destroy" learning when external effects, such as changing financing schemes, intervene and lead to intra-project crisis or to "lost" learning when inter-project learning or follow-ups are missing. An interesting result that emerged only in the specific case of learning in solar PV is the presence of learning across projects (e.g. spill-overs), which might suggest a longer term and more stable prospect for learning in PV; still keeping in mind that the analysis of cases on PV covers a project period of up to 7 years.

Differences with respect to the scale of analysis, the time-horizon, the treatment of complexity, as well as the representation of innovation make ambitious forms of integration between these two approaches not viable. Moreover, in this specific project the number and geographic coverage of the case studies examined was probably too limited to allow deriving more general patterns. For this reason, a soft form of integration between IBL and IAMs has been explored. We consider the resulting form of integration an example of "two-way recursive collaboration". First, IBL practitioners made an effort to draw stylized shapes of learning from the theoretical frameworks and empirical evidence that could be compared to functional forms in used IAMs. Second, the WITCH model, one of the IAMs used in the Pathways project, was used to compare the learning dynamics resulting from the IA modelling approach with the stylized shaped proposed by IBL. It turned out that the s-shape of learning assumed by WITCH is one of the likely learning dynamics identified by IBL. At the same time, the IBL cases stress the fact that learning may get lost (to some extent), thus learning may continue non-linearly in learning cycles (between preceding and following projects). However, this may only hold true for the short time horizons covered by the IBL cases (up to 13 years). In the long run scenarios covered by IAMs, learning may turn out to be more robust in the shape of s-curves. In the long run, the ups and downs in learning cycles may be straightened by an s-shape learning. This idea is underpinned by theoretical models of diffusion research. Third, given the abovementioned consideration of the actual values of learning parameters, a set of sensitivity analysis cases has been analysed using the WITCH model, where different parameterizations of learning have been explored. The analysis illustrates that different parameterization of learning within the range of what was observed in the empirical and modelling literature has significant implications on the model projections of technology penetration and costs. The resulting learning dynamics always fall within the stylized patterns identified by IBL.

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## Annex: Summary of selected case studies on considering social learning

**Table 8: Selected Case Studies on Transition Pathways considering Social Learning (Energy)**

| Article (Author(s), Journal, Title) | Example / Case study(ies)<br>Main actors<br>How they learn | Conclusions on Social Learning (SL) – Forms, Dynamics, Drivers, Barriers |
|---|---|---|
| Hoppe T. et al., 2015. Local Governments Supporting Local Energy Initiatives: Lessons from the Best Practices of Saerbeck (Germany) and Lochem (The Netherlands). Sustainability 2015, 7, 1900-1931 | Local Energy Initiatives (LEIs) in Saerbeck (Germany) and Lochem (The Netherlands). Community-led "grassroots innovations", social innovations developed at the local level.<br><br>Multiple societal stakeholders (business firms, local government, residents, the planning office, local citizen energy cooperative e.g. "Energie für Saerbeck", farmers) and the municipality. "Seedbed for innovation" **not limited** tot he local energy cooperatives only.<br><br>Socialization, meetings, planning, seeking solutions for problems that emerged over time (e.g. practical or due to regulations/bureaucracy rigidity –fear of the people employed in it to loose power/positions/resources…)<br>**Importance of the context: power structures, financial/tax schemes etc. may favour or hinder change; thus, importance of leadership**.<br>Different kinds of learning: **learning from technical, economic, institutional and social challenges**, learning by **educational campaigns**, learning in terms of the **adaptive role of the municipality in relation to local civil society**<br>Importance of the **role-model functions of social leaders**: teachers, people running successful businesses, people having a formal (possibly elected) function in the administration, elected members of the local council. Community projects also strengthen citizens in their (joint, collective) capacity to change societal structures. Community projects raise awareness and can foster sustainable behaviours, citizen participation and civic engagement. | - Importance of having process and **network managers** available to mediate between local stakeholders: in particular the municipality, citizenry and the (professionalizing) local energy cooperative.<br><br>- Local governments and LEIs learn from **challenges and setbacks**.<br>Local government supporting management of energy utilities by citizens, and involving **multiple civic groups** in awareness raising activities and campaigns (Saerbeck); by adapting the role of local government to become more supportive of citizens' initiatives (Lochem).<br><br>- Three key factors from Strategic Niche Management are fundamental: **building networks, managing expectations, facilitation learning**. Other success factors: strategic, community serving, responsive, reflexive leadership proper process management by public officials, close interaction and mutual trust between local government and representatives of the local communities.<br><br>- Importance of **leaders** able to find innovative solutions to unpredicted problems (e.g. regulations rigidity), to play their role strategically, and to understand the importance of involving the citizens and support them – importance of the support from change-oriented and supportive civil servants – i.e. **importance of change-oriented individuals at different levels of action**. Policies not involving the addressed stakeholders are very difficult to effectively implement!<br>- Importance of **networks** at the regional and national levels, used to attract attention and collect resources, **novel business models and partnerships**, innovative funding strategies (crowd funding), novel insights and instruments that local governments can deploy to facilitate LEIs. |
| Seyfang G. et al., 2014. A grassroots sustainable energy niche? Reflections on community energy in | Community energy initiatives in the UK (very detailed list p. 27)<br><br>Community groups, intermediaries, community energy consultants, farmers, researchers, businesses and local government.<br><br>Learning is shared 'upwards' with intermediary organisations who network | - Sharing learning with community energy intermediary organisations takes second place to sharing learning with other community groups;<br>- Learning being shared is overwhelmingly around **human/organisational and cultural capital, as well as social capital aspects** of running community energy projects<br>- Sharing learning is important - but the **types of learning**, and the people |

