Exploring the Future of Wind-Powered Energy

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Abstract

Although there is a trend towards more sustainable energy system, the future of renewable energies is still deeply uncertain. Among the renewable resources, wind energy is considered to be a promising one. However, in the presence of deep uncertainty, what will be the future of wind-powered energy? Decision making under deep uncertainty for such issues requires an explorative manner. Since predictions under deep uncertainty can be extremely misleading, exploration of plausible futures should be the main approach. In this paper, a new research methodology, Exploratory Modeling and Analysis (EMA), to deal with deep uncertainty will be presented. Three System Dynamics models about Wind-powered energy will be explored using EMA and results of possible policy implementations will be illustrated.

Keywords: Wind Energy, deep uncertainty, Exploratory Modeling and Analysis, Model-based decision support.

1. Introduction

1.1. Position of Wind Energy in the Energy Transition

Sustainable energy has been one of the most important discussion topics of today's world. There is a strong debate about the sustainability of current energy resources such as oil, coal or natural gas. The trend now is towards wind energy, solar energy, hydroelectricity, biomass, biofuel which are more sustainable energy resources. Among these, wind energy is one of the most promising resources that may meet a big portion of future energy demand of the world. Over the last years, the growth rate of wind energy has an increasing trend that is from 19% in 2004 to 31% in 2009 (Global Wind Energy Council, 2010). According to Europe 2020 targets (European Commission, 2010), it is planned to meet the %20 of energy demand by renewable resources and wind energy is an important resource for achieving this aim. However, even the current acceleration of wind energy is thought be not enough for meeting 20% renewable target. Although the capacity of wind turbines is increasing rapidly, there is still a need for better policies. There are various studies about the future of wind-powered energy, but the future of wind power still remains unknown. This paper aims to explore and shed light on the plausible futures of wind-powered energy under deep uncertainty.

1.2. Deep Uncertainty

Lempert et al (2003) define "Deep Uncertainty" as situations where analysts do not know, or the parties to a decision cannot agree on (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes. Wind energy and energy transitions are good examples of deeply uncertain issues. The appropriate model that represents the energy system; parametric and structural relationships inside the model and evaluation of outcomes are all deeply uncertain.

In the presence of a lack of knowledge or disagreement related to the model representation of a system and the evaluation of outcomes, decision making becomes a hard task. Deep uncertainty can also be considered as the situations "where enumeration of multiple alternatives without being able to rank order the alternatives in terms of how likely or plausible they are judged to be" (Kwakkel et al., 2010). Since there is a lack of information about the probability of alternatives, any of these alternatives should not be treated as the single true representation. This fallacy is a common problem for most of the methods/techniques dealing with (deep) uncertainty. The main focus should then be on the exploration of deep uncertainties- different model formulations, relationships among the variables, an ensemble of uncertainties. Hence, new methods/techniques that handle deep uncertainty in an explorative manner are needed.

Model-based decision support has been popular recently for dealing with deep uncertainty (Pruyt, 2010; Pruyt and Hamarat, 2010; Pruyt and Hamarat, 2010a). Models can be thought as formal representations of the real world. Mostly, the aim of the modelers is to represent the real world as a mathematical model and to use that model for supporting decision making. Modelers make many pre-analytic and analytic assumptions when modeling (parameter estimates, model structures and worldviews). Modelers, who try to predict the future, fall in the trap of assuming their assumptions are true. But in the presence of deep uncertainty, it is impossible to conclude that a single assumption about the future is true. For this reason, the use of models as predictive tools should be questioned. Furthermore, since predictions about the future are almost always wrong, it might be misleading to use models for predictive purposes. The goal of this paper is to illustrate the use of models for decision making in an exploratory manner- exploring an ensemble of plausible futures- instead of focusing on a single (or a few similar) future(s).

Uncertainty analysis for decision making is mostly focused on technical and shallow uncertainties about model parameters, input data or initial states. Dealing with model/structural uncertainties is much more complex and difficult. Furthermore, there is the common fallacy of ignoring deep uncertainty or making improper decisions based on inappropriate assumptions. In this paper, both parametric and structural uncertainties are explored and analyzed. Additionally, and more importantly, comparing three different models, uncertainty about the appropriate model is also questioned.

1.3. EMA

Exploratory Modeling and Analysis (EMA) (Agusdinata, 2008; Lempert et al., 2003) has emerged in the last years as a new method for exploring and analyzing deep uncertainty and supporting long term strategic decision making under deep uncertainty. EMA is a methodology that provides insights and understanding about the system functions and effectiveness/robustness of policies by using computational experiments. It originated at the RAND Corporation as Exploratory Modeling (Bankes, 2003) and was relabeled EMA by Agusdinata (2008).

EMA is not a modeling technique by itself. Instead, it is a methodology for using models in an explorative way -- more specifically more aggregated and still useful models. Various modeling techniques such as spreadsheet models, econometrics, agent based or system dynamics could be used. The choice of type of the model is in line with the outcome of interest. An agent based model can be useful for exploring the dynamics of a problem where there are different agents. System dynamics models may be more suitable for exploring the dynamics of a system as a whole.

