Of Stocks, Flows, Agents and Rules – ”Strategic” Simulations in Supply Chain Research

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Summary:
Simulation offers a middle ground between pure formal modeling, empirical observation and experiments for strategic issues in supply chain research. Although simulation models are formally specified, they are not limited to analytically solvable equation systems. Additionally, simulation approaches provide the possibility to include estimations of not easily measurable "soft" factors. The inclusion of such variables increases the real world relevance of simulation studies, similar to empirical investigations. Thus, strategic simulation experiments try to combine the clarity and generality of mathematical modeling with the practical relevance and external validity of empirical research.
The approach is demonstrated by a combination of system dynamics and agent-based simulation, two approaches that achieved high significance for the modeling and simulation of socio-economic systems. With the help of a simulation prototype we are able to test the stability of supply chain structures under different levels of uncertainty regarding future events, particularly changing demand.

Keywords:
Supply Chain Management, Simulation, System Dynamics, Agent-Based Modeling

1 Usage and Utility of Strategic Simulations

1.1 Modeling and Simulation as Research Methodology

Supply Chain Management (SCM) is one of the most popular management concepts these days. However, research in the field mostly concentrates on conceptual literature, reports on anecdotal evidence about various SCM techniques and tools, or tackles purely operational issues. The lack of supply chain research addressing strategic problems is often caused by methodological difficulties. For instance, empirical research is difficult to conduct in supply chains because it implies observing and surveying all companies within a given chain; mathematical modeling approaches are frequently restricted to binary supplier-customer relationships and require many unrealistic assumptions due to growing mathematical complexity. Few studies use experiments to investigate human behavior modes in supply chains because, for example, multi-person activities (which SCM usually comprises) are difficult to handle in experiments.[1]

Simulations offer a middle ground (or "third way"; Axelrod, 1997) between pure formal modeling and empirical observation and experimentation. Methodologically, they share a characteristic feature with classical experiments: the possibility to alter one variable and hold all other variables fixed (Conway et al. (1959) understood simulations as statistical experiments). Although simulation models are formally specified, they do not require specific mathematical forms that are analytically solvable. For example, relations in a supply chain can be modeled without paying attention to the question of whether the resulting set of equations can be solved analytically and whether an optimal solution exists, because simulations proceed step-for-step using numerical approximation methods. Additionally, some simulation approaches provide the possibility to include estimations of difficult-to-measure (and "soft") factors. This characteristic allows the inclusion of all important parameters based on real world data or on estimates from actors within supply chains.

In the context of this paper we define strategic situations as characterized by: (1) high detail complexity (many variables that are highly interconnected); (2) high dynamic complexity (non-linearities and time delays that dilute cause-effect relationships); (3) decisions that are based on the mental models of decision makers

[1] However, the literature reports on some experiments that used supply chain contexts but did not aim at finding out about supply chain issues. In these cases, the supply chain context is utilized for more general investigations in human decision making in complex environments (e.g., Sterman, 1989; Senge, 1990). We will not discuss these studies in this paper. See also Steckel et al. (2004), who used an experimental setting in a simulated context to examine supply chain issues such as the effects of the length of cycle times or information sharing.

(i.e. on perceptions, estimations, heuristics and simplifications); (4) many “soft” factors (e.g. image, politics).

While these characteristics make strategic decisions very difficult, such decisions are nevertheless usually very important at the same time. Therefore, trial-and-error decision making is rather dangerous. Simulations that support decision making in the strategic area are called “strategic simulations.” Strategic simulations try to combine the clarity and generality of mathematical modeling with the practical relevance and external validity of empirical research. A drawback is that strategic simulations do not necessarily provide optimal solutions or make it easy to find such solutions. Furthermore, the development and the analysis of strategic simulation models is – at least partially – still more an art than a technique, depending heavily on the skills, experience and creativity of the modeler.

In principle, modeling and simulation make it possible to examine the dynamic behavior of supply chains. Feedback loops, time delays and accumulations are a few of the most prominent structural causes of counter-intuitive dynamic behavior. Even relatively simple supply chain structures lead individuals to systematically make sub-optimal decisions due to the chain’s inherent feedback loops (e.g. between orders and incoming goods) and delays (e.g. order processing times). The (negative) effect of feedback loops and delays on decision makers’ performance has been demonstrated in various studies (Brehmer, 1992; Dörner, 1996). Simulation experiments allow for systematic investigations of cause-effect relationships that are separated by space and time, extreme conditions, and situations which cannot be observed in reality because of the costs or risks involved. Another reason for the use of simulations is the possibility to replicate the initial situation (Pidd, 1993). Finally, modeling and simulation are sometimes seen as the primary way towards scientific progress due to the inherent complexity of reality that makes direct conclusions from empirical observations questionable (McKelvey, 1999).