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| the UK. Environmental Innovation and Societal Transitions 13, 21–44 | and share experiences between local community energy groups.<br>In contrast, sharing of learning directly with other community groups was much more evident, and was engaged with to a greater extent (in this case: mainly through peer-to-peer information sharing – informal, ad hoc contact by telephone, email or at events, to acquire information and advice, developing replicable models, hosting visits to their projects. Fewer were involved in mentoring other projects directly and being a local test-bed for innovation, although this is a promising diffusion rout) – i.e. **different forms of sharing of learning and kind of learning shared depending on the actors involved.**<br>Sharing learning with community energy intermediary organisations takes second place to sharing learning with other community groups. Sharing learning within the projects themselves is very significant to the projects' development and progress.<br>Some of the learning has contributed not necessarily to developing a community energy niche, but rather to **supporting another niche** such as renewable energy or community development instead<br>Learning plays an important role within groups in developing, improving and evolving community energy initiatives. **Learning by doing** and **networking** (with a diverse set of partners, to gain support, information, and share their experiences) very important. | with whom it is shared, **varies over time** and according to different phases of the development of the sector.<br>- Learning has contributed to developing a community energy niche, and to supporting another niche such as renewable energy or community development instead.<br>- Projects needed to learn and acquire **additional skills** and resources to successfully embed their project into the local context<br>- Based on '**emotional stamina'** – the determination, resilience and soft skills needed to deal with setbacks and lengthy project development phases Only half of the projects were actively engaged in formal evaluation or monitoring processes whereby learning was consolidated and passed to intermediaries, and therefore key lessons have frequently been lost at the end of projects. Occasional exceptions exist where community energy intermediaries work more closely with the initiatives. Modes and methods of diffusion matter greatly.<br><br>**Each project faces some very context-specific challenges.** Successful projects do not necessarily have 'equal' amounts of all kinds of capital, rather, they need **particular configurations of capital** – just enough financial, just enough human and so on – and this will differ from project to project. |
| Forrest N., Wiek A., 2014. Learning from success—Toward evidence-informed sustainability transitions in communities. Environmental Innovation and Societal Transitions 12 (2014) 66–88 | Ashton Hayes, pioneer in community transitions, set itself the goal of becoming carbon neutral.<br><br>Engaged and informed citizens (the resident conceived the idea of a carbon neutral village and persuaded a handful of close acquaintances to join him in forming a core group), the parish council, local businesses (sponsorships)<br><br>Socialization: (public) meetings, personal relations, learning by doing and from each other – structural and behavioral changes (e.g. many villagers started acting to reduce their energy use immediately after the public meeting, reporting back to the core group with ideas and volunteering to help)<br><br>**Unintended outcomes** included a general increase in social interaction, energy use becoming part of village culture, and an increase in the community's capability for taking action. | Critical success factors for Ashton Hayes transition: professional skills of the core team and other community volunteers, particularly in organizing, managing, negotiating, and communicating, and the networks they were able to tap in to; available services; social cohesion; community action capability; community governance; core group & leadership; public support / participation; outside interest; management; partnerships (e.g. with universities). Also, a prevalence of concern about climate change (perhaps attributable to a relatively high community education level) meant that the community was ready to be led into action on this issue.<br><br>**Deliberate avoidance of "an organizational structure that would slow us down" –** strategy allowed to evolve and adapt. The core group of three volunteers operates **autonomously** though openly and **transparently**. **Public support and participation** identified as **essential** by the "core group".<br>The startup produced several important outputs and **outcomes that set the stage for later action**: strong public support for the initiative within the community; a committed core group and effective leader; widespread outside interest from media, government and universities; strategic partnerships with a university, non-profit, and local government; and the general management approach. Public support was especially important as it encouraged participation in interventions. In conjunction with parish |

