DIEGO GONZALES CHEVARRIA
PhD Candidate - Federal University of Rio Grande do Sul – UFRGS
Post-Graduate Programme in Management
Address: Rua Washington Luiz, 855. Porto Alegre, Rio Grande do Sul, Brazil
ZIP Code: 90010460
e-mail: diego.chevarria@feevale.br

EUGÊNIO ÁVILA PEDROSO
Associated Professor - Federal University of Rio Grande do Sul – UFRGS
Post-Graduate Programme in Management
e-mail: eugenio.pedrozo@ufrgs.br

MODELING TECHNOLOGICAL TRANSITIONS THROUGH MULTIAGENT SYSTEMS

Abstract

The paper proposes a computational model to study socio-technical transitions. Technological transitions are large processes of change into socio-technical regimes, which implies not only changes in technology, but rather changes on society as a hole. We adopted the Multi-Level Perspective, understanding technological transition as resulting from the interaction of three conceptual levels - niche, regime and landscape. We have proposed that the transition depends upon the spread of expectations among social actors. Expectations affect external pressures and support to the niche, in the same way that drives innovation and learning efforts. This paper thus explores the relevance of expectations about the future development of a technological niche to the process of transition.

We proposed that transition would take place from the erosion of the commitment of actors to the regime, and the progressive commitment towards the niche; the commitment results from the expectations of social actors about the future development of the niche. We also considered that expectations results mainly from a repertoire of narratives developed by different social actors, and are continuously adjusted by the actually observed performance of the niche.

To this end, we have adopted a Multiagent System (MAS) modeling approach. MAS are computer modeling processes, developed based on a group of semi-autonomous agents, which interact with each other to represent a particular process. MAS have been specifically adopted for representing phenomena occurring at multiple conceptual levels, due to its ability to represent the emergence of different patterns of aggregated behavior. Together, these multiple agents eventually come to conform observable group behaviors, as well as conform the dynamics of the environment in which they operate. The development of the Brazilian wind power generation park, which is understood as a transition in progress, was adopted as the base case for modeling.

As a result, the model suggests by the significant dependence in technological transition process of the initial spread of expectations in the technological niche, since it conduces the niche to a conjoint action. The proposed model therefore enables the study by computational modeling of a set of relationships among different variables that have been discussed in the literature on socio-technical transitions. The paper thus contributes to the extent that provides a formal and mathematical treatment of the technological transition process.

Key Words: Multi-Agent System; Technological Transition; Multi-Level Perspective; Computational Modeling; Technological Expectations

Introduction

Technology transitions are processes of modification and replacement not only of technological artifacts, but also of social structures - productive and economic systems, public policies, as well as the social and symbolic meaning of technology. It constitutes a large process of change, resulting in consequences that can have repercussions on society as a whole.

Starting from the propositions of Smith and Raven (2012), we propose that the transition depends upon the spread of expectations about the development of a niche among social actors. Expectations affect external pressures and support to a technological niche, in the same way that drives innovation and learning efforts. It is relevant to the society to comprehend how expectations about a technology shape the future. This paper explores the relevance of expectations about the development of a niche to the process of technological diffusion and transition.

To develop this idea, the objective of this paper is to propose a computational model to study socio-technical transitions. To this end, we adopt an understanding of the technological transition based on a multilevel perspective, as proposed in Geels (2002, 2004), which studies the process from the conceptual levels of niche, regime and landscape. The model proposed formalizes an understanding of the relations among different variables that have been discussed in the literature on socio-technical transitions. The paper thus contributes to the extent that provides a formal and mathematical treatment of the technological transition process.

To this end, we have adopted a Multiagent System (MAS) modeling approach. MAS are computer modeling processes, developed based on a group of semi-autonomous agents, which interact with each other to represent a particular process. MAS have been specifically adopted for representing phenomena occurring at multiple conceptual levels, due to its ability to represent the emergence of different patterns of aggregated behavior

This paper is structured in 6 sections. After this introduction, we discuss the theoretical structure that supports the construction of the research. In the following section, we introduce the concept of Multiagent System, and in the fourth section we present the computational model developed, and the process of simulation adopted. In the fifth section we discuss the observed results, and in the last section we present our last considerations.

Theoretical Background: The Concept of Technological Transition

Geels (2002, 2004, 2005, 2010), starting from the work of Kemp (1994) and Kemp et al. (1998), defines a socio-technical regime as a semi-coherent system of rules on a particular technological environment, adopted by different, but related, social groups. The major advance in the technological transition concept is the definition of inter-organizational community as the unit of analysis, thus incorporating new dimensions in the analysis. A socio-technical regime is a structure where physical artifacts (technology) and social artifacts (practices) are related, and thus are socially constructed and formatted.

The socio-technical regime incorporates the system of production and development of a technology, as well as the dimensions of the use and adoption of the technology, as presented in figure 1. The socio-technical regime set through the belief system of the technology developers and users which problems to solve.

This proposition defines more clearly the importance not only of the technological development, but also of its diffusion in society. Geels´s (2002, 2004) proposition incorporates symbolic and cultural meanings of technology, resulting in a structure of social regulation and integration. The socio-technical approach thus explores the interaction between society and technology in the creation of a regime, understanding this technology as part of a social function.

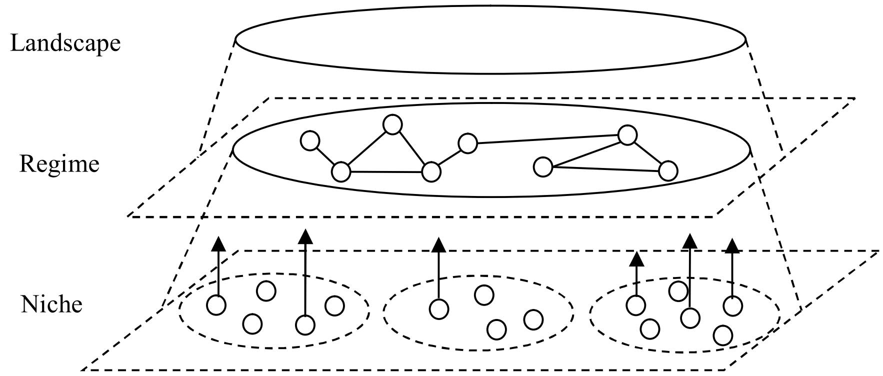
In this approach, a technological transition is understood as a significant change in the socio-technical regime, resulting in changes in both the adopted technologies, and consequent changes in the economic and social system related to the adoption, use and production of that technology (Geels, 2002). The technological transition is considered as a process where technology, itself, is only one of the dimensions of analysis (Geels, 2002, 2004, 2005). Therefore, it is a process involving a wide range of changes in the way society is organized.