1.4. Organization of the paper

In section 2, steps of ESMDA methodology will be explained and uncertainties to be explored will be presented. Three different models about the wind-powered energy will be introduced in section 3. Subsequently, computational experiments will be performed. Discussions and conclusions will be presented in section 5.

2. ESDMA Methodology

In this paper, System Dynamics models are used for EMA purposes. System dynamics models and EMA are in fact natural complementary allies (Pruyt, 2007). They are combined under the title of Exploratory System Dynamics Modeling and Analysis (ESDMA) (Pruyt and Hamarat, 2010; Pruyt and Hamarat, 2010a). ESDMA starts with the development of one or more small but useful System Dynamics models. Across an extended range of uncertainty, models are simulated and the resulting dynamics of the simulations are analyzed. Finally, under given uncertainties, the effectiveness and robustness of different policy options are tested.

As mentioned before; instead of prediction, exploration of an ensemble of plausible futures is the main focus. For this reason, the use of highly detailed and complex models is not necessary. Computational complexity of such models may seriously hinder uncertainty exploration. Small and aggregated models that can grasp the underlying dynamics of a problem may be more preferable and suitable for ESDMA.

So far, ESDMA has been used for dealing with parametric and some structural uncertainties (Pruyt and Hamarat, 2010; Pruyt and Hamarat, 2010a). In this paper, model or structural uncertainty (three different versions of a model) related to wind power development will be looked at.

2.1. Steps of ESMDA

Initial step of ESDMA methodology is the development of fast-to-build and aggregated System Dynamics models[1] of the related issue, followed by the generation of an ensemble of plausible futures by the exploration of uncertainty space. Afterwards, computational simulations are performed and the system of interest is analyzed using various visualization and data analysis techniques. The crucial step is the implementation of policies and comparison of the performance of a variety of policies.

The technical part of ESDMA methodology is done by using Python and Vensim in line with each other. Previously (Pruyt and Hamarat, 2010; Pruyt and Hamarat, 2010a), SD models in Vensim were converted into Python computational language and the analysis had been done so. However, we currently use a more efficient way that combines Python and Vensim. SD models in Vensim can be manipulated via Python. This method gives us the flexibility of modifying SD models and the strength of more efficient and more flexible analysis of the simulations.

2.2. Uncertainties to be explored

So, the three versions of the model introduce deep structural/model uncertainty. Moreover, each of the three models includes various parametric uncertainty and uncertainty about the functions used. Some of these uncertainties are specific for each model and some of them are common such as progress ratio or interest rate. For a better comparison, the common uncertainties are taken into account for uncertainty analysis. Progress ratio, cost surplus rate historic capacity, interest rate, lifetime wind capacity, operational and maintenance cost rate are the uncertainties that are analyzed for each model. Percentage growth net capacity of wind turbines is also a common variable but this variable is dependent on different concepts for each model. For this reason, this uncertainty is analyzed separately for each model. Besides these common uncertainties, the third model –elaborated system dynamics model- includes distinct but crucial uncertainties, which are net specific CO2 emissions avoided and world electricity supply. These uncertainties are considered separately for further analysis.

Progress ratio is the rate of learning effect on costs. In other words, this variable defines how much costs are after cumulative production doubles. According to the EWEA's report [6], the estimated progress ratio varies from 83% to 91%. In our analysis, the uncertainty range for progress ratio is extended from 70% to 98% to be able to include plausible values in the future.

Cost surplus rate historic capacity is a multiplication factor of initial cost 2001 which can make the capacity installed before 2001 more or less expensive. This variable is ranged between 0.75 and 1.25.

Operational and maintenance cost rate is the percentage of operational and maintenance costs over total cost capacity installed. This rate changes depending on the technology of the wind

[1] Since ESDMA is the combination of EMA and SD, it requires System Dynamics models. However, EMA can also employ other modelling techniques.

turbine and also during the lifetime of a wind turbine. The Danish Wind Industry Association reports that new generation wind turbines have a lower operation and maintenance cost rate than older ones (Krohn, 2002). 3% for older turbines and 1.5% to 2% for new turbines are the estimated rates. O&M cost rate has an uncertainty range of 1% and 20% in our analysis.

Interest rate is an important factor affecting the annual total cost of a wind turbine. Wind turbine installation is a capital intensive technology and most of the costs are required before the installation. Interest rates vary from country to country but on average, it is considered around 7-10%. In our uncertainty analysis, the range is taken as between 5% and 20%.

Lifetime wind capacity is an uncertain variable because it can vary depending on the size and the type of wind turbines. For example, according to (Krohn et al., 2009), average lifetime of an on-shore wind turbine is 20 years and 25 years for an off-shore turbine. Furthermore, the lifetime may vary with the intensity of the production. Taken the technological developments in the future into account, lifetime wind capacity variable is varied between 10 to 40 years in our analysis.

