Analyzing Simulations of Energy Transitions: Towards a Dynamic Path Approach

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Abstract. We postulate that the analysis of simulation results should include the statistical confirmation of a causal diagram as a whole. Traditionally, only individual causal relations are assessed at a time or time dependence is ignored. We formulate the criteria for a method that allows for the analysis of simulation data where time dependent data is acknowledged and where multiple relationships exist that can change in strength over time. Because we have not found a method that meets all criteria, we started the development of a *dynamic path approach*. A promising exploration is presented that leads to an improved analysis of existing simulation results and the related conclusions.

Key words: Data analysis, transition, energy transition, simulation models, agent-based simulation, structural equation modeling, path analysis, time series analysis, dynamic path approach.

1 Introduction

1.1 Socio-technical simulation and causal diagrams

In the empirical sciences, one starts with a hypothesis that is to be proven or falsified. This hypothesis describes the nature of a relation between two or more variables. In analogy, in simulation studies a *causal diagram*[1] describes the relations between variables observed in reality grasped in the simulations. Depending on the nature of a simulation study, its goal can be reformulated, from the specific modeling question to verifying the relations in the causal diagram by executing simulations[2].

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[1] A causal diagram is a drawing of parameters and their causal relations as directed arrows, for instance the diagram of Figure 1.2

[2] There are also simulation studies with a more exploratory nature. It may be that for such studies the modeler has no causal diagram in mind, but we conjecture it is fruitful for such a study to make at least some hypothetical causal diagram, so to benefit from the comparison of the modelers' conceptual ideas and the simulation results.

1.2 Context: Transition in CO_2 emissions from Power Generation

In this paper we will use a case on transition in CO_2 emissions from power generation. To move the power sector towards sustainability, it is now widely understood that we need to reduce CO_2 emissions. In Europe governments have committed to ambitious targets, up to 50% reductions of CO_2 in 2050. Two key policies to do that are carbon taxation (CT) and emission trading (ETS). In the literature, there has been a debate for long on what is better, in general economic terms: price or quantities [1–4] and applied to the energy case: tax or trading [5–8]. From the literature it is not clear whether these policies will lead to timely shift in power generation technologies and fuel choice to meet the ambitious CO_2 targets. We postulate that this requires a transition [9, 10] that needs to be managed [11, 12]. To enable such a transition, the policy needs to be an effective transition instrument [13]. We made a causal diagram of the relevant relations (see Figure 1.2). Fuel prices and electricity demand are exogenous to the system. Depending on the scenario, also the CO_2 price is exogenous: it is zero under no intervention, exogenously determined by government under carbon taxation, but an endogenous outcome of the market under emission trading. The electricity price is a real endogenous parameter: it is the result of the complex interaction of fuel and electricity markets, the actions of the agents in the model and, if apparent in the scenario, the CO_2 market. The portfolio of installations is a combination of the contributions of all possible technologies (coal, coal with carbon sequestration and storage (CCS), natural gas, biomass, wind). They change by investment or dismantling decisions of the agents. Investment decisions have a significant construction time. Therefore, those decisions are based on *the past* of many parameters in the model. The dependence on the past of electricity, fuel and CO_2 prices are relevant. The main indicator of progress is the level of CO_2 emissions, which is mainly determined by the portfolio of power plants. These relations were the basis of the development of the simulation model. However, the strength and significance of those relations, and whether that changes over time, is unkown ex-ante.

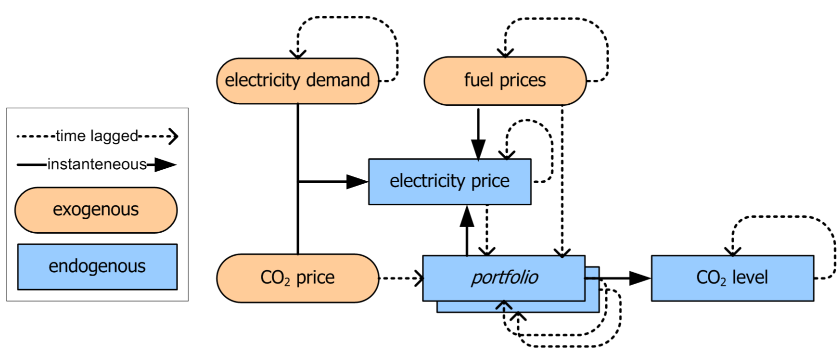

Fig. 1. Causal diagram, containing the relations thought to be relevant and important.

