Modelling paths of institutional change in organizations

Arne Petermann & Stefan Klaußner
Institute of Management, Freie Universität Berlin
arne.petermann@fu-berlin.de

Abstract

The role of institutional arrangements in organizations cannot be overestimated: *"Institutional change determines the development of social systems over time and thus is the key in the understanding of historic change. (…) The differences in economic performance over time depend heavily on how the institutions evolve." (North, 1990)*
Complementary effects and coordination effect are at the heart of positive feedback-loops that drive the process of institutional development. Path dependence theory suggests that under these conditions inefficient institutions may become locked-in, meaning that it is not possible to abandon them by action undertaken from within the system. The persistence of inefficient institutions over time can create a growing threat to an organization's viability.

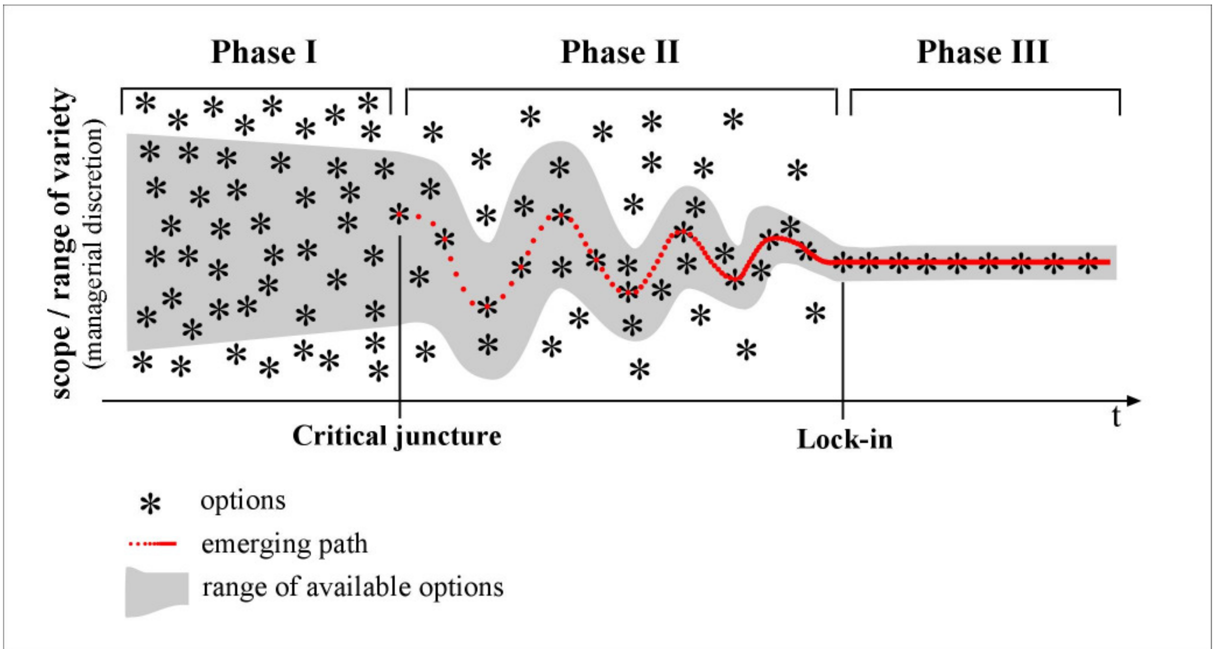
With the use of computer simulation, institutional change can be modelled as an interdependent multilevel-process. The results allow predictions of institutional long-term states of the system and the conditions, which may result in a lock-in situation. By varying the magnitude of the complementary effects and organizational design (hierarchy) as the two independent variables, the institutional evolution in social systems prone to increasing returns can be examined. The results add to both path dependence theory and the discussion about the choice of optimal organizational design.

Path dependence theory

As a dynamic theory path dependence theory basically assumes that initial decisions may increasingly restrain present and future choices. Paul David initiated the discussion on path dependence from an economic perspective (David 1985). Within his historical studies he explored the development of the QWERTY keyboard technology and describes how this inferior standard was diffused and maintained although superior technological innovations were available at some point. Similar studies were carried out by others on the technologically surprising dominance of inferior technologies (Cusumano et al. 1992, Katz & Shapiro 1986). As already noted, path dependence theory is basically based on the fact that history matters (Teece et al. 1997, Nooteboom 1997). Brian Arthur (1989, 1994) has formalized and to a minor extent also simulated path-dependent processes by highlighting the additional importance of self-reinforcing mechanisms.

