Meta-Analysis of Social Models

Revisiting Cederman's Emergent Polarity Model

Michael Köhler-Bußmeier und Alena Störmer

University of Hamburg, Department for Informatics and
HAW Hamburg, Department for Informatics

Zusammenfassung: In diesem Beitrag analysieren wir das prominente *Emergent Polarity Model* (EPM) von Eric Cederman von einer Meta-Perspektive. Wir variieren dazu die Modellparameter über einen großen Bereich hinweg, um so zu konkreten Modellinstanzen zu gelangen. Wir haben dann die Sensitivität in Bezug auf eine Veränderung dieser Parameter untersucht.

Wir können die Ergebnisse folgendermaßen zusammenfassen: Die Tendenz des Modells, Staaten zu größeren Einheiten zusammenzuschließen, erweist sich als sehr robust gegenüber einer Variation der Modellparameter. Weiterhin ist festzuhalten, dass ein größere Anzahl an Konfiguration so gut wie keine staatenbildende Dynamik entfaltet. Dies ist ein Hinweis darauf, dass die Parameterwerte nicht nur einen quantitativen, sondern auch einen qualitativen Effekt besitzen.

Die sich anschließende Forschungsfrage lautet daher, wie jene Konfiguration zu charakterisieren wären, die zur Staatenbildung führen und wie man diese von den anderen abgrenzen kann. Eng verbunden damit ist dann die Frage, inwieweit diese Eigenschaften der Modellkonfigurationen in Bezug auf die Empirie zu deuten wären.

Schlagworte: Social Simulation, Emergent Polarity Model, Meta-Analyse

Abstract: In this contribution we analyse the prominent *Emergent Polarity Model* (EPM) by Eric Cederman from a meta perspective. We vary the model's "magic" numbers over a wide range of plausible values to obtain concrete model instances of the EPM. Then we studied the sensitivity of the simulation dynamics with respect to variation of these configuration settings.

We can cautiously summarise these results as follows: The model's tendency to decrease the number of states in the long run is quite robust against variation of configurations. But on the other hand one can see that a majority of configurations tends to produce no nation development process at all: The number of states does not decrease significantly. Therefore, we obtain clear evidence that not all configurations lead to nation building while others do.

The subsequent research question that now arises is whether we can characterise those configurations that lead to nation building. And, assuming that we can identify coditions that separate these "effective" configurations from "ineffective" ones, we ask wehether these conditions can be interpreted with respect to empirics.

Keywords: Social Simulation, Emergent Polarity Model, Meta-Analysis

[1]Working Paper. (May 21, 2019)
Corresponding author: `michael.koehler-bussmeier@haw-hamburg.de`

1 Introduction

Simulation has been established as research area within the social science, at least as a complementary methodology. The very early beginnings have their origin in the 1970's, among them the Club of Rome studies of the world economy or Schelling's model for ethnic residential segregation to name only some (For an in-depth presentation of the historical development we refer to Gilbert and Troitzsch, 1999). Maybe the shift from e.g. differential equations to agent based models (the work of Epstein and Axtell, 1996 has to valued here) has popularised the approach for a broader audience.

Social models in combinations with nowadays computers allow for experiments that are out of reach for social scientist as one can set up artificial scenarios, test the consequences of different regulatory measures etc. We refer to (Edmonds and Meyer, 2013) for a in-depth presentation of simulating social complexity.

While the potential is clearly high there has been a long on-going debate about the scientific nature of simulation in general and the the status of models in particular. We come back to this point later in more detail, but some of the critics goes into the direction: "The model has too many arbitrary design choices and the model's predictions are too abstract and therefore hard to compare with empirical observations." One may argue that some critics is rather unfair, because even the simplest model exhibit a behaviour that is beyond the scope of a pure Gedankenexperiment. This is for example the case when we step away from dyadic interactions to situations with more actors that interact. But maybe the critics origins from the fact that simulation is no longer descriptive per se, but comes with a claim to predict and, even worse, to explain. Maybe this imposes too great demands on the preciseness of simulation outcomes, since it places social simulation right besides the mathematical models of science.

We like to take a pragmatic position here: A model is interesting whenever it likely captures a key feature of reality. The natural question, which immediately arises, is how we can measure this quality aspect of a model?

