Three Essays on Methodologies for Dynamic Modeling of Emerging Socio-technical Systems: The Case of Smart Grid Development

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"Nun, by the pen and what they inscribe"
(The holy Qur'an. 68:1)

To my parents and Maman Feri.

And to Mahshid,

The joy and meaning of my life

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Abstract

Socio-technical energy transitions are long-term and major transformations in incumbent energy infrastructures. They include fundamental changes in technologies as well as institutions and social patterns. Transition studies are primarily focused on frameworks for analyzing the entire transition process by investigating the historical cases of transitions. A multi-phase approach to transition posits this process begins with a pre-development phase characterized by technological and institutional lock-ins, and resistance from incumbent actors. This period is critical for a forward-looking approach to transitions, since early developments shape path-dependent and irreversible processes leading to the emergence of new transition pathways. However, our understanding about the mechanisms and dynamics of this phase is still very limited. This is mainly due to lack of data, weak conceptualization and the necessity of developing new methods proper to deal with these limitations.

This dissertation develops methodologies for investigating some complex questions arising in the pre-development phase, by focusing on the case of smart grid development. The first essay uses insights from modeling interventions in complex systems and builds a System Dynamics model to investigate the cost allocation problem of smart metering roll-out. The second essay takes ideas from Technological Innovation System approach and develops a method to analyze the emergence of spatial diversity in smart grid development by combining Social Network Analysis and Agent-Based Modeling. The third essay builds on ideas from network theory and evolutionary modeling to develop a method for identifying the main path of knowledge development and analyzing knowledge trajectories in smart grid initiatives.

Keywords: Socio-technical Transition, Complex Systems Approach, System Dynamics, Agent-Based Modeling, Social Network Analysis, Smart Grid

Résumé

Les transitions énergétiques sociotechniques sont des transition se déroulant sur de longues périodes, a travers des infrastructures énergétiques souvent anciennes. Ces transitions reposent sur des changements technologiques fondamentaux, des évolutions des pratiques sociales et de nouvelles institutions. L'étude des transitions sociotechniques se focalise en premier lieu sur l'utilisation de méthodologies cherchant à analyser de manière historique les transitions. Ces dernières commencent en général par une phase de pré-développement, souvent caractérisée par des blocages technologiques et institutionnels, et une résistance systématique de la part des titulaires. Cette période de pré-développement est cruciale, étant donné qu'elle influence en profondeur le développement de processus et interactions qui s'avèreront pour beaucoup être irréversibles, et influenceront le développent de chemins de transitions futurs. Cependant, notre compréhension de cette période de pre-developpement est pour le moins limitée, en raison du manque de données et de conceptualisations théorique. Il est donc important de définir de nouvelles méthodologies pour palier à ces limitations.

Cette dissertation vise, en se basant sur le cas de développement de réseaux électriques intelligents, dits smart grids, a proposer de nouvelles méthodologies pouvant contribuer à répondre a certaines questions complexes liées à la phase de pre-developpement. Le premier essai propose un modèle dynamique pour comprendre le problème d'allocation des couts dans le développement des réseaux électriques intelligents. Le deuxième essai suggère une méthode visant a analyser l'émergence de la diversité spatiale dans le développement de réseaux électriques intelligents, en combinant des concepts extraits de la littérature sur les Systèmes d'Innovation technologiques et l'analyse des réseaux sociaux. Le troisième essai propose une méthode basée sur la théorie des réseaux et la modélisation évolutive, afin d'identifier les principaux axes de développent de la connaissance dans les projets de développement de réseaux électriques intelligents.

Mots clefs: Transitions socio-techniques, approche complexe, System Dynamics, Agent Based Modeling, Analyse Réseaux sociaux, Smart Grids

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1 Introduction

1.1 General Scope of Research

1.1.1 Motivation

How should the costs of new technology deployment be allocated among beneficiaries in the energy transition process? How can policy makers balance short- and long-term consequences of implementing energy policies to incentivize all the actors to participate in the technology development process? What is the contribution of national policies and country-specific factors to the emergence of multi-national technological systems? How can policy interventions and internal dynamics of technology development lead to the relative dominance of some actors and technologies? Are there a few streams of knowledge that can summarize the major developments in the emergence of new technological systems?

The similarity of these questions is not in their domain, but the specific type and nature of the problems they are dealing with, and the methodologies needed to address them. These questions arise from a socio-technical approach to energy transitions or socio-technical energy transitions (Hughes, 1987; Ottens et al., 2006), and are related to the early years of development of this process. This is a period conceptualized in the multi-phase approach to transitions as the pre-development (Safarzynska et al., 2012) or the formative (Suurs et al., 2010) phase of the transition process.

Socio-technical systems are the systems in which social structures and institutions (such as norms, cultures and rules) are intertwined with technology (Ghorbani, 2013). Adapting a socio-technical perspective implies that a social network of actors and a technological network together form a complex adaptive system (Van Dam et al., 2012), a multi-actor network that determines the development and management of a technological system, which in turn influences the behavior of the actors. In this situation, actors can learn and respond to changes in their surrounding environment.

The concept of energy transition is a broad term referring to the dynamics of fundamental and long-term transformation in existing infrastructure and relationships (van den Bergh et al., 2011). A socio-technical transition refers to the interdependence and co-evolution of technological and social interactions, including changes in markets, actor practices, policies and cultural factors (Geels, 2004). This is a long-term and challenging process since incumbent energy systems are locked-in to their existing conditions due to sunk investments, technological infrastructures, current regulatory frameworks and established behavioral patterns (Unruh, 2000).

The concept of a multi-phase process in socio-technical transitions is often demonstrated by an S-curve, which depicts an ideal pattern of transition. It describes the transition process as occurring in four stages: pre-development, take-off, breakthrough and stabilization (Safarzynska et al., 2012; Rotmans et al., 2000). The pre-development phase is characterized by invisible changes and niche experimentation, and these experimentations shape innovative activities that reinforce each other in the take-off phase. Network and scale effects are the main mechanisms behind activities in the breakthrough phase, and when the system reaches a new dynamic equilibrium state, the transition enters the stabilization phase (Rotmans et al., 2000).

Interest in large-scale socio-technical transition to a sustainable energy system has recently increased. Recent literature has identified different systemic challenges as well as theoretical and practical issues arising over different phases of the energy transition process. These include conceptualizing structural transformations in the existing energy system (Chappin, 2012), deployment of interdependent technologies in different parts of the energy supply chain (Geels et al., 2008; Sandén and Azar, 2005; Rotmans et al., 2000), locking out of existing systems by overcoming resistance from incumbent actors, and changing social structures and practices along with technical developments (Safarzyńska et al., 2012).

Apart from addressing the socio-technical and multi-phase nature of transitions, these questions are relevant from a policy perspective. They all imply the necessity or the impact of policy interventions with long-term effects on actor behaviors and the emergence of collective outcomes. Furthermore, these questions are challenging since they are dealing with systems with many components and levels, involving different groups pursuing their own goals in an interactive environment.

In other words, socio-technical systems such as energy infrastructures are complex; heterogeneous actors and nonlinear relationships between them and with technological artefacts constitute these systems. It means policy interventions and other strategic decisions influence them in a multi-scale institutional context and create nonlinear dynamics. As a result, decision makers are faced with policy puzzles and scholars recommend the use of richly applicable technical tools and analytical methods (Rahmandad et al., 2015).

On the other hand, due to the complexity of these systems, the long period of analysis and data needed for a thorough analysis, the majority of studies on socio-technical energy transition has taken a backward-looking approach and tried to develop frameworks and tools for investigating different challenges through historical analysis of transitions (Verbong and Geels, 2007; Chappin, 2011). Nevertheless, analysis of the ongoing energy transitions and the challenges arising during these processes need to investigate the existing energy systems and the early developments in the transition process. Analyzing transitions from this perspective is different from taking a historical approach in terms of both problems and methodologies needed to address these problems. Unlocking the techno-institutional complex (Unruh and Del Rio, 2013) as the intertwined network of existing institutions and technologies, and dealing with resistance from incumbent actors are examples of systemic challenges that necessitate system analysis and policy intervention. Various systemic approaches to shape and influence the development of socio-technical systems have been proposed, from general systems theory to complex adaptive theory and simulation methods. These approaches have the potential to be used for analyzing the challenges and problems arising in the early stages of socio-technical transitions.

Recently, simulation models to investigate complex systems are increasingly becoming integrated to analyze problems in socio-technical systems and policy alternatives. These models are useful since they are able to grasp complexity and facilitate the understanding of non-linear relationships between different subsystems. In addition, they can be used to explain how system structure or interaction between individual behaviors may result in system-level or emergent outcomes. Policy design and model-based analysis are gaining more relevance due to the increasingly complex nature of the common challenges faced by firms and policy makers. This has created situations where human intuition often fails and simulation models are indispensable for decision making.

Advances in both social and engineering sciences have increased the applicability of simulation models for understanding and governing complex socio-technical systems. Furthermore, they provide insight into favorable and unfavorable outcomes from both social and technological perspectives. This is an important advantage especially for decisions and polices that cannot be easily tested in the actual setting, due to cost and social issues. In addition, these models are useful for analyzing the situations that do not exist or are not feasible in the real situation (Gilbert, 2004).

1.1.2 Research gaps

Apart from the application and usefulness of simulation models and the new scientific paradigm behind them, taking a complex system approach and using these models is still limited for analyzing the issues and dynamics of the early phases of the transition process. One reason is the lack of data, since for an ongoing energy transition the future energy system does not exist yet. Another reason is the inclination to distinguish the dynamics of unlocking the incumbent energy system from the structure and functionality of new energy system. This creates a methodological problem since in the early stage of transition feedback structures and nonlinearities between the components of the new energy system are widely missing; this creates a tendency to have a linear and simplistic view for analyzing ongoing energy transitions. However, in reality, any steering mechanism for the governance of ongoing transitions needs to unlock the incumbent energy system, which creates interdependencies and nonlinearities between the structure of the new system and dynamics of existing system. As a result, it confronts researchers with a complex system composed of interactions and nonlinearities for analyzing the early stage of socio-technical transitions.

This methodological gap highlights weaknesses in the conceptualization and operationalization of the issues arising in the early stage of transitions. In general, research on socio-technical energy transitions has a backward-looking approach to analyze the complete cycle of the transition process. The main reason is the availability of historical case studies and existing databases for problem formulation and theorizing the main dynamics of transitions. Early stage of transition is of special importance in a forward-looking approach for investigating ongoing or future transitions. Therefore, existing models and frameworks from transition research are hardly applicable for analyzing the issues and challenges arising in this period, including system lock-out, early lock-in or analyzing knowledge trajectories.

1.1.3 Research approach

The early phase in any socio-technical process is important, since any decision and activity can have substantial effects on the future state of the system and create path-dependent dynamics that are hardly reversible. As a result, understanding the dynamics and the effect of any system intervention in this phase is crucial. In this respect, this theoretical research takes a step forward in investigating the possibility of applying complex system approaches to improve methods for analyzing some of problems and issues arising in the early phase of the transition process.

To develop methods for investigating the patterns and resolving the issues in the early years of the socio-technical transition process, analysts need to understand the system dynamics and the nature of problems arising in this period. Currently, there are methods and models for analyzing dynamic problems and emerging issues in the transition process, from qualitative case studies to cost-benefit analysis and simulation models. However, there are various limitations in using the same approaches for analyzing socio-technical transitions in the early years of development. In this respect, the three essays in this dissertation focus on different theoretical problems arising in the early phase of socio-technical process from a complex system perspective, and propose new methods or enrich existing methods for responding to some of the questions already raised in the literature.

There are diverse sets of tools and methods for dynamic modeling and analysis of complex socio-technical systems. These methods are used for model formulation, estimation, analysis and decision support (Rahmandad et al., 2015). Therefore, the need for high-quality simulation models of socio-technical system dynamics is increasing. Furthermore, the use and supply of these models is constrained by the complexity of learning and skills needed for becoming a professional modeler, and the interdisciplinary knowledge required to apply such models.

For the governance of socio-technical transitions from a complex system perspective, understanding interdependent causalities between technologies, infrastructure and actors is crucial. In addition, understanding the dynamics or the rate and direction of innovations and their diffusion is critical for dealing with systemic problems such as lock-in (Unruh, 2000). By understanding these interdependencies and dynamics, governance principles can be designed to deal with the primary sources of policy failures and avoid overshoot dynamics such as early lock-in (Hekkert et al., 2005). There are different strands of research in the literature on socio-technical systems that have addressed issues and problems related to the early years of the transition process from different angles. Three strands of research that underlie the socio-technical foundation of this dissertation are briefly explained in §1.2.1.

Apart from the theoretical foundation, dynamic simulation models of complex socio-technical systems can be formulated based on different computational architectures. Taking different architectures into account may result in different modeling approaches such as differential equation-based modeling, agent-based modeling, or complex network approaches. Therefore, in §1.2.2 different computational approaches used in this research are briefly presented.

1.1.4 Research goals

Based on the research gaps and the research approach described in the previous sections, the primary objectives of this dissertation are the followings:

1. To demonstrate how a dynamic modeling approach is useful for conceptualizing the issues and challenges arising in the early stage of the transition process, by taking insights from complex system theory and combining ideas from related strands of research
2. To develop models and methodologies for investigating the system dynamics that underlie these challenges in the early stage of transitions, by using computational approaches for modeling complex socio-technical systems
3. To demonstrate how theoretical and practical solutions to these challenges can be obtained, by simulating early transition dynamics and empirical analysis, and how policy making can benefit from simulation results.

1.1.5 Scope

1.1.5.1 Scientific relevance

This is a multidisciplinary study aiming to improve methods of analyzing the dynamics of socio-technical transitions in the early stage of development, by using insights from complex systems theory. By analyzing the nature and dynamics of some theoretical issues arising in this period, concepts and theories from socio-technical systems literature are used to build models of complex energy systems. A formalization of these concepts and theories bridges the gap between socio-technical and computational foundations of analyzing energy transitions in the early stages of development, as conceptualizations derived from socio-technical literature would have computational representations that are useful in simulation models. This is of mutual benefit for research on both the theoretical and computational sides of socio-technical transitions; on the computational side, new issues and concepts from socio-technical systems literature can be captured in the artificial world, while scholars of socio-technical systems can use computational methods for addressing new problems and exploring more alternatives in their decision making process.

1.1.5.2 Context of research

Smart grid technologies and smart metering systems have been chosen as emerging socio-technical systems. Smart grid is a novel platform technology in the electricity sector in an early stage of development. In other words, although smart grid initiatives have moved beyond research and development projects, structural components are still in flux, which means smart grid technology is still in the early years of system development. It combines metering and control technologies with information and communication technologies to enable a variety of applications (Erlinghagen and Markard, 2012; Farhangi, 2010) including load management, demand response, dynamic electricity pricing, electric mobility charging or the integration of distributed and intermittent power generation, among others (Song and Yang, 2009).

Smart meters are part of the new metering system, which provide a bidirectional network of communication between suppliers and consumers. They are necessary to enable smart grid technologies and applications. They provide opportunities for actor participation through demand response programs, integration of new technological solutions such as distributed generation and large renewable energy sources to the smart grid (Siano, 2014). As a result, governments have started promoting the rolling out of Advanced Metering Infrastructure (AMI) and smart metering systems (McHenry, 2013)

For a successful energy transition, energy conservation and improvements in energy efficiency should reduce dependency to unsustainable energy sources; then, this reduced demand should be supplied by renewable energies. Smart grid includes interdependent technologies that enable different applications and contribute to solutions including decentralized power generation, integration of more efficient appliances and increasing the share of renewable energy sources. In addition, apart from the deployment of new technologies, smart grid incorporates behavioral and institutional changes such as consumer acceptance, prosumption as well as policy and regulatory changes; therefore, smart grid technologies contribute to socio-technical energy transitions.

1.1.5.3 Contributions

The contributions of this research can be classified in three areas:

Energy Transition Research – This research will add to research on energy transitions and complex socio-technical systems, by providing insights into the dynamics and challenges arising in the early stages of the transition process. Each of these three essays focuses on specific theoretical and practical questions and tries to improve the method for dealing with these questions. They further contribute to this line of research by combining ideas from complex systems perspective with concepts from socio-technical transition research to operationalize these problems in terms of dynamics and network interdependencies.

Modeling Socio-technical Transitions – This research contributes to the domain of modeling transitions by developing models and methods customized for investigating specific problems in the early stage of socio-technical transitions. The existing methods used by transition scholars have limitations for analyzing this period, due to lack of data and limited understanding of the dynamics in this phase as well as poor conceptualization of processes in terms of proper frameworks and models. By looking at several modeling approaches, this research tries to combine ideas from different perspectives to conceptualize and model specific theoretical questions. Therefore, it provides insight into the applicability of these modeling perspectives under different circumstances.

Policy Analysis – Finally, all of the essays in this dissertation have something to do with policy analysis in the context of socio-technical energy transitions. This research contributes to the policy analysis domain by presenting methods and models to improve the design and implementation of policies for resolving some of the issues arising in the early stages of socio-technical transitions. Furthermore, these methods are useful for analyzing the potential impact of policy interventions on future developments and creating undesirable side effects.

1.2 Theoretical Foundations

In the transition research, there are several theories and frameworks used to explain processes and dynamics of technological change in a complex system. To get an overall picture of the theoretical background underlying this research, it is difficult to find a single theory or framework from the socio-technical systems literature. Therefore, in this section, three primary strands of research are presented as the socio-technical foundation. These research lines are able to address theoretical issues arising in the early years of transitions and undergird the theoretical frameworks used in the three essays in the following chapters.

The frameworks and theories introduced in the socio-technical foundation are able to provide a conceptually comprehensive combination. Nevertheless, in order to develop model-based methods, some foundation on the computation side is also needed. Therefore, this section is followed by introducing the three computational approaches used in this research. Furthermore, complementary aspects of these modeling techniques for dealing with different socio-technical systems are briefly presented.

1.2.1 Socio-technical Systems Foundation

1.2.1.1 Technological Innovation Systems (TIS) approach

The Technological Innovation System (TIS) literature has considered the dynamics and mechanisms of success and failure for emerging energy technologies (Suurs et al., 2010). The premise is that for a new technology to develop successfully, it needs to be fostered by a network of actors, technologies and institutions, called a TIS, which embeds it. Actors, institutions and technologies are considered to be the structural factors and represent the static dimension of a TIS (Hekkert et al., 2007). Based on this approach, innovations gain momentum in a nonlinear process in which actors interact with a manifold of organizations and institutions. Such a complex process is characterized by feedback mechanisms and interactions (Freeman, 1988; Freeman and Soete, 1997; Lundvall, 2010; Nelson, 1993; Edquist, 1997).

The central link between the TIS framework and socio-technical transformation is that within the context of a TIS, emerging technological solutions are shaped and implemented. In the later phases of technology development, the TIS expands based on the growth of knowledge base, newcomers, network effects, and the emergence of supporting institutions (Hekkert et al., 2007). Furthermore, when a TIS develops, the rate of technological advances increases, which improves the possibility of technological success. In this respect, technological maturity and the TIS development can be considered as a case of co-evolution, since mutual influences shape a positive feedback structure.

This literature argues that a TIS does not come into existence overnight (Suurs et al., 2010) and the emerging technological systems enter a formative stage of development prior to being subjected to a market environment (Jacobsson and Bergek, 2004). This phase can be characterized by the fluidity of the emerging technologies, the weakness of surrounding institutional and technological structures, and the development of networks and institutions to make the technology fit with the surrounding structures (Jacobsson and Bergek, 2004). In addition, during this phase market diffusion is negligible or absent, while technologies and institutions are designed and adjusted (Suurs and Hekkert, 2009).

Apart from the advances in the TIS literature, our understanding of the dynamics and challenges arising during the early years of socio-technical changes is still very limited (Lundvall, 2008; Jacobsson and Bergek, 2004). This is a crucial problem since in the formative stage of system development the institutional factors are still expected to change (Collingridge, 1982, Suurs et al., 2010). As a result, the TIS literature is focused on actors, networks and institutions in this period (Dewald and Truffer, 2011). In addition, system functions such as knowledge development and diffusion or guiding the direction of research are more important for the performance of the TIS than other functions such as market formation during this period. However, the links between the development of technological solutions and the weight of each function or the contribution of functional interactions to system development is still unknown (Hekkert and Negro, 2009).

For a TIS to build up around an emerging technology, the key activities or system functions should be developed. The interaction between these activities creates reinforcing dynamics and accelerates the TIS development, a process called cumulative causation. This process can be understood as a trajectory of developments that includes the build-up process and increases the alignment between actors, institutions and technologies through creating virtuous (or vicious) cycles (Suurs et al., 2010, Hekkert et al., 2007; Jacobsson and Bergek, 2004; Bergek, 2002). Recent literature has tried to investigate the dynamics of interaction between different functions or sub-systems, and propose several forms of cumulative causation leading to virtuous cycles, called motors of innovation (Suurs and Hekkert, 2009a,b: Suurs, 2009), although in a qualitative way and by simplifying the patters of interaction and complex dynamics. For the formative stage of development, these interdependencies and motors are coupled with developments external to the TIS, such as policies, economic trends and technological developments. Although these external developments partially explain the TIS development (Suurs et al., 2010), they can determine its overall direction and influence future developments.

An innovation system approach is useful for analyzing system-level problems that limit the advancement and diffusion of innovations, as well as the conceptualization of the early stage of the transition process. Systemic problems are the interdependent sets of variables that hamper the development and deployment of new technological solutions. Taking a functional approach to transitions, a minimal base of knowledge regarding all subsystems is necessary for a successful transition. This is important since to build a new system knowledge of all the constituting parts is required (Hekkert et al., 2005). Furthermore, another important factor in the formative stage of TIS development is the existence of advocacy coalitions that lead to the legitimization of new institutions and activities. It means a process of change needs a community of actors that support the new system and lobby for the change process (Hekkert et al., 2005)

1.2.1.2 Evolutionary Theory approach

Transition science and evolutionary theory share several theoretical foundations and applications (Faber and Frenken, 2009). Since traditional neoclassical economics is not suitable for the analysis of system changes and transitions (Van den Bergh, 2007), especially for addressing the slow diffusion of renewable energy technologies (Negro et al., 2012), the evolutionary economics approach has been considered to be a valuable theoretical framework for analyzing innovations in system transitions. Evolutionary theory and thinking have been used in both complex systems theory and technological studies, and have contributed to understanding the emergence of new technological solutions and socio-technical transitions. They provide approaches and concepts for theorizing about transitions as multi-level, multi-phase, co-evolutionary and dynamic processes, and formalize them in evolutionary models. Evolutionary theorizing and policy analysis also combines theories of institutional analysis and innovation management to investigate the possibilities of escaping lock-in and preventing early lock-in of sub-optimal institutions and innovations.

Core mechanisms and elements in the evolutionary processes are diversity or variety generation, differential replication and selection, while path dependency, lock-in and co-evolutionary dynamics are complex patterns and structures that result from these mechanisms (Safarzynska et al., 2012). In evolutionary economics, these concepts are elaborated as innovation leading to diversity, progressive adaptations in the forms of competition, regulations or institutional changes that form selection mechanisms, and imitation as the main mechanism to replicate technologies and practices.

Innovation is the main mechanism for diversity generation in evolutionary theory. Accumulation of technical developments might be the primary systematic mechanism for the emergence of innovations (Safarzynska et al., 2012). It is shown as passing through technological paths, conceptualized as socio-technical regimes (Geels, 2002), innovation guideposts (Sahal, 1985), innovation paradigms (Dosi, 1982), and trajectories of knowledge (Nelson and Winter, 1977). Innovations are also considered to take the forms of recombination (van den Bergh, 2008; Fleming and Sorenson, 2001; Olsson and Frey, 2002) and evolution by modules (Baldwin and Clark, 2000; Langlois and Robertson, 1992).

Coevolution addresses a situation where two populations are interlinked and any change in one of them influences the trajectory of change in the other one (Kemp et al., 2007). Co-evolutionary dynamics underlie many socio-technical and socio-economic processes, describing the avalanches of innovation taking place as one innovation triggers the others through the concept of coupled fitness landscape (Kauffman, 1993; Caminati, 2006; Kauffman and Johnsen, 1991). For instance, individuals can copy others in network relations, and interactions change individual preferences or lead to the emergence of specific behaviors, which implies co-evolutionary dynamics between individuals and institutions. One important point for analyzing coevolution in transition research is that co-evolutionary dynamics imply diversity in two or more populations, subject to change due to the limitations as the selection mechanisms. Therefore, the transition process can be considered to be co-evolutionary if its subsystems consist of changing and heterogeneous populations (Safarzynska et al., 2012).

Applying an evolutionary theory approach to socio-technical energy transition research has led to proposing different pathways toward developing sustainable energy systems. The most prominent ones that have systemic views of the transformation process (Markard et al., 2012) are the multi-level perspective (MLP), technological innovation systems (TIS), transition management (TM) and strategic niche management (SNM) (Geels, 2002; Nill and Kemp, 2009; Loorbach and Rotmans, 2006; Carlsson and Stankiewicz, 1991; Moallemi et al., 2015). Therefore, evolutionary theory can be considered as part of the theoretical background of the TIS approach. Specifically, TIS makes use of evolutionary thinking to conceptualize the barriers and drivers of a socio-technical system transformation (Safarzynska et al., 2012).

In addition, evolutionary theory investigates the issues of increasing returns to adoption and network effect, related to some of the systemic problems in transitions such as lock-in (Arthur, 1989) and early lock-in (Hekkert et al., 2005). Internal diversity of innovative systems leads to a very low probability that the system can return to a previous state, shaping an irreversible and path dependent process (Van den Bergh, 2007). Path dependency of the selection processes may lead to reaching inefficient or unwanted equilibria, formalized as an early lock-in to inefficient technologies at the aggregate level. In other words, for the technological systems in the early years of development, diversity of the knowledge base may reduce the chance of heading for an inefficient and sub-optimal lock-in (Hekkert et al., 2005). The sequence of adopters in the competition between different innovations shapes the outcomes and creates a path-dependent process. Therefore, a small difference between the dominance of technologies in the early years can become reinforcing and lead to the irreversible lock-in of a system to a specific technology (Frenken et al., 2004); when this technology is sub-optimal, the problem begins. In the language of evolutionary theory, when increasing returns exist, fitness of a technology does not depend on only its intrinsic fitness, but also on its frequency in the population (Faber and Frenken, 2009). Therefore, an innovation with high intrinsic fitness but not enough adopters has difficulty to diffuse, although its adoption by market actors may provide benefits for all thorough network effects. In this case, the innovation system is locked-in to a sub-optimal solution. Such problems are strongly linked to the difficulty of transitioning to a new socio-technical system (van den Bergh et al., 2006; van den Bergh, 2007). They imply that in the early phases of development, chance events and historical accidents can heavily determine the characteristics of the system over a relatively long period of time. Early lock-in is less likely to happen when all actors in the system remain flexible in their technological choices and there is variety in the knowledge base (Hekkert et al., 2005).

1.2.1.3 Modeling Intervention in complex socio-technical systems

Complexity in socio-technical energy transition stems from nonlinear interactions between energy, economy and environment. It makes decision making a complex task and the formulation or evaluation of energy policies a dynamic challenge (Qudrat-Ullah, 2013). Therefore, this complexity has implications for influencing socio-technical system transitions and interventions by strategic decision makers (Chappin, 2011). Strategic decisions and tools for their implementation fail to solve the persistent problems arising in these systems, or they may even cause them. In this situation, efforts to manage and resolve complex problems create unwanted and unanticipated side effects, resulting in policy resistance or the tendency for system interventions to be reversed by system response to the intervention (Sterman, 2001).

In other words, policy resistance happens due to the mismatch between the dynamic complexity of the system under analysis, and the decision maker's cognitive ability to understand the dynamics. The result of poor understanding of the impact of decisions and impartial appreciation of complexity in the surrounding systems is the counter-effect of decisions on themselves in the long-run. It means for understanding the origin of system resistance, both the system complexity and the rationales behind decision-making need to be understood (Sterman, 2001).

Furthermore, there are deep uncertainties in the dynamics of energy supply and demand, energy prices, institutional environment and technological advancements (Agusdinata, 2008). One solution to these challenges is taking a systems approach, meaning the ability to see the surrounding environment as a complex system (Sterman, 2001), and try to identify the most critical tipping points in the system with a holistic approach to avoid policy resistance. Following this line of argumentation, scenario and model based analysis in policy design and implementation as tools for analyzing complex systems have become useful and applicable in the recent literature. However, successful intervention in complex socio-technical systems needs more than simulation models or analytical methods.

In a complex socio-technical system, governance mechanisms imply feedback structures that influence and steer interactions of actors and self-organizing communities. Difference between the goals and existing variables in a complex system justifies the necessity of intervening actions. These actions can be limited by dominant structures creating undesirable paths of system development (Ulli-Beer, 2013). In this situation, strategic interventions or steering mechanisms create governance dynamics that include activities of different actors affecting the emergent outcomes of the transition process.

Governance through policy intervention in socio-technical energy systems has a relatively long time span, during which system structure changes (Chappin, 2011). In this situation, deep uncertainty prevents researchers to determine the 'optimal' design. In other words, the notion of optimal design in complex systems is useless and these systems can be improved and developed by steering the path of development over a long period. As a result, intervention in complex systems aims to shape them toward a desired evolutionary direction while they are evolving (Chappin, 2011).

Some characteristics of policy implementation such as policy resistance, the experimentation costs, the required coordination between diverse actors and the necessity for an endogenous view calls for dynamic modeling approaches (Ghaffarzadegan et al., 2011). Modeling complex systems tries to simulate how a system may change over time and in the context of energy transition, allows different possibilities such as investigating the possibility of using policy instruments including policies for network formation, pricing policies, environmental taxes and information provision (Safarzynska et al., 2012). In practice, a variety of perspectives are necessary to grasp the complexity of these systems (Nikolic, 2009), using a variety of modeling paradigms (Yücel, 2010).

1.2.1.4 Complementary aspects of the socio-technical foundations

In this section, some of the complementary aspects and conceptual relationships between the socio-technical foundations are discussed. System failure is a new rational based on the TIS approach for policy intervention addressing some of the issues provided by evolutionary dynamics. Some of these system failures mentioned in the literature include infrastructural failures as the lack of physical or knowledge infrastructure (Smith, 2000; Edquist et al., 1998), transition failures as the actors' inability to follow innovative advancements (Smith, 1997), path dependency or lock-in failures as the lack of adaptation to new technological paradigms (Smith, 2000), institutional failures including hard and soft ones, as failures in the frameworks of regulations, political culture and social values (Johnson and Gregersen, 1994; Carlsson and Jacobsson, 1997), network failures as the blindness to see outside developments due to very strong or lack of linkages between actors (Malerba and Orsenigo, 1997; Carlsson and Jacobsson, 1997), and capability failure as the lack of firms' capabilities to learn effectively and rapidly (Smith, 1999; Malerba and Orsenigo, 1997).

Another link between the TIS approach and policy analysis comes from interactions between TIS system functions. As mentioned, functional interaction can lead to the emergence of vicious or virtuous cycles (Jackobsson and Bergek, 2004). These feedback structures reinforce each other and lead to the growth of the technological system. Since the vicious cycles can hinder the innovation system growth, from a policy perspective these interaction patterns should be comprehended, and then policy makers may understand system development and formulate policies to accelerate such developments.

