Energy Transitions towards Sustainability I: A Staged Exploration of Complexity and Deep Uncertainty

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Abstract

This paper illustrates the use of Exploratory System Dynamics Modeling and Analysis – a multi-method combining System Dynamics and Exploratory Modeling and Analysis to explore and analyze uncertain dynamic issues and test deep policy robustness. This paper gives an overview of the current state of this multi-method by means of an illustration. The multi-method is applied to the transition of the electricity generation system, more specifically the battle between old and new electricity generation technologies. Starting from a small System Dynamics model about the battle, uncertainties are added to turn it into an exploratory variant which is used as a scenario generator in the multi-method. In a follow-up paper, model and method uncertainties are added and explored by joint consideration of the exploratory model, another (large) System Dynamics model, and an Agent Based model. By reading both papers, the reader is taken step by step from the identification of uncertainties, development of System Dynamics models, transformation of these models into exploratory models by adding uncertainty-related structures and formulations, to the stage-wise exploration of different types of uncertainties – starting with parameter uncertainties, subsequently adding uncertainties related to functions, structures, models, and methods.

Keywords: Energy Transitions, System Dynamics, Deep Uncertainty, EMA, ESDMA

1 Introduction

1.1 Dynamic Complexity and Uncertainty of Energy Transitions

Energy Transitions are dynamically complex: they are governed by many feedbacks and long delays. Energy transitions are also deeply uncertain: major uncertainties –related to and for individuals, particular technologies, the entire system, and hence for policy/decision makers in the energy field– are omnipresent.

Energy technologies face many uncertainties and need to overcome many hurdles, even before becoming commercially viable and entering the energy technologies battlefield. Figure 1 shows for example the influence of uncertainty on entrepreneurial motivation and entrepreneurial action[1]: Many self-reinforcing uncertainties (on the left hand side) influence the perceived certainty related to a particular new technology. The lower the perceived certainty, the higher the perceived risk and the lower the willingness of entrepreneurs to acquire knowledge / experiment / lobby / . . . in order to bring the technology to the point where it is considered a good investment. Resources for actions to reduce uncertainties may actually help to take this hurdle and lead to more perceived certainty and raise perceptions about its potential success. This in turn (extrinsically) reinforces (intrinsic) entrepreneurial motivation, resulting in more willingness to act.

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[1]This Causal Loop Diagram summarizes the work of Meijer and colleagues on uncertainty and entrepreneurial motivation in energy transitions (Meijer 2008; Meijer, Koppenjan, Pruyt, Negro, and Hekkert 2010).
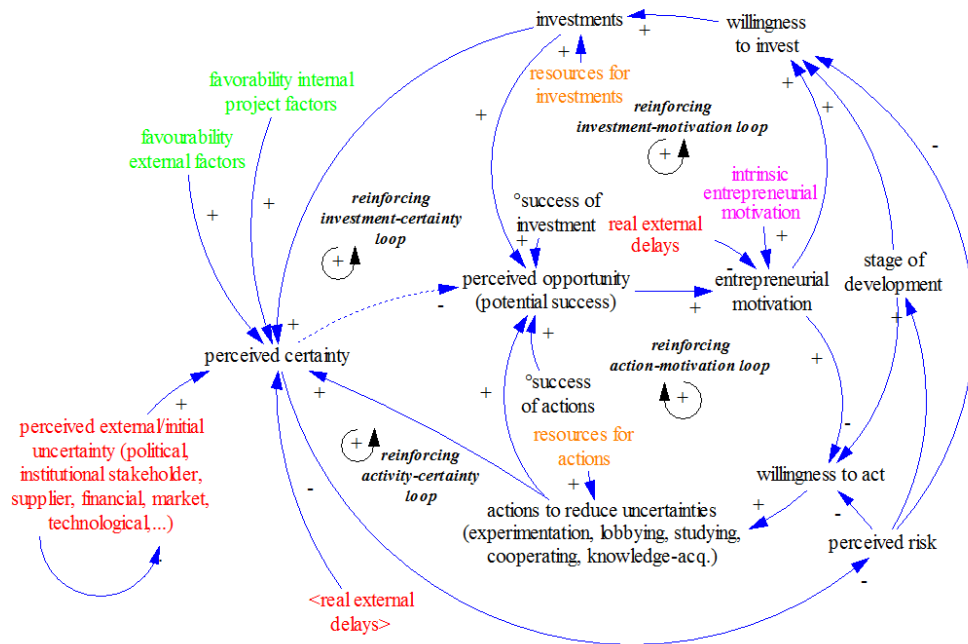
Figure 1: Causal Loop Diagram of the pre-battle stage: entrepreneurial motivation and actions and uncertainty based on (Meijer 2008)

A reduction of the perceived risk and an increase of the entrepreneurial motivation are the preconditions to (further the state of development and) increase the willingness of entrepreneurs and risk-taking energy companies to invest, which then leads to (more) real investments, contributing to the technology's success, reinforcing the willingness to invest, etc.

Or in terms of feedback loops: in order to bring a technology to the energy technologies battlefield, the *reinforcing activity-certainty* loop needs to be activated first, after which the *reinforcing action-motivation* loop needs to kick in, activating the *reinforcing investment-motivation* loop, which should lead to the activation of the *reinforcing investment-certainty* loop. Only then may the technology reach the technologies battlefield. The Causal Loop Diagram points out crucial prerequisites to get there: *(i)* entrepreneurs need to be intrinsically motivated; *(ii)* (perceived) uncertainties and risks need to be reduced; *(iii)* sufficient resources for actions to reduce uncertainties need to be (made) available; *(iv)* administrative/bureaucratic delays need to be avoided or kept to a minimum; *(v)* sufficient resources for initial investments need to be (made) available.

Quite often, entrepreneurs and technology developers bring a new technology to the *pre-commercial* stage, but due to a lack of investments, it does not survive this so-called 'valley of death' – the phase between (subsidized) entrepreneurial technology development and large-scale commercial take-off in which subsidies are (often) forbidden. It is hard to predict which promising technologies will actually make it, and hence, which might possibly become the technologies of the future.

After surviving the valley of death, technologies enter –from a technologies point of view– the technology battle field. The outcomes of the battle is also uncertain and impossible to predict. But even though the outcomes of the energy technologies battle may be unpredictable, the plausible dynamics may be 'explorable' by explicitly focussing on these uncertainties.

Figure 2 shows a Causal Loop Diagram of the competition of a new technology T2 with other technologies for new capacity additions, based solely on their marginal investment costs. Although the Causal Loop Diagram in Figure 2 is overly simplistic and only provides a narrow view of the intricacies of energy technologies competition, it may be a good starting point for a step-wise
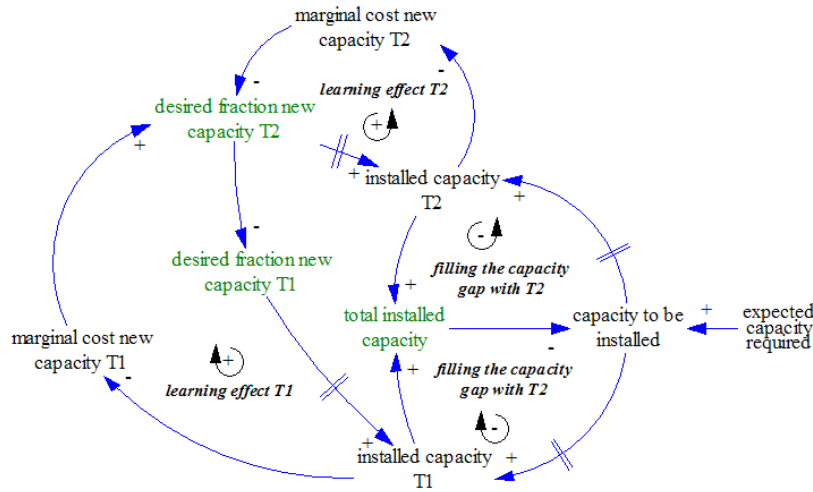
Figure 2: Causal Loop Diagram of the competition between T1 (all other technologies) and T2 (a new technology) based on the marginal cost of new capacity

methodological illustration of ESDMA applied to the technologies battle. But before jumping in section 2 to the basic SD simulation model corresponding to the Causal Loop Diagram in Figure 2, the methodology that will be used later in this paper is briefly explained in the next subsection.

1.2 Exploratory System Dynamics Modeling and Analysis: Why? What? How?

Exploratory System Dynamics Modeling and Analysis (ESDMA) –the combination of System Dynamics and Exploratory Modeling and Analysis– is useful for exploring and analyzing deeply uncertain dynamically complex issues and for testing deep policy robustness (i.e. policy effectiveness over all plausible futures). In this multi-method System Dynamics (SD) simulation models are –in a sense– (ab)used as scenario generators in the Exploratory Modeling and Analysis (EMA) methodology to generate (tens of) thousands of plausible transient scenarios.

EMA[2] consists more precisely of (*i*) developing 'exploratory' –fast and relatively simple– models of the issue of interest, (*ii*) generating thousands to millions of scenarios (called an 'ensemble of future worlds') by sweeping uncertainty ranges and varying uncertain structures and boundaries, (*iii(a)*) simulating and analyzing the dynamic behaviors, bifurcations, et cetera, (*iii(b)*) and/or specifying a variety of policy options (preferably adaptive ones), and simulating, calculating, and comparing the performance of the various options across the ensemble of future worlds.

EMA could thus be used to explore the influence of a plethora of uncertainties – uncertainties related to initial values, parameters, specific variable formulation, generative structures, model formulations, model boundaries, different models, different modeling methods and paradigms, and different preferences and perspectives related to different world-views, and policies. It could also be used for directed searches into problematic areas of the uncertainty and scenario spaces, and for deep policy robustness testing (testing policy effectiveness over the entire scenario space).

Although data analysis techniques (step (*iii*(a))) should –from an analyst's point of view– be used to investigate the effect of underlying mechanisms/(inter)actions/conditions, to separate different modes of behavior, to determine the conditions that lead to these different modes of behaviors, to find bifurcation points and critical variables, it may –from a policymaker's point

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[2]See among others (Bankes 1993; Lempert and Schlesinger 2000; Lempert, Groves, Popper, and Bankes 2006; Bryant and Lempert 2009; Agusdinata 2008; Agusdinata, Van der Pas, Walker, and Marchau 2009; Bankes, Walker, and Kwakkel 2010; Kwakkel, Walker, and Marchau 2010a; Kwakkel, Walker, and Marchau 2010b).

of view– be even more interesting to define different (adaptive) policies/strategies and test their (relative and absolute) effectiveness/robustness given all these uncertainties (step *(iii(b))*). The effectiveness/robustness of policies can then be evaluated over the entire multi-dimensional uncertainty space without needing to analyze/understand millions of outcomes. In other words, the effectiveness/robustness of policies/strategies could be evaluated and compared without reducing uncertainties related to the system of interest and without getting overwhelmed by combinatorial complexity. Decent analysis in step *iii(a)* may nevertheless be necessary/useful for developing appropriate policies for the entire uncertainty space.

