Modeling for Transition Management

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Abstract

A framework for the modeling and simulation of transitions is presented. A transition, "substantial change in the state of a socio-technical system", typically unfolds over a long timespan. We therefore suggest to use simulation to inform transition managers on the effect of their decisions. Transition models preferably meet five functional requirements: to allow for the representation of physical *and* social components, for material and immaterial interactions, to allow the system structure to change, to compute transition indicators and to capture the effect of interventions. Modeling the decarbonization of the power sector illustrates that an agent-based model allows us to let both the content and the structure of a system to emerge in a simulation.

Keywords: Transition, Socio-technical system, Simulation, Transition Modeling, Energy Infrastructure System

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1. Introduction

Change in or of large systems appears to be the connecting topic in the literature on *transitions* [cf. 1] and *transition management* [cf. 2, 3]. The notion of management implies that change can be directed or (partially) steered [4, 5, 6, 7]. However, transitions typically unfold over a long time-span [8], concern large-scale systems [9, 10], and many interactions on different scales [11]. For transition management this begs the questions 'how to decide on actions when their effects will only emerge possibly after years or decades and how to unravel the relations between causes and effects?' We conjecture these questions can be explored using modeling and simulation.

One particular class of large systems are energy infrastructures – "systems that satisfy needs for energy" [12]. Exploiting a glut of newly discovered fossil resources, in the 19th and 20th century these systems evolved to large networks that today include the mining and transport of crude oil, refining into oil products, the mining, transport and conversion of coal, gas and waste to heat and electric power, and finally the continental transport and regional distribution of natural gas, heat and electricity. However, if we want to keep the functioning of our infrastructures, these systems have to change because of the threat of climate change [cf. 13], the depletion of fossil resources [14], and concern over security-of-supply. Decarbonizing our energy system is

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one of the main targets of 'the energy transition'. Indeed, various European leaders have already set ambitious CO_2 reduction targets (compared to 1990 levels): -20% in 2020 and -50% in 2050, while -80% in 2080 is the current UK-government target. Furthermore, in the EU, the emissions-trading scheme (EU-ETS) is seen as the main instrument to let this transition materialize [15, 16].

This then leads to the question: can we simulate the development of our energy infrastructures towards 2020, 2050, 2080 using models that adequately represent energy infrastructure and generate results with sufficient resolution to discern the effect of decisions on company strategy, investment, innovation, on government policies, regulation or governance? If we thus can let transitions appear 'before our eyes', generating them *in-silico*[1], can we relate them to the mechanisms underlying change and thus help transition managers?

To this end, we first introduce the socio-technical system paradigm adopted for energy infrastructures and we define what transitions are and how transition management seeks to facilitate them. Second, we develop functional requirements for the modeling and simulation of transitions. Third, we introduce and review a number of modeling paradigms and assess them against these requirements. Fourth, we illustrate the process of model development and simulation by addressing decarbonizing the electric power generation sector. Discussion, outlook and conclusions complete the paper.

2. Framing systems, transition, and management

Today's energy infrastructures and their transitions can be understood by framing them as *socio-technical systems* [9, 18]. The energy sector not only comprises a large technical system, but also an extensive social system – a network of players, such as miners, refiners, power companies, traders, transmission system operators, brokers, industrial consumers, retailers, consumers, their associations, government, their agencies and NGO's. The sector includes markets for the trading of electric power, all kinds of contracts, and an extensive body of rules and regulation, policies, strategies and visions. Through the interaction of the technical and the social, the energy infrastructure system evolves as *complex* [19, 20] and *adaptive* [21, 22, 23] systems. This implies that from the present structure, content and states, it may evolve to the system of 2020, 2050 or 2080 via an infinite number of pathways – any decision, small or large, may cause the system to develop in a substantially different direction.

On the basis of this argument and an extensive review of the literature on transitions[2], we have defined a system transition as "a substantial change in the state of a socio-technical system" [27, 28].

