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Quantification Makes Sense Even When Empirical Data Is Limited

– A Model of the Bhopal Crisis

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Abstract

Quantifying and simulating formal models can be useful even when empirical data is limited. Models which are developed without extensive calibration against real world data are called 'conceptual simulation models'. When used with caution, additional insights from quantification, formulation of policies and simulation analyses outweigh potential problems regarding the external validity of such models. The discussion is exemplified using a conceptual simulation model of the Bhopal accident, which was developed to investigate the interplay of a system's structure and the bounded rational behaviour of agents.

Keywords: quantification, soft factors, simulation, system dynamics, Bhopal

There is an ongoing debate whether and when quantification and simulation add value to an analysis based only on insights and extrapolations from system structure, for instance, via causal loop diagrams (see, for example, Coyle 2000, Homer & Oliva 2001, Coyle 2001). Because no side in this debate really denies that there are issues where it is sufficient to stop with a qualitative model it is rather a debate about what should be emphasised. Put in other words, is it more that model simulation is a nice-to-have add-on to qualitative systems thinking but—in many cases—not really necessary or even misleading; or are systems thinking and simulation naturally tied together and two stages of one single process that only occasionally is stopped after the first, qualitative step?

This paper has two objectives. On the content side, the aim is to show that system dynamics (with its components systems modelling <u>and</u> simulation) can help to explain catastrophes like Bhopal by indicating that the system's structure in combination with the boundedly rational characteristics of its actors is likely to produce unfavourable behaviour under a wide range of conditions. On the methodological side, my claim is that 'conceptual simulation models' can provide insights into relationships between structure and behaviour, i.e. simulation models which are not extensively calibrated against real-world data can support understanding of complex phenomena (Lane & Husemann [2004] call these sort of models 'exploratory system dynamics models'). Additionally, simulation experiments allow finding leverage points for designing more robust policies and structures which cannot be derived from qualitative analysis only.

The rest of this paper is divided into five parts. The first gives a short summary of the historic events that took place in Bhopal in 1984. The second section examines the causality of the underlying problem structure that finally led to devastating results. Afterwards, a small, abstract simulation model is presented that is used to derive some insights into the system's behaviour. The simulation experiments are analysed in the fourth section. Finally, the paper discusses benefits and limitations of the simulation model in the context of investigating the coupling of bounded rationality and systems' structure.

The Bhopal Case

Biases, sub-optimality and systematic failures are evident characteristics of human decision-making in complex situations. As research, for instance, in psychology (Dörner 1996), economics (Simon 1959), system dynamics (Sterman 1994) and crisis management (Pauchant & Mitroff 1992) shows, humans are in principal not well prepared to make successful decisions or craft sound policies in environments when complexity is above a certain level. However, this complexity level is far below the complexity which must be assumed to exist in today's organisations and economic environments. It can be concluded that frequently decision-making is "bounded rational", i.e. limited by biological, psychological and sociological influence factors on the decision-maker whose decisions, therefore, are often far from optimal as we will see in the following case description.

In 1984 Union Carbide of India Ltd. (UCIL) was the twenty-first largest company in India primarily producing pesticides. UCIL employed more than 10,000 people; however, the plant only ran at half of its total capacity. Reasons for this were market pressure from competitors on the one hand; on the other hand climatic changes had led to a decreased demand for pesticides. Union Carbide that held 50.9 % of the shares of UCIL considered divesting this stake due to fierce competition within the world chemical industry. Many experienced top managers had left UCIL, de-motivated by a potential divesture. Most of the newly hired managers lacked knowledge and experience in the chemical industry.

The Indian government had encouraged the use of pesticides in order to boost agricultural yield. Furthermore, in order to develop an industrial basis in India they were hesitant to impose strict safety regulations for chemical plants. The chances to become employed by UCIL had driven more than 600,000 people to come to live in Bhopal, five times as much as twenty years before. Many of them literally lived across the street from UCIL's pesticide plant. Civil infrastructure was not capable to keep up with the exponential growth of population: housing, water supply, the telephone system, education and health facilities, all were in miserable condition.

The Bhopal accident occurred on December 2, 1984. A highly toxic gas (methyl isocyanate; MIC) used for producing pesticides leaked from the plant's production facilities. A few factors were responsible that this incident evolved into a severe accident which caused the death of 1,800 to 300,000 human beings, depending on which information sources are used and whether long-term victims are counted or not (Pauchant & Mitroff 1990):

- neither top management nor employees knew about the dangers of MIC and therefore they did not consider particularities of a safe production process;
- not or not correctly running technical systems (e.g., safety valves did not work) occurred in parallel with human errors (warning signals were turned off and problems were only slowly reported to superiors);
- people living next to the plant did not know about or understand potential dangers of pesticide production;
- local authorities also not knowledgeable about the danger commanded people to flee when staying next to the ground would have been a better alternative;
- Bhopal's basically not existing infrastructure did not allow to communicate with the population or to support injured people.