Currently, special attention is paid by several EMA researchers to the combination of dynamic complexity and deep uncertainty, and consequently to the combination of System Dynamics and EMA[3]. Simultaneously considering deep uncertainty and dynamical complexity is –technically speaking– feasible but often rather demanding. This, however, is changing rapidly.

Although Exploratory System Dynamics Modeling and Analysis is also a model-based methodology, it actually requires a very different mental mode than the traditional predictive one. Its main uses are exploration to broaden the horizon and deep robustness testing. If it reverts to prediction at all, then only to 'ensemble prediction' over the entire uncertainty space and claims about 'policy robustness'. It starts and ends with uncertainties. And design of adaptive policies and resilient systems is the final purpose.

Since EMA is appropriate for systematically exploring deep uncertainty and testing the robustness of policies, and ESD models are particularly appropriate for generating plausible behaviors over time, it follows that ESDMA is particularly appropriate for *systematically* exploring and analyzing thousands to millions of plausible dynamic behaviors over time, and for testing the robustness of policies over all these scenarios. As opposed to EMA, ESDMA therefore goes beyond the calculation of end states or static values, which makes it much more challenging.

Since EMA is a quantitative uncertainty analysis approach and mainstream SD modeling consists of making quantitative simulation models, it follows that ESDMA is mainly a quantitative multi-method, but which leads –just like traditional SD– to qualitative interpretations, conclusions and recommendations.

We currently use a shell written in Python to make an experimental design and to force Vensim DSS to execute experiments. Python stores the data when generated. Then we use a library of algorithms coded in python to analyze the artificially generated data set and (interactively) visualize the most interesting findings.

Formerly, we used either Python or Vensim. Using both Python and Vensim together has many advantages: modeling is much easier in Vensim, but Python outperforms Vensim when it comes to making, controlling, and playing with experimental designs, analyzing and visualizing outcomes of (thousands of) simulations, etc.

2 STAGE I: A 'Traditional' SD Model of the Energy Technologies Battle

2.1 Structure of the Energy Technology Battle SD Model

The structure (and dynamics) of the installed generation capacity is focused on here because of its importance for the energy transition: electric power plants mostly remain in use for some 25 to 65 years. Four technologies (T1, T2, T3, T4) are focused on at first (see Figure 3). T1 is the old 'regime technology' – a rather polluting and non-renewable technology. T2, T3, and T4 are new technologies, competing with T1 and –maybe even more so– with each other.

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[3]See for example (Lempert, Popper, and Bankes 2003; Pruyt 2010b; Pruyt and Hamarat 2010a; Pruyt and Hamarat 2010b; Kwakkel and Pruyt 2011; Pruyt 2011a; Pruyt and Kwakkel 2011; Pruyt, Logtens, and Gijsbers 2011; Kwakkel and Slinger 2011; Kwakkel and Yucel 2011).
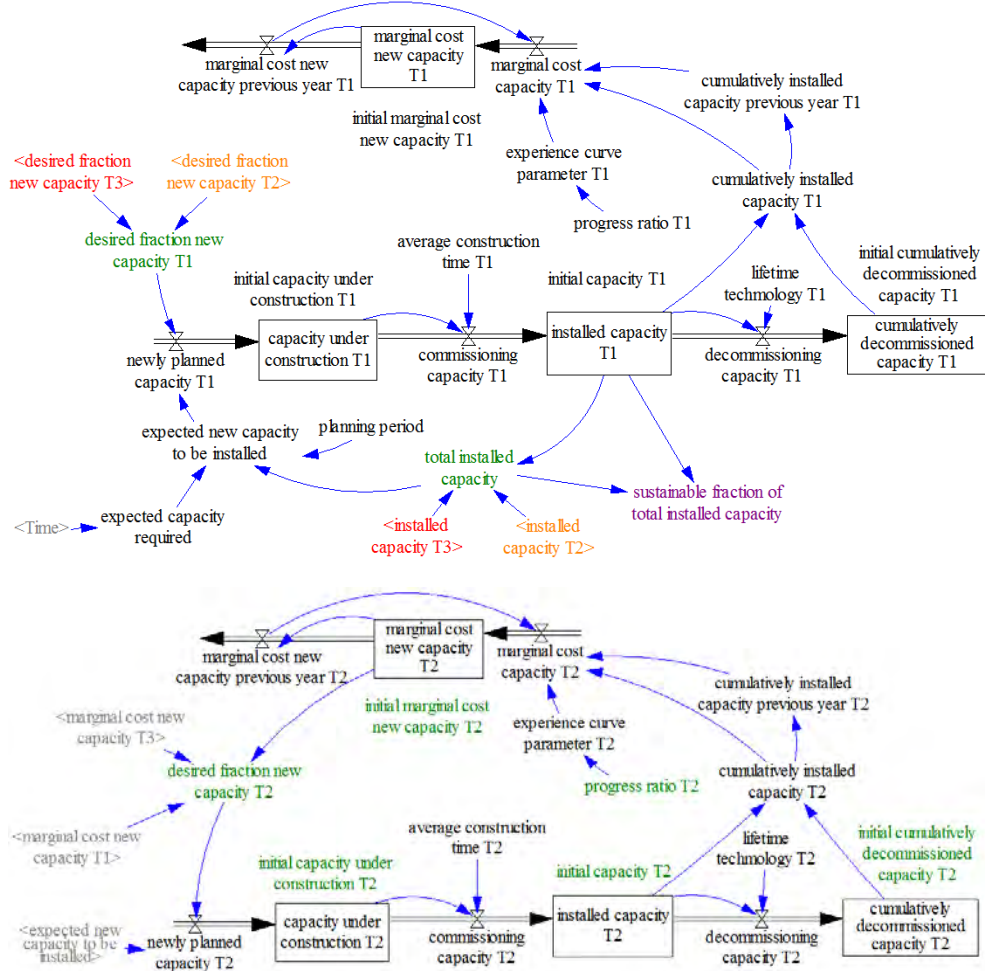
Figure 3: SFD of two out of four competing Energy Technologies

Learning curves of the following form are used:

$$C_t = C_{t-1}\Big(\frac{X_t}{X_{t-1}}\Big)^e$$

C_t stands for the investment cost per MW at time t, X_t for the cumulative historic capacity (i.o.w. all ever constructed capacity of that technology), and e for the learning curve parameter. These learning curves can be included –somewhat artificially– into System Dynamics models by adding a stock variable *marginal cost of new capacity Ti*. This stock variable has an outflow variable *marginal cost of new capacity Ti of the previous year* equal to the stock variable, and as inflow a variable *marginal cost of capacity Ti* equal to the *marginal cost of new capacity Ti of the previous year* multiplied by

$$\Big(\frac{cumulative\ ever\ installed\ capacity\ Ti}{cumulative\ ever\ installed\ capacity\ previous\ year\ Ti}\Big)^{-learning curve\ parameter\ Ti}.$$

The *learning curve parameter Ti* equals $-log_2(progress\ ratio\ Ti)$. A progress ratio of 90% means for instance that each doubling of the *cumulatively ever installed capacity* leads to a cost reduction of 10%.

In this model, the main output indicator related to the sustainability of the system is the *sustainable fraction of the total installed capacity.*

parameter	unit	base value (not shown)	normal SD sensitivity analysis ranges	ESDMA ranges
ini cap T1	MW	15000	14000-16000	14000-16000
ini cap T2,T3,T4	MW	1	1-2	1-2
lifetime technology T1	yr	40	30-50	30-50
lifetime technology T2,T3,T4	yr	22.5	15-40	15-40
initial cumulatively decommissioned capacity T1	MW	10M	5M-10M	5M-10M
initial cumulatively decommissioned capacity T2,T3,T4	MW	10	10-100	1-100
average planning and construction period T1	yr	3	1-5	1-5
average planning and construction period T2,T3,T4	yr	3	1-5	1-5
progress ratio T1		0.90	0.85-0.95	0.85-0.95
progress ratio T2,T3,T4		0.80	0.70-0.95	0.70-0.95
initial marginal cost new capacity T1	€/MW	1M	0.5M-1.5M	0.5M-1.5M
initial marginal cost new capacity T2,T3,T4	€/MW	7.5M	5M-10M	5M-10M
performance expected cost per MWe T1				1-2
performance expected cost per MWe T2,T3,T4				1-5
performance CO2 avoidance T1				4-5
performance CO2 avoidance T2,T3,T4				1-5
absolute preference for MIC		1		2-5
absolute preference against unknown		0		2-5
absolute preference for expected progress		0		1-3
absolute preference against specific CO2 emissions		0		2-5
absolute preference for expected cost per MWe		0		1-3
SWITCH T3, T4		1	1 / 0	1 / 0
ec gr t1				0.03–0.035
ec gr tx (other than t1)				-0.01–0.03
random PR min			1	0.9–1
random PR max			1	1–1.1
seed PR T1				1–100 (integer)
order lifetime T1,T2,T3,T4		1	1	1 / 3 / 10/ 1000

Table 1: Initial values and parameter values of the simplistic SD model for a non-specified case

2.2   Analysis of Behavior of the Energy Technology Battle SD Model

This variant of the model could be used –without further extensions and in a limited amount of time– to explore some (relatively minor) uncertainties: some parameter uncertainties (the parameters with ranges in the fourth column of Table 1), some scenarios (e.g. related to the *expected capacity required*), and some surprises (by de/activating one of the switches to turn technologies T3 and T4 on/off). However, the extent of such an exploration –or extended sensitivity analysis– should/could be questioned.

Figure 4 shows the results of 100 LH simulations with this model[4] and the rather large uncertainty ranges displayed in the fourth column of Table 1 – from top to bottom: total fraction new technologies; installed capacity T1; installed capacity T2; installed capacity T3; installed capacity T4; and total capacity installed. The total capacity installed increases exponentially in all simulations and the fraction of new technologies almost always displace the old/incumbent technology.

Figure 5 shows the corresponding envelopes of these 100 LH simulations for the same variables. The graphs of installed capacity T2 (third from the top) are most interesting: they seem to bifurcate. This makes sense knowing that T3 and T4 are switched on/off about half of the time. T2 takes (part) of their share if they are, and especially when they both are.

This finding is confirmed using a regression and classification tree using the C4.5 algorithm (Quinlan 1993) on the ensemble of 100 scenarios and forcing a modal split (two classes) on the end states of the variable *installed capacity T2*. The tree in Figure 6 was only restricted by the requirement that a minimum of 70% of the samples in a class need to belong to the same group. The tree shows firstly that deactivation of T4 leads to success for T2, and secondly that a very low progress ratio for T2 also leads to success.

The results obtained here should be compared with the results obtained in subsection 3.2.