1.2 System Dynamics and Agent-Based Simulation

According to Parunak et al. (1998) many computer-based models developed in the field of SCM use system dynamics (SD), an approach for modeling and simulating systems with the help of ordinary differential equations. However, the field of agent-based simulation (ABS) has attracted more and more attention among researchers from a wide range of different fields, leading (among other applications) to a number of agent-based supply chain models. In this section, both simulation methodologies, SD and ABS, are described in general before focusing on supply chain-related studies applying one or the other approach in the next section.

SD is a simulation methodology that employs continuous handling of time and an aggregate view on objects to model and analyze dynamic socio-economic systems. Many of its basic concepts stem from engineering feedback control theory. The mathematical model description is realized with the help of one or many ordinary differential equations. “The expressed goal of the system dynamics approach is understanding how a system’s feedback structure gives rise to its dynamic behavior.” (Richardson, 1991: 299) The structure consists of multiple interacting feedback loops as basic building blocks of the methodology. Together these feedback loops represent the policies and continuous processes underlying discrete events (Forrester, 1961). Feedback loops consist of stock (state) and flow (change) variables. Besides feedback loops, accumulation and delays are major constituting features of SD models (Forrester, 1968). Due to elaborated diagramming techniques, SD models can be rather easily inter-subjectively communicated and developed in groups (Vennix, 1996).

In SD, supply chain modeling and simulation is as old as the discipline itself. In 1958 Jay W. Forrester, the founder of the field, modeled a four-level downstream supply chain (Forrester, 1958). By simulating and analyzing this model, Forrester examined “…many current research issues in supply chain management […] including demand amplification, inventory swings, the effect of advertising policies on production variation, de-centralized control, or the impact of the use of information technology on the management process” (Angerhofer & Angelides, 2000: 342). The focus on feedback loops and time delays makes SD a valuable tool for the investigation of supply chains. One important advantage of SD is the possibility to deduce the occurrence of a specific behavior mode because the structure that leads to systems’ behavior is made transparent. The drawback of using a traditional SD model of a supply chain is that the structure has to be determined before starting the simulation. For instance, if a flexible structure is to be modeled, every possible participant has to be included into the model and linked to its potential trading partners in advance, thus increasing model complexity.

ABS represents systems as comprised of multiple idiosyncratic agents: “…much of the apparently complex aggregate behavior in any system arises from the relatively simple and localized activities of its agents” (Phelan, 1999: 240). In other words, phenomena result from the behavior of agents which are one level below these phenomena; global system control does not exist (Jennings et al., 1998). Therefore the basic building block of a system is the individual agent—in the supply chain case, usually a company. In contrast to SD, agent-based modeling is a bottom-up approach (Bonabeau, 2002). The dynamics of the system arise from the interactions of agents, whereby the behavior of an agent is determined by its “cognitive” structure, its schema. “Different agents may or may not have different schemata…and schemata may or may not evolve over time. Often agents’ schemata are modeled as a set of rules, but schemata may be characterized in very flexible ways.” (Anderson, 1999: 219)

In agent-based modeling a consistent understanding of the concept and its terms does not exist. This is contrary to SD which has a definite starting point in Forrester’s early work. Therefore, it is more difficult to derive common definitions. For instance, the concept of “agency” is not well-defined (Rocha, 1999). However, researchers have at least agreed on some features that an agent should possess: situated in an environment, reacts to this environment, acts autonomously, tries to achieve certain objectives, and socially interacts with other agents. Agent-based modeling can be assumed to be a reasonable methodology for the examination of supply chains, because in a supply chain, a number of individual companies interact with each other using specific internal decision structures. The structure of ABS models is highly flexible and can adapt to changing conditions, which is an advantage of agent-based modeling in many cases. Using this feature, dynamically changing supply chain structures can be modeled. A disadvantage is found in that agents' behavior frequently cannot be explained in detail because most agents are constructed as black-box systems and/or determine their behavior with the help of "non-transparent" schemata (e.g. by applying genetic algorithms, artificial neural networks, etc.).