Although there is not one single factor that was responsible for the catastrophe the combination of many led to disaster. Furthermore, it can be emphasised that not only novel, unforeseen situations caused the accident but a simultaneous occurrence of many small issues, which—taken individually—would not have precipitated a catastrophe (Rudolph & Repenning 2002).

In the next section, the causal network of factors is further examined. This section concludes with the remark that the accident further developed into a Bhopal crisis with people suffering for years, lawsuits, mistrust between the Indian government and Union Carbide, the public's general mistrust of the chemical industry, discussions about the ethical role of industries in developing countries, etc. These issues are not further examined in this paper (Pauchant & Mitroff [1990, 1992] describe distinguishing characteristics between accidents and crises).

Systemic examination of causes, symptoms and results

As already indicated in the last section, many factors were responsible for the accident. Figure 1 depicts the network of major influence factors which were derived from the literature about the Bhopal case (Bowonder 1987; Shrivastava 1987; Pauchant & Mitroff 1990). Unlike seemingly similar pictures in these references, I tried to create a figure that strictly follows established guidelines for causal-loop diagrams as given in books and papers on systems thinking (e.g., Senge 1990; Maani & Cavana 2000). These guidelines include for instance: the naming of variables in neutral or positive terms, the indication of link polarities and the indication of feedback loops.

In the centre of the diagram (also containing most of the feedback loops identified) one can find intra-organisational factors. Most prominent is the following chain of links: bad *financial performance* leads to *cost cutting* measures which lowers *staff morale* and *safety* which finally increases *probability of accident*. A first feedback loop (*staff's depression*) can be identified when we consider that low *staff morale* weakens the *financial performance*. In particular the variable *staff morale* is contained in a number of further feedback loops, for instance the *maintenance loop* (low *staff morale* leads to a low *maintenance level* which decrease *quality of production process* and, in a last step, *staff morale*) and the *knowledge loop* (low *staff morale* increases *staff turnover* which decreases intra-organisation *knowledge about production process*, *quality of production process* and, again, *staff morale*). Both are reinforcing feedback loops.

In the lower left part of the diagram factors are depicted that stem from the Union Carbide holding's influence on UCIL. Notable variables are *pressure for profitability* and *strategic changes* that lead to *divesture* and lower *commitment*, both affecting *staff morale*. Depicted around the centre are variables describing environmental or governmental factors. For instance, the Indian government's *emphasis on industrial growth* leads to lax *safety* *standards* which cause low actual *on site safety standards* but also have a positive influence on *financial performance*. The company's success causes a high number of people to live near the firm which negatively influences *appropriateness of infrastructure*, particularly *quality of emergency infrastructure*.