2 The Nature of Models: Black-Box vs White-Box

The pragmatic position taken here: *"A model is interesting whenever it likely captures a key feature of reality, e.g. one underlying mechanism."* seems a quite humble position, but it poses quite a challenge, which is hidden in the small word "likely". How can we gain confidence that our model really captures a key mechanism? The first obvious answer might be to compare the predictions to empirical data and then let statistics take over. From a scientific point of view this is a black-box position since we consider all models that are, more or less, in accordance with reality as equivalent to each other. Maybe Occam's razor helps us to rule out some of them (i.e. those models that contain more complicated assumptions); but besides this we do not judge on models.

From a philosophical point of view this seems to be neat and clean, but we argue that this way of thinking about models has a blind spot: Even the simplest models tend to have several parameters. We find them in formulations like “Whenever the internal state value x of the agent is *twice* as high as all the x-values of his neighbours, then he performs action a.” The nature of these parameters is ambivalent: On the one hand one needs them to calibrate the behaviour of model such that it becomes “near” to reality; but on the other hand the model might suffer from over-fitting, whenever the parameter space is huge enough to approximate almost any desired behaviour. The most extrem situation arises whenever the model shows the expected behaviour for a certain parameter value (the *magic* number) but a quite different one for other choices. Then our observation is – most likely – a pure artefact and its explanatory value typically tends to zero.

Of course the problem is not a new one and checking simulations is a common task (cf. Galán et al., 2013). But there is one point we like to emphasise here: The development process of a model involves at least three different roles: the domain expert, the modeller, and the programmer. In the first phase the domain expert and the modeller have to transfer aspects of the social setting into a (semi-)formal model; in the second phase the modeller interacts with the programmer to obtain an operational version of the model. Of course, both phases have a risk for errors and misunderstandings, but in our perception the literature concentrates more on the second relationship: To ensure a high quality of the operational version this phase adopts best-practices from software engineering, like verification and testing. But, the first relationship is much more subtle. One of us, Michael Köhler-Bußmeier, has a background in social modelling: *Socionics*. One of the central aims of this research program (run as a DFG-SPP from 1999 till 2006; cf. v. Lüde et al., 2003, 2009) was to incorporate social theory in multi-agent systems to improve their scalability, i.e. agent-systems should inherit beneficial mechanism of social systems to cope with a great number of agents having to coordinate within a changing environment. While this idea seems to be quite convincing at first sight the research soon realised that there is quite a gap between *the* social theory (whatever this might be) and a model capturing the concepts in a way that is appropriate for an incorporation within agent systems. This gap always imposes a temptation for the modeller to fill this gap by bridging (or even ad-hoc) concepts, which opens the door wide for the criticism of arbitrariness; and even worse this might be the source of artefacts as we have discussed above. Unfortunately in many cases the domain expert is not of much help in this situation, since it is usually unclear from the domain point of view how an “good” or appropriate bridging concept looks like; or the domain expert cannot oversee the subtle differences of expressing it – or both.

Maybe we should have not formulated the situation in such a negative manner: It is rather not a deficit that the first phase fills the gap between description and the model; quite the contrary – this is of the main purposes why one builds a model. It is a kind of hypothesis test. But of course we have to control that the new bridging elements do not a constitute a new theory on its own superposing – or even dominating – the “real” dynamics of model.

In the following we discuss how this evaluation can be undertaken and, even better, how the this evaluation can be lead to fruitful discussions and insight for the domain expert.

3 Meta-Analysis of Models

In principle we demand for a comparison of different models with respect to their design choices. When taking the black-box view on models this is of course not possible.

From an abstract point of view we like to compare a model M with a competing model M'. We might assume that whenever the models are similar[1] (i.e. the bridging concepts are similar) also the simulated dynamics when starting in the initial state x_0 – denoted $\mathcal{D}(M, x_0)$ – is similar. In other terms: We expect a continuity (in the mathematical sense) of the behaviour with respect to the modelling decisions. Putting it into formal notation, we expect:

$$M \approx M' \quad \text{implies} \quad \mathcal{D}(M, x_0) \approx \mathcal{D}(M', x_0) \tag{1}$$

This expresses the fact that our model is robust with respect to our design choices, since similar choices have similar dynamics. This kind of robustness indicates that we really capture the essence of a mechanism and not producing an artefact which relies on a fragile combination of magic numbers, i.e. the worst-case scenario for a researcher since it completely spoils any conclusion drawn from the model.

