Systemic Risks in Society and Economics[1]

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Many large-scale disasters have a strong human component. They cannot be solved by technical approaches alone, but require an understanding of the collective social dynamics. This is maybe most obvious for financial crises, famines and other shortages of resources, epidemic spreading of diseases, wars and international terrorism, revolutions, or the collapse of trust and cooperation in societies. This contribution presents a summary of how complexity contributes to the emergence of systemic risks in socio-economic systems. It is highlighted that large-scale disasters are mostly based on cascading effects, which are due to non-linear and/or network interactions. Different classes of spreading phenomena are distinguished and illustrated by examples, including the financial market instability. Sources and drivers of systemic risks in socio-economic systems are analysed, and related governance issues are identified. Typical misunderstandings regarding the behaviour and functioning of socio-economic systems are addressed, and some current threats for the stability of social and economic systems are pointed out. It is shown that linear, experience-based, or intuitive approaches often fail to provide a suitable picture of the functioning of social and economic systems. This leads to the illusion of control and a dangerous logic of failure, which can lead to paradoxical system behaviours, unwanted side effects, and sudden regime shifts. The application of complex systems methods, however, allows one to anticipate, avoid, or mitigate systemic risks and certain disasters resulting from them. It even enables one to use the self-organising, adaptive nature of socio-economic systems to reach favourable system behaviours, which are robust to external perturbations and adaptive to changing conditions.

[1] This paper accompanies the IRGC report "The Emergence of Risks: Contributing Factors" and is part of phase 1of IRGC's project on Emerging Risks. More information can be found online at http://irgc.org/Project-Overview,219.html

I. Introduction

When studying systemic risks, i.e. risks that can trigger unexpected large-scale changes of a system or imply uncontrollable large-scale threats to it, scientific research has often focussed on natural disasters such as earthquakes, tsunamis, hurricanes, volcanic eruptions, or on failures of engineered systems such as blackouts of electric power grids or nuclear accidents (as in Chernobyl).

However, many major disasters affecting human societies relate to social problems [1–4]: This includes famines and other shortages of resources, wars, climate change, and epidemics, some of which are related to population density and population growth. Financial instabilities and economic crises are further examples of systemic risks.

Let us illustrate these risks with some numbers: World War I resulted in more than 15,000,000 victims, and World War II saw 60,000,000 fatalities. The latter generated costs of 1,000 billion 1944 US$ and destroyed 1710 cities, 70,000 villages, 31,850 industrial establishments, 40,000 miles of railroad, 40,000 hospitals, and 84,000 schools. Moreover, the world has seen many wars ever since. The current financial and economic crises triggered an estimated loss of 4-20 trillion US$.

Climate change is expected to cause natural disasters, conflicts over water, food and land, migration, social and political instability. The related reduction of the world gross domestic product is expected to amount to 0.6 trillion US$ per year or more. Turning our attention to epidemics, the Spanish flu caused 20-40 million deaths, and SARS triggered losses of 100 billion US$.

Considering these examples, one could in fact say “The major risks are social”, but they are still poorly understood. In fact, we know much more about the origin of the universe and about elementary particles than about the working of our socio-economic system. This situation must be urgently changed (see Sec. V).

It is obvious that mankind must be better prepared for the crises to come. A variety of factors is currently driving the world out of equilibrium. The following are largely related to the contributing factors ‘social dynamics’ and ‘technological advances’ outlined in the report ”Emerging Risks: Why they occur, Why They are Unpredictable and How to Prepare for Them” [155]: Population growth, climate change, globalisation, changes in the composition of populations, and the exploitation of natural resources are just some examples. The president of New York’s Columbia University, Lee C. Bollinger formulated the problem as follows: ”The forces affecting societies around the world ... are powerful and novel. The spread of global market systems ... [is] ... reshaping our world… raising profound questions. These questions call for the kinds of analyses and understandings that academic institutions are uniquely capable of providing. Too many policy failures are fundamentally failures of knowledge.”[5]

We certainly need to increase our capacity to gain a better understanding of socio-economic systems, conditions triggering instabilities, alternative system designs, ways to avoid or mitigate crises and the side effects of policy measures. This contribution will briefly summarise the current knowledge of how systemic risks emerge in society, and give a variety of relevant examples.

II. Socio-economic systems as complex systems

An important aspect of social and economic systems is that they are complex systems (see Fig. 1) [6–38]. Other examples of complex systems are turbulent fluids, traffic flows, large supply chains, or ecological systems. The commonality of complex systems is that they are characterised by a large number of interacting (mutually coupled) system elements (such as individuals, companies, countries, cars, etc.) [7, 39–49]. These interactions are usually non-linear (see Sec. II A). Typically, this implies a rich system behaviour [7]. In particular, the behaviour of such systems tends to be *dynamic* rather than static, and *probabilistic* rather than deterministic. As a consequence, complex systems can show surprising or even *paradoxical behaviours*. The slower-is-faster effect [50, 51], according to which delays can sometimes speed up the efficiency of transport systems, may serve as an example.

Moreover, complex systems are often very difficult to predict and control. While we are part of many complex systems (such as traffic flows, groups or crowds, 2 financial markets, and other socio-economic systems), our perception of them is mostly oversimplified [52, 53] or biased [54–56]. In fact, they challenge our established ways of thinking and are currently a nightmare for decision-makers [52]. The following subsections will explain these points in more detail.

Note that there are at least three different ways in which the term ‘complexity’ is used:

1. *Structural complexity* applies, for example, to a car, which is a complicated system made up of many parts. These parts, however, are constructed in a way that makes them behave in a deterministic and predictable way. Therefore, a car is relatively easy to control.
2. *Dynamic complexity* may be illustrated by freeway traffic. Here, the interaction of many independent driver-vehicle units with a largely autonomous behaviour can cause the self-organisation of different kinds of traffic jams, the occurrence of which is hard to predict (see Fig. 1).
3. *Algorithmic complexity* measures how the computer resources needed to simulate or optimize a system scale with system size.