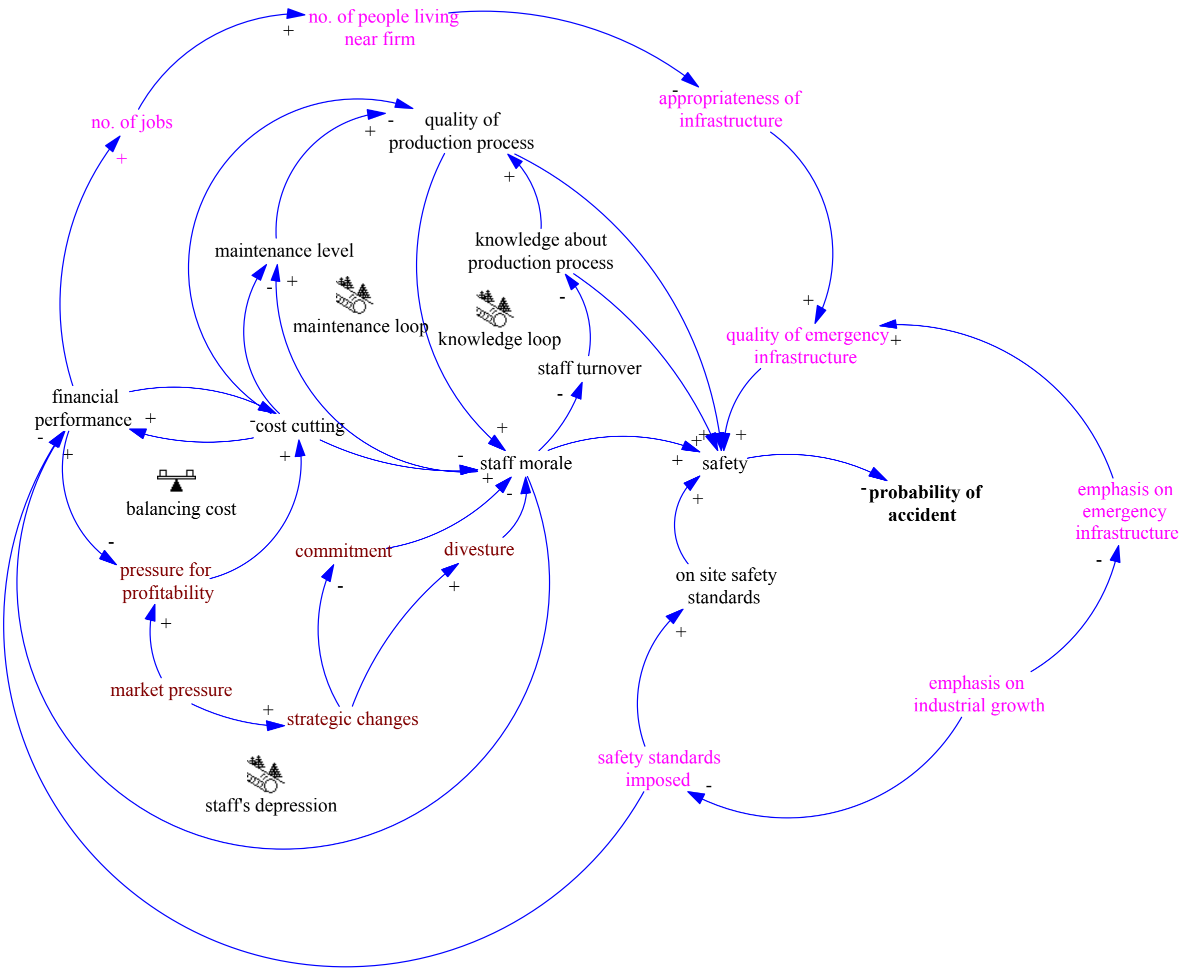

Figure 1: Causal-loop diagram of factors leading to Bhopal accident

The causal-loop diagram allows considering the interplay of many determinants of the accident. It integrates factors from all three perspectives examined in risk analysis: technical, organisational/societal and personal/individual (Bowonder & Linstone 1987). Causal diagramming highlights remote linkages between variables; in particular feedback loops can be identified. This feature appears to be particularly useful when the uni-directionality and mono-causality of most mental models are considered (Axelrod 1976; Hall 1976). However, in order to draw conclusions about the behaviour that derives from the system's structure simulation experiments are necessary. Human cognition is incapable of handling so many variables simultaneously (Miller 1956) or of considering the behaviour resulting from a big number of interwoven cause-effect relations (Mackinnon & Wearing 1980).

A system dynamics perspective: Quantification and simulation

Although the causal-loop diagram depicted above helps to derive valuable insights about the causes of the Bhopal accident, a more in-depth analysis can be accomplished by simulation experiments. With the help of a rather simple and abstract system dynamics model I want to emphasise the point that the causal structure as it occurred in the UCIL case can lead to disaster under a wide range of initial conditions. The model to achieve this goal is depicted in Figure 2 as a level-rate diagram (Forrester 1961). Organisation's resources and characteristics are modelled as stocks (depicted by rectangles) which are increased or decreased by related flow variables (valve symbol). Constants in the model are written in capital letters.