A note on our notion of robustness for those familiar with mathematical analysis of model dynamics, especially its phase space. Our notion of robustness is a concept on the *meta-level* since it compares different models, while typical concepts of robustness aim at different initial configurations x_0. The difference can easily be identified using the formal notation where "normal" robustness could be formulated as follows

$$x_0 \approx x_0' \quad \text{implies} \quad \mathcal{D}(M, x_0) \approx \mathcal{D}(M, x_0') \tag{2}$$

In other words we are using different spaces: Normal robustness compares different initial states of the same model, while meta-robustness compares different models. The problem to analyse meta-robustness seems to be far more complex than the normal one since the space of all possible seems to be less accessible when compared to the space of initial configurations.

3.1 Meta-Models, Parametrised Models

The mathematically inclined reader might wonder whether the similar definition of robustness and meta-robustness allow for similar analytical techniques. To give an answer we have to first observe that the dynamics $\mathcal{D}(M, x_0)$ depends on two quite different arguments. While a configuration x_0 is usually from $\mathbb{R}^n$, i.e. a n-tuple of numbers, the structure of all models M is not that nicely structured. This difference directly leads to fact, that similarity of configuration can be easily formalised (e.g. as the euclidean distance), while this does not hold for similarity between models.

We formalise model distances the following way. First, we make the assumption that all design alternatives can be expressed in such a way that they are

[1] Let us postpone the problem how to express a distance between models for the moment.

instances of a generic design. Of course this meta-model has to be quite generic. Consequently, the complete model M is a instance of generic model $\mathcal{M}$ that is parametrised with the meta-configuration of parameters α – which is typically a tuple of numbers:

$$M = \mathcal{M}(\alpha)$$

Since there is a one-to-one correspondence between meta configuration α and the model induced $\mathcal{M}(\alpha)$, we even consider α as a model whenever $\mathcal{M}$ is fixed.

As a first benefit the definition of model similarity comes almost for free: We can use this meta-model $\mathcal{M}$ to express the similarity of models (i.e. $M \approx M'$) as the similarity of meta-configurations of parameters α. For $M_i = \mathcal{M}(\alpha_i), i = 1, 2$ we define:

$$M_1 \approx M_2 \text{ if and only if } \alpha_1 \approx \alpha_2 \tag{3}$$

Since $\mathcal{M}(\alpha)$ is a normal model it could be equipped with an initial configuration x_0:

$$\mathcal{M}(\alpha; x_0) := (\mathcal{M}(\alpha))(x_0) \tag{4}$$

This notion expresses the fact that α and x_0 are on different levels, but technically they act as variable parts of the meta-model $\mathcal{M}$.

Using these meta-level notions our definition of meta-robustness in (1) could be reformulated as follows in a conceptual very simple way. A model is *robust with respect to modelling decisions* whenever the following holds:

$$\alpha \approx \alpha' \quad \text{implies} \quad \mathcal{D}(\mathcal{M}(\alpha; x_0)) \approx \mathcal{D}(\mathcal{M}(\alpha'; x_0)) \tag{5}$$

Sometimes it is interesting to ask about the oposite implication, i.e. the question whether similar dynamics can be traced back to similar configurations α. But, in general, this would hold only for very simple models.

3.2 Cluster Analysis of the Meta-Space

It remains to reflect on the notion of similar dynamics, i.e. situations where $\mathcal{D}(M_1, x_0) \approx \mathcal{D}(M_2, x_0)$. We try to avoid to represent the whole dynamics as a function over time. Instead, we assume that the dynamics can be understood by *indicator values*, which have to be chosen by the modeller. Then, a simulation can be understood by its "foot print", the tuple of all indicator values X, which is a value from $\mathbb{R}^n$ for some n. In this case we can describe similarity of dynamics by e.g. the euclidean distance of indicator variables.

Figure 1 shows an visualisation of this idea for $n = 2$ indicator variables. Therefore, each simulation run is characterised by a point in the two-dimensional plane. From a first look one can hypothesise that the simulation exhibits two classes of behaviour: one that is characterised by indicator values roughly around the point $c_1 = (0.2, 0.25)$ (i.e. the lower left cluster) and another one that is characterised by indicator value around $c_2 = (0.6, 0.7)$ (i.e. the upper right cluster). We find that the pure existence of different classes of behaviour that can be observed by a variation on the design configurations α provides a meaningful insight, which leas us to the next section.