From that perspective, path dependent processes are generally described as self reinforcing processes characterized by non-predictability, non-ergodicity, inflexibility, and potential inefficiency (Arthur 1989, 1990, David 2001, Pierson 2000). In other words, the path's final outcome among possible different alternatives is not predictable and might become a dysfunctional trap, inhibiting the organization to deviate from. So, path dependence is conceptualized as the outcome of a dynamic process that is ruled by one or more self-reinforcing mechanisms which lead to a narrowing of the variation and range of (managerial) discretion (Sydow, Schreyögg, & Koch, 2009). Path dependence describes a tapering process. Thus, a path constitutes a restriction of choice for a social or psychic decision-making system. While choice is not restricted to start with, it becomes restricted in the process of following that path. Figure 2 illustrates all three stages. The degree of path dependence increases with the duration of Phase II and is full-blown in Phase III (lock-in).

Fig. 1: The three stage model of path dependence (Sydow, Schreyögg & Koch, 2009)



The idea of self-reinforcing mechanisms implies a positive feedback. A self-reinforcing mechanism is a necessary precondition for what is defined as a path. That implies that agents act (consciously or unconsciously) upon these mechanisms and by doing so they reinforce the path-building effects. The diminishing variety and the increasing limitations of choices are collateral effects of this process. Hence, the hallmark of path dependence theory is its focus on self-reinforcing effects (Arthur 1994, David 1993, Bassanini & Dosi 2000). These effects are understood as the central triggering elements that drive path dependence (Sydow et al., 2009). Up to now, path dependency research has hallmarked the crucial elements that drive path emerging processes in phase II (see Figure 2) of the model which finally lead into a lock-in. At least six different forms of self-reinforcing mechanisms (Sydow, Schreyögg, & Koch, 2005) can be distinguished from a technological and from an institutional perspective: (1) economies of scale and scope, (2) direct and indirect network externalities, (3) learning effects, (4) adaptive expectations, (5) coordination effects and (6) complementary effects.

The first three mechanisms particularly apply to diffusion processes of technological standards. Economies of scale and scope refer to the market's supply-side and cost advantages due to production expansion as well as synergy effects of adjunctive product variety. Direct and indirect network externalities refer to the demand-side and cover the single agent's additional utility stemming from the technologies diffusion rate. Learning effects build on a rather individual level of the demand-side with illuminating experiences agents gain with their adoption of a specific technology. Learning effects also play an important role from an institutional perspective. Here the implementation and the repeated appliance of institutions lead to learning effects and the internalization of these institutions, resulting in deviation becoming less and less attractive. Adaptive expectations relate to the agents' interaction and their co-building of preferences. The more an agent expects others to prefer a particular product or standard, the more attractive it becomes.

From the institutional perspective of this paper the final two mechanisms are of most relevance. The coordination effect was introduced by North (1990) and refers to the general benefit of coordinated behavior. The more agents adopt a specific institution the more efficient the interaction among the agents becomes. In other words, shared rules contribute to the anticipation of other agents' behavior; reactions can be foreseen and uncertainty as well as coordination costs will be reduced. From the single adopter's point of view, it is attractive to adopt an institution while the attractiveness depends on the spreading of that institution. The well-known traffic-rule example illustrates this (Arthur 1994, 14): Imagine an island having roads but neither cars nor any traffic rule. Once cars are introduced, drivers have to decide for left-hand or right-hand driving in order to prevent unwanted collisions. Oncoming indifferent drivers coordinate their behavior, others accordingly adapt and at some point one alternative dominates the other one, with the obvious benefit of coordinated interaction.