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| | | council endorsement, it also provided the transition team with a democratic mandate to act on the community's behalf.<br>Community volunteers, often utilizing professional skills, help out and form workgroups, which operate largely autonomously, as needed by different projects and tasks. Similarly, local businesses have been supportive with cash and in-kind sponsorships.<br>**Communicating** with other communities to impart some of their experience to them: high priority. |
| Seyfang G., Haxeltine A., 2012. Growing grassroots innovations: Exploring the role of community-based social movements for sustainable energy transitions. Environment and Planning C: Government and Policy, volume 30, 381 – 400 | Transition Towns movement, UK<br><br>Transition town members and/or members-to-be<br><br>Networking, internal and external learning processes, sharing expertise and experience between local groups, consolidates learning through online resources, standardises 'transition thinking' through compulsory training for TT organisers, provides speakers for events, offers consistent messages through media relations, and disseminates information through publications and consultancy<br><br>Internally, the network offers codified learning through transition training both lessons and best practice from previous initiatives (**first-order learning**) and a unified construction of the issues at hand through coordinated and managed frame disruption (**second-order learning**). Internal learning very useful for creating shared visions, understandings, and frames of reference amongst the movement – for creating a coalition among disparate groups of activists. Externally, learning is also built in to the process of becoming a TT (awareness raising (learning) is a prerequisite for action and movement growth, but doubts about the effectiveness of this strategy – less effective at engaging with the wider public (external learning). | - If ***experiential* learning were prioritised above the *cognitive* approach**, TTs might attract a wider range of participants, while simultaneously meeting expectations to deliver change.<br>- Whereby **small affinity groups** meet regularly and support each other through the process of making carbon-reducing lifestyle changes<br>SNM theory claims that **successful niche development and growth depends on: the management of expectations and visions, networks, and learning processes**. In this case:<br>• Expectations: both internal and external expectation-management strategies at work with the TT movement. Cultivating expectations – or visions – is a key element of the internal process for TT initiatives.<br>• Networks: Networking is a core activity of the TT movement. Networking mainly internal to the niche itself – however successful niches are well networked with a range of stakeholders, who draw on resources to support the niche.<br>• Learning: considered as fundamental, both internally and externally. Second-order learning is a key component of its activities. |
| Rogers J. C. et al., 2012. Social impacts of community renewable energy projects: findings from a woodfuel case study. Energy Policy 42, 239–247 | Community biomass implant (woodfuel) in Eskdale, a small rural community England<br><br>Project directors<br><br>Public meetings creating opportunities for dialogue and opportunities for interaction between residents and experts, informal interaction between the directors and other residents, through visible demonstrations (physical installation of demonstration systems), dissemination of learning via social networks – grassroots community projects can have intrinsic value as a means of diffusing sustainability measures | - Importance of **personal connections**, in particular for "late adopters"<br>- the structure of community, **small and relatively cohesive**, appears likely to have enabled this mechanism<br>- All interviewees referred to a number of social connections with other local residents, either through business, formally organised activities (e.g. parish council) or **informal contact** (e.g. dog-walking)<br>- Importance of **leadership, change-oriented individuals** and **leaders with vision**: four members of the original group developed the initial concept and set up a limited company to deliver it which they ran as a social enterprise, acting as volunteer directors. Two further volunteer directors with relevant experience were recruited. These six directors could be termed direct project participants.<br>- Importance of **clear policy ambition** (also on higher levels), necessary to |