This study focuses mainly on *dynamic* complexity.

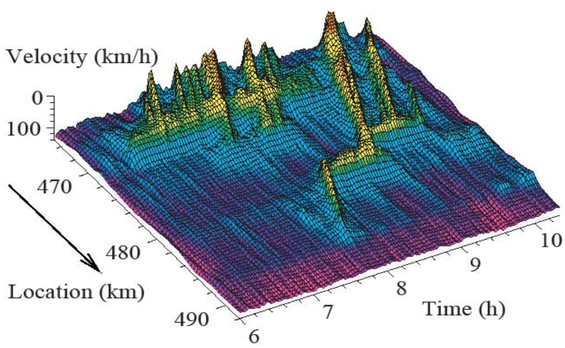

Figure 1: Freeway traffic constitutes a dynamically complex system, as it involves the interaction of many independent driver-vehicle units with a largely autonomous behaviour. Their interactions can lead to the self-organisation of different kinds of traffic jams, the occurrence of which is hard to predict (after [57]).

A. Non-Linear Interactions and Power Laws

Systems with complex system dynamics are mostly characterised by non-linear interactions among the elements or entities constituting the system (be it particles, objects, or individuals). Non-linear interactions are typical for systems in which elements mutually adapt to each other. That is, the elements are influenced by their environment, but at the same time, they also have an impact on their environment.

Non-linearity means that causes and effects are not proportional to each other. A typical case is a system that is quite un-responsive to control attempts, or which shows sudden regime shifts when a "tipping point" is crossed [58–63] (see Fig. 2). Examples for this are sudden changes in public opinion (e.g. from smoking-tolerance to smoking bans, from a pro- to an anti-war mood, from strict banking secrecy to transparency, or from buying pickup trucks to buying environmentally-friendly cars).

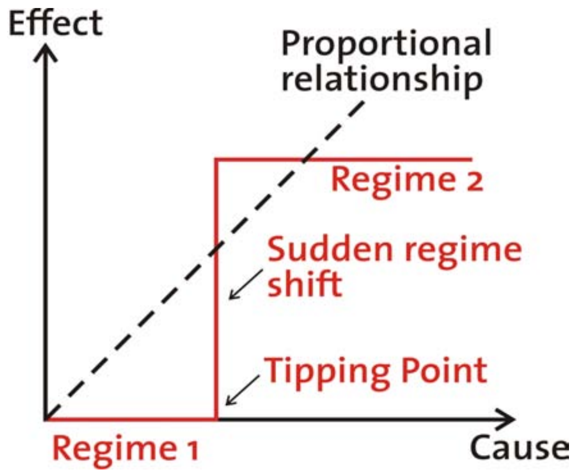

Figure 2: Schematic illustration of one of the typical behaviours of complex systems: In regimes 1 and 2, a "cause" (such as a control attempt) has essentially no effect on the system, while at the "tipping point", an abrupt (and often unexpected) transition to a different system behaviour occurs. A recent example is the sudden large-scale *erosion of Swiss banking secrecy*, after UBS handed over about 300 names of clients to a US authority.

B. Power Laws and Heavy-Tail Distributions

It is important to note that strong interactions among system elements often change the statistical distributions characterising their behaviour. Rather than normal distributions, one typically finds (truncated) "power laws" or, more generally, so-called heavy-tail distributions [48, 49, 58] (see Fig. 3 and Sec. IID). These imply that extreme events occur much more frequently than expected. For example, the crash of the stock market on Black Monday was a 35 sigma event (where sigma stands for the standard deviation of the Dow Jones Index on a logarithmic scale). Other examples are the size distributions of floods, storms, earth quakes, or wars [1–4]. Obviously, the occurrence of the respective heavy-tail distributions is highly important for the insurance business and for the risk assessment of financial derivatives.

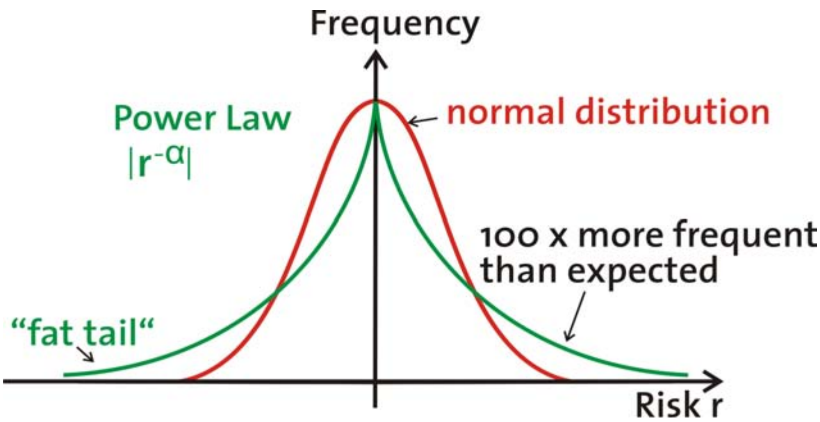

Figure 3: When system components interact strongly, the normally distributed behaviour of *separated* system elements often becomes (approximately) power-law distributed. As a consequence, fluctuations of any size can occur in the system, and extreme events are much more frequent than expected. Note that power laws are typical for a system at a critical point, also known as a "tipping point".

C. Network Interactions and Systemic Risks through Failure Cascades

A typical case of non-linear interactions are network interactions, which are ubiquitous in socio-economic systems [64–79]. These imply feedback loops and vicious circles or induce (often undesired) side effects [32]. (For example, the introduction of cigarette taxes has promoted smuggling and other criminal activities.) Moreover, network interactions are often the reason for a *cascade of failure events*. Examples for this are *the spread of epidemics*, the failure of the interbank market during a financial crisis, the spreading of *traffic congestion*, or the *blackout of an electrical power system* (see Fig. 4).