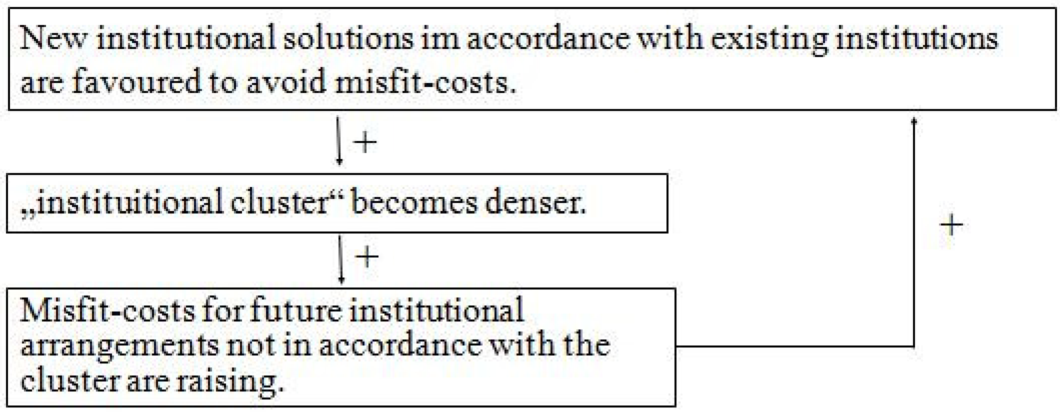
Complementarities result from plurality and connectivity between different institutions (Stieglitz & Heine 2007). Essentially, complementarities mean synergy resulting from the interaction of two or more separate and different institutions, the institutions' advantages do not just add up, there is a surplus based on the complementarity. In other words: an institution is reinforced by another one and vice versa. Referring to the traffic-rule example, introducing the institution of giving way at crossroads to drivers coming from the right reinforces right-hand driving.

At this point it should be stated that these effects can only be differentiated on an analytically level, empirically they are rather jointly at work rather than acting separately.

Conceptual argument of complementarity feedback

In our study we focus on one of the mechanisms: complementarity. Complementary effects form positive feedback loops that may pave the way for path dependence and lock-in. We adopt the understanding of David (1994) arguing that two (or more) institutions are complementary to one another when the existence (or more precise: a higher diffusion rate) of the focal institution makes the adoption of the other institution(s) more attractive for the relevant decision makers in the system and vice versa. David argues that in dynamic and complex environments new problems emerge all the time, creating the necessity of adopting new institutional solutions. In the process of finding, new institutional arrangements are able to solve the current problem; decision makers favour those institutions that are more compatible with already existing institutions over those which are less compatible. The main argument is the desire of decision makers to avoid so called misfit-costs. They include time and resources needed to solve conflicts resulting from the installation of less-compatible institutions. The tendency to avoid misfit-costs favours the emergence of a set of institutions that are highly compatible to each other (in the sense of having very low misfit-costs when existing together with the other institutions in the set). Such a set is called an institutional cluster (North 1990). Whenever a new institutional arrangement is highly compatible to the existing institutional cluster, the cluster becomes denser. This means that future misfit costs will significantly rise for institutions that are not compatible to the already established institutions in that cluster. Thereby chances increase for forthcoming institutional arrangements to be again in line with the institutional cluster – forming an even denser cluster. This conceptual argument of institutional complementarity is illustrated in figure 2.

Figure 2: conceptual argument of positive feedback created through complementary effects.



Because of the interdependency of the macro variables (density of the institutional cluster, diffusion rate of institutions) with the variable on the micro-level process (decision of members of the social system who adopt one institutional rule or the other), an analytical approach applying solely mathematical deduction is not promising, as the differential equations that describe the systems behaviour become intractable even with very restrictive assumptions and number of variables (see the work of Arthur et al. 1989). Davis et al. (2007) suggest a numerical solution when nonlinear, multilevel and longitudinal processes need to be modelled, and call for the application of computer simulations.

Computer simulations as scientific method

Besides logical deduction and empirical research computer simulations have become a third way of doing research in social sciences. When interdependencies between variables in complex and dynamic systems make the problem mathematically intractable, computer simulation offer a numerical solution to many problems. "Simulation is particularly useful when the theoretical focus is longitudinal, nonlinear, or processual, or when empirical data are challenging to obtain." (Davis et al, 2007) In simulation research a formal model is implemented into computer code and often run numerous times to uncover the system behaviour. When examining the development of institutions in organizations and disclosing path dependencies we face most of these difficulties. Thereby computer simulation seems a very promising method.

A Simple Model

In a simple Model we examine the process of institutional evolution in a multi-level, interdependent system. Our goal is to concentrate on the implications of complementary effects that trigger positive feedback loops. In the simple model we put aside the influence of organizational hierarchy which will be included later on in the advanced model.