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| | Projects can:<br>- **Raise awareness** of renewable energy technologies and increase uptake of renewables. Overall the case study project successfully changed the local social context for development of woodfuel heating, reducing risk for all involved in the future development of this sector, particularly in the immediate locality.<br>- Create opportunities for **dialogue** (public meetings that addressed lack of knowledge by creating opportunities for interaction between residents and experts); formal and informal interaction. | maximise projects' individual and collective impacts (the influence of each projects is necessarily local)<br>- Importance of providing **visible demonstrations** (e.g. physical installation of demonstration systems, important for changing attitudes and learning through design and implementation of the demonstrations – learning from each other) (the **wider public lack of awareness remains a barrier** to local installation for some)<br>- Importance of **designing the project to fit local context**<br>- Importance of **engagement with other renewables**<br>- Importance of **a shared vision, ideals and motivation are not necessarily sufficient** for communities to establish new sustainability practices fundamentally at odds with existing socio-cultural systems<br>- Importance of citizens' **information and awareness -> engagement** |
| van Mierlo B., 2012. Convergent and divergent learning in photovoltaic pilot projects and subsequent niche development. Sustainability: Science, Practice, & Policy, Volume 8, Issue 2 | Photovoltaic energy pilot project in The Netherlands. **Very diverse learning experiences**<br><br>Multiple stakeholders in 4 different projects (companies, local governments, private households) – **heterogeneous networks, different levels of ambitiousness of the projects, different negotiating processes, different kinds of network management.**<br><br>Learning is fundamental to understand niche development from a micro-level perspective.<br><br>Importance of the **contextual factors**, which may foster or hinder innovations (e.g. financial support from the government vs. too rigid structures/power structures etc.). | Criteria for beneficial learning conditions:<br>1) **Heterogeneous network** formation,<br>2) open and creative negotiation<br><br>- The importance of process conditions depends on 1) the **kind of learning** (convergent or divergent) and 2) the ambitiousness of the pilot project<br>- Divergent learning took place in all of the ambitious projects, so challenging many regime rules may be a condition for this type of learning.<br>- For convergent learning, heterogeneous network formation sufficed in the more mundane AC project<br>- Secondary effects: building new and **trusting relationships**, and forging novel practices and rules, and **network management**<br><br>**Different kinds of learning** (contributing to niche replication or splitting): convergent learning, organisational adjustments, repeated use in same market segments; divergent learning, exploration of different market segments) **and of learning experiences.** |
| Hargreaves T., 2011. What Lessons Get Shared? Case studies of community energy. Grassroots Innovations Research Briefing 9, September 2011 | 'Community energy niche' in the UK, 113 case studies drawn from a web-search of more than 90 intermediary organisations.<br>257 distinct activities (community energy projects have a wide range of different aims and objectives with, perhaps, tackling climate change and cutting carbon dioxide emissions emerging as a key issue or framing device, at least in certain situations)<br><br>Engaged community members, NGOs and charities, local authorities, private companies, schools, faith groups, local associations<br>**Sharing information and lessons in niches** (e.g. through educational visits and tours or giving talks in other communities) by intermediary organisations such as the Energy Saving Trust, the Centre for Sustainable Energy or EnergyShare. However, notable lack of internal networking | - Networking and partnership working is a crucially important aspect of the community energy sector in the UK at present<br><br>- community energy niche currently in the UK, it appears to be at a very early stage, being very **fragmented**, still **rapidly changing** and, as of yet, **not** having developed **common sets of experiences or lessons** across diverse projects<br><br>- In the reports, extremely wide range of lessons highlighted – e.g.: **need to ensure strong community support**, financial lessons, planning issues, need to have particular skills, specific technical issues.<br><br>Again, importance oft he **context: each specific project is learning quite** |