Table 1: Parametric uncertainties used in the analysis and their lower and upper bounds

Uncertainty	Type	Lower Bound	Upper Bound
Progress Ratio	Parametric	0.75	0.98
Cost surplus rate historic capacity	Parametric	0.75	1.25
Operational & Maintenance cost rate	Parametric	0.01	0.20
Interest Rate	Parametric	0.05	0.25
Lifetime wind capacity (years)	Parametric	10	40

Besides these parametric uncertainties, there are also structural uncertainties that are explored in our analysis. Percentage growth of new capacity[2] is modeled in the form of lookup functions but each lookup function is a function of different variables for each model. In the first model, percentage growth varies over time and it is a function of *gap maximum potential* in the second model. For the third model, percentage growth is dependent on the *expected profitability*. *Percentage growth new capacity of wind turbines* lookup is crucial in terms of determining the new capacity growth. Each variable for each model is varied as shown in Figure 1. Additionally, the second and the third models include a variable as *average windiness factor* which is triggered by lookup functions. Corresponding lookup functions are varied as shown in Figure 1.

[2] *Percentage growth of new capacity 0* corresponds to the first model, *Percentage growth of new capacity 1* is for the second model and *2* for the third model.

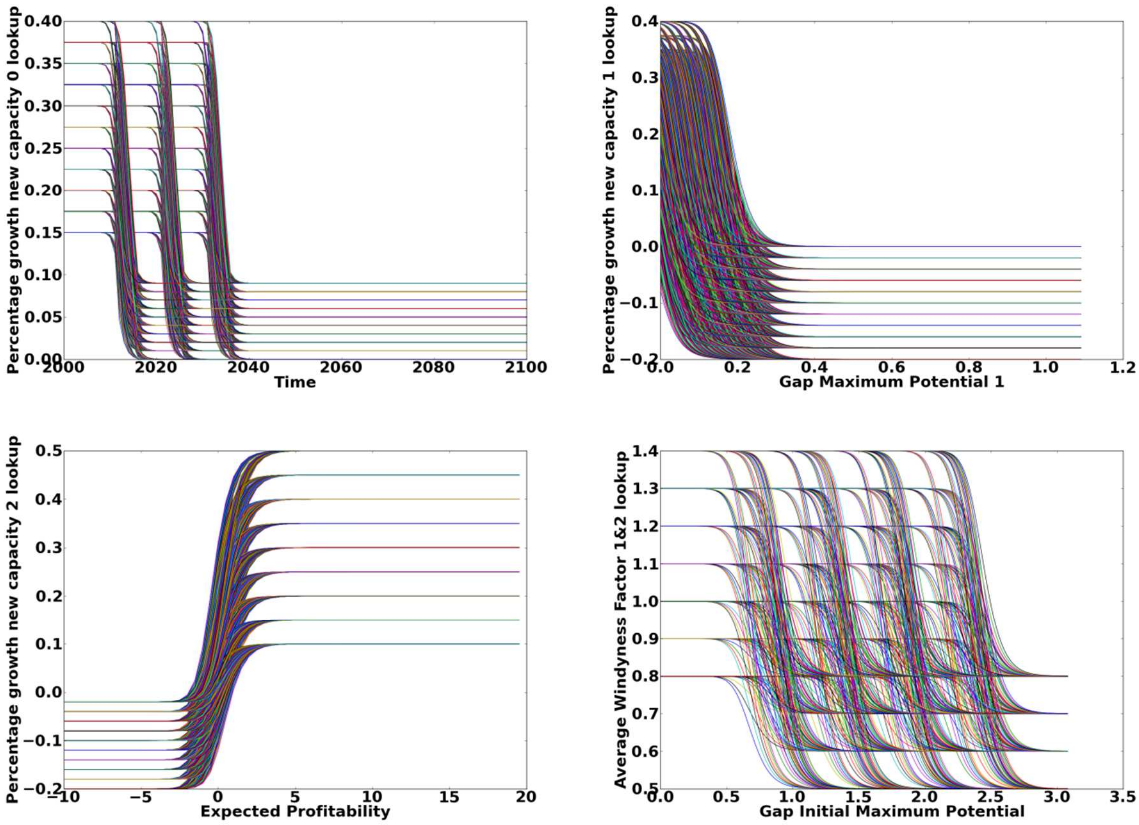

Figure 1: Structural uncertainties used in the analysis and their variation.

2.3. Very briefly, sampling and visualization techniques

For the uncertainties mentioned in the previous section, 5000 plausible futures are sampled using LHS sampling for each three models. For the aim of spanning the sample space as much as possible, the boundaries for uncertainties are kept intentionally large.

For a better understanding of our analysis, different visualization techniques are used in this paper. Total capacity, new capacity growth and total costs of installed wind turbines graphs for each model are illustrated over the time horizon. Additionally, envelopes of the maximum and minimum limits of each graph are depicted in line with the histogram illustrating the distributions of the final states.

3. Wind Energy models (3 different models)

In this paper, three different versions of a model about the future development of world wind power are used in order to illustrate the inclusion of structural / model uncertainty. The first version of the model is a replication of the spreadsheet model behind the Wind Force 12 report of the European Wind Energy Association and Greenpeace (European Wind Energy Association and Greenpeace, 2002). The static spreadsheet model used in that report was replicated by Pruyt (2004) by means of a simple System Dynamics model (see Figure 2).

The second version of the model (see Figure 3) is a more dynamic version which grasps relations (and hence dynamics) ignored by the first model, more precisely the influence of cost reductions on the maximum potentiality and of learning and maximum potential on the onsite capacity factor. The second model is thus the extension of the first model with, feedback loops, delays and non-linear causality. Major changes are highlighted in red. Finally, the third version of the model (see Figure 4) is an even more dynamic version of the second model including additional feedback due to the link between expected profitability of wind power investments and new capacity additions and drastic disinvestments. Since the main aim of this paper is to illustrate how different models can be used for explorative uncertainty analysis, the descriptions of the models are not detailed on purpose. For interested readers, the details of the three models are explained in more detail in this paper (Pruyt, 2004).