In the literature of systems of innovation, the concepts of path-dependence, positive feedbacks and cumulative causation are important for understanding technological transformations and long term socio-technical changes (Carlsson and Jacobsson, 1997; Carlsson and Stankiewicz, 1991; Lundvall, 2010). In this approach, lock-in and path dependency have a central place and are formulated as the results of systemic failures (Woolthuis et al., 2005). Lock-in is a complex composition of causes that verifies the technological interdependencies and its institutional environment. In this respect, a TIS-based technology policy should be reconfigured as a process of investigating the sources of lock-in and eliminating them in order to foster innovation at the firm and system levels. Thus, this approach can be considered as an instrument for evaluating the deployed policy programs.

Furthermore, looking at a multi-phase transition in the context of path-dependent processes (network effects, lock-in, early lock-in) underlines the role of policy intervention in complex socio-technical systems. Apart from linking the formative stage in the TIS approach to the evolutionary theory perspective, the concept of multi-phase transition also highlights the importance of the timing of system intervention for steering transition. The effectiveness of the adoption of an innovation might depend on the strength of lock-in and path dependency of incumbent processes, which vary over different phases of development. As a result, unlocking the energy system calls for the right timing of policy intervention (Foray, 1997; Faber and Frenken, 2009), along with other important factors such as the choice of policy instruments and creating new network externalities (Zeppini and van den Bergh, 2011).

It has been argued that un-locking policies are more effective in the early stages of socio-technical transition (Safarzynska et al., 2012). Furthermore, when the incumbent technology is in full development and there are a few niche markets, policy intervention may have negligible effects. Its effect may increase by increasing niche markets and slowing down the development of existing system. The importance of the timing of policy intervention has been reflected in the concept of 'windows of opportunity' to address the right time for political action aimed at stimulating sustainable technologies (Sartorius and Zundel, 2005). This concept is conceptually similar to what evolutionary theory calls systemic tipping points (Faber and Frenken, 2009), meaning the critical values under different circumstances that create opportunities for system intervention.

Another concern in policy-oriented research on socio-technical transition is to avoid a new lock-in to suboptimal technological solutions (David, 1985; Cowan and Gunby, 1996; Cowan, 1990; Cowan and Hultén, 1996). Given the uncertainty of environmental conditions and future developments, it cannot be fully understood when a lock-in is optimal (Van Den Bergh, 2007). Efforts for un-locking the incumbent technological system may favor the development of some technologies, even if it is not the policy objective. To avoid such an early lock-in, the preservation of technological diversity is a useful policy goal, even though a few systemic methodologies have been developed to assess the value of diversity in socio-technical systems (Stirling, 2007; Van Den Bergh, 2008). Preserving a portfolio of technologies helps to foster a wide range of technological developments for a longer period and gaining information about the characteristics and costs of different alternatives. These policies are clearly juxtaposed to the regular policy theme of efficiency (Van Den Bergh, 2007).

Finally, another insight from the evolutionary theory for policy making in the case of uncertain technological development comes from preservation of flexibility in the path of technology developments. For instance, technology options can be described as specific combinations of subsystems, and transition paths are conceptualized as the sequence of changes in these subsystems steering a transition from the incumbent system to a new one (Schwoon et al., 2006; Levinthal, 1997). This path can be understood as a sequence of mutations in subsystems, where each of them gradually improves the fitness of the overall system. Such an approach also depicts how advancement might be achieved in different ways without eliminating other possible developments in multiple trajectories that might be promising in the later stages of development.

1.2.2 Computational Foundations

1.2.2.1 System Dynamics Modeling (SDM)

Differential Equation (DE) models are a class of models that assume homogeneity and complete mix in all parts of the system. For policy analysis, these models take a deterministic approach and lead to a unique trajectory for each of the model variables. System Dynamics Modeling (SDM) is the dominant architecture of DE models (Rahmandad et al., 2015) that addresses dynamic problems arising in complex systems (Rahmandad and Sterman, 2008) and models nonlinear relationships. Any dynamic system includes interdependencies, circular causality, information feedback and mutual interaction. The concept of endogenous change matters, which focuses internally on the system level characteristics that lead to the generation or reinforcement of the perceived problem. In addition, it points to external factors as the parameters triggering system behavior emerging internally within the existing system structure.

The approach starts with defining problems in a dynamic way, by describing how they evolve and propagate over time, and then by mapping and modeling different stages. The primary application of this method is to comprehend the dynamics of complex systems in order to design and analyze policies. For this purpose, it uses tools and concepts such as causal loop structures, stocks and flows, dominance of feedback loops and takes a viewpoint internal to the system structure.

The feedback concept is at the center of this approach. Feedback structures in the forms of overlapping loops and circular causality constitute the conceptualization of a dynamic system structure. There is a feedback loop when the output resulting from some activities moves through a system and gradually comes back to its starting point, potentially influencing future action (Sterman, 2001). Using feedback loops enables the possibility of an endogenous view to the system structure.

Apart from the concepts of feedback structure and circular causality, the notions of active structure and loop dominance are crucial for understanding the dynamics of a complex system. Based on these notions and by taking a feedback approach, the interaction of nonlinear relationships shifts the loop dominance and addresses the change in the dynamics observed in reality, as the fundamental rationale for considering nonlinear patterns of socio-technical system dynamics.

The system dynamics approach emphasizes a continuous view looking beyond instances to capture the system archetypes or patterns behind them. It can simply encompass a diverse set of feedback structures, and generally aggregates actors into a few number of states. In this situation, perfect mixing within compartments means actors are assumed to be homogeneous and order of entry does not matter within each state variable.

In the context of socio-technical energy transition, system dynamics approach has been used to analyze national energy policies (Davidsen et al., 1990; Bun and Larsen, 1992; Qudrat-Ullah and BaekSeo, 2010), uncertainty in energy investments (Bun and Larsen, 1992), energy conservation and its related policies (Ford and Bull, 1989), energy efficiency analysis (Assili et al., 2008; Pereira and Saraiva, 2011) and policies for demand side programs (Ansari and Seifi, 2012).

From a policy perspective, system dynamics approach has a long tradition to address policy questions (Forrester, 1969; Forrester, 1971; Meadows et al., 2014) including energy policy (Fiddaman, 1997, 2002; Sterman, 2008; Ford, 1997, 2005) and sustainable development (Mashayekhi, 1998; Honghang et al., 1998; Saeed, 1998). System dynamics models have the strength to capture substantial dynamics and counterintuitive results for connecting behavior to the dominant feedback loops without ignoring the necessity of comprehensibility for strategic decision makers to understand and communicate the model structure and dynamics.

1.2.2.2 Social Network Analysis (SNA)

Social networks are prevalent in social and economic lives. They are important from a practical point of view to analyze how their structures affect individual behaviors and which structures are likely to emerge in a social or economic system. In this respect, social network analysis provides an outline of the structure of a social phenomenon linked to structural theories of action (Scott, 2012). Therefore, network structure has an important role here that addresses the reason this research distinguished between modeling social networks and other individual-based models (especially agent-based models).

Measures of network characteristics can provide a basis for studying system structure in terms of patterns of interaction (Streeter and Gillespie, 1992), centrality of specific nodes, homophily and community detection, among others. Interactions between system components and within a network are behind lots of dynamics of real social networks observed in reality (Homvand and Pitner, 2014, Reggiani et al., 2001). Centrality is another measure for identification of important nodes. It is a relational measure, meaning a node central in a network, can be peripheral in a larger or structurally different network. In addition, there are different measures for centrality (including degree, betweenness, decay, closeness or eigenvector centralities) that might lead to different results; and the choice of proper measure depends on the purpose of the network, meaning of the links and the problem to be addressed (Jackson, 2008).

Homophily refers to the degree that members of similar types prefer to interact among each other. The reason for this phenomenon in social systems can be attributed to opportunities or contact theory, relative benefits and costs, social pressure and social competition (Jackson, 2010). Finding communities is another important aspect in analyzing the structure of complex social networks. Communities are special sub-networks distinguished from rest of the network by intense interaction between their nodes, or higher density compared to the whole network.

Examining the structure of a complex social network is a formidable task regarding how to define and measure interactions. In addition, networks change over time and overlap in different ways, plus the fact that much of the information about the structure of these networks comes from limited measurements of links or secondary data interpreted as network measures. Since there are biases and idiosyncrasies associated with datasets and measurements, it is a cumbersome task to systematically determine specific characteristics across ranges of socio-technical settings (Newman, 2003; Watts, 1999).

Apart from the underlying network structure, that shapes the static aspect of network analysis, network dynamics and processes are of crucial importance, especially in growing networks. Issues such as diffusion over networks, complex contagion and thresholds, collective action and innovation through networks or learning by imitation are among the problems addressed as the processes in complex networks (Jackson, 2008).

Models of network growth are used to investigate the dynamics of network expansion, and two most prevalent models are the models of random network growth and preferential attachment growth. In the model of growing random network, it is assumed that every new node can be attached to every existing node with the equal probability. These models, including famous Erdős–Rényi and small world models, are used as benchmarks to analyze the degree of randomness in real growing social networks.

On the other hand, models of preferential attachment follow a power law or scale-free distribution, which are highly skewed and have a heavy tail. In these models, new nodes prefer to attach to nodes with many connections; therefore, they have a preferential attachment that causes cumulative advantage for hubs or nodes with lots of connections. Analyzing growing networks is also important for studying network structure, since the structure of a growing network is not necessarily fixed. Therefore, all the measures for investigating network structure, including centrality, clustering and community detection are affected.

1.2.2.3 Agent-based Modeling (ABM)

Agent-based modeling is an approach from the family of evolutionary modeling techniques (Safarzynska et al., 2012; Safarzynska and van den Bergh, 2008) for the simulation of social and adaptive systems, with a pertinent degree of complexity and dynamics (Luck et al., 2003). By focusing on a target phenomenon, this method considers the phenomenon as an aggregate property or outcome and assesses the impact of individual behaviors and interactions on this system-level outcome (Conte et al., 2001). The main distinguishing factor that sets agent-based models apart from other models of complex systems, especially System Dynamics models, is their focus on modeling actors or individuals who make decisions (Van Dam, 2009). Agents are computational entities in an environment, which can undertake some independent actions with the goal of satisfying their objectives (Wooldridge et al., 1999). Their interaction is characterized by increasing returns as well as feedback mechanisms (Safarzynska et al., 2012).

Agent-based models are proper means to model complex systems, when the problem has a distributed character and actors are autonomous to some extent, the subsystems operate in a highly dynamic setting, and subsystem interaction is characterized by flexibility (Van Dam, 2009). In addition, due to their bottom-up nature, agent-based models are suitable for modeling dynamic problems where system structure may change during the simulation time, or where strategic decision makers should do experiments with different configurations (Van Dam et al., 2012).

In this respect, one of the main applications of ABM is analyzing complex social systems to support policy or management decisions by providing rigorous explanations for observed patterns and phenomena (Moss, 2002; Luck et al., 2003). These models allow nonlinear relationships between a large group of independent and heterogeneous actors. Therefore, in contrast to SDM, ABMs are able to grasp the heterogeneity of individual characteristics and the network structure behind their communications; thus, they relax aggregation assumptions of DE models. In terms of model behavior, these models can be both deterministic and stochastic, capture feedback effects and in the stochastic model yield a distribution of outcomes.

In the context of socio-technical transition, these models allow researchers to observe the coevolution of social and technical communities, and the emergence of aggregate system behavior. Agent-based models can be used for ex-ante assessment of transition policy alternatives (Chappin and Dijkema, 2010). In this respect, the introduction of agent-based models has enabled the existing modeling approaches of large technical systems to be extended by incorporating the population and at the most detailed level, and embedding environment on an individual-by-individual basis (Vespignani, 2012).

Due to its applicability for modeling socio-technical transitions, this method has been used to explore issues such as designing scenarios for managing transitions (Frenken and Faber, 2009), formulating agency problem in socio-technical transitions (Vasileidaou and Safarzynska, 2010), community-based allocation and coordination in energy distribution (Dechesne et al., 2015), structuring complexity of socio-technical transitions (Nikolic and Ghorbani, 2011), institutional analysis in modeling socio-technical transitions (Ghorbani et al., 2010), impacts of policy intervention on transition in consumer lighting (Chappin and Afmen, 2013), analyzing the impact of policies on the emergence of innovation niches (Lopolito et al., 2013) and analyzing actor interactions in transition in biogas infrastructure in the Netherlands (Verhoog et al., 2013).

Furthermore, this method has been integrated into different methods and frameworks of transition; for instance, Ghorbani (2013) has developed a meta-model called MAIA, to integrate higher-level institutions into the agent-based models of socio-technical transitions. Or Schilperoord et al. (2008) have defined agents at different levels and built an agent-based model of societal transition based on the MLP framework (Geels, 2002) by defining niches and regimes as collective agents.

1.2.2.4 Complementary aspects of the computational foundations

Each of the computational methods has its own strengths and weaknesses; and the applicability of each of them depends on the level of aggregation needed in the model as well as research assumptions. More importantly, choice of the right method for addressing a problem depend on the purpose of analysis. For instance, when different models lead to different inferences for policy making, it is necessary to analyze the assumptions, compare the models and choose the most relevant one for the research question at hand.

As mentioned, one difference between DE models and ABMs is that for given parameters, the stochastic individual-based models generate a distribution of outputs, while the deterministic SDMs generate one path or output depicting the main series of outcomes under the mean field approximation (Rahmandad and Sterman, 2008). Another important distinction from a technical viewpoint is the efficiency and computation costs of different modeling approaches. While System Dynamics models are computationally efficient by assuming homogeneity and perfect mixing, individual-based models, Agent-based and Social Network models, have more computational requirements, which can limit sensitivity analysis (Rahmandad and Sterman, 2008). However, they are able to capture the interaction networks among individuals and the heterogeneity of actor attributes.

DE models including SDMs are proper tools to models the dynamics of interaction and feedback structures between system level variables. When individual heterogeneities are not important, SDM can analyze the impact of system structure and dynamics on the average individual behaviors. More importantly, by focusing on the system structure in a top-down approach, SDM presents generic behavioral structures or system archetypes (Wolstenholme, 2003) able to explain a variety of dynamic problems in the real world.

On the other hand, individual-based models help researchers to investigate problems not conveniently modeled by DE models, such as the simulation of random failures in risk analysis and targeted attacks, a problem normally addressed in analyzing preferential attachment networks and robustness analysis. In addition, individual-based models can show the link between individual-level interactions and the aggregate behaviors at the system, a concept called emergence in both social and biological systems (Johnson, 2002)

In practice, ABMs can incorporate social network models as well. Indeed, agents in agent-based modeling may represent actors or nodes in social network analysis. The main distinction made here is the focus of modeling different phenomena and the necessity of including network structure. While SNA focuses on network structure and its impact on node characteristics, ABMs focus on aggregate or emergent system properties that cannot be easily attributed to actor-level characteristics. Of course, SNA also deals with emergent properties such as the emergence of communities in growing networks, and ABMs can be used to measure network characteristics and analyze individual-level feedback structures that shape emergent system properties.

An in-depth analysis of the differences between differential equation models and individual-based models is beyond the scope of this research. More detailed analysis can be found in Axtell et al. (1996), Edwards et al. (2003), Jacquez and O'Neill (1991) and Rahmandad and Sterman (2008) among the others.

1.3 Research Outline

The rest of this manuscript consists of three essays and one concluding chapter. Following the multi-phase approach to transitions (Rotmans et al., 2000), this dissertation fits to the pre-development phase of socio-technical energy transitions. Each essay uses insights from part of the socio-technical foundation and applies method(s) from the computational foundation to develop a method for analyzing one of the challenges in the early stages of socio-technical energy transition. Figure 1 summarizes the links between the essays and both socio-technical and computational foundations.

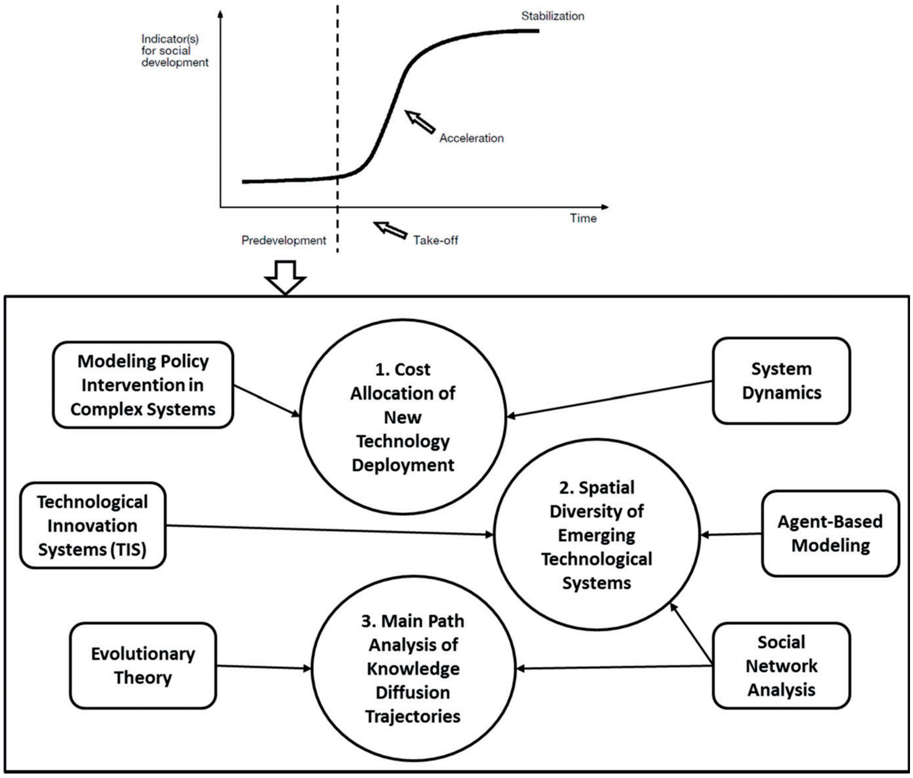


Figure 1-1. Link between three essays and theoretical foundations (The S-shape curve adopted from Rotmans et al. (2001))

The first essay (chapter 2) takes insights from modeling system intervention in complex socio-technical systems and applies the System Dynamics method to address the cost allocation problem of new energy technologies. By focusing on the case of smart metering deployment at the European Union level, the model starts from building a model of cost allocation based on the main variables used in cost-benefit analysis (CBA) approach. CBA is the approach currently used to deal with the cost allocation problem. Then, it investigates the dynamics of interaction between different beneficiaries and the impact of introducing new pricing policies.

This essay highlights the importance of taking a dynamic approach to resolve one issue with the CBA method. It is the problem of balancing short-term and long-term benefits and costs of new technology implementation to motivate all actor groups to participate in the technology deployment process. It means an efficient cost allocation depends not only on the costs and on the benefits for each actor, but also on the interdependencies between the behavior of different actor groups and the consequences over time.

Furthermore, by focusing on feedback structures shaping actor behaviors, the system dynamics approach opens the possibility of including other actor groups not directly involved in the implementation process, but their involvement helps defining more innovative strategies for a more efficient cost allocation process. As a result, three innovative solutions are proposed in the form of business and policy scenarios to incorporate secondary feedback structures. The results may explain why reluctance to participate in the technology deployment process persists even after introducing dynamic pricing policies, and what factors are more critical in analyzing the cost and benefit structures of the technology deployment.

The second essay (chapter 3) uses the Technological Innovation System (TIS) approach as the theoretical framework and takes a network perspective to develop a method for investigating the spatial diffusion of developing new energy technologies. Analyzing networks potentially allows investigating the spatial extent and structure of technological innovation systems. This essay follows the network perspective to spatial analysis of TIS development proposed by Binz et al. (2014) and takes one step further by analyzing the diversity and heterogeneity of spatial patterns emerging in network communities over time. This essay argues these spatial patterns and diverse configurations can be understood as emergent properties arising from country-level differences.

Interaction of innovative firms from different countries leads to the emergence of communities with different spatial diversity. Countries with preferences towards participation in national versus international activities, or with preferences to interact with firms from several counties contribute to the diversity of emerging network communities. In this respect, micro-behavior at the country-level leads to spatial diversity of communities at the system level. To detect these communities and measure their spatial diversity, this essay develops a model of social network analysis and takes insights from institutional analysis and complex system theory. By implementing the model to the case of smart grid development in Europe, it analyzes the emergence of different network communities over time with specific spatial characteristics and highlights the relative dominance of some countries over the others.

Then, to further investigate the importance of national characteristics for the emergence of spatial diversity, a simple agent-based model is build. This model tries to analyze the contribution of including typical counties with different preferences towards involvement in national and international activities, as well as interaction with several countries to the emergence of communities with different spatial diversity. The results confirm to understand the spatial diffusion of technologies, focusing on the relative weight of national and international activities is not enough. In other words, interactions between firms from countries with different spatial characteristics lead to the emergence of communities with different spatial patterns, forming a heterogeneous network at the system level.

The third essay (chapter 4) takes insights from evolutionary theory and builds a model of social network analysis to investigate the main streams of knowledge in an emerging technological system. While the literature focuses on the results of innovative activities, such as patents and publications, to identify the main path, for the early stages of innovation development these measures are absent or incomplete. Therefore, this essay takes an ex-ante approach to innovations and uses a cumulative network of innovative projects to identify the main path and trajectories of knowledge development.

First, by using ideas from complex network theory, this essay builds a hybrid model of random and preferential attachment networks to justify the existence of a main path. The primary idea is that to the extent a network is closer to a preferential attachment model, new nodes prefer to attach to the existing nodes, verifying the existence of a main path. Then, a revised version of the Clique Percolation Method (CPM) for analyzing overlapping communities is combined with measures from evolutionary theory to calculate the effective network diversity, as a proxy for the number of knowledge diffusion trajectories. Finally, the central projects and the main activities in the main path and each trajectory are described.

Implementing this method to the case of innovative smart grid projects in Europe proves the existence of one main path and four trajectories shaping around different technological applications. The results support the applicability of this method for investigating the cumulative network of projects to analyze the main streams of knowledge in an emerging technological system.

2 Scenario-based System Dynamic Modeling for the Cost Allocation of New Energy Technology Deployment: The Case of Smart Metering Roll-out

Keywords: System Dynamics, Smart Metering Roll-out, Cost Allocation, Dynamic Pricing Policy, Technology Deployment

2.1 Introduction

Socio-technical energy transition needs transformation in all the components of the energy system, including the transformation of the electricity supply chain (Meadowcroft, 2009). Although unbundling of the electricity system has already initiated the transformation, it has contributed to the increasing complexity of the system (Kröger, 2008) as well. In order for this transformation to be continued, improvements in the efficiency of the existing system should be facilitated, through the participation of all the actors involved in the supply chain, and introducing new technologies to contribute to energy conservation, efficiency and assure further innovative developments. However, insufficient government incentives, high investment costs and lack of information on energy usage are the common barriers to reach these goals (European Union, 2014a). Smart grid is a new pioneering solution to address these issues, and smart meters are the necessary requirements of the future grid. These new technologies provide opportunities for actor participation through demand response programs, integration of new technological solutions such as distributed generation and large renewable energy sources to the smart grid (Siano, 2014). As a result, governments have started promoting the rolling out of Advanced Metering Infrastructure (AMI) and smart metering systems (McHenry, 2013)

Smart meters add several short- and long-term advantages to the energy system, which can be exploited by different actor groups. Retailers can reduce the risk of varying market prices by using dynamic pricing strategies (Andrey and Haurie, 2013; Faruqui et al., 2012) and shifting peak demand (Faruqui and Sergici, 2010). Distribution System Operators (DSOs) can benefit from reduced operating costs, reduced peak load, better network optimization and the integration of new energy efficiency solutions in long-term (Ecorys, 2014). Consumers can benefit from shifting on-peak load as a result of dynamic pricing and increased awareness in order to reduce electricity bills, as well as the integration of energy efficient technologies and distributed generation technologies in long-term (MacDonald, 2007).

However, smart metering roll-out is a capital-intensive business and needs a risky and long-term investment. Investors are uncertain about the profitability of new technologies; therefore, there is a resistance from investors in the supply side to deploy smart meters since the cost recovery is not assured. On the other hand, any unjustified increase in electricity price leads to consumer dissatisfaction. Therefore, it calls for the need to policy intervention in order to encourage them to participate in the deployment process and benefit from the potential applications (European Union, 2014b).

Another challenge deals with the complexity of coordinating data exchange between the smart meters and relevant actors in a liberalized market (Strüker et al., 2014), a situation did not exist prior to the deployment of smart meters. In a deregulated market, huge data volume should be gathered every day, including consumption data, pricing updates, use of demand response programs, switching between retailers, etc. (Alahakoon and Yu, 2013). All the actors in the value chain need the information gathered by smart meters to make their operation more efficient and benefit from the potential applications. At the same time, utility companies do not have the required capabilities to meet these requirements; therefore, coping with the huge amount of data and compiling the information to be used in other services is a challenging task requiring a proper communication infrastructure (Strüker et al., 2014).

These challenges explain why allocating the costs of smart metering roll-out between involved actors is a complex task that needs to incorporate the preferences of all relevant actors. There are trade-offs between the costs and benefits of different actor groups, each motivated by their own incentives. As a result, there are conflicts of interest between these actor groups; for instance, between energy conservation and decreasing revenue for supplier, while the interaction between these actors is important for the success of the deployment process. On the other hand, some of the outcomes, if properly designed, can lead to cooperative interests. For instance, more efficient retail market mechanisms reduce the risk of demand fluctuation for retailer and provide saving opportunities for consumers, or increased distribution network efficiency decreases network tariff for consumers and technical losses for DSO. Therefore, when a systemic solution able to include the costs and benefits of all the actor groups is lacking, technology acceptance and actor participation by all the groups is very unlikely, since the investment costs are high and there are uncertainties about the future of this technology.

Since the benefits of smart metering roll-out in the short and long term are distributed between different actor groups, the costs incurred by its deployment should be allocated proportional to the distributed benefits. This highlights the need to a technical framework set up with clear responsibilities for the market participants (ICER, 2012). In this respect, this study takes the first steps toward investigating the dynamics of interaction between the benefits and costs of all the relevant actors by taking a systems perspective for an efficient cost allocation of smart metering roll-out.

2.2 Cost-Benefit Analysis of Smart Metering Roll-out

In an unbundled electricity network, where operation, generation and trading activities are separated, assets may belong to different actors. For the case of smart metering deployment, especially in Europe, DSOs are owners or renters of metering equipment (van den Oosterkamp et al., 2014). DSOs are also authorized to use the data available for the planning of the network or providing it to the other asset owners. In this context, the majority of the metering markets are regulated and network tariffs and DSO resources provide the required investment (European Union, 2014a). However, the critical factor for analyzing the functionality of smart metering system is to assure the benefit for all the relevant actors including the end-users, network operators and retailers, along with wider benefits for the society are included in the analysis (Giordano et al., 2012). These social benefits can be in the forms of increased market competition, enabling the integration of future technologies and exploiting business benefits through new products and services.

Prior to the deployment of smart meters, doing a Cost-Benefit Analysis (CBA) is a common approach, to investigate the relative weight of potential benefits and costs. In Europe, developing a methodology for economic assessment of smart metering roll-out is one of the main aspects of the European Commission (EC) recommendations to the

Member States[1] (European Union, 2014a). However, the dominant approach towards analyzing the cost allocation process is the economic approach (Giordano et al., 2012) that takes input data and model parameters along with deployment speed, penetration ratios and communication structure as the main scenarios and analyzes critical variables and the main benefits and costs for the beneficiaries (European Union, 2014a). In most of the countries where smart meters have been introduced, the cost recovery is based on regulated network tariffs or consumer bills (ICER, 2012; AEA, 2012) and the results show variation between the Member States, from decision on full and partial roll-out to pending decision for implementation (KEMA, 2010; Atkearney 2010; CER, 2011).

The methodology used in these studies looks for the long-term assessment of costs and benefits for investor and the actors responsible to pay back for the investments. Main costs as metering costs composed of capital and operational expenditures (CAPEX and OPEX) and data communication costs are attributed to DSO, passed to customer bills fully or partially through network tariffs. As a result, total benefits and costs of the DSO, consumer benefits resulted by energy savings and load shifting have central positions in the CBA, and these actor groups are normally involved in calculations. Even, there are CBAs that only focus on the DSOs and assume the benefits for the consumers are only the side effects of technology deployment. One possible explanation is that estimation of the benefits for these actors, as meter reading costs and non-technical losses are easier than for the other beneficiaries (McHenry, 2013).

An important fact in the deployment process is that, the smart metering infrastructures does not provide the benefits per se, but the proper usage of this infrastructure (Depuru et al., 2011). Therefore, there is the possibility of including a variety of options to exploit smart metering benefits by including other relevant actor groups, policy portfolios and more elaborated consumer-engagement mechanisms to reach this goal.

However, a few recent papers and reports have addressed these possibilities, although without elaborating on their operationalization. The report by the EU (European Union, 2014b) addresses the possibility of introducing innovative services (for instance home energy management and demand response programs tailored to

[1] EC Recommendation 2012/148/EU

consumers' needs) by using new business models and information retrieved from smart meters. Retailers can also use this information to provide customized services in a liberalized and competitive electricity market.

Addressing the complexity of data exchange in a liberalized market, Strüker et al. (2011) propose a non-regulated data exchange may bring new business opportunities by outsourcing IT tasks such as meter communications to more competent actors such as central communication providers that already have access to an appropriate infrastructure. Based on insights from Information System Theory, they conclude efficiency and cost advantages of these intermediaries can lead to resource savings for the system. In this situation, higher upfront costs for huge data centers increase the attractiveness of the intermediary role (Rangan, 2008; Siegele, 2008). These possibilities also address the lack of including other beneficiaries such as retailers in CBA approach. Since these actors have a mediatory role between DSOs and consumers, their behavior cannot be taken as independent from the behavior of these actor groups.

This paper takes this line of research and attempts to investigate the link between policy and business sides of smart metering roll-out, and to provide a systemic view on cost allocation as a dynamic problem. It aims to investigate how the cost allocation can be organized between all the parties involved in an unbundled electricity supply chain and the incentive should be provided to motivate the actors to make the best use of smart metering benefits. This problem is complex and needs a systemic approach to incorporate all the nonlinear relationships. Such an analysis can justify the necessity of policy interventions and the way they could bring numerous advantages for retailers, DSOs and consumers when analyzed at the system level. Therefore, this paper asks the following questions: How does a dynamic modeling approach contribute to the efficient cost-allocation of new energy technologies? What are the added benefits of dynamic modeling to the CBA method? How do the pricing policies influence the cost allocation process? How can different business and policy scenarios shape a coordinated strategy for the cost allocation problem? Finally, how do firm characteristics and contextual factors change the relative importance of different scenarios?

Two features characterize the contributions of this research. First, the literature on the cost allocation process is inclined to focus on DSOs and consumers as the main actors relevant for CBA. This approach not only neglects other actors directly influenced by smart meter roll-out (such as retailers), but also does not take into account the possibility of investigating the role of other actors to contribute to more innovative solutions and more efficient cost allocation. Second, this study addresses the endogenous dynamics of interactions in different conditions necessary to balance the short-term and long-term consequences of different policy and business scenarios. Furthermore, including different actor groups and their interactions over time, opens up the possibility of designing innovative and hypothetical scenarios for more efficient cost allocation.

