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Multi-methodology Modeling to Support Policy Analysis in Socio-technical Systems

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1 Introduction

1.1 Motivation

How would changes in the production rate of an electricity producer may influence the entire electricity sector? How can replenishment policy applying by a supply chain's member causes disruptions in the whole supply-chain systems? How does disturbance in the production of a gas producer influences other stakeholders involved in the system? All these questions - though are from the different domains- are addressing similar type of problem. These questions are typical from socio-technical systems, which involve networks of actors and networks of physical-technical elements. Furthermore, these questions are mainly concerned about the technical and operational part of these systems where activities of agents determine the dynamic of systems in terms of flow of material, energy, money, etc.

Socio-technical systems include both physical-technical elements, and interdependent agents (De Bruijn and Herder, 2009). On the one hand, the state of these systems, changes due to behavior of actors which is itself influenced by institutions and social rules- and on the other hand, it changes due to behavior of physical systems (Ottens et al., 2006). Therefore, the dynamics of a socio-technical system can be because of either actor-actor or actor-artifacts interactions. For example, actors involved in a socio-technical system, can compete, negotiate and cooperate which at the end results in the social dynamics. Simultaneously, they interact with artifacts producing, transferring, changing materials, and shaping the technical dynamics. Understanding this dynamics is a prerequisite for decision making and call for scientific tools, which facilitate the analysis of these complex systems. Furthermore, the change within these systems is very costly, in terms of financial and social cost, and once a decision has been made it is relatively hard to reverse it. Social scientist advocate using computational simulation to overcome these complexities helping decision-makers to get insight into, and test different scenario in these systems.

Agent-based modeling (ABM) is one of the popular simulation approaches, which has been used to study socio-technical systems. In ABM a socio-technical system is modelled by decomposing a systems into some heterogeneous entities, called agents which continuously interact with each other and with their surrounding environment. The global behavior of these systems is the result of interaction between agents and environment. Although ABM has become steadily a popular approach in the social science and in the modeling of socio-technical systems, its application has been facing several important issues. An issue with current ABM practice is that studying the feedback from emergence features of systems on the behavior of agents is not part of design steps of agent-based models (Sawyer, 2001). Particularly, in the case of Agent-Based Generative social simulation (ABGSs) proposed by Epstein (2006), this problem is very bold since in ABGSs- by definition- it is assumed that the macro behavior of a system is only the result of agent's behavior, and their interaction with each other (Epstein, 2006). Conte (2009) states that the ABGSS' view prevents it to take into account downward causation so that no full account of social phenomena is provided, since the causal autonomy of social systems is ignored.

The properties of the system at the emergent level can be classified to quantitative and qualitative properties. Qualitative features refer to the societies, rules, organization, localities, which may be emerged through the interaction of agents. Quantitative features refer to the aggregated state or statistical characteristics of the observable variable of a system (e.g., the number of people having a opinion) which influence agent's behavior . Apparently much of the research that addresses the importance of considering downward causation in ABM (e.g.,Conte (2009)) primarily focuses on the effect of qualitative properties such as norms on the behavior of agents. However, there are many of social examples (and theories), which evidence that quantitative properties of systems influence the behavior of individuals as well. For example, Sherif (1936); Asch (1956) present that opinion of an individual not only changes through the individual interaction with other agents but also the number of people as majority may also influence the actors opinion. These social theories which will be further discussed in the next chapter- illustrate that there are some feedback between quantitative properties of systems and behavior of agents that need be considered in developing agent-based models.

Another issue with current ABM practice is that there is a controversy about the explanatory of agent-based models. Grüne-Yanoff (2009) claims that ABM and particularly micro-macro modeling approaches (like ABGSs) are not explanatory since they cannot provide causal explanation. Richardson et al. (2003) argues that since there is a possibility that the result obtained in a simulation be generated in a number of alternative ways, ABM cannot be explanatory. Although this problem can be a generic problem of any computer simulation, it is more controversial in the case of ABM with emergence outcome where modelers may not be able to provide any insight into the chain of events. Conte (2009) believes that the *generative explanation* requires causal explanation, otherwise the explanation is irrelevant.

Marchionni and Ylikoski (2013) argue that to increase the understanding from the agent-based models, modelers should show how the assumption made about the agents result in the global behavior of the system; ABM models should be supported by making explicit the causal mechanisms driving the phenomena. Causal mechanism is a type of explanation, which has roots in the social science as well as philosophy of science (Hedström and Ylikoski, 2010). The core idea behind the mechanism approach is that to explain an event referring to the cause is not enough. We must provide the causal mechanism as well. Although, providing the causal explanation of agent-based models seems critical for enhancing their explanatory power, it has not received enough attention in ABM studies. ABM suffers from the lack of procedure, notation, and tool that help the task of capturing and presenting causal-mechanism involved in the agent-based models.

The last issue - that we address in this study- is that "ABM may impose a heavy computational and parametric burden. Tracking and scheduling a large number of interacting agents leads to serious computational requirements and analytical challenges." (Bobashev et al., 2007). Furthermore, "The complexity of agent-based models may easily reach a level that makes it almost impossible for a researcher to deduce any understanding form the simulations." These limitations have already been pointed out by many researchers arguing that to use ABM in scientific way, modelers should keep agent-base models simple following the KISS (Keep It Simple, Stupid!) slogan (Yücel, 2010). However, this simplification sometimes cost the accuracy of the models. Edmonds and Moss (2005) argue that "the difficult part in science is not finding attractive abstract models, but of relating abstract models to the world." The trade-off of simplicity and accuracy is a critical issue in the field of ABM. How can we simplify a model without losing the main dynamics driving the behavior of that system?

There are also some practical drawbacks for current ABMS practice. First, as Pavon et al. (2008) argue, while the actual users of ABMS are policy makers and social scientists who are usually not skilled in computer programming, agent-based models are complex to build and require substantial programming knowledge. Second, while a number of research advocates participatory modeling of ABM (e.g., Gilbert and Troitzsch (2005)), with current ABM tools, it is hard to involve different stockholders in the conceptualization and process of simulation. Currently, once an agent-based model has been implemented, we can present the out come of the simulation, whereas the structure of the model and the process involved in the system are implicit in the programming code. Getting involved stockholders in the process of modeling before implementation helps the process of validation of models through the expert validation, and it can reduce the cost of making change in the simulation (Ghorbani et al., 2013).

Using ABM for studying socio-technical system is insightful. However, by overcoming the aforementioned limitation (conceptual and practical) we can indeed increase the usability of ABM.

1.2 Terminology

Before continuing our discussion, it is necessary to make clear the definition of some words that will be used through this study.

- Paradigm: "A paradigm is a very general set of philosophical assumptions that define the nature of possible research and intervention." (Mingers and Brocklesby, 1997). Paradigms are fundamental assumptions which every methodology is built upon them (Lorenz and Jost, 2006). For instance, Emergence is the critical paradigm or in other word fundamental assumption in ABM. Whereas, In System Dynamics Modeling (SDM) feedback has been recognized as the main paradigm (Scholl, 2001).

- Methodology: "A methodology is a structured set of guideline or activities to assist people in undertaking research or intervention. Generally, a methodology will develop, either implicitly or explicitly, within a particular paradigm" (Mingers and Brocklesby, 1997). In this study ABM and SDM are example of simulation methodologies. Every methodology can comprise some phases. For instance, an agent-based modeling study may comprise following phases: Conceptual model building, Computer implementation, validation, Experimentation.

- Technique-tool: "A technique is a specific activity that has a clear and well-defined purpose within the context of methodology."; "tool is an artefact, often computer software. that can be used in performing a particular technique." (Mingers and Brocklesby, 1997). Every phase in a methodology has particular techniques or tools that help accomplish them. For example, Causal Loop Diagrams (CLD) is a tool which can be used in the phase of conceptual modeling of SDM.

1.3 Multi-paradigm simulation: an Alternative to Cope with These Issues

As we will extensively discuss and demonstrate in this thesis, multi-methodology simulation is an emerging solution to address the aforementioned issues. There are different types of simulation and modeling (S&M) methods which have been used to study Socio-technical systems. All of these methods have their special characteristic and assumption stemming from different paradigms. Meadows and Robinson (2002) point out that "Different modeling paradigms cause their practitioner to define different problems, follow different procedures, and use different criteria to evaluate the results." Adapting a specific paradigm is like seeing the world through a particular lens which reveals certain aspects of a situation overlooking others. Although different paradigms may be used to investigate the same problem, each paradigm may result in different explanation of the situation and seemingly incompatible policy advice. Hence, "adapting one paradigm inevitably gaining only a limited view of the problem situation" (Mingers and Brocklesby, 1997).

In recent years, developing multi-methodology has been the subject of several studies. Mingers and Brocklesby (1997) state following arguments in favor of multi-methodology: first, "real-world problems are inevitably highly complex and multi-dimensional. Different paradigms each focus attention on different aspects of the situation so multimethodology is necessary to deal effectively with the full richness of the real world." Second, Given that each method has some phases to be conducted, each method tends to be more useful in some phases of than others. So, combining them makes an immediate appeal. To combine different methodologies, Mingers and Brocklesby (1997) propose that methodologies can be combined at the paradigm level, methodology phases, and techniques.

To overcome the mentioned limitation of ABM, we propose to take advantage of System Dynamics Modeling (SDM) as a complementary tool for ABM. System dynamics and agent-based modeling are popular and widely used S&M methodology and their potential complementary use has been discussed in many recent studies (e.g., Wakeland et al. (2004); Schieritz and Milling (2003); Borshchev and Filippov (2004); Schieritz and Grobler (2003)). Scholl (2001) calls for cross studies and joint research of SDM and ABM to find ways that they can complement each other. He argues that "Individual-based modeling and aggregate feedback modeling may complement each other in ways that are unimaginable from today's perspective".

SDM and ABM can be combined at the paradigm level. Furthermore, the tools and techniques of SDM can be used at the different phases of ABM. In order, to combine SDM and ABM at the paradigm level we, should first recognize their paradigm then we justify how their combination can result in more reliable simulation method. Given that the phases involved in an agent-based model include the four main steps: Conceptual model building, Computer implementation, validation, Experimentation (Pidd, 1998), SDM tools and techniques can be used in some of these phases. As we will discuses later in more details, Combining SDM with ABM will help to address the first mentioned issue with ABM. Furthermore, Combining SDM with ABM at the technique level will help to alleviate the second and third mentioned issues with ABM.

ABM follows the bottom-up approach in investigating systems and the emergence is the key concept in ABM. Epstein (2006) states that "ABM is, by its very nature, the canonical approach to modeling emergent phenomena: in ABM, one models and simulates the behavior of the systems constituent units (the agents) and their interactions, capturing emergence from the bottom up when the simulation is run." In the contrary, SDM is considered as a top-down approach. In contrast to the concept of emergence, the scientific concept of feedback is the core of SDM (Scholl, 2001). To combine SDM and ABM at the paradigm level, we need to position the notion of feedback in the context of ABM. Feedback approach of SDM which is supported by using Causal Loop Diagram (CLD) and its focus on capturing the dynamics of the systems specially among the quantitative properties of the system at the macro level helps addressing the above-mentioned "downward causation" issue in agent-based modeling.

Agent-base Modeling: Computer simulation as a field of research which is at the intersection of social, mathematical, and computer science has been able to benefit from Multi Agent Systems (MAS) and Distributed Artificial Intelligence (DAI) which provide architecture and platform for implementing autonomous agents (Conte et al., 1998). The use of agent-based approach enhanced potential of computer simulation in studying, and theorizing social science issues (Conte et al., 1998).

ABM is suited for studying complex systems of interacting entities, like social system (Klügl et al., 2004). During the last decades it has been used to study in a broad range of disciplines such as economy (e.g.,Tesfatsion (2003)), socio-technical system (e.g., Van Dam et al. (2012)) and business (e.g., North and Macal (2007)). This growing interest in applying ABM indicates its advantages in comparison to other simulation approaches. We should emphasize that in this research we are referring to Agent Based Social Simulation (ABSS) as ABM.

Drogoul et al. (2003) point out that the power of ABM is in "its ability to cope with very different models of individuals, ranging from simple entities (usually called reactive agents Drogoul (1995)) to more complex ones (cognitive agents Jennings (2000))". ABM attempts to model the behavior of individual which is contrasted to macro simulation techniques (e.g., SDM) "that are typically based on mathematical models where the characteristics of a population are averaged together, and the model attempts to simulate changes in these averaged characteristics for the whole population" (Davidsson, 2001).

The main elements of ABM are individuals, which are called agent (North and Macal, 2007). Each agent evaluates its situation and makes decision based on set of rules. Agents may carry out different behaviors, for example buying, selling, or producing (Bonabeau, 2002). There is no common agreement on the precise definition of agent in literature (Macal and North, 2005). Some researchers consider agents as "self contained program that can control their own action based on their perception of their operating system" (Gilbert and Troitzsch, 2005). One of the main reasons that there is some confusion about the term of "Agent " is that this term has been used in many different fields of study in addition with social science (Gilbert and Troitzsch, 2005). Multi Agent System (MAS) uses the term of agent for software agents who interact in the real environment such as the Internet. Wooldridge and Jennings (1995) define 5 properties for computer agents in the point of view of MAS:

- autonomy: agents operate without intervention of other agents, and they control their actions.
- social ability: agents have the ability to communicate and interact with other agents
- reactivity agent perceive their environment and respond to its changes.
- proactivity agents not just response to environment, they are able to take initiative and engage in goal-directed behavior.

Macal and North (2005) address five properties for agents in ABM which is somehow different from the characteristics of agents in MAS:

- An agent is identifiable. having set of characteristics, rules which govern its behavior, and decision making capability.
- An agent is situated, living in and interacting with other agents through the environment.
- An agent is goal-directed, having goal with respect to its behavior.
- An agent is autonomous and self-directed. carrying out actions independently in its environment.
- An agent is flexible, having the ability to learn and adapt its behaviors.

SDM is one of the best ways to picture causal mechanism explanation Olaya (2009); this characteristic of SDM can help to address the second mentioned issue of ABM regarding the explanatory power of agent-based models. One of the main characteristics of SDM which makes it a powerful method for capturing and presenting the mechanism involved in the system is that SDM takes advantage of Stock and Flow Diagram (SFD) tool to describe the dynamics involved in a system. To enhance the explanatory power of ABM in terms of mechanism-based explanation, we will present a meta-model for conceptualizing the mechanisms involved in agent-based models. This meta-model, will help the process of capturing and presenting the mechanisms in ABM. Based on this meta-model, we will illustrate the types of mechanism which can be described by the help of SFD.

System Dynamics Modeling: System Dynamics Modeling (SDM) was introduced by Jay Forrester in 1950 at Massachusetts Institute of Technology (MIT). At the early stage, it was called "industrial dynamics" approach, mainly because for the first time it was used to study dynamics of industrial activity in an organization (Forrester, 1961a). It was defined as: the study of information feedback characteristics of industrial activity to show how organizational structure, amplification (in policies), and time delays (in decisions and actions) interact to influence the success of the enterprise (Forrester, 1961a). Later on through this fact that this approach has the ability to be applied in studying the dynamics of different systems it was called system dynamics. System dynamics root goes back to the control theory principal. Jay Forrester showed how control theory approach by the help of simulation can be useful to study social systems.

The main elements of SDM are stocks and flows. Sterman (2000) point out that "Stocks and flows, along with feedback, are the two central concept of system theory". He discussed that we can build a system by a network of these two elements. Stocks are the accumulation of flows which themselves are determined by the decision rules. System dynamics modeling commonly starts with creating a causal loop diagram in which the interaction between variables and especially the feedback between them is identified. Then Stock-

Flow model of systems are developed.

One of the main assumptions in SDM is that "The behavior of a system arises from its structure. That structure consists of the feedback loops, stocks and flows, and nonlinearities created by the interaction of the physical and institutional structure of the system with the decision-making processes of the agents acting within it" (Sterman, 2000).

The aggregate approach of SDM can help to address the third mentioned issue of ABM. According to Ghaffarzadegan et al. (2011),"aggregation reduces the size of the model, thereby decreasing the cost of developing and running models and allowing for more experimentation. Given limitations in individuals cognitive capacity, aggregation also allows users to focus on feedback ahead of agent level detail and therefore develop a more holistic and endogenous perspective to the problem." to apply the aggregate perspective of SDM in ABM, we propose to use SFD to model some parts of the agent-based models. SFD can be used as simulation technique, using equations to calculate the quantitative behavior of the system applying the aggregated approach of SDM. At the implementation level of an agent-based modeling study, SFD can be used to decreases the computational power usage of ABM. As we will discuss later, SDF can help ABM models to be simple and descriptive following the both KISS (Keep It Simple, Stupid!) and KIDS (Keep It Descriptive, Stupid) paradigm (Axelrod, 1997a; Edmonds and Moss, 2005).

1.4 Research Question

Governing and developing effective policies for socio-technical systems require decisions makers and policy analysts to understand the systems by testing and exploring the different scenarios. ABM can provide this unique opportunity. However, there are some limitations for ABM that should be overcome to increase the explanatory power and usability of this modeling approach. Therefore, the main question in this research is.

> How can we decrease the complexity of agent-based modeling process while increasing the explanatory power, and considering the effect of feedback from macro-properties on agents behavior in agent-based models using SDM as complementary approach for ABM?

To address this research question, some sub-questions needed to be addressed:

- What is the role of feedback in social systems and how it influences the modeling in ABM?
- How can we capture and explain the causal mechanisms (processes) involved in agent-based models?
- How can we simplify an agent-based model without losing the main dynamics driving the system?

1.5 Theory and methodology

Figure 1.1 demonstrates the methodology followed to answer the question of this research. The methodology is summarized in five phases: analysis, development, implementation, case study, and conclusion. The analysis (phase I) focuses on per-forming a literature review on the state of the art of modeling and simulating socio-technical systems. Issues of focus are agent-based modeling, system dynamics modeling, and hybrid simulation.

In phase II, three major components are identified. These are the cores of the developed hybrid simulation method and are addressed as follows. First, A framework for combining ABM with SDM at the paradigm level. Second, A framework that represent how SDM tools can be used for depicting causal mechanisms at the conceptual phase of a simulation study. Third, appropriate discrete-time system dynamics method is proposed that facilitates integrating ABM with SD method at the implementation level.

Phase III involves designing a software that integrates the simulation components of ABM and SDM on a single platform. Phase IV presents different aspects of proposed hybrid simulation by the help of one case study. Finally, Phase V presents the research conclusion. The challenges found in the research and lessons learned through the research will be presented in this section.

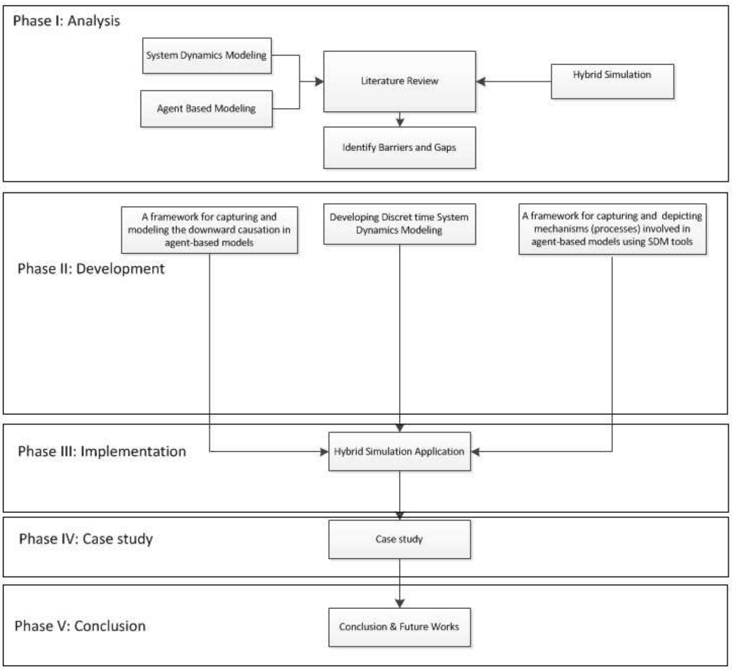


Figure 1.1 – Overview of the Research Methodology

1.6 Scope

1.6.1 Scientific Relevance

This a multidisciplinary research that aim to enhance the ABM as policy analysis tool by integrating Agent-based Modeling and System Dynamics Modeling. We identify the limitation and strong points of these two simulation methods and we present how they can be complementary to each other. A integrated method has some mutual benefits for both methods since ABM can take advantage of SDM strong points and SDM can benefits form the ABM.

1.6.2 Contribution

The contribution of this research can be classified into three areas:

Agent-Based Modeling This research will add to ABM research by providing a conceptual modeling tool which enhance the explanatory power of ABM by highlighting the mechanism involved in systems. It further contributes to ABM by facilitating the process of validation of Agent-based models.

System Dynamics Modeling This research will add to SDM by extending SDM with object oriented modeling which enhance the re-usability of SDM models.

Policy analysis This research contributes to the policy analysis field by providing a tool to get insight into the systems by presenting the underlying cause and effects and dynamics of the systems. It facilitates communication between modelers and other stockholders about the underlying dynamics involved in the systems.

1.7 Outline

The structure of this thesis is as follows. This thesis is organized in three part. The first part is dedicated to answer the firs sub-question of this research. the first part includes two chapters. In Chapter 2 we introduce the concept of quantitative and qualitative properties of systems at the macro level and we discuses about the importance of considering feedback from macro-level properties in ABM. In Chapter 3, we use a case study (opinion dynamics) to explore the effect of feedback from quantitative properties of systems in agent-based models.

The second part of the manuscripts is aimed to answer the second sub-question of the this study. In this part, Chapter 4 presents a how we can make explicit the process involved in the environment of agents using SFD; this chapter mainly focus on the dynamics between macro-level propoerties of systems and agents. In Chapter 5 we explain the importance of mechanism based explanation for agent-based models and we present a framework for using SFD to make explicit the mechanism involved in agent-based models at the operational, social , and macro level; We take advantage of a Bio-gas case study to illustrate our proposed framework.

The last part of this thesis is dedicated to answer the third sub-question. This part includes three chapters. In Chapter 6, we introduce Discrete-time System Dynamics Modeling (DT-SDM) that we use it later to combine with ABM. Chapter 7 is aimed to take advantage of a case study (The Bullwhip effect phenomenon) to explore the advantage of DT-SDM. In Chapter 8 we propose a framework for combining SFD with ABM; We presents how SFD can be used to simplify ABM models without loosing the main dynamics of the systems.

In Chapter 9, we introduce the software that we have developed for combining SDM with ABM called HybSim. In the Final chapter, we conclude by discussing our contribution and we give direction for future research.

Part I

Combining SDM with ABM at the paradigm level

2

Emergence and Feedback in Agent-based Modeling

2.1 Introduction

When we face a traffic jam on a road, we are likely to find a new road to reach our destination. During the time, we will learn about the pattern of traffic jam in the roads, and we try to avoid them in advance. However, the process of learning can be accelerated by some devices. For example, we can be informed about the traffic jam through the digital sign in the road or through the news which help us to avoid traffic jam. Traffic jam is a higher-level pattern which influences our decision to select or change our way to reach the destination. In fact, traffic jam is an example of emergence phenomena arising from the behavior of autonomous entities, which influence our decision to select or avoid a specific road. There is a feedback between the properties of traffic jam, as a higher-level pattern, on the micro level entities (Drivers) behavior.

Emergence is the result of upward causation arising from the individual's behavior and their interaction. However, there is also a top-down causation that limits individuals behavior (Sawyer, 2004). Gilbert and Conte (1995) argues that "not only do the agents' actions at the local level, when aggregated and observed at the global level, constitute the emergent behavior, but also the global emergent behavior can also be said to influence the local actions of the agents, in a form of feedback." Gilbert (2002) emphasizes that a fundamental characteristic which make the societies of human different from other complex systems is the fact that "people are routinely capable of detecting, reasoning, about and acting on the macro-level properties (the emergent features) of the societies of which they form part."

In agent-based models, "emergence is often viewed only as a bottom-up process, without effective downward causation" (Ferber et al., 2008). This problem is particularly highlighted in Agent-Based Generative social simulation (ABGSs) proposed by Epstein (2006). In ABGSs, by definition it is assumed that the behavior of systems is solely the result of agent's behavior and their interaction. Epstein (2006) states that to model a phenomenon "situate an initial population of autonomous agents in a relevant environment; allow them to interact according to simple local rules, and thereby generate–or "grow"– the macroscopic regularity from the bottom up." A quick search of the main key words of "downward causation", "immergence", and "second order emergence" in the Journal of Artificial Societies and Social Simulation (JASSS), which is one of the few journals focusing on social computer simulations, reveals that only 25 paper use these keywords. However, non of these papers models the downward causation in a simulation study. In the next chapter, we will address some famous opinion dynamics models (e.g., Deffuant et al. (2000); Hegselmann and Krause (2002)) which do not consider the downward causation from the state of the systems at the macro level on the formation of agent's opinion.

In this study we propose to classify the properties of systems at the macro-level (the features of emergence phenomena) to the quantitative and qualitative properties. While the structure, rules, norms, organizations, etc. are qualitative properties, quantitative properties refer to the aggregated state or statistical characteristics of the observable variable of a system which influence agent's behavior. Apparently, much of the research that addresses the importance of considering downward causation in ABM (e.g.,Gilbert (2002)) primarily focuses on the effect of qualitative properties such as higher-level structure and norms on the behavior of agents. For example, Conte (2009) states that *immergence* is the effect of social properties and entities such as norm, authorities, leaders on forming expectations of agents and rules of interpreting others. Sawyer (2001) introduce the effect of norm on the behavior of agents as downward causation.

The main characteristics that distinct qualitative properties form quantitative is that the qualitative properties can be initially be determined as rules of agent's behavior. However, qualitative features cannot be defined at the beginning, and they should be emerged. Quantitative features will not have a direct effect on the micro properties of the system through; they will influence the micro system through the behavior of agents. In other words, they are perceived by the agents and decisions of agents are influenced by these properties. To provide a full description of the social phenomena, agent-based modelers should explicitly model the effect of quantitative features of emergence phenomena on the behavior of individuals.

2.2 Emergence: a Closer Look

There have been many debates and discussion about the definition of emergence in the field of philosophy. The following definitions are the most popular definition of emergence: "Emergence is understood to be a process that leads to the appearance of structure not directly described by the defining constraints and instantaneous forces and functions that control a system" Crutchfield (1994). "a property is emergent if it cannot be explained from the properties and interactions of the lower-level entities" Boschetti et al. (2005). Some researchers criticize these definitions arguing that such definitions show that we are unable to make links between lower level entities and emergence phenomena. They argue that it is mainly because of lack of our knowledge, and in the future we may be able to make the links concept.

Although the concept of emergence first appeared in philosophy, it has been widely used in the domain of complex adaptive system, computer science (Deguet et al., 2006; Holland, 2000), multi agent systems, and consequently, in artificial society and agent-based modeling. Gilbert et al. (2005) in their pioneer book on agent-based modeling emphasize that emergence is a key concept in this field. They state that "emergence is one of the most interesting issues to have been addressed by computer scientists over the past few years and has also been a matter of concern in a number of other disciplines, from biology to political science." A comprehensive discussion about the emergence and the role of emergence in ABM can be found in (Gilbert and Conte, 1995; Sawyer, 2001; Ferber et al., 2008).