1.3 Application: Agent-Based model of Transition Instruments and Power Generation

An agent-based model (ABM) was developed to compare the effect of the two carbon policies on power generation [14] and we have presented a specific development of that model at the 2008 ESSA conference [15]. The ABM paradigm matches the structure of the electric power production sector, where independent power producers, governments and consumers are represented agents that compete and interact via markets. The model contains a social subsystem, that contains those agents and their interactions. In addition, the physical subsystem is modeled encompassing installations, their connections and flows of physical goods. Six independent electricity producing agents have different portfolios of power generation facilities. The agents negotiate contracts for feedstock, the sales of electricity and, in the case with emissions trading, emission rights. On a strategic level, the agents need to choose when to invest, how much capacity to build and what type of power generation technology to select.

The external world is represented by exogenous scenarios. The characteristics of the modeled system are emergent: the generation portfolio and merit order, fuel choice, abatement options, as well as electricity and CO_2 prices and emissions emerge as a result of the decisions of the agents. The model has been run for three cases: no carbon policy, emission trading or carbon taxation. As such, also a transition in emissions would be an emergent property of the model.

The outcomes of this simulation model have been presented in several ways. In general, we aimed at finding patterns in the output of simulation by comparing different groups of runs, each group representing one of the policies. The different groups are compared on one parameter at a time. In order to make such graphs, average values and a measure for the spread are calculated, so that the results can be interpreted. A number of different emergent indicator parameters were presented as outcomes of the above mentioned model: CO_2 emission levels, electricity and CO_2 prices and the portfolio of power generation facilities (see Figure 1.2 and figures 4, 5 and 7 in [14]).

1.4 Problem: drawing conclusions based on claiming causality and dependent observations

In this paper we want to raise two problems regarding the analysis of the simulation results as highlighted above.

First, there is the pitfall of *claiming causalities*. One could for instance come to the counter-intuitive conclusion that higher natural gas prices lead to more adoption of power plants running on natural gas. This can of course be caused by one or more other factors: coal prices went up more than natural gas prices, technology improvements, governmental subsidies, expectations of future natural gas prices and availability. In this example, it is obvious that if there is a direct relation between natural gas price and the related adoption of power plants, it can only be negative. However, when analyzing simulation outcomes it is not always as transparent. In general, one can only claim causality between A and

B if (1) there is a statistical relation found in the data, (2) A happens before B in time and (3) there is no other variable explaining both A and B. How can we prevent this pitfall in the analysis of simulation results if we can only plot one or two parameters at a time and base our conclusions on combining the several graphs? We therefore need to explicitly address all relevant parameters at the same time.

Second, there is the pitfall of *independent observations*. Many statistical techniques require independent observations to be valid. For instance if you want to predict next years electricity prices, you would make a regression model with as dependent parameters all fuel prices, since they are known to impact the electricity price. In that case you will have a fundamental wrong method, since the electricity price is dependent on its past: it is autocorrelative. Data analysis techniques either assumes independent observations (e.g. regression analysis) or they are not able to show how relations change over time (e.g. time series analyses). How should we draw solid conclusions based on time dependent data, without using classical statistical methods that require independent observations?

We face the combination of both problems. We have a conceptual causal model in mind of how parameters affect each other, with or without a time delay and we want to test the validity of such a conceptual model on the basis of simulation results. We might presume in such a conceptual model that a parameter is causal to another, but that the causal effect takes some time and is not instantaneously. On the other hand, there is more than one parameter affecting others, so we need to take into account more factors at the same time. If we can do that, we can get insight in contributions of individual parameters, for instance in order to weigh the impact of exogenous and endogenous parameters.

The main question of this paper is: *What method can be used to confirm a causal model by adequately representing the strength of multiple time-dependent relations between parameters, captured in data from simulations?*

1.5 Structure of the paper

Based on the problem addressed in this paper we will come up with a list of the criteria for the method to successfully analyze simulation results. Subsequently, we will give an overview of the methods from the literature relevant to this problem. We present the initial developments and experience of the *dynamic path approach*. The paper finished with conclusions and an outlook.