Considering the dynamics of interaction between actor groups and the impact of system interventions refocuses analyses on non-equilibrium dynamics in the system and, given the added complexity, calls for using simulation models. System dynamics modeling is a powerful approach as a member of differential equation models to investigate dynamic problems in systems with interactions in the forms of causal loop diagrams (CLD) and feedback loop structures (Sterman, 2001). In this study, each actor group is modeled as a bundle of its costs and benefits, and the conflicts of interest under different scenarios are investigated. Detailed analysis provides testable propositions regarding the costs and benefits of actor groups across different scenarios with different circumstances.

Simple representations of cost and benefit structure for each actor group are required for modeling the dynamics of interaction between these groups upon introducing smart meters and dynamic pricing policies. Therefore, the basic cost structures for all the relevant actor groups are presented in §2.3, followed by analyzing the interdependencies between the behavior of different actors, leading to conflicts of interests that justify policy intervention (§2.3.1). Then, the effect of dynamic pricing policies are added to the model as the widely accepted solution for cost allocation (§2.3.2). Next, three hypothetical scenarios are suggested for a more efficient allocation of costs by including other actor groups (§2.3.3). A smart metering tariff is analyzed to include retailers as a relevant actor group in the analysis (§2.3.3.1). Then, dynamic network tariff is presented for further investigating the impact of peak consumption (§2.3.3.2). Finally, the case of outsourcing communication tasks is briefly analyzed (§2.3.3.3). §2.4 discusses implications for policy and business decisions as complex decisions. §2.5 concludes.

2.3 Cost and benefit structure for actor groups in an unbundled market

Consider an unbundled electricity market, where the system is delivering electricity to consumers. Each actor is behaving according to its cost and benefit, and the system is in the equilibrium state. Introducing smart meters provides new costs and benefits for each actor group. Therefore, analyzing the structure of the costs and benefits for the actors is necessary to investigate the possible changes in the costs and benefits incurred to these actors. After completing this step, it is assumed that for recovering the investment costs, all the actors who have financial incentives to use this technology should be included in the solution. Therefore, the potential benefit of the actors from the use of smart meters, as retailers, DSOs and consumers are analyzed in this section. The main assumption for economic analysis is that smart metering roll-out should be profitable for the actors in order to stay in the market and compete for higher market shares in the long-term. Therefore, here the change in profit (or simply profit) is calculated based on changes in revenue and cost for each actor and needs to be positive for all the actors.

For DSO, cost structure is composed of investment, outage, loss and maintenance costs in long-term (Lakervi and Holmes, 1995). In this respect, costs are classified as fixed and variable costs. Fixed cost is a factor of company and network characteristics such as financing, investments, transmission network fees and losses (Hledic et al., 2016), which constitute a large share in the cost structure. In the case of Smart Metering deployment, fixed cost is incurred in the forms of capital expenditure (CAPEX) and operational expenditure (OPEX) per smart meter. Expenditures on metering device, installation, IT systems and implementation constitute CAPEX, while OPEX includes investments for the platform and communication systems. Energy consumption by the consumers also incurs some variable costs as congestion costs and losses to the DSO, which depend on the level of consumption. As a result, OPEX also includes a variable component that should be added to the DSO cost structure.

$$d(P_{DSO})/dt = R_{DSO}(t) - C_{DSO}(t) \qquad (2\text{-}1)$$

$$C_{DSO}(t) = CC(t) + OC(t) + VC(t) \qquad (2\text{-}2)$$

$$VC(t) = [Cg(t) + L(t)] \cdot Cp(t) \qquad (2\text{-}3)$$

Where:

- P_{DSO}: Change in DSO profit
- R_{DSO}: Change in DSO revenue
- C_{DSO}: Change in DSO cost
- CC: Capital expenditures (CAPEX)
- OC: Operational expenditures (OPEX)
- VC: Variable costs
- Cg: Congestion costs
- L: Technical losses
- Cp : Consumption

Profit margin for the DSO comes from the difference between network tariff and the cost of one unit of electricity sold, where network tariff is the tariff charged from consumers for providing the infrastructure and the transportation of electricity, composed of a fixed power-based component (NT^f) and a variable energy-based component (NT^v).

$$R_{DSO}(t) = Cp(t) \cdot NT^v(t) + NT^f\ (t) \qquad (2\text{-}4)$$

Considering these general equations for DSO's cost and benefit structure, introducing smart meters allows for remote reading of the devices and better data management. In addition, there are other potential benefits conditional to different situations and local circumstances such as the non-optimality of network configuration, network losses and non-standard equipment. Technical losses are physical losses, while non-technical losses are financial losses that concern not invoiced but delivered energy (such as theft, non-metered public lightening, etc.). Majority of non-technical losses in distribution network occurs in the Low Voltage (LV) network; therefore, DSOs operating this network can benefit from improvements in the losses. Smart metering would allow the localization of these losses by providing accurate metering data distributed all over the network and recover the losses (Andrey and Haurie, 2013). Thus, they are reflected in the variable cost of the DSO. A simple demonstration of the economic structure of the DSO is shown in figure 2-1:

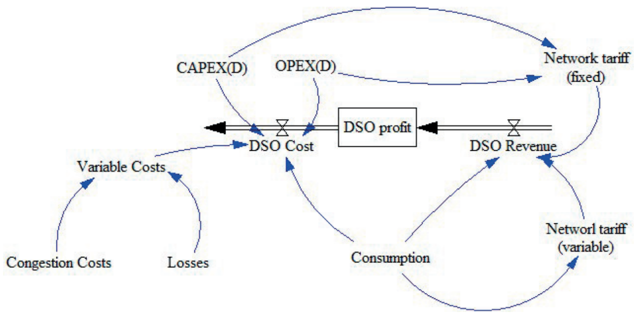


Figure 2-1. Mixed CLD of cost structure for DSO

For retailer, change in the cost structure is mainly driven by a variable cost, calculated as a factor of the market price of energy changing over time and electricity demand from the consumers. The second component in the cost structure of the retailer is the cost carried by the retailer due to demand fluctuations. Varying demand does not impose any further cost to consumers in short term, but changes the market price of electricity and shifts the risks of fluctuations to the retailer. As we will see later, a potential benefit of smart meter deployment is smoothing demand fluctuations by improving the control over consumption and a better predictability of demand in future by providing consumption profile for consumers.

$$d(P_{ret})/dt = R_{ret}(t) - C_{ret}(t) \tag{2-5}$$

$$C_{ret}(t) = MP(t).Cp(t) + FC(t) \tag{2-6}$$

Where:

- P_{ret}: Change in retailer profit
- R_{ret}: Change in retailer revenue
- C_{ret}: Change in retailer cost
- MP: Market price of electricity
- FC: the fluctuation cost

Revenue for retailer comes from selling electricity to the consumers based on the retail price. Before introducing smart meters, retail price is fixed for all consumption levels, while after the implementation of the new metering system, dynamic retail prices should be replaced. Therefore, at an equilibrium state, there is no significant fluctuation and retail price (RP) of electricity is close to its market price.

$$R_{ret}(t) = RP(t).Cp(t) \tag{2-7}$$

The main benefit for the retailer as an indirect consequence of smart metering roll-out comes from the reduced risk of demand fluctuation and peak-consumption, which cause fluctuations in the market price of electricity. Wholesale price of electricity is higher at the peak periods and shift of peak consumption can lower the market price, thus decrease the cost for retailer. Since the retail price cannot change according to fluctuations in market price, the risks are shifted to the retailer. Improved management of energy consumption can smooth demand and lower the fluctuations. Furthermore, potential dynamic pricing policies can contribute to smoothing demand and provide more flexible pricing schemes to lower the risks of demand fluctuations. Impact of these effects depends on the level of conservation, peak load shifts and initial market price of electricity. The benefit structure of the retailer can be demonstrated as figure 2-2:

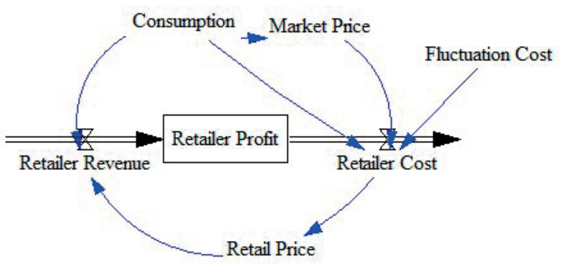


Figure 2-2. Mixed CLD of cost structure for retailer

Consumer is characterized by the consumption profile composed of peak and non-peak hours. In equilibrium state and before introducing smart meters, this classification does not influence the consumer's bill as the retail price is fixed. Only after smart meter deployment and introducing dynamic pricing schemes, different prices can be associated with off-peak and peak consumptions. The benefit for the consumer after the deployment and dynamic pricing policies would is formulated as the change in original bill and from two sources as load-shifting and conservation effects. Energy saving can be achieved either as more efficient use of energy or using more efficient devices.

$$d(B_{con})/dt = b^{o}_{con}(t) - b^{n}_{con}(t) \tag{2-8}$$

$$b^{o}_{con}(t) = RP^{o}(t).Cp^{o}(t) + NT^{o}\,(t) \tag{2-9}$$

$$b^{n}_{con}(t) = RP^{n}(t).Cp(t) + NT^{o}\,(t) \tag{2-10}$$

Where:

- B_{con}: benefit for consumers
- b_{con}^{o}: the old consumer bill
- b_{con}^{n}: the new consumer bill
- NT^{o} : the original network tariff
- RP^{o}: the original retail price
- RP^{n}: the new retail price
- Cp^{o}: the original consumption

These values at the individual household level depend on the lifestyle of the consumers, but the average value can be estimated based on the experimental values from pilot projects and theoretical estimations for electric devices. A simple representation of the benefit structure for the consumer is depicted in figure 2-3:

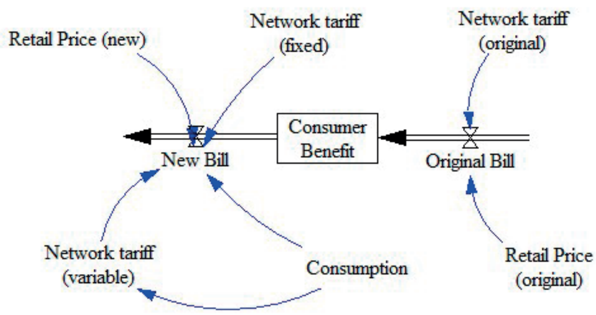


Figure 2-3. Mixed CLD of cost structure for consumer

Based on the conceptualization of costs and revenues for each actor group, the cost allocation process is centered on three stocks as change in profit for the DSO, change in profit for the retailer, and the benefit or change in bill for the consumer. All of the stocks change through their inflows and outflows. For DSO and retailer these are the changes in revenues and costs respectively, while for the consumer original and new bills constitute the flows. Therefore, investigating the dynamics of the system, which influence these flows is critical for understanding the system behavior.

There are company related variables that change the inflow and outflow of the main stocks. These are the variables that characterize the effect of smart metering roll-out (as conservation and load-shift) on different actors. The critical decision for a policy maker is how to allocate investment costs between different actor groups and in proportion to the benefits provided to each of them. The idea followed in the rest of this essay is that by looking at the financial incentives for different actors (retailer, DSO and consumer), the policy maker can use policy intervention mechanisms to allocate the costs in an efficient way, and all the actors react to different strategies in order to maximize their benefit. As a result, efficient cost allocation is a collective property of the system driven by the actions from all the actors.

2.3.1 Interdependency of costs and benefits of actor groups in smart metering deployment

The cost and benefit structures discussed in the previous section are not independent and have some critical variables in common. Therefore, changes in each structure induced by smart metering roll out influence the structure for other actors. Consumption and electricity prices (both retail and market) are the primary variables influencing the costs and benefits of all the actor groups. In this respect, they are considered as the central variables for further analysis, and the variables influencing these central variables (such as conservation effects and peak-load shifts) have high importance in shaping system dynamics. Figure 2-4 shows a simplified mixed CLD of the way electricity prices and consumption link the benefits and costs of different actor groups. This diagram represents the three main stocks addressing the payoffs of three actor groups, and depicts the three main reinforcing loops behind creating the main system dynamics. In this respect, the loop R1 addresses the impact of conservation effect, while the loop R2 highlights the impact of fluctuation costs and the loop R3 considers the impact of peak-load shift as the three main variables that change by smart metering introduction.

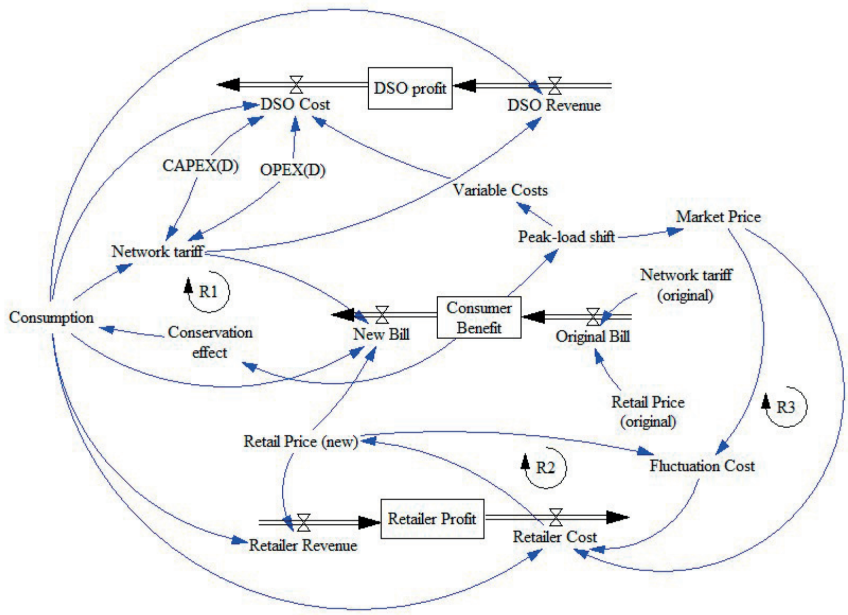


Figure 2-4. Overview of the aggregate cost structure

By introducing smart meters, since the DSO owns or rents the technology, technology implementation would result in a high CAPEX and recurring OPEX for the operator. On the other hand, smart metering deployment would lead to reducing consumption and non-technical losses due to the more efficient use and monitoring of electricity. These cost reductions are added to the model as reductions in variable costs deducted from DSO costs. Thus, these cost reductions contribute to the cost recovery of DSO's investment, although full recovery is not possible because of high investment costs.

Apart from potential cost reductions for the DSO, smart metering deployment triggers energy conservation and thus, provides momentum for the loop R1, by increasing control over consumption for the consumers, even in the absence of dynamic pricing policies. It results in decrease in consumption and network tariff. As a result, the conservation effect has a negative effect on the revenue of the DSO, but at the same time can reduce consumers' bills. Therefore, there is a potential benefit for the consumer, which provides incentive for technology acceptance and further conservation effect, but at the same time creates conflicts with the interests of the DSO.

These dynamics imply that the capital and additional operational expenditures change DSO costs as the owner of the metering devices, while direct benefits in the forms of OPEX reduction resulted from remote reading and reduction in non-technical losses as company-related variables provide benefits for DSO. The impact of energy conservation on the variable component of network tariff, and reduction of DSO's revenue can be compensated by the change in DSO costs due to reduction of network and transportation costs of energy. Therefore, the critical factor in analyzing cost recovery of DSO's investment is the relative magnitude of direct benefits compared to initial investments and operational costs. Since these costs are definitive and higher than the expected cost reductions, in the absence of new policy interventions or business solution, one expects to see negative profit for the DSO.

The same logic applies to the consumer. Taking all the other variables constant, conservation effect reduces consumption, leading to reduction in their bill and providing benefit for this actor group. Furthermore, consumption reduction has potential benefits for the retailer, reflected in the market price of electricity, and reduces the costs of electricity purchased by the retailer. Since in normal price-based contracts with the consumers and prior to the introduction of dynamic pricing policies the retail price remains constant, the retailer benefits from this price change. However, the operationalization of this relationship is complicated. As electricity is a necessity, its consumption would not decrease drastically even if its average price goes up. Therefore, although a possible recovery strategy for lost revenue could be reflected in electricity price, but as there is a trade-off between consumption and price, such an approach cannot provide a full recovery at first glance. Furthermore, any change in consumption patterns may lead to change in the market price of electricity, and the retailer would take the risk of such price fluctuations.

Combining the equilibrium state (before introducing smart meters) with the changes incurred by introducing smart meters provides the first insights into the impact of new technology development. A preliminary simulation shows the behavior of the main stocks under this condition, and before introducing any policy or business solutions (figure 2-5)[2].

As expected, figure 2-5 shows that the DSOs receive a negative pay-off. This is the reason the network operators in this industry are hesitant to undertake such a technical change and provides the basis for justifying the role of policy interventions and innovative business cases. On the other hand, consumers benefit from this new technology, since they can manage their bills and reduce consumption without taking any risk or paying for the new metering system. In addition, introducing this technology has the potential to provide small positive externality per consumer for the retailer. This benefit arises from cost reduction provided by decrease in market price fluctuations, a fact that should be added to analyzing costs and benefits of smart metering roll-out.

[2] Initial values of the model are driven by averaging over the values provided by EU reports on CBA of smart metering roll-out

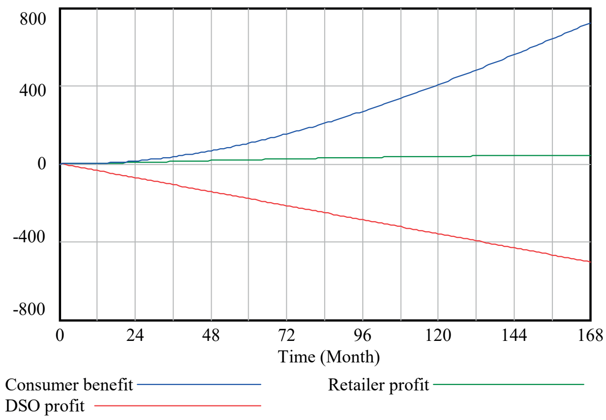


Figure 2-5. Benefits for actors after SM introduction

The common response to this hypothetical situation is providing new pricing policies to compensate for the investments done by DSOs and let the consumers to contribute to the cost allocation process without losing their incentives to cooperate. The following analysis addresses the case of introducing commonly used policy interventions to the dynamics of interaction between actor groups to partially recover the investment costs and exploit the benefits of smart metering roll-out.

2.3.2 The impact of policy interventions on the system dynamics

The rationale for policy intervention comes from the fact that huge investment costs for smart meter deployment by DSOs cannot be recovered solely though long-term benefits not even guaranteed, such as technical and non-technical loss reductions. The main challenge for policy intervention is incorporating costs and benefits of different actor groups, the structures that are interdependent and create a dynamic problem for the policy maker. The dynamics include factors such as the extent the behavior of each actor group is influenced by the reactions of the other actors and how their collective behavior can satisfy policy objectives.

Retailers in general are interested in reducing the energy costs, while the DSOs have the target to keep the quality of supply in the short term and reduce investments in the long run (Belonogova et al., 2011). Therefore, shifting peak load to non-peak hours provides benefits for both actor groups. On the other hand, any decision by the retailer, in order to be successful, needs consumer engagement. As a result, for smart metering deployment to be successful, any policy intervention needs to incentivize all the actors to act cooperatively. In this respect, here the effects of policy interventions in the forms of two simple solutions as introducing new network tariffs and dynamic pricing policies are analyzed.

DSOs in general charge consumers through network tariffs for partial recovery of the investments. It is added to the fixed component of the initial network tariff as a constant change in power-based network tariff ΔNT^p. This is a fixed increase in DSO's revenue and linearly changes the profit. As a result, equation 1-4 is changed to the following.

$$R_{DSO}(t) = Cp(t) \cdot NT^v(t) + NT^f(t) + \Delta NT^f(t) \tag{2-11}$$

Where:

- ΔNT^f: change in power based network tariff

The second part of policy intervention is in the form of dynamic pricing policies. The simplest form of pricing policy used here is distinguishing between off-peak and peak consumption and assigning two different prices as a type of Time-of-Use pricing (ToU). The extra cost of producing one unit of electricity during the peak period which increases the market price, is a good proxy for calculating the peak retail price of electricity. Therefore, off-peak retail price P_r^o and peak retail price P_r^p are added to the model. Total consumption C^t is also divided between off-peak consumption C^o and peak consumption C^p. Other assumptions are plausible or even more realistic; but for the sake of simplicity, it is assumed these two pricing strategies are able to explain the main dynamics of the model. Therefore, the new bill is calculated as equation 2-12.

$$b_{con}^n = RP^p(t). Cp^p(t) + RP^o(t). Cp^o(t) + Cp(t) \cdot NT^v(t) + NT^f\ (t) \tag{2-12}$$

Where:

- RP^p: peak retail price
- RP^o: off-peak retail price
- Cp^p: the peak consumption
- Cp^o: off-peak consumption.

The behavioral change induced by introducing the new pricing policy would shift the consumptions in peak-hours to non-peak hours, leading to changes in the system dynamics. Prior to introducing new policies, if the power level passes the limits, risk of power outage is burdened by DSOs (Belonogova et al., 2011). DSOs need to use extra capacity to keep the quality of electricity provision and in the long term, invest to increase network capacity. In this respect, peak shift contributes to the reduction of DSO's investment costs. Furthermore, another impact of peak-load shift in on the market price of electricity. During peak hours, energy suppliers need to connect more costly sources of energy to the grid. Dynamic pricing tries to reflect the extra cost in new prices; thus, risk of price peaks is partially transferred to consumer. This is different from the case of flat rate price, where risk is burdened by retailer (Belonogova et al., 2011).

These dynamics create reinforcing loops that exploit the potentials for peak shift and further conservation, compared to the case of no dynamic pricing policy, as well as smoothing fluctuations. On one hand, any reduction in fluctuations triggered by new pricing policies reduces the fluctuation costs, which is reflected in the retailer costs and reduces the retail price. It gives momentum to the loop R2 that triggers further reduction in fluctuation costs. In addition, new dynamic prices have impact on peak-load shift and reducing peak consumption that reduce the market price of electricity and retailer costs consequently. Such a cost reduction reduces retail price of electricity and reduces consumer bills; thus, it contributes to higher acceptance of new dynamic prices which triggers the reinforcing loop R3. Furthermore, by decreasing production costs, which results in lower market prices, retailers also benefit from introducing new pricing schemes. This extra benefit for the retailer is modeled as the sum of change in revenue caused by selling peak-consumption at new price (RP^n) and buying electricity at lower price (MP).

Figure 2-6 shows the results of simulation after introducing new policies and the updated benefits for the actor groups. Compared to figure 2-5, it shows although the benefits for the DSO can be positive in the long term, but this actor should take the risk of investment, receive a negative benefit for a long time and finally get lower profit per consumer in comparison to other actors. It also implies although the cost-benefit analysis may show a positive outcome, but it may not provide enough incentive for the DSO to take the risk. As expected, the consumers' benefit decreases in comparison with the previous model, since they should pay a higher price for peak consumption. In addition, lower market price and higher peak retail price are two sources of higher benefits for the retailer, which lead to a substantial increase in profit for this actor group.

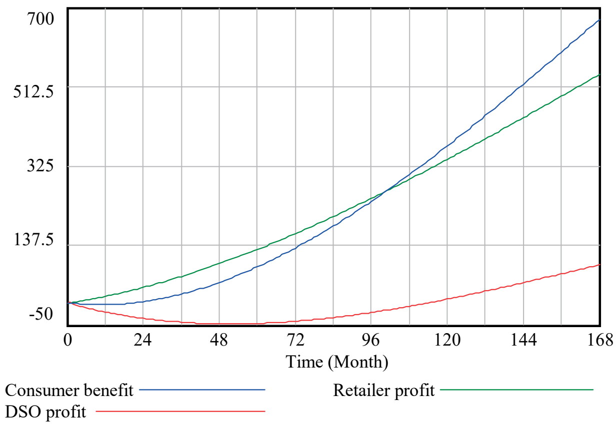


Figure 2-6. Benefits for actors after introducing Dynamic Pricing Policy

A closer look at the cost and benefit structure for the DSO reveals changes in consumption and the reduction in variable costs (equation 2-11) are the main factors behind the changes in the benefits and costs of the DSO respectively. On one hand, consumption reduction induced by conservation effects of smart metering roll-out creates a balancing feedback loop which leads to a reduction in DSO revenue. On the other hand, savings provided by the reduction of variable costs increase over time due to the increasing effect of peak-load shift to off-peak hours. In the early years, the impact of initial investment costs and consumption reduction dominates the system, and results in decrease in DSO profit. Gradually, consumption level approaches the limit imposed by potential conservation effect and benefits of peak-load shift dominate the system, leading to an increase in DSO profit.

The variable cost parameter in the model has two main components. One is the impact of peak-load shift to off-peak hours, and the other is the reduction of technical costs for the DSO. The impact of peak-load shift depends on the extra cost of providing one unit of electricity at the peak-hours (denoted as u), while reduction of technical costs depends on company related characteristics (aggregated and denoted as f). Figures 2-7 and 2-8 show the effect of changing these two parameters on the DSO benefit. Comparing these figures shows company-related characteristics have a higher impact on smoothing the initial costs in the early years, while higher unit cost of peak-consumption leads to more profit for the DSO in the long run.

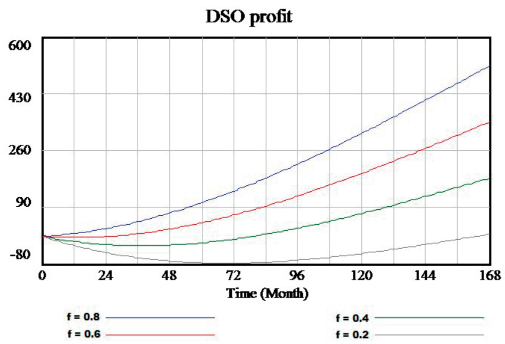


Figure 2-7. Impact of changing company related costs on DSO profit

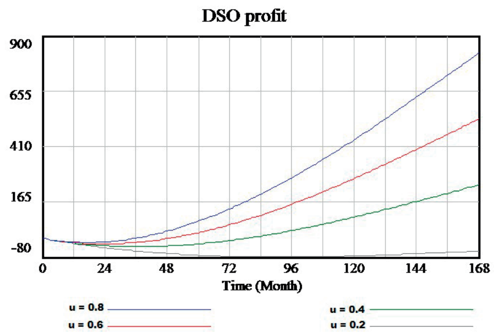


Figure 2-8. Impact of changing unit cost of peak consumption on DSO profit

Up to this point, the models use the same logic and parameters the ones currently used in common cost-benefit analyses, although with a dynamic approach. However, this paper argues further analysis is needed to investigate the possibilities of improving the efficiency of the cost allocation process and balancing the short-term and long-term consequences to incentivize all the actors. Therefore, in the next section, the possibilities of increasing the efficiency of cost allocation and creating innovative scenarios are investigated.

2.3.3 Scenarios for more efficient cost allocation

In this section, based on some ideas from literature explained briefly in section §2.2, and the results of simulations from previous sections, three hypothetical scenarios are presented. These scenarios aim to recombine the parameters already present in the model in order to provide solutions that are more efficient in allocating costs and resolving the conflicts of interest. It is assumed each of these scenarios is more relevant than the others under some circumstance; therefore, the analysis in each of the following sections is independent from the others. In other words, each scenario is added to the model presented in §2.3.2. After presenting all scenarios, the possibility of combining these scenarios are discussed in §2.4.1.

2.3.3.1 Cooperative smart metering tariff

The first scenario looks at the intermediary role of the retailers and the positive externalities brought by the implementation of new policies. As mentioned, the costs and benefits for this actor group are usually neglected in the CBA studies. Therefore, a smart metering tariff (SMT) is introduced as a cooperative strategy in order to include the retailers in the cost allocation process proportional to their potential benefits.

The general idea is that the retailer should pay for the availability of Smart Meters through tariffs. Retailers have advantages in the smoother production and reduced risk due to new pricing strategies. Therefore, they may contribute to the cost allocation of the DSOs by paying a share proportional to the potential benefits to the DSO as the smart metering tariff. In this situation, they pay a certain amount of money for each client who has a Smart Meter installed, as a fixed cost per client. It would represent a more plausible situation, where the retailer is motivated to exploit the benefits of this new technology and contribute to the costs. This fixed contribution in the revised model is calculated by multiplying a constant share of retailers' benefits (α) by the average potential benefit of retailer in the absence of smart metering tariff over the period of analysis. Therefore, monthly smart metering tariff for each consumer is calculated as:

$$SMT(t) = \alpha.\bar{P}_{ret}/T \quad (2\text{-}13)$$

Where:

- SMT: Smart Metering Tariff
- T: The duration of analysis
- α: Smart metering tariff coefficient
- $\bar{P}_{ret}$: average potential profit for retailer

The parameter α is set based on the initial investment of the DSO in order to reduce the negative benefits in the early years of technology development. Since the benefits for both retailers and DSOs increase over time, this new tariff partially shifts the collective benefits of the late years to the early years along with contributing to the cost allocation. Figure 2-9 shows the results of simulation after introducing the smart metering tariff.

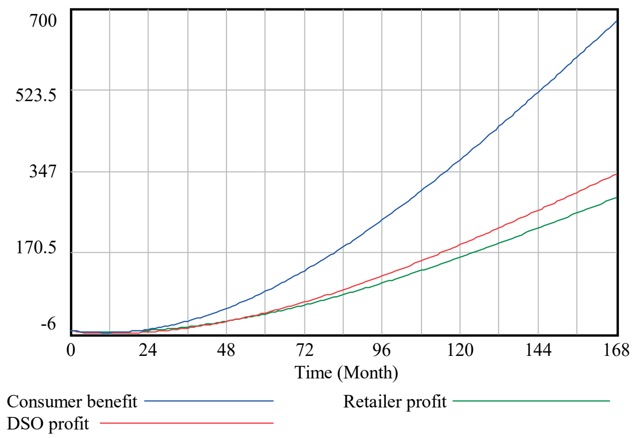


Figure 2-9. Benefits for actors after introducing Smart Metering Tariff

Compared to the results of dynamic pricing policies, figure 2-9 shows the new tariff does not substantially change the consumer's benefits since it has negligible impact on the variables influencing consumer's bill. However, it can lead to the convergence of retailers and DSOs profits and recovery of costs for the DSO in the early years. The critical variable in this scenario is the smart metering tariff coefficient (α) calculated based on the potential profit for the retailer over the period of analysis, and therefore the smart metering tariff.

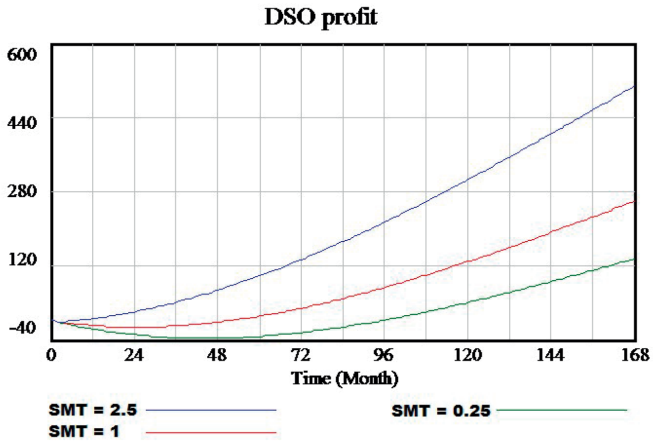


Figure 2-10. Impact of smart metering tariff on DSO profit

Figure 2-10 shows simulation results of DSO profit based on three different values of smart metering tariff. The results show moderate values of smart metering tariff can partially compensate for initial investments, but a full compensation requires a very high level of contribution from the retailer side (a smart metering tariff equal to 0.75 is equivalent to 50% contribution to smart metering installation cost by the retailer).