The multilevel perspective of transitions

Geels (2002, 2004) proposes the understanding of transitions in socio-technical regimes from a Multilevel Perspective (MLP), adopting three different levels of interrelated analysis: niche, regime and landscape, as shown in Figure 1 ahead. The socio-technical regime is defined at the meso level; it consists in a system of interrelated actors on different social groups and communities, which follows defined rules. A technological trajectory is made up to the regime level. The macro level - landscape - is defined from a wide range of external factors, but related to the socio-technical regime (Geels, 2002, 2004). At this level, dimensions such as economic pressures, culture, society, international conflicts and environmental issues are considered.

In this perspective, it is understood that innovations emerge and are usually developed at the niche - the micro level. Niches are small markets that present specific demands, or small communities that adopt a new technology, often experimental. These spaces are relatively protected from the pressures existing in terms of regime and landscape, through subsidy by the government or strategic investment by firms (Kemp et al, 1998; Smith and Raven, 2012).

Figure 1: Conceptual levels of technological transition



Adapted from Geels (2002, 2004)

Niches arise through the collective action of a group of actors with common interests. The action of Government is not understood, therefore, as central to this process. The idea of niches is also directly related to the possibility of learning and development of the technology involved in these protected areas (Schot and Geels, 2007; Smith and Raven, 2012). The literature on technological transition relies on the possibility of learning, especially when dealing with transitions that were somehow induced.

Learning in technological transition process should be understood fundamentally as a collective process (Van de Kerkhof and Wieczorek, 2005; Vergragt and Brown, 2007). This collective learning takes place when different social actors, representing different cognitive frameworks and competence structures, interact on an issue, problem or idea, in order to meet the best arrangement to solve the problem. The literature on technological transitions thus gives a clear emphasis on the concept of learning by doing (Vergragt and Brown, 2007; Brown and Vergragt, 2008; Van De Kerkhof and Wieczore, 2005; Schot and Geels, 2007).

Regime stability as a function of commitment

Regimes are understood as relatively stable structures. In the presence of a socio-technical regime, innovations are still met, but incrementally inserted, limited to the specific scope defined by the regime (Kemp et al., 1998). It therefore conditions the way the innovation processes evolve. Technological transitions are commonly view as long-term processes; the full transition may last decades.

Kemp (1998; Kemp et al. 1998) defines three reasons for the stability of a socio-technical regime. (i) Socio-technical regimes are immersed in formal and informal rules that guide perceptions, beliefs and actions of the agents (Geels, 2004). (ii) Agents are structured in networks of interaction and mutual interdependence, supporting each other actions. And (iii) socio-technical regimes feature certain inertia, because once those technological systems are settled, there are several costs associated with their replacement.

Turnheim and Geels (2012) propose that, during a transition, regimes gradually destabilize and, eventually, come to dissolve. Transitions may originate from pressures at the landscape level, by actors that require particular social or political behavior of the regime, as also from the maturation of existing innovations at the level of the niche. Geels (2006) observes a continuing pattern of balance between tension and adjustment in the process of co-evolution of society and technology, consisting of a recursive dynamic between regime and landscape.

The basic explanation for the destabilization of a regime is that it results of external pressures to this, deriving in the gradual erosion of the commitment of firms and other social actors towards this regime (as also in Geels and Schot, 2007), as well as the erosion of the regime legitimacy in society.

The stability of a regime is understood by Turnheim and Geels (2012) mainly resulting from an endogenous commitment of firms to the regime itself, and the legitimacy given by external public support. In our framework, we extend this understanding, proposing that *the emergence of a new regime depends crucially on the creation of commitment of social actors towards a niche*, as well as the development of legitimacy by this new niche towards society.

Narratives and expectations in the transition

Initial niche protection is taken as essential, given that innovations usually do not have initially how to compete with mature and fully developed technologies. In addition to the function of (i) protection, Smith and Raven (2012) propose that the niche play other two roles in the dynamics of the development of an innovation: (ii) nurturing and (iii) empowerment. Nurturing is defined as the process that supports the development of innovations, especially the disruptive ones. The main forms of nurturing are in the process of learning and of articulation of expectations among actors.

Empowerment mainly refers to efforts in convincing the social system external to the niche and the development of means of influence - through, for example, political action - changes in the external environment that facilitate the niche consolidation as part of the incumbent regime. Niches work as a space of coordination of views and joint expectations among different actors, and this is central dynamics in the consolidation of a socio-technical regime (Borup et al., 2006; Brown and Michael, 2003). Expectations are defined as cognitive processes developed by different actors, at the level of the niche and the regime, in response to an innovation (Rosenberg, 1976; Borup et al., 2006).

One reason that governments and society subsidize and cultivate niches that are developing not yet profitable innovations is the expectation that these technologies will play relevant social roles in the future. Expectations legitimate protection processes and niche cultivation (Smith and Raven, 2012; Smith et al, 2005). Because of these expectations, both society and the actors of this niche can accept the present disadvantages, allocating resources for the improvement and development of these innovations.

Smith and Stirling (2010) emphasize the role of the actors of the niche in establishing these expectations. Expectations on the development of niche and the technology are articulated by niche players in the form of narratives, particularly on the opportunities for niche development, as well as the socio-technical regime cultivated on it. The niche acts, therefore, shaping the expectations about the future of innovations, technologies and developing regimes.

Narratives work in the interaction of the niche with society mainly in three ways (Smith et al., 2005): (i) positive narratives about the future are presented by actors, to justify the existence of the niche; (ii) narratives also demands for changes favorable to the interests of the niche in regulation and public policies; and yet (iii) narratives challenges the existing socio-technical regime, emphasizing the contradictions and limitations of this regime, as well as the opportunities presented in the new niche.

Expectations are presented and mobilized mainly in a political form, aiming to convince society of the relevance of the niche. The discursive process settled in the development of narratives by niche players is the main form of niche empowerment - way in which this niche acts, above all, as a political actor, by means of its internal and external social networks. These narratives eventually conform the expectations about the evolution of the niche, and determine the dynamics of existing pressures on landscape.

The articulation of efforts present in the development of a niche involves interactions between different actors, through social networks and coalitions, and sometimes even including members of the current regime. In this perspective, the transition process is not the result of discovering new opportunities by individual actors; it involves the creation of a new reality, by means of a collective action (Garud and Karnøe, 2003).