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| | amongst community energy projects – still, networking and partnership working is a crucially important aspect of the community energy sector. Community energy projects are not well networked with one another, but they appear to be very well-connected to other kinds of partners such as local authorities and private companies.<br><br>Outcomes: cutting carbon dioxide, generating or saving energy – but also **skills development**, job creation, local energy security, generation of **funding for other local community projects – i.e. community energy projects generate multiple benefits for local communities in addition to cutting carbon dioxide and saving or generating kilowatt hours.**<br><br>A key aim for the analysed case study reports is as much to communicate that something is happening in the hope that this may inspire others, as it is to communicate specific and detailed lessons that will inform other community groups facing similar challenges. | **distinct sets of lessons specific to their local circumstances** -> at present, helping community energy projects to achieve their aims may demand quite **specific and tailored support** as there is not, as yet, a blueprint that can be readily followed across different projects.<br><br>No common sets of experiences or lessons across diverse projects yet. |
| Raven R.P.J.M. et al., 2008. The Contribution of Local Experiments and Negotiation Processes to Field-Level Learning in Emerging (Niche) Technologies Meta-Analysis of 27 New Energy Projects in Europe. Bulletin of Science, Technology & Society Volume 28 Number 6, 464-477 | Jühnde, a village,Saxony, Germany,<br>Sweden: Västerås, a townwith 100,000 inhabitants<br>2 case studies drawn from a meta-analysis of 27 new energy projects. They show how new projects are local reinterpretations and reinventions of a more generic, mobile concept of an emerging niche trajectory.<br><br>Two different projects, aims and settings (one rural, one urban) -> these local contexts provided different possibilities and constraints for the project. The rural context of Jühnde provided the possibility for intensive local participation and ownership, which might not be equally easy to accomplish in on an urban scale. In the urban setting, the alignment of expectations in the Växtkraft project took much longer and was much more complicated, in spite of an initial interest by project actors.<br><br>Local, regional national governments, cooperative and local farmers, investors,local residents, regional companies (e.g. engineering and construction firms in Germany, waste company and municipal energy company in Sweden), external experts (including a research institute), NGOs<br><br>Working groups, cooperative founded to operate the energy system, planning workshops, village meetings, joint forums, round tables with other communities (local knowledge transfer), formal and informal channels for influence and communication (e.g. also festivals and events for children) | - **Radical process** was made possible by a **participatory** decision process, into which all inhabitants were invited<br>- The participatory process was designed to secure compatibility with local needs.<br>- The waste management company interacted with local residents on an **ongoing** basis<br>- A system of coordination and information among the groups was established in the form of planning workshops and village meetings<br>- Formal and informal channel for communication<br>- Round table for other communities in Southern Lower Saxony, with the explicit purpose of gaining and transferring information. Also educational visits for other communities but also from abroad<br>- Important lessons have been gained concerning the mode of local organization, which is based on a local cooperative, broad participation in decision making, local customers, and local ownership<br>- The biogas developer community can learn from local experiments but also user groups such as urban planners or rural communities<br><br>The sensitivity to **local context** and the local embeddedness of the project were key aspects determining the immediate successfulness of the project. **Successful projects should be locally embedded**; provide local benefits; establish continuity with existing physical, social, and cognitive structures; and apply locally appropriate communication and participation procedures.<br><br>Both the translation of a generic concept into a local project variation as |

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| | Germany: The entire project has been based on a strong participatory ethic aimed to combine ecological goals and energy independency with the development of the local economy, the preservation of the local cultural heritage, and a strengthening of the local community spirit.<br><br>Sweden: municipalities were granted support for constructing biogas plants under the government program for sustainable development<br><br>Important: **not only did the context properties result in a project variation but the implementation of the project also changed the context**. Ready-made solutions cannot be dropped into a context without local negotiations. | well as the transfer of local lessons into global rules occur, but are difficult and require dedicated work. |
| Ornetzedera M., Rohracherb H., 2006.User-led innovations and participation processes: lessons from sustainable energy technologies. Energy Policy 34, 138–150 | Thermal solar collectors production (Austria); domestic biomass heating systems (Austria); sustainable buildings (Vauban, Freiburg im Breisgau )<br><br>Users or future users of technology<br><br>Socialization: (regular) meetings, group work, sharing experiences, learning from each other, collective planning)<br><br>In the case studies, **all forms of participation are linked with social learning processes.** Effects: technical innovations, dissemination of technology, social embedding of unconventional sustainable technology.<br><br>A specific form of social organisation seems to be particularly important: **autonomous social groups embedded in a wider social network and linked together by a coordinating structure.** The cooperation is mainly based on mutual **trust**, therefore it is helpful to form groups around existing social relations.<br><br>**A stable organisational unit enables long-term learning processes** between different user groups and between users and professional producers. | - Start up **stable learning processes** it is of crucial importance: 1) to find social niches with 2) highly motivated users, to 3) **organise communication** among them, and to 4) **link user experiences to producers and research units**.<br>The **collaboration of users of energy technologies** has not only contributed to a wider dissemination but also to technological development and product innovation. In many cases **technical improvements are realised during the diffusion phase by user feedback or re-invention by users**. User participation may be one tool (under certain conditions) which may help to improve such learning processes.<br><br>- Stable organisational unit enables long-term learning processes between **different user groups** and between users and professional producers.<br>- Particularly important in this respect: **autonomous social groups** embedded in a wider social network<br>- Collaboration of users contributed to a wider dissemination but also to technological development and product innovation<br>- Users organised within self-building planning groups have been involved notonly with behavioural questions but also with technological problems and institutional conditions<br><br>In order to start up stable learning processes it is of crucial importance to find **social niches with highly motivated users**, to organise communication among them, and to link user experiences to producers and research units. |
| Darby S., 2006. Social learning and public policy: Lessons from an energy-conscious village. Energy Policy | English village that had won an ‘energy-conscious village’ competition<br><br>Citizens of the village taking part to the survey and/or the competition<br><br>Wide range of sources, sporadically (e.g. energy label on appliances, | - Recognise and build up **tacit knowledge**<br>- The challenge is to recognise and build up tacit knowledge so that energy users can make more sense of the choices before them, in a world where energy issues are increasingly problematic. This means giving people clear **feedback** on their consumption and improving the ‘visibility’ and |