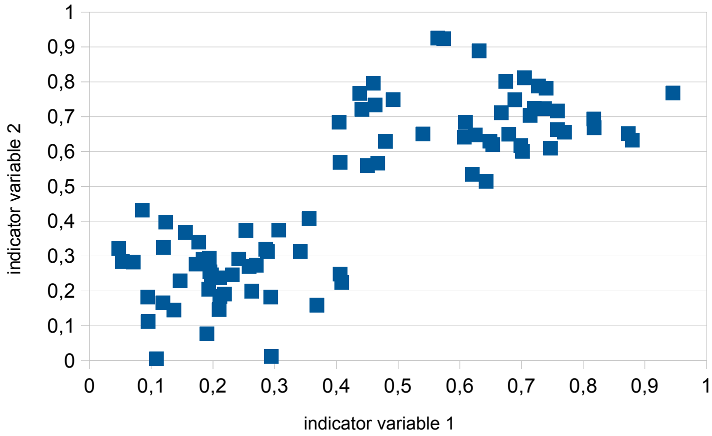

Figure 1: Plotting Simulations in the Indicator Value Plane

Up to now we have been interested in robustness of a model $\mathcal{M}(\alpha; x_0)$ when varying its design decisions, which are expressed by α. Our motivation was the heuristics that a robust model does not produces artefacts and therefore likely captures the essence of the mechanism under consideration.

But usually a model is only robust *locally* around a configuration α, i.e. there is a locality around α_1 and also locality around another α_2 where both systems are robust, but their dynamics $\mathcal{D}(\mathcal{M}(\alpha_i; x_0))$ might be quite different. Identifying these clusters of configurations with similar behaviour can be done with approaches from the area of machine learning (cf. James et al., 2013).

Whenever this happens it shows that our model is very interesting from an epistemic point of view. Assume the following: The model is quite robust locally around α. It exhibits a dynamics $\mathcal{D}(\mathcal{M}(\alpha; x_0))$ that is more or less assumed by the domain expert. But for another configuration α' the dynamics $\mathcal{D}(\mathcal{M}(\alpha'; x_0))$ is unexpected. This unexpectedness is *wonderful* situation as it shows that even the domain expert does not understands the system being modelled completely. At this point knowledge "flows" from the modeller to the domain expert, while, normally, knowledge is transferred from domain expert to the modeller. Thus, modelling provides a real benefit for the domain expert.

This kind of scientific approach has to identify clusters of parameters each having a similar dynamics, but being different from the others. Along with this comes the question about the borderlines between the clusters, as they indicate critical configurations, i.e. tipping points. The knowledge about the tipping point is essential when modelling has the purpose to give advise e.g. to political decision makers. In this case decision makers can try to directly influence the "rules of the game" (i.e. the α) to direct the system into a different cluster.[2]

[2] Note, that our setting does not supports a change of the configuration α. Therefore, the actions taken to modify α have to be part of a more general model. We do not deepen this aspect here.

4 Case Study

After setting out the conceptual background of our approach we like to present a model that acts as our show case. We have chosen the prominent *Emergent Polarity Model (EPM)* by Cederman (1997), a model that aims at explaining how states and nations develop and dissolve.[3] This model is well-known in the community. The model encompasses several aspects, like resources, aggression types etc. with a non-trivial rule set. It is therefore not that clear what kind of dynamics has to be expected by the simulation. Of course, many design decisions of the operationalisation can be questioned. But the central point is whether these decisions affect the behaviour in general.[4] This general problem has also been discussed by its author himself: "Parameter sensitivity poses the most serious threat to cas-based research. [...] [T]he Achilles' heel of fragile results remains, but its consequences can fortunately be mitigated." (Cederman, 1997, p.64)

4.1 The Emergent Polarity Model (EPM)

We assume that the reader is aware of the general setting of the Emergent Polarity Model (EPM) and recall the model very briefly (Cederman, 1997, p.64ff).