Building upon the work of Geels and others, notably Rotmans has stipulated that transitions are not only a phenomenon observed in man-made systems, but that transitions of these systems can be invoked and managed – transition management [2]. It is well-recognized that transition arenas [29, 30] can facilitate or invoke the transition process, which then subsequently is shaped by diverse actors over a prolonged period of time. Therein, actors may employ transition instruments for transition management. In management literature, a widely adopted definition of management is "the organization and coordination of the activities of an enterprise in accordance with certain policies and in the achievement of clearly defined objectives" [31]. Transition management's 'enterprise' then is a social system beyond a single company, while this enterprise

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[1] [17] coined the term *in-silico* which means via a computer simulation.

[2] The review included, but was not limited to [24, 1, 8, 25, 10, 2, 3]; for an extensive discussion see [26, chapter 2], `http://chappin.com/ChappinEJL-PhDthesis.pdf`.

may be seen to have both weakly defined objectives, such as sustainability, and very specific objectives such as the CO_2 emission reduction targets. In the EU for example, the energy transition involves many independent enterprises, each of which control only part of the energy infrastructure, and employ distinctly different (corporate) strategies to pursue their own objectives. It clearly then is the role of the EU Member States and the Commission to govern (manage) this transition by organizing and coordinating the actions of the relevant actors – citizens, companies and not-for profit (non-governmental) organizations. The combination of these activities can then be labeled as transition *management*. As of 2005, the EU's main transition *instrument* is the EU-ETS. It may thus be seen that EU climate policy invokes a transition of the EU energy infrastructures, with the objective to reach stated CO_2 reduction targets. Furthermore, the EU at large can be seen as the transition *manager*, employing the policy instruments EU-ETS.

3. Requirements for modelling and simulation

3.1. Modelling and simulation

Modeling and simulation can help us explore and anticipate the effect of a transitions instrument on a system – the effect of the EU-ETS on the energy infrastructure. This leads to a new question – how can we model the system studied and represent it as a complex, adaptive evolving socio-technical system? A *model* is an abstraction and necessarily a simplified representation of a real-world system. Models are used for several purposes: to improve the *understanding* of existing systems, to improve the *performance* of existing systems, to *predict* the future state of existing systems, and to *design* new systems. *Computerized* models allow for simulation of the real-world systems captured in a simulation model: *Simulation* is "the activity of carrying out goal-directed experiments with a computer program" [32, p. 77]. Therefore, during simulation "the system [. . .] progresses through time" [33, p. 4].

It thus appears that simulation models are a suitable tool to generate and explore transition and transition paths, as they allow us to play out multiple transition paths *in-silico*. The ensuing set of simulation runs may then serve to assess the transition instrument and subsequently facilitate the development of recommendations. In such an assessment, one may look at the transition paths wherein the structure, content, and performance of systems changes over time, while depending on the end-time of the simulation, of course, some end-state is calculated. However, this end of the simulation is not the end of the transition, as in these large-scale socio-technical systems, change is endemic.

3.2. Socio-technical systems

The very complexity of many a large-scale socio-technical system may imply, however, that we only have a certain chance of success to steer it towards some preferred state. Any action invokes a reaction, and this is certainly true for changing or new policy and regulation – government's instruments co-evolve with the socio-technical system.

Complex adaptive systems theory teaches us that this may be feasible, as many a complex system is characterized by a limited set of attractors – system states that the evolving, sometimes even chaotic system, given sufficient time, tends towards under a wide range of system parameters and initial settings [20, 23, 34]. What attractors may exist and under which assumptions and conditions (that provide opportunity for steering) they may be reached is subject to simulation. In order for a simulation model to be successfully developed, a set of requirements should be developed. Such requirements may help us to 1) select the appropriate modeling paradigm, 2) to make modeling choices and, eventually, 3) to underpin an appropriate course of action for transition managers.

The path of a transition is shaped by the set of components in the system and their relations, by the changes of and within the set of individual components, and by external influences. The way actors behave, respond and take decisions can be seen to be determined by various institutions [35, 36].

It may be seen that in such a complex system, it is the web of interactions that leads to and determines change. Transition *management* could, therefore, be seen as influencing this web, to divert the system's change towards a certain desired state, "to achieve clearly defined objectives" [31]. Acknowledging the complexity of socio-technical systems, such as energy infrastructures, then leads us to questions such as 'what is the likelihood of achieving a particular change?', 'what circumstances make it probable?', 'for whom it is a desired future and for whom is it not?', 'what transition paths are probable?', etc.