There are different classifications of emergence in the literature. Bedau (1997) propose the most common classification of emergence: week emergence in contrary to strong emergence. According to Chalmers (2002), the notion of emergence, which is common in philosophical discussions, refers to the strong emergence. In contrary, weak emergence is the notion of emergence which is most popular in complex adaptive systems and computer science. He argues that, for example, the emergence of pattern in cellular automata is a weak emergence. Although the pattern at the higher level is unexpected, but the formation of this pattern is deducible from the basic rules and initial condition.

Weak emergence is the view that a systems macro properties can be explained by its micro properties but only in an especially complicated way" (Bedau, 2008). Weak emergence has some characteristics: weak emergence is underivability without simulation, explainable only in an incompressible way. Bedau (1997) argue that "Weak emergence applies in contexts in which there is a system, call it S, composed out of micro-level parts; the number and identity of these parts might change over time. S has various macro-level states (macrostates) and various micro-level states (microstates). Ss microstates are the intrinsic states of its parts, and its macrostates are structural properties constituted wholly out of its microstates. Interesting macrostates typically average over microstates and so compress microstate information. Further, there is a microdynamic, call it D, which governs the time evolution of Ss microstates. Usually the microstate of a given part of the system at a given time is a result of the microstates of nearby parts of the system at preceding times; in this sense, D is local" Given these assumptions, Bedau (2008) defines weak emergence as the following:

> Macrostate P of S with microdynamic D is weakly emergent if P can be derived from D and Ss external conditions but only by simulation

In Bedau (2008), Bedau gives a new definition for the weak emergence. In this new definition he replace macro-states which are underivable except by simulation with macro-states that are explainable only in an incompressible way.

> If P is a macro-property of some system S, then P is weakly emergent if and only if P is generatively explainable from all of S' s prior micro-facts but only in an incompressible way"

A main concept in the majority of existing research that provides a classification or definition of emergence is the existence of *level*. For example, Deguet et al. (2006) identify tow principal conception regarding to the *level*. They distinguish between Design/Observation and Macro/Micro or Local and global levels. Gilbert and Conte (1995) argue though to sake of simplicity many researchers distinct between Micro and Macro level, due to complexity of systems it is not always applicable to make a clear distinct between these two levels. They propose that "it is better to consider a complex hierarchy of levels of emergence, rather than a straightforward division between Micro and Macro.

In order to avoid any confusion about the term of emergence in this study, especially because of exciting contradiction regarding the characteristics of this phenomenon, we follow the argument of Gilbert and Conte (1995) which emphasizes that "if we define emergence in terms of an inability to find an analytical solution, any particular emergent property stands the risk of being demoted from the status of emergence at some time in the future. This suggests that emergence may be neither a stable nor a specially interesting property of complex systems: what are interesting are the systems' macro properties and the relationship of those macro properties to the micro one."

2.3 Downward Causation: Feedback from Macro Properties in ABM

Sugarscape: Epstein and Axtell (1996) "models an artificial society in which agents move over a $50 * 50$ cell grid. Each cell has gradually renewable quantity of 'sugar' that the agent located at that cell can eat. However, the amount of sugar at each location varies spatially and according to how much of the sugar has already be eaten (most Sugarscape experiments are conducted on a landscape in which there are two 'peaks' of high sugar values in opposite quadrants of the grid). Agents have to consume sugar in order to survive. [...] Agents can look to the north, south, east and west of their current locations (but not diagonally) and can see a distance that varies randomly according to the agents' genetics endowment. [...] Agents not only differ in the distance they can see, but also in their 'metabolic rate', the rate at which they use sugar. If their sugar level ever drops to zero, they die. New agents replace the dead ones with a random initial allocation of sugar."(Gilbert and Troitzsch, 2005).

The role of feedback from the emergence features on the behavior of agents have been addressed by some researchers (e.g., Gilbert (2002),Sawyer (2001)). Gilbert (2002) introduced the notion of second order emergence. He argues that "second order occurs when the agents recognize emergent phenomena, such as societies, clubs, formal organization, institution, localities, and so on, where the fact that you are a member, or not a member, change the rules of interaction between you and other agents." Sawyer (2001) points out that the activities and interaction among the agents result in social structures and systems as artifacts which feedback on agents. Gilbert (2002) argues that second order emergence (immergence) is a specific characteristic of social systems since peoples can perceive the macro properties of the systems.

Top-down effect is part of reality, which cannot be captured by modeling agent's behavior. For example, in the famous work of segregation Schelling (1971), the emergence behavior of the system initially is determined by the preference of agents. However, these might be reinforced due to downward causation as soon as agents perceive the macro properties of segregation (Gilbert, 2002). Conte (2009) argues that this downward causation happens due to the process of social learning, which cannot be captured by the *generative paradigm* focusing on the bottom-up Properties.

In agent-based models, feedback from macro properties of systems is often ignored. This is mainly because they are often concerned with agent's behavior and interaction (Sawyer, 2001); studying the feedback involved in the systems is not part of design steps of ABM. The point is though some feedback are inherent in ABM model, some of them should be explicitly modeled. For instance, in the case of Sugarscape Epstein (2006), there is no need to model the feedback from the aggregated state of the system (the amount of sugercape) on the behavior of agents since the feedback is intrinsic in the system. On the contrary, in the case of opinion dynamics, we need to encounter the feedback of the majority opinion on the formation of opinion of an individual. In the case of opinion dynamics, it is impossible to capture the feedback for macro level of the system through the only interaction of individuals.

2.4 Quantitative Properties VS. Qualitative Properties

We can classify the properties of the systems at the macro (emergent) level to quantitative and qualitative properties while both influence the behavior of agents through the feedback. However, there is a difference between the form of applying this feedback. Qualitative properties can be applied initially in the models as rules that influence the behavior of agents. In this case though we have somehow downward causation, but it is not from the emergent properties of the system which are modified through the simulation. Sawyer (2001) emphasize that "these representations are not themselves emergent, but are part of the initial condition of simulation." Although applying the effect of qualitative properties as the initial condition makes the models somehow far from reality, this approach has been accepted in the ABM field.

In contrary to qualitative properties, quantitative properties should be emerged through the simulation and be available for agents to be perceived. Qualitative properties are not similar to qualitative properties - such as norms- which can be applied as rules or initial condition. They are observable states of systems at the macro level which are modified through the simulation. Hence, it is necessary to be modeled and be perceived by the agents through the simulation.

Normative agent-based social simulation models consider the feedback from norms which are qualitative properties of the system at the emergence level. However, in normative systems norms are implemented as built-in mental object. Even those studies that try to emerge the norm (e.g.,Savarimuthu et al. (2007)), start with some preexisting norms, and emergence happens through the integrating the initial norms (Conte et al., 2013). Andrighetto et al. (2007) reports the Emil (Emergence In the Loop: simulating the two way dynamics of norm innovation) which was aimed to address this problem of normative systems by investigating how new conventions and norm emerge and how they immerge in the mind of agents. To have a normative system in which norm immerge in the mind of agents, Conte et al. (2013) propose a new architecture for normative agents which is based on architectures of cognitive agents and has its roots in Artificial Intelligence. Since Emil project only focus on the feedback from norms and it contribute to the filed of normative agents, the out put of this project can not be used by the modelers which develop more simple agents without getting involved in cognitive science. We propose that in the absent of a true feedback from qualitative properties which modified through the simulation, at least quantitative properties should be modeled properly.

Although the quantitative properties of the systems at the emergent level can be representative of the norms, they are not only the representative of norms. The number of people who obligate a norm (a quantitative proportion at the emergent level) will result in social pressure which force agents to obligate the norm. However, all the social pressure are not due to norms. For example, In the case of opinion dynamics (see next chapter for more details), the number of people, who has the same opinion, either at the group or at the society level will influence the formation of opinion of an agent through the social pressure; in this case the number of people which has a opinion, which is different from the norms, effect the behavior of agents.

Some quantitative properties of the systems at the macro level can be assumed as information of descriptive norm. Norms can be injunctive or descriptive. Injuctive norms refers to what people approve while descriptive norm refers to what people do. Information about the descriptive norm (the average of people who conducting a action) influence the behavior of people (Cialdini and Goldstein, 2004). Schultz et al. (2007) study the effect information of descriptive norm on the electricity consumption of a group of householders. In this study, the householders with higher consumption of electricity were informed about the actual energy consumption of the average household in their neighborhood. The result of this study, presents that targeted householders reduced their energy consumption due to the effect of these information. Information about the descriptive norm which can be provided as average or majority number of people doing a specific action are quantitative properties of the system at the macro level which influence the behavior of agents.

Quantitative properties at the macro level can influence the behavior of agents trough the learning. In the case of traffic jam, mentioned at the introduction, drivers are influenced by the congestion of cars in a road, which can be modeled as average of cars , through the learning. Drivers will learn through the time where and when traffic jam happen so they can avoid them. This process of learning can be accelerated by the use digital sign in the road or the news.

2.4.1 Example of Feedback From Social Theories

There are some social theories that prove the existence of quantitative properties of systems at the emergent level and feedback from these properties on the behavior of agents. In the following, we introduce them briefly.

Bystander effect

The bystander effect refers to the phenomenon in which the probability of offering help to a victim by other individuals inversely related to the number of people who are present there (Darley and Latane, 1968). In other words, in the emergency case people are more likely to help a victim if there are few or no other by stander.

Darley and Latane (1968) study this effect through the conducting laboratory experiments. The found that the number of bystander had a major effect on the amount of time that participants take to report the emergency situation and to help the victim. They argue that bystander effect is due to diffusion of responsibility. Presence of other people reduces the individual's feeling of responsibility. Besides the diffusion of responsibility, ambiguity is another variable, which helps to explain why bystander effect occurs.

conformity

Social pressure is the influence of groups' behavior that encourages an agent to change his behaviors to follow the group norms. First attempts to study the effect of groups behavior on individuals behavior have been done by Asch (Asch, 1956) and Sherif (Sherif, 1936) Asch (1956) called this phenomena social pressure. Cialdini and Goldstein (2004) describe social pressure (conformity) as the act of changing one's behavior to group norms.

Aronson et al. (2005) explain that in many situations where individuals are uncertain how to act or think, they refer to the behavior of others to figure out what is going on in the situation and what is right to do. Deutsch and Gerard (1955) argue that 'Informational social influence' is a psychological phenomenon where people follow the action of other people in order to do the correct action. Aronson et al. (2005) argue that "Informational social influence" occurs when individuals see other people as a source of information.

2.5 The role of Feedback In ABM

In general, we can classify the feedback from quantitative properties at the macro level of agent-based models into two types. First, feedback which is inherent in agent-based models. For instance, in the modeling of diffusion of disease, there is no need to model the feedback from the number of infected people to determine the rate of *becoming infected* people because this feedback is intrinsic in the model, and people get infected through the individual interaction. Second, feedback which is not intrinsic in agent-based models and should be explicitly modeled. For example, in the case of opinion dynamics, opinion of agents is not only influenced through the individual interactions but also agents are influenced by the opinion of the majority through the social pressure (Sherif, 1936). Therefore, we need to model the effect of feedback from the number of people having an opinion (quantitative properties) on the opinion of an individual agent.

One of the reason that we emphasis on considering the role of feedback in ABM is that capturing and modeling inherent type of feedback is not always straightforward. Related on how in details we model a system they maybe captured. For example, there is a famous phenomenon called*economic scale* in the economic studies. These phenomena address the fact that "The cost per unit of product decreases with increasing scale since the fixed costs are spread over more products." This phenomenon can be captured through the ABM if we model the system in more details which involve the process regarding the pricing of the products. However, modelers often do not have the intention to model such details of the systems to keep the model simple. Consequently, they may miss this type of feedback which has critical role in formation of global behavior of systems. To capture this kind of feedback, modelers should be aware of their existence in advance, otherwise there is a high possibility that they be ignored in the simulation study.

2.5.1 Recognizing Feedback

A question may arise that how we can recognize feedback in ABM to see whether we can capture them through the simulation or we need to explicitly model them. System Dynamics Modeling (SDM) tools such as CLD has been approved as powerful tool for recognizing feedback involved in social systems. Jonassen and Ionas (2008) argue that CLD will help to recognize and figure out the causal loop and feedback. CLD is not only a presentation tool for depicting causal loops but also it help the process of recognizing feedback involved in the system.

2.6 Discussion and Conclusion

In this chapter, we discussed the importance of considering feedback in ABM. We addressed the issue that that studying the feedback from emergence features of systems on the behavior of agents is not part of design steps of agent-based models. Particularly, in the case of Agent-Based Generative social simulation (ABGSs).

We proposed to classify the properties of the systems at the emergent level to quantitative and qualitative. We discussed the important role of considering feedback from quantitative proprieties in the agent-based models. We provide some evidence from the social theories which prove the effect of quantitative properties of the system at emergent level on the behavior of agents.

In the next chapter, we will use a opinion dynamics models, to present the challenge of considering feedback from emergent properties: The way they would be perceived by the agents and how they get involved into the decision making process of the agents. Addressing these issues become more challenging when agents are not influenced by multiple emergent level at the different group and society level.

3

Opinion Dynamics Modeling - Case Study

This chapter is based on Hesan et al. (2014b)

3.1 Introduction

When faced with a decision (e.g. buying a new car) many people seek the opinion of others in order to support their decision. This is specially true, when people are not certain about their choices and options due to lack of information. Besides seeking the support of their peers and close relations, people are also influenced by the choices made by reference groups (e.g. celebrities, or experts). Social entities however, are not only influenced by direct contact with other entities, they are also affected by their own perception of the global trends whether in the society as a whole, or within their own local groups.

In agent-based models, the agents and their interaction determine the behavior of the system (Bandini et al., 2009). However, perceiving the global situation in a simulation is not the task of the agents in the simulation. Therefore, since the data is not available to the agents, they cannot take the over all perceptions into account while making decision about their activities. This limitation is partly due to the bottom-up nature of this simulation approach, but also related to the fact that it is difficult to capture run-time behavioral patterns in the simulation and allow the agents to take them into account in their subsequent decisions.

To overcome this problem, modelers take various approaches. For example, Jiang et al. (2009) implement agents that adopt identical average social strategies. In reality, however, agents are influenced differently by common behaviors based their own characteristics.

Furthermore, besides the aggregate behavior of the society, the agents are also influenced by the various groups they belong to, ranging from their families, to the work environment or even their neighborhood. The local aggregate behaviors in these groups may even be conflicting. Therefore, depending on which group has more priority, the agent behaves differently. Jadbabaie et al. (2003); Jiang and Ishida (2006) address this issue by defining neighborhoods and assigning average strategies as the overall behavior of each neighborhood.

Given the current state of art, the challenge still lies in the computational representation of aggregate behaviors, the way they would be perceived by the agents and the way these perceptions would be incorporated into the decision making process of the agents. The problem becomes even more challenging when we see that there are multiple groups, even with conflicting aggregate values, all being taken into account by individuals.

In order to represent aggregate values belonging to groups of agents in a simulation we present a framework for agent decision making where agents are exposed to different options for performing a behavior. The number of agents performing each option in every group the agent belongs to, influences the decision of that agent. Inspiring from TRA (Theory of reasoned Action) Ajzen and Fishbein (1977), we use the concept of intention that would lead to behavior in agents. Attitude toward a behavior and social pressure are the factors that influence intention. To illustrate how this framework can be applied, we use an example case of consumer lighting.

The structure of this chapter is as follows. In Section 6.2, we present the concepts that we will be using to define our proposing method. In section 4.4 we explain our proposed method. In Section 6.3, we will explain a working example based on our proposed method. In Section 8.8 we will finish with some discussion and concluding remarks.

3.2 Background

In order to find out how the aggregate behaviors of a system influence agent decision making, we need to (1) formalize how agents' decision is influenced by external factors, and (2) select a method for decision making that consider the aggregated behaviors of systems as a variable in the decision making process of individuals in addition to other factors that influence the decision.

The literature on opinion dynamics can helps us explain how the agents are influenced by external factors. Besides, for explaining the decision making process of the agents, we will use the theory of Reasoned Action.

3.2.1 Opinion Dynamics

Deffuant et al. (2000) and Hegselmann and Krause (2002) present two well cited continuous opinion dynamics models. In the first one, Deffuant and his colleagues present a model in which an agent readjusts his opinion with other agents when the differences between his opinion and one of his neighbors opinion is smaller than a threshold. In the second model, Hegselmann and his colleagues develop a model in which, in every iteration, agents take into account the opinion of all neighbors instead of one agent. None of these models consider the effect of group opinion as a whole on the formation of agents opinion. Since continuous opinion dynamics models see communication between agents as the source of changes of opinion Urbig (2003), they propose that opinion of agents change through the individual communication with other agents. Therefore, they do not consider the effect of groups opinion or opinion at the macro level of system (society) on the behavior of agents.

Among the discrete opinion dynamics models that have received more attention such as Ising modelGalam et al. (1982), voter model Holley and Liggett (1975), majority rule Galam (2002), Social impact theory Nowak et al. (1990), and Sznajd model Sznajd-Weron and Sznajd (2000), only Galam (2002) consider the effect of group opinion on the opinion formation of agents. Galam (2002) present a model in which agents take the opinion of majority instead of modifying their opinion through the individual interaction. However, Galam (2002) present the effect of group opinion in a linear way. For instance, there is no difference between the effect of a group with 99 percent similarity and a group with 51 percent on the formation of an agents' opinion.

3.2.2 The effect of group behavior on individuals

Social pressure is the influence of groups' behavior that encourages an agent to change his behaviors to follow the group norms. First attempts to study the effect of groups behavior on individuals behavior have been done by Asch (Asch, 1956) and Sherif (Sherif, 1936) where people were found to follow the rest of group opinion. Asch (1956) called this phenomena social pressure. Cialdini and Goldstein (2004) describe social pressure (conformity) as the act of changing one's behavior to group norms.

Aronson et al. (2005) explain that in many situations where individuals are uncertain how to act or think, they refer to the behavior of others to figure out what is going on in the situation and what is right to do. Deutsch and Gerard (1955) argue that 'Informational social influence' is a psychological phenomena where people follow the action of other people in order to do the correct action. Aronson et al. (2005) argue that "Informational social influence" occurs when individuals see other people as a source of information.

Besides the informational social influence, the "normative social influence" is the second psychological phenomena that social psychologist defined as the source of conformity. Normative social influence is conformity in order to be liked and accepted by others (Deutsch and Gerard, 1955).

Individuals don't always follow the behavior of groups. In the following situations the effect of social pressure is more powerful than normal situation Aronson et al. (2005):

- **Ambiguous situation** Ambiguity is the most crucial parameter that increases intention of people to follow others behavior.

- **Crisis situation** In the case of Crisis situation as people do not have time to evaluate multiple option they will look at other people actions.

- **When Other People Are Experts** When people are not expert in a topic they will follow experts.

- **When People are Member of a Group** Self-categorization theory Turner and Oakes (1986) explains that individuals are more likely to follow the group behavior when they perceive collections of people (including themselves) as a group.

In the next section we will classify the influential parameters of social pressure and explain how social pressure along with internal attitude determine the behavior of agents in a society. In order to do that we use the theory of reasoned action (TRA).

Theory of reasoned action Ajzen and Fishbein (1977) is an attitude-behavior theory. It explains that when a person has the intention to do an action, he/she should be in favor of doing it (attitude). Furthermore, the person may feel social pressure to do the action(subjective norm). Attitude and norm will shape the intention of individuals towards a behavior. Figure 3.1 presents the conceptual framework of TRA.

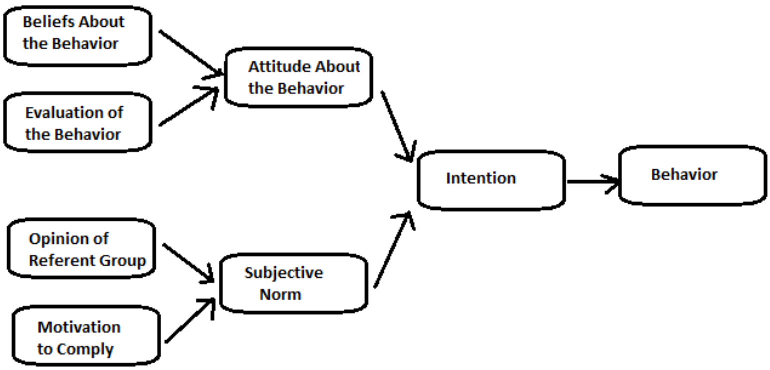


Figure 3.1 – The theory of reasoned action (Ajzen and Fishbein, 1977).

3.3 Modeling the Effect of Multiple Social Groups

Inspired by TRA, in this section we propose a framework for decision making process of agents which follows the idea that the behavior of agents is the consequence of their decision making process which is influenced by two parameters: social pressure and attitude towards the alternative options of a behavior. The framework classifies multiple parameters which influence the formation of attitude and the power of social pressure on the behavior of agents. As it is depicted in Figure 3.2 decision making of agents are influenced by the attitude and social pressure from multiple groups towards the multiple option of a behavior.

In the following, we explain every part of the model and their relationship in details based on social psychology literature.

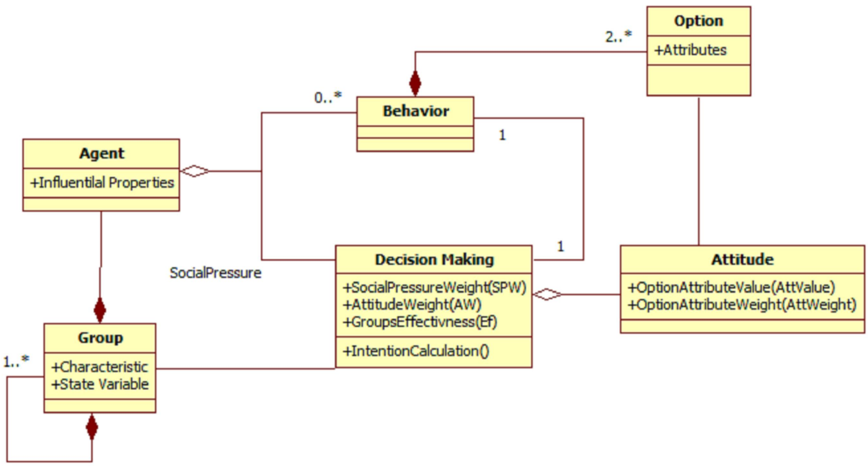


Figure 3.2 – Agent decision making with group influence

3.3.1 Attitude

Attitude towards a behavior is individual's positive or negative feelings about performing that behavior. When agents have multiple option to choose from, they will evaluate different attributes of every option and perform one with higher advantage and lower disadvantage. In reality, individuals do not give same weight to the different attributes of options. For instance, while a person may see an attribute of an option as an advantage, it may be seen as a disadvantage by another person.

Let n be the number of attributes of option j that agent i will be faced to perform one action. $AttValue_1$ and $AttWeight_1$ are value and weight of $Attribute_1$ from the point of view of agent i. A_i is the attitude of agent i towards option j.

$$A_i^j = \sum_{x=1}^{n} AttValue_x^j * AttWeight_x^j \tag{3.1}$$

The value and weight that agents give to the different attributes of an option change due to interaction and communication between agents. During communication agents share their information and experiences which result in changes in the value and weight given to options. Consequently, the attitude of agents towards different options change.

3.3.2 Social Pressure

Social pressure is the influence of groups' behavior that encourages an agent to change his/her behaviors to follow the group norms.

Norm refers to what is commonly done (what is normal) or to what is commonly approved (what is socially sanctioned). Despite the common label, these norms have different effects on the behavior of individuals. Cialdini et al. (1991) point out that "Descriptive norm" refers to what people do and "injunctive norm" refers to what people approve. Schultz et al. (2007) argue that `descriptive norm information` in a society influences the behavior of people.

We use the descriptive norm information (information about the number of people who perform a behavior) as the main parameter that shapes social pressure towards a behavior. Since in reality we are influenced by different groups, characteristics of each group is an important parameter which determines the power of social pressure. Furthermore, some agents are more influenced by social pressure due to their own internal characteristics which has to be taken into account when calculating the power of social pressure.

In the following, we present group characteristics and internal properties of agents which influence the power of social pressure.

Agent properties

Since in society not every one conforms to social pressure some researchers study the effect of different factors that affect the tendency of individual to conform with society. In our proposed framework we call these kind of factors "Influential Properties" of agents. As an example of such properties, people who belong to individualistic cultures, such as American and British cultures, are more likely to behave independently than those from collectivist cultures such as China and Japan (Bond and Smith, 1996). In collectivist cultures, group decision making is highly valued, while in individualistic cultures people are more concerned with their independent success than the well-being of their community. Besides the culture, gender and age also influence the tendency of people to conform with groups (Eagly and Chrvala, 1986). Women and younger people are more likely to follow the group's behavior than men and older people. Influential Properties of agents determine to what extent agents stick to their own attitude or be influenced by the social pressure.

Group Characteristic and states

Individuals are influenced by two kinds of groups in their decision makings. Those that they belong to and have direct connection with (e.g, family, colleagues, neighbors) and those groups that the agents don't belong to, but indirectly influence their behavior (e.g, movie stars, political groups). Although, the effect of both kinds of groups (direct, indirect) on the behavior of agents is almost the same, for more clarity, we formulate the effects of them separately. Every group has different level of influence on the behavior of individuals which is dependent on the characteristics of that group:

- **Unanimity** when the behavior of the rest of the group is unanimous, individuals are more likely to follow the group behavior.
- **Cohesion** groups with high cohesion result in more conformity of individuals.
- **Status** individuals are more interested to follow high status groups.

In the case of direct groups, as agents have more information about the characteristics of the group and the choice of other group members, all the mentioned characteristics hold and thus make direct groups more influential. In Formula 3.2, DEf_k^i presents the effectiveness of direct group k on the behavior of agent i.

Let m be the number of direct-groups which surround agent i. The direct social pressure (DSP) that forces agent i to choose option j is determined by Formula 3.2. In every group the number of agents which have chosen option j is multiplied by the effectiveness of this group from the point of view of agent i determines the social pressure of that group towards option j. Summation of every group pressure towards option j on agent i calculates DSP_i^j.

$$DSP_i^j = \sum_{k=1}^{m} DEf_k^i * (N_k^j / N_k) \tag{3.2}$$

In the case of indirect-groups, the effects of these groups is mostly due to imitation of agents from these groups. The status of groups and the average number of groups members which adapt a option are most important parameters which shape the effect of these groups towards an option.