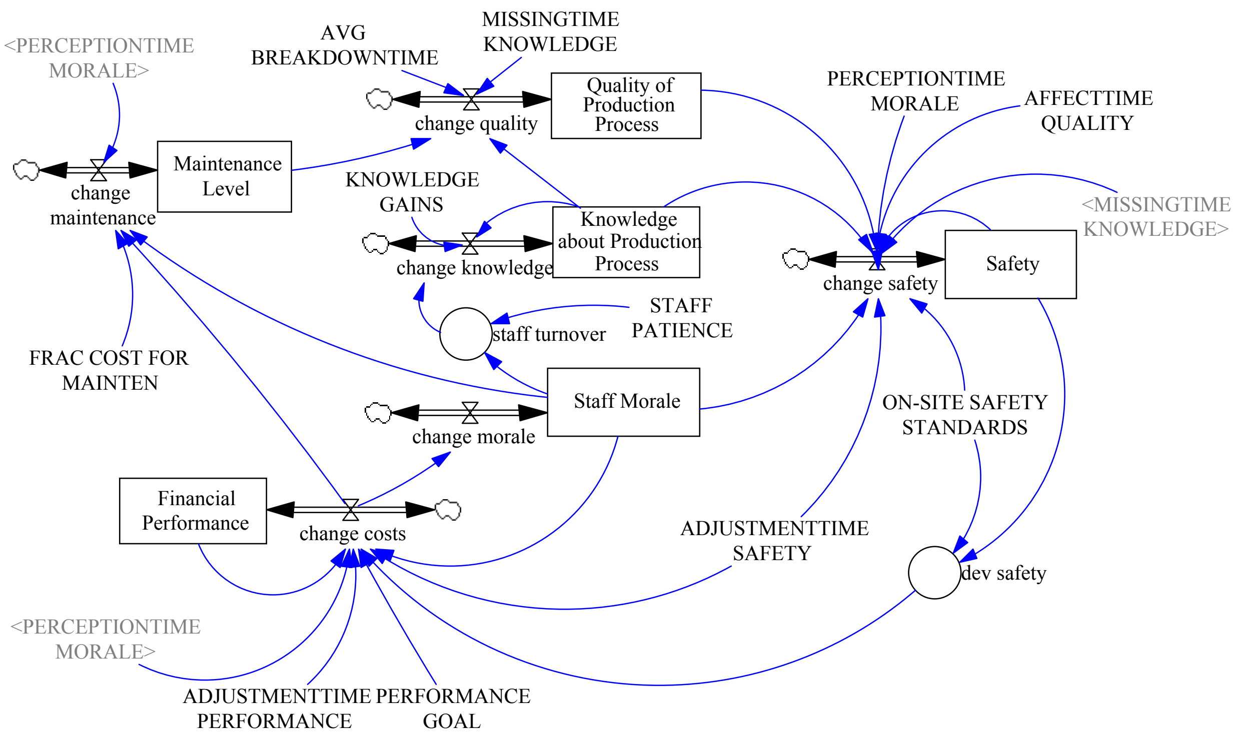

Figure 2: Level-rate diagram of intra-organisational factors of Bhopal accident

In the model the focus is on the intra-organisational factors identified in the centre of the causal-loop diagram in Figure 1. This part of the causal-loop diagram is completely transferred into a level-rate structure. However, this means that the systems represented in the two diagrams have different boundaries because most external factors from the causal-loop diagram (e.g. political and demographical influences) are not included into the level-rate diagram. Implicitly, these extra-organisational factors are embodied in financial relationships represented in the model: for instance, when pressure from Union Carbide on UCIL is big and the financial results are criticised, management will try to alter the cost situation faster than when pressure from the holding is low. In other words, factors outside the organisation influence the way how costs are perceived and how vigorously they are tried to be changed.

The quantification process was hampered by two factors. Firstly, I did not have access to actual empirical data from within UCIL and, secondly, for a few variables no direct numerical values exist, for instance *staff morale* or *safety*. Nevertheless, quantification was ventured because neglecting these variables would have caused either an even bigger error or would have made it completely impossible to conduct simulation experiments. To summarise, two main assumptions of the system dynamics approach are that

(1) computer-based simulation experiments can trigger substantial insights that could not be gained without numerical simulation (Forrester 1961);

(2) modelling heavily depends on not formalised information and even a rough estimation of a variable considered to be crucial is better than just leaving this variable out completely (Forrester 1994).

Basically all variables are modelled as abstract indexes. Although this does not allow for examination of absolute values, it does make it possible to compare variables with each other and to study their behaviour over time.

In the base run of the model all levels were initialised at 100 (index points); all time constants (for instance symbolising reporting or perception delays) are set to 6 months. It is assumed that a deviation between desired and actual financial performance leads to increased cost cutting measures (increasing *financial performance* in the following). A lack of actual *safety* compared to *safety standards* (due to expenses to adjust safety) and low *staff morale* (due to low productivity) increase costs (thus, decreasing *financial performance*), resulting in further cost cutting measures. In a more sophisticated version of the model, the parameter *safety standards* could be made an endogenous variable. Then, its value could change depending on staff's morale, the financial situation etc. Possibly, this could also lead to an "eroding goals" phenomenon (Senge 1990).

A major structural assumption is that cost cutting measures have direct negative effects on *staff morale*, also influencing knowledge, maintenance and quality. Further assumptions are that 5 % of all costs are used for maintenance work; knowledge autonomously increases by 1 % every month; *performance goal* is an endogenous, constant parameter and equals actual *financial performance* in the beginning of the simulation. I did not distinguish between actual and perceived values for the model variables (e.g., actual safety and perceived safety). This distinction is a possible model extension that could add further complications in the form of delays and biases to the system.