2.3.3.2 Dynamic network tariff

The second hypothetical scenario investigates the dynamics of interaction between DSO and consumers. The network tariff in general is composed of power-based and energy-based components (Belonogova et al., 2011). By introducing new policies described in §2.3.2, the increase in the power-based component of the network tariff is used as a compensation mechanism. This is an increase based on technical characteristics of the network and initial expenditures; therefore, it is independent from consumption profile. Although increased network tariff aims to compensate for the initial investments done by the DSO, consumers are heterogeneous in terms of their consumption patterns. It means different peak-time consumptions have different contributions to the future costs of network development, a parameter currently missing in the model. Therefore, a dynamic network tariff is proposed to find a more efficient compromise between the costs and benefits of individual consumers. The new dynamic tariff is calculated by adding the extra cost of consuming at peak times to the energy-based component of the original network tariff. As a result, the share of peak consumption in consumer profile is multiplied by the extra cost of supplying one unit of electricity over the peak hours. Then, the new network tariff is increased in proportion to the additional costs incurred to the system. Equation 2-14 shows the new network tariff to be used in the model.

$$NT_r^p(t) = NT^p(t) + Cp^p/Cp \,.\, UPC \tag{2-14}$$

Where:

- NT_r^p: Revised variable network tariff
- UPC: Unit Peak Cost

This dynamic network tariff shifts part of the benefit of the consumers to the DSO's revenue. However, its impact is limited since it further increases consumer bills already impacted by new network tariff described in §2.3.2. On the other hand, this new policy does not influence the profit structure of the retailer; therefore, a more plausible way to use this scenario is in combination with other solutions.

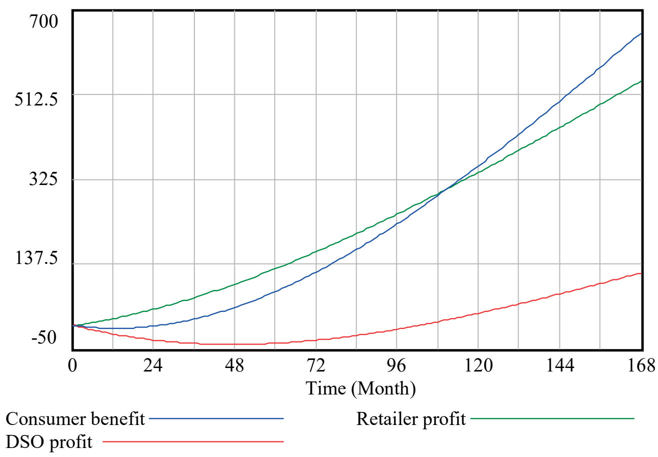


Figure 2-11. Benefits for actors after introducing Dynamic Network Tariff

The results of simulating this scenario as depicted in figure 2-11 are very similar to figure 2-6. This figure shows a very small portion of consumer benefit is shifted to the

DSO, while the retailer benefit is almost unchanged. In other words, network tariff constitutes a small portion of both DSO revenue and consumer bill; therefore, its impact on system dynamics is limited.

2.3.3.3 Outsourcing data exchange services

The third scenario analyzes the possibility of introducing an intermediary for outsourcing the new IT tasks. By deploying smart meters, a smart meter operator, which is the DSO, needs a secure and reliable communication infrastructure and capabilities to use the infrastructure in an effective way in order to exploit the potential benefits brought by smart meters. Such an infrastructure and its associated capabilities are not the general characteristics of the DSOs, incurring significant fixed costs for information technology (Strüker et al., 2011). However, an alternative approach is outsourcing IT tasks to a more competent actor with access to IT infrastructure, which can provide more innovative services for the consumers and lower the capital expenditure for the DSO.

Following Strüker et al. (2011), here the assumption is that such an intermediary can lead to resource savings and extra benefits for the DSO. Apart from lowering the initial investments for the DSO, such an intermediary can reduce contact costs between smart meters and market actors, and both contact and agreement costs within market actors by providing centralized data collection schemes. In addition, since the DSO is still the owner of smart meters and authorized actor to gather and the data, the gather data can be sold to the intermediary as an extra source of revenue for the DSO. Finally, the intermediary can provide more innovative solutions for the consumers to facilitate the introduction of demand management programs and improve control over consumption. Therefore, its role in the system is to provide the complementary ICT infrastructure, gather consumer data, distribute the data to the authorized actors, and distribute the messages back to the customers.

These benefits have a positive correlation with the number of smart meters added to the system. Such a network effect helps the ICT firm to benefit from economies of scale gained from increased capacity utilization and bulk data purchasing (bulk purchasing price can be reduced to 1/5 to 1/7 of the price offered to a medium-size data center (Rangen, 2008)). This creates a virtuous cycle; a lower price attracts more consumers to use smart metering services, which increases the network effect and leads to further decrease in contact and agreement costs; thus, more positive network externalities.

The impact is added to the model by deducting ICT infrastructure cost C^{IT} from smart metering installation costs and consequently from DSO costs. Therefore, equation 2-2 is changed to equation 2-15.

$$C_{DSO}(t) = CC(t) + OC(t) + VC(t) - C^{IT} \quad (2\text{-}15)$$

The second impact is the price of data sold by the DSO to the ICT firm as the information cost C^i. Total cost of the intermediary is the sum of information cost and operation cost of running the infrastructure. Information cost is also added to DSO's revenue. The intermediary provides new services for the consumers and constitute the revenue for the ICT firm. Therefore, equation 2-16 depicts the new revenue structure for DSO.

$$R_{DSO}(t) = Cp(t) \cdot NT^v(t) + NT^f\ (t) + C^i \quad (2\text{-}16)$$

It is assumed the new services have potential benefits for the consumers in the form of increasing potential conservation and peak-load shift effects. Therefore, the price of these services are added to consumer costs, through fixed increase in consumer bills or any other financial instrument (equation 2-17). In addition, the profit structure for the new ICT firm can be analyzed based on the revenue of ICT solutions as well as the information and operation costs affected by a factor representing the economies of scale provided by the network effect over the long-term (equation 2-18).

$$b^n_{con}(t) = RP^n(t).Cp(t) + NT^o\ (t) + C^{sol}_{con} \quad (2\text{-}17)$$

$$d(P_{ICT})/dt = R_{ICT}(t) - \ C_{ICT}\ (t) \quad (2\text{-}18)$$

$$R_{ICT}(t) = C^{sol}_{con} \quad (2\text{-}19)$$

$$C_{ICT} = e.(\ C^i + C^{op}) \quad (2\text{-}20)$$

Where:

- C^{sol}_{con}: cost of new ICT solutions for consumer
- P_{ICT}: profit of the ICT firm
- R_{ICT}: revenue of the ICT firm
- C_{ICT}: cost of the ICT firm

- e: economies of scale coefficient
- C^{op}: ICT operation cost

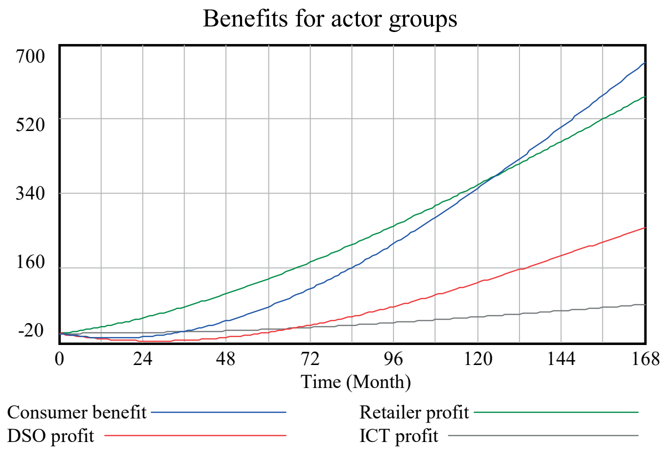


Figure 2-12. Benefits for actors after introducing the intermediary ICT firm

The results of simulating this scenario are depicted in figure 2-12. Based on this figure, adding the new intermediary firm has the potential to compensate for negative benefits of the DSO in the early years. The benefits of consumers and retailers slightly increase because of the value added of new innovative services to energy conservation and peak-load shift. The critical variable in this scenario is the impact of new ICT solutions on consumer benefits in the form of extending the range of both conservation and peak-load shifting effects. Increasing this factor improves profits and benefits for all the actor groups included in the analysis, but it depends on ICT firm-related characteristics.

2.3.4 Robustness of results

Model testing was done on both the structural assumptions and model parameters. Extreme conditions and integration error tests (Sterman, 2001) were used to test system response to changing system variables and technical specifications. Furthermore, pattern recognition testing (Yücel and Barlas, 2015) was applied to check the discrepancy between observed and expected patterns of behavior.

For the extreme condition test, the three scenarios were simulated at their extreme conditions as policies to the model. For dynamic pricing policies, extreme cost of peak consumption leads to the maximum peak-shift and conservation effects, and as a result imposes large cost to the consumer and provides large benefit for the retailer. For the cooperative tariff, changing the retailer contribution to the extreme value shifts all the installation costs to this actor, and results in recovery of investment costs in the early years for the DSO, and negatively increasing pay-off for the retailer over time. The same logic applies to the case of dynamic network tariff, where increasing the tariff to an extreme level fully recovers DSO costs but provide a large cost for the consumer. Finally, for the case of outsourcing ICT activities increasing the operational cost (C^{op}) to an extreme value is robust as far as the cost of IT infrastructure does not exceed the total cost incurred to the DSO. It is logical since the cost of IT infrastructure is part of the initial investment costs and cannot be considered as higher. Regarding the information cost, at the very high price of information sold to the ICT firm, the pay-off the this actor group becomes increasingly positive and reaches an equilibrium when the value of economies of scale approaches its maximum.

Furthermore, integration error test shows the results are not sensitive to changing time step and integration method. For pattern recognition testing a software called SiS developed by Boğ & Barlas (2005) was used to check the similarity of model behavior to a set of classified behaviors. For each scenario, the expected behavior is hypothesized and the results show all the hypotheses are passed.

2.4 Implications for policy making and new business models

The analysis discussed in the previous sections is based on three fundamental assumptions. First, the cost allocation process should be open to including all the relevant and potential actors, and not only the ones directly affected by the deployment process. Such an approach provides new opportunities to shift the risk burden by one actor to other actors that might be willing to contribute to the process, when enough incentives are provided. Second, policy intervention needs to find balance between short-term and long-term costs and benefits for all the actors. Focusing solely on the accumulated benefits might not provide incentive for actors to participate, since in the short and middle terms, the risks and costs can be substantial. Finally, new business strategies are complementary to policy implementation. There are parameters dependent of firm-level characteristics or firm decisions that can shift the dominance of feedback loops or change the behavior of other actors critical for the success of different scenarios. This section explores how policy choices and business-related factors can change the results.

2.4.1 Policy options and combining scenarios

The scenarios explained in previous sections were analyzed independently; however, each of them has a different contribution to the cost allocation process under specific circumstances such as contextual factors, regulations, consumer participation etc. Therefore, by considering these circumstances, there is the possibility of putting higher priority on each of them or combining these scenarios to create new and more effective scenarios.

For instance, when price fluctuations are high and retailers gain substantial benefit from smart metering deployment, introducing smart metering tariff can be more attractive as an innovative scenario than the situation where retailer is not willing to participate or technology acceptance is limited, even by providing incentives for consumers. A dynamic network tariff for peak consumption is more desirable when dynamic pricing policies are not very useful, since increasing bills when consumers are already responding to new policy may create reluctance and nullify the impact of peak-load shifts. As mentioned, this scenario does not influence the cost structure for the retailer; therefore, it needs to be combined with other scenarios for a more efficient cost allocation. Finally, when the network operator has no access to information and communication infrastructure, and the cost of IT infrastructure is high, introducing an intermediary ICT firm is attractive.

Furthermore, there are other policy implications for influencing the critical variables exogenous to system dynamics. For instance, the effectiveness of dynamic pricing policies depends on the range of possible conservation and peak-load shift effects, generally calculated based on designed experiments. Consumer life-style and behavioral patterns affect these possible ranges and policies for changing these patterns including the introduction or facilitation of demand-side management programs (DSM) might have a contribution to the effectiveness of dynamic pricing policies. In addition, motivating retailers to contribute to the cooperative smart metering tariff is another ground for policy intervention and increase the effectiveness of this scenario.

2.4.2 Firm-dependent parameters

The firm-level characteristics can influence the system dynamics via changing the relative dominance of different feedback loops. Operational costs are part of the initial investment costs and affect the initial conditions. These investments depend on the maturity of technological solutions, including the availability of standards and firm's dynamic capabilities (Rahmandad, 2012). Thus, technological and operational efficiencies determine the potentials of cost reduction for the company.

Since cost structures of different actors are sensitive to company-specific factors, these factors are the second critical exogenous factors that can change the availability of different solutions. For instance, operational costs of smart metering deployment and the potential savings brought by this new technology for the DSO depend on the operational efficiency of activities done by the firm. The same logic applies to the ICT company, where operational costs of running the IT infrastructure limit the possibility of successful collaboration between the ICT firm and other actors. In addition, cost of developing IT infrastructure is a variable depending on the communication capabilities of DSO for accomplishing IT tasks. Thus, this variable is critical for making decision on introducing the intermediary role for outsourcing IT tasks.

Simulation results also support the importance of these company-specific variables for the success of different scenarios. In the case of dynamic pricing policies, reduction of technical costs were one of the two important factors affecting system behavior and the balance between short-term and long-term pay-offs for the DSO. These technical costs are reflected in the operational costs for the ICT firm in the last scenario and influence the cost of providing ICT solutions as the critical variable in this scenario, which provides the basis for increasing the network effect as the motivation for the ICT firm to participate in the cost allocation process.

Finally, for the retailer the dynamic capabilities of the firm are critical since they affect the possibility of reducing fluctuation costs. This reduction is reflected in new dynamic pricing strategies and is an important factor for allocating the deployment costs and exploiting the benefits of new technology deployment.

2.5 Conclusions

The primary question related to smart metering deployment is not whether it is a beneficial technology for the consumers or a profitable business for the actors, but the efficiency of cost allocation process and providing incentives for beneficiaries to participate in the process. This study investigates the cost allocation problem as a complex challenge that needs to take into account the dynamics of interaction between different actor groups and keeping the track of incentives over time.

Although existing policies such as dynamic pricing policies in the forms of Time-of-Use (TOU) or Real-Time Monitoring (RTM) may lead to positive results for cost and benefit analysis, this study claims keeping the track of incentives over time is a key factor for a successful technology deployment, by balancing short-term and long-term consequences. Maintaining the incentives for all the actors over time has implications for policymaking. For instance, facilitating the emergence of a cooperative strategy based on the potential benefits over time, such as the smart metering tariff, without forcing any proposed cooperation is an important factor for incentivizing retailers as the missing actors in current CBA practices. Without finding collaborative and inclusive strategies, market forces can hardly reach an economically feasible solution.

The simple models proposed in this study try to grasp the primary factors shaping the system behavior. Apparently, there are other factors relevant for the cost allocation process, but they are beyond the scope of this paper. They include information ownership issues, access control, confidentiality and solution scalability among the others that remain out of the focus of this paper. In addition, as discussed in §2.4, institutional environment is an important external factor for analyzing the motivations of different actors. For instance, even in a liberalized market, not all the actors have access to the market (in countries like Switzerland, liberalization means only consumers with consumption higher than a threshold can have access to the market, and as result, households are out of the market). In different institutional contexts, the role of regulator can be different; but in general, it should act to balance the advantages of smart metering roll-out between actors by setting up institutions to protect the consumers against abusive cost recovery and increase social benefits of all the actors affected by technological change. Such broader roles can be reflected in the system structure behind simulation models, while detailed specifications should be customized based on contextual differences.

To sum, this study took a step further in the cost allocation problem by taking a dynamic approach and using simulation models for revealing the interdependencies and feedback structures that make the cost allocation problem a complex task. Paying attention to the endogenous dynamics is a necessary step for the identification of the tipping points and critical variables, which help to design more effective scenarios for system intervention.

3 A Multi-method Approach for Analyzing the Spatial Diversity of Technological Innovation Systems: The Case of Smart Grid Development

Keywords: Technological Innovation Systems, Social Network Analysis, Agent-based Modeling, Smart Grid, Spatial Analysis, Complex System Theory, Institutional Analysis

3.1 Introduction

The technological innovation system (TIS) approach has emerged as a key framework in innovation and transition studies (Jacobsson and Bergek, 2011; Markard et al., 2012). It has been devised to analyze the development of new technologies, highlighting the systemic interplay of actors, networks and institutional structures (Carlsson and Stankiewicz, 1991). In contrast to regional or national innovation systems approaches, the TIS framework does not depart from a spatial focus but takes technology as the starting point (Hekkert et al., 2007). As a consequence, the spatial focus of the analysis is a priori undefined as technologies cut across sectoral and spatial boundaries (Bergek et al., 2015).

However, many TIS studies have confined their inquiry to national boundaries, often without even discussing the consequences of such a focus setting. This practice has been criticized in recent years (Binz et al., 2014; Markard et al., 2015) and meanwhile, there are a few studies that explicitly study the spatial dimensions of TIS, primarily by taking a relational approach to space or doing comparative analysis between national networks (Bento and Fontes, 2015; Binz et al., 2014; Coenen et al., 2012; Wieczorek et al., 2015). Another issue with recent interest in studying spatial dimension of TIS development is to find out how contextual factors shape different spatial settings. It means from a theoretical point of view, spatial characteristics of a multinational network can be attributed to the spatial characteristics of the countries that constitute network interactions including the tendency to focus on national initiatives versus international collaborations, state of different TIS functions in the network and how spatial properties change over these functions, as well as the way past innovative activities shape the future developments and contribute to the emergence of new spatial diversity. These factors highlight national differences, the maturity of TIS functions and the path-dependency of network development respectively.

National differences can be explained as part of the argument that structural elements of a TIS such as actors, networks and institutions are embedded in the pre-existing structures of a territory. This embedding creates spatial dynamics resulting from structural coupling between a TIS and territorial innovation systems (Bergek et al., 2015). In order to understand the spatial dynamics at the TIS level, understanding the synergies between technologies and institutions at different spatial levels is required. In addition, the contribution of local and regional policies to system development is an important factor in shaping the diversity of spatial configurations at the system level. It means the institutional environment should be decomposed to identify different institutions at different spatial levels.

One way to investigate the impact of spatial properties and institutions of specific national innovation systems on the spatial properties of a TIS as a whole, is through analyzing the spatial diversity of TIS development and how this diversity emerges and changes over time in such a complex system. It means institutions at different levels contribute to the emergence of diverse spatial patterns, and this multi-level institutional environment should be analyzed to understand the impact of institutions at different levels of system development.

Addressing the concepts of diversity of spatial settings and multi-level institutional analysis open up some new questions for spatial analysis of TIS development. How can we investigate the spatial dynamics of TIS development resulting from interactions between heterogeneous actors over time and space? How does the interplay of institutions at different levels (such as EU policies vs. national differences) influence the emergence of spatial patterns in a multi-scalar TIS (e.g. a European TIS)?

Based on these lines of research, this paper takes a first step to analyze the diversity of spatial configurations as an emerging property of complex TIS dynamics. In this respect, spatial diversity of a TIS can be understood by analyzing the patterns of interactions between innovative firms over time and space, influenced and surrounded by the multi-level institutional environment (national, regional, TIS). For this purpose, it combines insights from different perspectives on TIS development with ideas from complex systems theory and institutional analysis to develop a multi-method approach for spatial analysis. Focusing on the case of smart grid development in Europe, first we develop a model of Social Network Analysis (SNA) for investigating the emergence of modules or sub-systems with different spatial diversities over time. Then, an Agent-based Model (ABM) is developed to further analyze the insights derived from SNA on the contribution of different countries with different spatial characteristics.

The paper is structured as follows. §3.2 explains the theoretical background of this study. §3.3 describes the data and explains the method developed for social network analysis. §3.4 presents the results, while §3.5 develops an agent-based model to complement the results of social network analysis. §3.6 concludes.

3.2 Theoretical background

In order to analyze the spatial diversity of TIS development, three strands of research are used in this paper to build the theoretical framework. First, different perspectives of TIS development are presented to see how an emerging technology develops in the context of broader institutional, spatial and temporal dynamics. In addition, the literature shows spatial dynamics cannot be analyzed independently from governing institutions and TIS functions. Second, a framework for decomposing the multi-level institutional environment is presented. Such a framework is required to distinguish institutions at different levels from network construction assumptions, and how institutional interactions shape the emergence of network diversity. Finally, the concept of diversity in complex systems is discussed to briefly explain how diversity is defined and measured in complex system theory, and demonstrate possible lines of reasoning for incorporating spatial diversity into the framework developed based on these three strands of research.

3.2.1 Different perspectives for the analysis of Technological Innovation Systems

Scholars who study technological innovation systems are interested in the dynamics of novel technologies, they seek to understand what drives them and what hinders their development (Bergek et al., 2008; Markard et al., 2015). Technological innovation systems have been analyzed from different, albeit complementary perspectives. Some of these perspectives can be related to the core elements of a TIS (actors, networks and institutions) and how they interact and affect technology development and TIS performance, including the TIS functions. Two further perspectives, spatial and temporal, are rather cross-cutting in the sense that they can be applied to each of the core elements (also in combination) and the functions.

Taking an actor perspective, scholars have studied how different actor groups contribute to the functions of a TIS (Markard and Truffer, 2008). One of the key interests in this line of research is to reveal differences among actors both with regard to how they depend on the focal technology and how they contribute to TIS performance (Konrad et al., 2012). A related interest is on strategies for system building, i.e. how actors – alone or in networks – deliberately create collective resources and institutions that support the development of the focal technology (Kukk et al., 2015; Musiolik and Markard, 2011).

From an institutional perspective, TIS scholars have analyzed how institutions affect TIS development, e.g. how institutions and technology evolve over time (Martin and Coenen, 2015), how different institutional context shape technological and organizational variants of a technology (Wirth et al., 2013), or how institutional changes affect the legitimacy of novel technologies (Markard et al., 2016). The institutional perspective directs attention to the role of context(s) (Bergek et al., 2015) and how variations in context affect technology development (Wirth et al., 2013). It is also central to show how certain designs become dominant and how path-dependency emerges in technological systems (Carlsson, 1997; David, 1994).

Overlap exists with the spatial perspective (see below), when scholars ask the question how the formation of institutional structures relates to specific places (e.g. Dewald and Truffer, 2012; Martin and Coenen, 2015). With regard to theory building, the institutional perspective emphasizes the co-development of technology and institutional structures and the role of context(s), including variations across contexts, for technology development.

Taking a specific interest in innovation networks, TIS scholars have explored, for example, how networks for knowledge creation change over time and in spatial terms (Binz et al., 2014), or how they spread across different regions (Klitkou and Coenen, 2013). In a similar vein, network structures have also been used to explain the particularities of a TIS in a specific country and its performance (Lai et al., 2012). The network perspective shows overlaps with the spatial perspective and also with the actor perspective. In theoretical terms, the network perspective directs attention to TIS structure, i.e. to the relationships among TIS elements. Compared to the other perspectives, it is probably the least developed as of yet, but nonetheless not less promising.

A spatial analysis is interested in the location of TIS elements – especially in relation to each other, which is where the overlap with the network perspective lies. TIS scholars have analyzed regional performance differences in TIS functions (Dewald and Truffer, 2012), the internationalization of TIS (Binz et al., 2014) or the relationships and complementarities of technological innovation systems in different countries (Bento and Fontes, 2015; Wieczorek et al., 2015). It is argued, among others, that international relationships should receive more attention in TIS studies (Binz et al., 2014; Gosens et al., 2015), which has implications for choosing boundaries of analysis (Markard et al., 2015). Current practice to confine most TIS studies to national boundaries has been criticized as potentially myopic, which is why scholars should rather take a network perspective and track the network development over time to identify spatial levels a posteriori (Binz et al., 2014).

As a key methodological approach, TIS scholars taking a spatial perspective have used social network analysis, e.g. to identify regional clusters of innovation activity in a TIS (Binz et al., 2014; Martin and Coenen, 2015). In theoretical terms, the spatial perspective highlights that proximity matters (thus explaining regional clusters and positive effects from co-location) and that institutional contexts for TIS development vary across space.

Finally, TIS dynamics can also be analyzed from an explicitly temporal perspective. This perspective is interested in the temporal patterns of TIS development, the identification and differentiation of specific phases (Jacobsson and Bergek, 2004) or how TIS functions develop over time (Suurs and Hekkert, 2009). This perspective has been applied in most TIS studies (e.g. as analysts distinguish different phases of TIS development), although not with a very explicit analytical interests. From a theoretical point of view, the temporal perspective directs attention to emergent effects in TIS, including path-dependencies, and also raises questions about typical stages of TIS development, e.g. in the sense of a life cycle.

Similar to the spatial perspective, the temporal perspective is often applied on top of (orthogonal to) one of the other perspectives (e.g. asking how institutional contexts change over time, Markard et al., 2016). Also spatial and temporal perspectives can be combined, e.g. when studying temporal patterns in the internationalization of TIS (Binz et al., 2014).

This comparison shows that each perspective comes with specific questions and highlights specific theoretical aspects of the dynamics of technology development. At the same time, due to the systemic nature of the TIS approach many of these issues are intertwined, which has two implications for analyzing the TIS spatial dynamics. First, spatial analysis as a cross-cutting perspective, needs to employ a framework to incorporate potential overlaps with other perspectives and show their dynamic interactions. Second, interplay of institutions at different scales in a network of heterogeneous actors over space and time creates a complex system with diverse spatial patterns that needs a powerful method to properly address this complexity and analyze patterns.

3.2.2 The Institutional Analysis and Development (IAD) framework

The institutional Analysis and Development framework (IAD) is a conceptual map rooted in classic political economy, public choice theory, transaction-cost economics and non-cooperative game theory (Ostrom et al., 1994) and originally developed to investigate individual choices in the self-organization of common pool resources. It is one of the most well-known and extensively used frameworks for institutional analysis in socio-technical or –ecological systems (Ghorbani, 2013; Ostrom, 2005); so it is helpful for the decomposition of a multi-level institutional environment, such as a technological innovation system. It clarifies the distinction between different types of institutions and specifies the connections between institutions and other aspects of a socio-technical system (Ghorbani, 2013). Therefore, it helps to categorize the primary variables for a systematic analysis of the structure of the situation to be analyzed, and how rules, events, and communities influence these situations (Ostrom, 2005).

The decomposition of the IAD framework is shown in figure 1. On the left side there are the underlying structures of the system, while the action arena for defining the conditions of interaction is located in the middle, and the patterns of interaction and outcomes, given a set of evaluative criteria, are located on the right side. Action arena is the central concept, in which actors interact. It includes both the actors and the action situation, or the activity that needs to be analyzed. One result of this system analysis is to understand the emergent patterns and collective properties based on the institutions working at different levels.

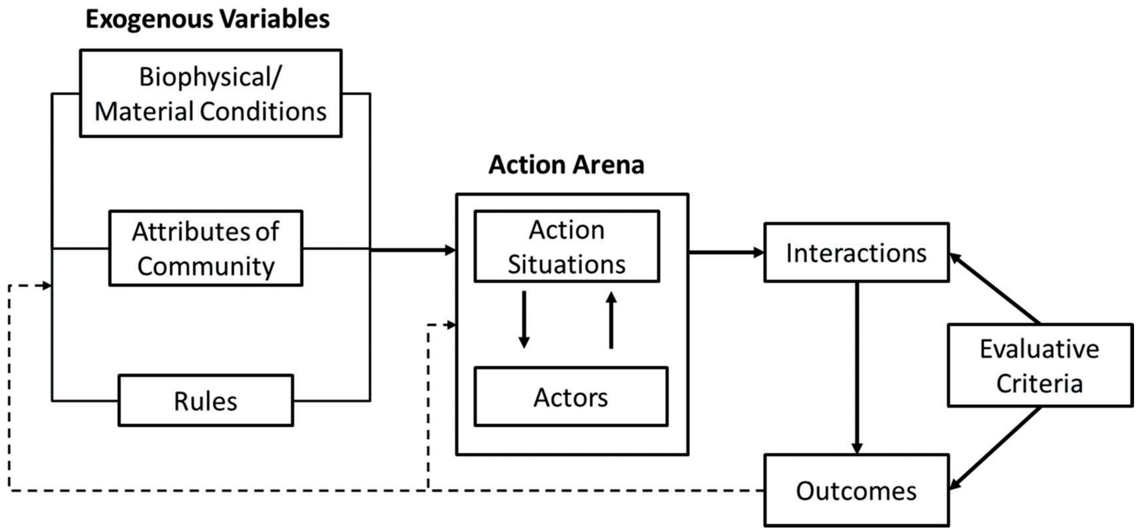


Figure 3-1. The IAD framework (Adapted from (Ostrom, 2005))

What happens in the action arena shapes the patterns of interaction and leads to the emergence of aggregate outcomes that can be evaluated based on the evaluation criteria. On the other hand, both actors and action situation are influenced by the characteristics and limitations of the material or biophysical conditions, the attributes of the community in which the actors or actions are placed (Kiser and Ostrom, 2000), and the set of rules that govern actor behavior at different hierarchical levels. These rules were operationalized later by Crawford and Ostrom (1995) as the grammar of institutions or ADICO.

Rules are formulated in the IAD framework as the set of instructions or expectations for creating an action situation in a specific environment. In other words, they are shared understandings by the actors affected by the rules on possible and prescribed behaviors. The set of rules may yield different action situations depending on the type of 'events' in the wider environment, including the technology available in the process (Ostrom, 2005).Therefore, the IAD framework classifies rules based on their direct impact on the working parts of action situation (Ostrom et al., 1994). Biophysical or material conditions also affect the elements of the action situation. These conditions confine the set of possible actions, range of potential outcomes and the ways actions are linked to outcomes; thus, these conditions incorporate the basic assumptions of system formation and put limits on system analysis.

The attributes of the community within which the activities are located are the third factor affecting the action arena. These attributes include accepted behaviors, homogeneity of actor preferences, the size and composition of communities, and access to resources located in the communities.

The framework has been used extensively by scholars in different fields of study to analyze the impact of institutions on patterns of interaction and generating outcomes. These include institutional analysis for the evaluation of infrastructure systems (Ghorbani et al., 2013), governing structures and regulations (Gordillo and Andersson, 2004; Schaaf, 1989), outcomes of common-pool resources settings (Schlager, 2004, de Castro, 2000, Ostrom, 2007) or the impact of institutional change in sectors (Andersson, 2002, 2004; Polski, 2012, Gibson, 2005).