Because of the relatively complementary characteristics of SD and ABS, some concepts for combining the approaches have been developed (e.g. Scholl, 2001; Schieritz & Milling, 2003). The approach of combining the two methods was also implicitly suggested by scholars from the agent-based approach: Phelan claims that agents' rules are to be modeled by using algorithms that enable the agent to adapt to its environment over time by feedback mechanisms (Phelan, 2001). More explicitly, when explaining an agent's internal schema, Choi et al. (2001) compare these schemata with the notion of mental models, i.e. an individual's set of norms, values, beliefs and assumptions (Senge, 1990).

1.3 Simulation Studies in the SCM Literature

This section reviews some examples of simulation studies in supply chain research. We start with studies employing SD modeling, proceed with those that use agent-based methodology, and finally present articles which describe combined approaches.

Angerhofer & Angelides (2000) present a literature review on the use of SD in supply chain modeling. They construct a portfolio consisting of the paper category (theoretical, practical and methodological) on one axis and the research area on the other axis and classify papers into this portfolio. As research areas in SCM that can be investigated with SD they identify: inventory management, demand amplification (e.g., the bullwhip effect; Lee et al., 1997), supply chain design and reengineering, and international SCM.

Towill (1996) focuses on the support function of SD when supply chains are to be reengineered. He presents various forms of diagrams that have been successfully used in supply chain modeling and reengineering. He proposes an integration of SD modeling and conventional business reengineering methods.

Akkermans et al. (1999) use qualitative SD techniques (causal diagramming) to study issues in international supply chain management. Following SD tradition, they focus on the feedback loops created by variables from the supply chain domain. An emphasis of the paper is on the identification of virtuous and vicious loops connecting these variables.

Anderson et al. (2000) present a SD model to investigate upstream volatility (or, the bullwhip effect) in the machine tools industry. By a series of simulation experiments they test several hypotheses about the nature of the bullwhip effect, e.g. how production lead times affect the entire supply chain.

Milling & Größler (2001) present a SD model of the well-known "beer distribution game" (Jarmain, 1963). Within this model of a four-tier supply chain, they conduct simulation experiments concerning the influence of shortened information delays and the availability of point-of-sales information at different stages of the chain.

Parunak (1998) uses ABS to examine dynamic effects in supply chains. Based on a four-tier supply chain model, various SCM topics are investigated, for instance demand amplification. The paper provides rich quantitative detail for the simulation runs and results.

Van der Pol & Akkermans (2000) base their usage of agent-based modeling for studying supply chains on the observation that most real world supply chains do not possess a central controlling instance. ABS can therefore be used to find out how favorable behavior emerges from the interactions of the supply chain members, which can generate success for the entire supply chain—without demanding a central process control.

Parunak et al. (1998) compare agent-based modeling and SD with the help of a case study from SCM. They describe an agent-based and a SD model of a supply chain and discuss which conclusions can be drawn from each of the two models. By doing so, they want to achieve guidelines for choosing either of the two simulation approaches.

Akkermans (2001) uses terminology from the agent-based modeling approach to describe a supply network in a SD simulation environment. The individual agents only differ "in the degree in which they base their relative preferences for customers and suppliers either primarily on their short-term performance towards the agent in question, or mainly upon the intensity of long-term relationships, or on both" (Akkermans, 2001: 9). He finds that, in general, the agents choosing customers and suppliers based on short-term performance achieve better results. Moreover, the relative preferences for a specific customer or supplier become fixed over time, i.e. a stable supply network emerges.

Schieritz & Größler (2003) use a combination of SD and ABS to study the connection between timeliness and volume of shipments and the development of stable supplier/buyer relationships. The focus of the paper, however, is on methodological aspects of an integration of SD and ABS and the presentation of a working prototype.

2 Stocks and Flows? Or Agents and Rules?

2.1 The Hammer and the Nail – Using the Right Tool for the Right Problem

The discussion in sections 1.1 and 1.2 of the paper as well as the examples discussed in section 1.3 have shown that each of the two approaches (SD and ABS) has its characteristic features that make it suitable for the investigation of different classes of problems, and that both have been applied to a wide range of problems in the field of SCM.