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| 34, 2929–2940 | electricity supplier, friend or neighbour, heating installer, TV, other fuel supplier,energy adviser)<br>People build up their energy knowledge over time through a combination of taking action, monitoring usage, and absorbing information from many sources in their environment. There is evidence that **energy consciousness**, including willingness to ask for advice and openness to the possibility of installing solar water heating, was built up **cumulatively** with exposure to different sources of information and feedback, and with the taking of action on installing energy efficiency measures. | comprehensibility of energy supply and consumption in general<br>- Funding and **training skilled energy advisers** who are able to communicate effectively with those whose tacit knowledge is slight,<br>- As well as supporting the learning of those who have a larger body of experience and know-how to draw upon.<br><br>- Also: potential importance of **affective factors** such as attachment to a way of life, or denial of the horrifying potential of climate change. Most of what householders learn about energy is constructed from a wide range of sources, sporadically. In the long run, awareness campaigns are likely to be a poor substitute for accurate, immediate information on consumption backed up by informative bills, although they could be a useful complement to such feedback.<br><br>Learning and communication are an integral part of policy aimed at introducing green electricity. Bare in mind the importance of social context in learning,<br>Learning is (hast o be) continuous and at all levels. |

**Table 9: Selected Case Studies on Transition Pathways considering Social Learning (Land Use/Agri-Food and Energy)**

| **Article (Author(s), Journal, Title)** | **Example / Case study(ies)**<br>**Main actors**<br>**How they learn** | **Conclusions on Social Learning (SL)** |
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| Forrest N., Wiek A., 2015. Success factors and strategies for sustainability transitions of small-scale communities – Evidence from a cross-case analysis. Environmental Innovation and Societal Transitions xxx–xxx (Article in press) | 4 small communities initiatives in the UK: Ashton Hayes,England; BedZED, an urban housing complex in London; Forres, a small Scottish town; and the Isle of Eigg, a remote Scottish island.<br><br>Engaged and informed citizens.<br><br>Socialization: (public) meetings, personal relations, experiences sharing, Learning by doing and from each other.<br>Frequent interaction with and between the actors involved communication, both internal and external, through a variety of media: prominent feature<br><br>Bare in mind: common to all cases was the generally favorable political climate in the U.K. | Household Energy:<br>- individual **feedback**, group feedback, and group forums can be particularly successful strategies<br>- missing **socialization** process prevents the emergence of **mediators** of social learning and new social norms, important for the diffusion of social innovations and can strengthen psychological determinants of sustained lower energy use<br>- **smaller communities**: population size and existing social cohesion appear to be critical factors that enabled these social mediators<br>- **group activities** are especially important in settings where inter-participant interaction is less likely to occur, such as in larger communities with dispersed participation<br>- **small population and strong social cohesion** creates ideal conditions for social innovation and diffusion<br>- there may be a population threshold somewhere between 1000 and 10,000, above which different strategies become necessary<br><br>-breaking down of individual barriers promotes skills and experience sharing, develops collective responsibility and cohesion amongst gardeners |

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| | | - **providing information** (practical advice, accessing resources, performance feedback) and **monitoring performance** (annual survey) were fundamental for the successful cases, together with presenting the change as a **collective challenge** (carbon neutral village: clear future vision – importance of **clear goals setting**). **Socialization** appears to have encouraged social learning and innovation in which new solutions and social norms emerged<br><br>**Structure, goals, and plans** provide **benefits** including: legitimacy, credibility, and accountability; communicating with the community; sustaining participation; administrative support; creating greater meaning beyond gardening only; and setting collective goals. Lacking of organized, grassroots, purposeful initiative hinder success<br><br>**Small population and strong social cohesion** creates ideal conditions for social innovation and diffusion (but they are not enough) |
| Feola G., Nunes R., 2014. Success and failure of grassroots innovations for addressing climate change: The case of the Transition Movement. Global Environmental Change 24, 232–250 | Grassroots belonging to the Transition Movement in 23 countries (N = 276)<br><br>Grassroots activists/members<br><br>Socialization: (public) meetings, personal relations, cooperation/partnerships, internet & social networking | - Achieve **concrete goals** in the community (organisation), i.e.produce change in, for example, technologies and practices<br>- social links to members of local communities, building capacity and empowering social actors.<br><br>- Transition-related learning processes may **peak or plateau** due to a limited supply of volunteer support.<br>- Alternatively: there may be a process of '**creative destruction'** or learning processes where old knowledge and ways of learning are discarded in favour of new approaches or recombined with new ideas or processes<br>- grassroots innovation success may be consistent with **learning cycles** of intermittent periods of coherence as well as fragmentation and variety whereby peer-to-peer knowledge dissemination complements a process of **dis/aggregation, re/consolidation and de/standardisation**<br><br>For a successful transition: need to achieve **concrete goals** in the community (organisation), i.e. not to limit the activities to informational or awareness-raising campaigns, but rather to **produce change** in, for example, technologies and practices, and to sustain motivation, enthusiasm and to promote a positive, ambitious approach<br><br>Importance of the **context** (also the **geographical location** of the transition initiative matters). |