3.2.3 Analyzing diversity in complex systems

Diversity is a multidimensional concept (Van den Bergh, 2008) and in complex systems has three major dimensions (Page, 2010): variation within a population, difference across populations and differences between compositions or communities across populations. Variation or diversity within a type addresses the differences in attributes or characteristics of the same population, while diversity of types as the differences between different populations. While these two types of diversity are more analyzed and used in the literature of complex systems, diversity of compositions underpins the modularity observed in complex social and economic systems (Ethiraj and Levinthal, 2004) including technological innovation systems (Van den Bergh, 2008). In this case, apart from modules as emerging entities forming around specific solutions (Guimera et al., 2004), modular diversity can be regarded as an emergent property of the system arising from interactions between actors with different characteristics. Emergence in complex adaptive systems refers to system-level behavior aggregated from individual or localized behaviors that cannot be deduced by looking at the original behaviors of the individuals (Miller and Page, 2009).

Diversity of communities is related to variation within and diversity across populations. In fact, interdependence of diverse populations is a hallmark of complex systems (Page, 2010)[3], while increasing species diversity is likely associated with more complex community structures (Ives et al., 2000). On the other hand, path dependency of system developments is an important factor for creating diversity (Arthur, 1994; Page, 2006). By including these interdependencies and the path dependency of system developments, the likelihood of emerging diverse configurations increases.

In this respect, different types of diversity under specific system characteristics may produce different complex patterns. In general, complex patterns emerge in systems with diverse rule-following actors with interdependent behavior interacting over a network. In addition, network structure, rates of change in characteristics and interactions can limit the level of diversity. Coordination or patterns of interaction can be both a cause and a constraint of diversity. Requirements to coordinate within a community reduce diversity within that community; but they can create diversity across communities (Ostrom, 2005).

In order to measure diversity, several indicators are used. However, they often use three dimensions or elements as richness (or variety), balance (or equality, evenness) and disparity (or dissimilarity) (Stirling, 1998; 2007). Richness refers to the number of types or categories in the system, while balance refers to the extent one or more types dominate the system in terms of size or number. Finally, disparity addresses the level of difference between types or categories in system. While these concepts are used to analyze diversity across types (such as entropy, distance and attribute measures), diversity of communities considers disjoint populations and tries to investigate changes in compositions by analyzing sensitivity to initial conditions, path dependence, and the stochasticity of processes (Page, 2010).

To summarize, in order to investigate the emergence of modules with diverse spatial characteristics, a complex system approach provides two compelling insights. First, it suggests analyzing the diversity of modules as an emergent system property

[3] The general mechanism for creating diversity across types is speciation with four different modes as geographic heterogeneity, isolation of a small subpopulation, divergent neighboring niches and diverse niches in a common environment. In evolutionary biology, they are called allopatry, peripatry, perapatry and sympatry respectively.

influenced by path dependent processes and in junction with diversity within and across types. Second, it offers indicators for measuring diversity across different dimensions (including richness, balance and disparity) and at different levels of analysis (within type, between types and between communities).

3.3 Data and method

Based on the ideas from TIS studies, institutional analysis and complex system theory, in this section the methodology and data for spatial analysis is presented. First, the case and of smart metering development is described as the context of this research, accompanied by the dataset used for analysis.

Then, the revised IAD framework is presented as the theoretical framework for decomposing institutions for spatial analysis and the inclusion of relevant measures from complexity theory. Following this framework, measures and indicators for spatial analysis are presented, followed by presenting an algorithm for detecting modules and calculating the measures of spatial analysis for the case of random network.

3.3.1 Context

Smart grid technology is a novel platform technology in the electricity sector in an early stage of development. It combines metering and control technologies with information and communication technologies to enable a variety of applications (Erlinghagen and Markard, 2012; Farhangi, 2010) including load management, demand response, dynamic electricity pricing, electric mobility charging or the integration of distributed and intermittent power generation, among others (Song and Yang, 2009).

It is a proper case for testing the methodology developed in this paper for three reasons. First, it is an emerging TIS in the early stages of development and although smart grid initiative have moved beyond R&D projects, structural components are still in flux, which mean the TIS is in the formative stage of development. Second, the dataset available and used for this study gathers smart grid activities at the European Union level, which provides the opportunity to analyze TIS development beyond national boundaries. Finally, smart grid includes a set of interdependent technologies which enable different applications that contribute to the ongoing energy transition towards decentralized power generation and increasing the share of renewable energy sources.

One of the challenges for smart grid technology is dependence on (mostly national) regulations. While in principle a technology that can be applied globally, the development of smart grid based applications typically depends on how access to the grid and to specific markets (e.g. for balancing power) is regulated. In addition, standardization is a key issue and international standards for smart grids are not yet in sight (Erlinghagen et al., 2015). As a consequence, we can expect to find networks of knowledge generation that are both national and international, while networks with the relative dominance of specific national or multinational collaborations may show different spatial and institutional characteristics.

3.3.2 Sample

3.3.2.1 Data

Our analyses are based on the 2014 database on smart grid projects compiled by the Joint Research Centre (JRC) of the European Union (Covrig et al., 2014). The 2014 JRC database is based on different sources with an online-survey as its backbone, in which data on projects is self-reported (typically by their leaders) and double-checked for consistency and accuracy by JRC staff. The database includes smart grid projects in Europe between 2002 and January 2014.

We performed a quality check on the existing data and made several changes. Duplicates were removed and inconsistencies (e.g. due to different spellings, languages or abbreviations) adapted. We also found some projects with no or more than one project leader. In this case we searched on project websites or other web-sources to identify the primary leader for each project. From project websites and the JRC online-database we also added project classifications in terms of content with seven overlapping categories: Smart Network Management, Integration of Distributed Energy Resources, Integration of Large Scale Renewable Energy Systems, Aggregation (Demand Response, Virtual Power Plant), Smart Customer/Smart Home, Electric Vehicles and Vehicle2Grid Applications, and finally Smart Meters (only if they are part of a wider Smart Grid project). Finally, we limited our analysis to the period of 2002 to 2012 because entries for 2013 and 2014 were incomplete.

The JRC data distinguishes between research & development (R&D) and demonstration & deployment (D&D) projects. The definition of R&D projects is in accordance with the Frascati Manual (OECD, 2002) and includes three activities: basic research, applied research and experimental development. Demonstration projects, in contrast, are “designed to test the performance of a technology in different operational environments, through to full market trials in which the technology is used in customer installations (Brown and Hendry, 2009)” (Covrig et al., 2014; p. 20). In our analysis, we use this distinction to explore different TIS functions (cf. Bergek et al., 2008): R&D projects are assigned to the function of ‘knowledge development’, while D&D projects are assigned to ‘entrepreneurial experimentation’. This is consistent with the indicators developed by Gosens et al., (2015) that proposed R&D projects as an indicator for knowledge development, and demonstration pilots, studies and field trials as the indicators for entrepreneurial experimentation.

With regard to the actors involved in smart grid projects, different information attributes are available. For our interest in the spatial network characteristics, the country of origin of the actors is particularly important. Moreover, we use the information that is available is about different types of actors. The JRC database distinguishes 10 categories, which we aggregated as depicted in the table below.

Table 3-1. Actor types (compiled based on Covirg et al., 2014)

JRC Database	***Aggregation***	***Remarks***
Association	*Association*	*Intermediary actors that represent specific interests*
Manufacturer/ Engineering services/ Contractors/ Operators/ Manager company	*Manufacturers*	*Industry actors that are involved in technology development*
IT company and Telecom	*ICT*	*Actors from the information and telecommunication sector*
Municipalities/ Public Authority/ Government	*Public*	*Public actors*
University/ Research centre/ Consultancy	*University*	*Universities and similar actors that concentrate on knowledge creation*
Distribution system operator	*Utilities*	*Actors from the electricity supply sector*
Transmission System Operator		
Generation company		
Energy company/ Utility company/ Energy retailer/ Electricity Service provider		
Other	*Other*	*Other actors*

3.3.2.2 Network construction

There are several options when constructing networks from data on 2-mode or bipartite networks. These include assumptions about i) the type of network, ii) who is connected, iii) the lifetime of ties and nodes and iv) inclusion of single actor projects.

i) Our database provides information about how actors are affiliated with projects. This generates a bipartite graph with two types of nodes, actors and projects. To apply SNA tools, bipartite (2-mode) graphs need to be transferred into 1-mode projections. In our case, we create a network of actors (nodes) that are connected by projects (ties).

ii) Who is connected: Our data includes information about the project leaders. This opens up two options (based on different assumptions) for the creation of the network (Breschi and Cusmano, 2004). First, it can be assumed that all partners in a project are equally in contact with each other, which leads to completely connected subgraph (clique) for each project. Second, it can be assumed that the leader has a central role in the project and acts as an intermediary, i.e. all information passes through the leader. This results in a star network. Both assumptions are strong and equally plausible and can be applied for addressing specific questions. We checked numerous project websites and in most cases found particular emphasis on the role of the leader, which is why we decided to work with the star network assumption for analyzing collaborations. On the other hand, path dependency requires considering involvements in projects over time, rather than collaboration with the project leader; therefore, the clique network assumption is used for path-dependency analysis.

iii) Considering the life-time of the ties, there are two basic options. We can either assume that the ties between actors only last for the duration of the project (network based on running projects) or that they continue even after the project has finished until the duration of analysis ends. The latter is based on the assumption that collaboration and knowledge exchange between actors continues even if they are not any longer connected by a formal project. In this case, the network increases with every new project (cumulative network). Below we look into data for the cumulative network over specific periods of analysis.

iv) Inclusion of single actor projects: 47% of the projects in our database involve just one actor. As we wanted to include them in our analysis as a benchmark for comparing spatial characteristics, we assigned each single actor a tie to itself with the consequence that these (national) ties are counted when determining the nationalization index (see below).

3.3.2.3 Determination of three periods

Our analysis encompasses a period of 11 years (2002-2012). Earlier research based on the same data has already pointed to qualitative changes during this period, i.e. a shift in the type of projects from R&D to D&D projects (Colak et al., 2015). Aligned with the revised IAD framework, institutions at the European level can be considered exogenous to the action arena, and the IAD framework operationalizes these institutions as specific events influencing interactions and the action arena. Towards this end, we compiled a list of major events related to smart grids in Europe in areas such as regulation, public funding of research, coordination of development and industry activities. We identified two points in time, when – in our view – important and qualitatively new events came together. From this, we derived three periods for analysis.

3.3.3 A revised framework for analyzing spatial diversity of network communities

The revised IAD framework for analyzing the spatial diversity of TIS development is shown in figure 3-2. On the left hand side, assumptions for link formation, and the path dependency of network developments over time constitute the material conditions. Project types (R&D vs. D&D) is the primary community-level attribute exogenous to activities. More importantly, two sets of institutions exogenous to the action arena are in place. First, EU policies and important events influence the whole system, which is why they are used to distinguish different periods of system development over time. Second, the tendency of countries to focus on national activities or collaborate with other countries is reflected in the two indexes for measuring the relative weight and diversity of multinational collaborations, called nationalization index and entropy respectively. Therefore, we assume these indicators are proxies for national institutions.

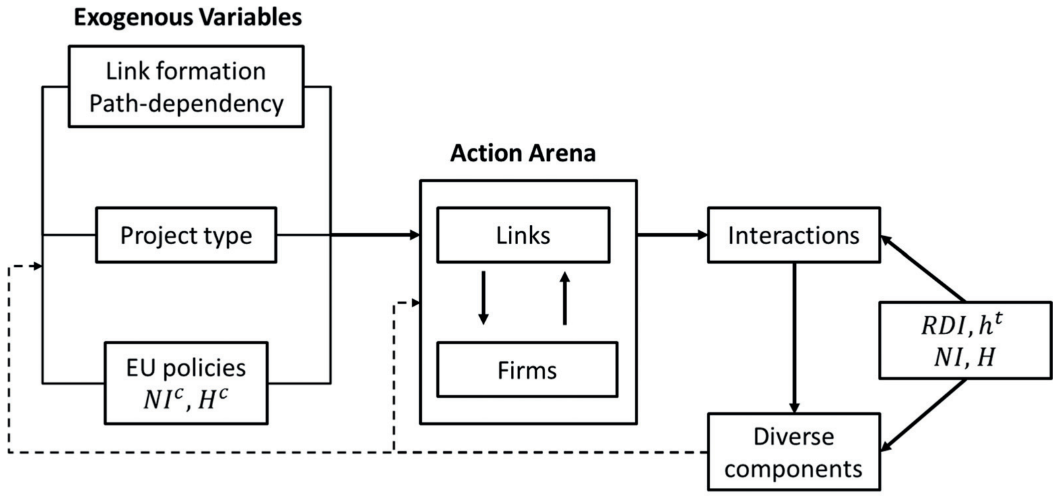


Figure 3-2. The revised IAD framework for spatial analysis

In the action arena, links represent the action situations and in our method, firms act in these action situations. Firms interact within projects and shape the network of interactions that result in the emergence of modules with different characteristics. After identifying the resulting modules, four indicators are used to evaluate the spatial characteristics of the resulting modules. These indicators are R&D intensity, modular nationalization index, modular entropy and type homophily. In the next section, the indicators for analyzing diversity at both national and modular levels as well as the methods for finding modules and analyzing path-dependency are presented. Then, the indexes for nationalization and diversity are calculated for the case of random network, as a benchmark for comparing the results of network analysis.

3.3.4 Measures and indicators

Based on the components of the framework presented in the previous section, different indicators are needed for measuring spatial variables in both exogenous factors and the evaluative criteria of diversity. These indicators are presented in this section. Functional maturity

Functional maturity addresses the relative importance of knowledge development activities, formalized in R&D projects, versus entrepreneurial experimentations, formalized in D&D projects. It is assumed that over time, the relative share of these activities changes when the TIS becomes more mature. In addition, the composition of actors over time and across different functions changes. It is assumed in the early years of TIS development, knowledge development function is dominant, and research centers or universities are the dominant actors. Over time, some of these research activities enter the experimentation and implementation phases, and the entrepreneurial activity function gains more share. Therefore, increasing TIS maturity from knowledge development activities to entrepreneurial experimentations logically leads to a decreasing dominance of R&D activities in an emerging TIS. Furthermore, research centers and universities start to collaborate with other actors, and their relative dominance diminishes as well. In this respect, two indicators are defined in order to address these two system characteristics.

R&D intensity (RDI) calculates the relative share of R&D ties in the network as:

$$RDI = \frac{l_{rd}}{L} \tag{3-1}$$

Where

- $l_{rd} = \text{ number of R\&D ties}$
- $L = \text{total number of R\&D and D\&D ties}$

The second indicator calculates the relative share of collaborations of actors of the same type and is called type homophily (h^t):

$$h^t = \frac{l_h}{L} \tag{3-2}$$

Where

- $l_h = \text{ number of ties between the same actor types}$

3.3.4.1 Nationalization Index

The first indicator for spatial analysis is the nationalization index (NI). It compares the share of national vs. international ties in a network. We calculate the nationalization index for the entire TIS or any sub-network as follows[4]:

$$NI = \frac{L_{nat}-L_{int}}{L_{nat}+L_{int}} \tag{3-3}$$

Where:

[4] This is different from the definition proposed by Binz et al. (2014) to avoid that every country has the same weight, regardless of its size (number of actors/links). NIs can also be calculated for sub-networks (e.g. actors in a selected region, country or cluster).

- NI: Nationalization index of a technological innovation system
- L_{nat}: Total number of national links. National links connect nodes (here: actors) with same nationality.
- L_{int}: Total number of international links. International links connect nodes with different nationalities.

A positive NI indicates that national collaboration dominates the network, a negative NI signals a stronger role of international collaboration. This measure ranges from -1 for a fully international network, to 1 for a fully national network.

At the country level, the nationalization index is calculated based on the total number of the links where at least one of the nodes for each link belongs to the country. At the country level, a high NI means firms from a specific country are inclined to national collaboration, while a NI implies tendency to participate in multinational collaboration:

$$NI^c = \frac{L^c{}_{nat} - L^c{}_{int}}{L^c{}_{nat} + L^c{}_{int}} \tag{3-4}$$

Where:

- NI^c: Nationalization index of country c
- $L^c{}_{nat}$: Total number of links connecting nodes from country c
- $L^c{}_{int}$: Total number of links between nodes from country c and nodes from other countries

3.3.4.2 Entropy

The concept of entropy is an indicator for the diversity across types in a population and belongs to a larger class of diversity measures called generalized entropy functions that can be written as:

$$G_m^\alpha = \left(\sum_{i=1}^{m} \gamma_i{}^\alpha\right)^{\frac{1}{1-\alpha}} \tag{3-5}$$

Where:

- G_m^α: Generalized entropy
- α: Entropy coefficient
- m: total number of categories
- γ_i: Number of members in category i divided by the total number of members

The case $\alpha = 2$ is the most common measure of diversity called with different names such as Simpson's index or Herfindahl index:

$$H = 1/\sum_{i=1}^{m} {\gamma_i}^2 \tag{3-6}$$

High entropy signals a high number of categories and an equal distribution among categories (e.g. countries), while low entropy indicates concentration (e.g. a majority of actors from one or just a few countries). Simpson's Entropy ranges from 1 (for the case when all members belong to one category) to m (for the case where all the members of the population are equally distributed between m categories).

Entropy can be analyzed for a range of characteristics, e.g. types, size, origin of actors, types of projects etc., and at different levels, e.g. country, community, network, etc. In this study we are interested in the diversity of nationalities at both country and community levels.

A simple way to calculate the diversity of a TIS in terms of nationalities would be to add the shares of actors from each country (and take the reciprocal value thereafter). Every actor would then be counted once, regardless of whether it is involved in one or several projects. To determine the entropy of project involvement we count the number of actors from a specific country for each project, adding them up over all projects and dividing it by the sum of all actors involved in each project:

$$\gamma_i = \sum_{\alpha}^{P} {n_c}^{\alpha} / \sum_{\alpha}^{P} N_{\alpha} \tag{3-7}$$

Where:

- ${n_c}^{\alpha}$: $number\ of\ actors\ from\ country\ c\ in\ project\ \alpha$
- N_{α}: $total\ number\ of\ actors\ in\ project\ \alpha$
- P: $total\ number\ of\ projects$

Then, shares of each country (γ_i) are used to calculate the entropy of population. Compared to the simpler approach, this way of calculation yields lower entropy values in cases characterized by a few actors participating in many projects.

At the country level, entropy is calculated by looking at the links where one node belongs to each country.

$$H^c = 1/\sum_{i=1}^{m} ({\gamma_i}^c)^2 \tag{3-8}$$

Therefore, share of other countries is calculated by:

$$\gamma_i{}^c = \sum_l^{l_c} n_i{}^l / \sum_l^{l_c} N_c \quad (3\text{-}9)$$

Where:

- $n_i{}^l: number\ of\ actors\ fro\quad country\ i\ in\ link\ l$
- $l_c: total\ number\ of\ links\ with\ one\ actor\ from\ country\ c$
- $N_c: total\ number\ of\ actors\ collaborating\ in\ links\ l_c$

3.3.4.3 Path-dependency

In order to analyze the path-dependency of TIS development over time, attachment of new modules to the modules existing in older periods is investigated. Here, attachment means to what extent actors in two modules share the same actors. In other words, it highlights the actors stay in the network and participate in newly launched projects. This is done in a comparative way and for each module calculates its attachment to all modules in the previous period by calculating the ratio of shared actors to total actors in each module.

3.3.5 Detecting modules

In social networks, nodes tend to form communities, where the actors tend to have tighter collaboration with each other than the rest of the network. For community detection, an algorithm called modularization is used, which assigns each node to a community and avoids overlaps between communities.

Modularity is a measure for finding communities, which considers the ties within and between a community and the other parts of a network (Clauset et al.; 2004). It tries to maximize the value of modularity shown in equation 3-10 by finding the edges most probably in the same community in comparison to a random network. In order to find modularity in our network, the main assumption is that collaborations take place inside project boundaries. In this respect, the possibility of including two firms involved in a project in the same module is higher than the case two firms are involved in different projects. Therefore, a network of all project collaborations between project members, is used to find modules.

$$Q = \frac{1}{2m} \sum_{i,j} [A_{ij} - \frac{k_i k_j}{2m}] \delta(c_i, c_j) \quad (3\text{-}10)$$

Where :

- Q: modularity
- m: total number of degrees
- $\delta(c_i, c_j)$: delta function, equal to 1 if edges i and j are in the same community, otherwise 0.
- A_{ij} : adjacency matrix
- $\frac{k_i k_j}{2m}$: probability of an edge between two nodes proportional to their degrees

For a random network, Q is equal to zero. We can decrease modularity to find larger communities, but in this paper, we look at the communities while the modularity is maximized.

3.3.6 Spatial diversity in a random network

Based on our model assumptions, since both entropy and NI depend on the size of the modules, a random network is created by considering the same assumptions in order to compare the relative spatial characteristics of modules. These assumptions include the relative network density, adding loops for project leaders and the relative share of countries in all activities. The NI and entropy for this hypothetical case can be computed as:

$$H^r = \sum_{i=1}^{c} [1 - ((N - n_i)/N)^{n_m}] \quad (3\text{-}11)$$

$$NI^r = \frac{w_1.N + w_2.l_n - w_3.l_i}{w_1.N + w_2.l_n + w_3.l_i} \quad (3\text{-}12)$$

Where:

- $H^r = entropy\ of\ random\ network$
- $NI^r = nationization\ index\ of\ random\ network$
- $N = total\ number\ of\ nodes$
- $c = total\ number\ of\ countries$
- $n_m = nodes\ of\ module\ m$
- $n_i = nodes\ of\ country\ i$
- $l_n = number\ of\ national\ links$
- $l_i = total\ number\ of\ international\ links$
- $w_1, w_2, w_3 =$ $relative\ weight\ of\ loops, national\ links\ and\ multinational\ links, respectively$

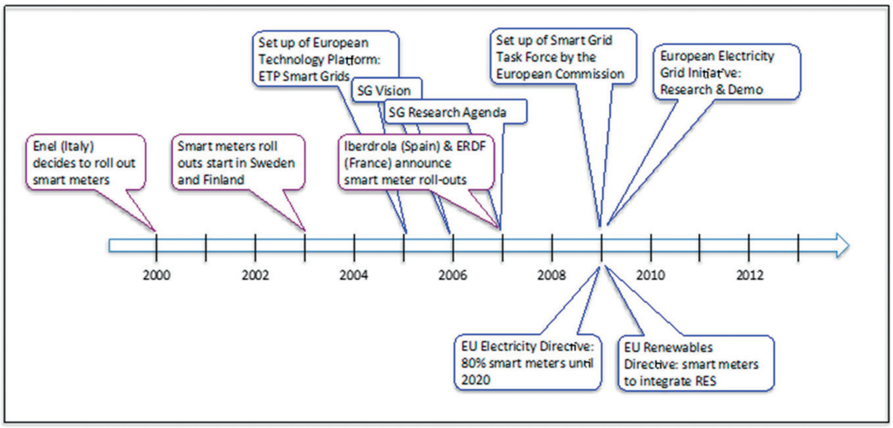
Here, entropy of the random network is not equal to the total number of countries and is a function of the distribution of nodes between countries as one of the network assumptions. In addition, relative weights in equation 3-12 account for network density reflected in both loops and links.

3.4 Results

3.4.1 General description

The European smart grid is still in the formative phase (Bergek et al., 2008) characterized by a key role for public R&D funding, entrepreneurial experimentation in pilot projects, competing technology standards and a large variety of immature business models (Suurs et al., 2010). At the same time, the field has seen major progress over the past two decades, e.g. in terms of specific visions and strong regulatory support. Below we shed light on this development through a list of exogenous institutions or major events in areas such as regulation, public funding of research, coordination of development, and industry activities.[5] We also use these events, or milestones, as indicators for different periods of early TIS development.

The decision of Italy's largest utility company Enel in 2000, to roll out smart meters to its entire electricity consumer base with more than 30 Mio meters can be viewed as the first major event in the history of smart grids in Europe. From 2003 onwards, also utilities in Sweden and Finland begin to install smart meters. In 2005, the European DG Research initiates a 'European Technology Platform for smart grids' (ETP SG) with the aim "to formulate and promote a vision for the development of European electricity networks".[6] Among others, the ETP SG publishes a first vision for the development of smart grids in 2006 and a strategic research agenda in 2007.



[5] We also include events related to smart meters here because they are major manifestations of industry activity and important elements of smart grids, even though we do NOT include smart meter rollout projects in our database.
[6] ETP website, accessed August-15, 2016: http://www.smartgrids.eu/Background

Figure 3-3. Milestones for smart grids development in Europe

In 2009, the European Commission sets up a Smart Grids Task Force with representatives from the Commission, electricity industry and consumers. It has the aim to "advice the Commission on policy and regulatory frameworks to coordinate the first steps towards the implementation of Smart Grids ... and to assist the commission in identifying projects of common interest in the field of Smart Grids".[7] In the same year, a novel EU Electricity Directive formulates the goal to install smart meters in 80% of the households until 2020 (European Commission, 2009b) and the Renewable Energy Directive views smart grids as an enabler for the integration of increasing shares of intermittent renewables (European Commission, 2009a). Also in 2009, the European Electricity Grid Initiative (EEGI) is established as a part of a larger European Strategic Energy Technology Plan. The EEGI has a budget of around 2 Billion Euros (over 10 years) to fund R&D and large-scale demonstration projects (Han et al., 2014).

Our analysis shows that there is a first accumulation of events around 2005/06 with increasing coordination of research and the formulation of visions at the European level. A second accumulation is in 2009 with the adoption new regulations, the launch of task force and targeted R&D funding. As a consequence we suggest distinguishing three phases: 2002-2005 (4 years), 2006-2008 (3 years), 2009-2012 (4 years).[8]In order to highlight the differences between these three periods, and show the relative impact of important institutions at the EU level, each period only consists of projects started during that period. It means the network in each period is the accumulation of projects started during that period, without including other projects started in the previous period(s).

Table 3-2. Summary of the properties of the network over three periods

Period	Projects	Firms	Edges	NI	Entropy	Countries	RDI	Type homophily
1	10	104	157	-0.53	11.89	21	0.94	0.42
2	66	248	330	-0.13	12.05	25	0.62	0.52
3	329	1265	2075	-0.04	13.71	30	0.44	0.43

Table 3-2 summarizes the general properties of the network over three chosen periods (for a more detailed descriptive analysis see Colak et al. (2015)). The TIS

[7] Task Force mission statement, accessed August-15, 2016: https://ec.europa.eu/energy/sites/ener/files/documents/mission_and_workprogramme.pdf

[8] Note that 2002 and 2012 are determined by the availability of our data.

develops as a small network of projects in the first years of development, with about 100 actors involved in 10 projects, most of which have a total investment below 2 M Euros (Covrig et al., 2014). Three large projects explain the majority of the dynamics in the first period. Even though the network is still small during that time, the actors stem from 21 different countries. Almost all the activities are at the R&D stage of development and the network is highly multinational.

In the second phase, the actor base increases more than double in the first phase and 66 new projects are launched, nearly half of which are small D&D projects. Nonetheless, the overall budget is 4.5 times higher than in the first phase (an increase from 81 M € to 368 M €). Network becomes less multinational compared to the first period, and RDI also decreases due to the launch of D&D projects, although the network is still dominated by R&D activities, since R&D projects are larger and more connected.

In the third phase, the number of actors increases almost 5-fold to a level of 1’265 actors from 30 different countries. The project count climbs to 329. Smart grid projects are also getting larger and some countries like the UK, Italy, France and Denmark very much increase their budgets for smart grid investment (Covrig et al., 2014), leading to their relative dominance in both D&D and R&D activities. In this period also the involvement of firms in D&D projects surpasses the involvement in R&D projects.

3.4.2 Spatial diversity of modular development

Implementing the modularization algorithm for three periods of analysis, leads to the identification of main modules in each period. In order to remove the impact of isolated projects, our analysis includes the modules that have actors at least from two projects. Considering the spatial nationalization and diversity of a random network presented in §3.3.6, the relative diversity and nationalization of the modules over different phases are depicted in figures 3-4 and 3-5 (modules depicted by ‘i’ denote the aggregation of isolated nodes in each period for further comparison). The dotted curves in these figures represent the values for the hypothetical case.

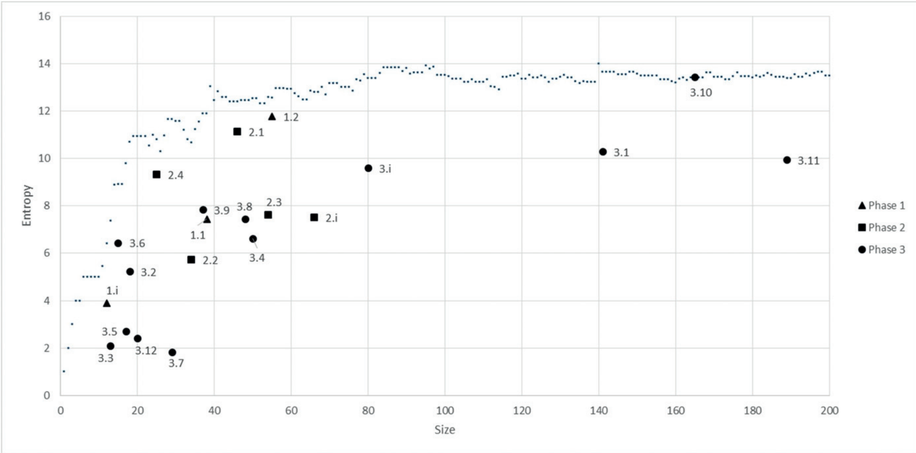


Figure 3-4. Entropy vs size for modules and isolates

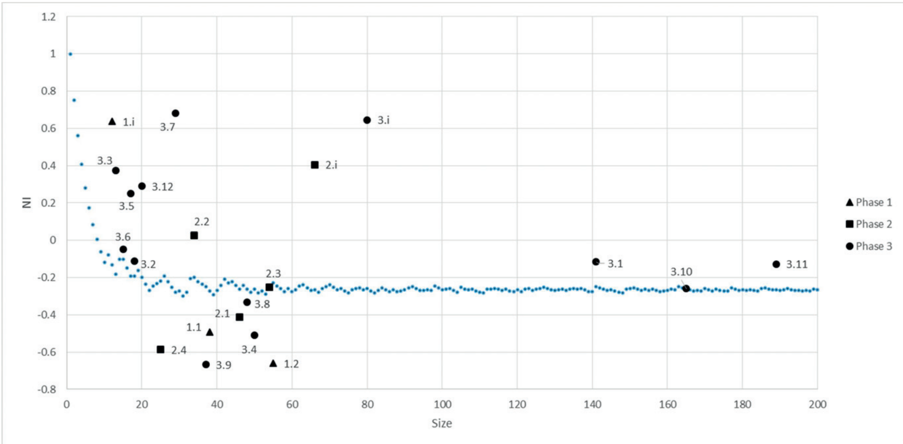


Figure 3-5. NI vs size for the modules and the isolates

For the case of random network, if the share of all countries from involved firms were equal, we could expect entropy reaches the maximum value equivalent to the number of involved countries. However, since distribution of firms between countries is not equal, by increasing the size of modules, this inequality appears in modular composition, and for our dataset entropy reaches to an equilibrium value of about 14. In addition, by assuming the same shares for countries and randomly assigning project leaders, the network modules become relatively multinational and NI reaches an equilibrium value of around -0.25.