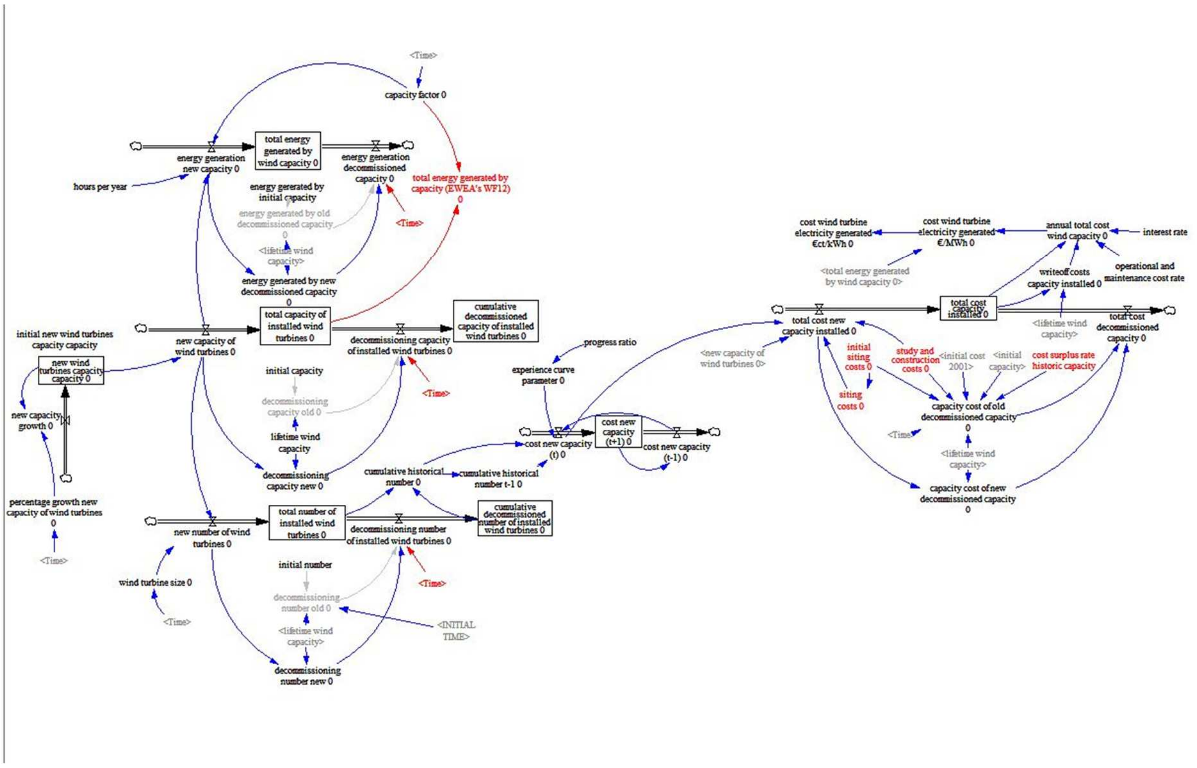

Figure 2: Stock-flow diagram of the Wind Force 12 model

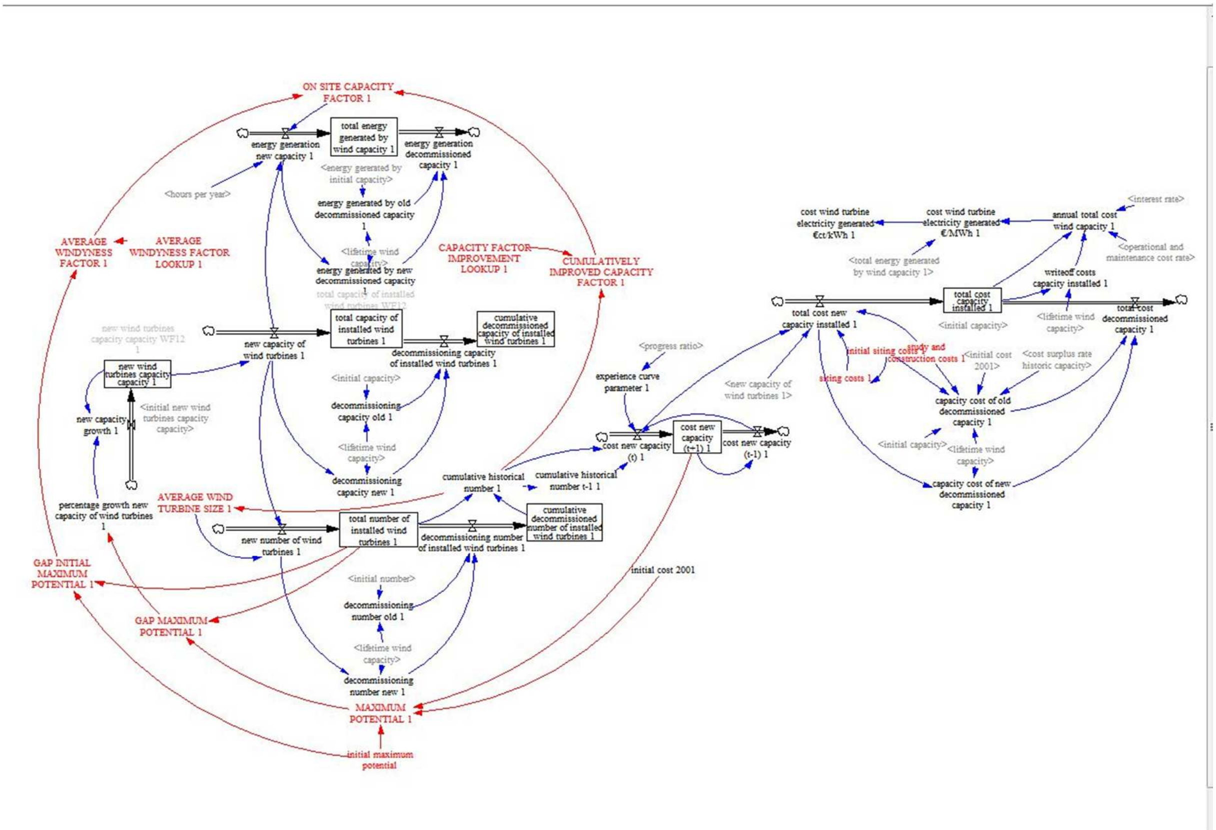

Figure 3: Stock-flow diagram