Let T be the number of indirect-groups which influence agent i. The indirect social pressure (IDSP) that encourage agent i to choose option j is determined by Formula 3.3. The average number of agents which have chosen option j is multiplied by the importance of a group from the point of view of agent i determines the social pressure of that group towards option j. $IDEf_k^i$ is the effectiveness of indirect-group k on the behavior of agent i. Summation of every group pressure towards option j on agent i calculates $IDSP_i^j$.

$$IDSP_i^j = \sum_{k=1}^{T} IDEf_k^i * (Ave_k^j) \tag{3.3}$$

Besides the two mentioned groups that influence agents opinion, the opinion of agents may be influenced by individual interaction. Every individual can be assumed as a group with one member. Therefore, the only parameter that influences an individual is the status that this individual has from the point of view of the agent.

3.3.3 Decision Making

Although TRA is aimed to study the intention of people towards a behavior, it can be applied to situations where people have multiple choices (Sheppard et al., 1988).

Individuals form intentions towards each alternative based on their attitude and subjective norm towards that alternative. The alternatives will be compared and the alternative with the strongest intention will be selected.

In our proposed framework, we assume that every agent has multiple choices to perform (e.g., voting for group A or group B, Buying LED lamp or incandescent lamp). Agents will form their intention towards each alternative based on their attitude and social pressure. They will then compare the strength of their intentions towards each of the alternatives and will choose and perform the alternative with the strongest intention.

Intention of agent i towards option j is determined by Formula 3.4. `Attitude Weight` (AW) and `Direct Social pressure Weight` (DSPW) and `Indirect Social pressure Weight` (IDSPW) determine how much an agent follows his or her attitude or is influenced by social pressure of direct-groups and indirect-groups. We already mentioned that `Influential Properties` of an agent and the situation that an agent is in (e.g, ambiguity and crises) influences the amount of "Attitude Weight" and "Social pressure Weight".

$$I_i^j = AW * A_i^j + DSPW * DSP_i^j + IDSPW * IDSP_i^j \tag{3.4}$$

3.4 Working Example: Consumer Lighting Choices

As an example,we take a consumer lighting case to explain our approach for modeling the effect of group behavior on the decision making of agents. This example is chosen because of the high level of uncertainty in choosing between different kinds of lamps specially because of the emerging technologies in the market.

Case description Developments in electric lighting technology have increased the life time of the bulbs and their energy efficiency (Gendre, 2003). For example, over 98% of the electricity used in the traditional incandescent bulbs is converted into heat and not into light. However, Compact Fluorescent Lamp (CFL) or Light-Emitting Diod (LED) are nowadays the more efficient alternative lighting products. Nonetheless, consumers have only partially adopted CFL and LED technology because of a number of obstacles (Menanteau and Lefebvre, 2000). First, CFL and modern LED saving lamp are characterized by high up-front costs for consumers and poor light quality. Second, halogen lamp are more attractive than CFL and LED lamps because they fit in popular designs and have favorable color and size.

Model Specification We model the changes in behavior of 2000 agent towards three options (buying Light Emitting Diod (LED) lamps, Compact Fluorescent Lamp (CFL) lamps, and traditional incandescent lamps). Attitude of agents towards these three options can be calculated based on the $AttValue$ and the $AttWeight$ every agent gives to the attributes of lamps such as price, light quality, and efficiency. Since this chapter aims to study the effect of group behavior on the behavior of agents, we assume that attitude of agents towards the three options will not change during the simulation and for every agent we assign three random numbers (uniform number between 0 and 1) as attitudes toward the three options. We assume that in the sake of social pressure agents will choose the option with highest attitude. Then they will shape their intention which is composed of their attitude and social pressure from the different groups towards the options.

In this example agents are influenced by the states of two direct-groups (family, and colleagues) and by two indirect groups (e.g, movie star) with different effectiveness. In order to evaluate the behavior of agents, we run the model with different effectiveness of groups (0.4, 0.6) which is similar for direct and indirect groups and different weights that agents give to their attitudes (AW) and social pressures (DSPW, IDSPW). We assume SPW as the summation of $DSPW$ and $IDSPW$ as the weight that an agent gives to the social pressures from both direct and indirect groups.

Model Results At the beginning of the simulation the number of people that have chosen every kind of lamp is almost equal. Figure 3.3 presents the effect of different AW and $DSPW$ and $IDSPW$ on the behavior of agents. As it is depicted, when AW is higher than SPW (DSPW+ IDSPW) although some agents at the beginning of the simulation modify their opinion due to social pressure but a number of them will stop to converge to a specific opinion and will keep their opinion. The increase in AW, results in more agents keeping their original opinion which is based on their own attitude.

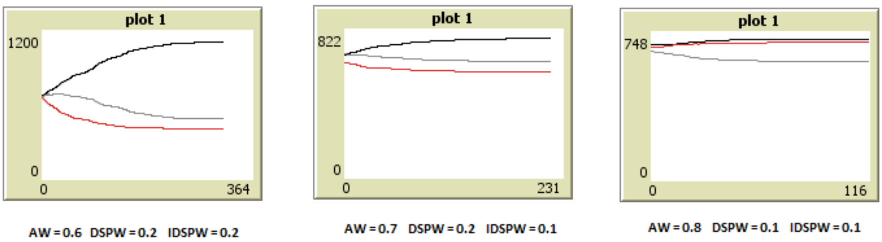


Figure 3.3 – The number of people choosing different kind of lamps with AW higher than SPW

As it is depicted in Figure 3.4, increasing the SPW will result in the convergence of agents behavior to a certain opinion. The increase of the weights of social pressure will result in agents converging faster to a specific opinion.

In the case of equal AW and SPW, agents will converge to a specific opinion during a longer time of simulation in comparison with the cases that SPW is higher than AW.

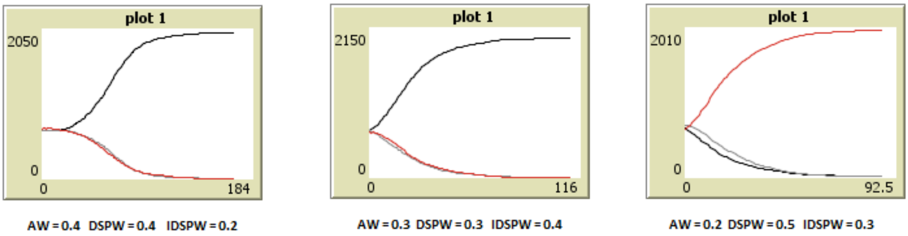


Figure 3.4 – The number of people choosing different kind of lamps with SPW higher than AW

3.5 Discussion and Conclusion

In order to explore the role of aggregated states of systems on the behaviors of agents, we proposed a method which presents how the decision making process of agents is influenced by the overall behavior of groups.

In agent-based modelling, it is common that agents do not take into account the aggregated behaviors of system and mainly focus on interactions or environmental states. However, in reality agents are influenced by the overall behavior of not only the system as a whole but also groups of agents whether they belong to them or no. In fact, the system can be considered as the biggest group that the agent belongs to. These groups may overlap. Furthermore, the overall behaviour of these groups may even be in conflict and thus the agent would need to prioritize the group that is most influential to her.

In order to implement the role of group behaviors on the behavior of agents, we proposed a conceptual framework that is mainly inspired from Theory of reasoned Action (TRA). We also used the literature on opinion dynamics to explain how agents choose from various options based on their own attitudes as well as the social pressure coming from groups.

To build this framework, we made several assumptions based on the psychological literature we studied. First, we assumed that the number of people in every group that has chosen a specific option will determine the amount of social pressure towards that option. Second, we also assumed that agents have perfect information about the behavior of other agents. However, we are aware that in reality, individuals may underestimate or overestimate the prevalence of a behavior in a society.

As this chapter aimed to study the effect of groups behavior on the behavior of agents, we did not focus on the role of interaction between agents. Interactions result in changes in the value and the weight of different options which consequently influences agents' decision. Besides looking more into interactions, in our future work, we will also look at how agents would only look at groups and individuals with close attitude and intention, referred to as bounded confidence (Deffuant et al., 2000).

Part II

Combining SDM tools with ABM at the Conceptual Modeling Phase

4

Modelling Environments in ABMS: a System Dynamics approach

This chapter is based on Hesan et al. (2015)

4.1 Introduction

Agent-based models provide insights into the social systems they represent. A social system consists of social and physical structures, external to the actors, that facilitate or constraint actors behaviors and interactions. These components, and their link with the agent however, are often implicit in agent-based models.

The social and physical components of an agent-based model make up the environment which is generally defined as independent abstraction providing the conditions for the agents to exist, enabling access to resources and facilitating interaction between agents (Weyns et al., 2007). Even though, environment is commonly viewed as a purely spatial entity in ABMS literature (e.g., in Netlogo), some researchers have defined the social and physical aspects of agent-based models (Gilbert and Terna, 2000; Pavon et al., 2005; Garro and Russo, 2010a; Ghorbani et al., 2013). For example, Ghorbani et al. (2013) defines physical environment in terms of physical components (e.g., computer, street, house). These components are connected to each other and to the agents. The social environment in these models is defined on the basis of institutions (e.g., eating norms, driving rules). These concepts define the environment around an individual agent. The limitation of their conceptual definition however, is in defining environment variables, whether social and physical, that are global to the whole simulation, influencing all agents behaviors and being influenced by them. This limitation also holds for other research in the literature because in

ABMS, the system is generally viewed as bottom-up and global variables that define the overall state of the system are not explicitly defined.

Besides the lack of definition for global state variables, another drawback of the current practices for modeling agent environments, is that the interrelation between the global level and individual level is also not captured. According to Coleman's bathtub model Coleman (1986) however, global variables influence the perception of individuals in a social system, which in turn affect their decision making behavior that changes the initial state of the environment. Therefore, to provide a comprehensive definition of environment in agent-based models, we need to have an explicit definition of social and physical environment variables that show the global state of the system. In addition, we also need to capture the interrelation between these variables and the agents.

To define global state variables and their interrelation with the agents, we propose to look at the variables and relations in terms of stocks and flows. For example, if *food resource* is an environment stock, we define *flow of food* that goes to the agents which in turn influences the availability of food in the environment. Likewise, a social environment stock such as *fashion*, affects agents perception about a certain product, and the agents behavior in turn determines what stays in fashion. In fact, this can also be considered as an indirect interaction between agents through the environment (Gilbert and Terna, 2000; Weyns et al., 2007).

In this chapter, we propose an approach to model global environment variables and their interrelation with agents using a system dynamics perspective. The reason we propose this solution is that system dynamics views the system in terms of aggregate values (Sterman, 2000). Tracking these type of values would help us study the influence of individual behaviour on global parameters of interest (e.g., resource availability, general acceptance of a product). These parameters show the general behaviour of a social system which are commonly the points of interest for many simulations and policy problems in general.

The structure of this chapter is as follows. In Section 6.2, we look into environment modeling more in depth, we explain system dynamics and present the concepts that we will be using to define our modeling approach. In Section 4.3, we present an example case which we will be using in Section 4.4, to explain our proposed approach. In Section 4.5, we will explain the consumer lighting model. In Section 8.8 we will finish with some discussion and concluding remarks.

4.2 Background

4.2.1 Environment in Agent Systems

In ABMS, agents interact with each other and with the environment to perform tasks that represent actual events in the system. Although the concept of agent as a social entity is relatively clear for modelers, the concept of the environment and its function and responsibility remain unclear (Bandini and Vizzari, 2007).

The common approach in ABMS considers environment as a spatial entity that facilitates interaction between agents and enables different forms of networks between agents. In fact, Amblard and Mailliard (2007) emphasize that environment in ABMS is a first order entity when the spatial dimension are important to be considered. Furthermore, Gilbert and Terna (2000) introduces environment in ABMS as a physical environment that imposes restriction on the location of agents. This kind of environment can be built by defining a 2D or 3D virtual space which is especially important in cases where spatial dimension is important (e.g., land use modeling). Besides the spatial definitions of the environment, Bandini and Vizzari (2007) investigate the role of environment in agent-based models by assigning regulation functions to the environment.

In contrary to ABMS, in multi-agent systems (MAS) literature, many studies have been conducted that indicate the role of environment as a first-class abstraction for the modeling of MAS (Weyns et al., 2007). Some of these studies propose conceptual models of the environment similar to the work of Ghorbani et al. (2013) for ABMS (e.g., Amblard and Mailliard (2007)). Bandini et al. (2005) proposes a multi-layered framework called: Multi Agent Situated System (MMASS) which provides a representation of the environment. In MMASS, an environment is modeled as a set of interconnected layers so that every layer's structure is an indirect graph of sites. These layers can be abstraction of the physical environment or can also be related to the logical aspects. In addition, connections can be specified between layers. Ricci et al. (2006) proposes a model of agents and artifacts. Artifacts are dynamically constructed and shared by the agents. Their research eventually lead to the CArtAgo (Common Artifacts for Agents Open framework) for prototyping artifact-based environmentRicci et al. (2007) which emphasizes the functionality of tools and objects (artifacts) and how agents work with these objects and tools in a system.

In both ABMS and MAS literature, besides the spatial representation, environment is viewed and used at the level of individuals through the definition of entities such as artifacts, physical components, norms and institutions. Such physical and social components are recognized by individual agents as entities that they can use or posses, or ones that for example restrict them. Therefore, although these concepts are external to the agents, they are viewed locally by them and they do not represent the global state of the environment in terms of aggregate variables (e.g., sum of all light bulbs in society, general perception about LED lamps). Nor do these concepts provide insights about how aggregate values in the environment would influence the agents or be influenced by them.

4.2.2 System Dynamics

System dynamics modeling is an equation-based approach for constructing simulations especially at the macro level. We use the general concepts of system dynamics modeling Forrester (1961a); Sterman (2000), namely stock and flow to extend the conventional environment in agent-based models.

Stocks

represent specific elements of a system whose values depend on the past behavior of the system. Stocks accumulate inflow minus outflow and their value represents the state of system.

Flows

represent the rate that changes the value of stocks in a system in every instance of time. Flows can be either inflow, increasing the stocks value or can be outflows, decreasing the stocks. The value of stocks are changed by their related flows.

The concepts of stock and flow are familiar concept that are being used in our daily lives. For instance, *bank balance* is a stock that is increased by the flow *deposit* and decreased by the flow money *expenditure*.

A global state variable of an agent-based environment can also be defined using stocks and flows at the macro level because the aggregation of agents' behaviors results in emergent states that are at a higher level than the agents themselves.

4.3 Working Example

As a running example,we take a consumer lighting case to explain our approach for modeling global state variables and their interrelations with the agents in ABMS.

Developments in electric lighting technology have increased the life time of the bulbs and their energy efficiency (Gendre, 2003). For example, over 98% of the electricity used in the traditional incandescent bulbs is converted into heat and not into light. However, Compact Fluorescent Lamp (CFL) or Light-Emitting Diod (LED) are nowadays the more efficient alternative lighting products.

Nonetheless, consumers have only partially adopted CFL and LED technology because of a number of obstacles (Menanteau and Lefebvre, 2000). First, CFL and modern LED saving lamp are characterized by high up-front costs for consumers and poor light quality. Second, halogen lamp are more attractive than CFL and LED lamps because they fit in popular designs and have favorable color and size.

Different studies have been conducted about how different policy may change the people's preference to buy more efficient lamp (Chappin, 2011). The European Union's phase-out of incandescent lighting is a clear strategy that will change the sector. It involves regulations designed to remove the cheapest forms of inefficient household lighting from stores. Afman et al. (2010) developed an agent-based simulation to study adoption of LED and CFL lamp technology by consumers in a virtual society. This model encompasses consumers that buy lamp, based on the available luminaries in their houses, their personal preferences and the preferences of their acquaintances. Furthermore, retailers sell different lamps and producers produce lamps in the model. The behavior of all these agents is affected by the government agent who implements different policies in the system with the goal of moving the society towards more efficient lighting choices. Afman et al. (2010) investigate three policy in their work: banning light bulbs, taxing light bulbs, or subsidizing energy efficient alternative.

In this chapter, we explain how our proposed method can be used to model global environment variables in an agent-based model of the consumer lighting example in order to study the effect of various policies on the global outcomes of the system.

4.4 A System Dynamics Agent Environment

In conventional ABMS, environment refers to the spatial space in which every agent has a location or is connected to other agents via a network (Gilbert and Terna, 2000). This definition however, does not provide an explicit representation of social and physical variables that represent the global state of the system.

We use the definition of social and physical structures in Ghorbani et al. (2013), to extend environment for ABMS by defining global variables and specifying their interrelation with the agents in the system.

Physical Environment The physical environment is composed of physical components (Ghorbani et al., 2013). Physical components have properties such as shape, color and price. These physical components may be used by agents to perform actions. We define *physical state variables* as variables that show the global state of the aggregation of such physical components. Therefore, while at the individual level, a physical component such as a lamp can be produced, bought, and sold by the agents, at the global level, the sum of all these lamps, which is affected by the same agent actions, influences their availability in the market or their popularity. For instance, when a producer agent produces a lamp, he decreases the amount of different raw material (stock) and increases the number of products in his inventory (stock).

Social Environment We consider institution as the building block of the social environment (Ghorbani et al., 2013). An institution is a rule, norm or strategy that is followed by agents in a simulation. We use institutions as flows that change the *social state variables*. Therefore, to define a *social state variable*, we define a variable that is influenced by a number of institutions. For example, if an institutional rule says that “the government must give subsidy to producers who produce LED lamps”, we define a social state variable that has an inflow of subsidy based on this institution and name it as *government support*. The rule “the government bans production of light bulbs” also relates to this social state variable. As another example, if a norm in the society is that “consumers talk to their neighbors about their experiences with lamps”, a social state variable that would take this norm as a flow, is *awareness*.

Both social and physical state aspects of the environment are defined as stock and linked to agents as we will explain in the next section. While the physical elements of an environment are tangible, the social elements are the less tangible part of the system. For instance, in our working example *awareness* about a product in society is an intangible part and the amount of products which are available in shops or market are the tangible part of the environment. The physical and social state variables are both essential for modeling and testing policies which are in fact the goal of many agent-based models. We will discuss this issue later on in the chapter.

Another point to mention here is that besides the immediate outcome of local interaction between agents (e.g., immediate outcome of buying lamp = ownership of lamp by buyer), agent interaction may also have global outcomes that are important to capture as state variables. For instance, the *awareness* variable defined previously, is the global result of agents communicating their opinion about lamps among each other.

The Conceptual Model

Figure 4.1 shows the UML class diagram of our proposed model of the environment. For the purpose of this chapter, we assume that the physical components owned by the agents or the institutions they follow are defined in the agent class [1], in order to have a clearer focus on how we define the state variables and how they are connected to agents.

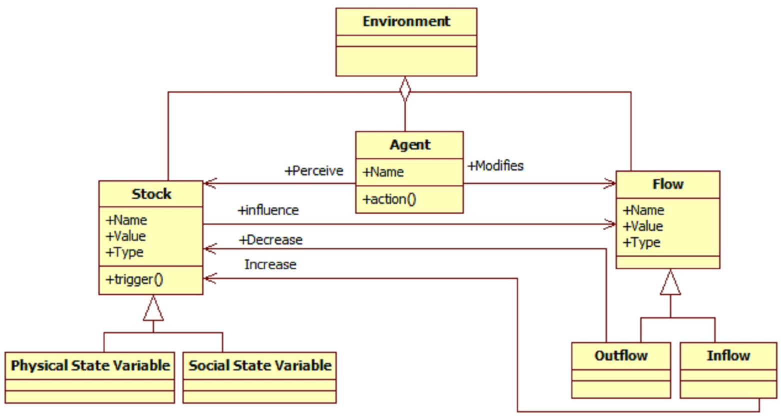


Figure 4.1 – The class diagram of the system dynamics environment

The environment consists of agents, stocks and flows. There are two types of stocks: physical state variable and social state variable. Flows are the means to connect these variables to the agents. The agents are the active entities whose

[1]Following the definition of Ghorbani et al. (2013), physical components and institutions are external to the agents. However, since in this chapter we are making a distinction between local and global entities, for now, we assume that all the local entities are within the agents.

actions, and perceptions of environment lead to changes in the physical and social stocks of the environment.

The state of the environment in every instance of time is a series of stocks' value that can be characterized as $S_t = \{s1_t, s2_t, s3_t, ...\}$. For example $s1_t$ is the value of stock number 1 at time t. Agents perceive the environment state and perform actions based on their decision mechanism. Agents' actions will change the value of stocks through the flows. We have two kind of flows: inflow, which increase the value of stocks, and outflow, which decrease the value of stocks. We can represent environment's state as the following:

$$\begin{gathered}\{s1_{t+1}, s2_{t+1}, s3_{t+1}, ...\} = \{s1_t + \sum_{i=1} inflow1_{a_i} - \sum_{j=1} outflow1_{a_j}, s2_t + \\ \sum_{i=1} inflow2_{a_i} - \sum_{j=1} outflow2_{a_j}, s3_t + \sum_{i=1} inflow3_{a_i} - \sum_{j=1} outflow3_{a_j}, ...\}\end{gathered} \tag{4.1}$$

Figure 4.2 illustrates how the state of the environment is changed by the agents activities. We use the consumer lighting example in the next section to show how this method works in more detail.

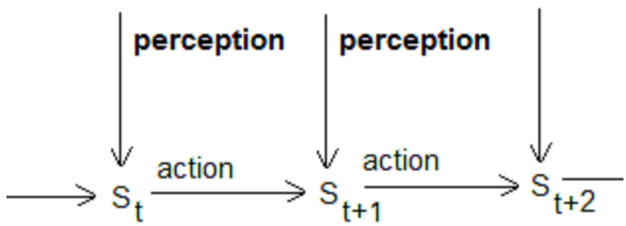


Figure 4.2 – Perception and Action Sequence

4.5 Consumer Lighting Model

Figure 4.3 illustrates the consumer lighting model. In this model, the rounded rectangles represent the stocks, the arrows show the flows and the dashed arrows show where the perceptions of the agents from the environment is coming from.

There are four types of agents in the model: `consumer`, `retailer`, `producer` and `government`. `Awareness`, `government support`, `retailer price` and `producer price` are the social state variables in the system. `Available lamps in shops`, `available lamps in market` and `lamps in society` are the physical state variables in the environment of the consumer lighting model. The goal of the `consumers` is to buy lighting products in order to have pleasant light in their house. The goal of the `producers` is to produce different kinds of lamps to offer in the market in order to have income. `Retailers` will sell lamps to `consumers` in order to increase their income. `Government` wants to reduce electricity consumption through different policy implementations. The agents actions which are defined according to their goals affect the environment's flows which in turn result in changes in the state of the system (environment stocks)

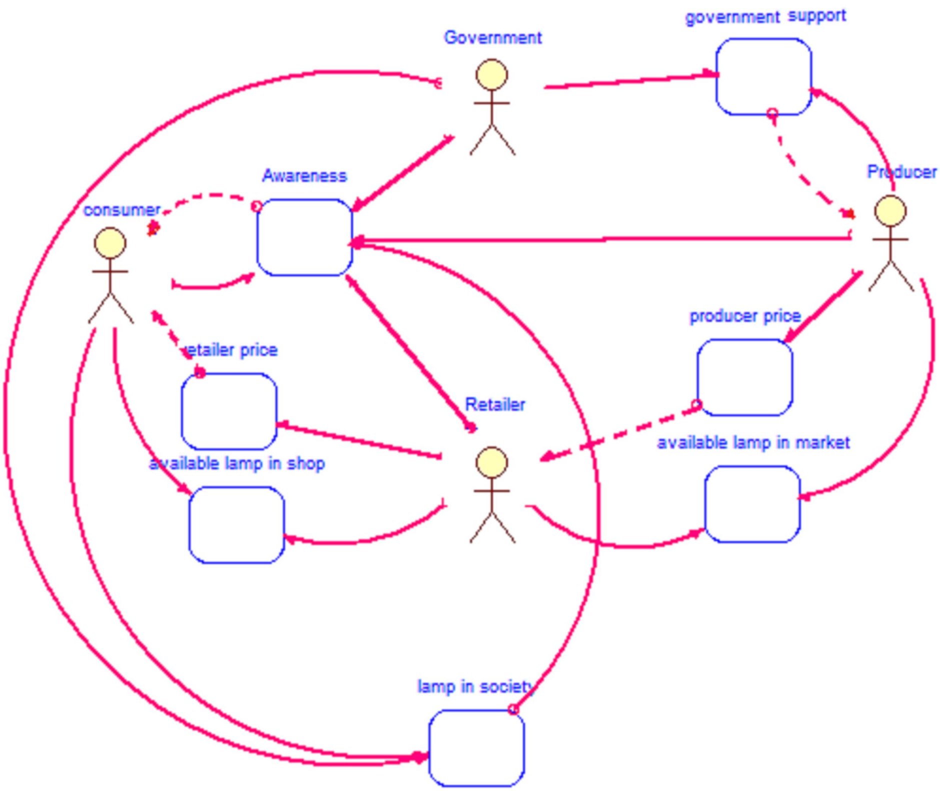


Figure 4.3 – Lighting Case Model

Consumers consider several criteria in their lamp purchase decision: preference for subjective lamp qualities (color, price, efficiency, and life time), opinions (perception) on the lamp's characteristics (lamp model, brand, and technology type), and popularity of LED lamps which is defined as `awareness` in the environment. `Consumers` buy lamps which declines `available lamps in shops` and they will change the `awareness` about the new efficient lamp by word of mouth. Consumers are influenced by the `price of products`, and `awareness` about the product in the whole environment.

Retailers will decrease `available lamps in market` by buying products and transferring them to shops. They will change the `retailer price` in shops and they will also affect the `awareness` about a product in the environment by advertising (shown as a flow between `retailer` and `awareness`). `producer price` influences the `retailers` decision making process about setting a price on the lamps in the shop.

Producers increase the `available lamps in market` by producing more lamps. They will change the `producer price` and influence the `awareness` about a product in the environment by advertising, similar to the `retailers`. The amount of `government support` is changed by the `government` by providing subsides to the `producers`. Besides, the amount of `government support` will encourage producers to produce more subsidized products. There is also a link between `lamps in society` and the `producer` which we will discuss later.

Government will intervene in society to support efficient lighting products. The link between the `government` and `awareness` shows that the `government` can increase `awareness` in society by some activity like advertising. In addition, the `government` increases `available lamp in society` by buying efficient lighting products for public area which triggers some important dynamics in the consumer lighting system.

Dynamics of the Model

Feedback is an important feature of a dynamic system: a system whose behavior changes over time (Aström and Murray, 2010). The notion of feedback refers to a situation in which two or more variables of the system are influencing each other which may lead to growth or decaying behavior. As we are studying the dynamic behavior of the lighting case, it is worthwhile to study the feedbacks which determine the dynamic behavior of system.

The first clear feedback happens between `consumers` and `awareness` in society. More `awareness` in society about efficient products results in increased popularity of the products, which will in turn increase the `awareness` in the environment. The second feedback is between `consumers` and the `available lamp in society` either in consumer's home or in public places. Ubiquity of a technology in society can influence the preference of consumer about a product. Therefore, if the government buys efficient lighting products, this triggers the feedback between amount of lamp in society and the preference of consumers.