3.3. Developing functional requirements

This implies that the simulation models we develop must allow 1) the representation of a complex adaptive socio-technical system, 2) the capture of the web of interactions and 3) the incorporation of instruments that may divert system change. If our models meet these requirements, running the simulations will provide insights on transition management.

How does this translate to requirements for a simulation model, or to be precise, to requirements for the modeling paradigm to be used? To answer this question, we have adopted the established method of functional requirements analysis [37, 38, 39]. This focuses on *what* the model and modeling paradigm should offer, not *how* it should be implemented.

Physical and social components. We have argued that our energy infrastructures are true socio-technical systems. When we then want to study or observe transitions *in-silico* through modeling and simulation, it follows that our models must capture the essential physical and social components of an energy system. A set of physical entities together constitutes an energy system: power plants, consumer appliances, industrial facilities, physical pipelines and powerline infrastructures. Together, this set's content and linkage defines the energy system, the interaction between components and its performance; during a transition, the energy system content and linkage may change. In a model these must be represented, therefore, to let transition be an observable phenomenon. The social entities comprise the *actors* and their behavior. Important actors are electric power producers, transmission system operators, consumers, market facilitators and government. Institutions are the formal and informal rules that determine actor's behavior. The essential characteristics of actors must be represented, because it is these actors who decide on system content, linkage and use! Social entities have linkage. Their interaction and actions effect technical system change and thus drive transition. It follows that their model representation is pivotal to make transition observable.

Interaction. In energy infrastructures the physical and social components interact. Interaction between physical components includes material, energy and information exchange. Interaction between social components encompasses negotiation and information exchange. Socio-technical interaction includes the control, ownership, and operation of physical components. In modeling, all these types of interaction must be considered, because the aggregate of the interaction determines the state and evolution of the system.

Table 1: Properties of modeling paradigms, partly based on [40, 41]

Aspect	Abstraction	Building block	Mathematical formulation	Dynamics
Scenarios	Static relations	Scenario	None or static	None
Econometrics	Correlations	Parameters	Stochastics	None
CGE	Economic relations	Equation	Optimization	Lurching
ABM	Disaggregated decisions	Agent	Mainly logic	Emergent
SD	Dynamic relations	Feedback loop	Differential equations	Feedback
DS	Physical relations	Equation	Differential equations	Feedback
DES	Event system	Event	DEVS	Events

Changing system structure. It is of crucial importance *how* the essential system components and their interaction are represented. We define the structure of the system as *the configuration of the social and physical components in the system and the linkage between those components*. Core to the concept of transition is 'substantial change of the system state (content, linkage, structure)', which leads to altered system performance. The root causes of system-state change are the set of system components and system structure. Both are the result of interactions – physical linkage, and actor decisions concerning physical components, linkage and use. Therefore, models preferably allow for the system structure to change and evolve in a simulation.

Transition indicators. Elsewhere we have argued there is a need for indicators for transition: We argued that in transition management literature performance indicators are lacking or ill-defined which creates ambiguity regarding what is a transition and what not, and whether a transition started, is underway or completed [27]. This translates into the requirement that models must reveal and show relevant indicators during simulation. These then cover system performance, content, structure and change thereof. Ideally, the set of indicators provides a clear fingerprint of the system during simulation and helps to assess whether a transition occurs.

Tracing specific interventions. To allow analysis of causes for transition, notably the effects interventions, it must be possible to trace these effects. Therefore, a model should be set up to let the simulation render sufficient resolution to discern the implications of single interventions, such as the implementation of a specific transition instrument. It follows that this would allow representation of a set of public policies, whereby simulations could be run to determine under what conditions such policies or interventions may lead to transition.

4. Modeling paradigms for simulating energy transitions

In this section, an overview is given of paradigms relevant for modeling transitions in energy systems. Where policy support is quantitative, simulations appear at the scene. Roughly speaking, (quasi-)static models comprise econometric models, scenario analyses and an abundance of Computable General Equilibrium (CGE) models. Modeling paradigms that capture dynamics are System Dynamics (SD). Discrete Event Simulation (DES) and Agent-Based Modeling (ABM). The main properties of these six paradigms are summarized in table 1.