However, the question regarding which kind of problem requires the application of what approach is mostly neglected in literature. As mentioned above, Parunak et al. (1998) compare SD and ABS with the goal of finding criteria for choosing the appropriate approach for a given SCM problem. However, their conclusion seems to be rather biased; a fact that can be observed for many scholars of the ABS approach and that might be explained by their attempt to establish their relatively new approach (Schieritz, 2004):

"ABMs [agent-based models] are better suited to domains where the natural unit of decomposition is the individual rather than the observable or the equation, and where physical distribution of the computation across multiple processors is desirable. EBMs [equation-based models] may be better suited to domains where the natural unit of decomposition is the observable or equation rather than the individual…ABM is most appropriate for domains characterized by a high degree of localization and distribution and dominated by discrete decisions. EBM is most naturally applied to systems that can be modeled centrally, and in which the dynamics are dominated by physical laws rather than information processing." (Parunak et al., 1998: 12)

If one accepts this statement, then the SD approach not only becomes superfluous for the analysis of strategic supply chain problems, but for the investigation of most socio-economic questions as well. Of course, the fact that the consequence is drastic cannot be a reason for rejecting Parunak et al.'s conclusion. With this in mind however, their opinion also contrasts with the variety of successful SD applications in the field of supply chain management as well as many other areas of social systems. It also contradicts Forrester's (1961) definition of the approach, which considers socio-economic systems to be information-feedback systems and SD an approach for modeling those systems. Forrester's introductory supply chain example is neither modeled centrally, nor are the dynamics dominated by physical laws. Instead, the dynamics are a result of delayed and distorted information exchanged between the participants of the supply chain.

The seemingly very catchy argument to choose a simulation approach according to the "natural unit of decomposition" of the domain under consideration appears weak when examined more thoroughly. The "natural unit of decomposition" depends on the level of aggregation the modeler chooses for the analysis of a given problem. From an application/problem-oriented point of view, every problem can be analyzed from an aggregated as well as a disaggregated view; it is however difficult to judge in advance which of the two will result in better insights (Sawyer, 2001). The "natural" unit of decomposition is therefore not as "natural" as it seems to be at first glance.

From a methodological point of view, one could argue that the "natural unit" is the agent in the ABS approach (Jennings et al., 1998) and the feedback loop in the SD approach (Forrester, 1968): Just like an agent-based model is always composed of individuals (that also can be companies), a SD model is always composed of feedback loops. Like the agents, the feedback loops are then composed of a number of variables: Parunak et al.'s "observables". The SD way of assembling a system is a result of the focus on policies instead of individual decisions. This different degree of abstraction often leads to a higher level of aggregation of a SD model compared to an agent-based model.

The problematic nature is intensified by the fact that the higher level of aggregation of a SD model is only a tendency (a fact that is also mentioned by Parunak, 1998), not a hard rule. Taking again Forrester's (1961) bull-whip example, he develops a four-tier supply chain by explicitly modeling every supply chain member, and every company; the overall system behavior is then a result of the interaction of the four members—an agent-based version of the model would probably have the same degree of aggregation. The chosen level of aggregation is adequate for an explanation of the problem and its causes; therefore disaggregating the model would only add more detail, and by that increase the complexity and prevent the user from gaining new insights.

Because it is difficult to identify absolute selection criteria, the task of choosing an appropriate simulation methodology still is an intuitive decision that depends a lot on the prior experience of the modeler. With the next two sections we want to give an idea of what we "feel" to be the differences between SD and ABS concerning their application domains. Instead of modeling one problem with both approaches the way Parunak et al. did (in such a case the chosen problem will always be more appropriate for one approach leading to a worse performance of the other one), we present an example of a combination of both approaches, each applied to that part of the problem where we consider its strengths to be best expressed.

2.2 Agents and Rules – Modeling Structural Emergence

A problem area where a combination of the features of both simulation approaches is helpful for efficient analysis is the investigation of supply network structures resulting from the interaction of (partly) independent companies. Following an integrative approach, a supply chain can be modeled with two levels of aggregation (Figure 1) where the macro level can be related to the agent-based approach, whereas the micro level is mainly modeled using SD.