We look at a very simple social system containing of a number of agents (i.e. 1000 agents), who decide to comply with one of two possible institutional solutions. In accordance with that simple traffic-rule example given above, the two institutional solutions are exclusive, meaning that they offer incongruous solutions to the same problem. In the simulation model colours are assigned to each solution, so for simplification it is possible to speak of a red and a blue institutional solution. The system contains of a set of agents while each agent has exactly one attribute which is the behaviour regarding the two contradicting institutional solutions red and blue. We applied a discrete timeline where time is counted in so called "ticks". For every tick, each agent decides whether he will realize the blue or red institutional solution. The decision function that defines the agent's decision is at the heart of the model. Driving from path dependence theory, random small events (David 1989, Arthur 1990) are present and potentially influencing the process with earlier occurring events being potentially more influential than later ones. Due to complementary feedback decision makers favour an institutional solution that is compatible to a denser cluster (David

1994). In the modelled system two institutional clusters exist, one containing the blue and one containing the red institution. (Note: Arthur (1989) showed analytically that in cases where the diffusion of only one technology respectively institution A enjoys positive feedback while the other one B does not, the domination of A is inevitable.) The independent variable is the magnitude of complementary feedback. The initial density of the two institutional clusters can be varied in different simulation runs. The results stated in this paper are obtained with equal initial density for each cluster at the beginning of each simulation run.

Implementation of simulation model

The formal model was implemented using netlogo 4.0 implementation environment. At every tick, all agents adopt red or blue behaviour according to the actual diffusion of institutional rules and the density of each cluster, taking into account the misfit costs arising from a choice that is incompatible to the denser cluster. The corresponding variables implemented in the simulation model are called 'pop-state' and 'complementarity'. 'pop-state' varies from -1 to 1 and shows whether agents actually favour the red institutional solution over the blue (pop-state < 0) or the blue institutional solution over the red (pop-state > 0). When 'pop-state' reaches the value of 1 (-1), the corresponding system behaviour shows a diffusion rate of 100% of the blue (red) institution, meaning that all individuals have fallen in line with the institutional solution compatible to the denser cluster. 'Complementarity' is the strength of the complementary feedback. It is the independent variable of the model. It regulates the impact of a higher diffusion rate of the focal institution on the institutional cluster's density. 'Complementarity' ranges from 0 to +1. A value of 0 means that an additional highly compatible institutional solution does not change the clusters density at all while a value of +1 means that an additional highly compatible institutional increases the clusters density dramatically. Also at every tick a random number is drawn for every agent, incorporating personal preferences and random small events into the decision process. In the netlogo implementation the corresponding variable is called 'random-number' which is a random number between 0 and +1. A value of close to 0 is associated with a very strong random tendency to choose red behaviour, A value close to 1 is associated with the very strong tendency to choose blue.

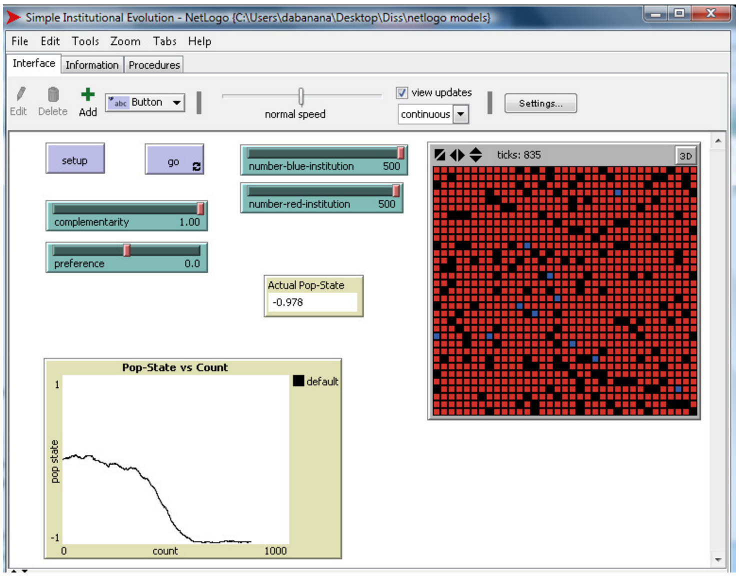
With every tick, one agent after another chooses to adopt the red or the blue institutional solution corresponding to the following decision rule:

*If random-number < exp (-(complementarity + a) * b * pop-state)*

choose the red solution otherwise choose the blue solution.

Note that a and b are parameters for scaling purposes only. Figure 3 shows the netlogo interface and a sample run of the simulation model.