of the system dynamics model derived from Wind Force 12

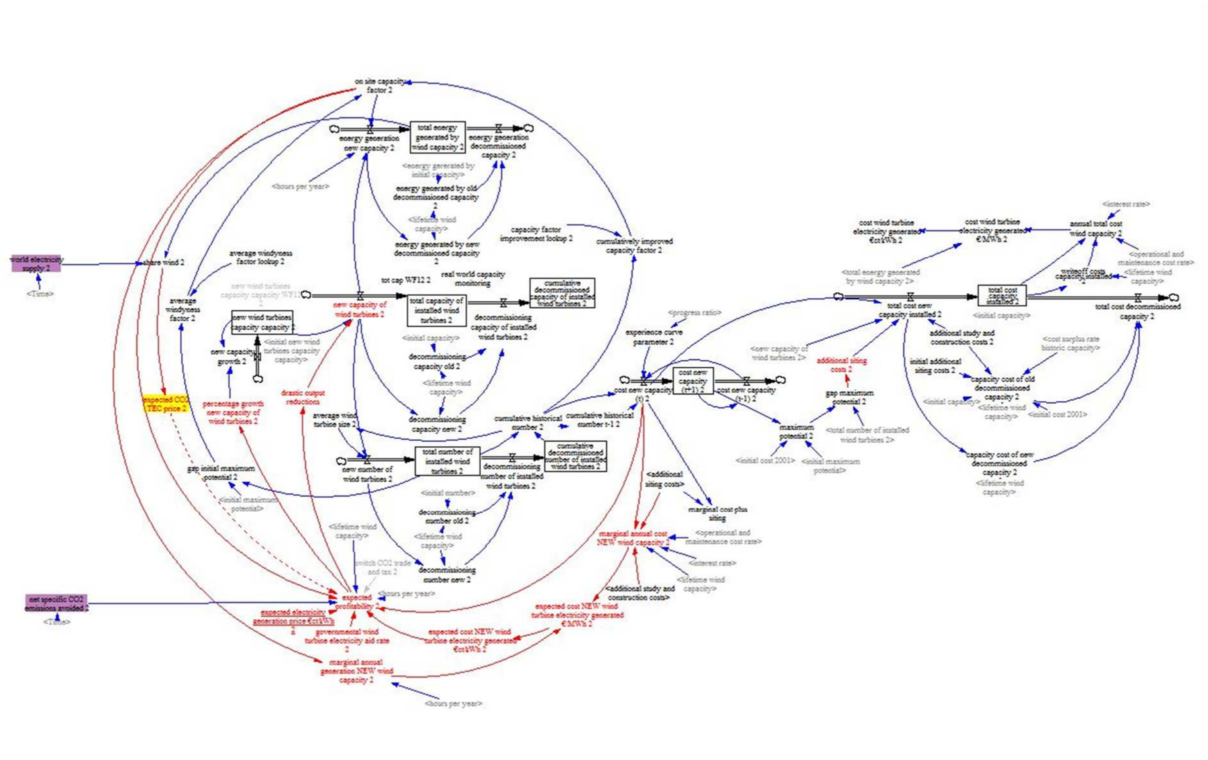

Figure 4: Stock-flow diagram of the elaborated system dynamics model.