One of the obstacles that discourages people to buy new efficient lamps is their high up front costs. Since people do not buy these new costly products, producers cannot produce them in an economic scale. Economic scale has a significant effect on the price of products. The cost per unit of product decreases with increasing scale since the fixed costs are spread over more products. The final important feedback that we will mention happens between `consumers`, the `available lamps in society`, the `producers`, and the `retailers`. Due to economic scale, when people buy more products, the price will go down which will then encourage people to adopt new efficient lamps instead of non-efficient ones.

Modeling Policies

As previously mentioned, many agent-based models are built for testing policies. Policies are implemented with a set of policy instruments which can be social (e.g., speed limit rule) or/and physical (e.g., speed camera) (Ghorbani et al., 2014). Policies also have goals which are usually aimed at achieving desired global outcomes through individual behavior (e.g., decrease number of deaths by car accidents) (Ghorbani et al., 2014). Both the instruments and the goals are covered in an agent-based model that is extended with the state variables.

Afman et al. (2010) propose three policies: banning light bulbs, taxing light bulbs, or subsidizing energy efficient alternatives. All these three policies were aimed at intervening in the supply part of the system. Along with these three policies, we propose two new policies in order to influence the demand part of the system: (1) increasing the awareness about the new lighting products by advertising and (2) increasing the number of lamps in society by installing efficient lamps in public areas. These policies can activate the word of mouth dynamics and economics scale dynamics which we discussed in the previous section.

4.6 Discussion and Conclusion

In this chapter, we proposed a method for modeling the global aspects of the environment in agent-based models and capturing the interrelation between the global states and local entities including the agents. We illustrate this method by applying it to a consumer lighting scenario.

In ABMS, the environment in which agents behave and interact in, is commonly considered as a spatial space to visualize agents and their interaction in the system. Nonetheless, some researchers define an agent-based model in terms of the social and physical aspects surrounding the agents, influencing their behavior and being influenced by them. However, even when the social and physical aspects are defined in the agent-based model, their level of abstraction is at the individual level.

The global aspects of the environment are essential for studying social systems because they provide insight into how individuals influence the system as a whole and how the global state of the system is perceived by the agents and influences their behavior. Therefore, in this chapter, we proposed a method to add global social and physical variables to agent-based models in order to address this requirement. Since system dynamics modeling also has a global perspective on the system, we were inspired from this modeling approach in our proposed method.

The proposed method contributes to ABMS is several aspects. Firstly, since we extended the definition of physical components and institutions in Ghorbani et al. (2013), our definition of an agent environment now has two levels: one at the agent level with concepts like house, driving norm etc, and one at the global level where aggregate concepts such as general awareness are defined. We have also defined the relationship between these two levels to show how the local environment can lead to aggregate states in the system. Secondly, the global outcomes of agent interaction can also be captured with our proposed method, which provides further insights into how individuals influence the system as a whole. Thirdly, the method provides enhancement in implementing policies and testing them. As mentioned previously, with the global state variables introduced in this chapter, the modeler can study how individuals influence the goal of a policy which can in fact be modeled as (a) stock(s). Of course, agent-based modeling platforms such as Netlogo and Repast already facilitate the definition of global variables. However, our contribution lies in the fact that we are using system dynamics as the method to implement such variables. Fourthly, by providing a visual representation of the environment as illustrated in Figure 4.3, it becomes easier for modelers to study the interrelations and feedbacks in the system.

One final contribution of this method is that since we are taking two fundamental elements of system dynamics modeling (stocks and flows), ABMS can become more within the reach of the system dynamics community. Although system dynamics modeling, as a macro-level approach, is traditionally constructed by stocks that are changed by flows, we propose that the concept of stock and flow is compatible with agent based modeling and can be integrated with the concept of agent. In practice, system dynamics modeling assumes agents to be all homogeneous and therefore takes one representative for the whole population. However, with our proposed method, system dynamics modelers can use the advantage of considering heterogeneous agents and different decision making processes.

In this chapter, we viewed agents as black boxes and did not go into the details of decision making processes or local interaction. However, it appears that the concept of stock and flow can also be considered in the decision making process of agents and their local interactions. Therefore, our next goal is to find out how the internal perception of the agents and their decision making behavior can be captured through this perspective.

5 Mechanisms in Agent-based Models

5.1 Introduction

Modeling and simulation is an powerful method for designing, and studying complex systems from all disciplines. Shannon (1998) defines simulation as the process of conducting experiment with a model for the purpose of understanding, analyzing, or examining different strategies for the operation of the system. Several methodologies have been proposed for a simulation study . Despite the differences between the terms, a generic procedure for a simulation study can be broken down to five main phases: Conceptual model building, Computer implementation, validation, Experimentation (Pidd, 1998).

Conceptual modeling is the first and probably the most critical phase - of a simulation study. Robinson (2006) defines Conceptual modeling as "the abstraction of a model from a real or proposed system". Robinson (2008) argues that conceptual modeling is most important phase of a simulation project which influence all other aspects of the study, in particular: "the data requirement, the speed with which the model can be developed, the validity of the model, the speed of experimentation and the confidence that is placed in the model results". In general, conceptual models presents an abstract view of systems without referring to the implementation details.A Conceptual model describes the elements, relationships, and assumptions in modeling a specific system (Robinson, 2006). A conceptual model may also facilitate the communication between dierent stockholders involved in a simulation study which consequently help in the validation of models and the simulation results (Pidd (1998), Robinson (2006)).

Although, the role of conceptual modeling is vital in the process of simulations, it is acknowledged as least understood phase of a simulation study (Robinson, 2006; Van der Zee et al., 2010). There is little study on a standard procedure and tool for this purpose. Just recently, the conceptual modeling has received some attention; still it suffers from the lack of a standard in procedure, notation, and tool. To cope with this challenge, some studies advocate using some tools which have been developed in Information Systems domain (Guizzardi and Wagner, 2012). Unlike the M&S, the field of Information systems and software engineering developed many modeling standards such as Unified Modeling Language (UML) for developing conceptual models.

Agent-based Modeling and simulation (ABMS), as a new simulation method- also suffers from the lack of a standard conceptual modeling tool. Although the modeling is part of the name of ABMS, in practice, often modelers overlook the modeling phase and jump from their mental model to implementation phase. ABMS tools has a limited support for the conceptual modeling and conceptual design of models. Guizzardi and Wagner (2012) address this problem by arguing that integration of conceptual models with execution information of simulation tools prevent replicability of the models. Sansores and Pavón (2005); Heath et al. (2009) state that a proper conceptual model help better understanding of the systems and contributes the process of validation of models.

Determining the causal links and the mechanism involved in a phenomenon is an essential part of a scientific study (Hedstrom and Swedberg, 1998; Little, 1991). Highlighting the causal mechanism involved in the system at the conceptual modeling phase will increase the understanding of the system and it can provide the opportunity for molders to involve stockholders in the core of simulation process. At the same time, highlighting the causal mechanisms will contribute to a better description of agent-based models. Furthermore, knowing about the mechanisms and cause and effects relations at different level of a system will help to interpret the holistic behavior of a system which consequently leads to a better policy design. Common practice in ABM, often do not specify the causal links and mechanism involved in the a system separate from the programming code. Consequently, causal links and mechanism are implicit in the agent-based models. Conte (2009) argues that to increase the explanatory power of agent-based models the cause and eect relationship involved in the phenomenon should be determined at the conceptual modeling phase of a simulation study.

How can one capture and present mechanism involved in a system? Although UML offers some valuable diagrams helping the process of conceptual modeling of agent-based models, non of its diagrams are aimed to present the causal relations in the systems. Given that a mechanism-based explanation is aimed to describes the causal process selectively and It does not aim at an exhaustive account of all details but seeks to capture the crucial elements of the process by abstracting away the irrelevant details. (Hedströ m, 2008), there is a need for a tool which supports modellers to present an abstract model of the underlying causal processes. However, non of the UML diagrams is aimed to present the causal process.

As we discussed in the previous chapter, using the Stock and flow Diagram (SFD) is useful to make the dynamics explicit in the agent-based models. In the previous section, we mainly focus on to present the dynamics involved in the global environment of agents, ignoring the process at the level of social agents where individuals interact with artifacts. In this chapter we provide a meta-model for describing the mechanisms involved at different levels of a system: mechanisms involved at the operational, social, and macro level of the systems and the inter layer mechanisms. Furthermore, we address the types of mechanism which can be explained through the use SFD.

UML For Causal explanation: UML provides a number of graphical notations which are used to to describe and design object oriented software systems (Fowler, 2004). UML offers more than 26 different types of diagrams which can be classified into two structural diagrams (e.g., Class Diagram, Composite structure Diagram) and behavioral diagrams (e.g., state machine diagram, use case diagram, sequence diagram). While Structural diagrams depicts the elements of a system, Behavioral Diagram are used to specify dynamics aspect of a system. Among these diagrams probably the class diagram, use case diagram, sequence diagram, and state machine diagram are the most useful diagrams.

Since we are focusing to explains the causal process in the systems, The behavioral diagrams may contribute to our aim. As following we describe briefly these diagrams

- Use case diagram:
- state machine diagram
- sequence diagram

Although state machine diagrams address the activity of the agents, but they do no depict what is the consequence of the actions on the states of the systems. In other word, they mainly present the causes, without specifying the effects. the relationship between the actions of agents and the observable state of the systems (specially in the form of aggregated states) is not specified by state machine diagrams.

5.2 Why Causal Explanation is important?

Unlike physical systems which underpinned by well established theories and universal mathematical laws, social systems are complex systems which their rules may be violated during the time. This characteristic of social systems questions the accuracy of models in social systems. One of the pervasive uses of models and simulation in natural science and engineering is to predict the behavior of the systems under different condition. However, in social systems -due to the mentioned problem-, it is mostly difficult if not impossible to use modelling and simulations for the aim of prediction. In social systems, models are mainly used to enhance our understanding of (and subsequently, explaining) the social phenomena (Rossiter et al., 2010). Gilbert and Troitzsch emphasize that "[...] social scientists tend to be more concerned with understanding and explanation. This is due to skepticism about the possibility of making social predictions, based on both the inherent difficulty of doing so and also the possibility, peculiar to social and economic forecasting, that the forecast itself will affect the outcome. (Gilbert et al., 2005, p. 6).

According to Abbott (1998), discovering the causal relationships is the main aim of social science that makes social science a real type of *science*. Hypothesizing about the cause of a phenomenon is the fundamental aspects of an explanation. Little (1996) states that "an important class of social explanations are causal explanations: to explain an outcome, we attempt to identify the causal circumstances that brought it about." The notion of causation and causal explanation has received considerable attention among the philosophers of science. However, there is a long debate regarding the relationship between causation and explanation. Some philosophers believe that social phenomena can be explained through the social law. On the contrary, other believe that there is no such covering law in social science (Sawyer, 2004).

Mechanism-based explanation is one of the relatively new approach among the casual explanation approaches which has recently received considerable attention. It is argued by several researchers that the central idea of causal explantion is the idea of causal mechanism (Little, 1991). "to assert that A causes B is to assert that A in the context of typical causal fields brings about B through a specific mechanism." (Abbott, 1998). Mechanism-based explanation tends to produce more precise and intelligible explanation by identifying the details of underlying mechanisms. A phenomenon can be well-understood and be explained by referring to the mechanisms that give rise to it (Hedströ m, 2008).

One of the fundamental attribute of ABM which make it so close to mechanism-based explanation is the bottom-up approach of ABM; both ABM and mechanism-bases explanation approach look for connecting the link between micro-level of the systems to the macro-level behavior. The association of ABM and mechanism-based explanation has been addressed by some researchers (e.g.,Gilbert and Ahrweiler (2009); Hedström and Ylikoski (2010)). For example, Sawyer (2004) found striking the parallels between causal mechanism approach and artificial society simulation foundations. In the same paper Sawyer emphasizes that "ABM model the mechanisms." adding that "when we write a set of computational algorithms (the program), formalizing the generative hypotheses of which are to be studied, what we are doing is hypothesizing a series of generative mechanisms."

Although the mechanism are modeled in the ABM, they are implicit in the programming codes. In an agent-based simulation study, modelers often make explicit what agents do which are the causes in the system. However, what would be the effect of these causes and the chain of cause and effects are implicit in the codes. Making these causal links and mechanisms of a model explicit improve our understanding of the systems, And help in analyzing the simulation results.

Meanwhile, there is an ongoing debate among the researchers about the explanatory power of ABM. It is often claimed that ABM are explanatory (Epstein, 2006; Axelrod, 1997b). However, there is an ambiguity about how they are explanatory. Grüne-Yanoff (2009) claims that agent-base simulations are not explanatory since they cannot provide causal explanation of social phenomena. He further argues that ABM cannot contribute to our understanding by only providing partial explanation of a phenomenon. For understanding a phenomenon, we need to know its possible causal history.

Mechanism-based explanation - which is a type of causal explanation - enhance the explanatory power of ABM. However, we should emphasize that when we are dealing with complex systems such as soci-technical systems, "mechanisms interact with one another forming concatenations of mechanisms." (Gambetta, 1998) and this characteristic make it some how impossible to interpret the behavior of these systems based on the causal links and mechanisms. However, it does not mean that we should not make the mechanisms explicit. Making the mechanism involved in the system explicit in our models help the explanatory process of agent-based models. As it is argued by Hedström and Ylikoski (2010), to have a proper explanation of a phenomena, we should understand the casual mechanism which are involved in the system. This argument is in the line with the suggestion of Conte (2009) which suggests that "producing causes and their link to effects must be hypothesized *independent of generation*: rather than wondering which are the sufficient conditions to generate given effect?", the scientists should ask "what is a general, convincing explanation, and only afterwards", they should translate it into a generative explanation." Determining the cause and effect relationships and process involved in the system at conceptual modeling phase will enhance the understanding of the modelers and is helpful in interpreting the quantitative outcomes of the simulation study.

Moreover, Mechanism-based explanation contributes to a better description of agent-based models. Grimm et al. (2006) argue that while ABM become a widely-used tools in many disciplines, it suffers from the lack of a standard protocol for describing models; Agent-based models are often described verbally that make them difficult to understand and to duplicate. In the favor of Mechanism-based explanation for describing systems, Marchionni and Ylikoski (2013) argue "Scientific understanding is constituted by knowledge of dependencies [...] and mechanisms can be understood as description of the networks counterfactual dependencies that characterize the system in question". Explaining the mechanisms involved in the system especially by the help of SFD, which is a diagramming tool, will help the process of describing agent-based models which consequently enhance understanding of the models.

5.3 Meta-Model

In order to make the causal mechanism involved in socio-technical systems explicit in an agent-based model, we first develop a meta-model for studying these systems. Ferber (1999); DeLoach and Valenzuela (2007) define a multi-agent system as having six basic element.

- An Environment, E
- A set of objects (artifacts) that exist in E.
- A set of agents, A.

- A set of relationship, R, which defies the relationship between objects and agents.
- a set of operation, O, which agents can use to affect objects.
- A set of universal law which determine the reaction of the environment to agent operations.

While these elements are essential for defining a socio-technical systems, it is also critical to highlight the hierarchy among the different level of environment and distinguish between social agents and nonsocial agents. Besides, It is also important to provide a meta-model which presents these elements in a abstract form. We first present a comprehensive topology of agent-based models. In this topology, we make a distinction between the environment of agents at the operation level where individuals interact with artifacts and the social level where social agents interact with each other (See Figure 5.1).

In line with Ricci et al. (2006) in describing environment, we use the notion of Workspace to extend the topology of environment. Workspaces are containers of agents and artifacts. They are at the same time- the nodes of an infrastructure network (Ricci et al., 2007). We classify workspaces into the two types: operational level workspaces, and social level workspaces. At the operational level, a workspace comprises simple agents and artifacts. However, social level workspaces includes artifacts and social agents. At the operational level workspaces, agents are involved in pragmatic actions interacting with artifacts. However, at the higher-level social agents are involved in communication action interacting with other social agents. Social agents are involved in communication actions they may negotiate, corporate, or compete with other social agents. We use the term of *communication action* for specifying activities of agents related to communication between agents and *pragmatic action* term for addressing the interaction between agents and artifacts. Communication actions can be carried out at the both level while Pragmatic actions are mainly carried out at the operational level workspaces.

Environment in ABM: Since the beginning of agent-based research, the term of agents has been along with environment. However, there have been conducted less research regarding the characteristics of the environment in comparison with agent part of systems. According to Maes (1995) "agents are computational systems that inhabit some complex, dynamic environment, sense and act autonomously in this environment." Wooldridge and Jennings (1995) define some characteristics for agents which are directly related to the environment. For instance. They argue that agents are reactive perceiving their environment. Odell et al. (2003) define environment as a world that "provide conditions under which an entity (agent or object) exists." Despite the important role of environment in agent-based models, it is often an implicit part of agent-related research, and it is commonly treated in an ad-hoc way (Weyns et al., 2007).

Most of the studies regarding the characteristic and role of environment have been conducted in the field of Multi-Agent Systems (MAS). Although traditionally environment is treated as "given" Okuyama et al. (2005), but recent research especially those that study situated multi-agent systems emphasize that environment needs to be modeled and provided for agents as it can help them to behave more appropriate. Due to this fact, Despite the fundamental difference between MAS and MABS that "MABS is a virtual representation of another system (including individuals, objects, etc.), whereas a MAS is an artifact that interact with environment", we can use the concepts of the environment in MAS for specifying environment in MABS (Klügl and Davidsson, 2013).

In the following we review, some of the meta-models regarded the environment of agents. Okuyama et al. (2005) introduce ELMS as a description language for specifying multi-agent environment. ELMS allows modeler to specify agents' perception, and the kind of interaction that a agent can have with the objects and perceptible representation of other agents involved in the environment. ELMS define the environment with the help *Grid construct* while grid can be defined two or three dimensional, and *Resources construct* which is used to define objects of environment. ELMS uses the XML syntax to specify environment.

Gouaïch et al. (2005) introduce MIC (movement, interaction, computation) to support interaction between agents. MIC assumes that autonomous agents sense and act through the deployment environment by sending and receiving interaction objects, interaction space is used to define interaction between agents. And the whole dynamics of deployment environment is the result of the movement, the interaction, and the computation functions.

Artifacts-based environment is the most cited approach for modeling the environment which has been introduced by Alessandro Ricci and his colleges. In Ricci et al. (2006) they introduce the notion of artifact as a first-class abstraction to model environment in MAS. It is argued that "Artifacts are runtime devices providing some kind of function or service which agents can fruitfully use both individually and collectively to achieve their individual as well as social objectives. Artifacts can be conceived (and programmed) as basic building blocks to model and build agent (working) environments". In Ricci et al. (2007) they provide a framework for prototyping artifact-based enviornmnet in MAS (CArtAgO). In Omicini et al. (2008) they define three abstractions for agent-artifacts meta-model:"

- Agents, to represent pro-active components of the systems, encapsulating the autonomous execution of some kind of activities inside some sort of environment;

- Artifacts, to represent passive components of the systems such as resources and media that are intentionally constructed, shared, manipulated and used by agents to support their activities, either cooperatively or competitively;

- Workspaces, as conceptual containers of agents and artifacts, useful for defining the topology for the environment and providing a way to define a notion of locality."

Ferber et al. (2005) introduce AGRE based on the AGR (Agent, Group, Role) plus the environment. AGRE is based on the idea that agents are situated in different spaces: physical or social. A physical space like geometrical space is called "areas'. And social space is represented by the "group". AGRE defines two modes for agents: body and role. Agents perceive and act through their bodies in the areas which are spaces that construct the physical world. In addition, Agents perceive and act through their roles in groups, which are spaces that construct organization. Agents may belong simultaneously to both social and physical world. While the number of role that a agent can take is not restricted, an agent can only has one body acting through the physical world.

In order to focus mainly on the characteristics of environment in ABM, at the following, we address the definition and attributes of environment in four ABM meta models, INGENIAS, Easyabms, MAIA, and AMASON. INGENIAS (Pavón and Gómez-Sanz, 2003) is a meta-model originally designed for supporting MAS then it was extended to cope with issues of ABMS as well. INGENIAS introduces five meta-models that describe a system: Agent model, interaction model, tasks and goals model, organization model, environment model. Environment in INGENIAS includes resources and contextual space. Pavon et al. (2008) argue that "The environment concept in INGENIAS is basically what agents can perceive or actuate, such as other agents, resources, etc. This concept has been extended to include space and scheduling considerations".

easyABMS (Garro and Russo, 2010b) is a methodology to support agent-based simulation defining an iterative process with seven subsequent phase for agent-based simulation. easyABMS structure a system with three models: society model, agent model, and artifacts model. In contrary to INGENIAS which clearly addresses the term of environment, easyABMS does not directly address it in its proposed conceptual structure. However, easyABMS define the artifacts model which can be assumed as the environment of agents. Garro and Russo (2010b) explain that artifact model "describes the behavior of an Artifact as a set of triggered Activities related to the offered services (Artifact Behavioral Model), and its interactions with other Artifacts and Agents (Artifact Interaction Model)".

MAIA (Ghorbani et al., 2013) is a meta-model which provide set of concepts for developing agent-based models based on the IAD (Institutional Analysis and Development) framework. MAIA proposes five structures for conceptualizing an agent-based system:

- Collective Structure: actors (referred to as participants in the IAD) and their attributes.

- Constitutional Structure: the social context.
- Physical Structure: the physical aspects of the system.
- Operational Structure: the dynamics of the system.
- Evaluative Structure: the concepts that are used to validate and measure the outcomes of the system.

MAIA does not directly address the notion environment of agents. However, it defines Physical Structure, which can be defined as environment of agents. Ghorbani et al. (2013) explain that physical structure comprises physical components which "can be accessed/used only by agents having a capability associated with the affordances of the component. Besides properties and affordance, physical components may also have behaviours (e.g., ageing of a computer). A physical component may be open for every agent to use or fenced (i.e., restricted). All the physical components in the e-waste example (computers, gold, etc.) are fenced, but a public road would be an example of an open physical component."

AMASON Klügl and Davidsson (2013) is a meta model aimed to capture the basic structure and dynamics of MABS model. AMASON recognizes three types of components for an agent-based model: *Body*, *Mind*, *Region*. Body represents a physical entity in a model; A body needs Mind to become an agent; Region represents the spatial environment where agents and objects are located. AMASON directly addresses the spatial environment and the objects which are situated in it. Klügl and Davidsson (2013) emphasize capturing the dynamics of environment. They argue that "Environmental dynamics happen without being triggered by an agent. Processes such as seasonal temperature dynamics, a tree growing, or rain starts to fall or a stone is heating up are examples. In the meta-model we associate such dynamics with regions. One can distinguish between dynamics that just affect the state of the region, and dynamics that affect the state of bodys that are located on the region."

As it is depicted in Figure 5.1, there are three different types of links which connect the elements of a system. Dashed links represent the interaction between agents. These links can either present the authority relationship or the communication channel between two agents. The interaction between agents and the artifacts are shown as straight lines. The last kind of link is part of the networks which connects different workspace as nodes. For instance, in the context of socio-technical systems, these links can be representative of gas pipeline, road, or electricity wires, which connect together multiple corporations, factories, etc.

In the Chapter 2, we had a discussion about the importance of considering feedback between properties of systems at the emergent level on the behavior of agents. Considered that argument, we need to emphasize that every workspace has a macro level. However, For the sake of simplicity, we take the social level workspace as macro level of operational levels. And we just assign a macro-level workspace for

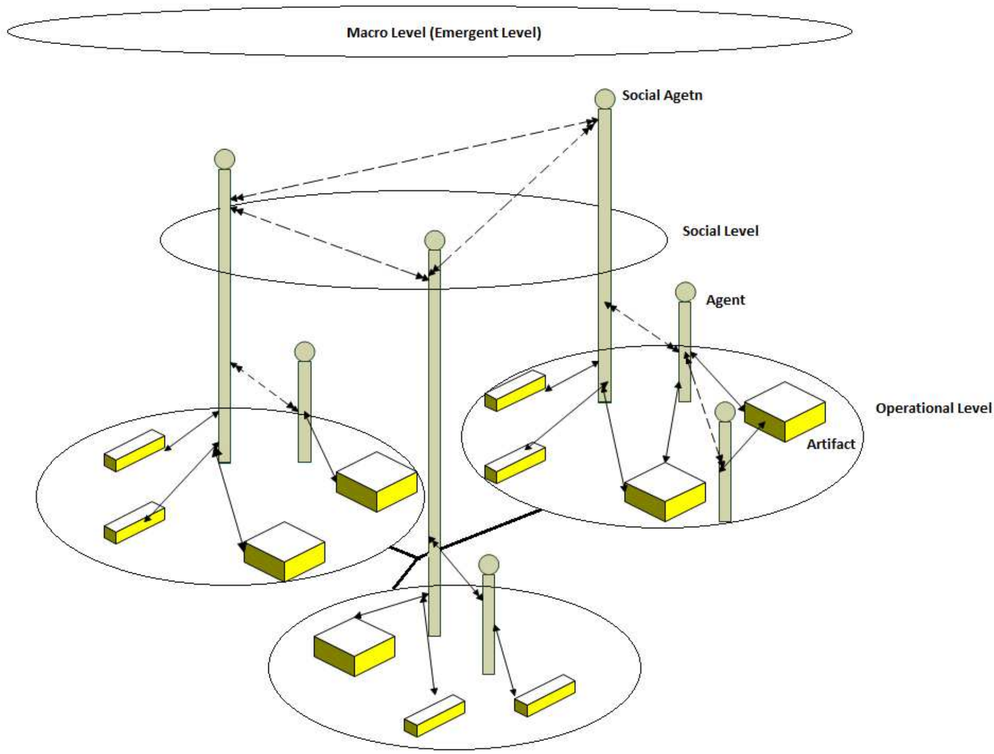


Figure 5.1 – Three layers meta-model

the social level workspace.

In a nutshell, we propose to break-down a system in three layers (see Figure 5.1): operational level, social level, and macro level so that social levels are the emergence level of the operational levels and macro levels are the emergence level of social levels. In the next section, we will use the meta-model proposed in this section to indicate different type of mechanisms involved in agent-based models.

5.4 Mechanisms in Agent-based Models

Inspired by the well known model of james Collman for conceptualization of social action, Macro-micro-macro model, Hedstrom and Swedberg (1998) define three different types of mechanisms which should be explained in order to have a proper explanation of a phenomena: Situational mechanisms, Action-formation Mechanisms, and transformation Mechanisms (see Figure 5.2). Those mechanism that explain the effect of macro properties on micro level are situational mechanisms. Action Formation mechanisms explain those mechanism that only operate at the micro level. Finally, those that explain how micro-level factors influence the macro level properties are transformational mechanisms.