2 Criteria for the needed method

This section contains the criteria for the method needed that should be able to successfully analyze the simulation results of the case presented. The method should allow for time delayed and instantaneous causalities to occur between endogenous and exogenous parameters. In addition, the strength of multiple relationships should be clarified in order to confirm a causal model containing the parameters.

Some criteria are on the type of parameters (exogenous, latent, discrete), some on the relationships (dynamic, autocorrelative, indirect, multiple) and some on the type of analysis (quantitative, confirmatory, comparative and exploratory). The criteria are must-haves except when noted otherwise. The criteria are:

2.1 Criteria on the type of parameters

Exogenous The method must be able to distinguish endogenous from exogenous parameters. An exogenous parameter is not influenced by other parameters. Endogenous parameters are influenced by other parameters. In the presented case, fuel prices are exogenous parameters.

Latent Second, it would be nice if the method discerns unmeasured variables based on indicator variables from measured variables. We could for instance use indicators to estimate underlying concepts, such as greenness of the power generation portfolio and the speed of transition, without explicitly measuring it.

Discrete The method must be able to deal with discrete data taken at a regular time interval.

2.2 Criteria on the relationships between parameters

Dynamic The method must be valid for instantaneous relationships and time-lagged relationships. New power plants take at least three years to build after the investment decision is made, so the impact of parameters on portfolio changes is by definition time-lagged. However, the impact of the CO_2 price on the electricity price is within the same year, so it is instantaneous in the model outcomes.

Autocorrelative The method must be valid for parameters that depend on themselves in the past, such as prices for fuels, electricity and CO_2.

Indirect The method must be able to discern direct relationships between parameters and indirect relationships, where two parameters depend only on each other through a third. For example, the impact of CO_2 price on actual CO_2 emissions, which is only through the power market.

Many-to-many The method must be able to deal with the fact that more than one independent variable is affecting more than one dependent variable.

Multiple The method must be able to deal with multiple causal relations between parameters. One could argue for repeating a method capable single relations, but it is intended that several relations are modeled and assessed simultaneously. Where a parameter is one of the dependents in one relation, it might be an independent in another.

Cyclic It would be nice to allow for the possibility of cycles in the set of relationships ($X \rightarrow Y \rightarrow Z \rightarrow X$). For this criterion, the multiple criterion is a requisite.

Variable relationships The method must be able to deal with relationships that appear and disappear and change in strength over the simulated time.

2.3 Criteria on the type of analysis

Quantitative The method can quantify the strength and type of relationships.

Confirmatory The method can confirm or reject a conceptual model of the relations of parameters.

Comparative The method can compare the performance of alternative models, for instance comparing the effect of two possible governmental strategies, emission trading and carbon taxation.

Exploratory It would be nice if the method is applicable for exploration of interactions of parameters and thereby for the development of new conceptual models.

3 Most relevant methods

We will now elaborate on the most promising methods in the literature that are applicable to these criteria or some of them.

The class of *path analysis methods* estimate multiple linear relations simultaneously. A path of relations among a set of variables is defined, resulting in a set of linear regression like equations. Structural Equation Modeling (SEM), the most common path analysis method, includes latent variables in the analysis, by using factor analysis, and allows for cycles. The main problem with applying SEM is that it assumes time-independent data.

Time series models [16] can estimate parameters that gives the best prediction of time series of one dependent variable. These parameters can be a combination of the past of the variable itself (that is called autoregressive), and other variables. The parameters are estimated for a single dependent variable and for one set of data at a time. Time series analyses are not applicable to our problem, because it does not allow for relations to appear, disappear or change in strength over time. An additional problem is that time series analysis does not allow for estimating multiple relations at once.

Dynamic structural equation modeling, an expansion of structural equation modeling, includes a time dimension by distinguishing all parameters in each time step [17]. It is therefore possible to include time-dependence and a time lag between parameters. The main disadvantage however is similar to time series modeling: the strength of relations is assumed to be constant: "if there is no coherence between time interval and causal lag, parameter estimates of the structural equation models can lead to wrong substantive conclusions" [17].