Figure 3: sample run of the simulation model

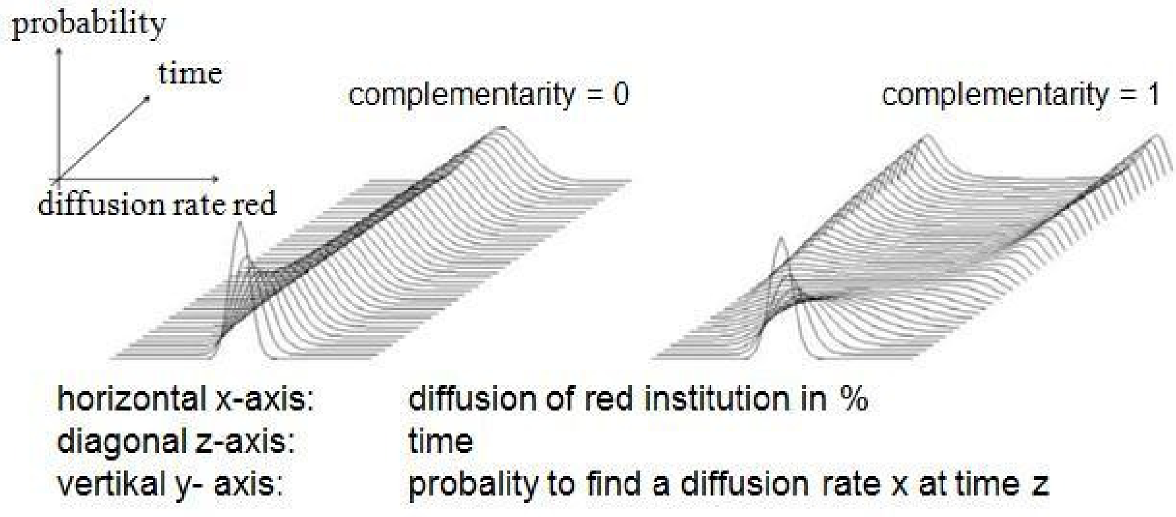


Results

Applying the Monte-Carlo method, the system behaviour can be examined over time for different degrees of complementary feedback strength. Figure 4 shows the results for complementarity = 0 and complementarity = +1. When complementarity equals 0, random small events govern the process. Because of 1.000 agents making simultaneous decisions every tick, the law of large numbers applies: In the long run both institutions persist with significant diffusion rates. Decision makers are not bound to a dominant behaviours rule but can choose dependent on their personal preferences and actual circumstances (small events).

In contrast if strong complementary feedback applies, the probability of finding a system with significant diffusion rates for both institutional solutions decreases with time, approaching zero in the long run. Dependent on the random small events governing the process in the early stage, one of the two institutional solutions becomes dominant and locked-in, being the only alternative for decision makers at some point.

Figure 4: Results of the simple model: high complementarity necessarily leads to a lock-in situation



The results shown in figure 4 are consistent with the results of Arthur's deductive analysis of positive feedback processes. With the applying of a computer simulation it was possible to model the process much more realistically and with less restrictive assumptions compared to Arthurs polya urn model (Arthur 1989).

Advancing the model: implementing organizational hierarchy

Path dependence theory is a market based approach (David 1985, Arthur 1989). The application to social systems like a firm is often criticized because a firm lacks some basic constituents of a market, especially the absence of power. While scholars of market-based approaches at least theoretically argue that total competition and the absence of power do exist, management scholars cannot neglect one of the fundamentals of a firm, which is the organizations structure that explicitly creates power inequalities. Thereby it seems necessary to include hierarchy into the model to address the fact that the organizational design might impact the evolutional diffusion processes of institutions (and technologies) within organizations.

In an attempt to embrace this argument, the notion of organizational hierarchy has been added to the simple model. A formal organizational structure is introduced by assigning a superior to every agent in the system. In the simple model, agents decide exclusively on the basis of small events and mis-fit costs arising from dense institutional clusters. Now a third variable influencing the individual decision making process is introduced, which is called 'hierarchyinfluence'. This variable includes explicit orders from superiors as well as more implicit elements, as individuals in organizations try to meet the expectations of their superiors. The individual's decisions are now dependent on random small events, complementary feedback *and* hierarchical influence of their superiors.