4.1. Econometrics and scenario analysis

Econometric models use statistical techniques to elucidate correlations. Thus, significant relations may be singled out and used to find key parameters that may be affected through public policy. Scenario analysis [cf. 42] fulfils a similar purpose. Scenarios are used to explicate a range of what-if cases. A number of internally consistent possible futures are defined. The effect of each policy intervention for each future in the set is then analyzed. A variety of scenario methods exists ranging from qualitative narratives to quantitative ('spreadsheet') calculations. Examples of quantitative scenario analysis of energy transitions are the *Energy Transition Model*[3] [43] and the Roadmap 2050[4] [44].

The Roadmap is the result of a large consortium of companies, institutions, and academia. It shows four 'possible' scenarios for achieving 80% reduction of CO_2 levels compared to 1990. In their analysis they show, for example, that in order to achieve European reduction targets the power sector needs to be decarbonized 90-100%. This is a valuable result, because it shows on what aspects public policy makers should focus.

4.2. Computable General Equilibrium

An important class of simulation models used for public policy is Computable General Equilibrium (CGE) models[5] [46, 47]. CGE models are data-rich, well understood and run relatively fast. Typically, they are *models of the economy*, with parameters referring to macro-economic notions, such as labor, market prices, and demands for goods. CGE models are fundamentally based on balancing linear macroeconomic equations [48]. They capture multiple-sector systems with aggregate top-down macroeconomic equations [49, p. 172]. CGEs use a technology-matrix [50] or a database [51], which generally contains the characteristics of technologies for the production of goods [52, 53]. In essence, the variables in the equations of CGE models are aggregates [51] and CGE models are continuous. For instance, the consumption by households of a certain good is aggregated into a single continuous parameter, heterogeneity of households is neglected and strict assumptions are made for the decision making of these households. Furthermore, to be able to solve CGE models and find an equilibrium many aggregate variables – defining technology, consumer tastes, and government instruments (such as tax rates) – are exogenous.

In CGE models it is assumed that between the simulated time steps the economy is able to stabilize in an *equilibrium*: a stable state of all parameters of the economy. The consequence is that "CGE models are not dynamic" [54, p. 71], though they try to deal with trajectories over time. Despite the fact that they are often classified as dynamic, such models are actually *lurching* – an equilibrium is found for each modelled time step [54].

Many important institutes for policy research and analysis use CGE models because of their focus on economic parameters. A classic example of a CGE model is one used to study the effect of subsidies on trade [55]. Another reason to engage in CGE modeling is that the modeling process is streamlined so that new results can be generated quickly. Amongst them are the World Bank, the International Energy Agency (IEA) and, in the Netherlands, the Netherlands Bureau for Economic Policy Analysis (CPB) and the Energy Research Center (ECN). This shows that CGE has developed into the *de facto* standard for supporting policy decisions throughout the world. As in general, the use of quantitative methods has increased with developments in computing,

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[3] `http://www.energytransitionmodel.com`

[4] `http://www.roadmap2050.eu`

[5] The notions of Computable General Equilibrium (CGE) and Applied General Equilibrium (AGE) models are fuzzy. CGE models have first been formalized by Arrow [45]. Although often reported otherwise, the mathematics of current CGE models are unrelated to that formalization. AGE models are based on foundations from micro-economics. Although both have different origins, throughout the years, research merged parts of both streams of models into both AGE and CGE models. In this paper we will only refer to CGE models.

CGEs are increasingly used. With a modern desktop PC, running a reasonable CGE model is done in a matter of minutes.

The IEA uses their *World Energy Model* to examine 20 years of future energy trends [56]. This model is data-intensive, compiled and updated by the IEA itself. The World Energy Model covers all energy markets and has a holistic, mono-actor approach. It is an interlinked set of models, of which some parts are modelled in different modeling paradigms to improve the model as a whole [57]. The IEA presents results in relation to a *reference scenario*, which is an extrapolation and functions as "a baseline picture of how global energy markets would evolve if the underlying trends in energy demand and supply are not changed" [56, p. 52].