The actors of the EPM are located on a 10×10 chess board. Each actor communicates only with its direct neighbours. Each state starts on one square only (its capital city). At the beginning of the simulation each state is assigned an amount of resources (on average 50 units with a variation of ± 20). Each actor is either of type *predator* or of type *prey*. Actors of type predator will attack its neighbour whenever it feels superior, i.e. when the ration of resources is greater than a constant (in the EPM this constant equals 3). Such a power struggle is resource intensive for both: attacker and defender. The actor that possesses more resources emerges victorious from the conflict. The inferior actor looses the square under attack. The superior actor usurps this square as a new province.

Each simulation last a fixed number of rounds. Each round is divided into three parts:

1. Decision making: A state decides how to interact with its neighbours. It can either decide to *cooperate* (C) or to *defect* (D). Actors of *prey* type simply recall the oponents decision from the last round, while *predators* may attack with a certain probability without a provocation whenever it is not already involved in warfare on another front and it feels superior.

   Whenever a neighbour cooperators its *trust level* increases.

[3] As the title "Emergent Actors in World Politics: How States and Nations Develop and Dissolve" indicates.

[4] This also has been noted in a review of the EPM: "The general question [...] regarding modelling is one of robustness - might slight changes to the model of no apparent substantive importance greatly change the observed dynamics? This is particularly a concern where there are assumptions embedded in operational decisions regarding the simulation." (Lazer, 2001)

config ID	trust threshold	threat threshold	win. res. prop.	attack threshold	init. res.	mean harvest	dev. init. res.	dev. harvest	battle cost	predator rate	prob. attack	tax rate	tax discount
6336	3	17	1,4	73	83	15	7	7	28	73	15	0,31	0,13
17927	2	2	3,7	43	189	18	5	5	151	41	26	0,91	0,73
15529765	12	17	1,3	30	158	25	6	6	109	68	78	0,41	0,86
18182668	12	14	2,6	20	56	15	12	12	34	43	71	0,48	0,47
24101181	19	4	4,8	130	200	5	4	4	172	85	98	0,63	0,15
30097265	5	1	3,3	154	39	16	15	15	30	52	33	0,8	0,27
35326272	21	12	4,4	40	99	17	1	1	59	98	50	0,08	0,19
35988309	22	22	3,6	176	112	58	14	14	106	99	16	0,62	0,19
42452505	19	35	1,1	172	50	7	12	12	6	7	68	0,71	0,69
43089389	14	23	2,2	190	116	44	3	3	110	51	74	0,96	0,83
45887614	7	11	2,2	114	57	71	54	54	2	4	36	0,11	0,36
64605810	5	7	1,8	33	169	19	0	0	167	30	57	0,81	0,6
72832996	23	19	1,1	70	173	34	13	13	23	58	71	0,18	0,35
74828086	4	16	2,3	30	20	63	42	42	8	62	87	0,82	0,19
76180605	12	21	2,9	108	15	165	33	33	10	18	57	0,98	0,94
78506875	7	11	2,4	167	95	25	12	12	0	11	73	0,22	0,84
80307340	21	17	1,7	120	140	120	80	80	67	3	75	0,6	0,66
84774681	4	9	4,4	23	171	21	14	14	110	71	45	0,72	0,97
88954901	7	3	4,1	141	195	58	20	20	166	21	92	0,85	0,81
93950730	16	19	1,1	207	53	7	7	7	9	5	70	0,63	0,72
95808906	23	8	2,2	68	69	38	27	27	37	82	47	0,55	0,81
96388395	12	22	2,8	58	183	59	29	29	130	67	70	0,49	0,46
99822714	3	25	3,9	128	91	6	2	2	38	61	90	0,61	0,31

Table 1: Some Configurations α used for the Models $M = \mathcal{M}(\alpha)$

2. Resource assignment ("harvest"): Depending on the interaction constellation (which is of one of the four types: *C*-*C*, *C*-*D*, *D*-*C* or *D*-*D*) resources are assigned. Conflicts destroy resources.

3. In the attack phase squares are conquered. If the square is only a province it is transferred to the superior actor. If the target square is the capital the state collapses. Whenever a transfer results in separation of the territory the separated squares evolve into independent states.

A state may decide to join a strategic alliance. If two or more actors feel threatened by the same predator (i.e. an actor with a low trust level) they automatically form an alliance. The alliance lasts as long as the threat lasts. All members are obligated to bestead an attacked allied. Since a predator compares its resources against the sum of all resources within the alliance, the likelihood of an attack decreases.