4. ESDMA simulations

In our ESDMA analysis, both parametric and structural uncertainties are explored over a plausible range of upper and lower limits. For each model, 5000 experiments are computed between years 2010 and 2130. Total capacity and new capacity of installed wind turbines[3] are the main outcome of interest. In Figure 5, trajectories of possible total capacities of wind turbines are shown for each model. The results of the first model illustrates that total capacity can go up to 500 billion MWs, which is extremely unrealistic. The reason for such a behavior is caused by the unrealistic representation of the real world. For the second model, upper limit of total capacity is around 6 million MWs, with an exception that goes up to 120 million MWs. The third model illustrates that total capacity can vary up to 90 million MWs. Although it is not apparent in the first model, there are different patterns of behavior, such as cyclic or chaotic, in the second and third models. Pattern analysis and data mining techniques/algorithms are very useful for such situations. However, these techniques/algorithms become very difficult to implement, when the data is a time-series. There is a work in progress currently going on about this issue and the results of pattern analysis algorithm for time-series data will be useful for a better understanding of the dynamics.

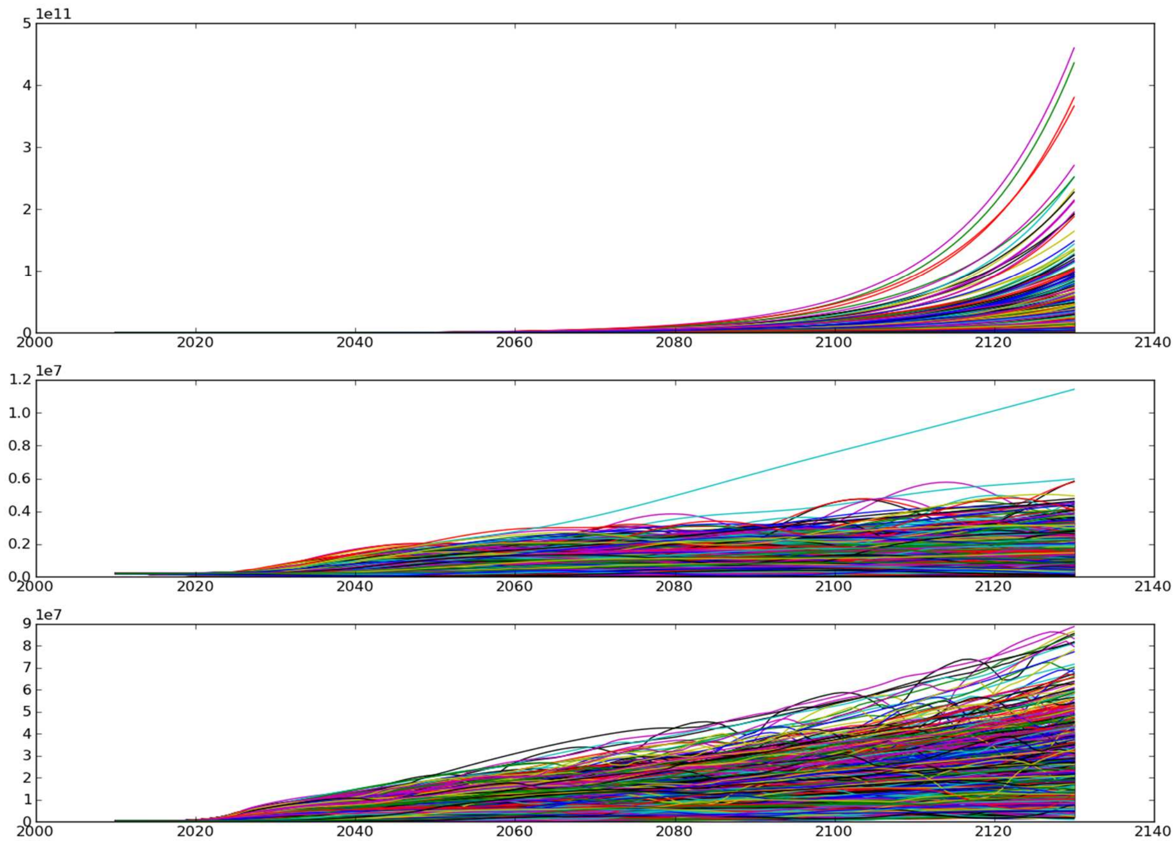

Figure 5: Total capacities installed wind turbines for three models. (From top to bottom: 1st, 2nd and 3rd model.)

[3] All the numbers in Figure 5, 6, 7, 8, 9 and 10 are in terms of MWs (Megawatt).

Another analysis technique used in this paper is the envelope and end state histograms. In Figure 6, envelopes of upper and lower limits for total capacities installed for each model are depicted. Although it seems like a similar approach to Figure 5, combined with the end state histograms, it gives a better understanding about the number of runs at certain levels. For instance, most of the runs for the first model remain below 100 billion MWs (still very unrealistic). Similarly, the bottom skewed tails of histograms for the second and third model illustrates that most simulations do not explode to higher total capacity levels.