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[4]10000 LH samples are taken too: the outcomes do not differ much from the ones obtained with just 100 LH samples.
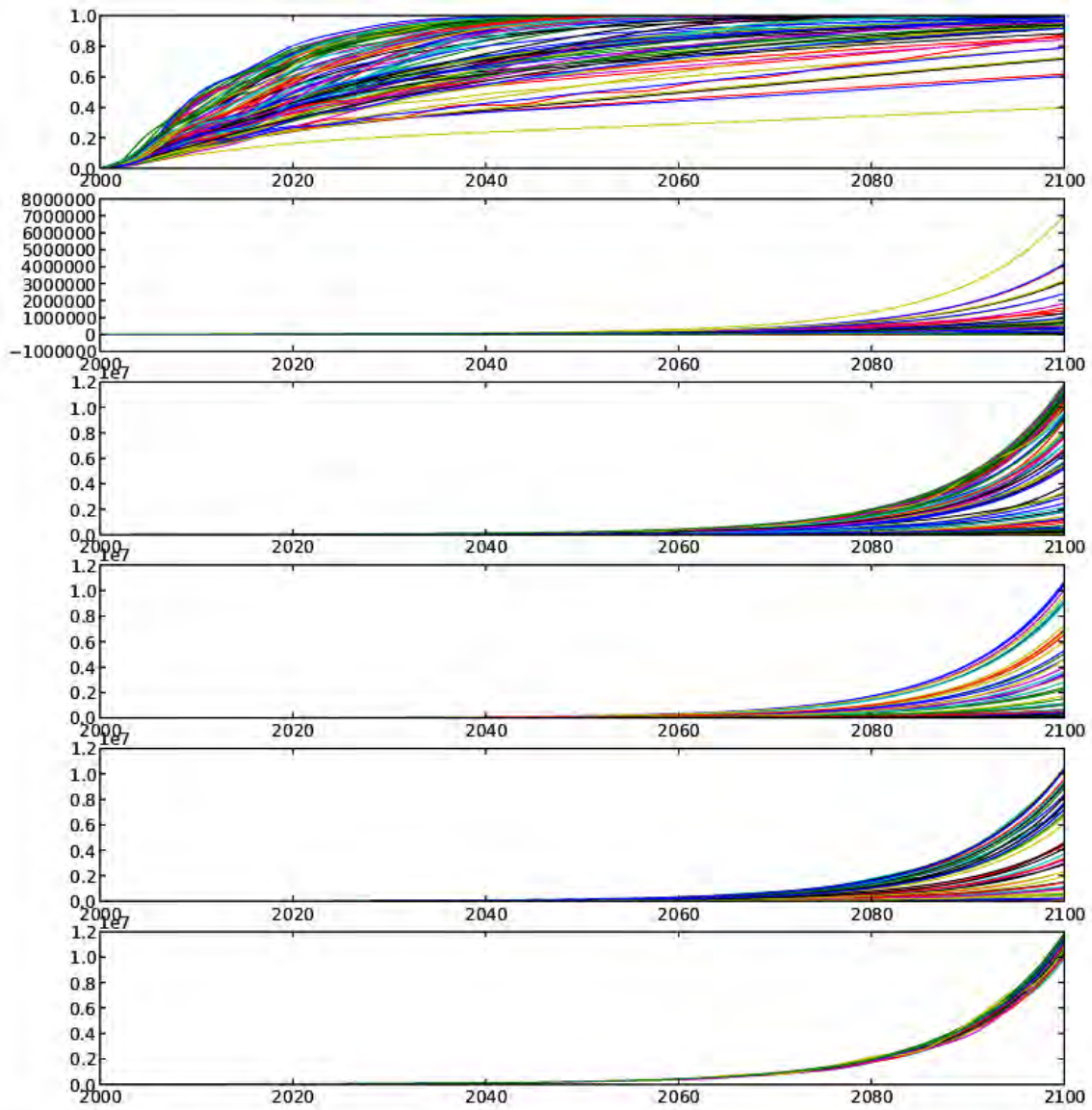
Figure 4: Latin Hypercube samples (100) for following variable (from top to bottom): total fraction new technologies; installed capacity T1; installed capacity T2; installed capacity T3; installed capacity T4; and total capacity installed.
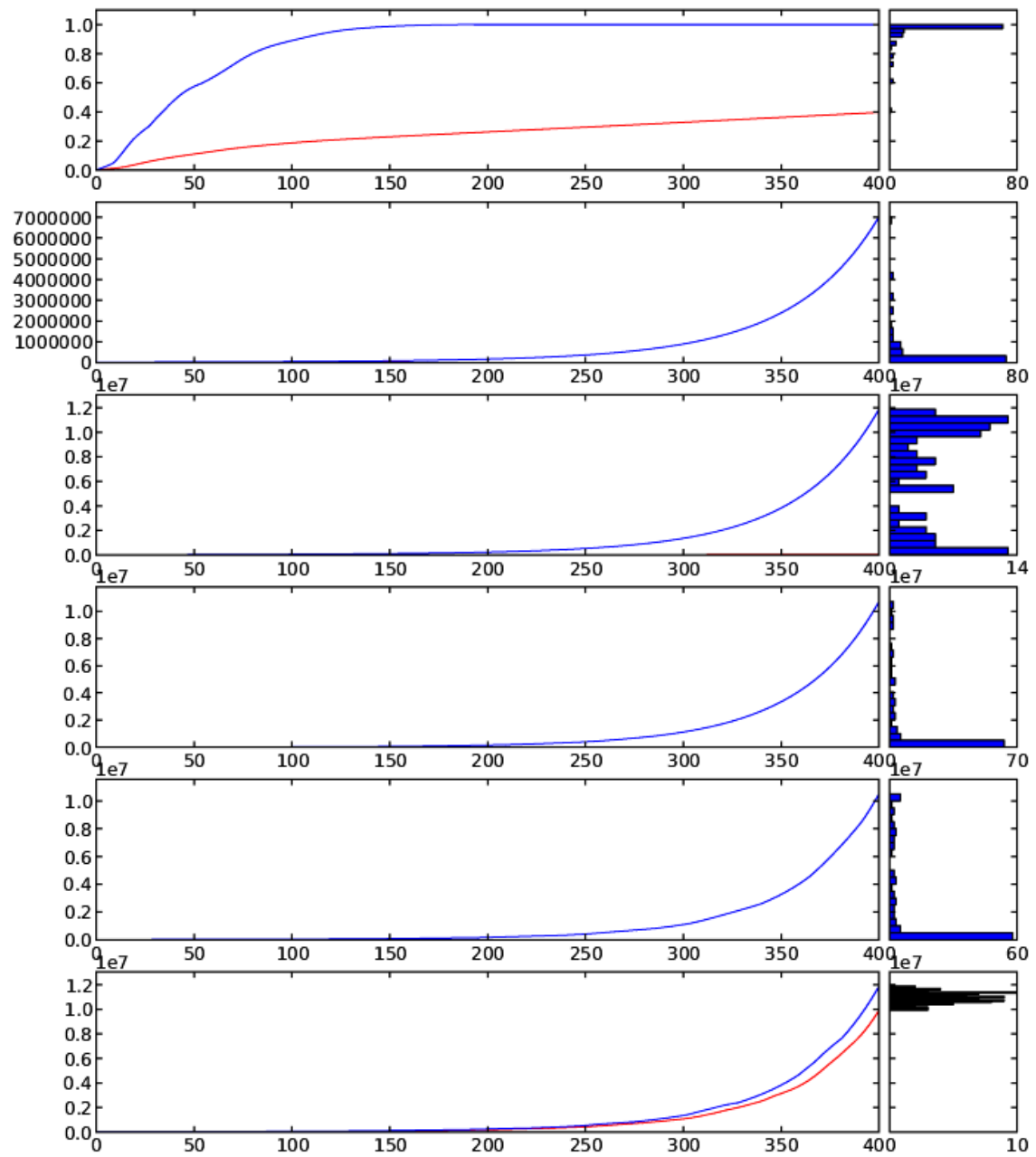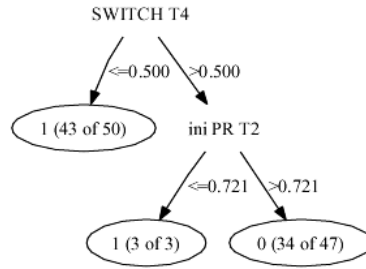
Figure 5: Envelopes and end state histograms for the 100 Latin Hypercube samples for following variable (from top to bottom): total fraction new technologies; installed capacity T1; installed capacity T2; installed capacity T3; installed capacity T4; and total capacity installed.

Figure 6: Tree generated on the 100 LH samples

3 STAGE II: An Exploratory SD Model of the Energy Technologies Battle

In this section, the previous model is –step by step– transformed into a SD model useful for ESDMA. The main focus of this section is thus to illustrate how a traditional SD model could be transformed into a model useful for ESDMA. Examples of specific structures and resulting behaviors are provided. An example ESDMA will be provided too.

3.1 Structure of the Energy Technologies Battle ESD Model

Starting from the previous model, uncertainties were identified and built into the Python shell and Vensim model (see Figure 7). Uncertainties considered include parameter uncertainties, function uncertainties, model structure uncertainties, random variations over time, and exogenous surprises. Typical structures used to transform the SD model into a useful one for ESDMA are described in detail below.

3.1.1 Sampling and Varying a Multi-Criteria Preference Structure

One of the main structural differences with the previous model is the uncertainty enhanced multi-criteria structure used for the capacity choice. Not only could the marginal investment cost of a technology be taken into account, its history and expected progress could be taken into account too, or not – depending on the experimental design imposed upon Vensim by the Python code.

3.1.2 Creating Periodic/Cyclic Random Patterns – Sampling, Linking and Smoothing over Time Intervals

Some of the parameters assumed to be constant in the SD model (for a particular run) are replaced by varying patterns within each run. One example is provided here.

One way to create periodic/cyclic random patterns is to periodically change random parameters (amplitude and frequency) of a cyclic function (e.g. SIN, COS) and put it on top of a base line behavior/trend. An alternative way of generating such behaviors is illustrated in Figure 8(a). The structure shown there is used to generate the behaviors in Figure 8(b): 10 random values sampled uniformly between -0.01 and 0.03, assigned to *ec gr t1*... *ec gr t10*, linked together in *ec gr t0t10* and smoothed in *economic growth*, generate behaviors such as in the topmost graph in Figure 8(b). The uncertainty ranges for *ec gr t1* ... *ec gr t10* are set and sampled from within Python.