4.2 The EPM Meta-Model and its Analysis

Thanks to the kind support of Erik Cederman we obtained a hard-copy of almost all the model's original source code. One of us, Alena Störmer, undertook a careful reverse engineering of the original code, written in Pascal, and reimplemented it completely from scratch using Python, a language much more common in the machine learning context.

One of the main objectives of the redesign was to start the model with a parametrisation, i.e. we have a meta-model $\mathcal{M}$ that is instantiated with concrete parameters α to obtain a concrete model $M = \mathcal{M}(\alpha)$.[5]

The EPM already has a huge number of these tuneable parameters:

1. Thrust threshold: the level at which trust is established between actors

[5] In our first case study we keep the model's rules fix; only some of its "magic numbers" are varied. A much more elaborated meta-model may also vary the rules of the game as well.

2. Threat threshold: the level at an actors feels threatened by another actors
3. Winning resource proportions: the ratio of resources that is sufficient for the attacker to win.
4. Attack threshold: the ratio of resources that leads to an attack decision of a predator
5. Initial resources: units of initial resources assigned to states
6. Deviation initial resources: deviation from the average above
7. Mean harvest: average number of resource units that are assigned in each round
8. Deviation harvest: deviation from the average number of resource
9. Battle costs: The units of resources a conflict imposes on both sides
10. Predator rate: The number of predator states among all states
11. Probability of Attack: The probability that a predator decides to attack.
12. Taxation rate: the tax rate for provinces
13. Taxation discount: the discount a province receives for greater distance to the capital

Each parameter is assigned to a random number chosen from an reasonable range. The table in Figure 1 lists some of our randomly generated configurations α. All in all, we generated $n = 110$ different meta-configuration α for our experiment at random.

To measure similarity in the runs, i.e. the dynamics $\mathcal{D}(\mathcal{M}(\alpha; x_0))$, we use two indicator values as characteristics $X = X(\mathcal{D}(\mathcal{M}(\alpha; x_0)))$:

1. the number of power struggles and
2. the number of states at the end of the simulation.

Therefore, each simulation dynamics is represented as point in $\mathbb{R}^2$. We simulated the model $\mathcal{M}(\alpha; x_0)$ for each α several times to obtain more reliable values for our indicator variables X. (Here we used 10 simulation runs for each α.)

Figure 2 (a) shows the results of our meta-simulation experiment. Figure 2 (b) shows essentially the same data but plots also the variance margins of the indicator variables.

As a result of our Meta-Analysis of the EPM we observe, that the data reveals a negative linear correlation of the number of power struggles and the number of states at the end of the simulation, i.e. whenever one doubles the number of power struggles the number of states at the end of the simulation is halved. This result seems to be quite robust over a variation of different configuration parameters α as we cannot observe any clustering here – at least not for the indicator space under consideration in this presentation.