At every tick, one agent after another chooses to adopt rather the red or the blue institutional solution corresponding to the following decision rule:

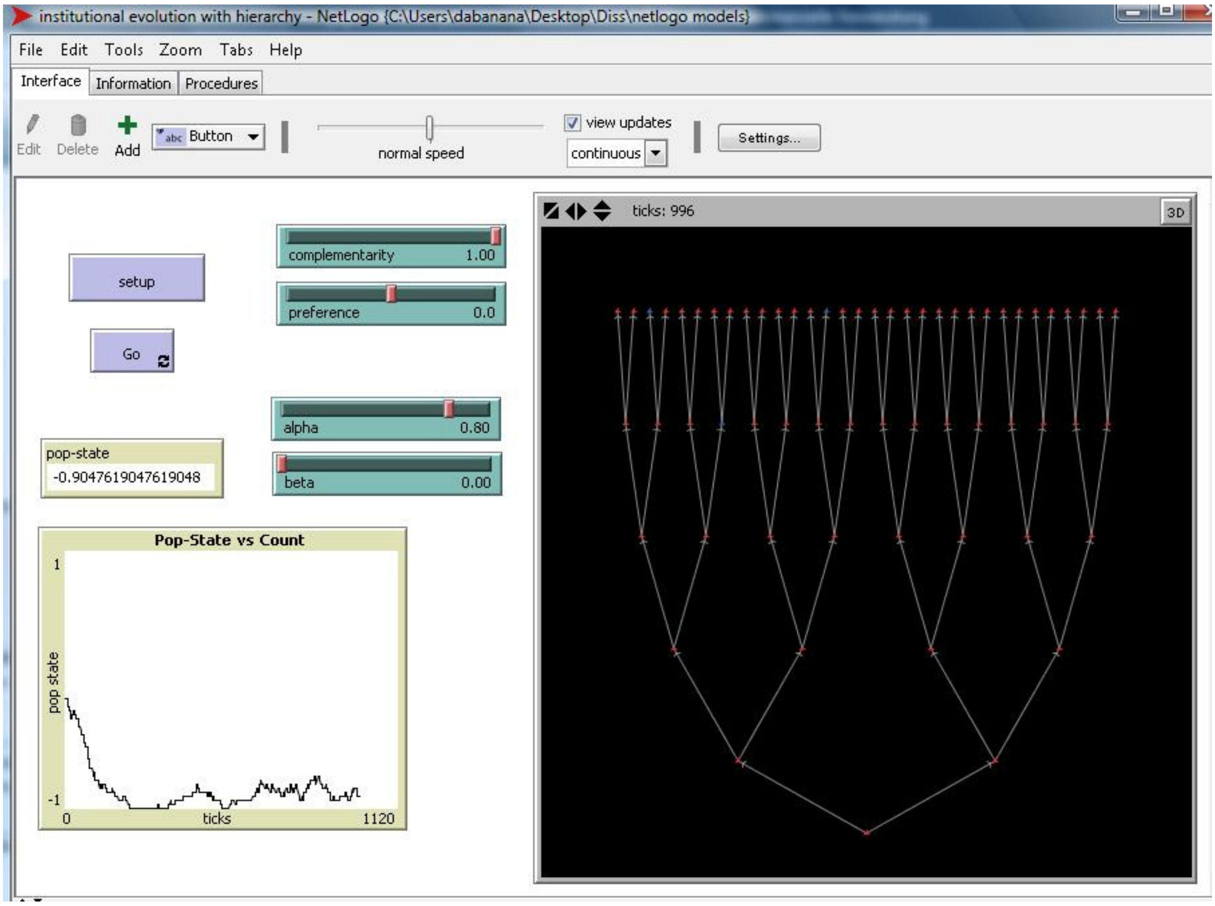
> *If random-number <*
> *exp (α * -(complementarity + a) * b * pop-state + β * hierarchyinfluence)*
> *then choose the red solution otherwise choose the blue solution.*

Note that a and b are parameters for scaling purposes only, and α is a weighting parameter between 0 and +1 and $\beta = (1- \alpha)$.

By varying the way of assigning superiors to agents different organizational designs can be modelled. According to Cohen et al (1972) typical organizational designs are the authoritarian, the hierarchical and the democratic design. In recent years the matrix organization has emerged as another important organizational design.

Advancing the simple model with the assigning of superiors who influence the decisions of their subordinates is our research agenda. A typical hierarchical organisational design has been implemented. The netlogo implementation is shown in figure 5.