Smith and Raven (2012) and Pesch (2015) understand this process as the agency of the technological transition. This thus results from a collective action of the niche, through networks of interaction that are both internal to niche, which seek to align and mobilize the actors belonging to this niche; as external to it, in which actors of the niche seek support from relevant social actors outside the niche, but able to establish contact with it.

Agency so would be carried out through actions where the internal networking of the niche uses external networks to develop the repertoire of narratives of the niche. The niche directs its narratives to representative audiences, in order to defend the interests, as well as the legitimacy of the niche (Smith and Raven 2012). This conception of agency acts through pressure for influence in the institutions that may support or constrain the actions of the actors. These narratives conform the existing expectations about the ability of the niche development, and influence the dynamics of existing pressures within the landscape.

Based on the literature on the sociology of expectations developed in Brown and Michael (2003) and Borup et al. (2006), we propose that expectations, as well as the resulting pressures and support of the landscape from these expectations, also result from the observed system performance, when compared with previous expectations and narratives developed by niche.

In the process of niche development, we propose that the main measure of performance would be in its ability to effectively undertake the learning previously proposed. Expectations would be continuously adjusted on account of this feedback process. Performances aligned with previous expectations tend to reinforce these; performances that contradict expectations tend to erode these.

The dynamic evolution of the system is understood, in its turn, as resulting of the learning process, as proposed by on Schot and Geels (2007), and Atkeson and Kehoe (2007), and Argote (1990). We thus adopt a concept of learning-by-doing, expressed through an expectation of growth in the return of capital, in the light of the experience and knowledge accumulated over time. Table 1 below summarizes the variables adopted in our framework, as well as their proposed relations, and references of support for each of this variables.

Table 1. Variables Adopted in the Proposed Conceptual Framework

Variable	Description	Relations	Reference
Narratives	Discursive process about positive visions of future	Agency	Pesch (2015) Smith and Raven (2012)
Expectations	Cognitive processes developed in response to an innovation	Function of narratives	Rosenberg (1976) Brown and Michael (2003) Borup et al. (2006)
Performance	Ability to effectively achieve what was previously expected	Function of learning	Borup et al. (2006) Brown and Michael (2003)
Commitment	Endogenous commitment of firms to the regime, and legitimacy given by external public support	Function of expectations	Gells (2012) Turnheim and Geels (2012)
Learning	Reduction in production costs, more than proportional to the amount of capital growth	Function of absolute production	Argote et al. (1990) Atkeson and Kehoe (2007)

Method: Multiagent System Modeling

This paper present an experiment developed from a multiagent computational model. A multiagent system is a process of computational modeling and simulation structured from a set of heterogeneous computational agents, which act autonomously and interact among themselves (Epstein and Axtell, 1996; Sawyer, 2003; Hegselmann and Flache, 1998; Macy and Willer, 2002; Zimbres and Brito, 2006; Dawid, 2006).

In social sciences Multiagent systems are denominated as *artificial societies,* and have been adopted to describe and explain social processes characterized by the interaction between multiple agents, especially when structured in different levels of aggregation. Together, these multiple agents end up conforming group behavior, as well as the dynamic of their own environment in which they operate.

MAS has been adopted in different fields, such as, Finance, (LeBaron, 2001), Economy (Axtell, 1999) and Social Sciences (Cederman, 2002, Saywer, 2003). Artificial societies based on Multiagent systems have been used, thus, in the research on complex and non-linear social behaviors, such as consumer behavior (Twomey and Cadman, 2002) and marketing (Rand and Rust, 2011), social learning and emergence of patterns (Sen and Airiau, 2007), infrastructure management and urban mobility (Camarinha-Matos, Afsarmanesh, 2006; Balaji and Srinivasan, 2010), evaluation of public policies (Zhang and Nuttal, 2011), dissemination of innovations (Zhang et al., 2011; Deffuant et al., 2006), cooperation and competition (Axlrod, 1997; Camarinha-Matos and Afsarmanesh, 2007),among others.

Despite the lack of widely accepted standards of evaluation on the rigor of the modeling (Rand and Rust, 2011), the growth of publications adopting artificial societies shows that the approach is becoming accepted in the international academic environment (Duan and Qiu, 2012). A MAS involves the representation of a conceptual model of understanding or abstraction of reality, by means of computational tools. (Gilbert and Terna, 2006). Models are rational simplifications of the reality that, although being simplifications, allow to study specific aspects of the reality.

As a research method, the validity of the computational simulation can be understood as being much more in the theoretical development and understanding of the problem, than in the predicting capacity of the model. Through Multiagent systems, it is possible to formalize the study of theories and propositions about complex social processes (Gilbert and Terna, 2006).

The merit of this approach is primarily in that artificial societies have the capacity to represent complex macro-behavior patterns, from the behavior of actors at the micro level. The observable macro-patterns in artificial societies can be thus used as a tool for the analysis of real society behaviors, particularly in the analysis of realities that are difficult to understand by means of traditional conceptual models (Epstein and Axtell, 1996).

The development of an artificial society comprehends (i) the definition of the model and rules of the agents behavior, their (ii) objectives, (iii) specifications of the environment, and the desing of the (iv) agent-agent, agent-environment and environment-environment interaction models (Epstein and Axtell, 1996; Sawyer, 2003). Agents are designed on the basis of its rules of action, consist of two parts: (i) condition, which specifies when the rule should be executed, and (ii) action, that determines what is the consequence of the activation of the condition.

Learning is an important dynamic in the process of development of artificial societies. Agents can have the ability to learn about (i) environment, from the (ii) consequences of their actions, and from their (iii) interactions with other agents (Price and Boutilier, 1999). The notion that the action of the agent is limited to a conceptual structure defined as environment is central in the development of Multiagent systems, as well as the understanding that the agent is capable of adopting an autonomous action facing this environment (Sawyer, 2003).

The interaction between the agents, and between agents and their environment, can be observed in the form of different patterns of behavior. The emergent behavior is defined as regularity coherent and noticeable to the macro level. This regularity at the macro level results from the interaction of the different types of behaviors performed at the micro level (Sawyer, 2003; Maa and Nakamori, 2005, 2009; Chan et al., 2010). Given this central feature of the artificial societies, the behavior of the system is said to be self-organizing (Duan and Qiu, 2012; Sawyer, 2003; Tesfatsion, 2006; Macy and Willer, 2002; Hegselmann and Flache, 1998; Gilbert and Terna, 2000, Holland and Miller, 1991; Dawid, 2006).