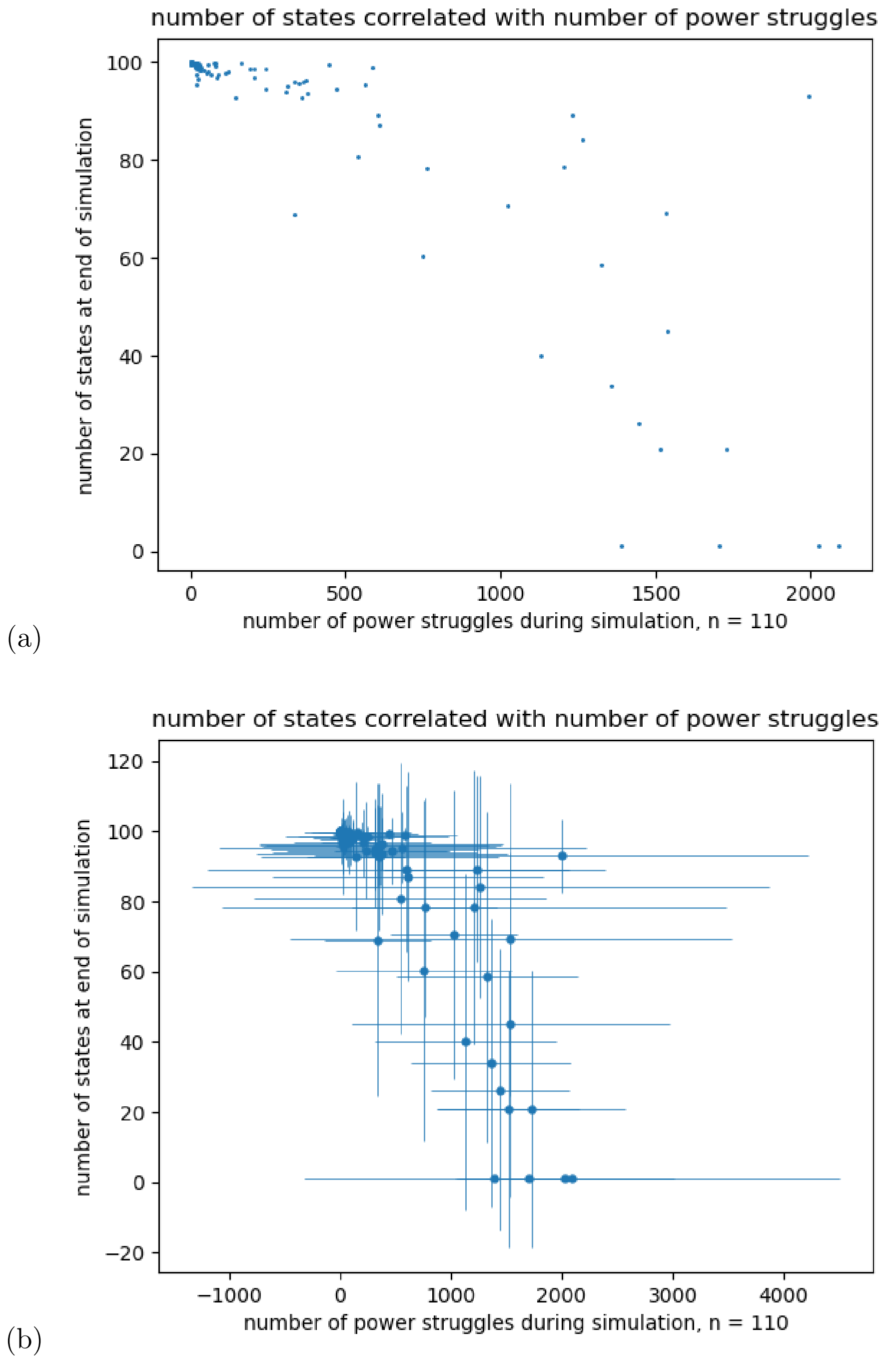

Figure 2: Plot of the Simulation within the two-dimensional charateristics-plane (a) without and (b) with variance margins

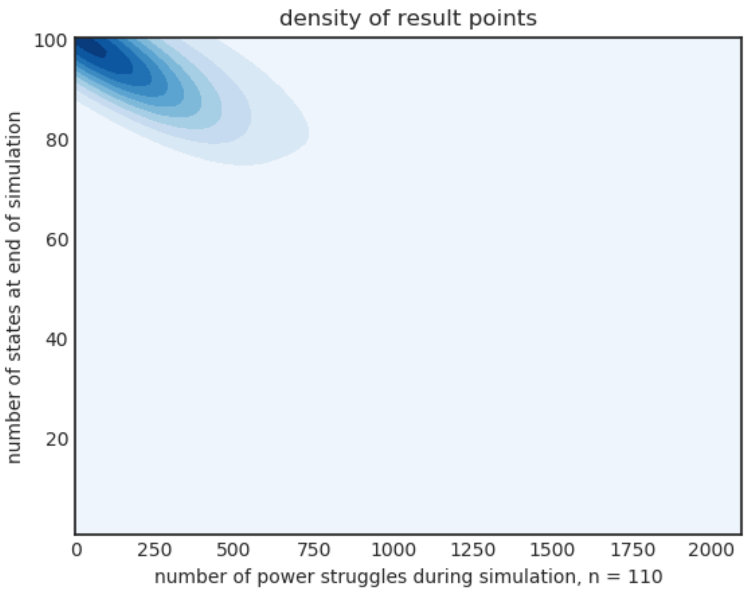

Figure 3: Density Map of the Simulations

In an ex-post analysis this result is plausible: Whenever there are no power struggles at all (or almost none) the number of states remains constant; whenever there is a huge amount of these power struggles the states are likely to dissolve during the simulation.