3.1.3 Sampling Entire Time Series and Lookup Functions

The second graph in Figure 8(b) is obtained by random uniform assignment of an integer value (1, 2, 3) from within the Python shell to the Vensim variable *lookup number elec intensity of ec growth*. This switch sets the variable *elec intensity of ec growth* for a particular run equal to one of three time series (*lkp elec intensity of ec growth A*, *lkp elec intensity of ec growth B* or *lkp elec*
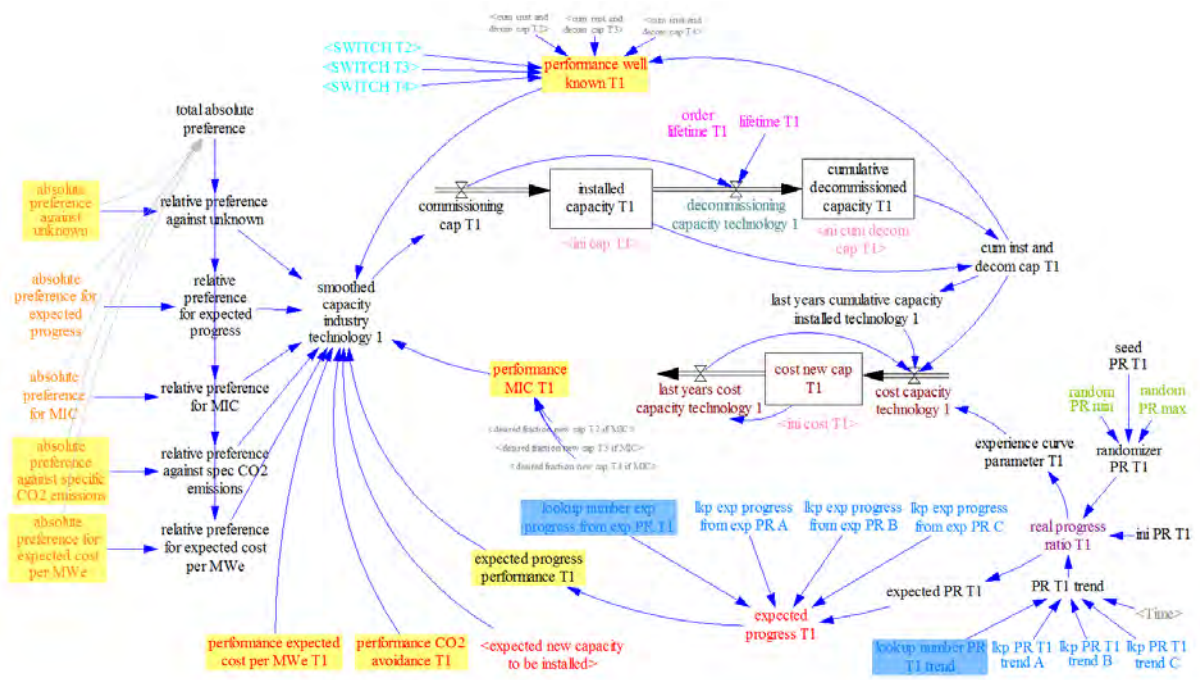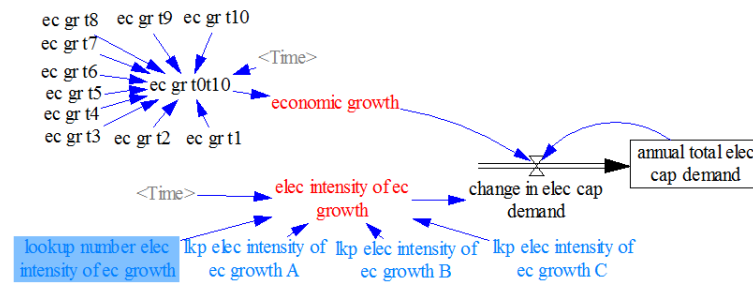
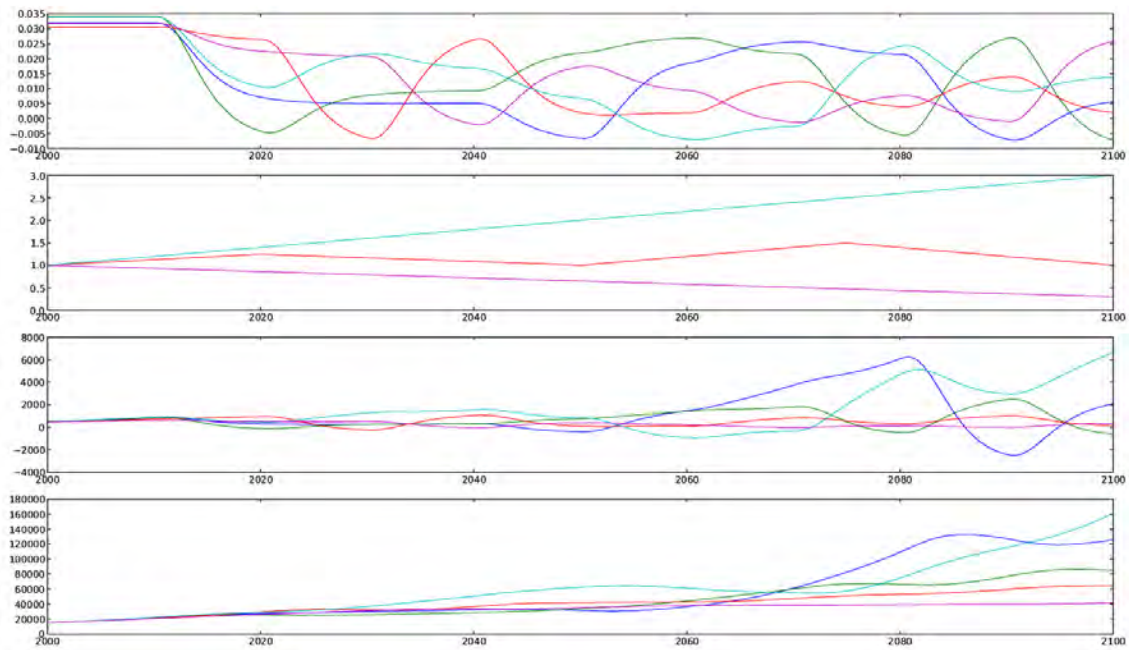(a) SFD of one of four competing Energy Technologies
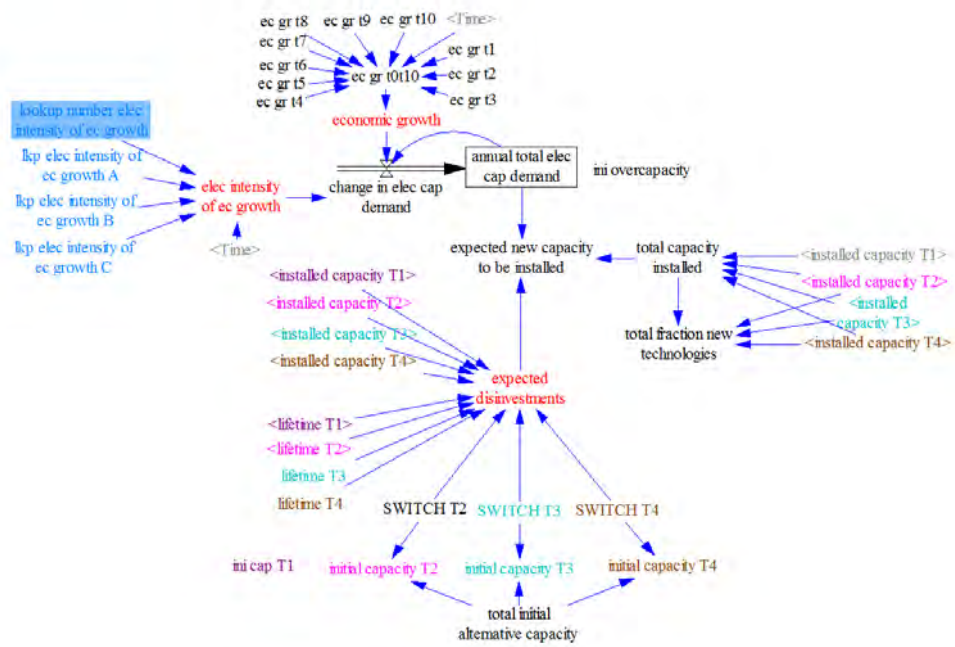
(b) Additional structures to include uncertainties

Figure 7: SFD of two out of four views of the SD model to be used for ESDMA

(a) Structure to generate patterns within a run and call one of three lookup functions for a particular run


(b) 10 sample behaviors generated with this structures, from top to bottom: (1) *economic growth*, (2) *elec intensity of ec growth*, (3) *change in elec cap demand*, and (4) *annual total elec cap demand*

Figure 8: Structure for sampling, linking and smoothing over time intervals and the and resulting behaviors

intensity of ec growth C) by means of a nested IF function[5]. Combining *economic growth* and *electricity intensity of economic growth* leads here to the behavior of the net flow *change in elec cap demand* as in the third graph from the top, resulting in the stock variable behavior as in the bottommost graph *annual total elec cap demand*.

3.1.4   Sampling Different Delays: Sampling Orders and Delay Times

It makes sense to treat orders of delays and 'constant' delay times as uncertain – unless delays are perfectly known and will not change. Delay times can be treated as parameter uncertainties if constant values for each run are acceptable. Orders can be treated as categorical uncertainties[6] if constant values for each run are acceptable (see Figures 9(a) for the corresponding stock flow structure and 9(b) for the response to a step-up step-down).
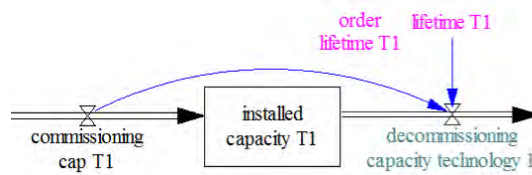
(a) Structure for a delay with random order and random lifetime
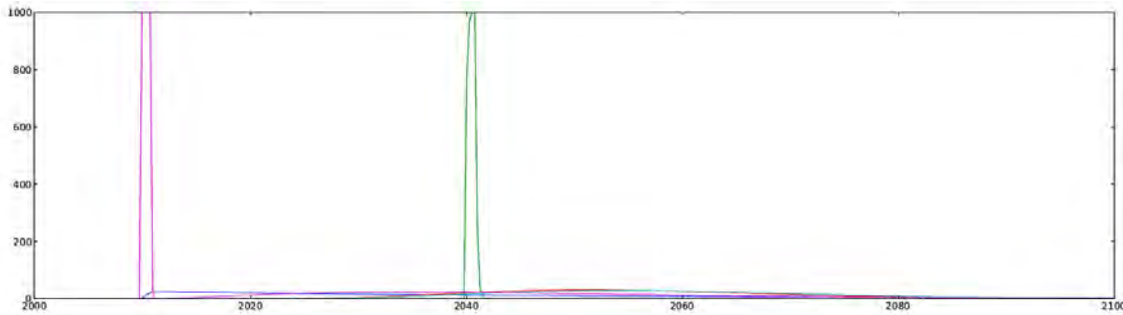
(b) Response of the random order (1, 3, 10, 1000) delay following a step-up step-down (pink pulse in 2010)

Figure 9: Structure and behavior for sampling orders of delays

And if constant values for each run are unacceptable, then –dependent on the situation– they could be turned into delays that are endogenously dependent on multiple/uncertain model variables (see 3.1.1), delays with random parameters (see subsection 3.1.5), delays following one or more time series (see subsection 3.1.3), and/or cyclic/periodic delays (see subsection 3.1.2).