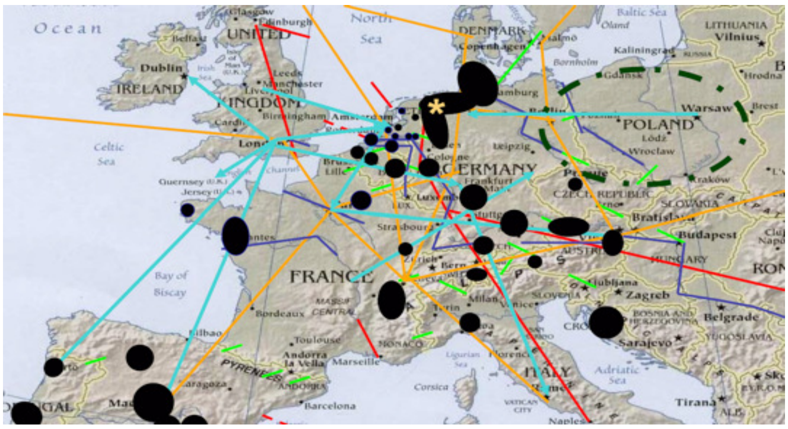

Figure 4: Example of a blackout of the electrical power grid in Europe (from: EU project IRRIIS. E. Liuf (2007) Critical Infrastructure protection, R&D view). To allow for the transfer of a ship, one power line had to be temporarily disconnected in Northern Germany. This triggered an overload-related cascading effect [80], during which many power lines went out of operation. As a consequence, there were blackouts all over Europe (see black areas). The pattern illustrates how counter-intuitive and difficult to predict the behaviour of complex systems with network interactions can be.

Failure cascades (which are also called chain reactions, avalanche or domino effects) are the most common mechanism by which local risks can become systemic [81–84] (see Fig. 5). Systemic failures are usually triggered by one of the following:

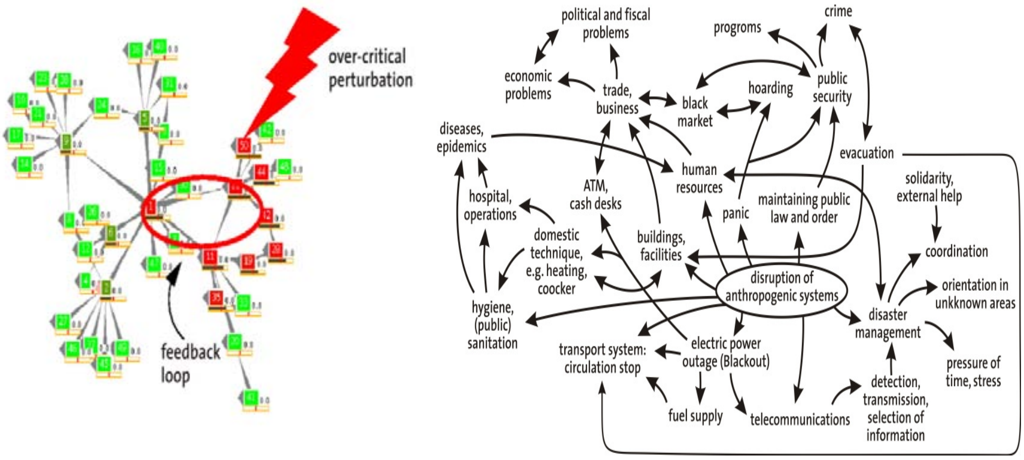

Figure 5: Top: Schematic illustration of a networked system which is hit by an over-critical perturbation (e.g. a natural disaster). The problem of feedback cycles is highlighted. They can have “autocatalytic” (escalation) effects and act like vicious circles. Bottom: Illustration of cascading effects in socio-economic systems, which may be triggered by the disruption (over-critical perturbation) of an anthropogenic system. A more detailed picture can be given for specific disasters. Note that the largest financial damage of most disasters is caused by such cascading effects, i.e. the systemic impact of an over-critical perturbation (after [85]).

1. The parameters determining system stability are driven towards a so-called “critical point” or “tipping point”, beyond which system behaviour becomes unstable (see Sec. II A). For example, the destabilisation of the former German Democratic Republic (GDR) triggered off spontaneous demonstrations in Leipzig, Germany, in 1989, which eventually caused the re-unification of Germany. This “peaceful revolution” shows that systemic instability does not necessarily imply systemic malfunctions. It can also induce a transition to a better and more robust system state after a transient transformation period. Further examples of spontaneous transitions by systemic destabilisation are discussed in Sections II D, III, and IV A.

2. The system is metastable (i.e. robust to small perturbations, which quickly disappear over time), but then an over-critical perturbation (such as a natural disaster) occurs, which harms the system functionality so much that this has damaging effects on other parts of the system [84] (see Fig. 6).

3. The system is metastable, but there is a coincidence of several perturbations in the network nodes or links such that their interaction happens to be over-critical and triggers additional failures in other parts of the system [83]. In fact, disasters caused by human error [86, 87] are often based on a combination of several errors. In networked systems, such occurrences are just a matter of time.