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| | | Transition initiatives' growth and development is linked to the combination of **local–global (trans-local) learning processes** (e.g. externally resourced transition training/permaculture training).<br><br>**Success takes time**: there may be an incubation period for success of approximately four years; a longer period before becoming 'official' is associated with high levels of success.<br><br>Importance of **online networking**, but the positive role played by networking among grassroots innovations for their success suggests the importance of 'offline' contact despite the growing use of 'online' tools for communication, information sharing and recruitment. |
| Nykvist B., 2014. Does Social Learning Lead to Better Natural Resource Management? A Case Study of the Modern Farming Community of Practice in Sweden. Society and Natural Resources, 27:436–450, 2014 | Large-scale farmers within Uppsala County<br><br>Mainly farmers<br><br>Interaction with collegues, visiting and interacting with other farmers (e.g. organic farms), professional support from advisors<br><br>In forming Communities of Practice, SL is a learning process in which actors meet, discuss, and start to develop a shared meaning | - **Limited time horizon** for decision-making processes is a key obstacle to learning<br>- **previous learning experience** forms a knowledge base and structures that can foster or hinder development (the time dimension is important)<br>- **strong leadership** or facilitation has proven a key factor in enabling SL, without the organizational capacity to facilitate collaborative efforts the impact of SL is highly uncertain<br>- **external events and crisis** have been shown to trigger reframing in both policymaking are<br>- SL following from crisis can offer a window of opportunity, and act as a trigger for change.<br><br>It is important to **share goals and priorities**.<br><br>SL takes place at a **gradual** pace and might be difficult to achieve. |
| Sol J. et al., 2013. Social learning in regional innovation networks: trust, commitment and reframing as emergent properties of interaction. Journal of Cleaner Production 49, 35-43 | Multi-stakeholder sustainability-oriented regional learning in the North of The Netherlands, "Westerkwartier" of the province of Groningen<br><br>Multi-actor network – different social sectors represented – the challenges of social learning processes are closely related to the complexity of multi-actor networks (each actor tends to be (semi)organized in some kind of stakeholder group or constituency and represents specific interests and goals, which influence their commitment of knowledge, creativity, resources and talents to regional development).<br><br>**Social learning in a multi-actor network is influenced by interactions between project members and their constituencies** (and a distinction can be drawn from the personal commitment of a participant in social learning process, and the organizational commitment of the orga- nization she or he represents) | - Generative social learning is a **dynamic process**, in which **trust, commitment and reframing** are continuously produced through the actions of the individual actors.<br>- Commitment, mutual trust, and (re)framing as equally important aspects of social learning, and treating them as dynamic and **emergent properties** of social learning.<br>- The importance of this notion is that it takes the **attitude, values, behaviour and actions** of the project partners as the basic building blocks of the social learning process.<br>- **Actor diversity** is often regarded as an important source for social learning, because it enables a broader and more integrated capacity for joint action and learning<br>- but diversity can also turn out to be barrier. Individual and organisational scale differences can further **complicate social learning**, because organisational interests and values often limit the freedom to act of the |