Dynamic Path Analysis uses time-indexed directed acyclic graphs [18]. Two outcomes are gained at: (1) to find adequate path diagrams reflecting the data at all points in time and (2) to distinguish direct and indirect effects and their contributions over time. Latent factors are not included yet, but could be a possible extension. This method however does not allow for cycles.

In conclusion, none of the methods is applicable to our problem as defined by the criteria above.

4 Towards a dynamic path approach

We postulate that a new approach is needed, combining some of the ideas of the above. The approach we are developing uses the following main characteristics, based upon the criteria as mentioned before. The approach uses discrete time points as input, collected during simulations. A network of relations is estimated, with time dependent data, allowing for change in strength and significance of each relation over time. As such, the approach should allow for confirmation of the before stated causal diagram.

4.1 Simplified case for developing the approach

We use the data that resulted from the model, as presented in the introduction. We will delimit our analysis to a smaller subset of the results in order to have a practical example while developing the approach. The used dataset contains yearly data points with values on all relevant exogenous and endogenous parameters. Each simulation run has 50 data points one for each simulated year. We have three scenarios, one related to each of the government interventions that was modeled. The governmental scenarios are: no carbon policy (NCP), carbon taxation (CT) and an emission trading scheme (ETS). For all scenarios 20 runs were completed. Therefore on all parameters we have 50 (years) times 20 (runs) times 3 (scenarios) equals 3000 data points.

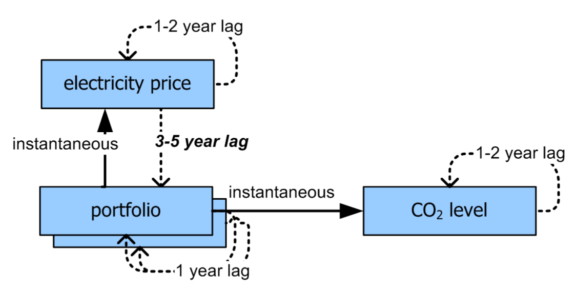

Fig. 2. Proposed relations in the model results based on the causal model.

Figure 2 gives an overview of the modeled relations and their characterization. Please note that the relations modeled are instantaneous and/or lagged. For parameters that autocorrelate we introduce a lag of 1 and 2 years as new parameters. Some other relations require a larger time lag. We will discuss all modeled relations below. Before we do that, first a notion why we do not take any exogenous variables into account. In the model, electricity demand and fuel prices are modeled as exogenous trends *without stochastics*. Therefore, the variance within each year for the exogenous parameters equals 0. As a consequence, any analysis that takes into account a single year at a time cannot incorporate these exogenous variables, it would just have no explaining power. The idea behind was that we could isolate the main parameters from exogenous trends, without being unrealistic. In the future we intend to include those variables, by including a variety of values in the parameter sweep. For now we exclude all exogenous variables from the analysis.

4.2 Setup

In the approach we need to find out which relations are relevant, we need to find out how much lag in time is relevant for each relation and we need to estimate the significance and the strength of the relations over time.

As a first exploration, we developed an ordinary structural equation model and a model taking into account time lags. We also propose the approach, visualized in Figure 3, to come to useful models per time step. On the vertical axis the number of years taken into account is denoted. Since each run has 50 simulated years, the maximum number of years that can be taken into account is 50, the minimum is 1. On the horizontal axis the number of years of lag that can be taken into account is depicted. A model with a lag of 0 assumes only instantaneous relations. Since there is no data available of before the simulation starts, a time lag larger than the simulated time is not applicable (the purple area). In addition, for variables that autocorrelate or depend on other parameters in the past, probably not all of the past is relevant. Higher time-lagged terms will be less significant for most parameters (expect when long time-cycles are observed). Therefore there will be some area (denoted as green) with insignificant parameters. The shape of that area is however unknown and should follow from applying the approach to the case.