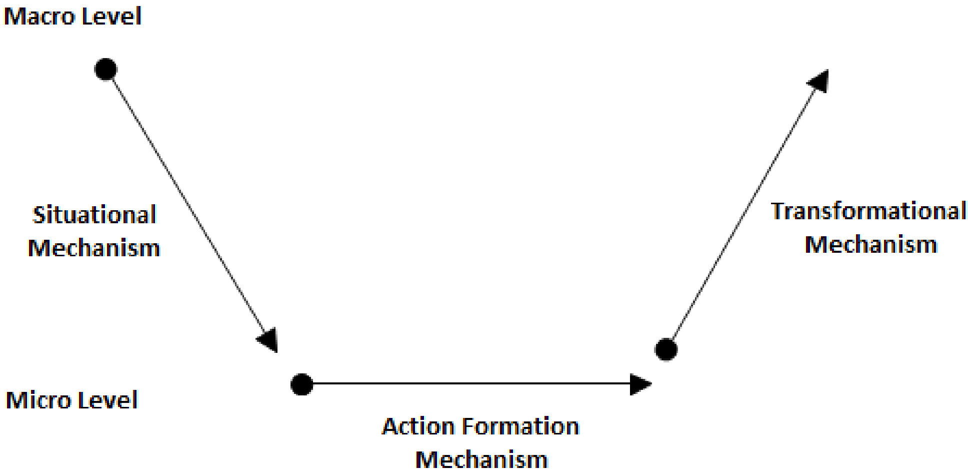


Figure 5.2 – A typology of social mechanisms

Inspired by this classification of mechanism, we present the structure and linkage of different types of mechanisms in a system- Based on the our proposed meta-model- to capture and present the underlying mechanisms of a socio-technical system (see Figure 5.3); we distinguished between mechanism in social layers, where social agents are involved in communication action, and operational level where agents are involved in pragmatic actions, and macro level which is the emergent level for social layer.

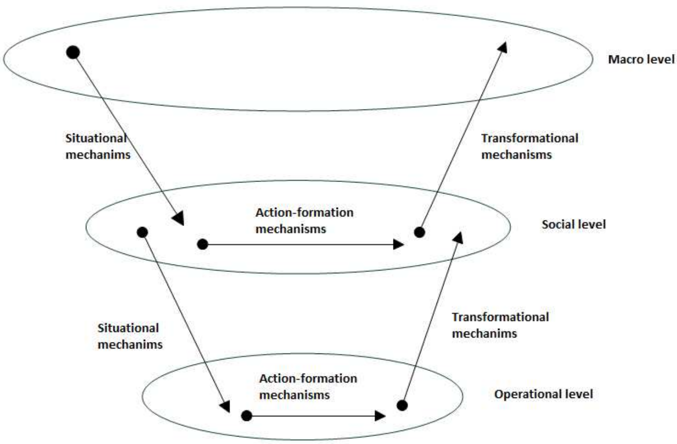


Figure 5.3 – typology of social mechanisms based on the proposed meta-model

At the operational level, we have three different mechanisms which can be classified as action-formation mechanisms.

- mechanisms in the mind of agents.
- internal mechanism of artifacts. The process of producing gas in a digester is a good example for this kind of mechanisms.
- mechanism which involve pragmatic action of agents. For example, the process of changing the number of cows on a farm which is determined by the action of the farmer (e.g., buying, selling).

Mechanisms at the social level can be classified into two types:

- mechanisms in the mind of social agents.
- mechanism which involve communication action of social agents.

In order to present a comprehensive picture of social systems we should specify how Macro-level properties will influence the social agents (Situational mechanisms). Furthermore, we need to show how social agents can influence the operational level properties. For instance, in the Biogas case, how the number of farmer who choose a technology will influence the opinion of other regarding the technology selection, or at the social level, customers choose their appropriate gas supplier (farmer), or they determine the price of gas while these activities influence the structure and dynamics of the system at the operational level.

5.5 How SDM can help Mechanism-based explanation

SDM is a special kind of causal mechanism explanation, which focuses on presenting the causal process involved in a system and capturing the feedback between its elements by using Causal Loop Diagram (CLD) and Stock-flow Diagram (SFD). Olaya (2009) states that SDM is one of the best ways to picture causal mechanism explanation. SDM tries to highlights that main mechanism (dynamics) of the system by implying an aggregated approach.

System dynamics modelers use the aggregated approach to abstract the model. One of the main characteristics of SDM which makes it a powerful method for capturing and presenting the mechanism involved in the system is that SDM tries to describe the dynamics using CLD and SFD tools. Although, in implementation phase of SDM lifecycle, modelers try to study the quantitative behavior of the system using equations, still one of the main aims of modelers is to enhance the understanding of the dynamics of the system using the CLD and SFD as a conceptual modeling tool.

Stocks represent observable states of the system which change through the flows. For instance, the number of cows and the amount of manure in a digester are two possible stock in a farmer workspace. Flows represent the rate that changes the value of stocks in every instance of time. The rate of flows changes due to either action of agents or through the equations which describe the internal process of artifacts or exogenous process. Auxiliary variable is the third element of SDM models, which are traditionally used to clarify the model. Exogenous variables- i.e., some attributes of artifacts, or parameters which are involved in decision-making process and consequently, the action of agents- can be presented by the auxiliary variables. For instance, in the Biogas case, *Birth Rate* is an attribute of cows that is presented as an auxiliary variable in the model.

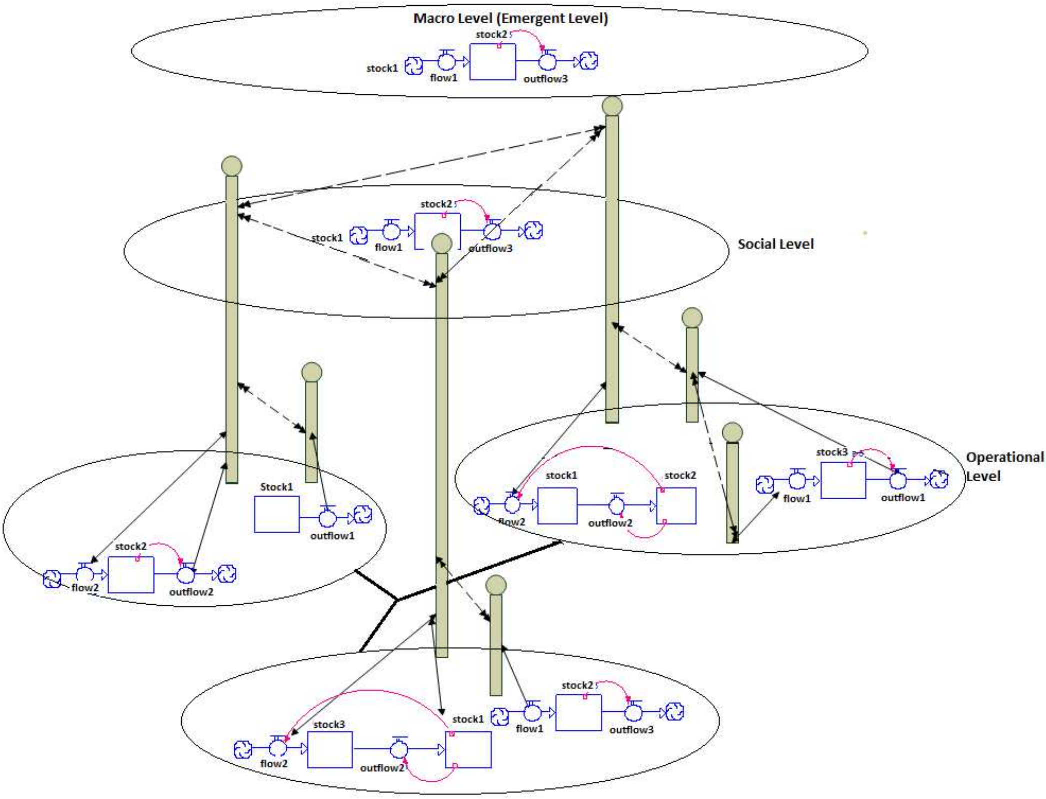


Figure 5.4

At the social level workspaces, Stocks and flows have different uses. While at the operational level, stocks and flows are used to show the process initiated be the pragmatical actions of agents or internal process of artifacts, at the social level workspace, stocks and flows are used to present the process which involve the aggregated state of lower-level workspaces. In other words, SDF is used to present the mechanisms arising from operational level workspaces (transformational mechanisms). Similar to the social level, at the macro level, SDF are used to present the aggregated state resulted from the action of social agents at the social level workspace (transformational mechanisms).

5.6 Biogas Model

The aforementioned environment topology is highlighted with a case of Biogas in this section. Biogas that is produced from cattle manure, is an emerging source of green energy in the Netherlands (Verhoog, 2013). It is especially a promising source for gas production because of its abundance in the Netherlands. To produce this type of gas, manure is collected from farms and digested to produce gas. However, the challenge is that producing bio-gas does not solve the problem of the excess of manure because the volume is not decreased as a result of gas production, leaving a material called digestate that is almost the same as manure.

System Description

Figure 5.5 illustrates the structure of Biogas case using SDM to depict the mechanism involved in workspaces. We define two kinds of workspaces at the operation level, and one workspace at the strategic level. At the farmer workspace, we defined two agents: Manager, and manager of financial activities (Accounting Clerk). At the social level, Manager do action on behalf of Farmer agent (Social agent) as well. At the consumer workspace, an agent has the role of gas consumer. At the social level, a farmer agent enact the role of a negotiator who interacts with a consumer's representative agent who can be a consumer as well.

System Elements

Farmers have four stocks:`Cows, Manure Inventory, Gas Inventory, Digestat Inventory, Asset, Debt, Receivable bill, Incomes`. Flows caused by farmers which change the level of stocks are: `Buy Cows, Loose Cows, Collect Manure, Transport Gas, Invest, Depreciate, Pay Debt, Cash Inflow, Payment`. They also have six auxiliary variables: `Selling Price, Depreciation time, Time to Reimbursement, Billing Delay, Direct Investment, Operation Cost`.

The internal process of Digesters and upgraders, which are artifacts in the farmer workspace, is modeled by SDM elements (Manure Inventory, Digestat Inventory, Use Manure, produce digestat, produce gas). In Figure 5.5, we distinguish their structure from the rest of the model with a dashed rectangular.

Consumers have two stocks: `Consumption` and `Gas Cost` which change through `Consume, Pay` flows. At the social level workspace, Agents interact with each other using negotiation artifacts or contract for determining the fee of gas or the term related to fine, in the case that a farmer does not provide enough gas. At the higher-level representative of consumer has access to the aggregated state of the consumer's consumption and production of gas. This information may be used to charge gas provider when there is imbalance in stock of gas.

Mechanisms Involved in BioGas

As it is depicted in Figure 5.5, in the production sector of farmers, the number of cows is increased and decreased through the farmer flows: `Buy cows, lose cows`. The number of cows along with `Rate of Manure` determines the amount of manure which

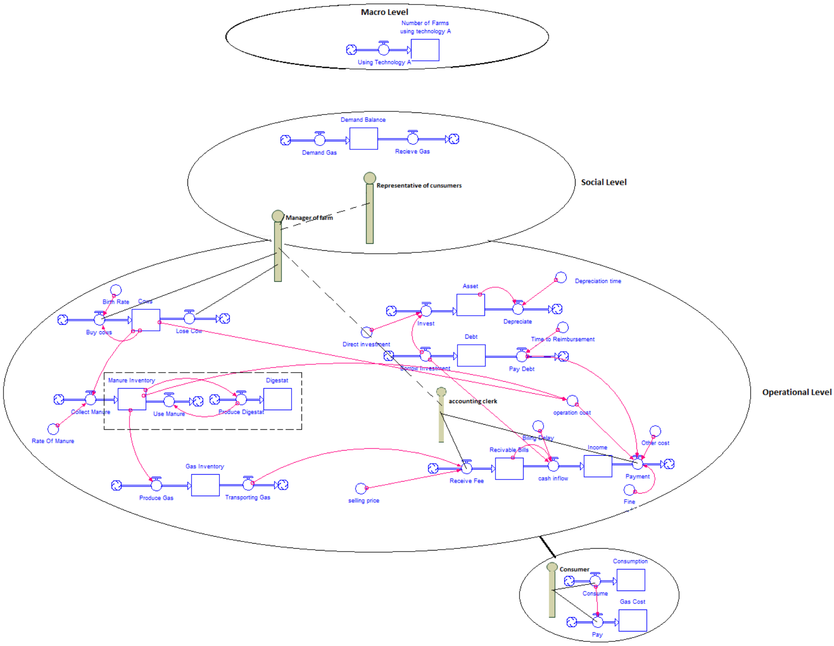


Figure 5.5 – Biogas System Dynamics Model

farmers are able to collect in every time step, aggregated in the `Manure Inventory`. Digestaters and upgraders, transfer Manure to Digestate and biogas through the `Produce Digestate` flow. The rate of digestate production determines the volume of Manure in the Manure Inventory. Digestater and upgraders cause another flow named `Produce Gas`. The Rate of gas production is dependent to the amount of manure in Digestat system. The amount of gas is aggregated in `Gas Inventory` stock which is decreased through the `Transfer Gas` flow.

In the finance sector of the Farmers, the amount of money that the Farmer receives through the `Receive Fee` flow is determined by the amount of gas which has been transferred and the `Selling Price`. After a *Billing Delay* Farmers will receive their receivable bills which will be aggregated in their `Income` stock. Through the `payment` Farmers pay `Operation Costs` which is determined by the cost of having cows and cost of producing gas. `Fine` is another cost, which might be required to be paid by the Farmer. Farmer use two sources for investing in production facilities, which are depicted in the finance sector. The amount of assets are increased through the `Invest` activity, and it will be decreased due to depreciation. Asset has its own behavior, which is `Depreciate` and is dependent to `Depreciation Time`. The amount of `Debt` is determined by the `Borrow Investment` activity and `Pay Dept` which happen based on *Time to Reimbursement*.

5.7 Discussion and Conclusion

In this chapter, we presented a meta-model for explaining the mechanisms involved in agetn-based models. We distinguish between three level of a system (operational, social, and macro) then we introduce the mechanisms involved in each of these levels and the inter-level mechanisms. Furthermore, we showed how SFD, can be used to describe some of these mechanisms. Using SFD, in the one hand, help to do abstract the mechanisms through the applying aggregated approach of SDM, and on the other hand, it help to describe the mechanisms visually.

This chapter contributes to ABM practice in the following aspects:

- The presented meta-model facilitate conceptualization of socio-technical systems by distinguishing between different level of the system (hierarchy) and different interaction between element of the system (See the extended version of this meta-model in Chapter 8).
- The classification of mechanisms presented in this chapter facilitate the process of explaining the mechanism involved in agent-based models in more structured manner.
- Using SFD to depict the mechanisms in ABM visualizes conceptualization of socio-technical systems models through the stock, flow, and auxiliary variable.
- Using SFD in combination with agent-based models assists participatory model development. SFD is the means of communication between between the modeler and other stakeholders involved in the simulation study. Highlighting mechanism through the SFD, produce a structured representation of the perception of modelers regarding the system which can be presented to different stakeholders and experts for verification before implementation phase.

Besides these contributions we see an additional benefits for using SFD in the process of conceptualizing agent-based models. Using SFD help to increase the ability of system thinking of modelers. System thinking is a holistic approach which focus on how systems work over time by studying how elements of a system interrelate to each other. The importance of system thinking for studying complex systems was recognized by many researchers. for more information we can refer to Mingers and White (2010) which review some of these studies. The fundamental concepts of system thinking in general include "parts/whole/sub-systems, system/boundary/environment, structure, process, emergent properties, hierarchy of systems, positive and negative feedback, information and control, open systems, holism, and the observer" (Mingers and White, 2010).

The next part is dedicated to explain how we can decrease the complexity of agent based models using system dynamics tools. We start with introducing Discrete-time System Dynamics Modeling (Dt-SDM) that we will use to implement hybrid models in chapter 8.

Part III

Combining SDM tool with ABM at the Implementation Phase

6

Discrete-time System Dynamics Modeling

This chapter is based on Hesan et al. (2014a)

6.1 Introduction

In the field of social sciences, simulation is accepted as a powerful tool that helps researchers to get more insight into the system, especially in cases where practical experiments are not feasible. However, depending on which approach and tool we select to model a system, the quantitative and qualitative results of the simulation may vary.

Dealing with time is one of the main issues that every modeler should think of, before selecting a tool for simulation. Some researchers see social systems as continuous-time systems and therefore use differential equation-based tools to simulate a system. In the contrary, other researchers consider social systems as discrete time systems. Therefore, they select discrete-time simulation tools.

System dynamics modeling (SDM) takes a continuous-time approach and constructs models with differential equations. While flows that get in or out of stocks can be represented continuously or in discrete points of time Sterman (2000), system dynamic modelers argue that it is an "acceptable approximation" to consider individual items as continuous streams that can be divided infinitely (Sterman, 2000). For instance, in a organization, people are individuals and are hired in discrete manner, but system dynamic modelers assume that the flows of people are continuously divisible.

Besides the approximation that is caused by assuming discrete flows as continuous streams, another source of approximation is using average delay instead of pure delay. For instance, system dynamic modelers assume that since in a post office with a large number of letters, all the letter are not delivered at once and there is a distribution around the average delivery time, it is an acceptable approximation to use average delay to model such cases.

System dynamics modeling is aimed to study long term behavior of systems at the macro level. This modeling approach is commonly used to study large organization or global phenomena. Therefore, these approximations are acceptable. However, the concepts of stock and flow have the potential to be used for studying systems at the micro level and to explore behavior of small organizations or phenomena (e.g, hiring system in a small organization, a supply chain system constructed by a few people). However, the problem is that the main characteristic of these kinds of system is that their flows are discontinuous and most of the time there are not many items in delay. Therefore, using differential equation to construct these kinds of system can lead to inaccurate quantitative results. In order to avoid these inappropriate approximation, we propose using difference equations instead of differential equations as the basic mathematical operator that determines the relation between a stock and its flows. This method of constructing system dynamics models allows us to model discrete flows and pure delay.

The structure of this chapter is as follows. In section 6.2, we look into difference equation and differential equation modeling. In section 6.3 we present a example case which we will be using to illustrate difference between the quantitative result of both approaches. In section 6.4, we propose our method. In section 6.5, we rebuild the working example with the help of the method. In section 6.6, we compare the quantitative results of the working example. In section 6.7, we will finish with some concluding remarks.

6.2 Background

6.2.1 Difference Equations and Differential Equations

Control theory classifies dynamical systems, whose state varies during time, into two subdivisions: continuous-time (CT) dynamical system and discrete-time(DT) dynamical system. In CT-systems, the state of the system changes after every infinite short interval of time while in DT-systems the state of the system varies at distinct points in time.

Differential equation is the basic operator for modeling continuous time systems. A simple population model with the growth rate r in the CT approach is modeled by the differential equation(integral) as following:

$$\int_0^t r \times p(t)dt \tag{6.1}$$

Difference equation is the basic operator for modeling discrete time systems. The simple population model that we already represent with differential equation can be modeled by a difference equation in discrete time approach as following.

$$p_n = (1 + r) \times p_{n-1} \tag{6.2}$$

Population in time n is equal to population in previous time p_{n-1} plus $r * p_{n-1}$.

Difference equation as the main operator of discrete-time modeling has been used recently, especially after developing digital computers(Oppenheim et al., 1983).

6.2.2 Discrete-time modeling in Literature

System dynamics literature rarely addresses discrete-time modeling. Sterman (2000) emphasize that instead of first order systems in continuous time modeling which can not generate oscillated behavior, first order systems in discreet-time approach can oscillate or even generate chaotic behavior. Barlas (2007) points out that the equations which construct a system dynamics model can be either differential equations or difference equations. Barlas (2007) argues that although a system dynamics model can be continuous, discrete or hybrid, in practice, SD takes discrete systems as continuous system since continuous-discrete hybrid model can be cumbersome to build and analyze. Barlas and Gunduz (2011); Barlas and Özevin (2001) point out that by replacing dt of a system dynamics model with 1 we can have a discrete-time version of system dynamics.

Besides system dynamics literature, social simulation literature addresses different approaches for modeling discrete time systems with the help of difference equations. Inspiring from control theory studies, some researches use Z-transform to build and analyze discrete-time models. Burns and Sivazlian (1978) analyze a discrete-time model of a four echelon supply chain system with the help of Z-transform. Disney and Towill (2002) study the dynamic stability of a vendor managed inventory supply chain by constructing a discrete transfer function of the system.

Besides the Z-transform approach to study discrete-time systems, some researcher use mathematical representations and state space approaches. Mathematical representations of a system is mostly used when the system is constructed by one equation. Cvitanovic et al. (2005) develop a mathematical model of a simple population model called Logistic model. Allen (1994) develop a discrete-time version of epidemic model. Neubert et al. (1995) study pattern formation of the discrete-time predator prey model. The state-space approach is a mathematical representation which is used where the system is constructed by a few number of difference equations. Papanagnou and Halikias (2005) applied the state-space approach to study bullwhip effect in a simplified supply chain. Lalwani et al. (2006) represent a generalized order-up-to policy in supply chains using the state-space approach.

Discrete event simulations (DES) may also be considered as discrete time methods, as they are suitable for modeling the systems in which variables change in discrete-times (Özgün and Barlas, 2009). DES view systems as discrete sequence of events in time. In other words, DES is an event-based modeling approach that is different from the other mentioned approaches that are equation-based.

So far, we mentioned changing dt of system dynamics modeling, z-transform, mathematical and state-space approach as the main approaches for discrete-time modeling. We will later explain that although the first approach: changing $dt = 1$ in system dynamics modeling, seems a acceptable way to model a system with discrete time, it may result in inaccurate behavior of system. Using Z-transform and mathematical representation of discrete time system are suitable for linear system.

However, constructing system dynamics models with difference equations can be used for both linear and nonlinear system. Besides, our proposed method takes the advantage of the diagramming aspect of the formal system dynamics modeling which can be more powerful than Z-transform or other mathematical approaches for participatory modeling and for giving insights to the clients.

6.3 Working Example

As a running example, we take a one-echelon supply chain adopted from beer game distribution Sterman (2000, 1989) to present the innovative aspects of our method. The reason for selecting this example is due to the fact that in the beer game distribution model we study the micro behavior of a small group of individuals. Therefore, we can show how difference equation can benefit the result of simulation. Figure 6.1 depicts the stock and flow diagram of this case.

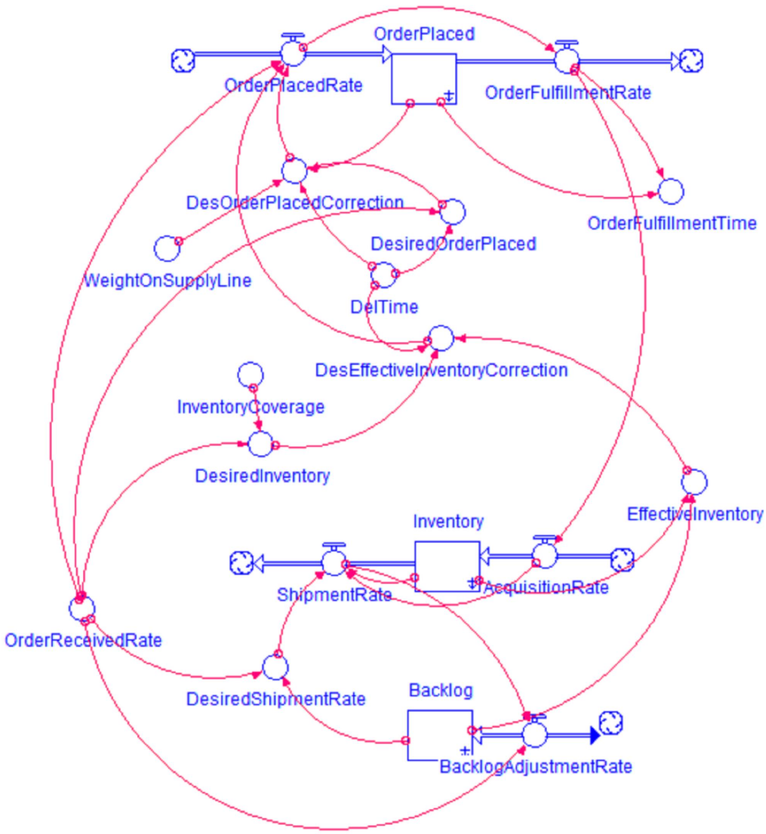


Figure 6.1 – Beer Game Example

Description of System The system under study is a typical cascade production-distribution system consisting of one retailer. Customer demand is exogenous and retailer must supply the amount of product requested by the customer. If there is insufficient product in stock, the retailer will keep surplus order in backlog until delivery can be made. All the retailer's orders will be fully satisfied after delay (4 weeks) and there is no limitation for the wholesaler to supply the retailer.

Order Policy The retailer tries to keep the level of inventory at the desired level (1.5 times of order received). Every order is determined by the number of orders that the retailer has received and two adjustments (correction) for inventory and supply line.

$$\begin{aligned}&OrderPlacedRate = MAX(OrderReceivedRate + DesEffectiveInventory\\&Correction + DesOrderPlacedCorrection, 0)\end{aligned} \tag{6.3}$$

$$\begin{aligned}&DesEffectiveInventoryCorrection = (DesiredInventory - Effective\\&Inventory)/DelTime\\&DesiredInventory = OrderReceivedRate \times InventoryCoverage\\&EffectiveInventory = Inventory - Backlog\end{aligned} \tag{6.4}$$

$$\begin{aligned}&DesOrderPlacedCorrection = WeightOnSupplyLine \times (DesiredOrderPlac\\&ed - OrderPlaced)/DelTime\\&DesiredOrderPlaced = OrderReceivedRate \times DelTime\end{aligned} \tag{6.5}$$

Shipment and Demand Policy The desired shipment rate is the accumulation of the backlog and the order that the retailer has received. Due to limitation in inventory, it is not always possible to satisfy desire shipment. Shipment rate is determined by the minimum of desired shipment rate and inventory. It means if inventory is lower than the desires shipment rate, the retailer will support a part of order and backlog equal to the level of inventory. Otherwise, he can satisfy all the order and backlog.

In order to put the model in the steady-state, we set $OrderReceivedRate$ to 4 and $InventoryCoverage$ to 1.5. The initial amount of inventory is 6 equal to $DesiredInventory$. The initial amount of $OrderPlaced$ would be 16. At time 4 we increase $OrderReceivedRate$ to 8 in order to analyze the behavior of model.

$$ShipmentRate = Min(DesiredShipmentRate, (Inventory/dt) + AcquisitionRate) \tag{6.6}$$

6.4 System Dynamics Modeling with Difference Equation

Although, differential equation is traditionally used as the mathematical operation that determines the relation between stocks and flows, difference equation is also compatible with the concept of stock and flow (Ossimitz and Mrotzek, 2008). Therefore, it can also be used as the basic operator of SDM.

Using differential equation (Formula 6.7) in order to study the micro level behavior of systems or the short term behavior of small organization in which flows are not changed in every instance of time, renders the model far from reality and leads to in inaccurate quantitative results of the simulation. For instance, when modeling the process of 'making orders by retailers', if there are many retailers in the model, assuming that an order takes place every instance of time is reasonable. However, when there is only one retailer in the system (or a limited number of them), making the assumption that an order is taking place in every instance of time is unrealistic. Therefore, for such cases, using difference equation is a more reasonable option.