Artificial societies allow to develop virtual experiments, based on simulations that represent specific research questions. Notably, based in the modeling process, the conditions on which certain empirical observations are achieved can be investigated, (Janssen and Ostrom, 2006), thus enabling the formal analysis of complex systems (Garcia and Jager, 2010).

To the extent that the computational simulation has the ability to replicate patterns, stylized known facts and empirical data, the similarity between the behavior of the model and what is observed in real world can be considered as evidence of the validity of the model (Gilbert and Terna, 2006; Berger and Schreinemachers, 2006). The capacity of a model to replicate the empirical data, suggests therefore/consequently the acceptance of its conceptual structure of the base.

In the development of the model, we adopted the Macal and North tutorial (2010), and as considerations on the development of MAS in social sciences, as suggested in Gilbert and Terna

(2000) and Bonabeau (2002). The modeling developed in this paper adopted as a basis the NetLOGO environment. NetLOGO is a open license simulation platform, developed by the *Center for Connected Learning and Computer-Based Modeling* of Northeastern University. The adoption of NetLOGO environment was justified by being this a widely used plataform, whit a good level of development and documentation (Railsback et al. 2006).

For the presentation of Multiagent model developed in this paper, we adopted the Protocol of description and documentation proposed by Grimm et al. (2006, 2010), denominated *Overview, Design Concepts, and Details* (ODD). This protocol consists of three blocks of information, overview, design concepts and details, which are subdivided into seven distinct elements: purpose, state and scales variables, process overview and programming, design concepts, startup, entries and sub models. The next section presents the development of MAS as proposed in the ODD protocol.

Computational Model

This section explores with the computational model developed based on the conceptual structure proposed, and that emulates the structure and development of the wind energy industry in Brazil. It has been observed an expressive growth in the installed capacity of wind power generation in Brazil, as shown in Table 2 below, which we understand characterizes the process as a transition in progress.

Table 2. Installed capacity evolution (data expressed in MW)

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Installed Capacity	27	27	235	247	398	602	927	1,425	1,886	3,391	6,390

Source: EPE (2013, 2014)

At the end of 2014 254 generating parks were operating in the domestic market, reaching a total 6.39 GW of installed capacity. Between 2009 and 2014, and especially in recent years, 13.8 GW in new projects of wind power generation were contracted through public auction. Considering the contracted projects, the installed capacity of the Brazilian industry should reach 14.4 GW in 2018.

The cost of instalation, perceived as high compared to other energy sources, is usually the main limitation for the expansion of wind generation parks. The average price of generation through wind power has shown significant reduction in the Brazilian market. The average contracted prices from US$ 270.32 / MWh in 2002 to US$ 148.39 / MWh in 2009, US$ 122.69 / MWh in 2010, and the 2011 auction obtained average prices of around US$ 100.00 / MWh (EPE, 2014).

As provided in Epstein and Axtell (1996) and Sawyer (2003), this section develops (i) the model of agents' behavior, as well as their (ii) objectives, and it also presents the (iii) agent-agent, agent-environment and environment-environment interaction models. The modeling proposed in this paper is based in previous models by Bergman et al. (2008) and Köhler et al.

(2009), as well as the work of Safarzynska and Van den Bergh (2010, 2011) and Safarzynska et al. (2012).

Particularly, the modeling proposed in Bergman et al. (2008) and Köhler et al. (2009) tries to replicate the multi-level structure proposed by Geels (2002, 2004), and the transition from the regime to niche. For such, it features a design of aggregate individual agents, representing the conceptual levels of the niche, empowered niche and regime. It is proposed in this paper a modeling approach that adopts groups of autonomous and fragmented agents, both at the level of the niche, as well as of the regime and landscape, presenting characteristics and behaviors heterogeneous among themselves.

We adopted three conceptual levels of agents, each level composed by active agents, different from each other in terms of functions and objectives. The conceptual level of landscape was modeled and composed by agents *a*, which represents public opinion and the various groups of social active actors at the level of the landscape.

The conceptual levels of regime and niche are composed of agents of 2 types, agents *p* of the niche and agents *f* of the regime; agents *p* and *f* emulate the actions of the social actors that generate electric power. The regime will also be composed by a single buyer *C*, that will emulate the function of buyer currently exercised by government. The function of the buyer is to provide the quantity demanded by agents acting on the landscape. The buyer must choose how much of bids characterized as the niche he will buy, in rounds of successive purchase.

The agent of the niche *p* will always and exclusively sell to the buyer agent *C*. The objective function *U* of the agents of the niche is to increase its produced quantity, as well as the size and quantity produced of the niche.

$$U_p = max \sum (Q_{pt}) \qquad \text{that}$$

$$Q_{pt} = f(Of_{pt} * P_{pt})$$

Where Q_p is the quantity actually produced and sold by agents of the niche *p*, and it is the function of supply *Of* and from P of price and the agent *p* at time *t*.

The offer of the agent *p* of the niche represents the available capacity that each agent has for sale. Each agent *p* can sell on its maximum its offered capacity. The initial conjoint offer of the niche is of a small quantity, and in this model it is understood that this offer grows as new agents are attracted to the niche. Thus:

$$Of_{pt} > Q_{pt} \qquad \text{and}$$

$$\sum (Of_p)_t > \sum (Of_p)_{t-1}$$

Of_{pt} represents the offer of agent *p* of the niche at time *t,* and $\sum (Of_p)_t$ represents the total supply of the system at time *t*. Agents of the niche *p* increase the sold quantity influencing actions of the Buyer, as well as influencing actions of other actors of the regime and the niche. Agents of the niche act through narratives mainly directed to agents in the landscape, but also directed to others agents of the niche and regime. The narratives are constructed in terms of expectations of future quantity and future price of the offer of the niche. Thus we have:

$N_T = f(\sum Of_{p,\,t+n}\,,\, P_{p\ t+n})$ that

$\sum Of_{p\,t+n} > \sum Of_{p\,t}$ and

$P_{p\,t+n} < P_{p\,t}$

Where n represents the narratives performed at time t, $\sum Of_{p\ t+n}$ represents the expectation of future offer/bid/supply at time $t+n$, and $P_{p\,t+n}$ represents the expectation of future price at time $t+n$..

Agents a of the landscape, as well as agents p of the niche and agents f of the regime, act according with their expectations, and adjust these expectations individually as a function of the narratives exercised by niche; positive narratives generate positive expectations and negative narratives, negative expectations. The higher the volume of narratives presented by niche, the greater the capacity to influence agents. Agents also have a specific sensitivity to narratives, and individually adjust their expectations regarding this sensitivity.