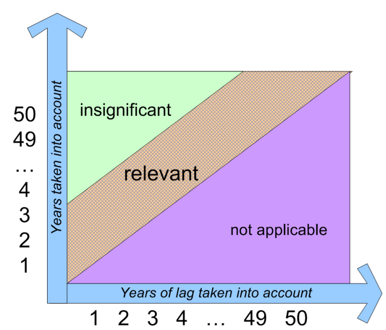

Fig. 3. Years taken into account versus the lag taken into account

There are 9 parameters in the simplified dataset (7 contained in portfolio, 1 in the electricity price and 1 in the CO_2 level, see Figure 1.2). By the introduction new parameters, reflecting time-lagged parameters, this number rises to some 40 parameters. Since we need to estimate models for each time step we used the scripting facilities of AMOS [19]. Later on we opt for developing a new tool in a software that allows for even more flexible programming.

4.3 Results

Model 1: Ordinary Structured Equation Model In the first model we only included the instantaneous relations. From this model, which is an ordinary Structural Equation Model (SEM), we could explain all regression weights, displayed in Table 1. Overall model fit statistics were high, i.e. goodness of fit indexes (GFIs) of 0.841, 0.943 and 1.000. This indicates that the path model explains the data well. However, although the statistical significance is high, the interpretation may be not and we cannot be sure without assessing the next model. As will be shown below, interpretation with this model is a problem.

Model 2: First successful model following the *dynamic path approach* Next, we included all time lags as shown in Figure 2. We were again able to estimate models for all three scenario's. We removed the years for which no time-lagged data is available (the first years of the simulation). The model fit statistics were again good, i.e. GFIs of 0.799, 0.810 and 0.840. The regression weights are presented in Table 1 and show quite different results.

Model 3: Outlook to models using the *dynamic path approach*, estimating the parameters per simulated year In our final trial, we took subsets for each year. We were not able to estimate the models, because the dataset available, 20 cases, is too small. Therefore we are not yet able to show how the relations change over time. We are confident however, that we will be able to do that with a bigger dataset. Using such models is however fruitful, therefore we intend to adapt our simulation setup and increase the number of simulation runs.

4.4 Analysis of Model 1 and 2: the benefit of the *dynamic path approach*

Only model 2 offers results on autocorrelation We found that autocorrelation of the portfolio components (each technology type) is very high (standardized regression weights vary between 0.9 and 1.0) and that the differences in autocorrelation between scenarios are very small. Also emission levels and electricity prices autocorrelate, but the results from the emission trading case is quite different from the other two: The second order time lag of the electricity price is under emission trading more relevant than the first order time-lag. The electricity price is predictable under no intervention, which shows in a high autocorrelation (0.638). The contributions of the portfolio composition is significantly different under the scenario's. They can be explained by taking into account the patterns in portfolio compositions.

Striking is the contrast of the autocorrelation of the emission levels. It shows how different (and unpredictable) the impact of the emission trading scheme is: Only under that scenario, autocorrelation is almost absent (first order 0.253 and second order -0.032). Under the other two scenario's this is very high (first order

0.808 and 0.967 and second order -0.113 and -0.125). Also that finding can be explained by earlier results: the emissions are only volatile under this scenario. Under the other two, they go down far more steadily.

This implies that in the case of emission trading the electricity price and emissions are less predictable. This information is only available in model 2 and this leads to an additional conclusion.

Model 2 results in different strength and directions of some of the relations, leading to different conclusions Some of the strengths of the relations are quite different in model 2, compared to model 1 (see the italics in Table 1). How in model 1 the coal price affects the actual emissions is overestimated in the case of no intervention and carbon taxation, but not in the case of emission trading. Model 1 overestimates the impact of the natural gas price on the electricity price, but only in the case of no intervention. And even worse: model 1 estimates relationship between coal CCS and the electricity price to be negative instead of positive, as it is in model 2.

These results clearly show that - only taking into account constant relationships over time - the dynamic path approach leads to more and different results and therefore also to different conclusions. The advantage of using the approach will only grow, when we further develop it and arrange for more data from simulations. We expect for instance the importance of specific portfolio parameters to change over time: coal with CCS is only available after the first 10 simulated years and can therefore only be apparent in the later part of the simulation. In contrast, conventional coal disappears in the simulations with carbon taxation and emission trading, so we must be able to see that in the strength of the relationships of coal with other parameters. It is likely that if we can analyze the change in those parameters *in combination with* the strength of the impact of exogenous parameters, such as fuel prices, we will gain new insights in the dynamics of the possible transitions in the power generation sector.