Figure 5: Advanced model with hierarchical organizational design



Discussion and future research

We formally modelled the impact of complementarity effects in the process of institutional development. By means of computer simulation we formally validated the predictions made by scholars of path dependence theory about the importance of positive feedback in institutional evolution. Our model is much more sophisticated (i.e. agents can revoke their decision as time goes by) than the polya urn model introduced by Arthur (1989). The consistency of our results with Arthur's mathematical deduced solution to the polya urn model is a good means of validation for our work. In the near future results will be driven for different organizational designs. This approach enables us to clarify if and to what extend the predictions of path dependence theory hold when asymmetric power structures are incorporated in the observed system. The results may also give some insights to answer the questions, which organizational designs are more or less prone to the dangers of path dependence and lock-in. The results will thereby add to the ongoing discussion about optimal organization design.

References

Arthur, W. B. (1989): Competing technologies, increasing returns, and lock-in by historical events, in: Economic Journal 99 (394), 116-131.

Arthur, W. B. (1990): Positive feedbacks in the economy, in: Scientific American February, 80-85.

Arthur, W. B. (1994)(Hrsg.): Increasing returns and path dependency in the economy, Ann Arbor.

Bassanini, A. P./Dosi, G. (2000): Heterogeneous agents, complementarities, and diffusion. Do increasing returns imply convergence to international technological monopolies?, in: Dalli Gatti, D. (Hrsg.): Market structures, aggregation an heterogeneity, Berlin, New York, 185-206.

Cohen, M.D. /March, J.G.& Olsen, J.F. (1972): A Garbage Can Model of Organizational Choice, in: Administrative Science Quaterly, 17, 1-25.

Cusumano, M. A./Mylonadis, Y./Rosenbloom, R. S. (1992): Strategic maneuvering and mass-market dynamics: The triumph of VHS over Beta, in: Business History Review 66 (1), 51-94.

David, P. A. (1985): Clio and the economics of QWERTY, in: The American Economic Review 75 (2), 332-337.

David, P. A. (1993): Path-dependence and predictability in dynamic systems with local network externalities: A paradigm for historical economics, in: Foray, D./Freeman, C. (Hrsg.): Technology and the wealth of nations: The dynamics of constructed advantage, London, 208-231.

David, P. A. (2001): Path dependence, its critics and the quest for "historical economics", in: Garrouste, P. (Hrsg.): Evolution and path dependence in economic ideas: Past and present, Cheltenham UK und Northampton USA, 15-40.

Davis, J.P./Eisenhardt, K.M. & Bingham, C.B. (2007): Developing theory through simulation methods, in: Academy of Management Review, Vol. 32, 480–499.

Katz, M./Shapiro, C. (1986): Technology adoption in the presence of network externalties, in: Journal of Political Economy 94, 822-841.

Nooteboom, B. (1997): Path dependence of knowledge: Implications for the theory of the firm, in: Magnusson, L./Ottosson, J. (Hrsg.): Evolutionary economics and path dependence, Cheltenham, 57-78.

North, D. C. (1990): Institutions, institutional change and economic performance, Cambridge.

Pierson, P. (2000): Increasing returns, path dependence, and the study of politics, in: American Political Science Review 94 (2), 251-267.

Stieglitz, N./Heine, K. (2007): Innovations and the role of complementaries in a strategic theory of the firm, in: Strategic Management Journal 28 (1), 1-15.

Sydow, J./Schreyögg, G./Koch, J. (2009): Organizational Path Dependence: Opening the Black Bo, in: Academy of Management Review, 34 (forthcoming).

Teece, D. J./Pisano, G./Shuen, A. (1997): Dynamic capabilities and strategic management, in: Strategic Management Journal 18 (7), 509-533.