In the same way, agents adjust their expectations as a function of the overall observed performance: system performances below existing expectations result in reduction of future expectations, performances above expectations result in growth of future expectations. Thus, expectations E can be expressed in terms of:

$$E_p = f(\sum N_{t-1} * Sn_p + E_{p\,t-1} * D_t)$$

$N_{p\ t-1}$ representing the narratives observed by agent p at time $t-1$, D_t representing the overall system performance at time t, and Sn the sensitivity to narratives of each one of the agents. Agents p are heterogeneous among themselves in terms of their initial expectations regarding the development of the niche, as well as their sensitivity Sn to expectations. Agents of the niche are also heterogeneous in terms of the size of their offer Q_P.

System performance is expressed in terms of prices and quantities offered in present time. It is not the interest of agents of the niche to develop narratives that will not be observed in reality.

$$D_t = f\sum(Of_{p\,t} * P_{p\,t})$$

In its turn, agents of landscape act by means of the pressures exerted on the buyer C, as well as on other agents of landscape, and on agents of niche and regime. Positive expectations about the niche generate more favorable pressure to niche; positive and more widespread expectations among the agents of the landscape result in a greater number of pressures being exerted.

To exercise its function of purchasing the demanding quantity, the buyer must consider the quantity and prices offered by producers p, and the pressures exerted by other agents a of the level of the landscape. The pressures exerted on the buyer C results on the creations of demand for the provision by the niche; the greater the pressure exerted by agents of the landscape, the greater the demand of the buyer.

The purchaser must seek to acquire the demanded quantity, and is sensitive to the price offered by agents. To reach this market demand, the buyer will accept the offer presented by the niche, giving preference for the lowest price. The objective function of the buyer is:

$U_C = min \sum (P_{PT} * Q_p)$ restricted to

$\sum (Q)_t > Qd_t$

Where Qd_t represents the demand for the niche. The function of demand is expressed by:

$Qd_t = f \sum (E_t)$ restricted to

$\sum(Q_p) < \sum(Of_p)_t$

Where $\sum (E_t)$ represents the sum of the expectations of agents of the landscape at time t, $\sum(Q_p)_t$ represents the total purchase made by the buyer until the time t, and $\sum(Of_p)_t$ represents the sum of offerings of agents p at the time t.

The learning process is represented in the model in terms of the reduction of the price of the offer of the niche for the account of the produced quantity accumulated by the niche as a whole. While the purchaser decides by a greater quantity of acquisition of the niche, the possible price of the offer tends to decrease. As the entire process of technological development presents a natural and inherent risk, it also adopts a term that represents this risk, in the form of a random adjustment on the learning factor effectively observed at each step. This learning process is expressed by:

$P_{p\,t} = f (P_{p\,t-1} - \sum Q_{p\,t-1} * F_{apr} * \beta)$

Where P_p is the price of the offer of the niche p, and $\sum Q_p$ is the cumulative quantity of production of the niche, F_{apr} is the niche factor of learning for the account of the accumulated production, and β represents the risk of learning and technological development. Agents of the niche will submit bids for the buyer C regarding its commitment to the niche; the action of agent presupposes the existence of commitment towards the niche. Thus:

$Q_{p\,t} = f (Com_{p\,t})$

Where $Com_{p\,t}$ represents the commitment of the agent p at time t. In its turn, agents adjust their commitment to the niche according to their expectations E to the development of niche.

$Com_{p\,t} = f(E_{p\,t-1,})$

Likewise, narratives are carried out by agents of the niche p who present a certain degree of compromise with the niche. The process of narratives and commitment as a whole proposed

here is intended to replicate the concept of contagion developed in the literature. The greater the commitment and attitude/size of the agent, the greater its capacity to generate narratives.
Thus,

$$N_{p\,t} = f\,(Com_{\,t-1})$$

Where $N_{p\,t}$ represents the narrative presented by the agent of the niche p at time t.

Simulation process

The simulation process was designed in sequential simulation rounds, each of these rounds adopting a different initial condition of simulation. In order to enable the manipulation of the system, and allow to test the consistency of the proposals and findings on various initial conditions, a MAS can adopt a group of manipulation variables, which compose independent variables into the analysis.

Initial values were assigned to the manipulation variables (i) *sensibility to narratives* - Sn_p; and (ii) *learning factor* - F_{apr}. Initial values were also assigned to the (iii) *initial expectation* - $E_{p\,t0}$ of the Buyer, in order to analyze the impact of the Government support to the development of the process. Variables average *offer per agent* - Of_{p0} and average *initial price* - $P_{p\,t0}$ were adopted in the simulations in values similar to the empirically observed at the Brazilian wind energy market.

The specific coefficient of each of the manipulation variables is assigned to each individual agent by the system, adopting a random dispersion around the average value set for each simulation condition. The heterogeneity among agents results of this dispersion assigned by the system. An agent is also assigned randomly with a high degree of expectations on the development of niche, in order to constitute a catalyst agent of niche expectations.

A MAS also adopts a set of internal state variables, which represent dimensions and relations proposed by the conceptual model tested. The main internal state variable was the degree of agent autonomy. Autonomy defines the probability of the agent to follow or not the system behavior dimensions - especially when deciding on their narratives and expectations, as well as its offer and price. The autonomy of the agent was kept constant throughout each simulation.

We thus defined 125 different simulation conditions. Each of the 3 groups of simulations conditions constituted an individual computational experiment, and table 3 summarizes the conditions adopted. For each of the simulation conditions it was performed a group of 10 simulations. We have adopted in this process the *behaviorspace* tool, provided in NetLOGO suite, which enables the implementation of automated computational experiments. A total number of 1,250 simulations were performed.

Each simulation was designed representing week intervals, at a ratio of 3 steps for each week. At every step, niche players seek to randomly establish connections with other agents, considering the restrictions set for simulation. These connections represent the process of *narratives* and *pressures* proposed in the conceptual model. Agents update their *expectations* and *commitment* according to the interactions established in the step.

Table 3. Conditions of simulation and experiments

Variables	Experiment	Simulation conditions		
average offer per agent - Of_{p0}		32 MWh		
average initial price - $P_{p\,t0}$		U$ 182.00/MWh		
Initial niche size		6 agents		
		min	**max**	**nº of conditions**
sensitivity to narratives - Sn_p	*E1*	.1	.9	5
learning factor - F_{apr}	*E2*	.1	.9	5
initial expectation - $E_{p\,t0}$	*E3*	200	800	5
Simulations per scenario				10

System *performance* is updated in every step, in terms of quantities actually produced by niche, and offered prices. Agents also update their *expectations* and *commitment* in accordance with the observed performance of the system.