An example of the intensified use of CGE models can be found in the Netherlands, where the Netherlands Bureau for Economic Policy Analysis (CPB) uses CGEs for policy support [58, 59]. Nowadays, The CPB evaluates the political plans of many of the parties in times of national elections. The CPB predicts how their plans will affect economic growth and number of jobs and other macro-economic parameters. CPB has become the main organization that supplies such advice. For their long-term predictions, the CPB developed the *WorldScan* model [60], fed by data from the Global Trade Analysis Project (GTAP) database [61]. Exogenous system drivers include labor supply, employment growth, population growth, and age distribution. Equations in the *WorldScan* model contain consumer goods markets, producer markets, capital markets, and the labor market. ECN has developed a portfolio of CGE models for policy support [62], of which a few focus on the medium to long term [e.g. 63, a model of the energy use in buildings].

CGE models typically have a large number of equations and variables, for which common solvers (such as Excel or Matlab) are insufficient. The industry-standard software for CGE models is GAMS, which is only commercially available.

4.3. Agent-Based Modeling

Agent-Based Modeling (ABM) emerged from the fields of complexity, chaos, cybernetics, cellular automata and computers [64]. A common definition for an *agent-based model* is "a collection of heterogeneous, intelligent, and interacting agents, which operate and exist in an environment, which for its part is made up of agents" [65, 66]. In other words, "the components of an agent-based model are a collection of agents and their states, the rules governing the interactions of the agents and the environment within which they live." [67]. ABMs "emphasise modeling behavior at the lowest practical level, with an interest in studying the emergence of [. . .] agent interactions, as well as the evolution of strategies for agent interaction with the environment and other agents. [. . .] Agent-based models are well suited to model strategies of different stakeholders, their interactions and the outcome of such interactions" [68].

In general, ABMs provide us with a laboratory for capturing evolving systems in models. Therefore, an ABM is a *playground* for scientists, to *explore* emergent outcomes of the interaction of a set of autonomous agents. Traditionally, ABMs are applied in the social sciences [e.g. 69, 70, 71]. Applications related to technology and markets have appeared as well, such as models of electricity markets [72, 73, 74, 75, 76, 77, 78, 79].

In addition to general ABMs, a large body of literature has emerged on the subject of Agent-Based Computational Economics (ACE), which are essentially ABMs containing agents with rules from economic theory – a subclass of ABMs. ACE is "the computational study of economic processes modelled as dynamic systems of interacting agents" [80, p. 3]. A relevant example of ACE is the EURACE project[6] in which a very large, policy-design oriented agent-based model

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[6] `http://www.eurace.org/`

of the European economy is being developed.

A large variety of software is available for developing ABMs. Common in the social sciences are Netlogo, Repast, and MASON, all open source. Commercial tools, such as Anylogic are also available.

According to a recent review of existing transition models [81], ABM has been used in a few transition papers [i.e. 82, 83, 84, 26, 85].

4.4. System Dynamics

System Dynamics (SD) is “the study of information-feedback characteristics of industrial activity to show how organizational structure, amplification (in policies), and time delays (in decisions and actions) interact to influence the success of the enterprise” [86]. Typically, SD models are used to “understand the long term behavior of states in a system for which there is a deterministic way for how a state evolves” [87, p. 1]. The stream of models called Dynamic Systems (DS) [88] refers to system dynamic models applied to *physical systems*, but system dynamics is broader than that and includes non-physical system elements.

An SD model is defined by a set of differential equations. Each equation represents a process which is conceptualized as flows between stocks of, for instance, materials, energy, knowledge, people, or money. Additional parameters determine the values of the flows [89]. SD models are inherently continuous. SD models were originally coded in DYNAMO, a commercial software, now unavailable. Although there are less common open source and/or freely available alternatives, common modern software for system dynamicsm such as PowerSim, Vensim, and iThink/Stella, is commercial. Much of the software is well developed in terms of GUIs, graphs, and built-in solvers. Modern software allows for some relaxation of the restrictions of the continuous domain such as step functions.

Typically, SD modelers intend to look at feedback loops and delay structures. SD does not model individual events, for instance the decisions of a person to become an adopter. Events are rather aggregated to flows. Therefore, in system dynamics a flow of people can refer to people changing their state, in this case the number of adopters of a certain technology [90].