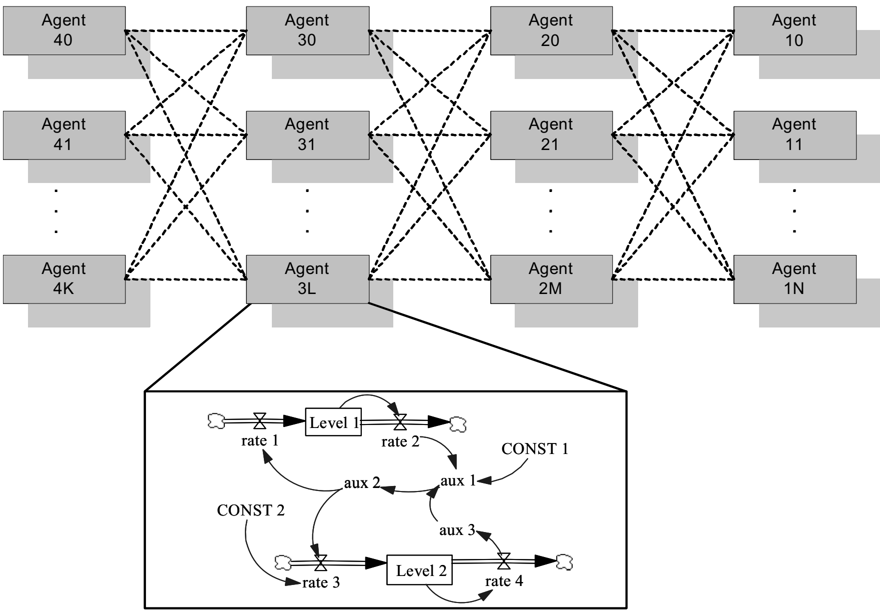

Figure 1: Macro and Micro Level of a Supply Chain

The macro level shows a network of agents that are potential supply chain participants. Every link between two agents can be interpreted as a potential customer-supplier relationship. Which of the relationships becomes active is determined during the simulation run: At any specific point during a simulation run, the structure of the supply chain is determined by the interactions between the agents that in turn result from the implementation of the agents' policies (the micro level) as well as the state of the environment.

Supply network structures as phenomena emerging from the interactions of the participating companies (instead of being expressed by macro equations) are analyzed using an agent-based model where structural changes can be implemented very efficiently, especially when a high number of agents are involved. A SD representation of the macro level would have the following two implications (both made us choose agents for this level):

(1) When deciding for a disaggregated representation as depicted in Figure 1 (meaning that every company is explicitly modeled), model complexity super-proportionally increases with the number of companies involved in the supply network, as every company has to be linked to every potential exchange partner in advance. Moreover, it is not possible to change model structure during the simulation run, meaning companies cannot enter or exit the market.

(2) The use of an aggregated representation requires the knowledge of macro equations that express the development of network structures. In such a case, the network structure is characterized by a number of variables (e.g. stability, number of exchange partners) and the interrelationship is modeled between those variables and others that influence them (e.g. external demand, ordering policies). If the macro equations are known, such a model can result in a very clear and easy-to-understand and -communicate representation of the problem. If, however, the effect of the individual companies' policies on the overall network structure is unknown and cannot be found out by e.g. case studies, a valid aggregated representation is difficult to achieve.[2]

2.3 Stocks and Flows – Modeling Complex Decision Making

A company's policies represent the internal structure or schema of that company; they are implemented on the micro level (the agent level) and are responsible for the structural changes on the macro level. In our approach, SD is used to model the more complex policies, whereas the simple, mechanical ones are modeled using discrete rules. As soon as policies reach a critical level of complexity, and decisions are not based on simple rules, the structural representation of causal relations as well as the focus on feedback loops and delays renders SD suitable for policy modeling. Policies do not only change when triggered by external events, but might change continuously in the cognitive schema of the agents. SD is designed to model such continuous decision making processes (Forrester, 1961).

In the simulation model described in the following, the internal structure of an agent can roughly be divided into four sub-structures: ordering, production, shipping and evaluation. Whereas the first three can be assigned to the ABS approach, the last one – due to its complexity – is modeled using SD.

Ordering sector: Every company uses the same order policy: As soon as the inventory level falls below the safety stock, an order is placed with the preferred sup-

[2] The last comment results in the conclusion that a disaggregated model can also be used to support the construction of its often simpler aggregated counterpart.

plier. The order size is determined by the inventory level (material on stock plus material ordered and not yet received), the safety stock level as well as a fixed maximum inventory level. The safety stock level is not fixed; it changes as customer order forecasts change.

Production sector: A very simple production process is assumed. Whenever unfulfilled customer orders exist or the amount of finished goods on stock falls below a certain level (which again is influenced by customer order forecasts), the company produces the amount necessary to fulfill the orders and bring the finished goods inventory back to its safety level. Different production stages and the resulting variations in production time are not taken into account explicitly, but they are represented by using a third order Erlang distribution for production time. As soon as customer orders are backlogged, maximum production capacity is utilized; in times of in-stock production capacity utilization is reduced.