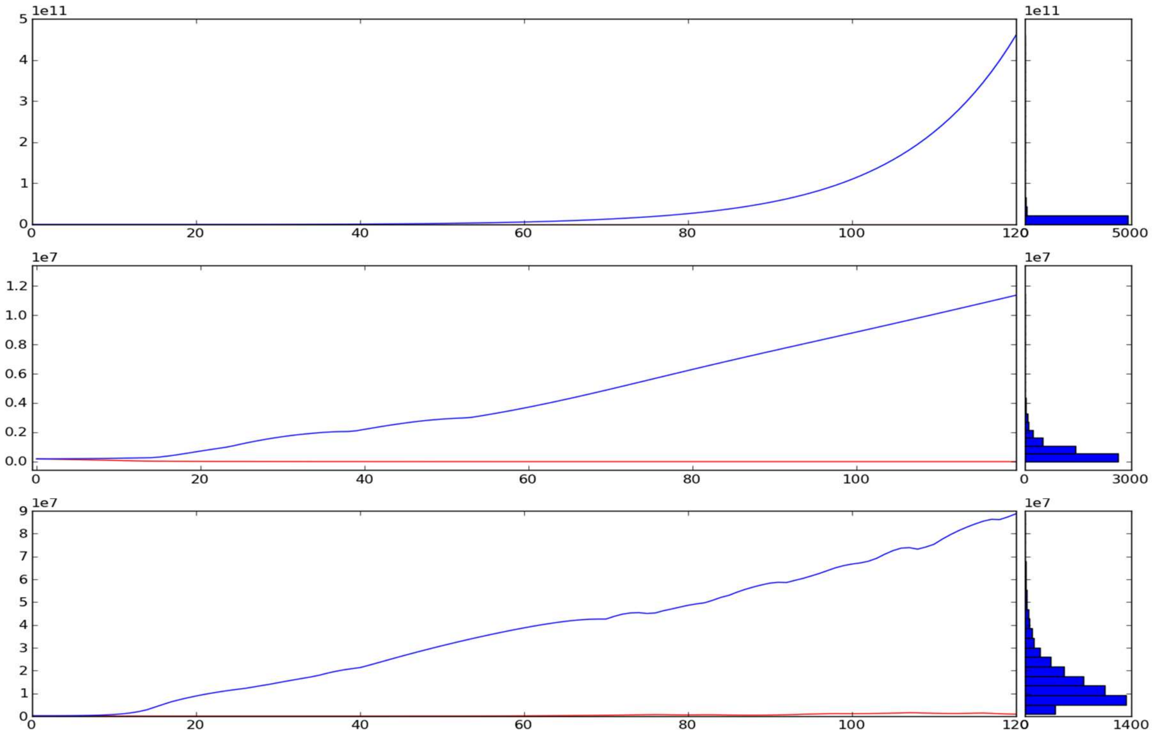

Figure 6: Envelope trajectories of total capacity installed over time and histogram illustrating the distribution of end states.

It is not very surprising that the new capacity installed shows a similar pattern with the total capacity installed (See Figure 7 and 8). What can be interesting to analyze is the cyclic patterns in the second and especially third model outcomes. With the pattern analysis techniques that are being developed currently, it can be possible to extract clusters of similar patterns and analyze the reasoning behind these behaviors. Furthermore and more importantly, these behavior clusters can be very helpful for developing adaptive policies according the characteristics of patterns.