### 3.1.5   Varying Randomized Trends and Lookup Functions

Figure 10(e) shows the effect of combining random randomizers, sampled trends, and sampled lookups: the topmost graph shows 10 behaviors of the variable *randomizer PR T1* which is a random uniform Vensim function with arguments *random PR min*, *random PR max*, and *seed PR T1*, all of which are sampled uniformly from within the Python shell.

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[5]elec intensity of ec growth = IF THEN ELSE(lookup number elec intensity of ec growth = 1, lkp elec intensity of ec growth A(Time), IF THEN ELSE(lookup number elec intensity of ec growth = 2, lkp elec intensity of ec growth B(Time), lkp elec intensity of ec growth C(Time)))

[6]e.g. CategoricalUncertainty((1,3,10,1000), 'order lifetime T1', default = 3) in the Python shell samples a value out of the pre-specified values/categories 1, 3, 10, and 1000. And in Vensim: decommissioning capacity technology 1 = DELAY N(MAX(commissioning cap T1,0), lifetime T1, installed capacity T1/ lifetime T1, INTEGER(order lifetime T1)).
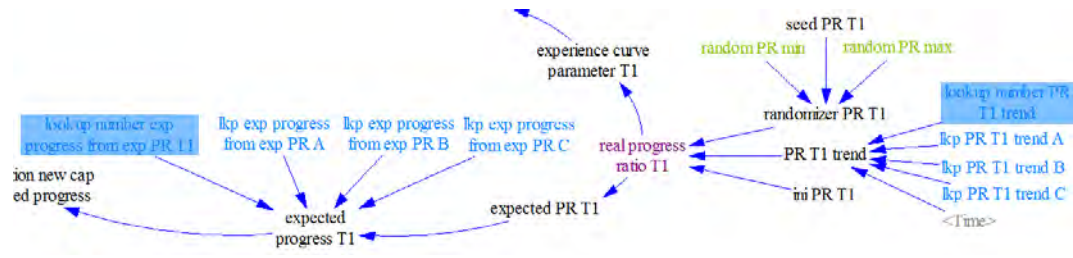
(a) Stock-Flow structure to vary Randomized Trends and Lookup Functions from within the Python shell
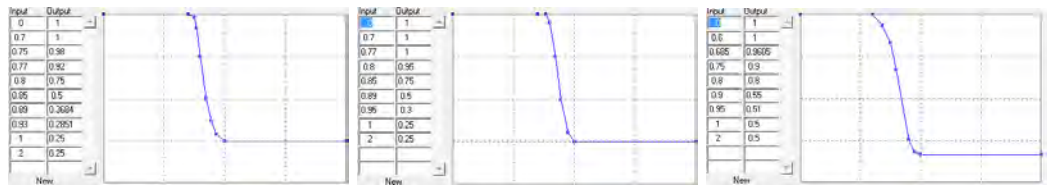
(b) First of three plausible lookups

(c) Second of three plausible lookups

(d) Third of three plausible lookups
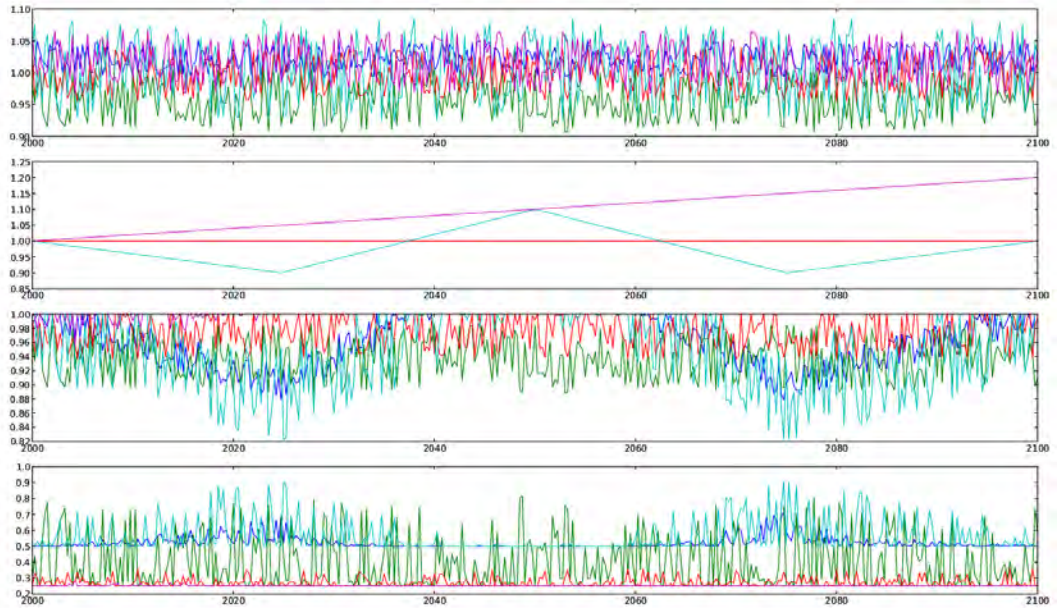
(e) Behavior generated with the structure displayed above – from top to bottom: Randomized randomizers; randomly varied trends; Randomized randomizers combined with randomly varied trends; randomly varied trends imposed on the combination of randomized randomizers and randomly varied trends

Figure 10: Structure to vary randomized trends and lookup functions, constitutive lookups, and behavior

These random functions generate random values within each run and they are instantiated with arguments that are randomly sampled per run – hence the label 'random randomizers'. The *PR T1 trend* selects one of three time series as explained above. Both are combined with a base value (e.g. *ini PR T1*) into the *real progress ratio T1*. The variable *expected PR T1* in Figure 10 then uses the *real progress ratio T1* to generate a forecast[7] with a maximum value of 1. And the *expected progress T1* once more contains a lookup switch[8] that allows the Python shell to select one of the three lookup functions at the bottom of Figure 10. That was the quick and dirty way. Since all three function are S-shaped functions, there is a cleaner way (see subsection 3.1.7).

3.1.6 Varying Scenarios

Vensim scenarios (CIN files) can be varied and called from within the Python shell. Using scenario files for example allows to simulate consistent developments of several (exogenous) variables. Three different CIN files are randomly called here, just to illustrate random sampling of CIN files: each CIN file contains the values of one lookup function to be used to generate a time series. Note that CIN files containing just one lookup function are rather useless – these lookups could also have been sampled using structures discussed in subsections 3.1.5 and 3.1.3.

3.1.7 Sampling Mathematical Functions

Uncertainty in pure mathematical functions can be dealt with by treating the parameters as uncertain. If all functions that could possibly be called can be generated by changing the parameters of mathematical functions and the functions can be modeled, then that option should be the preferred over the option to call a limited number of functions using the lookup number construction (see subsection 3.1.5). This approach is preferable, because it allows to analyze continuous drivers of the scenario space instead of discrete drivers. Artificial discontinuities may hinder or bias (e.g. artificial bifurcations) some analysis (e.g. classification/regression trees) of the scenario space. Depending on the function, we could either call the function in Python or we model it in Vensim and sample the parameters of the function in Python.

If uncertainty exists about a function, but all plausible functions can easily be expressed as mathematical functions, than a categorical uncertainty can be used in Python to switch between the different mathematical functions and parameters of the functions can be sampled simply from within Python.

3.1.8 Using Switches to De/Activate Structures and Simulate Surprises

Switches can be used to sample over different model structures, for example to simulate different types of markets. The Python shell then samples integer values and passes them on to Vensim where nested IF functions activate a structure and deactivate all other structural variants.

Switches can also be used to simulate the occurrence of exogenous surprises or acute incidents/crises (not illustrated here).

3.2 STAGE III: Uni-Model ESDMA of the Energy Technologies Battle

3.2.1 Exploration and Analysis

All structures and scenarios discussed above and all parameter uncertainties, categorical uncertainties, and switches displayed in Table 1 (first column from the right) are simultaneously varied here (randomly uniform, Latin Hypercube, 100 samples). Comparing the small-sample graphs in Figures 11 and 12 with the small sample graphs in 4 and 5 already leads to following (preliminary)

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[7]expected PR T1 = MIN(1,FORECAST(real progress ratio T1, 3 , 3)) –note that the forecast parameters could also be (but are not) varied

[8]expected progress T1 = IF THEN ELSE(lookup number exp progress from exp PR T1 = 1, lkp exp progress from exp PR A(expected PR T1), IF THEN ELSE(lookup number exp progress from exp PR T1 = 2, lkp exp progress from exp PR B(expected PR T1), lkp exp progress from exp PR C(expected PR T1)))
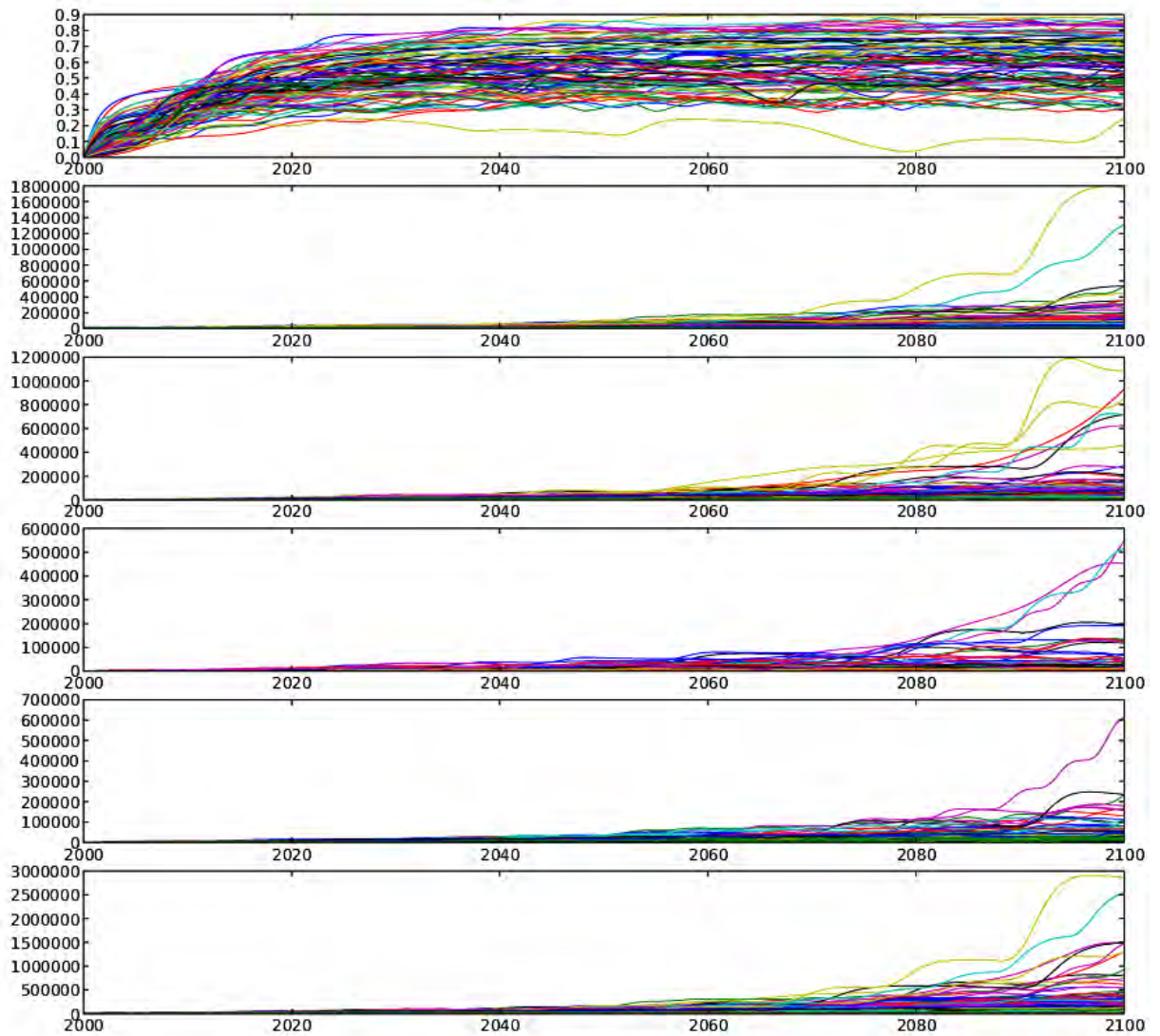
Figure 11: Latin Hypercube samples (100) for following variable (from top to bottom): total fraction new technologies; installed capacity T1; installed capacity T2; installed capacity T3; installed capacity T4; and total capacity installed.