Shipping sector: The companies only ship complete orders. They are then transported to the customer without any delay; in case enough goods are in stock, an order can be filled immediately. Shipping does not take place in a first-come-first-serve manner, as the best customers (being the high-volume customers) are preferred.

Evaluation sector: Contrary to the relative simple decision rules applied in the three sectors that have been described so far, the policy used for selecting an appropriate supplier is more complex in that it involves a higher number of interconnected parameters as well as a lot of “soft” variables. The evaluation sector can be interpreted as a company’s mental model of its suppliers whose performance is continuously rated. It consists of a number of evaluation models like the one depicted in Figure 2; a company holds as many evaluation models as potential suppliers exist.

An agent’s final supplier selection criterion—Ttrust—is modeled as a level variable (indicated by a rectangle in the diagram in Figure 2) that integrates the difference between the inflow and the outflow. The range of values of the variable Trust lies within [-1,1]. The trust decay rate reflects the degree to which an agent values the past performance of its suppliers. The inflow (respectively outflow) trust change rate is determined by two sub-criteria: Order Volume and Time Order Placed. Together with Order Variance and the two switches (Open Order Switch and No Open Order Switch) they are the input data of the model (input and output data are marked with gray circles). In order to enable comparability between the two different supplier evaluation criteria—waiting time and volume—the value of these two variables is transformed into an attractiveness measure with the help of the functions Wt Effect Table and Volume Effect Table. The higher the number of supplies received from one supplier, the higher the absolute value of the Trust Coefficient for this particular supplier—all other variables being of constant value. The behavior of the delivery time is opposite: the higher the delivery time, the lower the absolute value of the Trust Coefficient. As soon as the delivery time exceeds a critical value, its effect becomes negative, which leads to a negative Trust Coefficient. The effect of the Trust Coefficient on the trust change rate depends on the current Trust state. A Trust Coefficient greater than actual Trust will lead to a positive trust change rate and therefore to an inflow in the level Trust. However, trust evaluation only takes place when a company is waiting for an order to be filled (the Open Order Switch is 1). In every other case, only the outflow from the trust level is active.

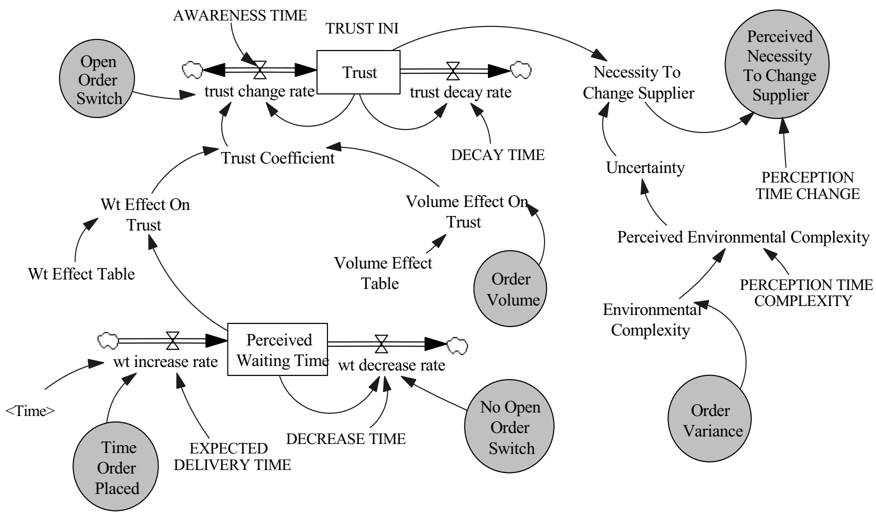

Figure 2: Potential Evaluation Sector in System Dynamics Notation

The second level variable, Perceived Waiting Time, represents the way a company perceives delivery delays: Every deviation of the delivery time from the expected delivery time is accumulated. By this, the exponentially increasing annoyance resulting from increasing delays is modeled. As long as a customer is waiting for its order to arrive, the No Open Order Switch equals zero; only after all orders are delivered does the annoyance start to decrease. However, as long as Perceived Waiting is not zero, a further delivery delay is amplified because of the still- existing annoyance from earlier shipments.