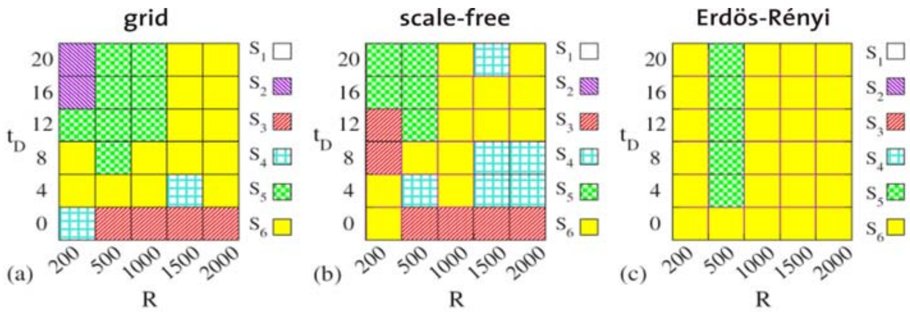

Figure 6: The most efficient disaster response strategy depends on many factors such as the network type (after [84]). Here, we have studied six different disaster response strategies for regular grids, scale-free networks, and Erdös-Rényi random networks. The best strategy is a function of the resources *R* available for disaster response management and the time delay t_D before practical measures are taken. Obviously, there is no single strategy that always performs well. This makes disaster response challenging, calling for scientific support.

D. Self-Organised or Self-Induced Criticality

A system may get into a critical state not only via external influences affecting its stability. It is known that some endogenous processes can *automatically* drive the system towards a critical state, where avalanche or cascading effects of arbitrary size appear (reflecting the characteristic heavy-tail statistics at critical points, see Sec. II B). In such cases, the occurence of extreme events is expected, and we speak of *"self-induced"* or *"self-organised criticality"* (SOC) [88, 89].

It is likely that *bankruptcy cascades* can be understood in this way. The underlying mechanism is that a company or bank tries to make a better offer to customers or clients than competing companies or banks. This forces the competitors to make better offers as well. Eventually, the profit margins in a free market become so small that variations in the consumption rate can drive some companies or banks out of business, which creates economic problems for other companies or banks. Considering the interconnections between different companies or banks, this mechanism can cause bankruptcy cascades. Eventually, the number of competitors will be smaller, and as a consequence, they can charge higher prices. Therefore, their profits go up, which encourages new competitors to enter the market. In this way, competition increases again and automatically drives the system back to low profits and bankruptcies.

Another example concerns *safety standards* [86, 87]. These are usually specified in such a way that normal perturbations would not cause serious harm or even systemic failures. As a consequence, most man-made systems are constructed in a way that makes them robust to small and moderate perturbations (in other words: metastable). However, the requirement of cost efficiency exerts pressure on decision-makers to restrict safety standards to what really appears to be needed, and not more. Consequently, if a large-scale failure has not occurred in a long time, decision-makers often conclude that the existing safety standards are higher than necessary and that there is some potential to reduce costs by decreasing them somewhat. Eventually, the standards are lowered so much that, sooner or later, an over-critical perturbation will occur, causing a systemic failure. As a consequence, the safety-standards will be increased again, and the process will start from the beginning.

As a third example, let us discuss man-made systems with capacity limits such as *traffic or logistics systems*. These systems are often driven towards maximum efficiency, i.e. full usage of their capacity. However, when reaching this point of maximum efficiency, they also reach a tipping point, at which the system becomes dynamically unstable [90]. This is known, for example, from freeway and railway traffic. As a consequence, the system suffers an unexpected *capacity drop due to optimisation efforts*, shortly after the maximum performance is reached.

Attempts to avoid the occurrence of congestion in urban traffic may use re-routing strategies. However, a closer analysis reveals that this optimisation leads once more to a sudden breakdown of the flow, once the maximum throughput is reached [91]. One may, therefore, conclude that optimising for the full usage of available system capacity implies the danger of an abrupt breakdown of the system performance with potentially very harmful consequences. To avoid this problem, one must know the capacity of the system and remain sufficiently clear of it. This can be done by requiring sufficient safety margins.

E. Limits of Predictability, Randomness, Turbulence and Chaos

A large number of non-linearly coupled system components can lead to *complex dynamics* (see Fig. 7). Well-known examples for this are the phenomena of *turbulence* [92] and *chaos* [42, 93], which make the dynamics of the system unpredictable after a certain time period. A typical example is weather forecasting.

This large sensitivity to small perturbations is sometimes called the *"butterfly effect"*, suggesting that (in a chaotically behaving system) the flight of a butterfly could significantly change the system behaviour after a sufficiently long time. A further obstacle for predicting the behaviour of many complex systems is a *probabilistic* or *stochastic dynamic* [94, 95], i.e. the importance of *randomness.*

In socio-economic systems, there is furthermore a tendency towards *self-fulfilling* or *self-destroying prophecy effects* [96] (and it is hard to say which effect will finally dominate, see the current response of the population to the swine flu campaign). *Stock markets* show both effects: On the one hand, the self-fulfilling prophecy effect leads to *herding behaviour*, which creates *bubbles* [97]. On the other hand, the competition for the highest possible returns eventually destroys any predictable gains (otherwise everybody could become rich without having to work, thereby creating a "financial perpetuum mobile"). Altogether, this competition creates a (more or less) "efficient" and unpredictable stock market. A generalisation of this principle is known as *Goodhart's law.*

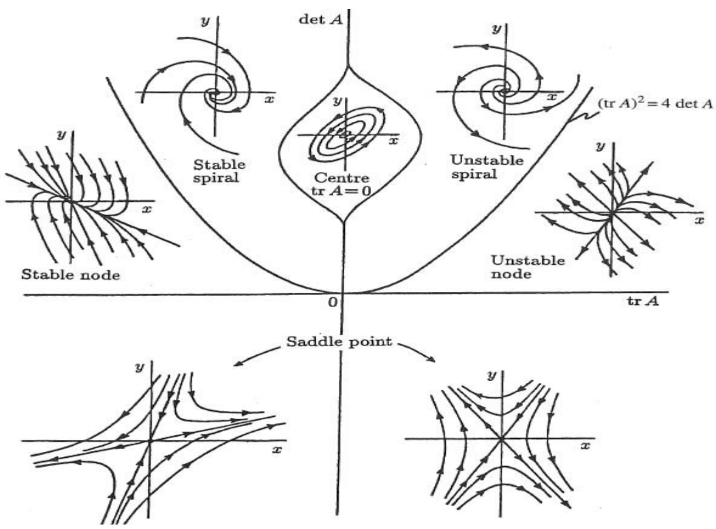

Figure 7: Illustration of various cases of non-linear dynamics that can occur in complex systems (from [98], p. 504; reproduced with the kind permission of J. D. Murray). Deterministic chaos and turbulence constitute further and even more complicated cases of non-linear system dynamics.