Internal validity of the model is satisfactory. It produces replicable outcomes. Results from extreme conditioning tests and sensitivity analyses show consistent and robust model behaviour: parameter variations in a wide range produce basically the same behaviour mode (i.e. oscillations). Concerning external validity one has to keep in mind the aim for which the model was built. Although I claim that the model structure (variables and their connections) represents reality (as described in the many literature studies about Bhopal) the objective for building the model was not to reproduce behaviour in a numerically exact way that can be compared to real values. Rather, as mentioned above, basic behaviour modes of the structure are to be investigated. The model is useful (and therefore valid) for this purpose (Oreskes et al. 1994).

Lessons learned from simulation experiments

The simulation results for some of the variables of the model are depicted in Figure 3. The graph illustrates that—although the model is initialised with rather favourable, optimistic values for the constants—the variables oscillate. Although one might argue about the exact amplitude of the oscillations, sensitivity analyses varying numerical values of the constants show that the general oscillating dynamics of the model are relatively stable regarding changes in constant values. An explanation for this outcome is the existence of delayed feedback loops between model variables, which are the primary reason for the observed behaviour. By parameter changes the oscillations can only be dampened; the system cannot completely be brought into equilibrium.

Transferred to the real case of UCIL it can be concluded that at least the probability for an accident increases when we assume a structure like the one represented in the model. Thus, an accident was maybe not unavoidable; however, it has become more probable over time. It also can be emphasised that the potential for disaster lies within the structure of the organisation. External factors are not necessary (and not modelled in the simulation model) to generate unfavourable outcomes and increase the probability of an accident. Assumingly, external influences just amplify the system behaviour found here. Thus, they further increase the probability of an accident. In the same way as external factors are not causing the oscillatory behaviour of the system, it is not necessary that individuals with bad attitudes or cognitive limitations affect the system to produce oscillations: a system's structure determines its basic behaviour (Forrester 1969, ch. 6; Meadows 1982).