The buying process seeks to emulate the conditions observed in the wind energy niche, as described in previous sections. The acquisition is through a simple auction process, where niche agents are required to submit bids. The buyer acquires the offers presented, with preference given to the lowest price. The auction occurs on a random basis, according to the market demand, and with an average frequency of 2 to 3 times a year. At each step, the market demand is also updated.

The simulation process was stopped when all agents of the niche have already sold all its capacity, and new agents are not attracted to the niche. The simulation process was also interrupted if the expectations of all niche agents fall to 0. If these conditions are not met, the limit of 2,400 steps for each simulation was established.

Findings and Model Validation

According to Gilbert and Terna (2006), Berger and Schreinemakers (2006), Axelrod (1997) and Bonabeau (2002), it is understood that the ability of the Multiagent system to emulate empirical observations and stylized facts indicates for the acceptance of the proposed conceptual model. To validate our proposed model, we adopted data regarding the development of the Brazilian wind energy niche, observed in monthly terms, in the 25-year period ranging from 1994 to 2018. Our objective was to observe whether the proposed conceptual model has effective capacity to represent the process of setting up this technological niche.

We adopted as indicators (i) the *effective capacity produced by niche*; and (ii) *price of the niche offer*; these can be characterized as dependent test variables of the computational experiment. The simulation results were observed in terms of historical series for each of the defined indicators. The resulting time series, compared with the actual empirical data, are presented in the following figures 2 for the estimated capacity produced, and figure 3 for the estimated price offer.

Figure 2 – Simulated time series - effective capacity produced by niche

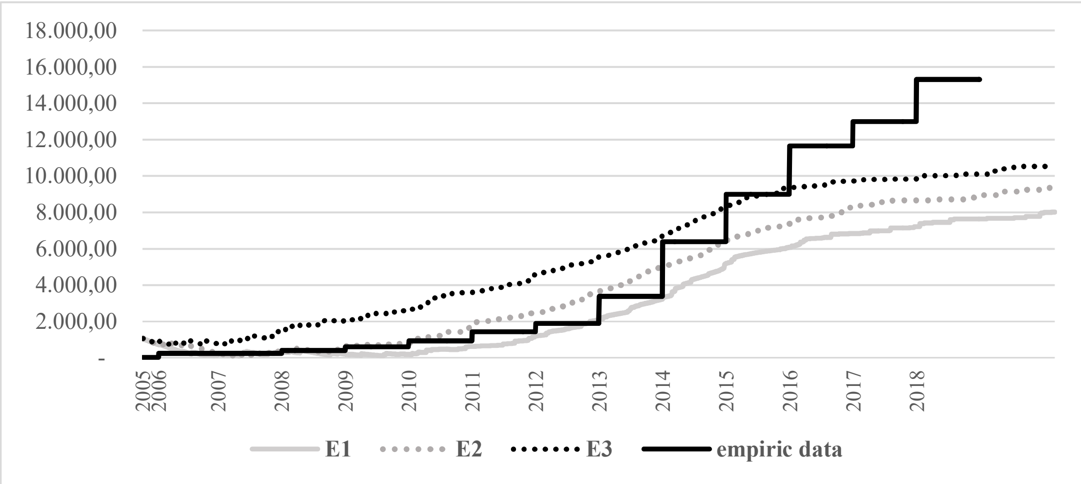
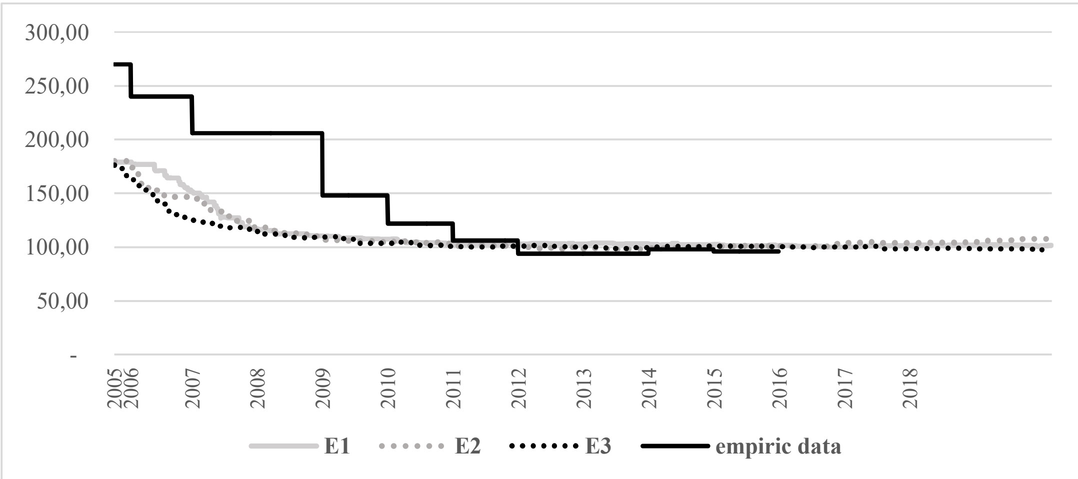


Figure 3 – Simulated time series - price of the niche offer



Results were also evaluated in terms of the correlation among time series generated in the simulation, in the different simulation conditions, and time series observed empirically. This was estimated by Pearson correlation coefficient, and were calculated using the SPSS 22 software. The correlation coefficients are shown in the following tables 4 and 5.

The correlation presented in Tables 4 and 5 suggest for a good approximation among the simulation results and the patterns observed empirically. The observed correlation coefficient between simulation and empirical data for the total capacity produced by the niche ranged most for above .900, which suggests by a very good fit. In the data about niche offering price, the correlation ranged from .726 to .889. Although having a of lower consistency, we understand that results observed still are sufficient for the validation of the proposed model.