There is another result: When considering the density map of the simulation results (given in Figure 3) one can additionally observe that a majority of $\approx 75\%$ of all simulations tends to be in the "upper-left corner", i.e. the number of states is stable (or decreases only slightly) till the end of the simulation for a wide range of values for the number of power struggles. Whenever all configurations α (i.e. the possible worlds) are equally likely, then the rise of empires is a quite unlikely process. On the other hand, since we do oberserve empires at rise, this means that we either live in a world with a configuration α that is non-representative for the set of all possibility (for reasons unknown at the moment), or not all configurations α are equally likely (also for unknown reasons).

Also this is plausible in an ex-post analysis: When there are many power struggles provinces are likely to be conquered. But, when we have many predators the provinces are conquered by other over and over again without building more complex states.

As a third result, we like to note, that similarity of configurations α is a sufficient condition for similar simulation dynamics $\mathcal{D}(\mathcal{M}(\alpha; x_0))$, but it is not a necessary condition: A closer look at the simulation data reveals that indicator values X that are very close to each other may belong to quite different models, i.e. quite different values for α. So similar values for α leads to similar dynamics $\mathcal{D}(\mathcal{M}(\alpha; x_0))$; but the whenever the dynamics $\mathcal{D}(\mathcal{M}(\alpha; x_0))$ is similar, it is not clear whether the configurations α are similar, too. The concrete reason for this is subject to current research.

5 Conclusion

In this contribution we analysed the prominent *Emergent Polarity Model* (EPM) from a meta perspective. As a first step, we varied the configuration parameters α – the model's "magic" numbers – over a wide range of plausible values to obtain concrete instances $\mathcal{M}(\alpha; x_0)$ of the EPM. Then we studied the sensitivity of the simulation dynamics $\mathcal{D}(\mathcal{M}(\alpha; x_0))$ with respect to a variation of α.

We can cautiously summarise these results as follows: The model tendency to decrease the number of states in the long run is quite robust against variation of configurations as we cannot observe separable clusters In the indicator variable plot. But on the other hand, one can see that a majority of configurations tend to produce no nation development process at all: The number of states does not decrease significantly. Therefore, we obtain evidence that not all configurations lead to nation building while others do.

The subsequent research questions that now arises is whether we can characterise those configurations α that lead to nation building. And, assuming that we can separate these "effective" configurations from those that aren't, we might ask, how these separation lines can be interepreted with respect to empirics?

References

Lars-Erik Cederman. *Emergent Actors in World Politics: How States and Nations Develop and Dissolve.* Princeton University Press, Princeton, NJ, 1997.

Bruce Edmonds and Ruth Meyer, editors. *Simulating Social Complexity: A Handbook.* Springer-Verlag, 2013.

Joshua M. Epstein and Robert L. Axtell. *Growing Artificial Societies: Social Science From The Bottom Up.* Brookings Institution Press MIT Press, 1996.

Josá M. Galán, Luis R. Izquierdo, Segismundo S. Izquierdo, José I. Santos, Ricardo del Olmo, and Adolfo López-Paredes. Checking simulations: Detecting and avoiding errors and artefacts. In Edmonds and Meyer (2013), chapter 7, pages 95–116.

Nigel Gilbert and Klaus G. Troitzsch. *Simulation for the social scientist.* Open University Press, 1999.

G. James, D. Witten, T. Hastie, and R. Tibshirani. *An Introduction to Statistical Learning.* Springer-Verlag, 2013.

David Lazer. Review of *Emergent Actors in World Politics: How States and Nations Develop. Journal of Artificial Societies and Social Simulation*, 4(2), 2001. URL `http://jasss.soc.surrey.ac.uk/4/2/reviews/lazer.html`.

R. v. Lüde, D. Moldt, R. Valk, M. Köhler, R. Langer, H. Rölke, and D. Spresny. *Sozionik: Modellierung soziologischer Theorie.* Wirtschaft – Arbeit – Technik. Lit-Verlag, Münster, 2003. URL `http://www.lit-verlag.de/isbn/3-8258-5980-0`.

Rolf v. Lüde, Daniel Moldt, and Rüdiger Valk, editors. *Selbstorganisation und Governance in künstlichen und sozialen Systemen*, volume 5 of *Wirtschaft – Arbeit – Technik. Perspektiven gesellschaftlichen Wandels.* Lit Verlag, Münster, 2009. URL `http://www.lit-verlag.de/isbn/3-8258-10057-3`.