F. The Illusion of Control

Besides the difficulties of predicting the future behaviour of complex systems, there are other effects which make them difficult to control:

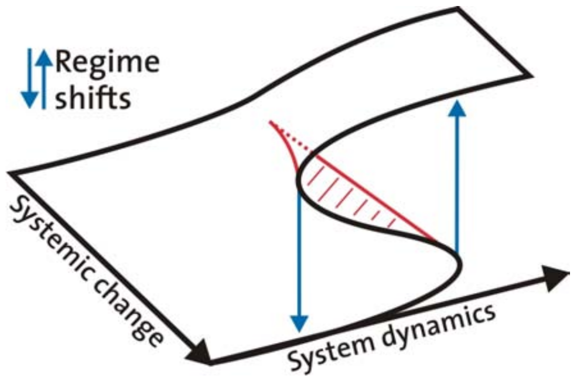

Figure 8: When a complex system is changed (e.g. by external control attempts), its system parameters, stability, and dynamics may be affected. This figure illustrates the occurrence of a so-called *"cusp catastrophe*". It implies discontinuous transitions ("regime shifts") in system dynamics.

1. On the one hand, big changes may have *little or no effects* (see Fig. 2) and, when considering network interactions (see Sec. II C), even adverse effects. This reflects the *principle of Le Chatelier*, according to which a system tends to counteract external control attempts.

2. On the other hand, if the system is close to a "critical" or "tipping point", even small changes may cause a sudden *"regime shift",* also known as "phase transition" or "catastrophe" (see Figs. 2 and Sec. 8). In other words, small changes can sometimes have a big impact, and often very unexpectedly so. However, there are typically some *early warning signals* for such critical transitions [99]. This includes the phenomenon of *"slow relaxation",* which means that it takes a long time to dampen out perturbations in the system, i.e. to drive the system back to equilibrium.

   Other warning signals of potential regime shifts are *"critical fluctuations",* which normally obey a heavy-tail distribution (see Sec. IIB). In other words, perturbations in the system tend to be larger than usual—a phenomenon which is also known as "flickering".

3. Control attempts may also be obstructed by "*irreducible randomness*", i.e. a degree of uncertainty or perturbation which cannot be eliminated (see Sec. IIE).

4. *Delays* are another typical problem that often lead to a failure of control [100]. The underlying reason is that delays may create unstable system behaviour (which can also occur when people attempt to compensate for delays through anticipation). Typical examples are the *breakdown of traffic flows* and the occurrence of *stop-and go traffic*, which result from delayed speed adjustments of drivers to variations in the vehicle speeds ahead.

   Since many control attempts these days are based on the use of statistics, and compiling such statistics is usually time-consuming, delays may also cause instabilities in other areas of society. *Business cycles*, for example, may result from such delays as well (or may at least be intensified by them).

5. Finally, there is the problem of "*unknown unknowns*" [101], i.e. hidden factors which influence system behaviour, but have not been noticed before. By definition, they appear unexpectedly. "*Structural instabilities*" [39] may create such effects. The appearance of a new species in an ecosystem is a typical example. In economics, this role is played by *innovations* or new products, which happen to change the social or economic world. Well known examples for this include the invention of contraceptives, computers, or mobile phones.

G. The Logic of Failure

As a consequence of the above, complex systems cannot be controlled in the conventional way (like pressing a button or steering a car). Such control attempts will usually fail, as Doerner's book "The Logic of Failure" has impressively shown [52]. A typical failure scenario is as follows: A decision-maker tries to change the social system. It turns out that the measure taken does not have any effect (see Fig. 2). Therefore, he or she decides to intensify the measure. The effect may still not be as expected. Hence, an even more forceful control attempt is made. As a consequence, the system undergoes a sudden regime shift (see Figs. 2+8) and the system organises itself in a different way (but not necessarily in the desired way). The decision-maker now tries to re-gain control and counteracts the unexpected change. If attempts to stabilise the system are delayed, this can lead to oscillatory or chaotic system dynamics.

The right approach to influencing complex systems is to support and strengthen the *self-organisation* and *self-control* of the system by *mechanism design* (see Sec.IV A). This basically means that coordination and cooperation in a complex system will appear by themselves, if the interactions among the system elements are well chosen. That is, regulations should not specify *what exactly* the system elements should do, but set bounds to actions (define "rules of the game"), which give the system elements enough degrees of freedom to self-organise good solutions. If the interaction rules are suitable, such an approach will usually lead to a much more flexible and adaptive system behaviour. Another advantage is "systemic robustness", i.e. the ability to cope with challenges from external perturbations. Note however, that everything depends on the interactions of the system elements. Unsuitable interactions can, for example, cause the system to behave in a dynamically *unstable* way, or to get trapped it in a *suboptimal ("frustrated") state*. Hence, finding the right rules of interaction is a great challenge for decision-makers, and complex systems scientists are needed to address them properly.