Table 4. Correlation among empirical series and simulation results - total capacity

			Simulation condition				
Experiment	**Variable of manipulation**		**1**	**2**	**3**	**4**	**5**
E1	Sn_p	Correlation	0.784**	0.868*	0.859*	0.953*	0.938*
		Final results	8,024	9,347	9,780	9,929	10,583
E2	F_{apr}	Correlation	0.988*	0.967*	0.982*	0.963*	0.984*
		Final results	7,689	7,015	7,198	7,427	6,821
E3	$E_{p\,t0}$	Correlation	0.976*	0.957*	0.947*	0.941*	0.926*
		Final results	7,774	7,720	7,324	7,770	8,001

* statistically significant at $p^2 < .000$ ** statistically significant at $p^2 < .00$

Table 5. Correlation among empirical series and simulation results – offer prices

			simulation condition				
Experiment	**Variable of manipulation**		**1**	**2**	**3**	**4**	**5**
E1	Sn_p	Correlation	0.851*	0.889*	0.847*	0.816*	0.784**
		Final results	136,20	140,91	143,74	142,19	137,88
E2	F_{apr}	Correlation	0.841*	0.860*	0.832*	0.786**	0.772**
		Final results	141,78	132,60	128,73	112,89	101,63
E3	$E_{p\,t0}$	Correlation	0.830*	0.851*	0.803*	0.768**	0.726**
		Final results	101.72	107.77	97.55	111.17	98.67

* statistically significant at $p^2 < .000$ ** statistically significant at $p^2 < .00$

These findings were observed in the 3 experiments, considering simulations with different initial conditions in the variables (i) *sensitibility to narratives* - Sn_p; and (ii) *learning factor* - F_{apr}, and (iii) *initial expectation* - $E_{p\,t0}$ of the buyer, thus showing a reasonable consistency of findings. We understand that the correlation data observed, together, suggest for acceptance of the proposed model - especially in its possibility to understand the process of expectations diffusion through narratives produced by agents, as central to the technological transition.

As expected, final observed prices have been observed as sensible to the learning factos adopted in each of the simulations conditions of experiment E2, as shown in Table 5 above. But notably, as shown in Figure 1 and in Table 4 above, we observed a significant dependence on the final results of the conditions adopted for the variable *sensibility to narratives*- Sn_p . This observation occurred because in simulation conditions where it was assigned to agents a high sensitivity, expectations have spread quickly in the niche, conducting it to a more effective conjoint action. The model thus suggests by a significant dependence of the initial spread of expectations in the technological niche.

Final Considerations

This paper proposed a computational model to study socio-technical transitions, based on a multiagent system. By the model proposed in this paper we discussed ways to study the relevance of the construction of expectations to the process of technological diffusion and transition. In the development of this model, we have adopted the Multilevel perspective as a conceptual support, understanding that transitions depends upon the spread of expectations among different social actors. We have developed the model based on the case of the development of the Brazilian wind energy industry, which we consider is an ongoing transition.

Final results have given support to the acceptation of the proposed model, in terms of the correlation between empirically observed data and simulation generated data. It also points to the dependence on the transition of the initial dispersion of expectations in the niche. This paper thus advances the literature about transitions, as it proposes a formal, structured approach to understanding the dynamics involved in technological transitions.

Despite the discussed in this paper, it is understood that this research has several limitations, the main one being the way of its construction. It is observed that the acceptance of a conceptual model structured on a MAS as true should be done with relative caution. Results of agents based modeling should be comprehended as a possible explanation of a behavior - and this does not allow the understanding that this is the only, or even the best, explanation for this behavior.

Considering the state of development of the theoretical framework adopted in this paper, it is understood that the replicability of findings observed in this paper to other cases is limited. We suggest as a proposition for new studies the modeling of other processes of technological transitions, in order to improve and validate the theoretical background developed in this work.

References

Argote, L, LS Beckman and D Epple (1990). The persistence and transfer of learning in industrial settings. *Management science*, *36*(2), pp. 140-154.

Atkeson, A and PJ Kehoe (2007). Modeling the transition to a new economy: lessons from two technological revolutions. *The American Economic Review*, pp. 64-88.

Axelrod, RM (1996). *The complexity of cooperation*: Agent-based models of competition and collaboration. Princeton University Press.

Axtell, R (1999). *The emergence of firms in a population of agents: local increasing returns, unstable Nash equilibria, and power law size distributions.* Mimeo. Center on Social and Economic Dynamics.

Balaji, PG and D Srinivasan (2010) Multi-agent system in urban traffic signal control. *Computational Intelligence Magazine, IEEE*, 5 (4), pp. 43-51.

Berger, T, P Schreinemachers (2006). Creating Agents and Landscapes for Multiagent Systems from Random Samples. *Ecology & Society*, 11 (2).

Bergman, N, A Haxeltine, L Whitmarsh, J Köhler, M Schilperoord, and J Rotmans (2008). Modelling socio-technical transition patterns and pathways. *Journal of artificial societies and social simulation*, *11*(3), pp. 7.

Bonabeau, E (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America*, 99 (3), pp. 7280-7287.

Borup, M, N Brown, K Konrad, and H Van Lente (2006). The sociology of expectations in science and technology. *Technology analysis & strategic management*, *18*(3-4), 285-298.
Brown, N and M Michael (2003) A sociology of expectations: Retrospecting prospects and prospecting retrospects. *Technology Analysis & Strategic Management, 15* (1): pp. 3-18.
Camarinha-Matos, LM and H Afsarmanesh (2006). Virtual enterprise modeling and support infrastructures: applying multi-agent system approaches. *Multi-agent systems and applications*. Springer Berlin Heidelberg, pp. 335-364.
Cederman, L-E (2003). Modeling the size of wars: from billiard balls to sandpiles. *American Political Science Review*, 97 (01), pp. 135-150.
Chan, WKV, Y-J SON and CM MACAL (2010). Agent-based simulation tutorial-simulation of emergent behavior and differences between agent-based simulation and discrete-event simulation. In: *Proceedings of the Winter Simulation Conference*. Winter Simulation Conference.
Dawid, H (2006). Agent-based models of innovation and technological change. *Handbook of computational economics*, 2, pp. 1235-1272.
Deffuant, G, S Huet and F Amblard (2005). An Individual-Based Model of Innovation Diffusion Mixing Social Value and Individual Benefit. *American Journal of Sociology*, *110* (4), pp. 1041-1069.
Duan, W and X Qiu (2012). Fostering artificial societies using social learning and social control in parallel emergency management systems. *Frontiers of Computer Science*, 6 (5), pp. 604-610.
Empresa de Pesquisa Energética - EPE (2013). *Anuário estatístico de energia elétrica*. Brasília: Empresa de Pesquisa Energética.
Empresa de Pesquisa Energética - EPE (2014). *Balanço Energético Nacional*. Brasília: Empresa de Pesquisa Energética.
Epstein, JM and R Axtell (1996). *Growing artificial societies*: Social science from the bottom up. Cambridge: MIT Press.
Garcia, R and W Jager (2011). From the Special Issue Editors: Agent-Based Modeling of Innovation Diffusion. *Journal of Product Innovation Management*, 28 (2), pp. 148-151.
Geels, FW (2002) Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study. *Research policy*, 31 (8): pp. 1257-1274.
Geels, FW (2004). From sectoral systems of innovation to socio-technical systems: Insights about dynamics and change from sociology and institutional theory. *Research policy*, 33 (6): pp. 897-920.
Geels, FW (2005). Processes and patterns in transitions and system innovations: refining the co-evolutionary multi-level perspective. *Technological forecasting and social change*, 72 (6): pp. 681-696.
Geels, FW (2010). Ontologies, socio-technical transitions (to sustainability), and the multi-level perspective. *Research policy*, 39 (4): pp. 495-510.
Geels, FW (2012). A socio-technical analysis of low-carbon transitions: introducing the multi-level perspective into transport studies. *Journal of Transport Geography*, *24*, 471-482.
Geels, FW and J Schot (2007). Typology of sociotechnical transition pathways. *Research policy,* (36) 3, pp. 399-417.
Geels, FW, MP Hekkert and S Jacobsson (2008). The dynamics of sustainable innovation journeys. *Technology Analysis & Strategic Management*, 20 (5).
Gilbert, N and P Terna (2000). How to build and use agent-based models in social science. *Mind & Society*, 1 (1), pp. 57-72.
Grimm, V. et al (2006). A standard protocol for describing individual-based and agent-based models. *Ecological modelling*, 198 (1), pp. 115-126.
Grimm, V. et al. (2010). The ODD protocol: A review and first update. *Ecological Modelling*, 221 (23), pp. 2760-2768.
Hegselmann, R. and A Flache (1998). Understanding complex social dynamics: A plea for cellular automata based modeling. *Journal of Artificial Societies e Social Simulation*, 1 (3).