conclusions: (1) total capacity installed are much lower, (2) T2 is not characterized by a modal split, and (3) the total fraction of new technologies seems to remain somewhat lower. Surprisingly, there are also a number of case (9 out of 100) in which the new technologies do not penetrate at all.

These preliminary results are confirmed by 10000 runs (see the envelopes and end state distributions in Figure 13): more samples lead to more broader envelopes than in the small sample case, but the end state distributions are similar to the ones of the small sample case. Filtering out the outliers may allow to explore the higher density scenario space. Algorithms could also be used to classify the (filtered) data set on particular features or modes of behaviors.
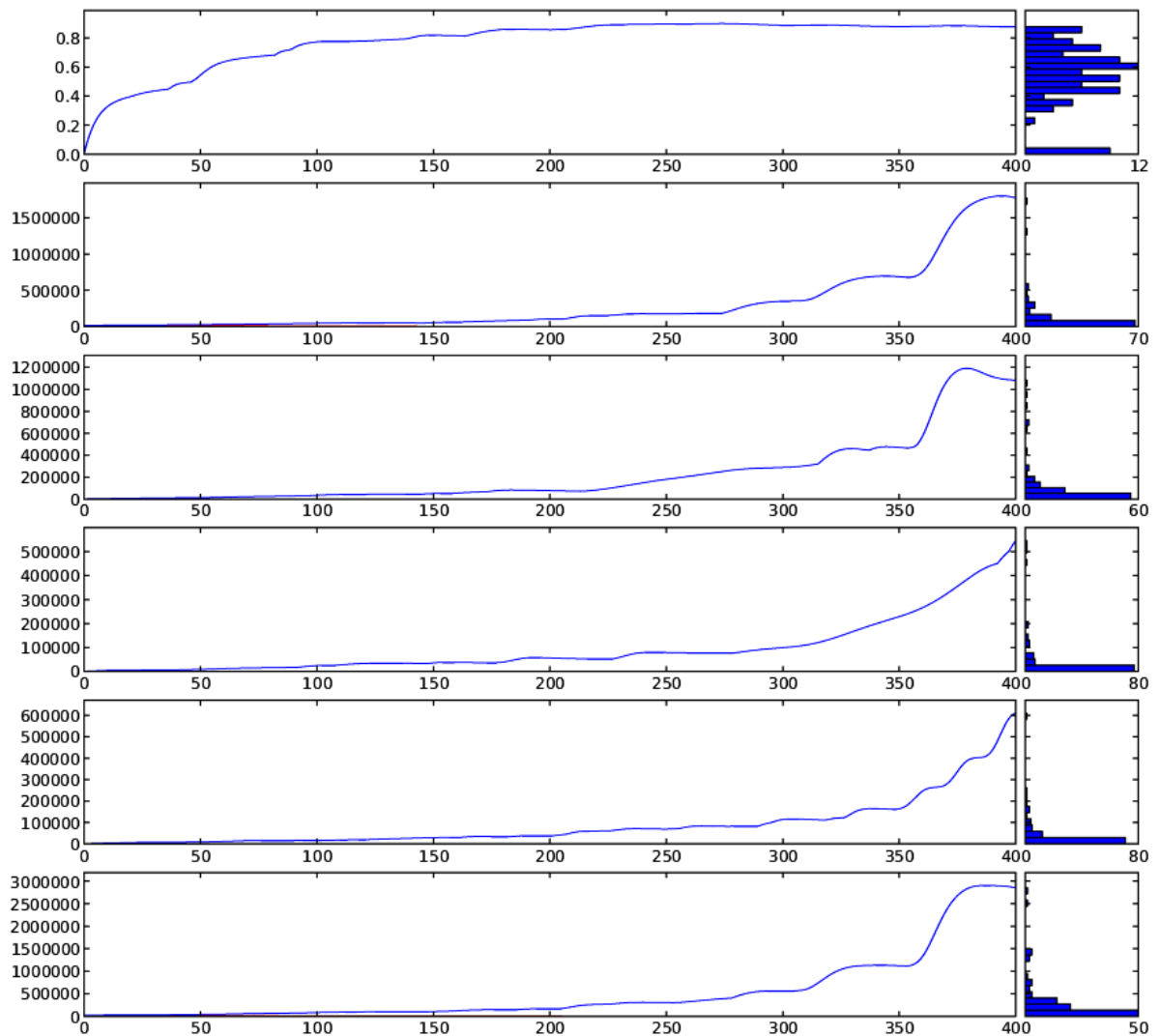

Figure 12: Envelopes and end state histograms for the 100 Latin Hypercube samples for following variable (from top to bottom): total fraction new technologies; installed capacity T1; installed capacity T2; installed capacity T3; installed capacity T4; and total capacity installed.

Figure 13 shows broad envelopes but also high density areas of scenario end states of all technologies near the lower boundary of the envelopes. Hence, it would be interesting to find out –using for instance regression trees– what causes scenarios to end up near the upper or lower boundary of the envelope. Splitting the data set in two (or more) subsets and analyzing and visualizing them separately may in such cases be fruitful.
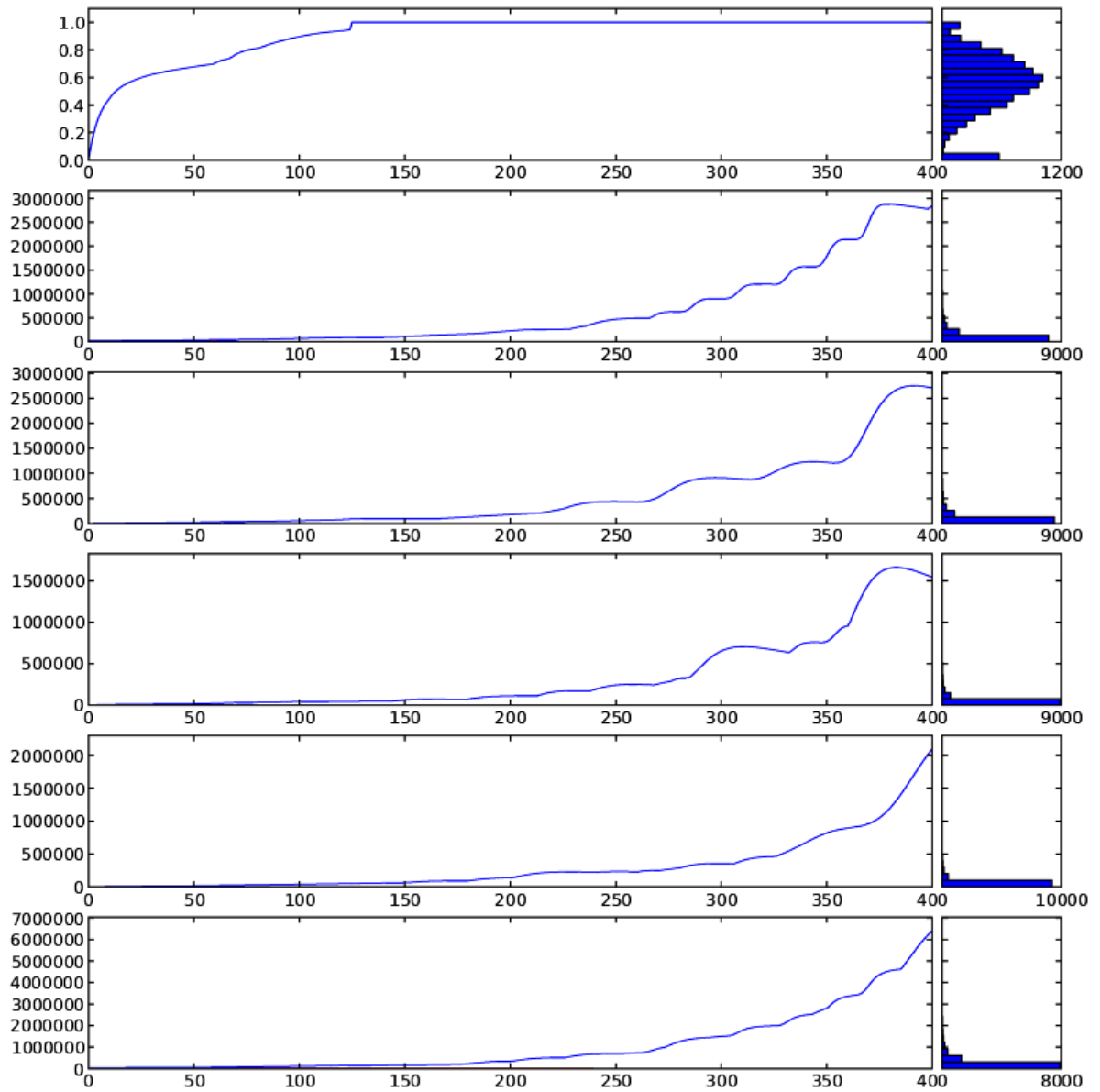
Figure 13: Envelopes and end state histograms for the **10000** Latin Hypercube samples for following variable (from top to bottom): total fraction new technologies; installed capacity T1; installed capacity T2; installed capacity T3; installed capacity T4; and total capacity installed.
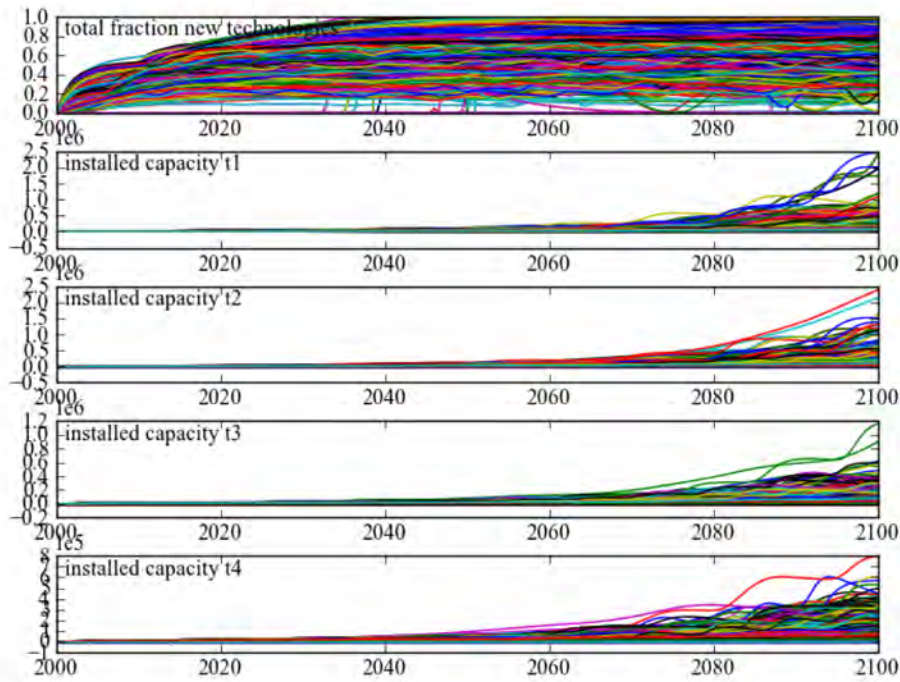
Figure 14: 1000 Latin Hypercube samples for different policies