Time delays often play an important role in the dynamics of systems. How we model delay in systems is very crucial in determining the behavior of models. Using average delay (Formula 6.8) instead of pure delay to model a system at the micro level or study short term behavior of a small system or organization can bring some inaccuracy in quantitative result of simulation. For instance, in our working example, as we are modeling the behavior of a individual retailer, there is no distribution of delay time. The retailer will receive his product after a constant delay of time. Therefore, it would not be appropriate to use average delay in these kind of cases as it is far from reality.

$$stock(t) = \int_0^t (inflow(t) - outflow(t))\, dt + stock(0) \tag{6.7}$$

$$outflow(t) = \frac{stock(t)}{D} \tag{6.8}$$

In order to avoid the mentioned inappropriate approximation, we propose to use difference equations to construct system dynamics models. In this approach, the amount of stock is calculated by Formula 8.1 which calculates the amount of stock based on the inflow and the outflow and the previous amount of stock in every discrete point of time. In order to model D step time pure delay depicted in Formula 8.2, the amount of delayed outflow is equal to amount of inflow in time $t - D$. The amount of the stock that is linked to the delayed outflow is equal to summation of all inflow which are in queue to become outflow.

$$stock[t] = stock[t-1] + [inflow - outflow] \tag{6.9}$$

$$\begin{aligned} outflow(t) &= inflow[t-D] \\ stock[t] &= \sum_{t=t-D}^{t-1} inflow(t) \end{aligned} \tag{6.10}$$

Although, in practice, all simulation software use difference equation to calculate differential equation with the help of Rungg Kutta or Euler numerical method, it does not mean that we can change a system dynamics model constructed by differential equation to the difference equation version by setting dt to 1. Due to the fact that changing the sequence between events in discrete time modeling changes the numerical result of models, setting $dt = 1$ may result in chaotic behavior of formal system dynamics model as we do not consider the sequence between events during the steps of time. Even if we set dt to 1 in formal system dynamics models because we cannot model pure delay the numerical result of our model would be different from the difference equation version of that model.

DT-SDM approach has some distinctive characteristics in the modelling of secrete-time systems as summarized in the following:

Simplicity in Modelling:

A major characteristic of System Dynamics modelling is its simplicity in the model development process. The core concepts in this approach - i.e., $Stock$ and $Flow$ - are so generic that System Dynamics can be conveniently used to model a wide range of systems/problems in different application domains (Sterman (2000)). It is also well-equipped with different tools for the conceptual modelling - like Causal Loop Diagrams and Stock and Flow Diagrams - which also make it easy to formulate the model and explain the results. DT-SDM is primarily defined based on the main concepts in the System Dynamics approach. Therefore, most of these tools can also be used for the conceptualization and analysis of simulation results.

Modelling Nonlinearities:

One of the main characteristics of DT-SDM -which is also originated in the principal features of the formal System Dynamics approach - is the capability to model the nonlinearities in the system. Other discrete-time modelling approaches - like Z-transform and mathematical modelling - are mainly useful in modelling a linear system. Using these analytical methods can become easily too complicated when nonlinearities are involved in the system modelling. However, building System Dynamics models with difference equations can support modelling both linear and nonlinear aspects of a system.

Modelling of Logical Statements:

In the formal System Dynamics Modelling, the logical statements such as $if...then...else$ cause sharp discontinuities and must be avoided in the modelling process (Sterman (2000)). On the contrary, modelling such logical statements in DT-SDM method is very straightforward. This provides a significant degree of flexibility in the model development, especially, in modelling the actual decision making processes in a system.

Modelling Memory in the Decision Processes:

Traditional System Dynamics approach assumes dt as an infinite short step of time. Therefore, it cannot represent the notion of the previous time step in the modelling process. On the other hand, in most actual cases, the states of the system in the previous time steps is the basis for making a specific decision at the present time step. In DT-SDM, however, the state of system in every time step is available. This provides a suitable context for the development of more flexible/realistic models of a system.

Modelling Event Sequences:

As mentioned in Section 6.2, replacing dt with "1" in the traditional System Dynamics approach is sometimes discussed as an option to model a discrete-time system. The rationale for this choice is that - in practice - most of simulation packages for System Dynamics Modelling use a numerical method - like Eulers or Runge-Kutta method- to compute the differential equations. By setting dt to "1", the continuous-time model can be transferred to a discrete-time one - especially in the case of Eulers method. However, this can be sometimes inadequate - or even problematic - because the temporal sequence of events is not explicitly addressed in the model. In some cases, this sequence of events may have a direct influence on the simulation results. For instance, in a stock management process - which is, in fact, the representative of decision in each stage of the beer game - the sequence of "fulfilling an order of a customer", "receiving the products from a supplier for a previous order" and "placing a new order with a supplier" may influence the quantity of next orders and subsequently, the overall behaviour of the system. This logic is primarily defined by the logic of the operation in a real case. This point is further elaborated by a simple numerical case in Figure 6.2. In this case, we assume that the value of "flow2" is dependent on the quantity of "stock1" (as presented in Equations 6.11). The initial amount of both stocks is set to zero. The value of "flow1" is fixed and is equal to 5. To calculate the stock variables, two sequences of events are considered here. In the first case - i.e., case A in Table 6.1 - at every time step, we first calculate the amount of "stock1" and consequently, the updated value ($stock1(t)$) is used in the calculation of "flow2". The simulation results for this system would be different if we calculate "stock2" before updating "stock1" - case B in Table 6.1 - because "flow2" uses the amount of "stock1" in the previous time step ($stock1(t-1)$).

$$
\begin{aligned}
flow1 &= 5 \\
flow2 &= stock1
\end{aligned}
\tag{6.11}
$$

If we model this illustrative case in the continuous-time System Dynamics paradigm with a standard package (like Ithink) - by setting dt to "1" - the simulation results would be similar to those of case A in Table 6.1. In these software packages, the amount of stocks in time $t - dt$ is usually used to calculate the flow variables or auxiliary variables whose values are dependent on the stock levels. Different settings for dt result in different values for "flow2" (and consequently, different

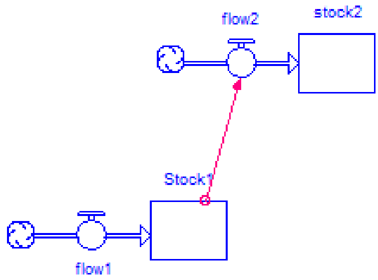


Figure 6.2 – The structure of illustrative case

time	flow1	stock1	flow2	stock2
initial		0		0
1	5	5	5	5
2	5	10	10	15
3	5	15	15	30
4	5	20	20	50
5	5	25	25	75
6	5	30	30	105
7	5	35	35	140
8	5	40	40	180
9	5	45	45	225
10	5	50	50	275
11	5	55	55	330
12	5	60	60	390

A

time	flow1	stock1	flow2	stock2
initial		0		0
1	5	5	0	0
2	5	10	5	5
3	5	15	10	15
4	5	20	15	30
5	5	25	20	50
6	5	30	25	75
7	5	35	30	105
8	5	40	35	140
9	5	45	40	180
10	5	50	45	225
11	5	55	50	275
12	5	60	55	330

B

Table 6.1 – Result of illustrative case for two sequences of events

results for “stock2”), as shown in Figure 6.2. This has two implications for the simulation results. Firstly, setting *dt* to “1” in the formal System Dynamics approach has an inherent assumption about the sequence of events which is not necessarily the same as the ones in a real case. Furthermore, the accuracy of results is dependent on the value of *dt* - instead of the real structure and sequence of decisions in a system.

In the next section, we will rebuild our working example with the proposed method.

6.5 Working Example Constructed by Difference Equation

In Section 6.3, we described our working example which has been developed with differential equation. In this section, we will rebuild this model with the help of difference equation and we will compare the quantitative results of both approaches. In order to apply this new approach, we developed software in Python programming language. As in most SD tools, this software supports graphical definition of equations.

time	flow1	stock1	flow2	stock2
initial		0		0
1	5	5	0	0
2	5	10	5	5
3	5	15	10	15
4	5	20	15	30
5	5	25	20	50
6	5	30	25	75
7	5	35	30	105
8	5	40	35	140
9	5	45	40	180
10	5	50	45	225
11	5	55	50	275
12	5	60	55	330

dt= 1

time	flow1	stock1	flow2	stock2
initial		0		0
1	5	5	2,25	2,25
2	5	10	7,25	9,5
3	5	15	12,25	21,75
4	5	20	17,25	39
5	5	25	22,25	61,25
6	5	30	27,25	88,5
7	5	35	32,25	120,75
8	5	40	37,25	158
9	5	45	42,25	200,25
10	5	50	47,25	247,5
11	5	55	52,25	299,75
12	5	60	57,25	357

dt =0.1

time	flow1	stock1	flow2	stock2
initial		0		0
1	5	5	2,47	2,47
2	5	10	7,47	9,95
3	5	15	12,48	22,43
4	5	20	17,48	39,9
5	5	25	22,48	62,38
6	5	30	27,48	89,85
7	5	35	32,48	122,33
8	5	40	37,48	159,8
9	5	45	42,47	202,28
10	5	50	47,47	249,75
11	5	55	52,47	302,22
12	5	60	57,47	359,7

dt=0.001

Table 6.2 – Result of the illustrative case in traditional System Dynamics approach with different values for *dt*

The order, shipment and demand policy of this new model is the same as the differential equation based model. The only difference is the stock and flow relation and delay construction. Since inventory and backlog are both stocks that are not used to model delay, we determine the mathematical relation between these stocks and their flows using Formula 8.1.

To model the delay between $OrderPlacedRate$ and$OrderFulfillmentRate$, Formula 8.1 is used to construct pure delay, depicted in Formula 6.12:

$$\begin{aligned} OrderFulfillmentRate(t) &= OrderPlacedRate[t-4] \\ OrderPlaced[t] &= \sum_{t=t-d}^{t-1} OrderPlacedRate[t] \end{aligned} \tag{6.12}$$

Besides defining mathematical operations for constructing a model, another issue that is important to determine, is the sequence between the events in every step of time. Depending on how we define the sequence between events during the time steps, the quantitative results of our model will change. For instance, in our case we have three main events: placing new order, shipping and backlogging, receiving previous order. How we arrange the sequence between these events will result in different behaviors in the system. The final issue that must be considered is about the steady state of the system. The steady state of the model must be determined based on the arrangement between events.

6.6 Results Comparison

We assume that the retailer at the beginning of the week will receive their previous order in the supply line. Then, he will calculate the order that needs to be placed and will satisfy costumer's order by shipping and will adjust the backlog. In order to put system in the steady state, we set the initial value of inventory to 2 based

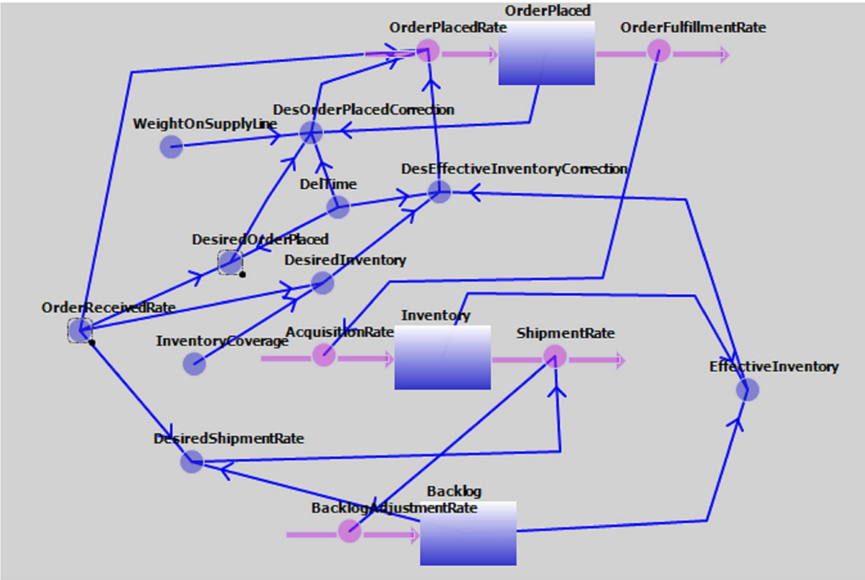


Figure 6.3 – System Dynamics Supply Chain Example constructed by difference equation

on the assumption that a retailer will ship all *OrderReceived* during the week and what will be left in inventory would be half of *OrderReceived* which is equal to 2.

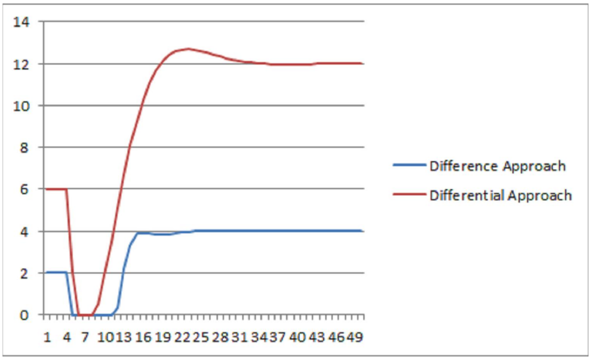


Figure 6.4 – Inventory in both approaches

Figure 6.4 shows the difference between the level of Inventory in both approaches. As it is depicted, inventory in the first approach shows a smooth oscillation while in the second approach there is no sign of oscillation.

Examining different $WeightonSupplyLine$ in both approaches shows the fact that in the differential approach, the more $WeightonSupplyLine$ gets close to 1, the more the system presents behavior with lower oscillation. While in the difference approach the more $WeightonSupplyLine$ closer to 0.5, the more the system shows lower oscillation. Figure 6.5 and Figure 6.6 present the level of inventory for 3 different values of $WeightonSupplyLine$ parameter of the differential and difference approach models.

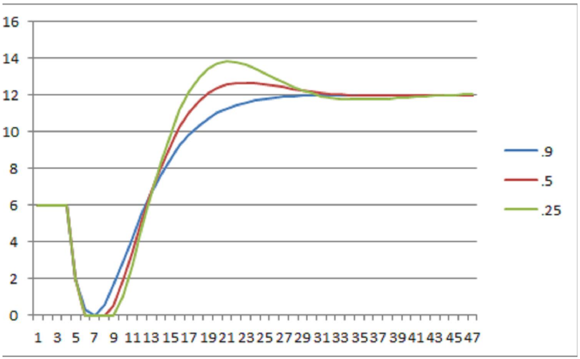


Figure 6.5 – Inventory with different values for $WeightonSupplyLine$ in the differential approach

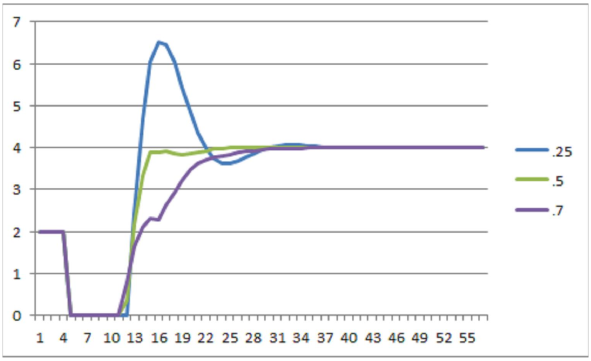


Figure 6.6 – Inventory with different values for $WeightonSupplyLine$ in the difference approach

Comparing the results of both approaches indicates that with the same $WeightonSupplyLine$ setting, in first approach the retailer is placing order more than what he needs to adjust the inventory and therefore it causes oscillation in inventory behavior. However, in the second approach the oscillation in inventory behavior is not as strong as it is presented in the differential approach which means that the retailer take in to account the existence of delay and the amount of product in delay more than the retailer in the differential approach.

Besides the different quantitative results, we observe qualitative differences especially when defining hypotheses for simulations. For example, as it is depicted in Figure 6.4, in the difference equation model with the $WeightonSupplyLine$ equal to 0.5, inventory does not oscillate. This fact can challenges the hypothesis that oscillation in the behavior of beer game distribution is because of ignoring the amount of product in supply line.

6.7 Discussion and Conclusion

In this chapter, we proposed constructing SDM models with the help of difference equations instead of differential equations. We illustrated this new approach by applying it to a supply chain system.

In SDM, the mathematical relationship between stocks and flows is commonly determined by the differential equation. However,the stock and flow concept is also compatible with difference equation and therefore, we can use difference equation as the basic operator of SDM which leads us to more accurate quantitative result where we study the micro level behavior of a system or small organization.

The proposed approach contributes to SDM in several aspects. Firstly, it provides the opportunity to apply the SDM concept at micro level systems where individual activities change the flows of systems in discrete points in time. Secondly, it can result in more accurate quantitative result for cases that are not large enough to assume their flows as continuous streams. Thirdly, opportunities to use logical statements and memory as explained in Section 6.4, enhance our ability to model complex systems.

Another contribution of this approach is that since we are constructing discrete-time models with the stock and flow concepts instead of using Z-transform or mathematical representations, it will contribute to the field of discrete-time modeling as it gives an opportunity to modelers to construct a model graphically and allow them to model and analyze nonlinear discrete-time models.

One final contribution of our proposed method is that since our proposed method and discrete event simulation both study the behavior of systems in discrete points in time and use queues to model systems, it may be possible to merge the system dynamics approach with the discrete event modeling. In discrete event simulation, flows of entities that get through the process are determined by random numbers which means that we are dealing with passive entities. However, by merging both concepts, we can develop more deterministic behavior for the flows of entities so that they can be effected by the state of system due to feedback.

As this method is proposed for the first time, it needs more evaluation process to be proved as a reliable approach for constructing system dynamics models. In order to use the ability of this approach for studying the micro behavior of systems a possible option for future work can be merging this method with agent based modeling.

7

Avoiding Bullwhip Effect - Case Study

This chapter is based on a paper submitted to the International Journal of Production Economics (IJPE)

7.1 Introduction

Bullwhip effect is a famous phenomenon in the world of logistics and supply chain management which influences the productivity of supply chain members in a negative way. The rational behavior of supply chain members in determining the quantity of orders results in oscillating behavior of inventories amplifying through the supply chain from downstream members to upstream members. Empirical evidence from the real supply chain clearly shows the existence of this phenomenon. Due to negative effect of this phenomenon on productivity of supply chain members it has been subject of many studies (Lee et al., 2004). "The bullwhip effect occurs when the demand order variabilities in the supply chain are amplified as they moved up the supply chain" (Lee et al., 1997). Bullwhip effect distorts demand information from downstream of supply chain to upstream, which leads to tremendous inefficiencies. Lee et al. (1997) argue that relying on distorted demand rate for production forecasting and capacity planning may result in enormous problems such as excessive inventory, poor product forecasts, inefficient or excessive capacities, and poor customer service due to long backlog.

Many different approaches have been exploited for studying the bullwhip effect. Lee et al. (2004); Warburton (2004); Lee et al. (1997) study the bullwhip effect through analytical approaches.Sterman (1984); Laugesen and Mosekilde (2006); Mosekilde and Laugesen (2007) use System Dynamics Modeling to study the dynamics of supply chain. They specifically focus on the effect of lead-time on decision-making of supply chain members as the main cause of bullwhip effect. Dejonckheere et al. (2004); Disney and Towill (2002); Disney et al. (2004) take advantage of discrete-time control theory approach to study bullwhip effects. Miragliotta (2006) identifies two schools of thought regarding the bullwhip effects: system thinking school, operation manager school. System thinking school sees the bullwhip effect as a result of irrational behavior of supply chain members who ignore the feedback of the systems. On the contrary, operation manager school views the bullwhip effects as a result of rational reactions of supply chain members. These schools come up with different suggestions for reducing the bullwhip effects. For instance, Sterman (1989), from the system thinking school, proposes that if actors involved in a supply chain do consider the amount of products in supply line in their ordering policy rules, it will prevent bullwhip effects and oscillation in the supply chain. Lee et al. (2004), from the operation manager school, propose centralized demand information method. They argue that providing each member of supply chain with actual information of their customer demand can reduce the bullwhip effect. According to Lee et al. (2004) there are four main factors contribute to the bullwhip effect:

- Demand forecasting. Forecasting methods are the only tools that managers can predict the future trends of demands in a supply chain. However, these methods are not always reliable and give some results which are far from reality.
- Order batching refers to a popular behavior of companies in a supply chain trying to order a large amount of products in order to decreasing the cost of transportation or receiving discount.
- Rationing game happens when there is a shortage of products in a market so that manufacturer provides a ratio of demands. In this situation, customers will exaggerate their actual demand in order to receive a sufficient amount of products.
- Price variation causes bullwhip effects since when price changes dramatically due to, for example, price promotions, the demand will be increased when products are cheap, and it will be decreased when the price of products is normal or high.

Investigating the role of different factors in formation of bullwhip effects, reveals that the role of demand forecasting and ordering policy are more significant than the other factors. The effective factors such as order batching and price variation distort the information that upstream supply chain members use in the formulation of their ordering policy. The point is when a bullwhip effect is initiated by some reasons (e.g., order batching, price variation), the orders which are received by the upstream members are based on distorted demand information which are not reliable for determining future demands and placing orders. Avoiding the use of distorted demand rate information helps reduce the bullwhip effects. In general, one can avoid using distorted information either through the information sharing or through the use of an ordering policy which do not relay on the past behavior of demands. Current ordering polices which have been used to study bullwhip effects often use the information about the past behavior of demand. For instance, Lee et al. (2004)

use average forecasting method as part of an order-up-to policy while this ordering policy relies directly on the past behavior of demands. Sterman (1984) employs a more complicated formulation as order-up-to policy which indirectly relies on the past behavior of demands.

In this chapter, to minimize the bullwhip effects, we propose a new ordering policy, called Shipment-Refined (SR) policy, which does not relay on the past behavior of demands. To formulate this ordering policy, we follow the approach of control theory in controlling systems. Control theory uses feedback to close the loop of a system and to eventually control its behavior. We develop a controller to reduce the error between input (demand rate) and output (shipment rate) of every echelon in a supply chain. SR policy is based on a hypothesis that the main problem of supply chain members is not oscillation on their demand rate. Their main problem is that they do not have enough information regarding the behavior of their upstream members; they cannot predict the time and the amount of products that they will receive when they place an order. SR policy helps get feedback form the behavior of upstream members of every supply chain members which helps the process of their ordering policy. In order to test the effectiveness of SR policy, we will use simulation. Furthermore, in order to show the effectiveness of our proposed SR policy, we compare the results of using two different kinds of ordering policy (Order-up to policy) with the result of SR policy.

The structure of this chapter is as follows. In Section 2 we illustrate control theory principles and our simulation technique, Discrete-Time System Dynamics Modeling (DT-SDM), that we use to develop SR policy. In Section 3, we illustrate the specification of the working example that we use to test the SR policy. Section 4 is dedicated to explain the concept of SR policy. In Section 5, we study the behavior of the working example using two different order-up-to policies. Section 6 is dedicated to compare the results of applying SR policy with the results two other policies calculated in the previous section. Finally, the chapter is concluded in Section 7.

7.2 Methodology

The methodology used in this chapter is based on control theory (Oppenheim et al., 1983). The history of using control theory to study supply chains goes back to the work of (Simon, 1952). He applied continuous-time control theory principles to control production rate in a simple system with one product. One of the main characteristics of the Simons work was using continuous-time approach in studying supply chains. Later on, Vassian (1955) applied discrete-time control theory principles to study supply chains (in continuous-time approach, it is assumed that the state of system varies after every infinite short interval of time, while, in discrete-time approach, the state of system changes at distinct point in time). Vassian (1955) takes advantage of Z transform methodology to control the level of inventory in a system (Ortega and Lin, 2004). Forrester (1961b) introduced the methodology of industrial dynamics, which is now referred to as system dynamics. System dynamics has its root in servomechanism and control theory. The approach of control theory in conceptualizing a system by the help of two main elements: rate (flow) and source (stock) is applied in system dynamics modeling. However, in contrary to the control theory practices which use transformation functions changing the domain of systems from time to frequency, system dynamics study systems in the time domain by the help of computer simulation. This characteristic of system dynamics makes it a powerful tool for studying nonlinear systems whereas control theory has limitation in studying nonlinear systems. Towill (1982) presented a model called Inventory and Order-Based Production Control System (IOBPCS) for studying supply chains using S transform methodology . Later on Disney and Towill (2002) developed a discrete-time version of this model using Z transform methodology. So far, different versions of IOBPCS model have been presented in the literature. As an example we can name Variable Inventory and Order Based Production Control System (VIOBPCS) (Towill, 1996), and Automatic Pipeline Inventory and Order Based Production Control System (APIOBPCS) (Dejonckheere et al., 2003). There are some common components which are used in the construction of these models (Sarimveis et al., 2008):

- Lead time, which represents the time between placing an order and receiving the goods.
- The target inventory, which can be a multiple of average of sales rate or a fixed number.
- The demand policy is a forecasting method, which makes an average of the market demand.
- The inventory policy, which is a feedback to control the rate of depletion of inventory (difference between desired inventory and the actual inventory).
- The pipeline policy, which is a feedback loop to control the rate of changes in work in process (differences between orders in pipeline and the actual level of work in process).

In this study, we take advantage of feedback approach of control theory method in designing controllers for influencing the behavior of systems. However, to apply this approach we do not change the domain of the system to the frequency. We take advantage of simulation to apply this approach in the time domain. We deal with supply chain as a discrete-time system and we take advantage of Discrete-Time System Dynamics Modeling (DTSDM) as simulation method. We decided to adopt this approach mainly because there is an innate advantage for discrete-time modeling approach over continuous-time modeling in supply chains studies which is due to the fact that supply chains are discrete-time systems in essence. There is often sharp discontinuity in the behavior of supply chains which cannot be modeled properly by using continuous-time models. Furthermore, continuous-time approach has limitation in modeling pure-time delay involved in supply chain systems. Due to this compatibility, using DTDM will result in more accurate quantitative result of supply chains (Hesan et al., 2014a).

7.2.1 Control Theory

Control theory is a well-established filed of research, which focuses on analyzing and controlling dynamic systems specially engineering systems (Oppenheim et al., 1983). The main objective of control theory is to control a system by closing the loop of system through feedback. In order to make the output of a system, y, in a desired way, it is usually done by manipulating the input of systems, u (Doyle et al., 1992). Depending on the system subject to the study, one may try to keep y close to a reference point r or keep it close to the u by feed-backing the error signal (e) to the system (see Figure 7.1).

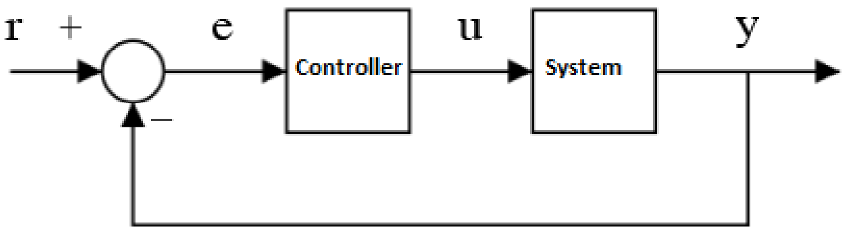


Figure 7.1 – Feedback approach (Doyle et al., 1992)

For instance, to control and keep the behavior of an electrical motor, similar to a reference signal, at first, the output of the motor, which is the velocity of the motor, is captured by the sensors. Then it will be feed backed to the system. The error between the output signal and the reference signal will get back to the system through a controller. PID controller is one of the most popular controllers, which has been extensively used to control engineering systems. As it is depicted in Figure 7.2, PID generates proportional, integral, and derivative signal of error to control the system by minimizing the error signal. Depending on the underlying process of a system, a system can be controlled by one of the three controllers or a combination of two or three of them. K_p, K_i, K_d are parameters which are used to tune the controller.