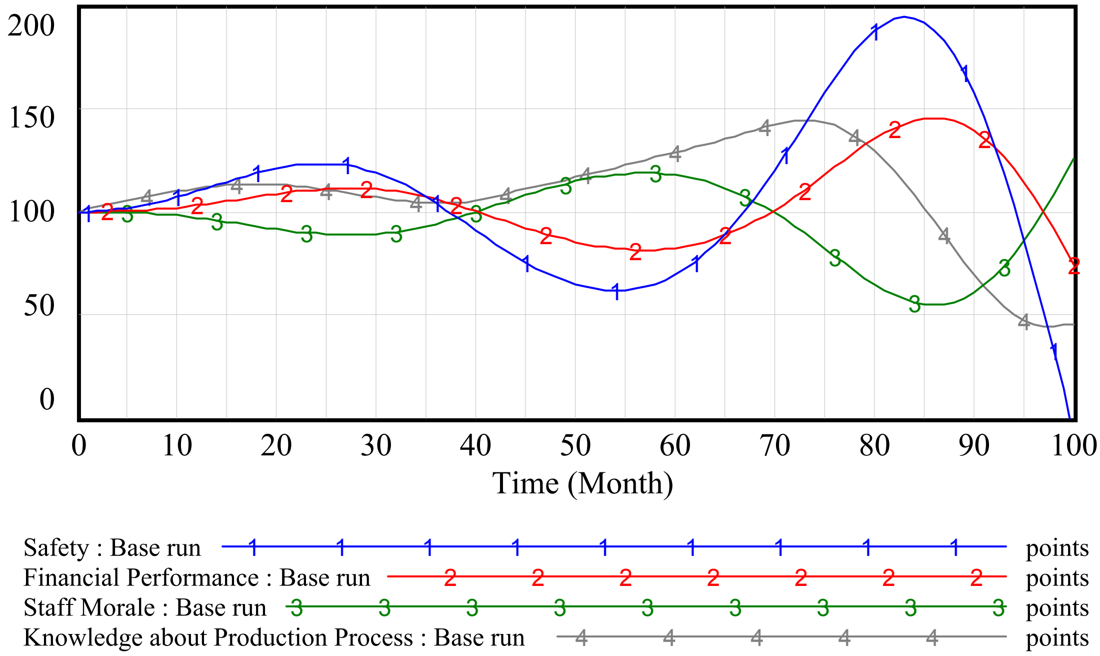

Figure 3: Base run of simulation model

Another feature of the model's dynamics is that lower amplitudes of the "soft factors" *knowledge about production process* and *staff morale* recur amplified in the oscillations of the goal variables *financial performance* and *safety*. This simulation result can be interpreted as supportive to the notion that managing tacit resources is crucial (Warren 2002); in particular technologically trained engineers are likely to underestimate this fact (Bowonder & Linstone 1987). In a similar vein, one must note the different salience of the two goal variables *financial performance* and *safety*. While economic problems might lead to direct consequences, safety issues will probably not result in immediate action (Marcus & Nichols 1999). In many cases, the safety situation of an organisation appears to have a broader range of what is acceptable than the profit situation. This could be an interpretation for the higher amplitude of *safety* as compared to *financial performance*.

The increasing amplitudes of all variables depicted in Figure 3 can be interpreted in the way that the organisation becomes less adapted to inter and intra-organisational influences in the course of the simulation. Following ideas from organisational learning and configuration theory, when the deviation from an acceptable achievement level becomes too substantial the organisation needs to perform a “quantum leap” in order to stabilise behaviour above a satisfying level and dampen oscillations (Miller & Friesen 1980). As was said above, parameter changes are not sufficient to achieve this, structural changes are necessary. Figure 4 presents the effects of three structural changes on *safety* compared to the base run of the simulation.