Appendix

A. Implemented netlogo 4.0 code for simple model

```
globals
[
  blue-count          ; population of blue turtles = 1
  red-count           ; population of red turtles = 0
  blue-fraction
  pop-state           ; fraction of blue agents
  frequency-ny        ; parameter which is of least interest
]

to setup
  clear-all
  ;; create turtles on random patches.
  set frequency-ny 0.005
  ask n-of (number-blue-institution + number-red-institution) patches
    [ sprout 1
      [ set color blue
      ]
    ]
  ;; turn part of the blue patches red
  ask n-of (number-red-institution) turtles
    [ set color red
    ]
  set blue-count number-blue-institution
  set red-count number-red-institution
  calc-pop-state
  clear-output
end

to go
  tick
  calc-opinions
  calc-pop-state
```

```
  plot-counts
end

to calc-opinions
  ask turtles
    [

      ifelse color = blue
      [
          let random-number random-float 1.0
          let pBlueToRed frequency-ny * (exp (-(preference + (complementarity + 0.5) *
1.5 * pop-state)))
          ifelse random-number < pBlueToRed
          [
            set color red
          ]
          [
            set color blue
          ]
      ]
      [
        let random-number random-float 1.0
        let pRedToBlue frequency-ny * (exp (preference + (complementarity + 0.5) * 1.5
* pop-state))
        ifelse random-number < pRedToBlue
        [
          set color blue
        ]
        [
          set color red
        ]
      ]
    ]
end
```

```
to calc-pop-state
  set blue-fraction count (turtles with [color = blue]) / count turtles
  set pop-state ((2 * blue-fraction) - 1)
end


to plot-counts
  set-current-plot "Pop-State vs Count"
  plot pop-state
end
```

B. Implemented netlogo 4.0 code for advanced model

```
;; every link breed must be declared as either directed or undirected
directed-link-breed [red-links red-link]
red-links-own [ weight ]  ;; link breeds can own variables just like turtle breeds
turtles-own [ number generation  ]

globals
[
  blue-count           ; population of blue turtles
  red-count            ; population of red turtles
  blue-fraction
  pop-state
  ; coupling           ; strength of coupling of the individuals to the majority
  ; preference           ; populationwide preference, preference=0: in the absence of
coupling there is no preference
  frequency-ny         ; frequency; parameter which is of least interest
  hierarchyinfluence
]
```

```
to setup
  clear-all
  create-turtles 1 [ set generation 0
    set xcor 0
    set ycor 5
    set color blue
    if random-float 1 > 0.5 [ set color red ]
  ]
  ask turtles [ givebirth ]
                                                ; show list count turtles " generated."
  set frequency-ny 0.005
  set hierarchyinfluence 1.0




end

to givebirth
  if generation > 4 [ stop ]
  let current-number 0
  let offset 1
  hatch 2 [
    set current-number current-number + 1
    set generation [ generation ] of myself + 1
                                                ; show ( list " I am " self " my father is "
myself " my generation is " generation ", " current-number )
    set color blue
    if random-float 1.0 > 0.5 [ set color red ]

    if generation = 1 [ set offset 16 ]
    if generation = 2 [ set offset 8 ]
    if generation = 3 [ set offset 4 ]
    if generation = 4 [ set offset 2 ]
```

```
    if current-number = 1 [ set xcor [ xcor ] of myself + offset ]
    if current-number = 2 [ set xcor [ xcor ] of myself - offset ]
    set ycor generation * 14
    create-red-link-from myself
    givebirth
  ]
end

to go
  tick
  ask turtles [ calc-opinions ]
  calc-pop-state
  plot-counts
end

to calc-opinions

   ifelse color = blue
      [
          let random-number random-float 1.0
          ifelse one-of in-link-neighbors = nobody
          [
            set hierarchyinfluence 0
          ]
          [
          ifelse [color] of one-of in-link-neighbors = blue [ set hierarchyinfluence 1 ] [
set hierarchyinfluence -1 ]
          ]

          let pBlueToRed frequency-ny * (exp (-( (1 - alpha - beta) * preference +
alpha * (complementarity + 0.5) * 1.5 * pop-state)) + beta * hierarchyinfluence )
          ifelse random-number < pBlueToRed
          [
            set color red
```

```
        ]
        [
          set color blue
        ]
      ]
      [
        let random-number random-float 1.0
        ifelse one-of in-link-neighbors = nobody
        [
          set hierarchyinfluence 0
        ]
        [
          ifelse [color] of one-of in-link-neighbors = red [ set hierarchyinfluence 1 ] [
set hierarchyinfluence -1 ]
        ]
        let pRedToBlue frequency-ny * (exp ((1 - alpha - beta) * preference + alpha *
(complementarity + 0.5) * 1.5 * pop-state) + beta * hierarchyinfluence)
        ifelse random-number < pRedToBlue
        [
          set color blue
        ]
        [
          set color red
        ]
      ]

end

to calc-pop-state
  set blue-fraction count (turtles with [color = blue]) / count turtles
  set pop-state ((2 * blue-fraction) - 1)
end
```

```
to plot-counts
  set-current-plot "Pop-State vs Count"
  plot pop-state
end
```