A company evaluates the importance of a relationship based on trust according to the existing environmental conditions. A higher environmental complexity – modeled by a higher Order Variance – results in a higher uncertainty which reduces the willingness of a company to change its supplier. As soon as the Perceived Necessity To Change Supplier, which equals a delayed Necessity To Change Supplier, exceeds a threshold, the company is willing to change its suppliers.

However, whether a change actually takes places depends on the company's perception of the other suppliers in the market. Perceived Necessity To Change Supplier and Trust are the output variables of the evaluation sector.

The structure described above represents the internal structure of all agents that are not located at the end points of the supply chain. They are called Producers in the following. Final Customers and Raw Material Suppliers are structured similarly; however, Final Customers are missing a production and shipping sector; Raw Material Suppliers do not contain an ordering and evaluation sector.

3 …or Both?

The intention of the last paragraphs was to shed at least some light on the problem of deducing appropriate application areas from features of the two simulation approaches SD and ABS. This was achieved with the help of an integration of the two simulation methods and their application to the problem areas they fit best. The following paragraph now aims at the presentation of a problem area that we identified as possessing features that require an integrative approach: the emergence of supply chain structures. It introduces some simulation results of the model explained above and continues with a possible supply chain question that could be analyzed with the help of such a model.

The simulation model was implemented using the software AnyLogic.[3] It is a multi-paradigm simulation tool that allows for an integration of the paradigms SD and ABS by offering a wide range of different modeling tools like stock and flow diagrams, table functions, discrete and continuous state-charts, algorithmic representations etc. Figure 3 shows a screenshot of a simulation result including the AnyLogic user interface.

The prototypical supply chain displayed in Figure 3 consists of four tiers and ten organizations. External demand from the market (complexity of the environment) is constantly set to 50 units/simulation period. The behavior graphs in the small boxes depict trust variables linked to the potential suppliers of an agent. Trust influences the stability of a supplier-buyer relationship according to a company's internal model described above. The stability is indicated by the lines between supply chain members: The thicker a line, the more stable the particular relationship. Therefore, the overall supply chain structure emerges in the course of the simulation as a result of the members' individual policies in a given environment (market demand). With the experimental setting shown in the figure, the effects of environmental complexity on the development of trust and ultimately supply chain

[3] See www.xjtek.com/anylogic/ for a list of features, limitations, computational requirements etc. of this software. Equations are available from the authors.

structures can be studied. More specifically, the dynamics of many, autonomously acting agents can be simulated by the integrated approach, and supply chain structures that originate in their interaction can be observed.

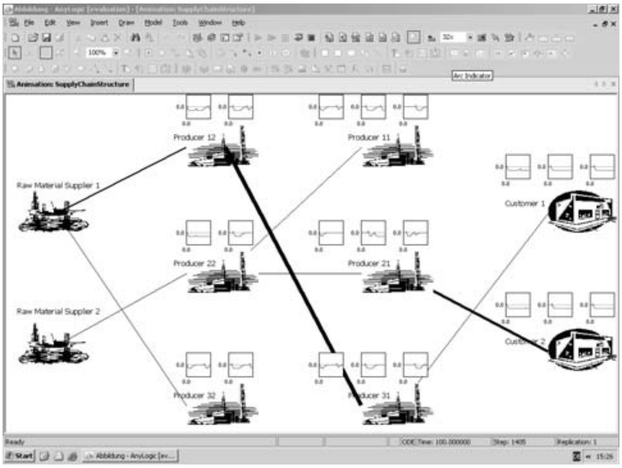

Figure 3: Screenshot of Integrative Supply Chain Simulation Using AnyLogic

AnyLogic allows for an easy duplication of agents. Therefore, the number of potential members of the supply chain can easily be increased. This could even be done dynamically, e.g. when buyers experience long delivery times from all suppliers in the supply chain, they may look for a new partner which then enters the supply chain. In a similar vein, a supplier not trusted by any of its customers might leave the supply chain completely. Furthermore, the schemata of the agents can be varied in order to investigate the effects of different evaluation policies. It might be an interesting question to find out what effects are caused by the combination of, for instance, tolerant buyers and opportunistic suppliers. Another point for further research that is only touched upon in this paper is to study what effects an increase in external complexity (e.g. caused by demand fluctuation) has on the stability and viability of the supply chain structure. Finally, more sophisticated agents' schemata may certainly also be implemented. For example, more criteria other than just trust can be incorporated in the selection of suppliers.

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