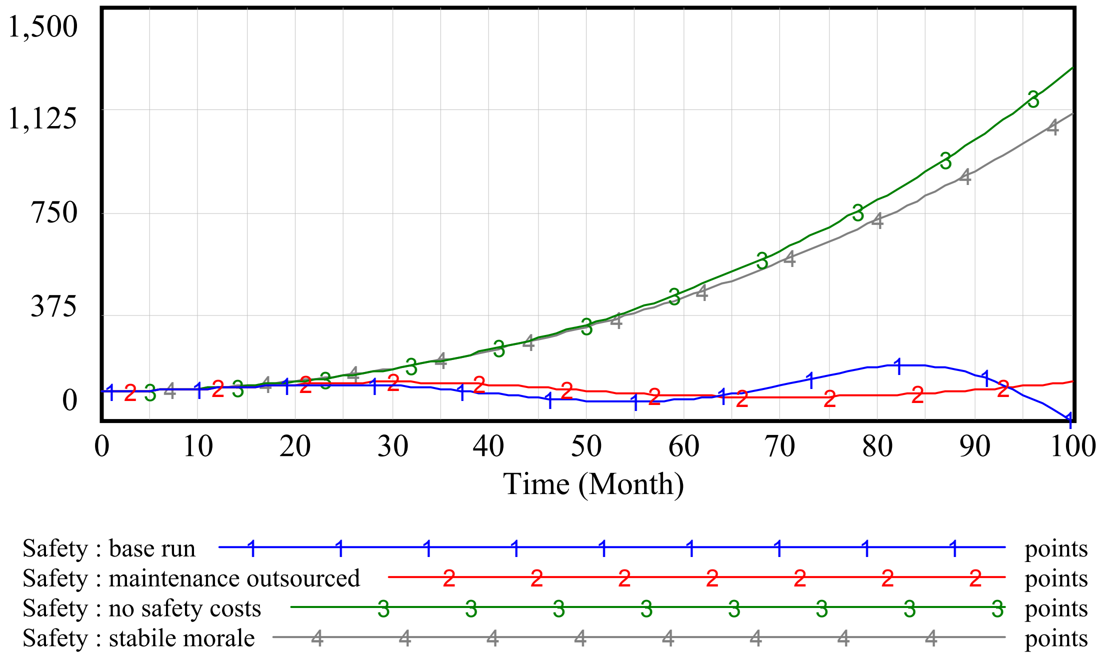

Figure 4: Effects of structural changes on *safety*

In the simulation run ‘maintenance outsourced’ it is assumed that maintenance of machines has been outsourced and, thus, does not depend on *staff morale* (at least of the organisation’s staff) any more. As one can see the oscillation is dampened significantly; nevertheless, it still exists and *safety* does not reach a level significantly above its starting point. The runs ‘no safety costs’ and ‘stabile morale’ both show very desirable behaviour modes for *safety*, which grows exponentially. In ‘no safety costs’ costs to fulfil safety standards are not included in the calculation of *change costs* and, thus, they do not affect *financial performance*. The simulation run ‘stabile morale’ supposes that the organisation somehow is able to de-couple *staff morale* from *change costs*, i.e. staff is not influenced by cost cutting measures any more. Although both structural changes yield favourable outcomes regarding *safety*, they have different effects on *financial performance*, as Figure 5 shows. Although one has to keep in mind that the results are ceteris paribus, i.e. no other, for instance external influences on financial performance are investigated (resulting in an exaggeration of outcomes), it is clear that ‘stabile morale’ yields better financial performance than ‘no safety costs'. Thus, ways to stabilise *staff morale* and make it independent from cost cutting are those that promise both, high safety and increasing financial performance. With a structural change like this, the organisation could take advantage from a positive feedback loop (MacIntosh & MacLean 1999). At the same time, a de-coupling of costs and staff's morale is hardly conceivable and, therefore, probably the most difficult to achieve change in the structure of the organisation. Matters are further complicated by the different delay times that the employees' morale and the financial situation of an organisation possess: while the financial performance can be changed within a rather short time frame, staff morale can only slowly be build up, but can probably be destroyed quickly.

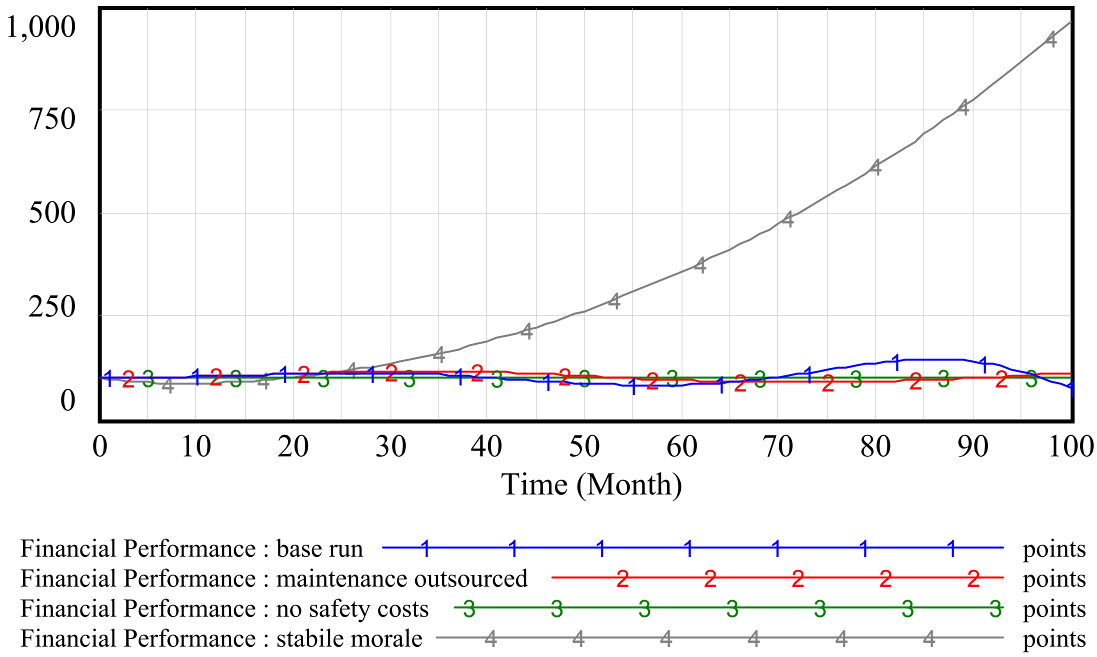

Figure 5: Effects of structural changes on *financial performance*

The simulation results achieved when changing the model's structure strengthen two propositions from above. First, *staff morale* is a high leverage variable in the system and, second, feedback loops are mainly responsible for the behaviour of the system. Because the two promising changes basically cut the feedback from *financial performance* to *staff morale* to *safety* and back to *financial performance*, feedback loops seem to be responsible for the oscillating behaviour of the system. Thus, implications to increase the safety of the plant would include (1) improving *staff morale* through training, incentives and participation, and (2) de-coupling intangible factors (e.g. morale, knowledge, etc.) from *financial performance.* An even more advanced improvement than represented by just cutting the feedback between *staff morale* and *financial performance* would be a policy that—by the introduction of appropriate incentives—assures that staff morale and knowledge remain stable, when financial performance decreases; when it increases, however, morale and knowledge go up as well. We can summarise that improvements have to focus on the agents in a system and on its structure.