III. The example of financial market instability

One example of systemic risks that deserves more attention here is financial market instability [102–108]. The recent financial crisis shows very clearly how cascading effects can lead to uncontrollable dynamics and a relatively sudden systemic crisis. What started with local problems concerning subprime mortgages eventually affected the mortgage companies, the home building industry, the financial markets, the US economy, and the world economy. This crisis has been explained in many ways. Widely discussed reasons include:

- the deregulation of financial markets
- the explosive spread of derivatives (which reached a value of 15 times the gross product of the world),
- the apparently “riskless” securitisation of risky deals by credit default swaps, lowering lending standards,
- the opaqueness (lack of transparency) of financial derivatives,
- the failure of rating agencies due to the complexity of financial products,
- bad risk models (neglecting, for example, correlations and the heavy-tail character of fluctuations),
- calibration of risk models with historical data not reflecting the actual situation,
- insufficient net assets of banks,
- low interest rates to fight previous crises,
- the growth of over-capacities and other developments with pro-cylical effects,
- short-term incentive structures (“bonus schemes”) and “greed” of investment bankers and managers.

Recently, the following points are increasingly paid attention to:

- the possible destabilization of stock prices by “naked short-selling”,
- the multiplication of fluctuations and the large market impact of hedge funds due to their high leverage (i.e. due to their speculation with huge amounts of lent money),
- mutually agreed trading strategies (e.g. joint bets against the Euro),
- high-frequency trading,
- manipulations of and by ratings of stocks and financial derivatives,
- an non-transparent and unregulated market for credit default swaps and the misuse of this financial instrument,

- a lack of separation between classical banking (giving loans to people and companies) and investment banking ("gambling" with stocks and financial derivatives).

Less debated, but not less relevant problems are [109–111]:

- The complexity of the financial system is greater than what is knowable. For example, many portfolios appear to contain too many different assets to support a reliable optimisation with the amount of data available [112].

- In the "*arms race*" between banks (and other agents) with the regulators, regulators are sometimes in the weaker position. Therefore, financial market instability may result from the fact that instability is *beneficial* for some interest groups: An unstable market re-distributes resources and allows some people to become very rich in a short time. Instability implies opportunities for good investments, even when GDP grows slowly.

- This financial architecture has created a *complex system*, with hard-to-predict and hard-to-control dynamics. Financial products ("derivatives") were constructed in a multi-level way, very much like a house of cards.

- The world-wide *network interdependencies* of all major banks spread local risks over the entire system to an extent that produced a *systemic risk*. It created a "global village" without any "firewalls" (security breaks).

- Delays in the adaptation of some markets build up *disequilibria in the system* with the potential of earthquake-like stress reliefs. As examples for this, one may take historical crashes in currency markets or recent drops in the values of certain AAA-rated stocks.

- The financial and economic systems are organised in a way that allows for the occurrence of *strong correlations*. For example, when the strategies of companies all over the world become more and more similar (due to "*group think*" [113] or asking the same consultancy companies), the result is a *lack of variety* (lack of heterogeneity) in the system. This implies that the number of defaulting companies is either negligible, or many companies fail at the same time.

- An important factor producing *herding effects* [114, 115] and bubbles is the continuous information feedback regarding the investment decisions of others [116]. In this connection, it is important to underline that repeated interactions between decision-makers support consensus, but create *over-confidence* (i.e. a false feeling of safety, despite misjudgements of reality). Therefore, this undermines the "wisdom of crowds" [117, 118]. This problem may be further intensified by the *public media* which, in the worst case, may even create *mass hysteria*.

- The price formation mechanism mixes material values and *psychology* in a single, one-dimensional quantity, the price. Therefore, prices are sensitive to factors such as trust, risk aversion, greed, and herding effects (imitation of the behaviour of others) [54–56, 119].

- The stability of single banks does not mean that the banking system cannot enter a state of *systemic instability*. (Monetary value is a matter of trust, and therefore a single event such as the failure of Lehmann Brothers was enough to cause banks to cease lending money to each other. This implied a liquidity crisis so big that it would have triggered the failure of the world financial system, if central banks had not quickly provided huge amounts of liquidity.)

- Lack of trust also reduces lending of cheap money to troubled companies, which may drive them into bankruptcy, thereby increasing a bank's problems.

- More generally, the economic system seems to have a tendency towards *self-organised critical behaviour* (see Sec. II D).

Many of the above factors have contributed to strong non-linear couplings in the system. Furthermore, strong network interdependencies have been created through the interbank markets and complex financial derivatives. These features are already expected to imply cascade-like effects and heavy-tail statistics (see Sec. II B). This tendency is likely to be *further* amplified by anticipation attempts in fluctuating markets. However, even more dangerous than the occurrence of fluctuations in the markets is the occurrence of *strong correlations*. These can be promoted by economic cycles, herding effects, and the coupling of policies or regulation attempts to global risk indicators.

The worldwide crisis in the automobile sector in 2009 and the *quant meltdown* in August 2007 are good examples of the occurrence of strong correlations. The latter may be understood as follows [120]: Returns of hedge funds largely depend on their leverage. Therefore, there is an "evolutionary pressure" towards *high leverage*, which can increase volatility. In case of huge price jumps, however, banks tend to demand their loans back. This decreases the leverage of the affected hedge funds and thereby their chances to perform well in the future. Hence, large system-wide leverage levels are prerequisites for collapses, and crises can emerge virtually "out of nothing", just through fluctuations. This example illustrates well how unsuitable risk-averse policies can create pro-cyclical effects, through which banks may harm their own interests.

IV. Managing complexity

Having discussed the particular challenges of complex systems, one may be left with the impression that such systems are just too difficult for us to handle. However, over the past few decades, a variety of scientific techniques have been developed to address these challenges. These include:

• large-scale data mining,

• network analysis,

• systems dynamics,

• scenario modelling,

• sensitivity analysis,

• non-equilibrium statistical physics,

• non-linear dynamics and chaos theory,
• systems theory and cybernetics,

• catastrophe theory,

• the statistics of extreme events,

• the theory of critical phenomena and, maybe most prominently these days,

• agent-based modelling [129–133].