Based on these figures, a heterogeneous network is observed in all three periods, and this is the reason spatial dimension of TIS development, for the case of smart grid, cannot be easily reduced to an ideal pattern. Based on figure 3-4, relative entropy of all modules is lower than the random network, which reveals there are dominant countries in all modules even by controlling for the unequal distribution of firms among countries.

For NI, the picture is even more heterogeneous, and while small modules tend to have a relatively national character, medium modules are more international than the random network. One explanation discussed later in more details is that small modules form around a national center, while medium modules form around a central and multinational project. Largest modules on average show a slightly less international character than the random network, which can be attributed to their relatively low entropy, and dominance of a few countries.

3.4.2.1 Period 1: 2002 – 2005

Table 1 summarizes the modules and isolates in the first period. Based on this table, two small modules emerge in this period. Both modules are fully R&D (RDI= 1) and highly international. Figures 3-4 and 3-5 show that one module (1.1) has slightly lower NI and lower entropy relative to the hypothetical case. The other module (1.2) has an entropy close to the hypothetical case, but lower NI compared to it. In addition, module 1.1 shows a higher type homophily since collaboration between universities is the dominant pattern of collaboration, while in module 1.2 utility companies collaborate with universities and manufacturers.

Table 3-3. Summary of the characteristics of modules and isolates in the first period

Module	Projects	Firms	Edges	NI	Entropy	Countries	RDI	Type homophily
isolates (1.i)	6	12	11	0.64	3.90	7	0.09	0.64
1.1	2	38	71	-0.49	7.44	12	1.00	0.51
1.2	2	55	59	-0.66	11.77	19	1.00	0.24

A closer look at the modules by considering the spatial characteristics of countries (figure 3-6) reveals the country-level differences behind the structure of two modules. Indeed, although all countries are primarily involved in international collaborations and the majority of countries have a low entropy, two countries, Germany and France, have the maximum entropy values in this phase, implying the large share of actors from these countries collaborating with actors from other countries. However, the relative dominance of German and French actors in module 1.1 (research institutions) makes the difference by reducing the total number of countries and evenness of spatial distribution in this module. On the other hand, in module 1.2 the majority of countries with smaller shares collaborate in projects with higher evenness and diversity. This result can be counter-intuitive in the sense that the involvement of high-entropy countries does not necessary lead to a diverse module.

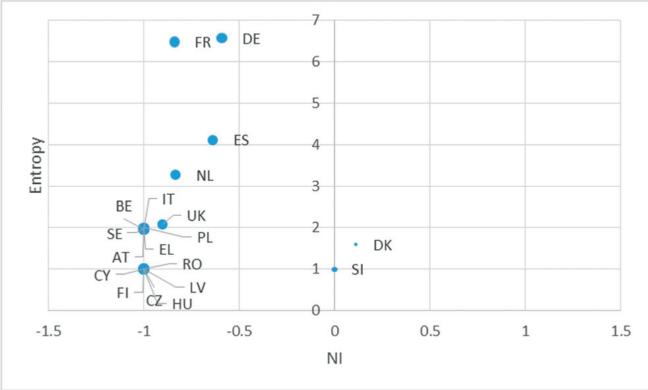


Figure 3-6. National spatial characteristics in phase 1. Node size represents RDI

The special case of Denmark and Slovenia in figure 3-6 can be explained by the lack of presence of D&D activities in the two modules. Therefore, these two countries are involved in isolated and national D&D projects.

3.4.2.2 Period 2: 2006 – 2008

The second period is composed of four modules summarized in table 3-4. This period keeps the dominance of R&D activities in the center of the network, but the most significant change compared to the first period is the emergence of one module (2.3) with a substantial share of D&D activities (50%) and composed of small R&D projects, mainly around Technical University of Denmark. Indeed, in the center of this module is a large D&D project called "More Microgrids" that is highly multinational. The high number of German firms collaborating with firms mainly from Greece, Spain, France, the Netherlands and the UK has led to the relatively low entropy for this module.

Table 3-4: Summary of the characteristics of modules and isolates in the second period

Module	Projects	Firms	Edges	NI	Entropy	Countries	RDI	Type homophily
Isolates (2.i)	25	66	74	0.41	7.51	13	0.23	0.52
2.1	6	46	51	-0.41	11.14	16	0.98	0.31
2.2	6	34	41	0.02	5.72	13	0.78	0.68
2.3	21	54	80	-0.25	7.63	14	0.50	0.63
2.4	4	25	29	-0.59	9.33	15	1.00	0.79

The other three modules are composed of a small but middle-size number of international R&D projects (4-6 projects with 6-7 actors) and show different characteristics. Modules 2.1 and 2.4 both show relatively more international and equally diverse characteristics compared to the hypothetical case (figures 3-4 and 3-5). However, module 2.1 has a low type-homophily caused by the involvement of universities, manufacturers, utilities and IT firms with a central role of the University of

Manchester, while module 2.4 has a high share of utility companies and high type-homophily.

Finally, module 2.2 is a special case composed of national activities in Austria with the involvement of different actor groups, in collaboration with multinational activities dominated by the research institutions centered around Vienna university of technology (Austria), Ricerca sul Sistema Energetico RSE SpA (Italy) and SINTEF Energy Research (Norway).

Considering the path-dependency of spatial diversity, tracking the actors active in the first period in the second phase reveals more information. In general, the firms active in the first period are the central firms and project leaders in the second period; however, their involvement in different modules leads to the variation in modular diversity.

Module 2.3 has the highest attachment to module 1.1, which explains the relative dominance of German firms and relatively low diversity of module 2.3. Considering the RDI of module 2.3 implies R&D projects are breeding the first emerging D&D module in the TIS development. Module 1.2 has the highest number of actors in modules 2.1 and 2.4. Similar to the first period, both of these modules have a higher diversity than the other modules. In addition, module 2.1 shows similar spatial composition to module 1.2 (involvement of countries with small shares of activities), while module 2.4 shares the relatively high number of utility companies with module 1.2. It implies the multinational network of activities led by utility companies breeds two distinct modules with different characteristics in the second phase. Finally, module 2.2 has less and mixed attachment to the modules of the first period and shows a rather national development of a network attached to the larger and multinational network of collaborations.

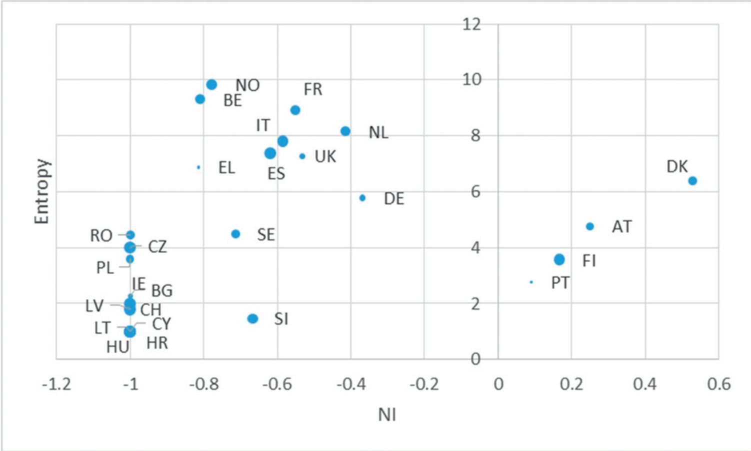


Figure 3-7. National spatial characteristics in phase 2. Node size represents RDI

A closer look at these modules by analyzing national measures (figure 3-7), depict four countries (Denmark, Austria, Finland and Portugal) have a high share of national activities. However, among them, only Austria has a visible share in the modules, where its presence in module 2.2 leads to a relatively high NI in this module.

The countries in the lower left part of figure 3-7 have a substantial presence in module 2.1 and in collaboration with firms from Belgium, UK and Germany, leading to a higher diversity compared to the other modules. Another module with relatively high diversity is module 2.4 with rather equal share of medium-entropy countries such as Germany, Czech Republic and Spain. This relatively equal distribution is a factor of the tendency to involve utility companies from different countries in this module.

Finally, the large share of German actors in module 2.3, in collaboration primarily with the actors from high-entropy countries such as the UK, France, the Netherland and Spain (five countries with a share of about 70 percent in this module) leads to a relatively low spatial diversity for this module. Again, a module mainly composed of countries with diverse profiles shows a rather low diversity at the aggregate level.

Isolated nodes in this period include some large and international D&D projects. It has led to the relatively low NI for this period, which implies international D&D projects are not necessarily using the resources shared with the majority of the actors.

3.4.2.3 Period 3: 2009 – 2012

Modules in the third period can be categorized to three groups based on their size, summarized in table 3-5. Looking at figures 3-4 and 3-5 reveal small modules show rather higher NI and lower diversity than the hypothetical network. On the other hand, the majority of medium modules show rather lower NI and entropy than the hypothetical case, while two out of three large modules are less multinational and diverse than the hypothetical case. These initial observations may imply patterns of spatial diversity at the modular level based on the underlying spatial structures at the country level.

Table 3-5: Summary of the characteristics of modules and isolates in the third period

Module	Projects	Firms	Edges	NI	Entropy	Countries	RDI	Type homophily
Isolates (3.i)	50	80	96	0.65	9.58	18	0.35	0.69
3.1	46	141	217	-0.12	10.29	21	0.66	0.44
3.2	5	18	27	-0.11	5.23	8	0.00	0.44
3.3	3	13	16	0.38	2.09	3	0.06	0.25
3.4	2	50	53	-0.51	6.61	9	0.00	0.17
3.5	7	17	24	0.25	2.70	4	0.17	0.54
3.6	7	15	21	-0.05	6.43	9	0.62	0.57
3.7	4	29	50	0.68	1.82	5	0.22	0.50
3.8	6	48	60	-0.33	7.43	16	0.15	0.27
3.9	2	37	36	-0.67	7.82	12	0.75	0.44
3.10	23	165	197	-0.26	13.42	24	0.32	0.42
3.11	42	189	298	-0.13	9.93	20	0.41	0.41
3.12	3	20	31	0.29	2.41	5	1.00	0.52

Indeed, small-scale modules in this period are mainly small groups of firms formed around a national center or national projects in collaboration with multinational firms in small projects. For instance, we see national and multinational collaborations around the Royal Institute of Technology in Sweden, university of Aalborg in Denmark and Nord Trondelag Elektrisitetsverk AS (NTE) in Norway as well as groups of national firms from Finland, Austria and Denmark taking part in multinational activities. In these modules, one firm in a national network or one country in a multinational network has the dominant role. In general, these are the countries with rather higher NI compared to the rest of Europe (figure 3-8). Furthermore, these small modules have negligible attachment to the actors from the previous periods, implying they are niches developed by some countries to work on innovations and new technologies.

In medium-scale modules, the same pattern holds, but the dominant role shifts to larger and multinational D&D projects. Again, these modules are rather isolated from the rest of network and there is negligible attachment to previous periods. However, the distinction from the smaller modules can be explained by addressing the central projects mainly international and dominated by Germany, Italy and Spain. This leads to lower NI and diversity compared to the hypothetical case. It implies the countries with high entropy and moderately international activities contribute to the niche experiments that are larger and more geographically diverse than the niches dominated by countries with rather national activities. While different actor groups collaborate on D&D activities dominated by actors from Germany, France, Spain and the UK (modules 3.4 and 3.7), Italy has a substantial share in the R&D activities with the active enrolment of universities and manufacturers (module 3.8).

Three large modules show different structural characteristics, although spatial patterns are more similar and different actor groups are present in all of them. Module 3.10 is close to the hypothetical case, composed of relatively large and multinational D&D projects and small national R&D projects. Analyzing path-dependency reveals very low attachment to the modules in the second period (modules 2.1 and 2.3) through actors from the Netherlands, Belgium and Greece, countries with low NI and active role in decentralized modules. In addition, Spain, Italy and Finland are involved in national activities in smaller projects. It causes the very low share of German and French actors, and the substantial contribution of countries such as Portugal, Bulgaria, Austria, Norway and Sweden, as the countries with low NI and moderate entropy, as well as counties with very low shares in the TIS development. As a result, this module shows larger diversity and lower NI compared to the other large modules.

Module 3.11 is composed of small and international projects at the D&D stage of development, with a substantial share of actors from Germany, France, Italy and Spain, leading to a relatively lower diversity and higher NI than the hypothetical network. Path-dependency analysis shows it has moderate attachment with module 2.3, also with a high share of actors from Germany, France and Spain, and the relative dominance of D&D activities.

Finally, module 3.1 is similar to module 3.11 in the sense it has relatively higher NI and lower diversity compared to the hypothetical case and the substantial share of a few high-entropy countries. However, it is mainly composed of a few EU-funded D&D projects and several R&D projects. Apart from Spain, Italy and Germany, some other countries such as Belgium, Austria, UK and Norway have an active role, leading to a relatively low entropy. Tracking the path-dependency shows a mixed combination of actors from modules 2.2, 2.3 and 2.4, the modules with lower diversity and the active role of utility companies and universities in separate modules. These actors place the leading roles and collaborate with new actor types, especially manufacturers; therefore, we see a shift from interactions within actor groups to interaction between universities, utility companies and manufacturers.

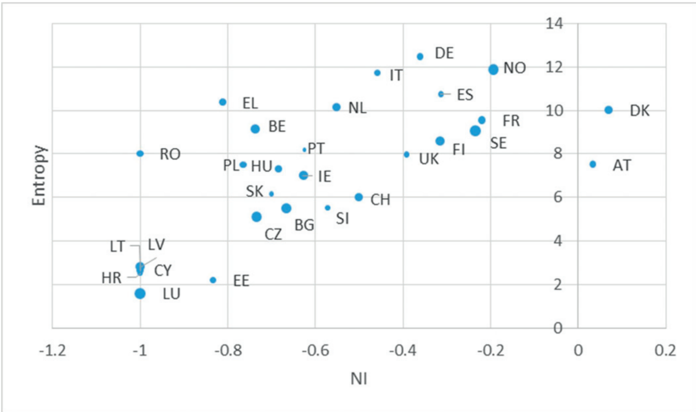


Figure 3-8. National spatial characteristics in phase 3. Node size represents RDI

Isolated nodes in this period include some large number of small R&D and D&D projects. It has led to a larger RDI compared to the previous periods, and implies along with the emergence of small modules as the niches for new innovations, the decentralization pattern continues in smaller niches isolated from the main centers of activities.

3.4.3 Summary

Using insights from the IAD framework, a combination of the ideas of path-dependency and emergence of spatially diverse communities from complex system theory, functional maturity and random network theory can explain the spatial dimension of smart grid development as a TIS. In the early years, when knowledge development is the major function, in parts of the network with higher share of collaboration among universities, diversity is rather low and the network is less multinational. This is the pathway that gradually breeds the D&D projects and leads to the emergence of a diverse and multinational module of D&D activities over time.

On the other hand, in the more multinational and diverse module of R&D projects in the early years, the network is inclined to collaboration between utilities and universities. Over time, the utilities from different countries take the dominant role and keep doing research in the subsequent years with the higher share of firms from countries with higher R&D budgets such as Austria, Denmark and Belgium.

In addition, part of the network moves toward the domination of countries with the highest share of smart grid investment in Europe. Firms from Spain, Italy, France and Germany tend to collaborate in several projects. This pattern continues in both R&D and D&D activities, leading to the emergence of a large module in the third period, with relatively low diversity.

Finally, we see the emergence of small and medium modules in the third phase formed around a national network or an international project respectively. These modules have negligible attachment to the previous activities and show similar patterns: high NI and diversity close to the hypothetical case for small modules and low NI/ low diversity for medium modules dominated by a few countries.

No attachment of small and medium sized modules in the third period shows the system goes towards decentralization and more heterogeneity in terms of the actors involved in the network.

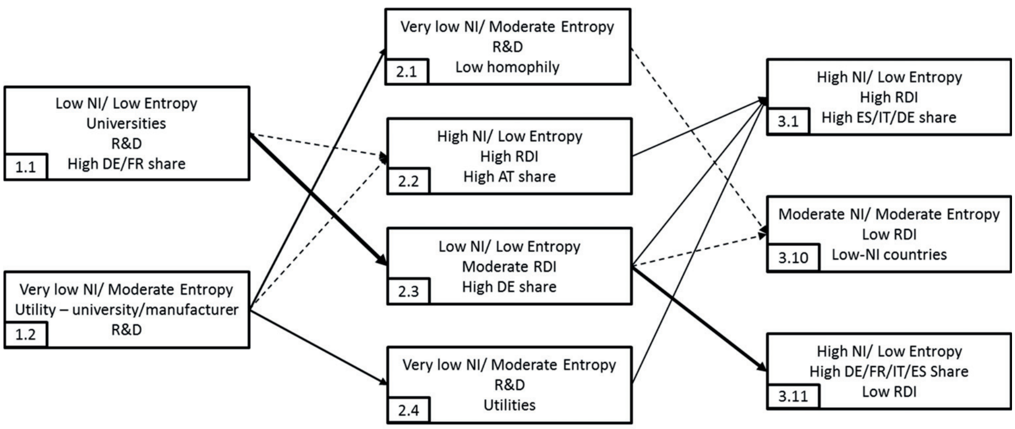


Figure 3-9. Summary of Path-dependency over three phases

Figure 3-9 summarizes the path-dependency of the main modules over time, including their spatial characteristics. Weight of the arrows connecting two modules represents the strength of overlap between the nodes of the modules, or the attachment of a module to the modules in the previous phase. Based on these figure, one natural path of development with the highest attachment can be specified. This path starts from multinational network of R&D activities dominated by firms from France and Germany, which breed D&D activities in the second period (low RDI compared to other modules in the second period), where German firms maintain their dominance. This path of development in the third phase continues by the growth of D&D activities in relatively national networks, and increasing dominance of countries with large investment in smart grid projects, such as Germany, Italy, France and Spain (JRC, 2014).

Furthermore, these countries are involved in a network of R&D activities in the third phase, with mixed attachment to the previous modules, and here large EU-funded R&D projects can be observed, as an explanation why this module diverges from the main path. Finally, countries with less involvement in smart grid activities form a relatively diverse and multinational module in this period, with low attachment to modules of the second period. It shows a module with negligible path-dependency to older modules and less affected by external factors, such as EU funding, is the closest to a random network.

3.5 Agent-based modeling of spatial patterns

To further investigate the impact of entropy and NI at the country level on the spatial characteristics of modules, a simple agent-based model is presented in this section. Based on complex system theory, while the actors with extreme characteristics decrease system-level complexity and facilitate system analysis, these cases are rare in the real world; on the other hand, these are the actors with moderate characteristics that create complex systems and emergent phenomena (Page, 2010). In this respect, four typical scenarios are created by including four categories of agents (firm) with different NI and entropy values representing four different types of countries. One of these scenarios represents the extreme case, and acts as the base scenario for comparison.

- Scenario 0: four countries with similar spatial characteristics, with no preference for national activities over multinational collaborations and no preference in international collaborations. Therefore, for all actors, NI equals zero (equal share of national and international activities) and entropy is high. An agent with these characteristics is called type 1.
- Scenario 1: four countries with four different spatial characteristics. These categories represent the patterns observed in the empirical results of this study. These include actors that are highly national with no international preference (type 2: high NI, high entropy), highly multinational with no international preference (type 3: low NI, high relative entropy), multinational with

international preference (type 4: low NI, low relative entropy) and type 1 as described in scenario 0 (NI = 0, high relative entropy).

- Scenario 2: the same categories as in scenario 1 with gradually increasing dominance of type 3 (low NI, high relative entropy). In other words, a country with high share of multinational activities and collaboration with several other countries becomes more active and relatively dominant. (similar to the case of Germany or France in the empirical results)
- Scenario 3: the same categories as in scenarios 1 and 2, with increasing share of activities for types 1 and 4. This scenario focuses on the role of countries with average and smaller shares in multinational collaborations.

The scenarios were implemented using NetLogo (version 5.2.0), a multi-agent programmable modeling environment (Tisue and Wilensky, 2004). Each scenario runs for 200 ticks to reveal the long-term convergence of spatial parameters in different scenarios. In each tick, new firms are added to the network that create new links to the others based on their country-level characteristics. In order to calculate network diversity, the share of each category in activities (link formation) is calculated.

Figures 3-10 and 3-11 show the results of simulation for these scenarios. Based on figure 3-10, scenario 0 or the base scenario implies high entropy at the country level for all countries leads to the maximum diversity at the network level.

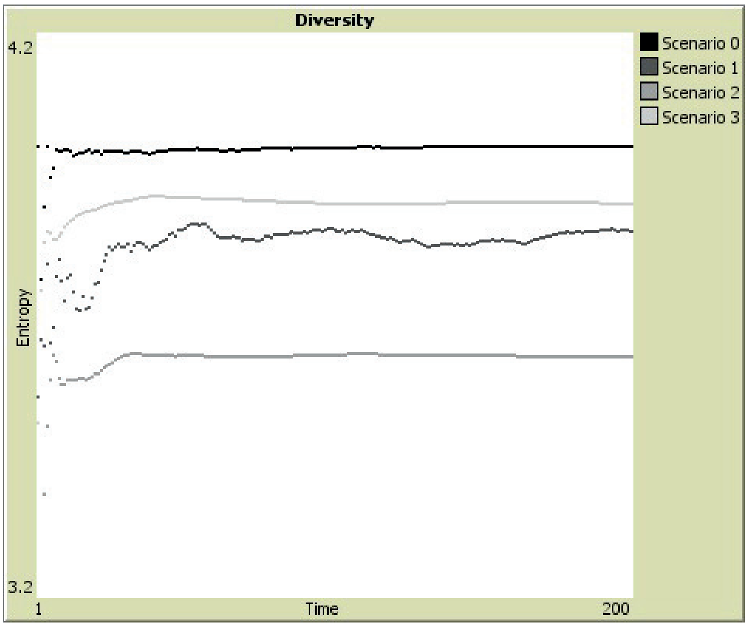


Figure 3-10. Network diversity in four hypothetical scenarios (visualized by NetLogo 5.0.2)

Scenario 1 shows maximum variety of country characteristics leads to the reduction of network diversity, since countries collaborate in multinational activities and with higher number of categories find a relative dominance over the other countries. These two scenarios assume either the same categories or the same shares, and can be considered as ideal cases of network development. Based on empirical results, the two remaining scenarios are more probable. If the share of activities for high-entropy and multinational category increases (scenario 2), it leads to further reduction in network diversity, since one category starts to dominate the network. However, in the case the share of countries with average involvement in collaborations increases (scenario 3), the network diversity increases to even a higher level than in scenario 1.

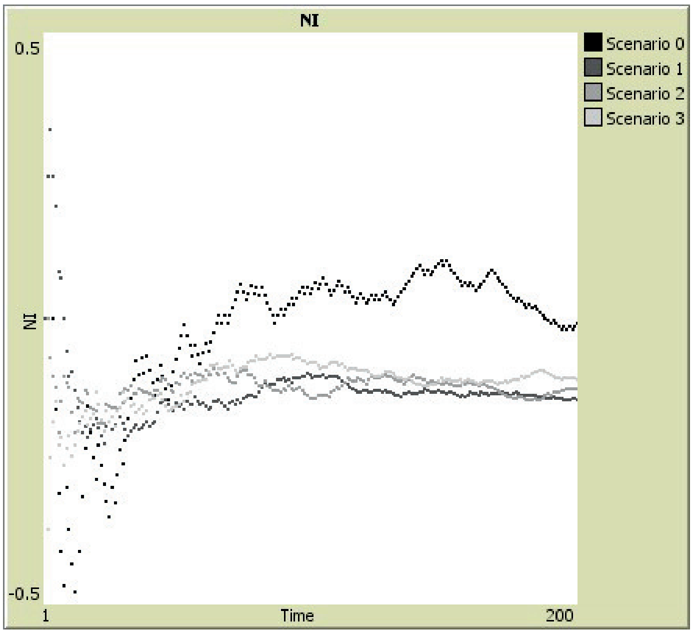


Figure 3-11. Network NI in four hypothetical scenarios (visualized by NetLogo 5.0.2)

As figure 3-11 shows, apart from the base scenario, all the other scenarios have similar levels of NI. It shows in order to understand the spatial characteristics of different networks, focusing on the relative weight of national and international activities is not enough for grasping the spatial differences between those networks. Therefore, country-level characteristics and their contribution to system-level diversity should be taken into account.

3.6 Discussion

The main findings of this research support the applicability of this method for analyzing the spatial diversity of TIS development. Country profiles depict a heterogeneity in tendency of countries to collaborate in national projects and diversity of multinational collaborations. These national differences lead to the emergence of diverse modules in each period, as well as different modular patterns over time. Second, analyzing the path-dependency of modular development over three periods reveals a main path of smart grid development, by the involvement of actors from countries with the highest share of innovative firms. Large modular attachment in this path, keeps the spatial diversity of smart grid activities low, which means a group of firms dominated by a few countries incline to collaborate together over time. Finally, maturity and dominance of specific TIS functions can be interpreted in light of both path-dependency and spatial diversity. The main path, follows a sequence of activities dominated by R&D projects, then breeding small D&D projects, followed by the emergence of larger and relatively national D&D projects. Furthermore, larger investment needed for D&D activities, can be an indicator for the emergence of the multinational and relatively diverse network of firms from countries with lower levels of investment in smart grid initiatives.

Some of the results of this study can complement some ideas raised in the literature on the spatial dimension of TIS development. First, Bento and Fontes (2014) classify countries as core countries and followers based on the state of their TIS. In this paper, comparing country profiles (figures 3-6 to 3-8) show countries can be classified based on their NI and entropy, where countries with higher share in smart grid activities and innovative firms show similar spatial patterns.

Second, Binz et al. (2014) argue that the development of an emerging TIS follows a centralization-decentralization-centralization pattern. In other words, cooperative ties form around a few central nodes in a dense network, followed by a rapid expansion phase in a decentralized network, and a consolidation phase in which knowledge development gets intensified among the existing firms. Focusing on R&D activities as the primary source of knowledge development in this research verifies this general pattern over three periods of analysis. However, since countries with different states of technology development and collaboration in smart grid activities are involved in modules across a TIS, this pattern is not taking place simultaneously in all parts of the network.

Finally, in this paper NI and entropy at the county level are interpreted as the tendency of a country to focus on national markets or collaborate in international projects. These indicators can be compared to other measures in literature to address the national tendency for international collaborations. Wieczorek et al. (2015) analyze the territorial embeddedness of a TIS, and by measuring system function fulfilment over a scale, evaluate this tendency. For instance, when knowledge development and entrepreneurial activities are high, but market formation and resource mobilization are low, they conclude the country prefers to participate in international projects.

There are some limitations in the method and the presented results. First, although this research took the first step to investigate spatial dimension across two interdependent functions, these functions are not developed equally in all the involved countries, and a thorough analysis needs to incorporate interdependencies with other TIS functions. Second, although research argues no specific boundary should be defined for analyzing the spatial dimension of TIS development, but the case of smart grid development in Europe is analyzed, due to data availability issues. Finally, this method leaves space for technical and methodological improvements, as well as testing other data sources. For instance, current method does not address any correlation between spatial characteristics and the emergence of larger modules, or national institutional contexts are not directly analyzed through including national policies and regulation. Some of the observed patterns and behaviors can be attributed to the bias of projects reported by the Joint Research Center toward projects funded by the European Union. For a more unbiased view, other data sources on smart grid projects can be combined.

3.7 Conclusions

This study aims to take the network approach for spatial analysis of TIS development a step further. It argues instead of solely criticizing the TIS literature for limiting enquiry to national boundaries and revealing the multinational nature of TIS developments, the contribution of country-specific institutions and spatial characteristics to the emergence of diverse spatial patterns should be analyzed. Therefore, the place of national characteristics changes from the unit of observation, to the underlying factors necessary to explain observed spatial patterns. For this purpose, it develops a method by using the IAD framework as the theoretical ground to decompose the structural components and applying insights from complex system theory to investigate the emergence of diverse modules and measure their spatial properties.

The analysis shows how specific spatial properties at the country level, may lead to spatial diversity at the modular and network levels, and create different spatial patterns in a path-dependent process. Agent-based modeling is a powerful tool for investigating the collective properties resulting from individual behaviors. The simple agent-based model developed in this paper, can be extended by adding other heterogeneous actor groups, and non-spatial parameters to improve the results and understand other dynamics such as the size and structure of large modules.

This paper has implications for research in studying technological innovation systems. Analyzing the structural components (actors, networks and institutions) can benefit from including complex dynamics such as interactions, path-dependency and pattern formation. In addition, functional maturity and the link between different functions can shed light on understanding spatial dynamics in TIS development.

Furthermore, the results support the argument that by looking at a multinational or spatially diverse network, the patterns of collaboration and tendency of countries to focus on national initiatives versus international partnership cannot be easily deduced, except for some extreme cases. It means we are faced with a heterogeneous network of spatial patterns, and system interventions for steering specific types of collaboration may lead to different consequences in different parts of the network. Therefore, this study might have implications for policymaking as system intervention and analyzing its impact on TIS development. On the one hand, choice of policies for the development of specific technologies might be influenced by the spatial diversity of the countries involved in the development of technologies. On the other hand, these policies can influence the diversity of TIS development, for instance by contributing to the dominance of a few countries though funding or supporting initiatives.

4 A Method for the Main Path Analysis of Knowledge Diffusion Trajectories in Emerging Technological Systems: The Case of Smart Grid Technologies

Keywords: Technological Systems, Social Network Analysis, Preferential Attachment, Main Path Analysis, Knowledge Diffusion Trajectory, Research and Development Projects

4.1 Introduction

In the early years of development of new technological systems, different innovative ideas compete and contribute to the emergence of new technological solutions. These ideas are applied by innovative firms in research projects aimed for development and diffusion of knowledge (Cattani, 2006). These innovative activities develop and influence each other in a co-evolutionary process, leading to incremental innovations and emergence of different directions for knowledge diffusion. As a result, development of new technologies is associated with incremental innovations by firms that compete and usually imitate the dominant and original innovating firms (Verspagen, 2007). On the other hand, economic goals and broader restrictions to innovation (Park and Magee, 2016), such as innovation policies and landscape pressures (e.g. climate change and economic shocks), limit the pool of options for the innovative firms and shape the main direction in which innovations and new technologies develop. These interacting internal and external dynamics shape a path-dependent process that in long term, contributes to technological change.

Scholars have approached the analysis of this path-dependent process through the concepts of main path and trajectories of technologies, innovation or knowledge diffusion (Dosi, 1982; Xiao et al., 2014; Verspagen, 2007). These notions focus on the role of incremental innovations in the emergence of new path-dependent processes leading to technological change. While the main path shapes the primary direction of technological developments (Mina et al., 2007), incremental innovations lead to some variations in the main path and shape different trajectories or the main streams of knowledge connected through the network of interconnected ideas and innovative activities.

In the early years of development of a new technological system, path-dependency is not a powerful force for shaping the dominant trajectories (Berkhout, 2002). This has implications for an emerging and complex socio-technical system, since even small differences in the alternatives or the trajectories in the early stages of development of the innovation system can lead to completely different patterns or solutions in the more mature states. These notions of path-dependency and alternative trajectories are formalized as "cumulativeness" and "selectivity" of the main path and trajectory analysis (Dosi and Labini, 2007). One way to operationalize these notions is through investigating the convergence of the main activities or streams of knowledge to a limited set of innovations, and the extent new activities or innovative firms grasp to the main streams of knowledge or start forming new trajectories.