At the first glance, the results of the causal diagramming and the simulation study seem to render the concept of bounded rationality unimportant: when the system's structure alone is capable of lowering the plant's safety and of increasing the probability of an accident, the quality of individual decisions does not seem to make a difference any more. However, there are two counter arguments:

1. As was emphasised in the simulation study, the system's structure only increases the chance of an accident, it does not cause it. The accident was caused by individual decisions, for instance, to run the production process despite of broken safety valves, to turn off alarm signals, to produce with not experienced personnel (Bowonder & Linstone [1987] present a list of "human errors" in the Bhopal case together with similar faulty decision-making for the "Three Mile Island" and "Chernobyl" accidents). These decisions were reinforced by the system's structure but they were not unavoidable. With knowledge about the underlying structure, the potential dangers and the actual catastrophe, hopefully those production decisions would have been different.
2. From a meta-perspective on the systems involved, the structure of the organisation and its contextual system were built on decisions (for example, from managers, politicians, employees, etc.) as well. Assumingly, these decisions and the policies that created them were biased by bounded rationality. Again, the same argumentation as above holds: with knowledge about what likely behaviour (and potential dangers) the system's structure might produce and an idea of the actual catastrophe, hopefully those decisions would have been different, i.e. a more robust structure would have been designed.

Benefits and limitations of conceptual simulation models

This paper deals with one of the oldest and still most pressing issue in system dynamics: "when to map and when to model" (Richardson 1996, 150). While the earlier literature in system dynamics mostly is quite definite on this point (namely that system dynamics always includes simulating quantified models; Forrester 1961), some doubts have been explicated during the last decades (Wolstenholme & Coyle 1983; Wolstenholme 1999). Mostly, proponents of qualitative modelling do not deny that deriving behaviour from a complex model based on human cognitive skills alone is virtually impossible; their claim is that mapping of system structures *per se* (i.e. without succeeding simulation) has value. In some cases, their argument continues, it is even preferable to quantification and simulation because—when empirical data is lacking or spurious—simulation results might be totally distracting or plainly wrong (Coyle 2000). While proponents of a more simulation-focused approach do not doubt the usefulness of mapping itself they hardly see reasons to omit simulations as long as resources permit it because it always adds further knowledge about the system that is studied (Homer & Oliva 2001).

Although this paper is more in line with the latter perspective (considering simulation as *quasi* always possible and useful), it appears rather obvious that validating conceptual simulation models is a crucial but difficult endeavour. When simulations are run that are based on uncertain data and estimations of soft variables, one critical validation step is only possible in a limited way: behaviour validation (Barlas 1996). Even when we accept that structural validation is more important in system dynamics anyway, the impossibility to compare historical and simulated behaviour means that one of the most intuitive arguments for the usefulness of a simulation model is not available. Furthermore, the missing chance to validate the model against real-world behaviour raises the difficulties and the necessary rigour for the rest of the validation process.

But, what is the use of conceptual simulation models if direct comparisons with and transfer to real-world systems is neither possible nor intended? As can be seen in the Bhopal case described above, model simulation has—nevertheless—the following advantages

- More than causal-loop diagrams and other tools from qualitative modelling, a fully quantified simulation model demands that underlying assumptions about relations between variables are made explicit, i.e. simulation improves transparency
- Possible behaviour modes of the model can be generated by simulation which helps to gain insights into the dynamic consequences of the assumed cause-effect relationships (Lane [2000, 17] names this a paradox: “the results of a quantitative system dynamics study are qualitative insights”)
- Analyses of simulation results offers an additional way to detect inconsistencies in the model

- By use of techniques such as optimisation, units check, sensitivity analysis, etc. further confidence in the validity of the model can be gained and critical parameter settings can be identified, thus allowing for additional empirical research or refined estimation

In my view, these advantages justify the usage of conceptual simulation models, even when—as was the case here—data is limited and estimations are abound. In the light of the ongoing discussion described at the beginning of this section, this paper supports the second view, which is that simulation adds value in most cases. However, the possible dangers of conceptual models should have been made clear as well. First, validation is more difficult and second, the transfer to the behaviour of real-world systems can only be made in principle: the behaviour of any specific, real system will most probably deviate from the behaviour of a conceptual simulation model.

Methodologically, the value of conceptual simulation models lies in the area of developing and scrutinising theories. System dynamics provides a structural theory of social systems (Lane 2000). This structural framework can be used to explore and test content theories of social systems. For example, in this paper the relation between system's structure and bounded rational agents was investigated. The model and simulation analyses of a case study were used as a means to explore possible elements and relations of a theory of bounded rational behaviour in complex systems.

In the case presented here both, systems thinking and simulation can also help to design more robust systems, i.e. systems that are tolerable to faults. More detailed simulation models might also comprise the costs connected with designing and implementing error-proof systems. With such system structures, negative effects of boundedly rational decision-making can be mitigated. In a broad sense, this might even mean to prevent accidents, crises and catastrophes.

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