In the next section, inspired by control theory, we develop a controller to reduce the bullwhip effects in supply chain.

7.2.2 Discrete-Time System Dynamics Modeling

In Hesan et al. (2014a), inspiring from the principal of discrete time systems in the control theory and System Dynamics Modeling principal developed by (Forrester, 1961b), the concept of Discrete-Time System Dynamics Modeling (DTSDM) was developed. DTSDM is a discrete version of the traditional SDM using three elements: stock, flow, and auxiliary variables to construct a model, which are briefly introduced as follows.

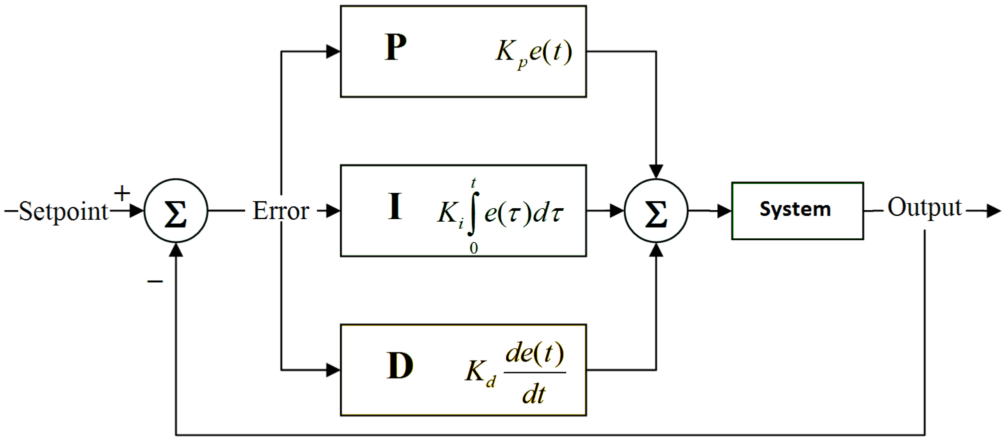


Figure 7.2 – PID controller (Doyle et al., 1992)

Stocks represent specific elements of a system, values of which depend on the past behavior of the system. Stocks accumulate inflow minus outflow and their values represent the state of the system.

Flows represent the rate that changes the value of stocks in a system in every instance of time. Flows can be either inflow, increasing the stocks value, or outflows, decreasing the stocks. The values of stocks are changed by their related flows.

Auxiliary variables are commonly used to clarify the model and ease the communication. An auxiliary variable can be a function of stock, constant, or an exogenous output, which contributes to formulation of the flows (Sterman, 2000).

The cornerstone of this modeling approach is using difference equations (as presented in Equation 7.1) instead of differential equations (as shown in Equation 7.2) to construct stocks-flow relationships in a system. Furthermore, the proposed method uses pure delay to model the time lags, d in a system (Equation 7.3, 7.4). Those who are interested to know more about different aspects of DT-SDM, may refer to (Hesan et al., 2014a).

$$stock\,[t] = stock\,[t-1] + [inflow - outflow] \tag{7.1}$$

$$stock\,(t) = \int_0^t (inflow\,(t) - outflow\,(t))\,dt + stock\,(0) \tag{7.2}$$

$$outflow\,(t) = inflow\,[t-d] \tag{7.3}$$

$$stock\,[t] = \sum_{t=t-d}^{t-1} inflow\,(t) \tag{7.4}$$

7.3 Working Example

Here we use an example of a three-echelon supply chain to test the results of implementing our proposed ordering policy and to compare these results with the results of using two different ordering policies. In order to test the effect of different ordering policies, we first put the system at the steady-stat. We assume that all the echelons receive a stable demand. Then we increase the demand of first echelon.

7.3.1 Description of the system

Figure 7.3 depicts the structure of the model. A supply chain with three players: a retailer, a wholesaler, and a manufacturer. Figure 7.4 shows the structure of each player using stocks and flows diagram. Every player has three stocks (OrderPlaced, Inventory, Backlog), which represent the states of the players system influenced by the associated flows. There are two material and information delay between each echelon which are presented through Material Delay and Information Delay. The Manufacturer, as the last echelon, will have a production delay equal to summation of both information and material delay. The structure of shipment policy of the model is specified now. However, the structure of ordering policy will be determined later based on the ordering policy that we choose to implement.

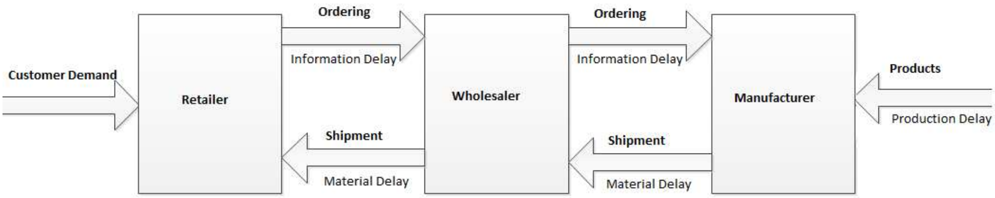


Figure 7.3 – Structure of the Supply Chain

In each period t, the following sequence of events happens. All the players first receive their orders, then the demand is observed and shipment of products will be arranged. Next, players observe the state of system (e.g., level of inventory) and finally place a new order based on their ordering policy. In the case that there is not enough inventory, all the unfilled demand will be backlogged; players will satisfy them when they receive enough amount of products.

7.3.2 Shipment policy

In order to calculate the Shipment Rate we use the term of Desired Shipment Rate which is determined by Equation (7.5). Desired Shipment Rate is the accumulation of the backlog and the demand that players have received. In every step of time, the players try to satisfy both backlog and the demand rate if there is enough products in inventory. Otherwise, they will satisfy part of it which is equal to the available inventory.

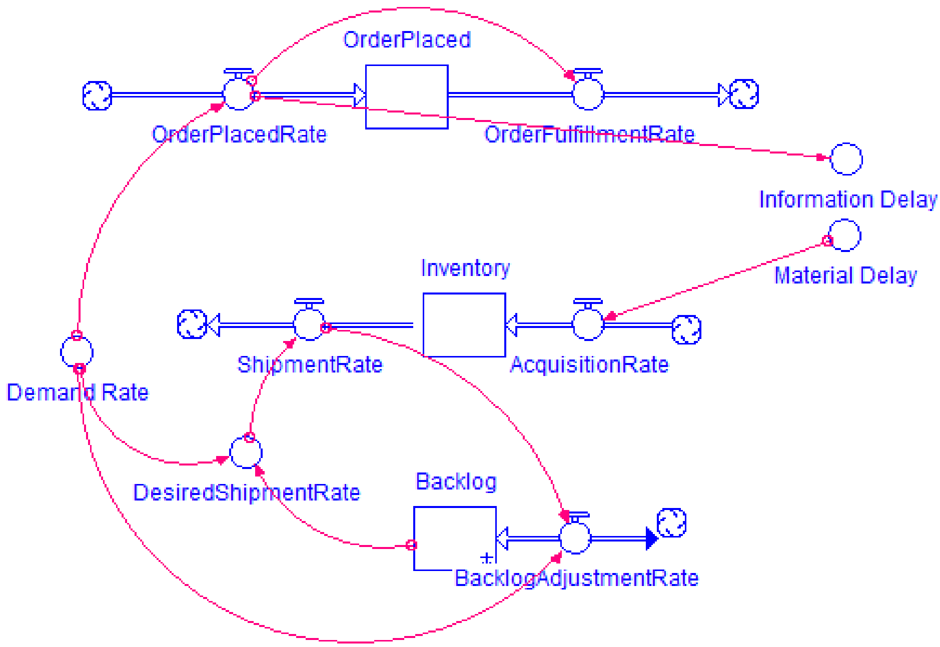


Figure 7.4 – Internal System of Every Player

$$DesiredShipmentRate = Backlog + DemandRate \tag{7.5}$$
$$ShipmentRate = Min(DesiredShipmentRate, Inventory) \tag{7.6}$$

7.3.3 Testing Scenario

In order to test the effectiveness of our proposed ordering policy in the formation of bullwhip effects, we use a step function as Demand Rate of the retailer changing from 4 to 8 at the time 4 of simulation. The simulation will be started with the steady state situation in which the demand rate of the retailer and the orders of all players are 4. Besides, the inventories have an initial quantity equal to 2. When the demand rate of retailer gets to 8, the players will increase their orders to compensate the shortage of their inventories. However after some time the system will reach its steady state where all the orders are equal to the demand rate of the retailer. In order to compare the effects of different ordering polices on the bullwhip effects, inspired by the work of (Chen et al. 2000) ,we use the order rate variance ratio which is the ratio between the variance of orders at the downstream and upstream of supply chain (Cannella et al., 2013; Miragliotta, 2006).

7.4 Shipment-Refined: An ordering policy to minimize the bullwhip effect

Following the approach of control theory in closing the feedback of a system and using controllers to control its behavior, we propose a new ordering policy which helps us to control the behavior of supply chain minimizing the bullwhip effects. One of the challenges we face in applying this approach to the case of supply chain is that we are not dealing with a simple system with one input and one output. Every echelon has different inputs and outputs interconnected to each other while the configuration of one echelon influences the others. For each echelon, we should have a controller to control the whole behavior of the supply chain. It becomes clear that the only part of the system that the players have the power to change is the ordering part of their system, which is why we use the error signal as a part of Order Placed Rate.

In order to control such interconnected system, we develop a simple proportional controller for every player. Equations 7.7 and 7.8 present the formulation of the SR policy. error is defined as the positive difference between Demand Rate and Shipment Rate, which is, indeed, the shortage of products in each time period. Equation 7.8 defines Order Placed Rate as the summation of Demand Rate and the error multiplied by the proportional parameter k_p, which is used to determine the amount of orders and consequently, control the level of inventory by the players. Figure 7.5 shows the structure of the retailer with SR policy.

$$error = Max\left(DemandRate - ShipmentRate, 0\right) \tag{7.7}$$

$$OrderPlacedRate = MAX\left(DemandRate + \left(k_p * error\right), 0\right) \tag{7.8}$$

The logic behind this formulation is that with this policy players try to fill out the gap between Demand Rate and Shipment Rate instead of bridging the gap between Inventory and a desired inventory level which is used in order-up-to policy. Furthermore, this formulation is based on a (more realistic) hypothesis that the problem of the supply chain members is not always oscillations in the demands; the problem is that they cannot predict how many products they will receive when they place an order. Actually, the players who use moving average and APIOBPCS ordering policy rely on the past behavior of demands to place a new order; they do not take into account any feedback from the part of the system that really causes the problem. However, in SR policy we provide an opportunity for players to have feedback from their upstream system.

To study this SR policy, we first investigate the behavior of a one-echelon-supply chain with one retailer; next we model our three echelon case-study. Figure 7.6 presents the behavior of inventory of the retailer with different K_p. For $K_p = 1$, the retailer will add what he needs to satisfy the backlogged demand to the actual demand which is the differences between DemandRate and ShipmentRate. In this configuration, the retailer will lose the safety inventory, and the inventory will be stable at zero. As it is depicted, there is no oscillation or over ordering in the behavior of the system.

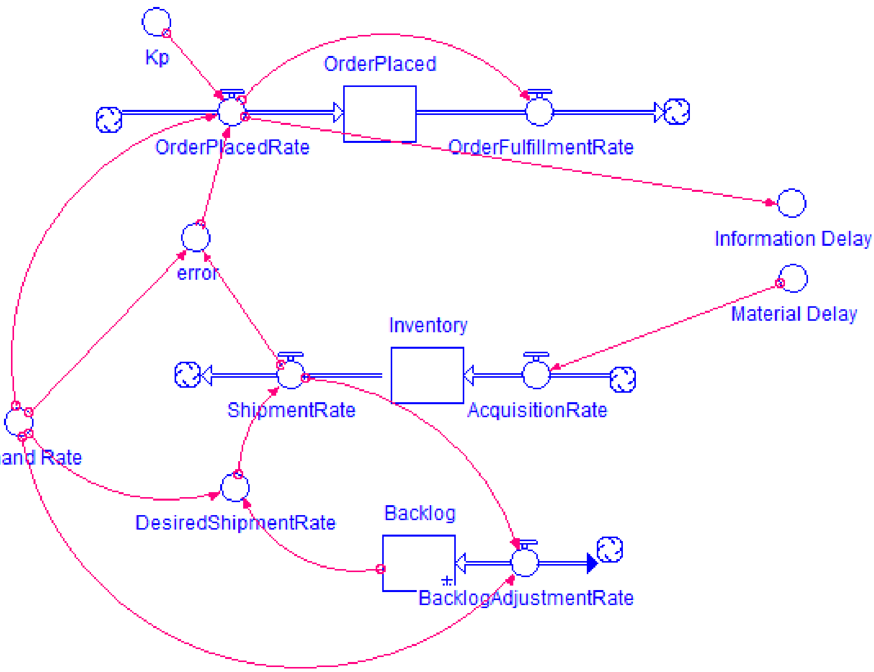


Figure 7.5 – Structure of the retailer with SR ordering policy

Increasing K_p will increase the level of inventory As its shown, the level of inventory is very sensitive to the amount of K_p. In order to adjust the level of inventory at the desired level, we should calculate the related K_p. To do that we use an optimization with target function equal to the holding cost of the inventory and one constrain to keep the level of inventory at the desired level. AS it is shown, With $K_p = 1.28572$ the inventory will reach the desired level which is the half of Demand Rate.

Since in this simple case, the retailer will receive the amount of products equal to his orders after four-week delay, with $K_p = 1$ the system works well as the error is equal to actual shortage of products. However, in the two-echelon or three-echelon systems, a retailer will not receive the exact amount of products that he has already ordered due to limitation in the inventory of the upstream players. We expect a lower-than-one K_p for these cases.

In our three echelon working example, to determine the amount of K_p for each player, we use an optimization method as well (In this case Generalized Reduced Gradient (GRG) Nonlinear optimization method). Due to connectivity of the players, changing K_p of one player will influence the results of the others. Therefore K_p of each player should be determined related to the other K_p's. By using the GRG method with a target function equal to the holding cost of all players inventories, We try to minimize the holding cost of all the players by changing the K_p. There are three constraints in the systems which are designed to keep the level of inventories

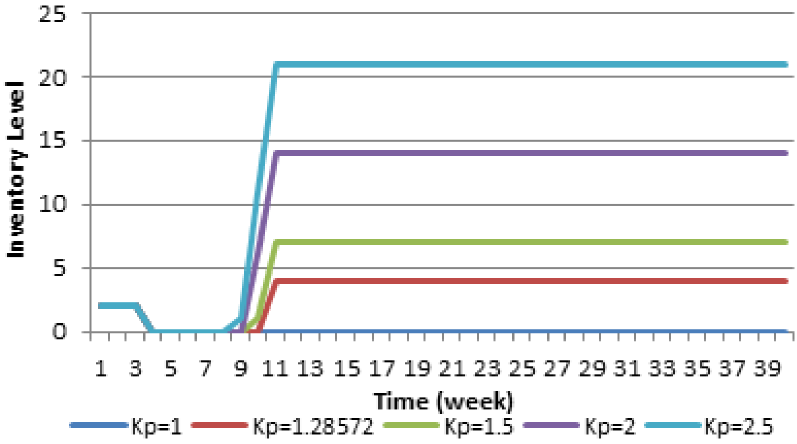


Figure 7.6 – Inventory level of one-echelon model with different Kps

at the steady state level.

Figure 7.7 depicts the level of Inventory of each player using the SR policy. As it is shown, inventories reach the desired level without any oscillation. Table 7.1, presents the amount of orders that each player places during the forty-week time horizon. As we discussed earlier, to measure the bullwhip effect as an increasing variability of orders from the retailer to manufacture, we calculate the variance of the orders for each player. The ratio between Demand Rate of retailer and OrderPlacedRate of the manufacturer presents the strength of bullwhip effect, which, in this case of applying SR policy, is equal to 10.21.

In the next section we first investigate the behavior of our working example using different ordering policies. Then we make some comparisons between the results of applying two other policies with SR policy.

7.5 Bullwhip effect caused by order-up-to policy

In this section we investigate the role of two popular kinds of order-up-to policy in generating bullwhip effects. So far, two different formulations of this policy have received more attention for studying the bullwhip effects. Chen and Samroengraja (2000) use moving average forecasting policy; Disney and Towill (2002); Dejonckheere et al. (2003) use an ordering policy called Inventory and Order Based Production Control System (APIOBPCS). In the following, we briefly present the related formulation of these policies and we study the effect of these policies on bullwhip effect through the simulation.

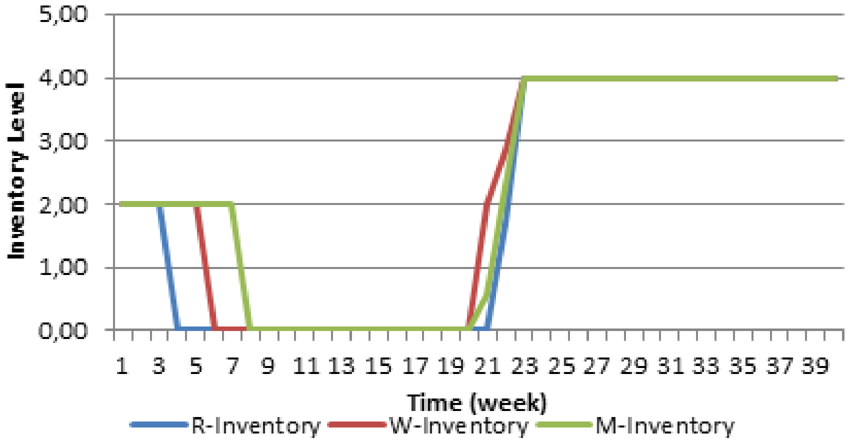


Figure 7.7 – Inventories level using SR policy with Kp = 0.428571, Kp1 = 0.45, Kp2 = 0.62096

7.5.1 Order-up-to policy based on moving average forecasting

Moving average forecasting method is a popular method which has been used for studying bullwhip effects (Lee et al., 2004). Here, the formulation of this method is presented; for more information and detailed discussion see, for instance (Chen et al., 2000; Lee et al., 2004).

$$\hat{D}_t^L = L\left(\frac{\sum_{i=1}^{P} D_{t-i}}{P}\right) \tag{7.9}$$

$$\hat{\sigma}_{et}^L = C_{L,p}\sqrt{\frac{\sum_{i=1}^{P} (e_{t-i})^2}{P}} \tag{7.10}$$

$$y_t = \hat{D}_t^L + z\hat{\sigma}_{et}^L \tag{7.11}$$

$$O_t = y_t - y_{t-1} + D_{t-1} \tag{7.12}$$

In Moving average method, it is assumed that supply chain members follow a simple order-up to inventory policy in which y_t(order up-to point) is estimated from the observed demand through the Equation 7.11 and its related equations 7.9 and 7.10 and orders are calculated through the Equation 7.12. Where:

- $\hat{D}_t^L$: estimated mean of demand for period t considering lead time L
- $\hat{\sigma}_{et}^L$: estimated standard deviation of forecast error for L periods at the time t.
- z: standardized z value
- e_t: forecast error for period t.

Week	Demand rate	*Order Placed* (SR Policy)		
		Retailer	Wholesaler	Manufacture
1	4.00	4.00	4.00	4.00
2	4.00	4.00	4.00	4.00
3	4.00	4.00	4.00	4.00
4	8.00	8.86	4.00	4.00
5	8.00	9.71	4.00	4.00
6	8.00	9.71	10.14	4.00
7	8.00	9.71	12.29	4.00
8	8.00	8.86	12.29	12.71
9	8.00	9.71	12.29	17.43
10	8.00	9.71	10.14	17.43
11	8.00	9.71	12.29	17.43
12	8.00	8.86	12.29	10.14
13	8.00	9.71	12.29	12.29
14	8.00	9.71	8.86	12.29
15	8.00	9.71	9.71	12.29
16	8.00	8.00	9.71	8.86
17	8.00	8.00	9.71	9.71
18	8.00	8.00	8.00	9.71
19	8.00	8.00	8.00	9.71
20	8.00	8.00	8.00	8.00
.	.	.	.	.
.	.	.	.	.
40	8.00	8.00	8.00	8.00
Variance	1.14	1.94	5.19	11.62

Table 7.1 – Quantity of orders using SR policy with Kp = 0.428571, Kp1 = 0.45, Kp2 = 0.62096

- $C_{L,p}$: constant function of L, p,
- P: number of previous periods of time
- O_t: order quantity for period t (Order Placed Rate)
- $\hat{D}_t$: the amount of demand (DemandRate) for period t

Figure 7.8 depicts the structure of the first echelon of our working example using the moving average method. The structure of other echelons is the same as the first one. We use a simplified version of this method by setting z to zero. Besides, since in our working example the sequence between events is different form the work of (Chen et al. 2000; Lee et al. 2004), we use Formulation 7.13 instead of 7.12.

$$O_t = y_t - y_{t-1} + D_t \tag{7.13}$$

The behavior of inventories of each player is depicted in Figure 7.9. As it is shown, while the level of inventory at the steady state situation is equal to 4, inventory of manufacturer, in some points, reaches the level of 64 which is 16 times higher than the desired level. Although, the behavior of both orders and inventories are along with severe changes, the supply chain reaches the steady state situation after 25 week. Table 7.2 shows clearly the consequence of using moving average forecasting method in the formation of bullwhip effect. While the desired amount of orders is eight, the wholesaler order reaches the level of 20 and the manufacture, in some

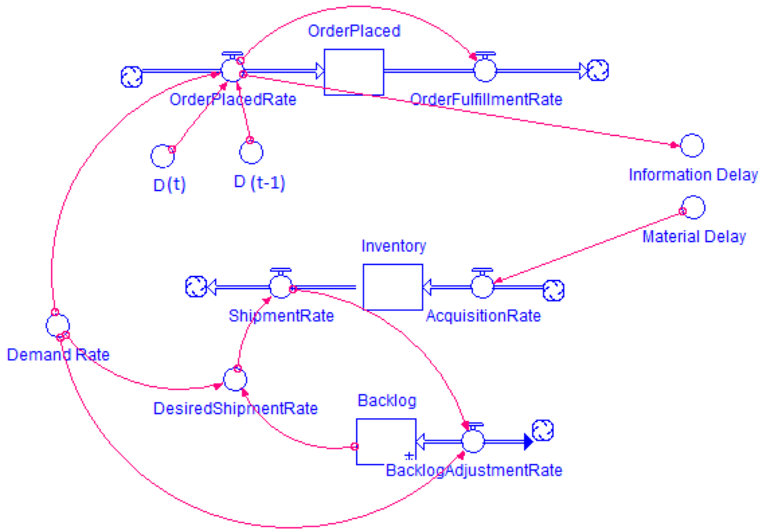


Figure 7.8 – Structure of the retailer with moving average ordering policy

points, plans to produce 36 products which is 4 times more than the desired order. As it is shown in Figure 7.9, both wholesalers and manufactures orders are along with severe oscillation. Particularly, the manufacturer, its orders in some points get negative values. The negative order means that the manufacturer needs to cancel its previous plan of production due to over producing. The ratio between Demand Rate of the retailer and OrderPlacedRate of the manufacturer presents the strength of bullwhip effect, which in the case of applying this policy is equal to 90.95.

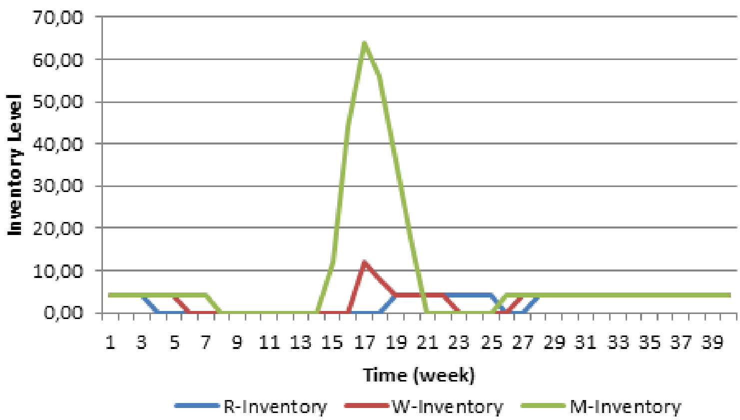


Figure 7.9 – Inventories level using moving average ordering policy

Week	Demand rate	Order Placed		
		Retailer	Wholesaler	Manufacture
1	4.00	4.00	4.00	4.00
2	4.00	4.00	4.00	4.00
3	4.00	4.00	4.00	4.00
4	8.00	8.00	4.00	4.00
5	8.00	12.00	4.00	4.00
6	8.00	12.00	8.00	4.00
7	8.00	12.00	16.00	4.00
8	8.00	12.00	20.00	8.00
9	8.00	8.00	20.00	20.00
10	8.00	8.00	20.00	32.00
11	8.00	8.00	12.00	36.00
12	8.00	8.00	4.00	36.00
13	8.00	8.00	4.00	24.00
14	8.00	8.00	4.00	0.00
15	8.00	8.00	4.00	-12.00
16	8.00	8.00	8.00	-12.00
17	8.00	8.00	8.00	-12.00
18	8.00	8.00	8.00	0.00
19	8.00	8.00	8.00	12.00
20	8.00	8.00	8.00	12.00
21	8.00	8.00	8.00	12.00
22	8.00	8.00	8.00	12.00
23	8.00	8.00	8.00	8.00
.	.	.	.	.
.	.	.	.	.
40	8.00	8.00	8.00	8.00
Variance	**1.14**	**2.86**	**16.73**	**103.54**

Table 7.2 – Quantity of orders using moving average ordering policy

7.5.2 Order-up-to policy based on APIOBPCS method

Inventory and Order Based Production Control System (APIOBPCS) method is a modified version of the anchoring and adjustment heuristic introduced by (Sterman, 1984). "Anchoring and adjustment is a common strategy in which an unknown quantity is estimated by first recalling a known reference point (the anchor) and then adjusting for the effects of other factors". According to Dejonckheere et al. (2003), the quantity of order, O_t, is given by the following formula:

$$O_t = \hat{D}_t^{T_a} + \frac{1}{T_S}\left(TS_t - S_t\right) + \frac{1}{T_{SL}}\left(TSL_t - SL_t\right) \tag{7.14}$$

where:

- $\hat{D}_t^{T_a}$ is the foretasted demand of period t using moving average forecasting method with
- parameter T_a.
- S_t: net stock (Effective Inventory) of period t.
- TS_t: target level of stock (DesiredInventory) for period t.
- SL_t: amount of products in supply line(OrderPlaced) for period t.
- TSL_t: target level of SL_t (DesiredOrderPlaced) for period t.