Janssen, MA and E Ostrom (2006). Empirically based, agent-based models. *Ecology and Society*, 11 (2), pp. 37.
Kemp, R (1994). Technology and the transition to environmental sustainability: the problem of technological regime shifts. *Futures*, 26 (10): pp. 1023-1046.
Kemp, R, J Schot and R Hoogma. (1998). Regime shifts to sustainability through processes of niche formation: the approach of strategic niche management. *Technology analysis & strategic management,* 10 (2): pp. 175-198.
Köhler, J, L Whitmarsh, B Nykvist, M Schilperoord, N Bergman and A Haxeltine. (2009). A transitions model for sustainable mobility. *Ecological economics*, *68*(12), pp. 2985-2995.
Ma, T and Y Nakamori (2005). Agent-based modeling on technological innovation as an evolutionary process. *European Journal of Operational Research*, 166 (3), pp. 741-755.
Macy, MW and R Willer (2002). From factors to actors: Computational sociology e agent-based modeling. *Annual Review of Sociology*, 28.
Price, B and C Boutilier (1999). Implicit imitation in multiagent reinforcement learning. *International Conference on Machine Learning*. pp. 325-334.
Rand, W and RT Rust (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing*, 28 (3), pp. 181-193.
Safarzyńska, K and JC van den Bergh (2010). Evolutionary models in economics: a survey of methods and building blocks. *Journal of Evolutionary Economics*, *20*(3), pp. 329-373.
Safarzyńska, K, K Frenken, and JC van den Bergh (2012). Evolutionary theorizing and modeling of sustainability transitions. *Research Policy*, *41*(6), pp. 1011-1024.
Safarzynska, K., & van den Bergh, JC (2011). Industry evolution, rational agents and the transition to sustainable electricity production. *Energy Policy*,*39*(10), 6440-6452.
Sawyer, RK (2003). Artificial societies, multiagent systems and the micro-macro link in sociological theory. *Sociological Methods & Research*, 31 (3), pp. 325-363.
Schot, J and FW Geels (2007). Niches in evolutionary theories of technical change. Journal of Evolutionary Economics, 17(5), 605-622.
Schot, J and FW Geels (2008). Strategic niche management and sustainable innovation journeys: theory, findings, research agenda, and policy. *Technology Analysis & Strategic Management*, *20*(5), 537-554.
Sen, S and S Airiau (2007). Emergence of norms through social learning. *Proceedings of the Twentieth International Joint Conference on Artificial Intelligence* (IJCAI-07), pp. 1512.
Smith, A and A Stirling (2010). The politics of social-ecological resilience and sustainable socio-technical transitions. *Ecology and Society,* 15 (1): pp. 11.
Smith, A and R Raven (2012). What is protective space? Reconsidering niches in transitions to sustainability. *Research Policy*, 41 (6): pp. 1025-1036.
Smith, A, A Stirling, A. and F Berkhout (2005) The governance of sustainable socio-technical transitions. *Research policy*, 34 (10): pp. 1491-1510.
Smith, A, JP Voß and J Grin (2010). Innovation studies and sustainability transitions: The allure of the multi-level perspective and its challenges. *Research policy*, *39*(4), pp. 435-448.
Tesfatsion, L (2006). Agent-based computational economics: A constructive approach to economic theory. *Handbook of computational economics*, 2, pp. 831-880.
Turnheim, B and FW Geels (2012). Regime destabilization as the flipside of energy transitions: Lessons from the history of the British coal industry (1913–1997). *Energy Policy,* 50, pp. 35-49.
Twomey, P and R Cadman (2002). Agent-based modelling of customer behaviour in the telecoms and media markets. *Info,* 4 (1), pp. 56-63.
Van de Kerkhof, M and A Wieczorek (2005). Learning and stakeholder participation in transition processes towards sustainability: Methodological considerations. *Technological Forecasting and Social Change*, *72*(6), pp. 733-747.

Verbong, GP and F Geels (2007). The ongoing energy transition: lessons from a socio-technical, multi-level analysis of the Dutch electricity system (1960–2004). *Energy policy*, 35 (2): pp. 1025-1037.
Verbong, GP and FW Geels (2010). Exploring sustainability transitions in the electricity sector with socio-technical pathways. *Technological Forecasting and Social Change*, 77(8), pp.1214-1221.
Vergragt, PJ and HS Brown (2007). Sustainable mobility: from technological innovation to societal learning. *Journal of Cleaner Production,* v. 15, n. 11, pp 1104-1115.
Winner, L (1977). *Autonomous technology: Technics-out-of-control as a theme in political thought.* Cambridge: MIT Press.
Zhang, T and WJ Nuttall (2011). Evaluating government's policies on promoting smart metering diffusion in retail electricity markets via agent-based simulation. *Journal of Product Innovation Management,* 28 (2), pp. 169-186.
Zhang, T, R Gensler; RA Garcia (2011). A study of the diffusion of alternative fuel vehicles: An agent-based modeling approach. *Journal of Product Innovation Management*, 28 (2), pp. 152-168.