System dynamics is used throughout many fields of research, such as studies related to populations and ecological and economic systems. In addition, SD is relevant for policy analysis: “Because dynamic behavior of social systems is not understood, government programmes often cause exactly the reverse of desired results. The field of system dynamics now can explain how such contrary results happen” [91]. The most important example is the model behind the *limits to growth* [14] that Forrester [92] further refined into the *World3 model*. Other SD studies have modelled the electricity market [93].

A recent review of existing transition models [81] notes several transition models based on SD methodology or differential equations [94, 82, 95, 96].

4.5. Discrete Event Simulation

In Discrete Event Simulation (DES) the operation of a system is represented as a chronological sequence of events [97]. Events occur in a system with a fixed structure. Such events change the state of the system, including the state of the entities in the system and these changes trigger new events.

Underlying DESs, is the discrete event system specification (DEVS), developed by [98, 99]. This specification allows for various discrete-event formalisms that can be adopted for developing DESs. DEVS represent events by defining how the system state changes based on a set of input and output events. Although it is only one possible formalism [100, 101], a typical DES application is represented as entities that "travel through the blocks of the flowchart where they stay in queues, are delayed, processed, seize and release resources, split, combined, etc." [102, p. 27]. The simplest form of a DES is a queue system that holds the entities. "Simulation progresses by repeatedly dequeuing events, computing their consequences, and reporting the consequences either by updating the global state of the simulated system or enqueuing notices of additional future events. Any number of events may be scheduled as a consequence of one event. Some events only change the global simulation state, while others schedule large numbers of new events." [103, p. 301].

A variety of software tools is available for DES, such as Arena. DESs are mainly used to analyze and improve the design of handling systems. Examples of DESs are container handling in ports [104], global supply chains [105, 106] and dynamics in electricity markets [107].

5. Analysis of modeling paradigms

We have argued that transition management would benefit from appropriate modelling that represent the system and its interactions, allow for transitions to occur and be observed, and allow to explore the impact of 'management'.

5.1. The extent to which requirements are typically met

The requirements and modeling paradigms can now be combined to arrive at an indication how typical use of the modelling paradigms matches with the requirements for simulating for transition management. This is summarized in table 2. In typical uses[7], the paradigms differ widely. There are not many definite *no*'s, which implies that all of the paradigms can play a meaningful role for transition management. However, for all of the paradigms, some requirements are met implicitly; the consequence is that it may be unconventional, counter-intuitive or more difficult to develop useful simulations for transition management. Figure 1 shows theses differences in more detail. For each of the paradigms, the core reasons to select them and their main disadvantages are listed below.

The main differences are between four categories (see):

Designing. The first category is where the modeller designs future desired system states. **Scenarios** provide a way to think outside current conventions and can provide vision and discussion. They are, however, less fit for elaborating the impact that management has on the developments towards that scenario.

Fitting. The second category is where a structure is fit to the collected real-world data. **Econometrics** is data rich and gives insight in the current system. It is however, unconventional to model radical changes.

Optimizing. The third category is where the system is optimized, typically to the objective if minimizing societal costs. **CGE** is strong in the representation of our economy. This can be highly detailed and provide insights of interventions that change the structure of our economy. However, it is less appropriate for systems that are in flux, for which the basic assumptions (e.g. regarding rationality) are problematic.

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[7] The 'scores' on the requirements do not refer to fundamental differences between the modelling paradigms persé, but rather on how they typically are used, what is intuitive or what is commonly accepted

Table 2: Requirements fulfilled in typical use per modeling paradigm.
Legend: Yes: requirement for explicit representation is typically met. No: requirement is typically not met. Implicit: modelling paradigm meets the requirement, but typically not in an explicit fashion.