Apart from the importance of analyzing main path of knowledge development and innovation trajectories in the early stage of technology development, the common methods for analyzing the main path and trajectory analysis are focused on finding main streams of knowledge through ex-post measures of innovation, such as publications or patent citation networks (Zhong and Verspagen, 2016). These methods, although powerful for finding the main path and trajectories with a historical perspective, have two major limitations for analyzing the early years of development of an emerging technological system. First, these approaches take the existence of a main path as granted, and try to find the primary innovative activities shaping the main path, or technological trajectories competing within the limitations of a technological paradigm. However, for an emerging technological system, it is not a necessarily valid assumption since the path-dependent forces are weak and standardization is not fully present. Therefore, prior to finding the math path, its existence should be verified.

Second, for an emerging technology, the number of publications, citations or other outputs of innovation activity are limited and incomplete, so these measures are not very useful for investigating the network of emerging ideas in the field. In other words, focusing on the results of innovative activities misses the opportunity of analyzing 'ex-ante' measures of innovative activities such as research projects that are more relevant for analyzing the early years of technological development, and later can provides outputs for analyzing trajectories in more mature phases of development.

In this respect, this paper develops a method for the identification and analysis of the main path of knowledge development in an emerging technological system and finding its associated trajectories of knowledge diffusion. For this purpose, the proposed method is composed of three steps. First, the existence of a main path is justified by using the concept of preferential attachment from network theory. Then, the main path and its variations as the knowledge diffusion trajectories are identified. Finally, the main advancements and the focal activities in different trajectories are described and compared in more details.

4.2 Main Path Analysis and Technological Trajectories

The role of knowledge diffusion and incremental innovations in the emergence of path-dependent processes underlying socio-technical transitions are focal to the ideas of technological paradigms and technological trajectories (Dosi, 1982). Dosi defines a technological paradigm as a pattern of seeking solutions for technological problems, and proposes that the usual path of knowledge development is very selective in terms of the technical frameworks are taken by innovative firms. This leads to the fact that from all possible directions technological development, only a small portion is realized. In this sense, the term paradigm is often used to describe the first general selection made from all possible research directions in a path dependent and cumulative process (Verspagen, 2007).

Thus, a technological paradigm dominating the path of techno-economic developments for a long time is set out of a small number of innovative ideas and technological solutions. Along with the paradigm, incremental innovations create variations, although the main direction is limited by the main path or paradigm. In other words, there is some space for choices along with the main path, and these choices are governed by specific circumstances in which the technology develops (Dosi, 1982). These variations are called trajectories of technology, innovation or knowledge diffusion, based on the maturity of the system or the focus of observation. As a result, the concept of variety is crucial for describing the trajectories as the sets of branching and merging technologies (Frenken et al., 1999).

While looking at the inner dynamics of the main path and different trajectories, the main interest is not the commercial applications, but to map the technological interconnectedness (Perez, 2009). In fact, the notion of trajectories considers technological innovations as sequential and interrelated events (Liu et al., 2008), and suggests within the network of interconnected ideas and innovations, a few main streams or main paths of knowledge exists that summarize the major developments in the field. In this respect, the main path of the network corresponds to the primary flow of ideas.

This main flow of ideas has a degree of selectivity over the main path, in the sense what emerges as the primary stream of ideas is focused on a limited portion of technology space, and other technological solutions and innovations, although might be searched and tested, do not have a substantial contribution to the main stream (Verspagen, 2007). One way to operationalize this idea is to investigate whether the main activities or streams of knowledge are converging to a limited set of innovations in a path-dependent process or wandering in a non-convergent way. Furthermore, the selectivity of the main path can be studied by analyzing the extent the new activities or innovative firms grasp to the main trajectory of knowledge or start forming new trajectories.

Apart from selectivity, the second important concept in analyzing the main path is cumulativeness, which leads to path dependency of the activities and trajectories. However, due to uncertainties of innovative activities, as well as coevolution with economic and social factors, one can expect to see some direction change in trajectories and variations in the main path. It leads to occasional splitting of the main path, along with convergence or fusion of separate trajectories. This mix of persistence and exploration of new directions is a critical factor in generating and exploiting innovations. It is also an important factor for analyzing the early years of development of a new technological system, where the path-dependency is not very high and there is the possibility of changing or redirecting the main path of knowledge development.

Path-dependency of incremental innovation processes in a complex socio-technical system implies that small differences between different alternatives or the trajectories of development of the innovation system can lead to completely different solutions in the future states of the system. Therefore, understanding these possible trajectories is important for the formulation and implementation of possible scenarios to maintain the level of competition in the innovation ecosystem as well as preventing the rapid convergence to suboptimal solutions, a problem called 'early lock-in' (Faber and Frenken, 2009).

This is the aim of this paper to formalize the notions of selectivity, cumulativeness and path-dependency in a method to investigate the main streams of knowledge in an emerging technological system. This study proposes to use the network of research projects for main path and trajectory analysis. The particular case of smart grid development is studied and Research and Development (R&D) projects are used to map the link between innovations in this field.

The rest of this paper is structured as follows. In §4.3, the proposed methodology and data used in this paper are explained. First, a hybrid model of random and preferential attachment networks is presented to verify the existence of a main path (§4.3.1), followed by a social network analysis of the network of projects for finding the main path of knowledge development and the knowledge diffusion trajectories (§4.3.2). Then, the context of this research is presented (§4.3.3); where the database used is briefly presented. §4.4 presents the results and explains the main projects in each trajectory. §4.5 discusses some possible explanations of the emerging trajectories and implications for policy makers. §4.6 concludes.

4.3 Methodology

Following the discussion above, constructing a network of projects is the first step for identification of the main path and trajectory of knowledge diffusion. To do so, three assumptions are taken for network construction. First, a cumulative network is needed for analyzing path-dependency and tracking and identification of the main path; therefore, once a node is added to the network, it remains there until the end of analysis. Second, the main mechanism for knowledge diffusion between projects is diffusion through shared firms; thus, once a new project begins, a link is formed between the new project and all the existing projects that have at least one firm in common with the new project. Finally, the intensity of knowledge diffusion, and the involvement of two projects in the same trajectory is associated with the number of firms they share. As a result, the weight of each link between two nodes or projects equals the number of firms shared between two projects.

Considering these assumptions, a new methodological approach is proposed by using social network analysis, an approach that provides routines for investigating actor-network evolution (Binz et al., 2014; Wasserman and Faust, 1994). The analytical framework based on this approach is operationalized in three steps. First, the existence of a potential main path can be justified by insights from complex network theory and applying a hybrid model of random and preferential attachment networks. Second, by combining insights from evolutionary modeling with a community detection algorithm called "Clique Percolation Method" (CPM), a revised algorithm is used for finding the main path of knowledge development and the effective number of knowledge diffusion trajectories. Finally, main activities and projects in the main path and the trajectories are explained. While the activities in the main path can represent the logical sequence of activities associated with increasing maturity of the technological system over time, the trajectories can be considered as core areas of innovative activities branching from the main path.

4.3.1 A hybrid model of random and preferential attachment networks

The first step in the methodology is to check for the existence of a main path, before putting effort to analyze it. To do so, insights from complex network theory are used in this section to justify the emergence of the main path. In network theory, a fat-tailed or scale-free degree distribution (Simon, 1955) exists in growing networks when the degree of a node increases in proportion to its existing degree (Jackson, 2008). In other words, the more neighbors a node has, the larger the likelihood that it will get new neighbors. In the literature of social networks, such a process of link formation is called "preferential attachment" (Barabási and Albert, 1999). Two important features are necessary for a network with preferential attachment; first, the system should grow over time and new nodes enter the network. Second, the degree of existing nodes grow proportional to their size (Jackson, 2008). The second feature is the well-known systemic effect that rich get richer.

The implications of analyzing preferential attachment for a cumulative network of projects and the emergence of a main path is that when a new node (a new project) is added to the network, the tendency of joining the main path or existing projects is proportional to the size of the existing nodes. In other words, if the existing projects have many firms shared between different projects, in a network with one dominant path, the likelihood of sharing firms with new projects is high in a network with preferential attachment. As a result, in the extreme case where there is only one main path without any variation, the new nodes attach to the existing nodes in proportion to the degree of existing nodes, and the degree distribution is fully fat-tail or scale-free. On the other hand, in a completely random network, new projects randomly attach to the existing nodes. It means the level of randomness in creating new links opens the space for variations in the main path and emergence of new trajectories or new paths. In reality, lots of social network show neither a fully random behavior nor the preferential attachment process, but a degree distribution lies between the two extremes. Therefore, finding the relative balance between a random network versus a scale-free network is critical for justifying the existence of the main path, leading to the emergence of hybrid models of random and preferential attachment (Kumar et al., 2000; Dorogovtsev and Mendes, 2001; Cooper and Frieze, 2003; Vázquez, 2003; Pennock et al., 2002; Jackson and Rogers, 2007).

Following Jackson (2008), for a preferential attachment network with indexed nodes based on the time of entering the network, node i's degree at time t is shown as:

$$d_i(t) = \delta_t(i) \tag{4-1}$$

where $\delta_t(i)$ is an invertible decreasing function of i, meaning newer nodes have lower degrees. Since degree increases with age, the fraction of nodes with a degree higher that d are the ones entered the system after node i satisfying $\delta_t(i) = d$ or entered the network before $t = \delta_t^{-1}(d)$. So, for time t degree distribution is equal to:

$$D_t(d) = 1 - \delta_t^{-1}(d)/t \tag{4-2}$$

A hybrid model of link formation that mixes random and preferential attachment networks assumes a new node uses two processes to attach to the existing nodes, as uniformly random versus preferential attachment. The new node has m links, with a probability of α for attaching randomly to the existing nodes, versus a probability of $(1 - \alpha)$ for link formation based on preferential attachment.

$$Hybrid\ model = \alpha\ (random\ model) + (1 - \alpha)(preferential\ attachment\ model) \tag{4-3}$$

Therefore, the mean-field approximation for the change in the degree of each node over time follows the degree distribution as:

$$dd_i(t)/dt = \ \alpha m/t + (1-\alpha)m\, d_i(t)/2mt \qquad (4\text{-}4)$$

The first expression in equation (4-4) is associated with link formation based on random network, while the second expression implies a preferential attachment process. This is a differential equation with the solution of:

$$d_i(t) = \delta_t(i) = (m + 2\alpha m/(1-\alpha))(t/i)^{(1-\alpha)/2} - 2\alpha m/(1-\alpha) \qquad (4\text{-}5)$$

From (4-5) one can calculate:

$$\delta_t^{-1}(d) = t((m + \frac{2\alpha m}{1-\alpha})/(d + \frac{2\alpha m}{1-\alpha}))^{2/(1-\alpha)} \qquad (4\text{-}6)$$

Therefore, the degree distribution equals:

$$D_t(d) = 1 - ((m + \frac{2\alpha}{1-\alpha})/(d + \frac{2\alpha m}{1-\alpha}))^{2/(1-\alpha)} \qquad (4\text{-}7)$$

In equation (4-7), when $\alpha = 0$, the degree distribution equals $1 - (\frac{m}{d})^2$ which is the degree distribution for pure preferential attachment and when α approaches 1, the distribution approaches $(1 - e^{-\frac{d-m}{m}})$ which is the distribution for a uniformly random network. As a result, the main task for justifying the main path is to approximate the parameter α as the level of mixing between a random and a preferential attachment distribution.

It is done through a rough check and by simulating the process for some parameters and approximate parameter α. To do so, the degree distribution of the nodes over time is fit to the equation (4-7) to estimate α (Jackson and Rogers, 2007; Pennock et al., 2002). Since equation (4-7) is non-linear in α, a simple iterative least square regression approach is used for approximation by using equation (4-8).

$$Log\big(1 - D(d)\big) = \frac{2}{1-\alpha}\log\left(m + \frac{2\alpha}{1-\alpha}\right) - \frac{2}{(1-\alpha)}\log(d + \frac{2\alpha m}{1-\alpha}) \qquad (4\text{-}8)$$

Beginning by an initial value of α_0 and regressing $Log\big(1 - D(d)\big)$ on $\log(d + \frac{2\alpha_0 m}{1-\alpha_0})$, an early estimation for α in $\frac{2}{(1-\alpha)}$ can be obtained. By continuing the iteration until the estimates converge, the final value for α is found.

4.3.2 The method of main path identification

In order to find the main path of knowledge development as well as knowledge diffusion trajectories, a method is devloped by combining the "Clique Percolation Method" (CPM, Palla et al., 2005) from network theory and a diversity index (Stirling, 2007) from evolutionary modeling. Then, a simple algorithm is used to investigate the resulting main path and its associated trajectories.

4.3.2.1 Clique Percolation Method (CPM)

The original algorithm used by CPM aims to find overlapping communities by locating the k-clique communities of unweighted, undirected networks. Here, a community is a group of nodes more densely connected to each other than nodes outside the community, and in real networks these communities often overlap. A clique is a complete graph; in other words, a subnetwork with all the nodes connected to each other and a clique with k nodes is called a k-clique and two k-cliques that share $k - 1$ nodes are called adjacent. Then, CPM creates the matrix of all the overlapping cliques and aggregates the adjacent cliques to create larger communities. In some variations of this method for finding overlapping communities[9], by setting the parameter k, any two modules with at least $k - 1$ nodes in common are considered as adjacent and can be used to find very large communities by lowering the threshold for k.

For the purpose of this paper, a modified version of algorithm is used to find the main path of knowledge development and its associated knowledge diffusion trajectories. A clique is constituted from all the projects a firm is a member of. A firm with involvement in several projects forms a large clique. In this respect, each clique can be considered as the firm's innovation trajectory. Involvement of several firms in the same projects leads to overlap between these innovation trajectories of the firms. For each pair of overlapping cliques, if k is the size of the smaller clique and the cliques have

[9] As an example look at the algorithm used in CFinder for community analysis at http://www.cfinder.org/ (accessed 4.1.2017)

$k - 1$ nodes in common, then they are merged and form a larger clique. This analysis is done for all the possible pairs and the process is repeated for the resulting cliques until no new clique is formed. Each of the resulting cliques is a combination of different firm-level innovation trajectories that are partially overlapping.

In other words, if the resulting cliques were fully independent, then the network could be easily classified as a set of distinct knowledge diffusion trajectories without a single main path of knowledge development. However, for the case of overlapping cliques, a measure of diversity from evolutionary studies is used to calculate the efficient value of distinct cliques.

4.3.2.2 Effective Network Diversity

In evolutionary studies, the diversity of a population can be calculated based on the richness (or variety), evenness (or balance) and disparity of its properties (MacArthur, 1965; Pielou, 1969; Wietxman, 1992; Solow and Polasky, 1994; Shannon and Weaver, 2002; Junge, 1994). Richness is the number of distinct categories in the population, evenness is the relative share of categories from the members of the population, and disparity is the relative distinction between the categories. Stirling (2007) combines these measures and defines diversity as the sum of pairwise disparities, weighted in proportion to contribution to the population diversity:

$$D = \sum_{ij}.\, d_{ij}^{\alpha}.\, (p_i.\, p_j)^{\beta} \qquad (4\text{-}9)$$

where p_i and p_j represent the share of categories i and j in the population and d_{ij} is the degree of disparity between them. Parameters α and β are binary variables and provide the possibility of including disparity and balance in calculations respectively. Diversity can range from 1, when one category is fully dominating, to the maximum number of categories, when all the categories are independent and have the same share of the members from the population.

For the case of overlapping cliques, the intensity of overlap is a factor of the number of firms shared between two cliques. Therefore, the overlap is proportional to the number of links shared between two cliques. As a result, disparity is calculated as the proportion of existing number of links in the network to the potential number of links in the absence of any overlap. In addition, balance equals the average number of links in each community divided by the maximum number of links in the existing communities. Therefore, equation (4-9) can be operationalized by averaging over the whole network as:

$$D = N.\frac{\bar{l}_i}{l_i^{max}}.\frac{L}{\sum l_i} \tag{4-10}$$

where N is the number of communities identified by CPM, l_i is the number of links for each community, $\bar{l}_i$ is the average number of links for all the communities, l_i^{max} is the maximum number of links within the communities and L is the total number of existing links in the network. When one community fully dominates the network, D equals one, and when there is no overlap and each community has the same number of links, D equals N. For other values between these two extremes, there is the possibility of identifying one or more main paths and some variations for each path.

Finally, in order to analyze the main path and the trajectories of knowledge diffusion, the basic structure can be derived based on the strength of link formation. In this respect, for each year the nodes attached through strongest links (highest weights) are part of the main path. Then, for multiple links with the same weights, the ones forming the largest clique are in the main path in order to maximize the average link weight. For cliques with several link weights, all the nodes are in the same trajectory as the nodes involved in the links with highest weights. The remaining nodes involved in several cliques are part of the clique with lowest average link weight to avoid weight strength loss in the main trajectories. As a result, over time the main path is formed around the network of links with highest weights.

Following these simple steps results in identification of the main path of knowledge development based on tracking the high-strength links over time, and the knowledge diffusion trajectories based on the overlapping cliques formed around high-strength links.

4.3.3 Context and data

In order to illustrate the benefits of applying this method, it will be implemented to the case of knowledge development and diffusion in smart grid technologies across Europe. Smart grid is an emerging platform technology in the energy sector and an early stage of development. It aims to combine information and communication technologies

(ICT) with metering and control technologies for enabling different applications (Farhangi, 2010; Erlinghagen and Markard, 2012) such as demand response, dynamic pricing, integration of large scale or distributed renewable energy sources and electric mobility among the others (Covrig et al., 2014). Regulation and standardization are two issues for the development of smart grids, since regulations influence access to resources such as the grid and specific markets, and widespread standards are not present in the field (Erlinghagen et al., 2015), as expected. Therefore, one can expect a variety of knowledge development and diffusion networks over different technologies and applications. The European smart grid is not an exception and is in a formative stage of development (Bergek et al., 2008), characterized by substantial R&D funding, demonstration projects and experimentation, and a variety of immature business models (Suurs et al., 2010), along with the emergence of specific visions for the future of the field. In this situation, the technologies are subject to particular uncertainties due to lack of standardization and the active role of both small start-ups and large transnational companies in collaboration with universities and research institutes (Covrig et al., 2014).

4.3.3.1 Data

The data used in this study comes from the 2014 database on smart grid projects collected and compiled by the Joint Research Centre (JRC) of the European Union (Covrig et al., 2014). The database is composed of research & development (R&D) and demonstration & deployment (D&D) projects. R&D projects usually aim for knowledge development; therefore, they are used for analyzing the main path of knowledge development and diffusion in this study. The definition of R&D projects in this database is based on Frascati Manual (OECD, 2002) and includes three activities: basic research, applied research and experimental development (Covrig et al., 2014). The database covers smart grid projects R&D in Europe started between 2002 and January 2014.

A quality check was performed on the existing data to improve the consistency and applicability for the model. Duplicates were removed and inconsistencies (e.g. due to different spellings, languages or abbreviations) adapted. The applications and focus of each project were extracted from the project websites to accompany the method in analyzing different trajectories. The JRC online-database also includes project classifications in terms of content with seven overlapping categories: Smart Network

Management, Integration of Distributed Energy Resources, Integration of Large Scale Renewable Energy Systems, Aggregation (Demand Response, Virtual Power Plant), Smart Customer/Smart Home, Electric Vehicles and Vehicle2Grid Applications, and finally Smart Meters (only if they are part of a wider Smart Grid project). This classification was used as a complementary source for following the path of development of different trajectories. The analysis was limited to the period of 2002 to 2012 because entries for 2013 and 2014 were incomplete. It resulted in identifying 191 R&D projects in total.

4.4 Main Path Analysis

In this section, first the main path of smart grid development in Europe is identified and described, with a focus on the main projects and applications. Then, different variations in the main path, as the relatively distinct trajectories of knowledge development are discussed to cover the main advancements in the field. Analyzing the trajectories is followed by a discussion on the emergence of a new dominant trajectory that develops along with the development of the main path and its variations.

4.4.1 Intensity of preferential attachment in network formation

Following the discussion in §4.3.1, the degree distribution of data is fitted to a hybrid model to find the parameter α that specifies the range of network between two extremes of uniformly random attachment and preferential attachment. Based on the network construction assumptions and the algorithm for finding the main path, the hybrid model is developed by including the links with a weight higher than 1, in order to include the firms contributing to the emergence of the main path.

In this respect, the first task is to calculate m. Since it equals the number of new links formed in each year, it is half of the added degree. The overall degree is $2tm$; therefore, m is half of the average degree. The average degree for the network of R&D projects between 2002 and 2012 equals 14.042. So m is 7.021.

The next step is to approximate α, by using equation (3-8) and starting with an initial guess for α_0 and finding α_1 and continuing the with a grid of values to find the final value, as shown in table 4-1.

Table 4-1. Initial parameter estimates and estimated values for α

α_0	0.50	0.40	0.30	0.20	0.10	0.01	0.06
α_1	0.35	0.28	0.21	0.15	0.08	0.03	0.06

Table 4-1 depicts the estimate for α is close to 0, meaning the degree distribution of the network of R&D smart grid projects in the hybrid model is close to one extreme, in which linked are formed by preferential attachment. The results verify the existence of a main path, or the high tendency of new created nodes to attach to the existing nodes in proportion to their degrees.

4.4.2 The main path of knowledge development

Following the method described in §4.3.2, the results of running the CPM algorithm and calculating the diversity of the resulting communities are summarized in table 4-2.

Table 4-2. Summary of diversity analysis over time

Year	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Projects	1	2	3	5	14	28	43	74	115	148	191
Cliques	0	0	0	1	1	3	7	18	24	36	52
Richness (communities)	0	0	0	1	1	2	3	4	3	4	14
Evenness	0	0	0	1	1	0.77	0.83	0.94	0.60	0.59	0.62
Disparity	0	0	0	1	1	0.77	0.57	0.38	0.62	0.56	0.23
Diversity	0	0	0	1	1	1.18	1.42	1.44	1.12	1.33	1.97

Based on this table, the cumulative network of 191 projects forms 52 cliques (figure 4-1), and the CPM is able to aggregate these cliques into 14 communities, with a substantial jump in the last year from 4 to 14. This relatively high increase is reflected in the network diversity as well (figure 4-2), where by calculating diversity the effective number of distinct trajectory oscillates between 1 and 2 with a relatively high increase (48%) in the last year from 1.33 to 1.97. It implies a possible structural change in the network by the launch of new projects that show a relatively high value of clustering within themselves and independence from the existing network. This special case is discussed later in §4.4.3.

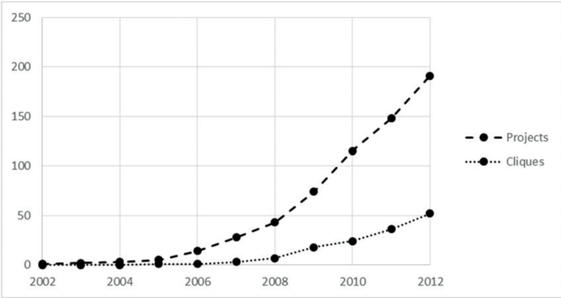


Figure 4-1. Number of projects versus cliques

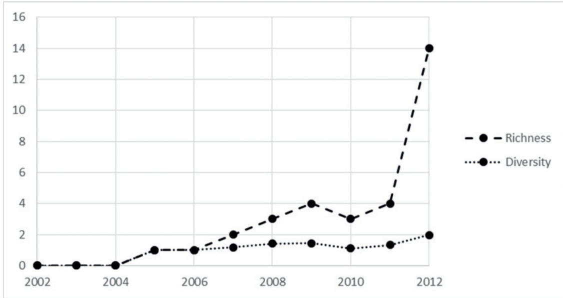


Figure 4-2. Number of communities versus diversity

In the next sections, the structural components in the main path and different trajectories are presented and the underlying streams of knowledge are discussed.

4.4.2.1 Structure of the main path

In the very early years of knowledge development in smart grid projects over the period of analysis, the main path begins by around projects developing solutions for integration of distributed energy systems and large-scale renewable energy sources (figure 4-3). To be more specific, the path shapes around methodologies and frameworks for the integration of renewable energy to the grid, including the development of methods, tools and control mechanism for the integration of distributed energy systems and renewable energy sources (Dispower), investigating the technical and non-technical barriers of distributed energy deployment (EU-Deep) and analyzing the contribution of distributed energy sources to the power system (Fenix). These focal projects also link the integration of renewable sources to aggregation technologies and solutions, and starts two variations in the main path, as discussed later.

In terms of renewable and distributed energy sources, wind energy is the primary focus of the main stream of R&D activities in the early years. Projects form around issues such as the large-scale integration of wind farms (Windgrid), forecasting methods and uncertainty analysis for wind generation (Safewind) and collaboration between wind generation companies and Transmission System Operators for wind integration (EWIS). The last project opens a new avenue for the emergence of TSO-coordinated activities, a trajectory discussed in §4.4.3. These projects were followed by more market-oriented research projects such as market design for wind and solar energies at the European level (ReServices) and validating markets designed to integrate flexible power generations regionally dispersed (Optimate).

These developments are followed by developing conceptual and technical frameworks for increasing user participation, along with the possibility of using information and communication technologies (ICT) for different purposes. Of special importance are two central projects; the first one (ADDRESS), aims to develop commercial and technical frameworks for active demand (AD) by investigating the triggers of actor participation from domestic and commercial markets. It is the pioneer for shaping a trajectory based on demand side management and user participation. The second project (SEESGEN-ICT) investigates the options to accelerate the introduction of ICT to smart distribution grid and formulates different scenarios and policy options. It opens new opportunities for systemic and integrated ICT-based solutions, and natural development of the path towards more practical applications of ICT in the energy system.

In the last years of our analysis, the focus of the central activities in the main path shifts towards involvement of ICT actors in the dynamics of the smart energy system and providing solutions based on the new IT infrastructure. On one hand, ICT-enabled applications such as electric mobility and electric vehicles (EV) are investigated through developing frameworks for impact analysis of large-scale EV introduction (G4V) and more systemic issues such as interoperability of interfaces along with the development of new business models (IOE). On the other hand, focusing on standards for ICT-based innovations and Advanced Metering Infrastructure (AMI) as the requirement for integrating ICT-enabled solutions (Open Meter) highlights the importance of restructuring the infrastructure to exploit the benefits of smart grid. On the other hand, facilitating collaboration between actors from the energy sector and ICT firms to co-define new solutions and standards (Finseny) addresses the necessity of collaboration between incumbent firms and newcomers.

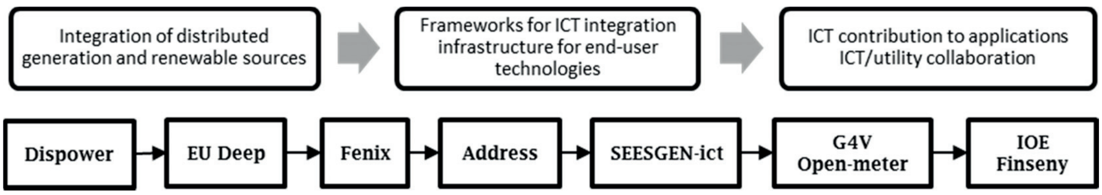


Figure 4-3. The hubs in the main path of smart grid development

Figure 4-3 summarizes the main stream of knowledge development, explaining the natural path of R&D activities towards maturation. Integration of large-scale and distributed renewable energy sources to the grid was the first motivation behind R&D activities. These initiatives were followed by solutions for improving the infrastructure to optimize the demand and supply sides of the system through smart network management, and analyzing the introduction of ICT infrastructure. Finally, analyzing advanced solutions and applications, along with developing standards and interoperability measures are necessary to exploit the potential benefits provided by the smart energy system. These focal activities create variations in the main path, depicted as the knowledge diffusion trajectories presented in the next section.

4.4.3 Variations in the main path: knowledge diffusion trajectories

Along with the main path of knowledge development, which depicts a sequence of ideas in the field, some variations form around these ideas as the knowledge diffusion trajectories. In other words, these trajectories build upon the knowledge and resources developed in the main path, while they are different in terms of the focal technologies and applications. Below, these variations are explained briefly.

4.4.3.1 End-user aggregation in smart infrastructure

The first trajectory emerges around developing solutions for aggregation of demand side solutions and improving the underlying infrastructure. Starting from one of the main projects in the main path (Address), it aims to enhance actor participation in power system markets by providing technical and commercial frameworks, where two important DSOs (Iberdrola Distribucion Electrica S.A. and Enel Distribuzione S.p.A) collaborate with other utility companies, manufacturers and research institutes. The second advancement in this trajectory is focused on developing the Advanced Metering Infrastructure necessary for enabling demand side solutions. The same DSOs active in "Address" collaborate with other firms on developing public and open standards for AMI (Open Meter), and later on improving interoperability for smart meter operation, integration of automation devices and volatility monitoring (OpenNode).

Integration of electric vehicles (EVs) towards smart mobility is the other central activity in this trajectory. Starting with developing an analytical framework to evaluate the impact of large-scale introduction of electric vehicles to the grid infrastructure (G4V), analyzing challenges and opportunities are followed up by more practical research projects. Study of intelligent charging systems and real time data exchange for electric vehicles (e-Dash), opened the space for collaboration between universities and firms from automobile industry (e.g. Renault SAS and VOLKSWAGEN AG). As expected, the share of ICT firms and contributions of advancements in information technologies increased over time in this trajectory. For instance, ICT applications for optimal integration of electric vehicles through energy management systems (Open ECOSPhERE). Figure 4-4 summarizes the hubs in the aggregation trajectory.

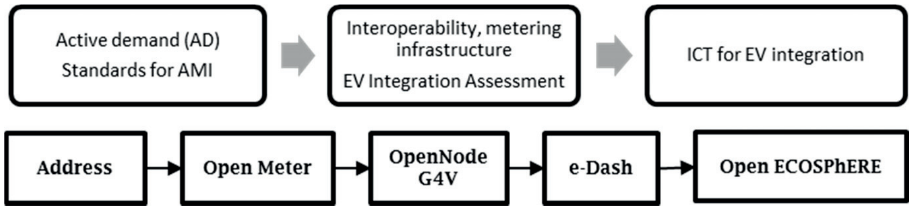


Figure 4-4. Hubs in the aggregation trajectory

4.4.3.2 Smart network management by supply/demand optimization

Integration of distributed and large-scale renewable energy sources, as the primary focus of projects in the main path, naturally leads to control and optimization problems in the distribution grid. Advanced optimization models and ICT-enabled services are potential solutions to these issues; therefore, it is not surprising to see research institutes active in distributed generation and demand aggregation projects to collaborate on developing systemic and advanced solutions to distributed power generation grid (Address and SEESGEN-ICT). These two projects shape a new trajectory focused on advanced methods for network management and optimizing demand and supply during the aggregation process.

Applying virtual synchronous machines (GSV) for stabilization of frequency in the distribution networks high penetration of decentralized power generation (VSYNC) is the first major advancement in this trajectory. It was followed by several projects aimed to balance supply and demand and optimize network operations from different angles. Developing methods for efficient design and operation as well as coordination of different applications (Smart Power), platform for real time optimization and monitoring of demand in neighborhoods to increase efficiency (ENERsip) and developing a hierarchical system model for optimizing energy consumption in mobile consumers (GeoGreen) are the central activities of interest.