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| | Bare in mind: **sustainability problems are best addressed when multiple actors with diverse interests and perspectives develop a shared frame on a jointly perceived problem or challenge, which enables joint action**. This process is increasingly referred to as social learning. Social learning can facilitate innovation and possibly foster the pathway for positive transitions in socialeecological systems. | people that represent them.<br>- also important: the process of social learning is embedded in a **web of power- and trust-relationship**s. Social learning requires that a certain level of **trust** is maintained,<br>- facilitation of social learning is particularly important when feelings of mutual **insecurity and uncertainty** emerge,<br><br>Importance of the **context:** the process of social learning is ***embedded*** in a web of power- and trust-relationships. Facilitation of social learning is particularly important when feelings of mutual insecurity and uncertainty emerge. |
| Axelsson R. et al., 2013. Evaluation of Multi-level Social Learning for Sustainable Landscapes: Perspective of a Development Initiative in Bergslagen, Sweden. AMBIO, 42:241–253 | 18 local development initiatives in the network of Sustainable Bergslagen in Sweden<br><br>Local: public, civil, and business sectors. Regional/national: governmental organizations or regional NGOs, universities, agencies<br><br>Exchanged experiences when they met, most often at network level meetings. No or very few attempts toward structured social learning at the network level.<br><br>Sustainability policies: SL needs to be adopted and regarded as **an integral part of the policy implementation process**.<br><br>SL defined as a process where **stakeholders collaboratively learn how to steer the development towards sustainability** – a combination of (1) reflections about experiences, values, ideas and the context for learning, (2) systems thinking to allow for a more holistic understanding, (3) integration of scales, world views, research disciplines, decision-making and synthesis, (4) negotiation and collaboration to handle conflicts and develop common ground, and (5) participation and engagement as a prerequisite for and to allow social learning. Social learning includes an understanding of interde-pendencies, learning about the places and their ecosystem services, while at the same time the collaborative dimension is emphasized. In the context of social learning conflicts are often seen as an opportunity for change and learning<br><br>Key challenge: to move from local experiences and results to local tacit knowledge, and from tacit to explicit knowledge | A collaborative learning process with stakeholders from different societal sectors and levels in social–ecological systems, or landscapes, need to consider issues like trust, norms, the interests of each stakeholder and the design and setting of the learning process<br><br>- Learning and knowledge production will benefit if the stakeholder group includes **different sectors and levels, different interests,** and if people have different experiences and backgrounds<br>- collaborative learning process with stakeholders from different societal sectors and levels need to consider issues like trust, norms, the interests of each stakeholder and the design and setting of the learning process.<br><br>Main barriers to joint collaborative learning:<br>(1) Public sector organizations have problems to **collaborate as equals** with stakeholders.<br>(2) Civil sector stakeholders often have a **problem with competence**.<br>(3) Private sector businesses are steered by owners' economic ambitions and caught by surprise when **norms and values** change.<br><br>Other important factors: **project ownership, collaboration, joint knowledge production, networking**.<br><br>As always, importance of the **context** |
| Albert et al., 2012. Social learning can benefit decision-making in landscape | Elbe valley biosphere reserve, Gartow, Germany<br><br>37 local actors | Several challenges in implementing the concept of social learning<br>- **scale-limitations** of social learning processes (in this case, successful social learning process originating from a relatively small community and only some external experts) |

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| planning: Gartow case study on climate change adaptation, Elbe valley biosphere reserve. Landscape and Urban Planning 105, 347–360 | Participatory planning process (workshop – overall outcomes: increased factual knowledge, technical skills, complex thinking, collaboration, communication and interaction, awareness, trust, social relations -> influence future attitudes and behaviours)<br><br>SL defined as a **change in understanding and skills that becomes situated in groups of actors/communities of practice through social interactions**. | - the need for **personal involvement** of key actors<br>- **limitations in time** and resources availability<br>- the time-sensitivity of social learning ( specific issues and learning outcomes **change over time** and may even **be forgotten**<br>- the configuration and **power structures** of the participants<br>- long-term adaptation success will require continued multilevel collaboration<br>- social learning can also be **destructive** for collective decision-making (e.g. if the interactions led to intensified **conflicts**)<br><br>Important: long-term adaptation success will require continued multilevel collaboration |
| Garmendia E., Stagl S., 2010. Public participation for sustainability and social learning: Concepts and lessons from three case studies in Europe. Ecological Economics 69, 1712–1722 | Sustainable energy systems in Austria; energy transition in Southeast England; and sustainable management of the Urdaibai River Basin, a Biosphere Reserve in the Basque Country (Northern Spain)<br><br>Local, national and regional stakeholders, professionals and lay-persons<br><br>Workshops designed to foster social learning | When dealing with complex issues and high uncertainty the search for optimal solutions (substantive rationality) is less useful than a focus on the quality of the decision process (procedural rationality), which includes that **learning among the counterparts** will become an essential part of the outcome.<br><br>- Deliberative approaches that enhance collective learning processes among a **diverse group** of social actors, with **different types of knowledge and perspectives**, are thus central in the creation of new responses to threats for socio-ecological systems.<br><br>Learning is an important element of management, if the situation is characterized by incomplete knowledge, presence of novelty or surprises and qualitative changes that can lead to irreversibility. |