The methods developed by these fields allow us to better assess the sensitivity or robustness of systems and their dynamics, as will be briefly discussed in the following sections. They have also revealed that complex systems are not our "enemies". In fact, they possess a number of favourable properties, which can be used to our benefit.

A. How to Profit from Complex Systems

Understanding complex systems facilitates the utilisation of their interesting properties, which, however, requires one to work *with* the system rather than *against* it [121–128]. For example, complex systems tend to show *emergent (collective) properties*, i.e. properties that the single system components do not have. This is, for example, relevant for the possibility of *collective intelligence* [134–136]. One may also benefit from the fact that complex systems tend to self-organise in a way, which is adaptive to the environment and often *robust* and *resource-efficient* as well. This approach has, for example, been successfully applied to develop improved design principles for pedestrian facilities and other systems.

Technical control approaches based on self-organisation principles are becoming increasingly available. While previous *traffic control* on highways and in cities was based on a centralised optimisation by supercomputers with expensive measurement and control infrastructures, approaches currently being developed are based on *decentralised coordination strategies* (such as driver assistant systems or traffic lights that are flexibly controlled by local traffic flows).

Centralised structures can allow for quick information exchange among remote parts of a system, but they become unstable beyond a certain critical size (as the *collapse of political states* and many unsuccessful *mergers of companies* show). In comparison, decentralised approaches are particularly suited to achieving a flexible adjustment to local conditions and local coordination [137].

Some decentralised concepts for real-time control already exceed the performance of centralised ones, particularly in complex, difficult to control, fluctuating environments, which require a quick and flexible response to the actual situation [138] (see Fig. 9). In fact, in a strongly varying world, strict stability and control are no longer possible or are excessively expensive (as *public spending deficits* show). Therefore, a paradigm shift towards more flexible, agile, adaptive systems is needed, possible, and overdue. The best solutions are probably based on suitable combinations of centralised and decentralised approaches.

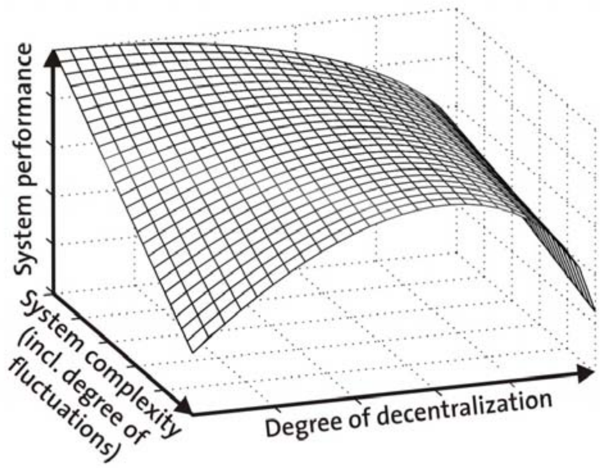

Figure 9: One advantage of centralised control is quick large-scale coordination. However, disadvantages result from the vulnerability of the network, a tendency towards information overload, the risk of selecting the wrong control parameters, and delays in adaptive feedback control. Because of greater flexibility to local conditions and greater robustness to perturbations, decentralised control approaches can perform better in complex systems with heterogeneous elements, large fluctuations, and short-term predictability (after [139]; reproduction with the kind permission of Katja Windt).

In social systems, the principle of self-organisation, which is also known as the principle of the “invisible hand”, is ubiquitous. However, self-organisation does not automatically lead to optimal results, and it may fail under extreme conditions (as is known, for example, from financial and traffic systems as well as dense pedestrian crowds).

A particularly important example of self-control is the establishment of *social norms*, which are like social forces guiding the behaviour of people. In this way, *social order* can be created and maintained even without centralised regulations such as enforced laws. Nevertheless, one must be aware that the principles on which social cooperation and norms are based (for example, repeated interaction, trust and reputation, or altruistic sanctioning of deviant behaviour) are fragile. Simple computer simulations suggest, for example, that a change from repeated local interactions (between family members, friends, colleagues, and neighbours) to non-recurring interactions with changing partners from all over the world may cause a breakdown of human cooperation [140]. Therefore, *naive globalisation* could potentially destabilise our social systems [141–143] (see Fig. 10), which largely build on norms and social cooperation. (Remember, for example, that the breakdown of the interbank market, which almost caused a collapse of the world financial system, was due to a breakdown of the network of trust.)

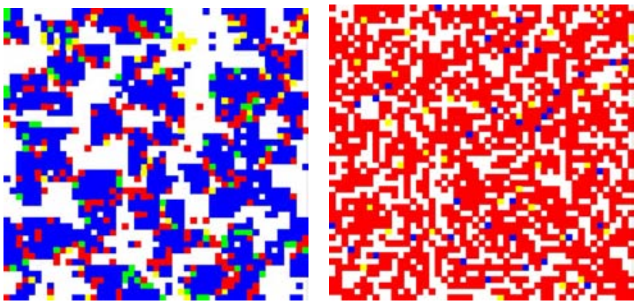

Figure 10: Establishment of cooperation in a world with local interactions and local mobility (left) in comparison with the breakdown of cooperation in a world with global interactions and global mobility (right) (blue = cooperators, red = defectors/cheaters/free-riders) (after [140]). Note that the loss of solidarity results from a lack of neighbourhood interactions, not from larger mobility.