Similar to the aggregation trajectory, in the last years of our analysis, ICT-enabled solutions become more practical for other purposes. Here, advanced and monitoring solutions for optimizing transmission and distribution systems through adding novel functions to power components (CIPOWER) and enabling and design of active distribution networks for facilitation of customer involvement through interoperable ICT systems (INSTINCT) are two major advancements. Figure 4-5 summarizes the hubs in the smart network management trajectory.

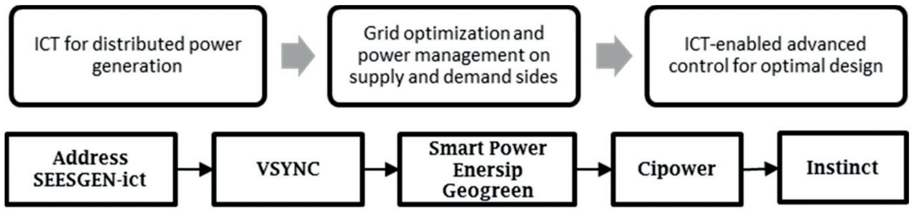


Figure 4-5. Hubs in the SNM trajectory

4.4.3.3 ICT for smart energy solutions

The role of ICTs in the development of smart grids is not negligible. Emergence of ICT-oriented research projects and ICT-enabled solutions can be considered as part of the natural path of smart grid development. Indeed, aggregating distributed renewable energy sources into large scale virtual power plants (LSVPP) to increase penetration (Fenix) and analyzing the potential contribution of ICTs to distributed generation systems (SEESGEN-ICT) are the first advancements in this trajectory. As expected, integration of distributed energy systems as the focal application in the early years of smart grid development, is the testbed for analyzing the applicability of ICT-enabled solutions and innovations.

These developments were followed by collaborations between actors from energy and ICT sectors on defining requirements of the smart energy system and preparing case trials for domain-specific enablers (FINSENY) and investigating interoperability issues along with needed business models for integrating new applications such as electric vehicles (IOE). Over time, the actors involved in these advancements shift their attention toward preparing the needed infrastructure to exploit the benefits provided by ICT firms. Platforms for integrating appliance-level services at consumer side by gathering consumption data for new business opportunities (BeAware) and data management infrastructure to boost prosumers' responses and active participation in smart distribution grid (INERTIA) are two examples of developing infrastructures to integration information technologies.

At the end of this trajectory, tools for data management, developing information systems and related enabling technologies gain a larger share in the main activities. Grid sensing and metering technologies for gathering information are analyzed to improve control and management mechanisms as well as design and topology of the smart system (E2SG). Configurable information systems are another systemic solutions for reaching objectives such as power quality monitoring, remote sensing and developing the smart metering platform (IMPONET). Finally, other projects (e.g. I3RES and OiDG) focus on data mining techniques, data management tools and decision support systems in a bi-directional information system to assist different actors in analyzing the huge amount of data gathered from both consumption and distributed generation profiles.

Figure 4-6 summarizes the main hubs in the ICT trajectory. It starts from developing frameworks for integrating ICT-based applications and systemic solutions, followed by investigating the possibilities of collaboration between incumbent firms and ICT firms as the newcomers. Then, new platforms and interfaces are analyzed as the necessary components of the new infrastructure, complemented by tools and methods for data mining, managing information systems and dealing with big data.

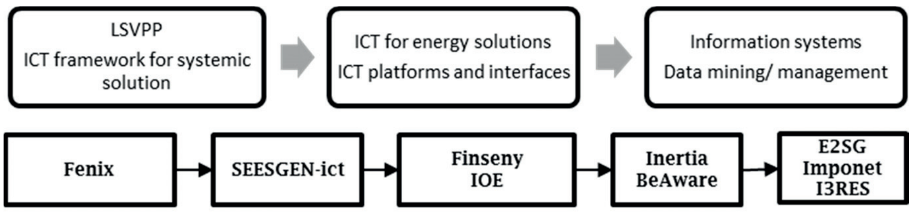


Figure 4-6. Hubs in the ICT trajectory

4.4.4 Emergence of a dominant trajectory

As briefly discussed in the beginning of §4.4.2, although the gradual increase in the number of projects and cliques continues in the last years of analysis (figure 4-1), a substantial increase is observed in the number of communities and diversity of the network in the last year. This increase can be better understood by tracking the network development over time and the emergence of a trajectory that gradually less connected to the other trajectories of the network. Figure 4-7 shows a rough representation of this trajectory, by removing the less important nodes and low-weight links. On the left side, the main path and the hubs of its trajectories can be seen, while the hubs of the new trajectory are place on the right side. These two parts of the network are mainly connected via less focal projects shown in the middle.

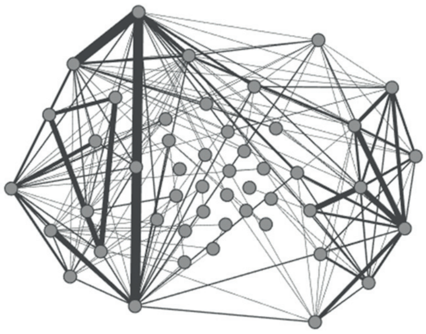


Figure 4-7. Schematic representation of the emerging dominant trajectory (on the right side)

Indeed, the emergence of this trajectory can be traced back to the projects focused on the integration of distributed energy resources. Integration of wind farms (Fenix, Windgrid) and analyzing solutions for the main wind integration challenges to the European transmission network (EWIS) show the focus of these early projects and the centrality of wind energy in these activities. However, the more important point is the involvement of Transmission System Operators (TSOs) in these projects, especially the initiative "EWIS" established by the European TSOs in collaboration with the European Commission (EC) that leads to the emergence of a trajectory centered on transmission issues and TSOs.

The presence of TSOs can be observed in later projects as well. A consortium of partners mainly composed of TSOs and research centers analyzed optimization and simulation frameworks in high and extra-high voltage transmission networks (PEGASE) in Europe, followed by developing tools and methods for optimal design of the transmission network in the European Union (REALISEGRID). Over time, the focus of the main projects shifts toward advanced control and optimization technologies in the form of smart network management applications. Technologies such as Wide Area Monitoring and advanced network controllers in flexible AC transmission (FACTs) and high voltage direct current (HVDC) systems are analyzed to develop new tools for monitoring the power grid (ICOEUR) and test platforms for validating different market designs for the integration of massive flexible generation are developed with the high involvement of TSOs (OPTIMATE).

Consistent with advancements in other trajectories, with the potential contribution of ICT firms and introduction of ICT-enabled technologies, the share of these technologies and their applications increases in this trajectory. Analyzing the vulnerability and contingency planning of the energy grid by including ICT systems (AFTER) and enabling robust smart grid control by using the communication infrastructure (SmartC2Net) are two of the applications of new ICT systems.

These advancements in the last year of analysis are followed by large and EU-funded projects claiming to support a "pan-European" transmission system, which focus on smart network management programs. Of special importance are three projects with the substantial share of TSOs. The first one (iTESLA) aims to develop a toolbox to increase the coordination of operating procedures by TSOs and optimize the transmission capacities of the grid at different spatial scales. The second project (e-Highway2050) focuses on developing a methodology for planning the European transmission network and ensure the reliability of renewable energy delivery. Finally, the third project (UMBRELLA) focuses the grid security for TSOs by simulating uncertainties and real-time optimization for coordination and stability of the European transmission system.

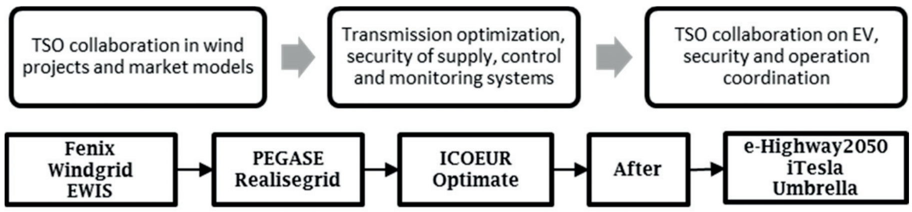


Figure 4-8. Hubs in the emerging TSO trajectory

Figure 4-8 summarizes the hubs in the TSO trajectory. It is different from the other discussed trajectories in two ways. First, although a normal path of development can be observed in all trajectories from integration of distributed energy sources to applied ICT-enabled solutions, but in this trajectory the activities center around TSOs as the focal actors. However, in other trajectories such a centrality does not exist and normally the dominance of universities and research centers decreases over time by gradual increase in the maturity of R&D projects and entrance of new actors.

Second, although EU-funding has a substantial role in development of the projects and innovations in the database, large EU-funded projects are more common in this trajectory. Especially in the last years, these projects partially change the network structure and shape a large community composed of a relatively large number of cliques. In addition, since the TSOs have a central role in this trajectory, it is not surprising the main activities are focused on the challenges and issues in the transmission network, especially at the European level.

4.5 Discussion

Figure 4-9 summarizes the main streams of knowledge in the development of smart grid initiatives in Europe. The projects in the main path represent the general developments, and depict the broader interests in the maturation process within the network of R&D projects. However, these developments do not reflect the variety of technologies, applications and collaborations; therefore, knowledge diffusion trajectories are interpreted as the variations in the main path. These emerging branches show a divergence in the early years of development and a converging pattern in the later years of analysis. They reveal the tendency of actors involved in connected projects to apply specific tools, methods and technologies. Therefore, the changing diversity of the network can be used as an indicator of the relative variety or decentralization of technological solutions in different parts of the network.

Considering the central projects of the main path in the left side of figure 4-9, three of the trajectories emerge in the later years of analysis. This part of the main path depicts the higher importance of ICT systems, where systemic solutions based on ICT integration are investigated (e.g. Address and SEESGEN-ict), required components for a proper ICT infrastructure are provided (e.g. Open Meter and Finseny) or when practical aspects of ICT-enabled applications are analyzed (e.g. G4V and IOE). As a result, projects such as Address and SEESGEN-ict have several firms in common and part of different trajectories, a reason the network diversity does not significantly change by adding new projects.

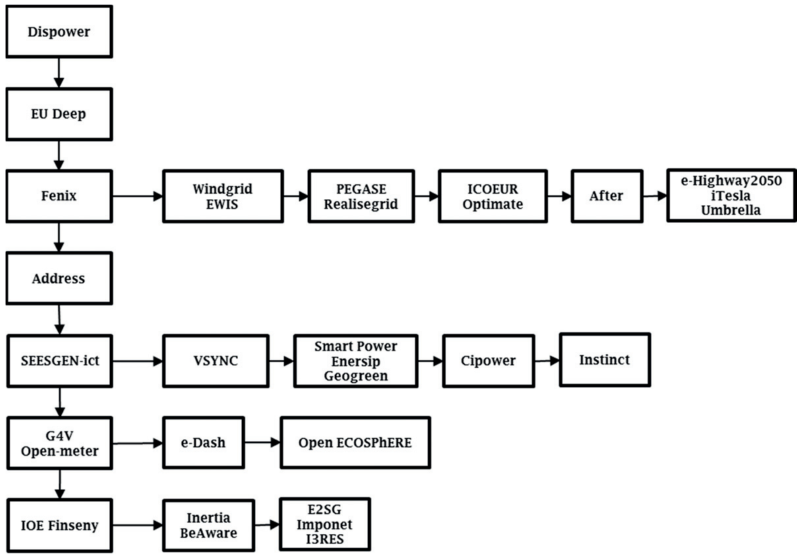


Figure 4-9. The main path and trajectories of smart grid R&D projects

On the other hand, the last trajectory branches from the main path in a different way. Starting with associations and consortiums of TSOs, this trajectory bridges the activities around integration of distributed energy sources to smart network management and optimization challenges in the transmission network. One explanation for this difference might be the special situation of the focal actors. TSOs are a group of powerful incumbent firms in the energy system that are losing their market share and position power by the introduction of smart energy solutions. As a result, they need to collaborate to develop new business models and solutions to keep their position as a powerful actor in the new energy system. They are also empowered to be able to deal with the new challenges such as control and optimization of the revised power grid after the introduction of distributed systems, leading to a focus on smart network management initiatives and advanced ICT-enabled control solutions to manage these challenges.

4.6 Conclusions

This study proposes a methodology for exploring the main path of knowledge development and its associated knowledge diffusion trajectories in the early years of development of an emerging technological system. Focusing on the case of smart grid development in Europe, it examines the R&D projects and initiatives launched between 2002 and 2012. Based on the network of connected projects through shared firms, the paper investigated the possibility of an existing main path of knowledge development by fitting data to a mixed model of preferential attachment and random networks. Data on smart grid projects was used to build a cumulative network of projects; then, by applying an algorithm based on diversity measures, the knowledge diffusion trajectories were determined and visualized through social network analysis software.

In this respect, the primary goal of this research was to demonstrate how a main path analysis based on the network of research projects can be helpful to analyze the main streams of knowledge in an emerging technological system. This approach is also helpful to reveal the sequence of ideas and the focal applications and technologies in each trajectory, and even the centrality of specific actor groups. The method presented in this paper takes an ex-ante approach to innovation that can complement the more common and ex-post approach in literature such paper citation or patent citation networks.

This paper has implications for the field of smart grid development in Europe. The results show there is a main path of knowledge development in R&D smart grid projects and depict the most important projects in this path. Furthermore, distinct but interrelated trajectories of knowledge diffusion are branching from the main path. These trajectories are focused on different applications and challenges of smart grid development, and among them, one trajectory centered on a specific actor group is gaining relative dominance, leading to more diversity in the network. These results verify this method is useful for tracking and analyzing different streams of knowledge in a network of highly overlapping communities.

Such an analysis can be improved by gathering data on the future developments of the field, and tracking the changes in the explored trajectories. Especially for the unexpected developments observed in the last year analyzed in this study, further investigation is needed to verify whether it is the first sign of the emergence of a new path, or just a divergence from the main path that may converge toward other trajectories.

To summarize, this study developed a new approach for exploring the structure behind the principal streams of knowledge in an emerging technological system. It was done by analyzing the main path of knowledge development and tracking its associated knowledge diffusion trajectories. Such an approach is not only helpful for investigating the network of projects, but can be also useful for analyzing other social networks with a substantial contribution to the development of emerging socio-technical systems.

5 Conclusion

5.1 Research Summary

5.1.1 Achievements and Limitations

This dissertation developed methods and models by taking a complex system approach to improve the analysis of complex patterns and dynamics arising in emerging technological systems. Emergence of new technological and innovation systems is of special importance in the early stages of socio-technical transitions, and this dissertation focused on the case of socio-technical energy transition to smart grid in order to verify the applicability of developed models and methods.

Although socio-technical energy transitions have been analyzed from different perspectives and by using a variety of methods and models, the knowledge about the early period of the transition process is still limited. By focusing on the emergence of new technological systems, this research attempted to address some of the questions arising during the development of new technologies, including the cost allocation of these technologies among potential beneficiaries, the spatial diversity of technological developments, and the emergence of knowledge diffusion trajectories.

Furthermore, there are issues in analyzing the emergence of new technological systems in the early phases of the transition process, such as data availability or lack of conceptual frameworks. This dissertation took a systems approach and tried to investigate how different simulation methods and techniques could assist researchers to develop innovative models or improve the existing solutions to deal with such issues.

There are different strands of literature that are insightful for the conceptualization of processes and issues in the emergence of new energy technologies, or are addressing the same issues in other contexts. This dissertation used these research lines in conjunction with different modeling approaches to develop methods, and implemented these methods to the case of smart grid development in Europe. A summary of the achievements and the drawbacks of each essay is briefly discussed in the following sections.

5.1.1.1 Essay 1 – cost allocation of new technology deployment

The first essay investigated the problem of cost allocation for new energy technologies deployment. It assumed costs of new technology deployment should be allocated among beneficiaries to provide incentives for all actors to invest in novel technologies and research initiatives and took this issue as a central point in the smart metering deployment process. In this respect, this essay took a complex systems approach and tried to investigate how policy intervention in a complex system of interactions influences the dynamics and leads to short-term and long-term consequences.

By applying the system dynamics approach and through simulation experiments, this study verified that a dynamic modeling perspective to the cost allocation problem adds three advantages to the common cost-benefit analysis (CBA) approach. First, it provides a balance between the short-term and the long-term payoffs of the deployment process, which are important for analyzing the incentive structure of actor groups over time. Second, it provides the possibility of including actors benefiting from technology deployment in an indirect way, but are not included in the cost allocation process. Finally, by identifying and investigating the tipping points, it provides the opportunity to design scenarios for policy intervention and a more efficient cost allocation process. In this respect, three scenarios were developed in this essay.

The first scenario considered introducing a cooperative smart metering tariff to include the intermediary role of the retailer in the cost allocation process. The idea is that smart metering implementation provides positive externalities such as the smoother production and reduced risk of price fluctuations for retailer, and as a result, retailer have incentive to participate in the cost allocation process. The second scenario proposed a dynamic network tariff to include the heterogeneity of consumption profiles in the cost allocation process. It means since peak-time consumptions necessitates future investments for network development, the extra costs of peak consumption could be added to the bills of consumers with a higher contribution to peak consumption. Finally, the third scenario suggested introducing an ICT firm and outsourcing data exchange services to this actor as an intermediary. Introducing an intermediary role can reduce both investment and contact costs by providing the required ICT infrastructure, data gathering and designing innovative solutions.

The results can explain why reluctance to participate in the technology deployment process can persist even after introducing dynamic pricing policies, and what factors are more critical in analyzing the cost and benefit structures of the technological system. However, system dynamics modeling averages over all the parameters and consumption profiles and even in the case of dynamic network tariff, the results are added to the system as the average values. Therefore, the heterogeneity of actors in the same actor group cannot be fully grasped by using this modeling approach, as the main drawback of using system dynamics modeling.

5.1.1.2 Essay 2: spatial diversity in emerging communities of innovative firms

The second essay looked at the diversity of emerging communities of innovative firms during technological innovation system (TIS) developments. Contributing to research on the spatial dynamics of TIS development, this essay addressed the emergence of spatial configurations in network modules. Addressing a multinational network of collaborations, the spatial diversity is an aggregate property at the modular level, which can be understood by analyzing both country-level differences across modules and the interaction of countries within emerging communities.

Starting by a network approach to the spatial TIS analysis and the nationalization index proposed by Binz et al. (2014), this study applied insights from complex system theory and proposed that modular diversity can be analyzed as an emergent system property, as a result of country-level differences, path-dependency of innovative activities as well as the maturity of TIS functions. By focusing on the case of smart grid development in Europe as an emerging TIS, a social network model was developed to investigate the emergence of modules with different spatial characteristics. This analysis revealed how multinational collaborations are distributed over modules and how they change over time. Then, an Agent-based Model (ABM) was developed to further investigate the impact of country-level differences on the emergence of modular diversity.

The results of both SNA and ABM confirmed that apart from analyzing the relative weight of national and multinational collaborations in innovative activities, other factors such as the path-dependency of network formation, functional maturity and national institutions are crucial for grasping the diversity of national and multinational collaborations, and therefore analyzing the spatial dimension of TIS development. However, this method does not consider the emergence of modules in terms of their size and other non-spatial characteristics that might influence spatial dynamics, and only focuses on the spatial analysis of the modules found by the modularization algorithm. Another drawback is ignoring the 'why' question to spatial analysis, meaning there is no discussion on why, for instance, some countries are more willing to collaborate in national networks, while some others are inclined to international collaborations. Finally, the agent-based model developed is quite simple in order to depict the difference between the impact of Nationalization Index and entropy; so, it excludes the impact of many other variables and measures.

5.1.1.3 Essay 3: main streams of knowledge in research projects

The third essay developed a method for investigating the main path of knowledge development and the constituting knowledge diffusion trajectories in an emerging technological system. It offered a novel approach for the identification of the main streams of knowledge in a cumulative network of research projects. In addition, this study looked at the possibility of existing a main path, before analyzing the emergence of different trajectories and then, discussed how these trajectories constitute the main path of knowledge development.

The method proposes three steps for a thorough investigation of the main streams of knowledge. In the first step, a hybrid model of random and preferential attachment networks is developed in order to verify the existence of a main path, and implies a main path can be identified by following the sequence of new projects added to the system. Then, the main path is identified by using three algorithms for finding the overlap between projects (finding cliques), cliques (Clique Percolation Method, CPM) and communities (effective diversity). Finally, the main trajectories of knowledge diffusion branching out from the main path are investigated by focusing on the sequence of projects entering the network and their technical applications.

Such an analysis helps to identify the focal projects and the main activities in the main path and each trajectory. The results of analyzing the case of smart grid projects at the European Union level support the applicability of this method for investigating the network of innovative projects to analyze the main streams of knowledge in an emerging technological system. However, this methodology investigates trajectories in a qualitative way, which adds subjectivity to the analysis. In addition, it does not include the impact of exogenous factors such as policies and regulations on the emergence of specific trajectories, and focuses on the internal dynamics or the consequences of any policy intervention on network formation. Furthermore, lack of data for a long period in an emerging technological system limits the understanding of the anomalies in the network. It highlights the importance of investigating the main path and its trajectories over time to understand the long-term behavior of the network.

5.1.2 General Insights

Although the three essays presented in this dissertation address three different issues and deal with different theoretical perspectives and modeling approaches, an encompassing view of all the approaches and insights can be provided. In this respect, some general insights are briefly described by special focus on the complementary aspects of each approach, with reference to their contribution to conceptualizing the early stage of the transition process, and the general insights provided by complex system theory.

From a methodological viewpoint, the methods and models presented in this dissertation can be complementary or alternative to the existing methods or models applied for analyzing the early stage of the transition process. Complex systems theory helps to add a dynamic view to system analysis by incorporating nonlinear relationships and interactions at the individual level. Therefore, it contributes to including dynamics and interdependencies into cost-benefit analysis (essay one), grasping heterogeneity and complexity of system development for spatial analysis (essay one) and distinguishing the signal from the noise in a dense network (essay one).

Furthermore, these models and methods shed light on different aspects of socio-technical transformation in the early stage of transitions, thus complement each other. As discussed in the introduction (chapter one), individual-based and system-based methods are complementary and choosing between them depends on problem formulation and the research question. Following the results of this dissertation, a system-based approach like System Dynamics is more applicable for analyzing the structural dynamics that influence actor behavior. In this situation, system transformation leads to gradual change in system structure, which contributes to new actor behaviors. For instance, in the first essay, each scenario either changes structural dynamics (the first and the second scenarios) or changes system structure (the third scenario).

An individual-based approach is helpful for analyzing transformations resulting from actor interactions. In other words, system transformations are emergent properties and cannot be understood by looking at system structure or individual behaviors. In this respect, an individual-based model can be used for empirical cases of system transformations as emergent system properties, in which Social Network Analysis is helpful for investigating the reality of actor interactions (essays two or three). In addition, Agent-based modeling was used to analyze hypothetical cases of system transformation to evaluate the impact of critical variables (essay two).

Considering the early stage of socio-technical transitions, dynamic modeling provides new formulations for some of the main challenges arising in this period. On one hand, it highlights the role of interdependencies for understanding problems or providing solutions. For instance, analyzing the interdependencies of cost and benefit structures of different actor groups is crucial for designing scenarios for more efficient cost allocation of new technology deployment (essay one), or interactions among innovative firms or projects that shape system level characteristics such as spatial diversity or the main trajectories of knowledge development (essays two and three).

On the other hand, path dependency and emergence as the primary concepts from complex systems theory, are important to explain part of the results presented in this dissertation. In order to balance the short and long term payoffs of technology deployment for different actor groups, path dependency or accumulation of investments should be handled, especially in the early years of development (essay one). In addition, path dependency is responsible for the spatial diversity of technological innovation systems as an emergent property, by creating some system inertia that maintains existing diversity to some extent (essay two). Furthermore, emergence of a main path in a network of innovative activities is highly dependent on the path dependent process of knowledge accumulation in the network and project breeding over time (essay three). Therefore, emergence of a system-level property such as spatial diversity or a main path can be interpreted as the accumulation of small feedback effects at the individual level, which links the concepts of emergence and path-dependency at the system level.

5.1.3 Policy Recommendations

From a policy perspective, the analyses and results presented in this dissertation are in favor of promoting competition by policy makers. It means in the early stage of the transition process, the primary role of policy making is to remove the barriers of competition or supporting an environment for innovative firms to compete their ideas and solutions. The same conclusion can be reached by looking at the implications of each essay for policy makers.

In the case of cost allocation (essay one), the primary barrier of competition is initial investment cost, and providing innovative solutions for the compensation of this investment in the early years is the main implication for policy makers. In this respect, this essay proposed three scenarios that assign specific roles for policy makers. These include setting new dynamic pricing policies to reflect heterogeneity of consumption profiles and indirect benefits for actor groups, as well as facilitating the outsourcing of IT infrastructure provision to the third party through regulations.

Analyzing spatial diversity (essay two) has implications for policy making at the international level. In order to consider smart grid as a technological innovation system at the European level (a European TIS), different parts of this network should be developed in parallel and in a consistent way. It means without providing a balance between the states of technological development across space, some counties gain dominance through either external factors or internal dynamics. Competition has an important role here, by providing opportunities for countries with small share in smart grid activities to remain in the innovation ecosystem. As a result, policies for supporting these countries have contributions to maintaining competition and the formation of a European TIS.

Finally, emergence of a main path of knowledge development (essay three) implies accumulation and development of a network of innovative projects through a natural sequence of activities. From a policy perspective, it means policy should be directed toward providing space along with the main path to promote different trajectories, as the spaces for experimentation and idea generation. It is different from a policy intervention that may promote the emergence of a new path or support specific trajectories, which divert sequence of activities from their natural path formation process.

5.2 External Validity

The focus of this dissertation was on developing and enriching methods for addressing questions arising in the early years of socio-technical transitions, by taking a complex system approach to energy transition and technological change. Therefore, the methods and insights can be extracted from their contexts and generalized for analyzing similar issues in other contexts, or other relevant problem. In this respect, the primary ideas behind each method worth taking away are summarized in the following sections.

5.2.1 System Dynamics for policy analysis in complex socio-technical systems

The idea behind the first essay implies analyzing policy intervention in a complex system such as energy infrastructure needs to incorporate the system reactions over time and for different actors. Considering the specific case of cost allocation, such a system-level analysis has two further implications for generalization to other cases.

First, dynamic modeling can be used as an approach to analyze the interdependencies and feedback structures that govern behaviors and trigger unexpected consequences. Therefore, it can be considered as an alternative or complementary approach to CBA for balancing long and short-term benefits of new technology deployment. In other words, investigating interdependencies helps to find trade-offs between the costs and benefits of actor groups, and compromise the costs and benefits of each actor group over time.

Second, dynamic modeling helps to find tipping points and the dominant feedback loops necessary to formulate innovative scenarios for more efficient policy intervention. It means by broadening system boundaries and including factors normally missing from analysis, more elaborated solutions can be formulated to deal with side-effects in a complex systems. Including the actor groups that are indirect or potential beneficiaries of technology deployment or can be influenced by policy intervention in the analysis was among of the potential solutions for cost allocation in the case of smart metering roll-out.

5.2.2 Network perspective to diversity generation in technological innovation systems

A network approach to TIS development, as a novel perspective that has been already raised in the TIS literature, is able to link different system functions. Linking two different functions for spatial analysis and by defining the functional maturity index, shows tracking network development over time is a useful approach for conceptualizing the interdependency or sequence of functions in a growing TIS, as an idea developed in the TIS literature in the forms of feedback loops between the TIS functions or motors of innovation. Apart from the case of spatial analysis, for a growing innovation system one can see how network characteristics differ across different system functions.

Furthermore, the concept of diversity as an emergent property of system is generalizable to other dimensions of TIS development rather than the spatial dimension, including the technological or economic dimensions. For instance, the diversity of technical knowledge or applications as well as type of actors or actor collaborations may change over TIS development and across different system functions.

Finally, results of agent-based modeling reveal how different scenarios can lead to different patterns of diversity generation. More generally, the results show how heterogeneity at the micro-level can lead to the emergence of system-level diversity. As a result, policies for fostering diversity in a complex system need to consider other factors such as patterns of collaboration or clustering, rather than promoting diversity at the individual level.

5.2.3 Network analysis of the system development

The third essay claimed before looking for the main path or existing trajectories of system development, the possibility of the existence of the main streams of knowledge or innovation should be verified. The same logic is transferrable to other contexts to analyze the direction of socio-technical system development or pathways of system transition.

In addition, for an emerging technological system, a cumulative network of projects is a good proxy for analyzing the main innovative activities, an as a result, for finding the main path and knowledge trajectories. Therefore, it is a useful method for investigating the main streams of ideas and knowledge in other technological fields.

Furthermore, the measures and indicators from evolutionary modeling and network theory revealed how the main direction of network development can be analyzed in a cumulative network of R&D projects with high clustering coefficient and overlapping communities. This method can be used to investigate network structure and analyze other complex networks with a high degree of density and clustering coefficient, as well as the identification of influential nodes such as firms, actors, or projects.

5.3 Outlook on Future Research

There is still much to be understood about the dynamics and problems arising the in early stage of socio-technical transitions and the emergence of new technological systems. Specifically, the complex and multi-faceted issues addressed in this dissertation raise different theoretical and practical questions not reducible to a single research question. As a result, elaborating on some theoretical and methodological aspects of these issues in each essay brings in more question for future research.

Efficient cost allocation of new technology deployment depends on the innovation ecosystem, including the institutional environment and existing infrastructure surrounding the development of new technologies. This dissertation focused on the strength of dynamic modeling to broaden the scope and investigate the possibility of formulating innovative solutions. However, for specific cases at the national and regional levels, the limitations imposed by the existing energy infrastructure, regulations and actor capabilities to participate in the cost allocation process should be taken into account.

In addition, the heterogeneity of potential consumers is currently missing from the model, and all the consumers are considered homogeneous. In this case, a single consumer is modeled as a representative of the consumer group. Investigating the impact of heterogeneity on the demand side, with other methodologies such as agent-based modeling to grasp heterogeneity, can be another direction for future research.

Analyzing the spatial diversity of TIS development is part of a network perspective to system development. Taking this approach enriches our understanding of the interdependencies and emergence of patterns and collective outcomes, but also raises further questions. Apart from the diversity of resulting modules, what is the link between the micro-level characteristics, such as actor preferences to collaborate with specific actor groups, and basic network characteristics such as the size or density of resulting communities?

Furthermore, although the second essay tried to explain the contribution of country level differences to the diversity of spatial configurations, it assumes national institutions are reflected in firm-level preferences to participate in national or multi-national collaborations. A more comprehensive analysis is needed to investigate the role of policies and regulations, along with country-level differences in terms of technological and business capacities in the development of multinational innovation system.

The analysis of the main path and different trajectories can be expanded by tracking the development of technological advances over time. For an emerging technological system such as smart grid, tracking the main streams of knowledge over time is crucial to understand whether the identified trajectories merge or branch, and how the new policies or other system interventions may change the path of system development. In addition, some behavioral or interaction patterns in the last years of analysis can be investigated and explained by gathering data on the later years of development.

From a technical viewpoint, the method presented in the third essay verifies the existence of a main path and then uses an algorithm to reveal the major developments and effective network entropy. However, this method can be improved by adding an algorithm able to identify the main projects in each trajectory, and measure the contribution of each trajectory to main path development. Analyzing trajectories is currently done based on qualitative analysis and can be improved in future research.

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Publications

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