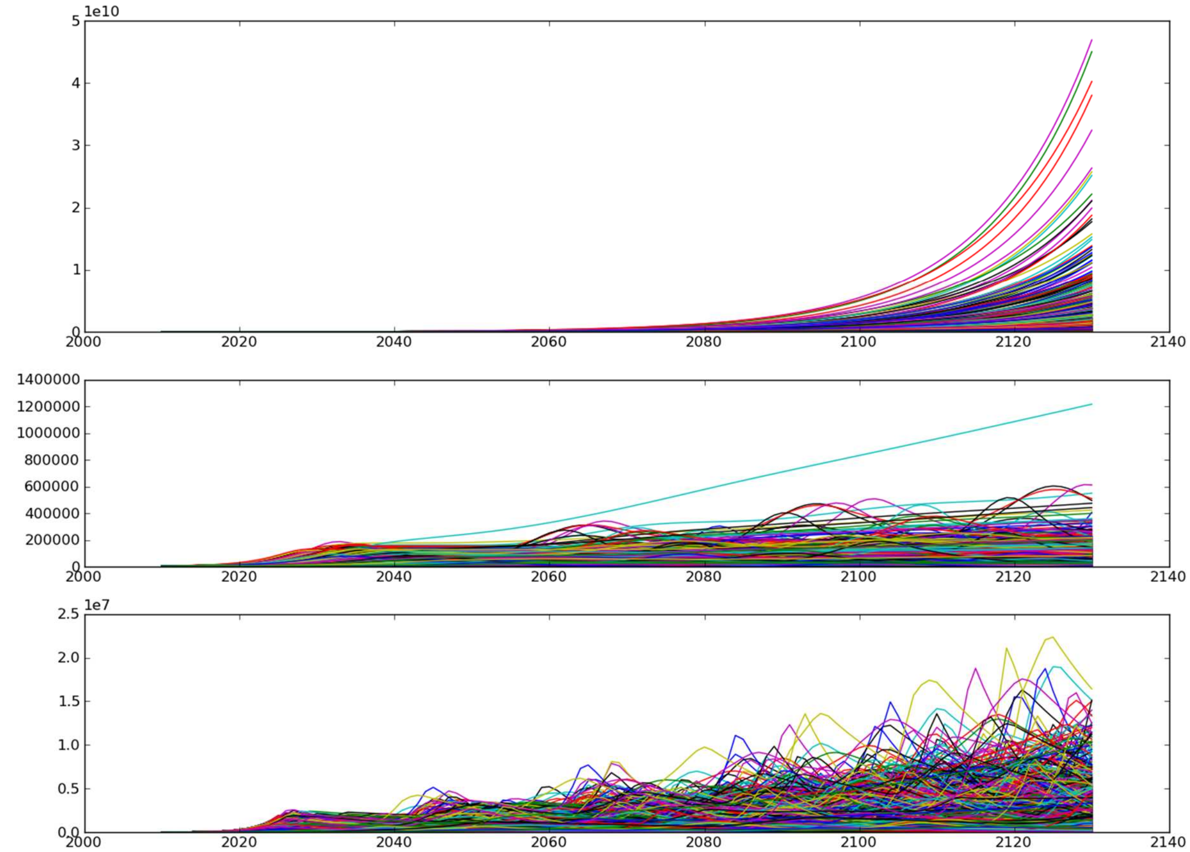

Figure 7: New capacities installed wind turbines for three models.

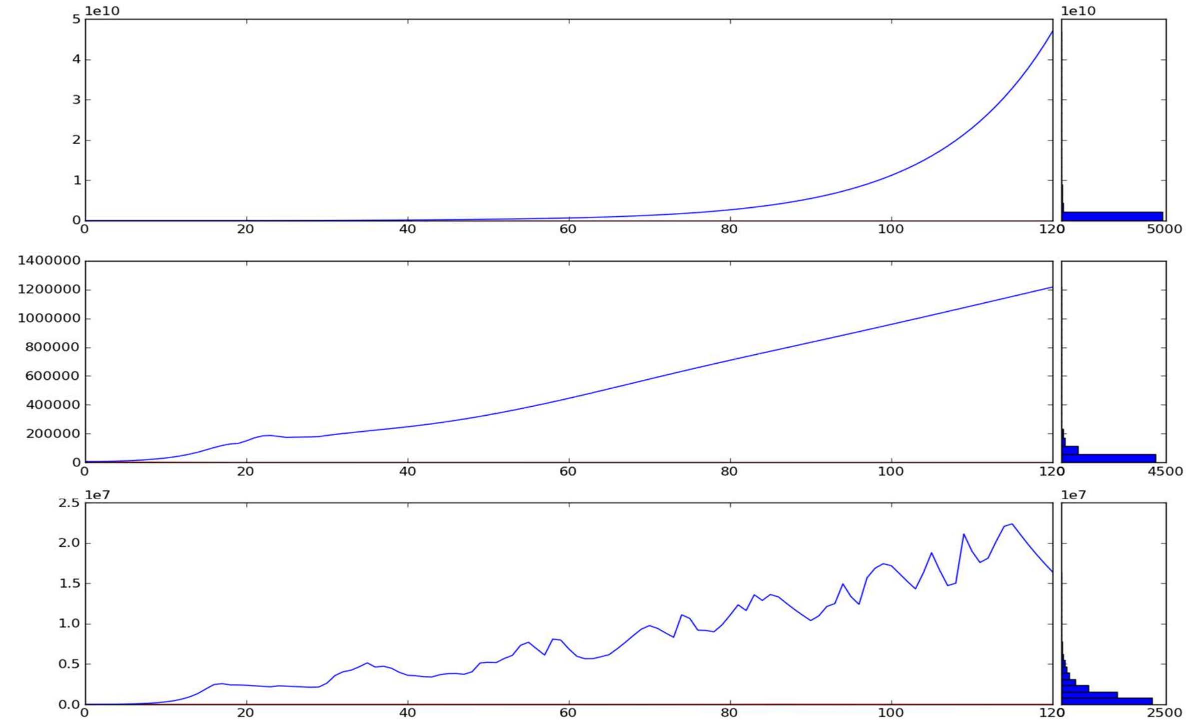

Figure 8: Envelope trajectories of new capacity installed over time and histogram illustrating the distribution of end states.

5. Discussions & Conclusions

This paper puts an emphasis on a new research methodology – EMA – that analyzes deeply uncertain and dynamically complex systems in combination with System Dynamics modeling. Our analyses on three different SD models about wind-powered energy illustrate that parametric and structural uncertainties have a great importance on the dynamics of a complex and deeply uncertain technology management problem. However, not only the exogenous or endogenous uncertainties but also the model itself has a great importance in terms of uncertainty. It is shown that even three different models can present very different dynamics. So, trying to explore only parametric and structural uncertainties being limited to only one model can be misleading. The main aim of this paper is to show how different multiple models can be used for exploration of uncertainties.

As a future work, data mining techniques are very interesting in terms of the results that can be revealed. As can be seen from most of the figures, trajectories seem very messy and dirty in terms of practicality of analysis. There are some different seeable patterns but it is not very easy to extract different modes of behaviors easily, especially for time-series data. However, there are available algorithms from the literature of pattern analysis or data mining. Extraction of behavior modes using data mining techniques will, for sure, reveal very interesting results and conclusions. Pattern analysis and data mining on time-series data is currently under development as our future research.

EMA is a new methodology for dealing with complex and deeply uncertain policy problems. Until now, EMA has performed quite well for handling parametric and structural uncertainties. A future work for improving this methodology can be the exploration of different modeling paradigms. For instance, an agent based model, a system dynamics model and a spreadsheet model for the same problem can be analyzed together for exploring the modeling paradigm uncertainty.

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