However, it is much more relevant to do this in a full multi-model ESDMA (see the follow-up paper), because else the model becomes the focus instead of the uncertainties and the ensemble of plausible behaviors.

3.2.2 Policy Analysis and Robustness Testing

In this section, three fictitious policies are applied and compared across the same experimental design.

- The first policy is not a real policy: it is a *laissez faire* policy – the *no policy* case.

- The second policy is a static policy hindering/boycotting *technology T3* resulting in less than 10% commissioning of new capacity of what would have been the case without this policy. The idea behind this policy –restricting one of these new technologies– is that too many new technologies may actually lead to slower learning per technology, slowing the transition as a whole – in other words, that concentration of efforts and subsidies speeds up the transition.

- The third policy is a dynamic policy influencing the multi-criteria allocation by ensuring that two rather different criteria –the *absolute preference against specific CO_2 emissions* and the *absolute preference for expected cost per MWe*– are always taken into account (the other criteria are randomly switched on/off) and are non-linear (S-shaped).

Figure 14 displays plausible futures for the combination of these 3 policies and 1000 experiments without information about the particular policy applied in each case.

Based on Figure 15 which displays the envelopes of the ensembles for each of the policies, one may conclude that the static policy performance (in green) is slightly inferior to the no policy case (blue): hindering/blocking new technologies to favor other technologies may not be a good

idea under deep uncertainty. It also seems that in the long term, the dynamic policy (in red) is good for T1, T2, and T4. This adaptive policy leads to more certainty: it is less risky, but it also provides less opportunities.
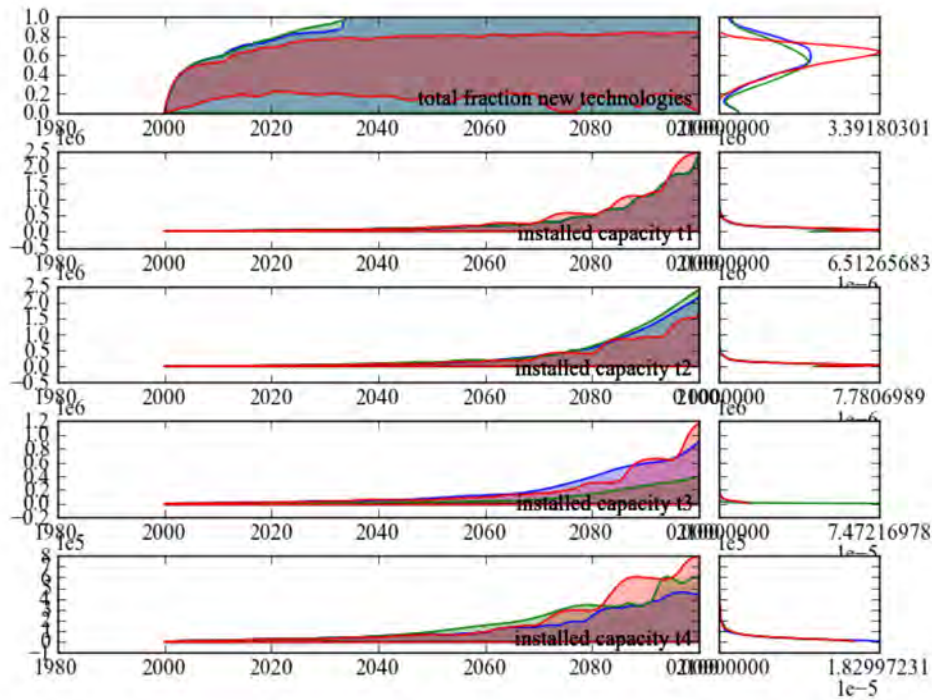

Figure 15: Envelopes for 1000 Latin Hypercube samples for each of three policies

The individual trajectories displayed in Figure 16 show that the aggregated visualizations in Figure 15 may –except for the topmost graph– be misleading at the edges of the envelopes. Traditionally one would remove the outliers. From an experimental point of view, doing so would result in losing precious information about a few but nevertheless plausible scenarios.

If these policies would be real policy options, then further analysis –using for instance multi-dimensional regret analysis, direct searches and regression trees– and better visualizations would be desirable.
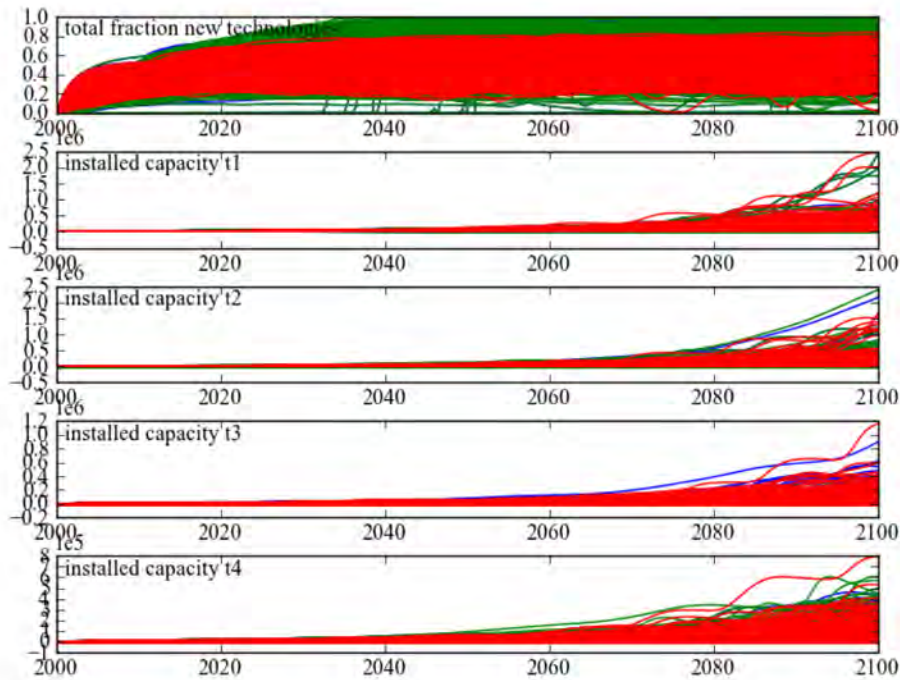
Figure 16: trajectories of 1000 Latin Hypercube samples for each of three policies

4 STAGE IV: Full ESDMA of the Energy Technology Battle

In the fourth stage, three rather different models of the Energy Technology Battle are explored simultaneously using EMA:

- the small ESD model developed in the previous sections adapted to the EU27 context,

- a large SD model described in detail in (Pruyt 2007a; Pruyt 2007b) which was *not* specifically developed for ESDMA but was one of the triggers that lead to the development of ESDMA,

- an Agent-Based Model described in detail in (Yucel 2010), used by Kwakkel and Yucel (2011) for EMA, and adapted to the EU level.

However, it was decided not to add this full ESDMA to this conference paper. A sequel paper will focus only that part of this project. The main reason for splitting the paper in two and only presenting the development of an ESD model from a SD model for ESDMA in this first paper is to avoid overloading readers with too many messages. Readers interested in a sneak preview may want to contact the corresponding author.

5 Concluding remarks

This first of two related papers illustrated the (gradual) transformation of a simple SD model to a simple ESD model useful for ESDMA. More insights were also provided into the use of a Python shell (for designing and executing the sampling plan, for firing commands, for storing each experiment, for using analysis and visualization algorithms) and Vensim (for visual modeling and

for executing experiment per experiment). And practical Vensim model structures to generate uncertainties or receive uncertainties generated by the Python shell were presented.

Based on this work, it can be concluded that:

- uncertainty structures need to be added to make SD simulation models interesting for deep uncertainty exploration;

- dealing with uncertainties paradoxically leads to more certainty about the appropriateness of policies, and hence about the robustness of policy recommendations;

- uncertainty matters when it comes to policymaking with regard to energy transitions: different conclusions are distilled from work ignoring / focused on deep uncertainty.

The sequel paper is the first attempt to apply ESDMA simultaneously on very different models from different modeling traditions: more precisely a tailor-made ESDMA model, a large(r) SD model, and an Agent-Based model.

This experiment is conducted in view of methodological learning: the case-based development approach followed by our research team implies that our cases always need to go one step further. This case will allow us to answer questions like:

- Are tailor-made ESDMA models better than slightly adapted SD models for ESDMA purposes? (In other words: is it better to adapt existing SD models or to make ESDMA models from scratch?)

- What are the main difficulties encountered when using multiple models about the same issue within the same ESDMA?

- What are the main difficulties encountered when using multiple models from different modeling traditions within the same ESDMA?

- How could these difficulties be overcome?

- What is the room for improvement? In other words: what are the sampling / analysis / visualization algorithms that need to be developed to bring ESDMA one step beyond the current state of the art?

For answers to these questions, see the sequel paper that will be presented at the 2012 International Conference of the System Dynamics Society. The sequel paper is also relevant from an applied point of view: the development of the EU electricity sector under deep uncertainty and adaptive policies to steer it into desirable directions.