Requirement	Scenarios	Econometrics	CGE	ABM	SD	DES
Physical components	implicit	implicit	implicit	implicit	yes	yes
Social components	implicit	implicit	implicit	yes	implicit	yes
Interactions	implicit	implicit	implicit	yes	implicit	yes
Changing system structure	implicit	implicit	yes	yes	implicit	no
Transition indicators	yes	yes	yes	yes	yes	yes
Tracing specific interventions	no	yes	yes	yes	yes	yes

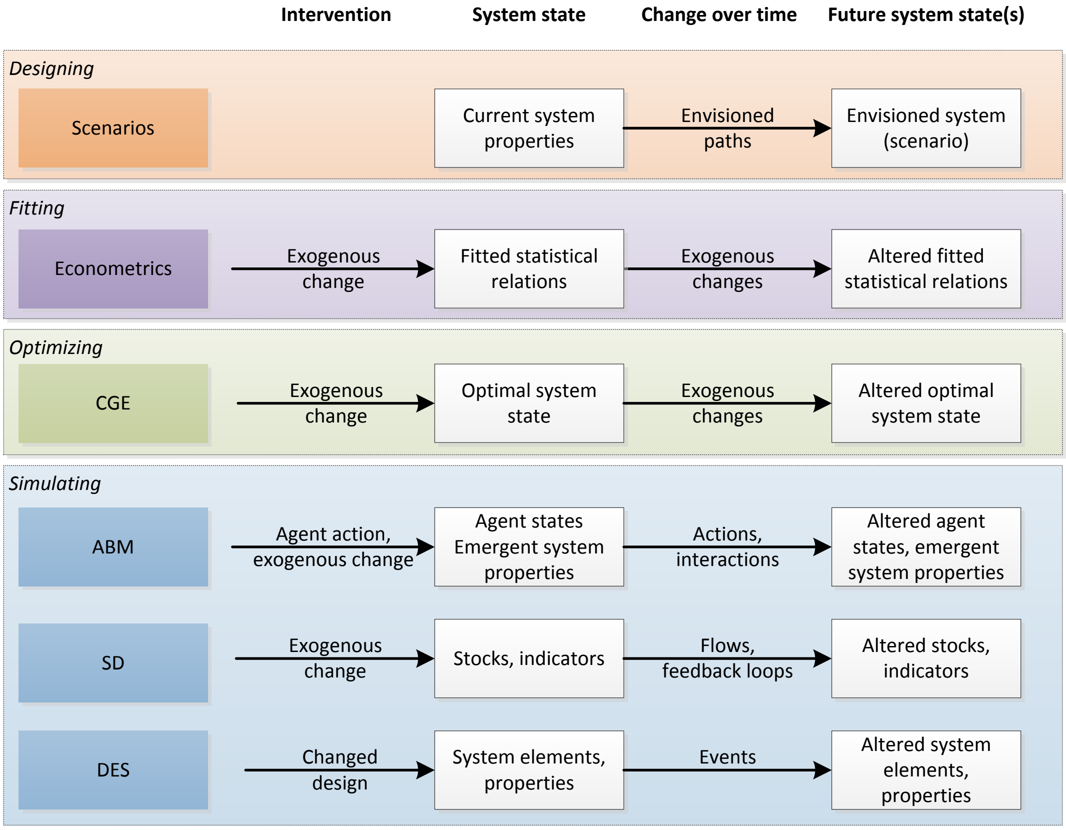

Figure 1: The way in which modelling paradigms represent and capture interventions, the system state and changes over time.

Simulating. The last category enables exploration and discussion of the *dynamics* of the systems under observation.

- **SD** is quick to develop because of the high level of aggregation used, it is quick enough for vast explorations and it is intuitive. However, a good system representation (or aggregation) should be known or need to be found and the the structure of the system is fixed by the equations selected. The validity of the model depends strongly on the aggregation used.
- **ABM** can represent decisions and heterogeneity of actors intuitively. An advantage is that the system structure is fluid: it is the emergent property of the decisions of and interactions between the actors. However, ABM so far is applied fewer to include physical/technical systems. The validity of the model depends largely on the selection of actors and the model of the decisions they make.
- **DES** is very strong in capturing a large number of events, triggered by a given system structure and by each other. A strong point is that the interaction of events leads to emergent patterns. The main disadvantage is the firm and fixed way the system is represented.

5.2. Application: agent-based modelling of decarbonization of the power sector

We illustrate this with an agent-based model for the case of decarbonization of electric power generation in the Netherlands[8].