5 Conclusions and outlook

We see the need for improving the process of analysis and presentation of the simulation results. It is uncommon to test a theoretical causal diagram with the data resulting from the simulation. We have identified the criteria for a new approach to improve the analysis simulation results. Current methods do not meet the criteria we formulated.

In order to meet the stated criteria we started the development of the *dynamic path approach*. That approach is to be capable of dealing with a path of relations between variables that can be simultaneous and/or time-lagged. In addition, the approach will allow relations to change in strength and significance over time. The results of our exploration were insightful: using the dynamic path approach leads to much more information and partially different conclusions on the same data. We found that we need to modify our simulation setup to allow for the next step. We aim at taking that next step by developing a new tool that allows for analyzing the true nature of time-dependent data from simulations.

Independent → Dependent	Model 1			Model 2		
	NOI	CT	ETS	NOI	CT	ETS
Portfolio						
natural gas L^1 → natural gas				**0.974**	**1.013**	**0.969**
electricity price L^3 → natural gas				0.001	-0.02	0.006
electricity price L^4 → natural gas				0.003	0.027	-0.002
electricity price L^5 → natural gas				0.003	-0.054	0.009
coal CCS L^1 → coal CCS					**1.002**	**1.007**
electricity price L^3 → coal CCS					0.002	-0.003
electricity price L^4 → coal CCS					0	0.023
electricity price L^5 → coal CCS					0.011	0.028
coal L^1 → coal				**0.99**	**0.973**	**0.939**
electricity price L^3 → coal				0.055	0.009	0.022
electricity price L^4 → coal				-0.009	-0.002	-0.037
electricity price L^5 → coal				-0.014	0.026	-0.073
biofuel L^1 → biofuel				**0.935**	**0.993**	**0.997**
electricity price L^3 → biofuel				0.009	-0.002	-0.005
electricity price L^4 → biofuel				0.024	-0.009	0.012
electricity price L^5 → biofuel				-0.016	0.009	0.03
uranium L^1 → uranium				**0.94**	**0.914**	**0.933**
electricity price L^3 → uranium				0.021	0.061	0.019
electricity price L^4 → uranium				0.01	-0.014	0.039
electricity price L^5 → uranium				0.01	0.025	-0.008
wind L^1 → wind				**0.903**	**0.934**	**0.958**
electricity price L^3 → wind				0.026	0.037	-0.004
electricity price L^4 → wind				-0.014	0.005	0.02
electricity price L^5 → wind				-0.015	-0.031	0.008
Emission level						
natural gas → emission	0.121	**0.675**	**0.638**	0.041	*0.171*	**0.553**
coal CCS → emission		0.071	**-0.391**		0.084	**-0.29**
coal → emission	**1.029**	**0.566**	**0.934**	*0.317*	*0.148*	**0.81**
biofuel → emission	-0.014	0.049	**-0.405**	0.001	0.051	**-0.309**
uranium → emission	-0.106	-0.023	-0.009	-0.041	-0.009	-0.012
wind → emission	-0.185	-0.049	-0.261	-0.092	-0.008	-0.196
emission L^1 → emission				**0.808**	**0.967**	**0.253**
emission L^2 → emission				-0.113	-0.125	-0.032
Electricity price						
natural gas → electricity price	**0.689**	**1.407**	**1.077**	*0.187*	**1.263**	**1.111**
coal CCS → electricity price		**0.685**	-0.021		*0.91*	*0.061*
coal → electricity price	-0.077	**0.499**	**0.621**	-0.13	*0.742*	**0.701**
biofuel → electricity price	-0.073	**0.339**	-0.106	-0.005	**0.477**	-0.038
uranium → electricity price	-0.238	0.006	-0.045	-0.176	-0.003	-0.05
wind → electricity price	*0.011*	0.172	-0.079	*-0.018*	0.158	-0.012
electricity price L^1 → electricity price				**0.638**	**0.354**	-0.046
electricity price L^2 → electricity price				-0.015	-0.043	**0.221**

Table 1. Result of model 1 and 2: standardized regression weights of all relations. Time dependent relations are taken into account only in model 2, as time lagged parameters, a one year delay noted as L^1.

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