B. Reducing Network Vulnerability

In Sec. II C, we have seen that systemic risks are mostly based on cascade spreading effects in networks. However, the vulnerability of networks to such spreading events can be reduced. The following measures are often quite effective:

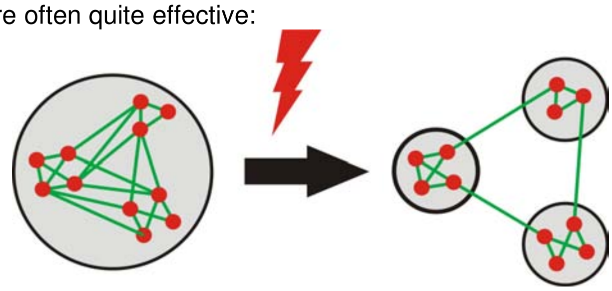

Figure 11: A networked system should be constructed in a way that allows its quick decomposition or de-compartmentalisation into weakly coupled (or, if necessary, even uncoupled) sub-networks. In such a way, failure cascades all over the system (or large parts of it) can be avoided, and most parts of it can be protected from damage.

- Network structure can often been improved by redundancy, i.e. the provision of alternatives, so that an over-critical perturbation only occurs if several nodes fail or several links break simultaneously.

- However, too much interconnectedness may be harmful, as this provides the "infrastructure" for the system-wide spreading of an unexpected problem. Therefore, it makes sense to *limit the degree of connectedness* and the size of networks (in order to avoid a "too big to fail" problem).

- Alternatively, one can introduce *"firewalls"*: Having several networks, each of them characterised by strong links, while the connections *between* the networks are weak, would allow a decoupling of the so-called supernetwork into several subnetworks (see Fig. 11). This principle of de-compartmentalisation allows one to prevent the spreading of a problem to the whole system, if the disconnection strategy is well chosen. The principle of firewalls to protect computer systems from malicious intrusion or the principle of electrical fuses to protect an electrical network from overload could certainly be transferred to other networked systems such as the financial system.

- For similar reasons, a reasonable degree of heterogeneity (variety) among the nodes and/or links of a network (in terms of design principles and operation strategies) will normally increase its robustness.

- When fighting failure cascades in networks, a *quick response* to over-critical perturbations is absolutely critical. If the time delay of disaster response management is small, its effectiveness depends in a complicated way on the network structure, the amount of resources, and the strategy of distributing them in the network (see Fig. 6). In case of significant delays, there is little chance of mitigating cascade spreading, even when large amounts of resources are invested.

- A *moderate level of fluctuation* may be useful to destroy potentially harmful correlations (such as financial bubbles) in the system. Such fluctuations could be created by central banks (for the purpose of "bubble control") or by other regulators, depending on the system. Note, however, that a large degree of fluctuation can cause over-critical perturbations or coincidences of perturbations.

- An unhealthy degree of volatility can be lowered by introducing conservation laws and/or frictional effects in the system. This is expected to dampen fluctuations and, thereby, to reduce the likelihood of events that may trigger systemic risks.

Rather than applying these concepts permanently, it can make sense to use them adaptively, depending on the state of the system. When designing networked systems according to the above principles, one can certainly profit and learn from the experience of physicists and engineers with other systems.

V. Summary, discussion and outlook

In this contribution, we have summarised the properties of complex systems and identified factors that contribute to creating fertile ground for the emergence of systemic risks in socio-economic systems. Complex systems cannot be easily controlled. Rather, they tend to follow self-organised *eigendynamics*, and conventional control attempts often have counter-intuitive and unintended effects.

As the example of ecosystems shows, a networked system can have an astonishing degree of robustness without any central control. Robustness just requires the right interaction rules, which may be implemented, for example, by social norms, laws, technological measures etc., depending on the system. Properly chosen rules will lead to *self-regulation* or *self-control* of the system, but improper specifications can lead to low performance or systemic instability. For example, if the failure rate of system elements is reduced, this may lead to larger systemic failures later on. Moreover, it is probably good if the system is regularly exposed to stress, as this is expected to strengthen its immunity to perturbations.

Emphasis was put on the fact that, in any larger networked system, it is essential to have “firewalls” (security breaks), which facilitate its quick decomposition or de-compartmentalisation into disconnected or weakly connected subnetworks before a failure cascade has percolated through the whole system or large parts of it.

Among the success stories of complex systems research, one may mention the Nobel prizes of Ilya Prigogine, Thomas Schelling, and Paul Krugmann. Some examples for application areas of complexity science are [144–148]

• the organisation of the internet,

• modern epidemiology,

• the prevention of crowd stampedes,

• innovative solutions to improve traffic flow,

• understanding the causes and impacts of environmental or climate change,

• enhancement of the reliability of energy supply,

• modern disaster response management,

• prediction markets and other methods using the wisdom of crowds.

However, many socio-economic crises still occur because the system dynamics are not well enough understood, leading to serious management mistakes. In order to support decision-makers, scientists need to be put in a better position to address the increasing number of socio-economic problems. These mainly result from the fact that social and economic systems are rapidly changing, i.e. in a transformation process rather than in equilibrium.

We must close the gap between existing socio-economic problems and solutions, and create conditions allowing us to come up with solutions before a problem occurs. This requires building up greater research capacities (a “socio-economic knowledge accelerator”). It will also be necessary to establish a new study direction (“integrative systems design”) to provide decision-makers with solid knowledge regarding the behaviour of complex systems, how to manage complexity in politics and economics, and how to cope with crises.

Finally, scientists need to have access to better and more detailed data. Special super-computing centres (as for climate research) would allow scientists to simulate model societies and study the impact of policy measures before their implementation. They would also support the development of contingency plans and the investigation of alternative means of organisation ("plan B"). Such centres will require a multi-disciplinary collaboration across the various relevant research areas, ranging from the socio-economic, to the natural, to the engineering sciences. For this, one needs to overcome the particular challenges of multidisciplinary research regarding organisation, funding, and publication.

Considering that we know more about the origin of the universe than about the conditions for a stable society, a prospering economy, and enduring peace, we need nothing less than an "Apollo project for the socioeconomic sciences". There is no time to lose, since there are already signs of critical fluctuations indicating possible regime shifts [149–154]: The recent riots in Greece, for example, are speaking a clear language.

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