Agent-based modelling. Because of the fact that for decarbonization of the power sector, the heterogeneous and independent electricity producers are crucial actors, we selected agent-based modelling as a core paradigm. The model reflects the real-world situation of six of those producers who have different generation portfolios and who make different decisions regarding the operation of their generators, investment, and decommissioning. The agents in the model have operational behavior – power producers need to negotiate contracts for feedstock, the sales of electricity and, in the case of emissions trading, emission rights. They also exhibit strategic behavior – in the long-term the agents need to choose the moment of investment, the amount of capacity, and the type of power generation technology. Agents interact through negotiated contracts and organized exchanges and are subject to the physical flows, their characteristics and constraints.

Exogenous scenarios. The electricity demand is given; its profile consists of 10 steps per year which reflect a typical load-duration curve. Demand and fuel prices are modelled as trends. CO_2 rights, power and fuel markets are modelled as exchanges. The time step of the model is one year and the simulations span a horizon of 50 years. The government agent implements policy interventions – it collects taxes and induces penalties.

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[8] In earlier work we reported the findings of our modeling research in terms of the effect on the power generation sector of the two most prominent transition instruments – an emissions-trading scheme, as implemented in the EU, and a carbon taxation scheme, implemented on a smaller scale in Norway. A more extensive and comprehensive description and analysis of power sector decarbonization, modeling and other transition models can be found in [108, 109, 26, 85, 110].

Transition policies. The two main policies are the EU emissions-trading scheme (EU ETS) and an alternative, a taxation on CO_2. The results are compared to a no intervention base case. The main policy variable of the EU-ETS is the emissions cap, which in the model reflects the current phase of the EU-ETS (phase 3, running 2013-2020): the CO_2 cap starts at 50 Mton for the power sector in the Netherlands and is reduced every five years by 3 Mton. A 50% reduction is achieved in little more than 40 years. To allow a fair comparison between ETS and the carbon tax, the tax level starts at 20 €/ton and is on average calibrated to the resulting CO_2 prices in EU-ETS simulations.

Simulation results and analysis. The main indicator for transition is CO_2 emissions, but it can only be considered in its context: the patterns in electricity and CO_2 prices, the generation portfolio of the electricity producers. We explored the simulation outcomes and used those to discuss its relevance for current policy to improve transition management in this sector.

We analyzed that intervention, such as the EU-ETS or CO_2 taxation is needed in order to curb emissions. The pressure that carbon policies put on the power generation system is reflected in the electricity prices, since power companies pass through their CO_2 costs to consumers. When kept in place, their long-term impact is significant and will bring about transition: the policies cause structural differences in the electricity prices, and therefore, the eventual transition in terms of generation portfolio and CO_2 emissions is profoundly different. These portfolio shifts that emerge in the simulation are not perfect predictions, but they lead to the discovery of patterns that occur in this sector, which were not prominent in economic theory. We found that a reasonable carbon tax would a more effective and efficient instrument for decarbonization than the current EU-ETS. At the end of the day, this result contributes to the discussion of how to improve European carbon policy. The fact that a implementing a EU carbon tax may well be infeasible for the power sector does not mean we cannot be inspired to develop and implement related mechanisms, such as minimum and maximum prices on credit auctions or taxes in member states.

6. Conclusion

The work reported in this paper aims to support the development and execution of simulation models for transition management. Change in or of large systems appears to be the connecting topic in the literature on transitions and transition management. Adopting the socio-technical, complex adaptive system paradigm led us to the notion that these systems evolve and change over time. Using these insights allowed us to develop functional requirements for simulating energy transitions.

Using this perspective, five functional requirements for transition models were deduced. These models preferably allow for the representation of (1) physical *and* social components, (2) material and immaterial interactions, (3) a changing system structure, (4) transition indicators, and (5) interventions. We discuss econometric modeling, scenario analysis, computable general equilibrium models, system dynamics and discrete event simulation and Agent-Based Modeling (ABM) regarding these requirements and provide an example application.

We hope the work presented in this paper inspires transition theorists and modelers alike. More work is needed to flesh out the possibilities and limitations of transition *management* and the predictive capabilities of simulation models. As in any system study and modeling activity, both the depth and detail of the models and the breadth of the systems modeled can be expanded. We encourage the use, expansion and modification of the framework, particularly because it is often the modeling process that provides insight, not the model result. Through model results, insights and expert judgment, we can get better at realizing desired transitions – not by trusting in precise predictions of our energy infrastructure systems, but by embracing their complexity.

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