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A   The Transition towards Sustainable Energy Systems Case

This section contains a 'hot teaching/testing case' related to the SD model presented in section 2. For a discussion of this teaching and testing case, see (Pruyt 2011b). For other teaching and testing cases in line with this case, see (Pruyt 2009) and (Pruyt 2010a).

The case deals with the competition of new energy technologies with existing technologies and other new technologies, and could be extended to spreading/concentrating subsidies for innovative renewable energy technologies. The *Energy Transition towards Sustainability* case description can be found below. Students found this staged case difficult and lengthy.

First students need to make a SDF (Figure 17(a)) and a detailed Causal Loop Diagram (Figure 17(b)) of a small part of the model description. Second, students need to add a learning curve structure 17(c)) and plot the *marginal cost.* Then they need to extend the model with a sustainable alternative (similar to Figures 3(a) and 3(b) on page 5), simulate it, and make graphs of the *marginal cost of the new capacities of T1* and *T2* and a graph of the *sustainable fraction of the total installed capacity.* Students also need to make an aggregated Causal Loop Diagram (similar to the one in Figure 2 on page 3) and explain how the structure generates the behavior. They need to test the sensitivity of the model for changes in the parameters of the learning curve and for changes in a function. Finally students need to add another sustainable technology (Figure 3(c) on page 5) and test the influence of spreading investments over two alternatives. Extensions of the case require students to explore uncertainties.

Energy Transition towards Sustainability (/25)

Introduction: Transition Dynamics

'Energy transitions' are the talk of the day. And although many conceptual transition models exist, there is a need for useful simulation models to simulate plausible transition dynamics. The ministry of Economic Affairs therefore asks you to make a series of SD models concerning the long-term dynamics of the electricity generation, from the year 2010 until the year 2100. The dynamics of the installed generation capacity is important for the transition because electric power plants remain some 30 to 40 years in use. Hence, the starting point...

'Grey' development (/5)

Suppose, at first, that there is just one 'regime technology' –technology T1– which is a rather polluting and non-renewable technology. The *installed capacity of T1*, initially equal to 15000MW, increases through *commissioning of capacity T1* and decreases through *decommissioning of capacity T1.* Newly *planned capacity T1* –initially equal to 700MW– needs to be built before it can be commissioned: the *capacity under construction T1* initially amounts to 700MW and the *average construction time of T1* to 1 year. The newly *planned capacity T1* is non-negative and equals the *desired fraction of new capacity T1* of the total *new capacity to be installed.* Suppose for the sake of simplicity that the *new capacity to be installed* equals the difference between the *expected capacity required* (of all types – although currently it is assumed that only one type exists) and the *total installed capacity* (idem). The *desired fraction of new capacity T1* amounts of course to 100% since there is only this technology T1 in this subsection. Hence, the *total installed capacity* consists only of *installed capacity* of technology *T1.* Assume that the *planning period* for planning *new capacity to be installed* amounts to a year. Suppose that the *expected capacity required* increases from 15700MW in the year 2010 to 45000 in the year 2100.

1. (/2) Make a SD simulation model of the description above.
2. (/3) Make a detailed *causal loop diagram* of this model.

Learning effects (/5)

Even old technologies like technology T1 keep on descending their learning curves if they are invested in, which makes that the marginal investment costs keep on decreasing further –although slower than in case of newer technologies. Learning curves can be written mathematically as:
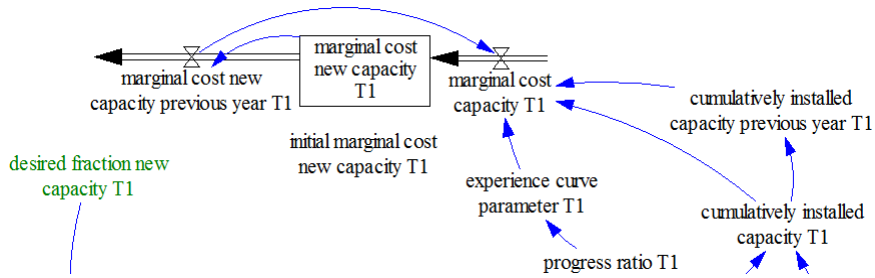
$$C_t = C_{t-1}\left(\frac{X_t}{X_{t-1}}\right)^e$$
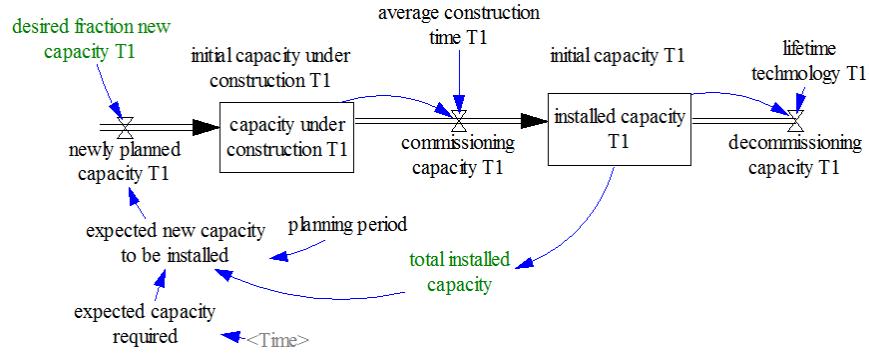
(a) SFD of the first partial Energy Transition model
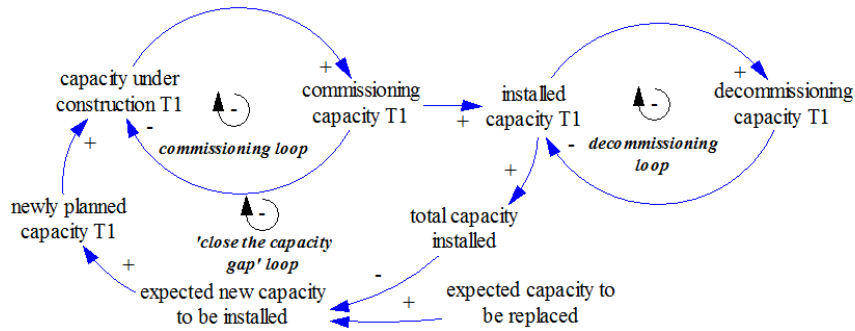
(b) Full Causal Loop Diagram of the first partial Energy Transition model

(c) SFD of the learning curve added to the first SFD

Figure 17: Partial SFDs and Causal Loop Diagram of the Energy Transition model

C_t stands for the investment cost per MW at time t, X_t for the cumulative historic capacity (i.o.w. all ever constructed capacity of that technology), and e for the learning curve parameter.

This learning curve can be included –somewhat artificially– into a System Dynamics model: add a stock variable *marginal cost of new capacity T1* with an initial value equal to €1.000.000 per MW. This stock variable has an outflow variable *marginal cost of new capacity T1 of the previous year* equal to the stock variable, and as inflow a variable *marginal cost of capacity T1* equal to the *marginal cost of new capacity T1 of the previous year* multiplied by

$$\left(\frac{cumulative\ ever\ installed\ capacity\ T1}{cumulative\ ever\ installed\ capacity\ previous\ year\ T1}\right)^{-learningcurve\ parameter\ T1}.$$

The *learning curve parameter T1* equals $-log_2(\texttt{progress ratio T1})$. Suppose that the *progress ratio* of technology T1 is 90%, which means that each doubling of the *cumulatively ever installed capacity* leads to a cost reduction of 10%. This *cumulatively ever installed capacity T1* equals the sum of the *installed capacity of T1* and the *cumulatively decommissioned capacity T1* of 10.000.000 MW. The value of the latter stock variable increases through the corresponding flow variable *decommissioned capacity T1* through which the *installed capacity* of this technology is decommissioned after an average *lifetime* of 30 years.

1. (/4) Add the learning curve construction to the simulation model. Verify the model briefly.

2. (/1) Simulate the model and make a graph of the *marginal cost of new capacity T1*.

Development with a sustainable alternative (/12)

Add an alternative 'sustainable' technology (T2) to the model. Almost the same structure as used above can be used for that purpose. The main differences relate to the initial values: *initial capacity T2 =* 3MW; *initial capacity under construction T2 =* 1MW; *initial cumulative decommissioned capacity T2 =* 10MW; *progress ratio T2 =* 0.8; and *initial marginal cost new capacity T2 =* €8.000.000 per MW.

Not to be copied, but requiring adaptations, are common and/or interface variables such as the *total installed capacity*, the *new capacity to be installed*, and the *expected capacity required*.

Suppose furthermore that the *desired fraction of new capacity T1* now becomes (100% - *desired fraction new capacity T2*). This fraction –like similar fractions– lies between 0 and 1. Set the *desired fraction new capacity T2* equal to:

$$\frac{1/marginale\ kost\ nieuwe\ capacity\ T2}{1/marginale\ kost\ nieuwe\ capacity\ T1 + 1/marginale\ kost\ nieuwe\ capacity\ T2}.$$

Finally add an important output indicator: the *sustainable fraction of the total installed capacity*.

1. (/4) Extend the simulation model.

2. (/3) Simulate it. Make graphs of the *marginal cost of the new capacities of T1* and *T2* and a graph of the *sustainable fraction of the total installed capacity*. From which year is half of the installed capacity sustainable?

3. (/1) Explain how this structure generates this behaviour.

4. (/2) Test the sensitivity of the model for changes in the parameters of the learning curve. Explain what could be concluded from these sensitivity tests.

5. (/2) A continued linear demand growth such as described above is rather unrealistic. Suppose that the demand for generation capacity develops as follows: 15700MW in 2010, 22000MW in 2020, 19500MW in 2030, 25000MW in 2040, 27000MW in 2050, 34000MW in 2060, 30000MW in 2070, 40000MW in 2080, 46000MW in 2090, and 45000MW in 2100. Does the *sustainable fraction of the total installed capacity* change much? And the *newly planned capacities*? Explain by means of the graphs.

6. (/3 BONUS) Make an aggregated Causal Loop Diagram of the competition between two technologies, in line with your simulation model.

With more sustainable alternatives and uncertainty (/3) (+2 BONUS)

Now it is up to you to investigate whether the overall outcomes change if there are several sustainable technologies instead of just one. . .

1. (/2) Suppose that there are two sustainable technologies, 'T2' and 'T3' instead of just 'T2'. Suppose –in order to make a decent comparison with the dynamics of the previous version of the model– that both sustainable technologies have identical characteristics and each only 1.5MW installed capacity and 0.5MW capacity under construction. Model and simulate this new system. Are there major differences in terms of the *sustainable fraction of the total installed capacity*?

2. (/1) Suppose that there is a difference between the two sustainable technologies: one of them has a *progress ratio* of 0.75 and the other of 0.85. What can be concluded now concerning the *sustainable fraction of the total installed capacity*?

3. (/2 bonus) Now add some more uncertainty – alternatives may seem promising now, but may not live up to the expectations. Analyse the investment decision (concentration versus spreading) under uncertainty.