- T_S: adjustment time for the level of stock.
- T_{SL} : adjustment time for supply line.

In line with the formulation of anchoring adjustment method introduced by Sterman (1989) and to simplify the model, we assume the players use their actual amount of demand instead of the foretasted demand $\hat{D}_t^{T_a}$ in the formulation of their next order. To make the model more understandable, we use different notation for parameters of the system. In this formulation, we assume that the players try to keep the inventory at the DesiredInventory level which is determined through Equation 7.16).

$$DesiredOrderPlaced = DemandRate \times DelTime \tag{7.15}$$

$$DesiredInventory = DemandRate \times InventoryCoverage \tag{7.16}$$

$$EffectiveInventory = Inventory - Backlog \tag{7.17}$$

$$DesEffectiveInventoryCorrection = \frac{1}{T_S}\left(TS_t - S_t\right) \tag{7.18}$$

$$DesOrderPlacedCorrection = \frac{1}{T_{SL}}\left(TSL_t - SL_t\right) \tag{7.19}$$

Figure 7.10 shows the structure of the retailer. The structure of the other players is similar to the first one connected to each other. We have set some of the variables of the model as follows:

- InventoryCoverage = 0.5
- DelTime = 4
- $T_S = 4$
- $T_{SL} = 8$

Figure 7.11 presents the level of inventory in the model. As shown, there is a severe oscillation in the inventories of the players so that the retailer and the wholesaler still after 40 weeks cannot reach the steady state situation. The Inventory of the manufacture and the wholesaler reaches the point of 90, which is ten times bigger than the desired level.

Table 7.3 depicts the amount of OrderPlaced of each player. The ratio between Demand Rate of retailer and OrderPlacedRate of the Manufacturer presents the strength of bullwhip effect, which in this case of applying this policy is equal to 134.38.

7.6 Results Comparison

In order to show the effectiveness of our proposed SR policy in reducing the bullwhip effect, as mentioned before, we selected two other popular ordering policies for the

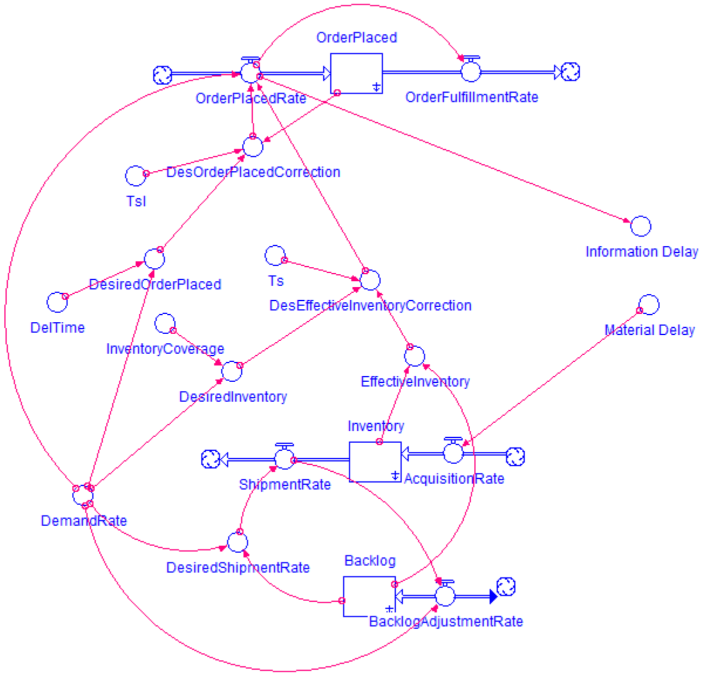


Figure 7.10 – Structure of the retailer with APIOBPCS ordering policy

comparison purpose. That is to say, we consider a three-echelon supply chain (retailer wholesaler - manufacturer). We then randomly generate demand (a number between 0 and 16) for the retailer for a forty-week time horizon. We then apply the three ordering policies (SR, Moving Average (MA), APIOBPCS), and run the three policies for 43 runs. We then calculate the variance for demand and for the three ordering policies for the three different players.

As the variance of demand for each run for each ordering policy is different, due to generating the initial demands randomly, we normalize the variance of each method for the three players by dividing the variance of the orders of the players by the variance of the initial corresponding demand. We call this normalized variance variance ratio.

Table 7.4 shows the mean and standard deviation of variance ratios of the three ordering policies for 43 runs. We used t-test to compare the results of applying the three policies, to see if the ratios found from different policies are statistically different. The results of t-test are shown in Table 7.5.

As can be seen from Table 7.5, SR significantly performs better than both MA and APIOBPCS.

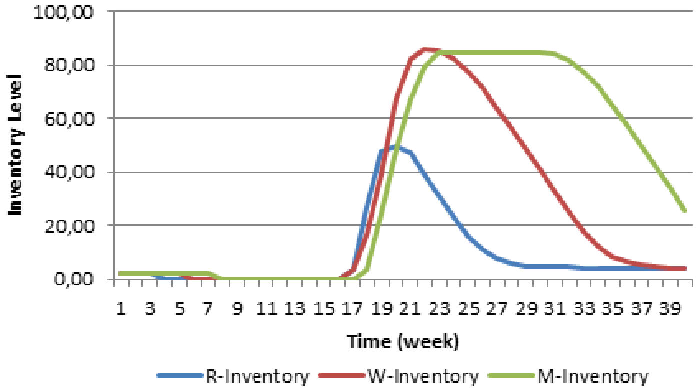


Figure 7.11 – : Inventory level using APIOBPCS ordering policy

7.7 Discussion and Conclusion

Bullwhip effect is one of the famous phenomena in the world of supply chain management, which has received a great deal of interest in the past decades. Numerous studies have made an attempt to provide answer to the very important question of how the effect of this phenomenon can be reduced. Despite its popularity, there is still no consensus among the researchers on how we can avoid or reduce the bullwhip effect. In this chapter, we introduce a new ordering policy method called Shipment Refined (SR) policy, and illustrate how this policy can alleviate the bullwhip effect in supply a chain. Our approach to ordering policy is based on the control theory principle using feedback to control the behavior of a system. We propose a proportional controller (P-controller) in which the difference (error) between the shipment rate, as output of the echelons in supply chains, and demand rate, as input, is used in the formulation of the SR policy. The controller attempts to reduce the error over time. The coefficient k_p of the P-controller is targeted to reduce the error and keep the level of inventory of supply chain members at a desired level, which is determined using optimization. SR policy is based on two hypotheses. First, the main cause of bullwhip effect is using distorted information of demand rate in calculation of future orders. Second, the main problem of supply chain members is not only the lack of information about the future demand rate but also the lack of information about the behavior of their suppliers, so that they cannot predict what percent of their orders will be satisfied on time. Respectively, SR policy avoids using the past behavior of the demands in its formulation and attempts to take into account the behavior of the suppliers through the feedback. We examined the effectiveness of SR policy on reducing bullwhip effects in a three echelon supply chain using discrete-time simulation. We assess the extent, SR policy influences the bullwhip effect and we compared the results of the two different popular ordering policies with SR policy. We use order rate variance ratio to measure the bullwhip effects in the models. The results show that SR policy significantly reduces the bullwhip effect so that order

Week	Demand rate	*Order Placed* Retailer	Wholesaler	Manufacture
1	4.00	4.00	4.00	4.00
2	4.00	4.00	4.00	4.00
3	4.00	4.00	4.00	4.00
4	8.00	11.50	4.00	4.00
5	8.00	11.56	4.00	4.00
6	8.00	11.62	18.06	4.00
7	8.00	11.67	18.30	4.00
8	8.00	11.21	18.50	30.37
9	8.00	12.24	18.68	31.03
10	8.00	13.16	17.41	31.61
11	8.00	13.97	21.23	32.12
12	8.00	14.18	24.64	23.29
13	8.00	14.81	27.68	27.95
14	8.00	15.49	22.85	32.13
15	8.00	16.20	19.14	35.89
16	8.00	10.32	16.47	27.46
17	8.00	5.05	14.66	18.70
18	8.00	0.37	3.51	11.62
19	8.00	0.00	0.00	5.94
20	8.00	0.00	0.00	0.00
21	8.00	0.58	0.00	0.00
22	8.00	3.05	0.00	0.00
23	8.00	4.71	0.00	0.00
24	8.00	6.12	0.00	0.00
25	8.00	7.21	0.00	0.00
26	8.00	7.62	0.00	0.00
27	8.00	7.87	0.00	0.00
28	8.00	7.95	0.00	0.00
29	8.00	7.92	0.63	0.00
30	8.00	7.92	2.66	0.00
31	8.00	7.92	4.26	0.00
32	8.00	7.92	5.72	0.00
33	8.00	7.95	6.81	0.00
34	8.00	7.96	7.37	0.00
35	8.00	7.98	7.74	0.00
36	8.00	7.99	7.89	0.00
37	8.00	8.00	7.94	0.14
38	8.00	8.00	7.97	2.34
39	8.00	8.00	7.97	4.11
40	8.00	8.00	7.97	5.64
Variance	**1.14**	**17.74**	**68.15**	**152.99**

Table 7.3 – Quantity of orders using APIOBPCS ordering policy

rate variance ratios applying SR policy is almost ten times lower than the two other ordering policies.

In this chapter, we assumed that all the echelons of supply chain follow an identical ordering policy. However, one might argue that this assumption is not realistic in some situations. Therefore, as a future research direction, we suggest studying SR policy in such cases. We also suggest studying how we can calculate the k_p of every echelon of real supply chains using their data regarding the demand and shipment rate. Another suggestion would be to study the influence of SR policy approach on the behavior of the players of a serious game experiment similar to Beer Distribution Game (BGD) (Sterman, 1989, 2000).

Ordering policy	Player	N	Mean	Std. Deviation
SR	Retailer	43	1.36	0.07
	Wholesaler	43	2.87	0.60
	Manufacturer	43	3.08	0.58
MA	Retailer	43	2.03	0.26
	Wholesaler	43	13.41	4.97
	Manufacturer	43	8.29	2.05
APIOBPCS	Retailer	43	3.51	0.72
	Wholesaler	43	75.53	36.74
	Manufacturer	43	19.15	4.78

Table 7.4 – Mean and standard deviation of variance ratios of the three ordering policies for 43 runs

SR-MA	*t*	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Retailer	-16.335	84	.000	-.66856	.04093
Wholesaler	-13.792	84	.000	-10.53771	.76406
Manufacturer	-16.041	84	.000	-5.21588	.32516
SR- APIOBPCS					
Retailer	-16.335	84	.000	-.66856	.04093
Wholesaler	-13.792	84	.000	-10.53771	.76406
Manufacturer	-16.041	84	.000	-5.21588	.32516

Table 7.5 – t-test for SR-MA and SR- APIOBPCS

8 Combining ABM with SDM in Practice

This chapter is based on Hesan and Behdani (2015)

8.1 Introduction

Finding a related model to the real world phenomena is one of the main challenge of simulation studies. Edmonds and Moss (2005) argue that "the difficult part in science is not finding attractive abstract models, but of relating abstract models to the world. There is a famous slogan which advocate that modelers should keep their model simple. However, this simplification sometimes cost the accuracy of the model. Although, very complex behavior may be emerged form the simple rules, but, of course, it does not mean that complex phenomena are reducible to simple models. Edmonds and Moss (2005) suggest a new slogan "Keep It Descriptive Stupid". They suggest that one should start with a descriptive model and then simplifies it if there is a justification for doing it.

Aggregation is a popular way of simplification which has a long history in the field of modeling and simulation. For instance, a large number of models in economy such as supply-demand follow the aggregation approach by considering the average of demand of whole society instead of individuals' demand. Aggregation helps to focus on the main dynamics of the system, and it help to decrease work effort, execution time of the simulation, and computational power usage Moris et al. (2008). However, it may cost the accuracy in the simulation result because of over-simplification. For example, Bobashev et al. (2007) argue that in a number of situation such as the spread of a disease, it is important to avoid aggregation and capture the more detailed micro level process mainly because that "aggregated equation-based representations may be too general and hence misleading".

In contrary to aggregation view, which is inherently taken by SDM, systems can be studied at the micro level where heterogeneous entities interact with each other. This approach, which is taken by ABM, enables Modelers to capture the global behavior of the system through modeling the behavior and interaction of entities. ABM approach help modelers in capturing the local interaction of entities and providing a natural representation of systems as well. However, these advantage are along with cost. "ABM may impose a heavy computational and parametric burden. Tracking and scheduling a large number of interacting agents leads to serious computational requirements and analytical challenges." (Bobashev et al., 2007). Furthermore, "The complexity of agent-based models may easily reach a level that makes it almost impossible for a researcher to deduce any understanding form the simulations." These limitations have already been pointed out by many researchers arguing that to use ABM in efficient way, modelers should keep agent-base models simple following the KISS(Keep It Simple, Stupid!) slogan (Yücel, 2010).

Aggregation is an efficient and reliable way to simplify agent-based models. The process of simplification is so sensitive as it may cause missing some dynamics which are fundamental in determining the behavior of the system. Aggregation helps to simplify agent-based models without missing the main source of dynamics. In this study we propose combining SDM with ABM as an efficient way to simplify ABM through the aggregation. We argue that the combination of SDM with ABM, on the one hand, keeps models simple and, on the other hand, keeps them descriptive.

ABM and SDM are widely-used simulation methods which have different approaches in dealing with complex systems. ABM follows a bottom-up approach in studying the behavior of entities at the micro level and letting the global behavior to be emerged from the interaction of entities. SDM follows a top-down approach studying the feedback between different elements of systems. However, both are aimed to study the complex systems. Although so far there has been little discussion between two these two modeling schools (Lättilä et al., 2010), in the last few years, much more research have been conducted to explore the synergies between ABM and SDM. It is also recognized that they have the capacity to deliver complementary insight to deal with complex problems (Duggan, 2008). For example, Akkermans (2001) developed a hybrid model to study dynamics of networked corporations. Schieritz and Grobler (2003) study the dynamics of a supply chain case study. Borshchev and Filippov (2004) use Bass diffusion model to demonstrate how two approaches can be combined. A recent review on hybrid simulation can be found in (Lättilä et al., 2010).

How can one combine these two approaches? In terms of architecture, there are many different possibilities for this combination. For instance, Bobashev et al. (2007) suggest that in the case of epidemic disease modeling, modelers should use ABM at the start of their simulation where uncertainty is high but when the emergent properties have established they should switch to SDM. Schieritz and Grobler (2003) use SDM to present internal system of agents. Borshchev and Filippov (2004) use SDM to present the global structure of the system at the macro level. Although these architectures are valuable works, none of them present a comprehensive architecture which presents the corresponded elements of two approaches. For instance, although

Schieritz and Grobler (2003) use SDM to model internal system of agents but they don't specify which part of the agents can be modeled through the SDM. Do SDM models present the decision making process of agents? Or they just model the interaction between agents and artifacts. Furthermore, some of them are not generic enough which can be used in different situations. For example, the former approach is applicable when one study the diffusion phenomena or spread of disease.

In this section, we will propose a generic architecture for combining SDM and ABM; we present how SDM elements can be used at different level of a system corresponded to different part of agent-based models. Furthermore, we will address the difference between SDM and ABM in dealing with time as an important barrier to combine these two approaches in one platform. While SDM is a continuous-time modeling approach - using differential equations to specify the relationship between stocks and flows-, ABM is a discrete-time modeling approach. To tackle this problem, we propose using DT-SDM instead of SDM in combination with ABM. Using a case of a supply chain, we will also illustrate our proposed hybrid method.

8.2 A review of literature on Hybrid simulation

There are three main streams in the literature that use the notion of hybrid simulation. The first approach proposes the combination of continuous systems, and discrete systems as hybrid simulation (Mosterman, 1999), the second one concerns with integrating analytical modeling with simulation Shanthikumar and Sargent (1983), and the last one proposes merging different modeling approach (SDM, ABM, Discrete event simulation). The literature that is related to the topic of this chapter is indeed the last one.

Scholl (2001) tried to introduce areas in which SD and ABM complement each other, and where they overlap. He calls for cross studies and joint research of two approaches. He emphasizes that "Agent-based modeling and complexity theory on the one hand, and System Dynamics on the other hand, have both produced rich bodies of research and literature on widely overlapping fields of application. Both have a high capacity of explanatory power. The cross study of these bodies of literature is overdue". Wakeland et al. (2004) compare two approaches in the context of modeling cellular receptor dynamics to find out how "two paradigms may help to generate complementary insights and increase the researchers' understanding of the dynamics of systems and processes".

Rahmandad and Sterman (2008) conduct a cross study of a epidemic case using SDM and ABM in parallel to investigate the differences between their result and study the compatibility of these approaches to different situation. As a highly-cited works in this domain, Parunak et al. (1998) discussed that "within an individual agent in an ABM, behavioral decisions may be driven by the evaluation of equations over particular observables (stocks), and one could implement an agent with a global view whose task is to access system-level observables and make them visible to local agents". Schieritz and Milling (2003) conduct a cross study of SDM and ABM contrasting primary predisposition of both approaches and identifying potential of integration of them. They conclude that "an integrated approach possibly has the potential to help decision makers develop the capacity of thinking at one and the same time of both" approaches.

Schieritz and Grobler (2003) developed a hybrid model in the field of supply chain. The SD part of their work was developed in Vensim software, and the ABM part is conducted by using Repast software. They provide a software for interacting both models. Bobashev et al. (2007) propose combining two approaches in order to decrease computational demand in a epidemic modeling case. Borshchev and Filippov (2004) illustrate the ability of Anylogic software to develop hybrid simulation by combining SD,ABM, and Discrete Event Simulation.

Vincenot et al. (2011) discuss three typical pattern of combination of SDM and ABM in the field of ecology. First, individuals interact with a single SD model. An example of fishes living in a lake is a good example of this case in which the behavior of fishes is determined by the ABM models while the characteristics of lake (e.g, water level, temperature) are modeled by a SDM model. Second, SDM submodels embedded in individuals. In this case, some properties of individuals are calculated dynamically with SDM models. The last case represents models in which individuals interact with a space made of SDM models. In parallel to these research studies, several software tools have also presented modules for hybrid simulation in the recent versions. For instance, Vensim which is one of the famous SDM software has recently introduced the new features of Vensim software to deal with the heterogeneous agents in the context of system dynamics. They called their new approach "Entity-based System Dynamics" which support object-oriented modeling. Collection of entities, attributes, relation-ships, aggregation and allocation functions, and actions are the new elements which are added to the existing elements of SDM in this new approach. Myrtveit (2000); Tignor and Myrtveit (2000) propose extending SDM with the object-oriented modeling. They mainly focus on enhancing the reusing ability of SDM models.

Despite the some of the interesting work in the field of hybrid simulation, this field still suffer from the lack of a conceptual framework. Our work will explicitly defined the concepts that allow the combination of ABM and SDM at the different level of a system.

8.3 Advantage of Hybrid Simulation

Besides the advantage of combining SDM with ABM in decreasing the complexity of agent-based models, this combination help each of these modeling approaches to take advantage of the strong points of other approach.

8.3.1 Applying Control Theory Techniques in ABM

Constructing agent-based models by the help of of flow (rate) and stock (sink) will provide a opportunity for modelers to take advantage of control theory principles in ABM. Control theory has a long history in studying the behavior of dynamical systems and has been approved as powerful technique for studying the behavior and controlling dynamical systems. Presenting the the process involved in agent-based models as flow and stock will reveals the input, output, and specially the feedback involved in the system helping to apply the control theory techniques in agent-based models. In the Chapter 7, we present the advantage of using control theory approach in controlling the behavior of a simple supply chain with three agents. In this example, stock and flow are used to present the internal system of agents involved in a supply chain. Making clear the structure, inputs, outputs, and feedback involved in this system help us to design a proper controller for it. Once we recognize the structure and feedback involved in a system by the help SFD, we are able to to extend the control theory approach for studying a more complex system with higher number of agents. However, applying such approach in pure agent-based models it is mostly difficult if not impossible- due to the fact that structure and process involved in the systems are implicit in programming codes.

8.3.2 Changeable structure in SDM

One of the limitation of SDM addressed by Schieritz and Grobler (2003) is that the structure of the system dynamics models remains constant during the simulation. This drawbacks of SDM prevents scientists to capture some dynamics of the real system. For example, once we construct a system dynamics model of a supply chain system comprising different players (e.g.,retailer, wholesaler, manufacturer) connected to each other, their connections remains constant during the simulation. However, in the real supply chain we are dealing with the changeable structure so that a new corporation may joint the supply chain or some members may change their suppliers.

8.4 The conceptual model for combining SDM with ABM

In Chapter 5 we propose to model the environment of agents using the concept of workspaces inspiring form Ricci et al. (2007). Furthermore, we propose to distinguish between operational, social, and macro levels of a system (See Figure 8.1). In this chapter we use the classification and assumption proposed in Chapter 5 to combine SDM with ABM at the implementation phase. In Section 5, we use SFD as a modeling tool aimed to describe the mechanism involved in the agent-based systems. However, in this section we aim to use SFD as simulation tools. In order to reach this goal we extend our proposed meta-model by adding some new characteristics.

8.4.1 Corresponded Elements

As it is depicted in Figure 8.2, Sterman (2000) distinguish between decision rules of the participating agents and physical and institutional structure of a system. He states that "The physical and institutional structure contains the measurement and reporting processes and produces the information cues that are then passed on to the decision maker. The decision maker interprets the available information cues by applying his/her decision rules (the policies). The output of a decision process,

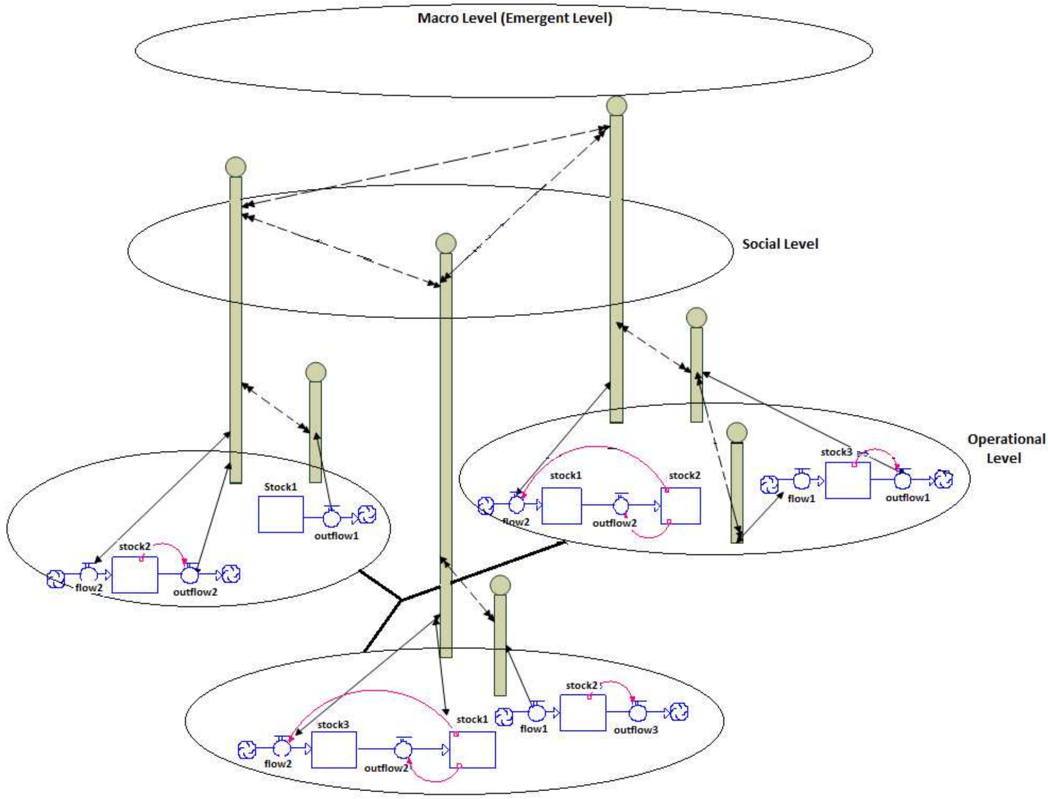


Figure 8.1 – Hierarchy of agent-based models

the decision, results in action which then alters the state of the system leading to a change of the information cues."

Inspiring by this argument, we propose that flows can be used to present the actions of agents or behavior of artifacts. Those parameter which are involved in the action (precondition, decision making, institution, agent or component properties) are presented as auxiliary variables which contribute to the condition and formulation part of flows. Eventually, the rate of flows will change the quantitative property of artifacts (Stock) or the quantifiable properties (Stock) of agents (e.g., the financial level).

8.4.2 Social Structure of Workspaces

In a workspace, the agents' activities change the state of stocks while the sequence between these activities is critical in determining the systems' behavior. In order to consider the sequence of activities, we need to expand the boundary of workspace to include social aspects of a workspace as well. In agent-based modeling literature, the social part of the environment is commonly conceptualized through the term of

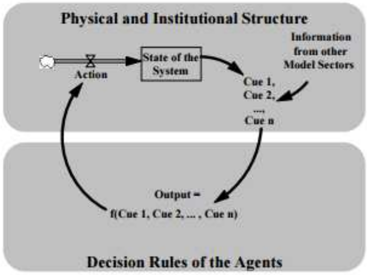


Figure 8.2 – Basic Structure of Decision Process

organization (Ferber et al., 2003). The social part of a workspace can be modeled using existing organization meta-models (Opera (Dignum, 2004), Moise (Hannoun et al., 2000), AGR (Ferber et al., 2003)) which are very detailed and technical meta-models in MAS. In order to clearly define the social part of the workspace - without getting involved in the details of the organization meta-models- we briefly discuss some important parameters that need to be declared as social part of a workspace.

- Role: is one of the main concepts within a social structure of workspaces which represents the functional position of an agent. A role constrains the behavior of agents and specifies what agents have to do. However, the agents are free to choose how they want to carry out these actions. For example, as a specification of the retailer role, a retailer agent places an order with an upstream actor (i.e., a supplier) or ships the products to its downstream actor (i.e., a consumer), However, the procedure for that (which defines when and how he will do this) is dependent on his individual decision making.

- Work-flow: determines the process and sequence between activities which are conducted by different agents in a workspace.

Agents can enact multiple role in different workspaces either at social level or operational level. For example, at the operation level of a supply chain, a retailer must perform some specific tasks (e.g., placing orders or shipping products) while he can take the role of a negotiator at social-level workspace and negotiate, communicate and, cooperate with other retailers or suppliers.

The role of work- flows at the operational level workspace is different from the social-level workspaces. Social-level workspaces are more agent-centered compared to operational-level workspace which are organization-centered. Therefore, in contrary with the lower level workspace -which can have predefined work-flow -, there is not always a fixed predefined work flow at the higher level. Despite the agents at the lower level, agents at the higher level are more autonomous and are not restricted by their role specification and the rules which dominate their workspace.

Figure 8.3 shows the UML class diagram of our proposed method. In a nutshell, this diagram shows that every system consists of workspaces which consist of agents, stock, flow, role, and work-flow. These workspaces can be at the operational level, or social level.

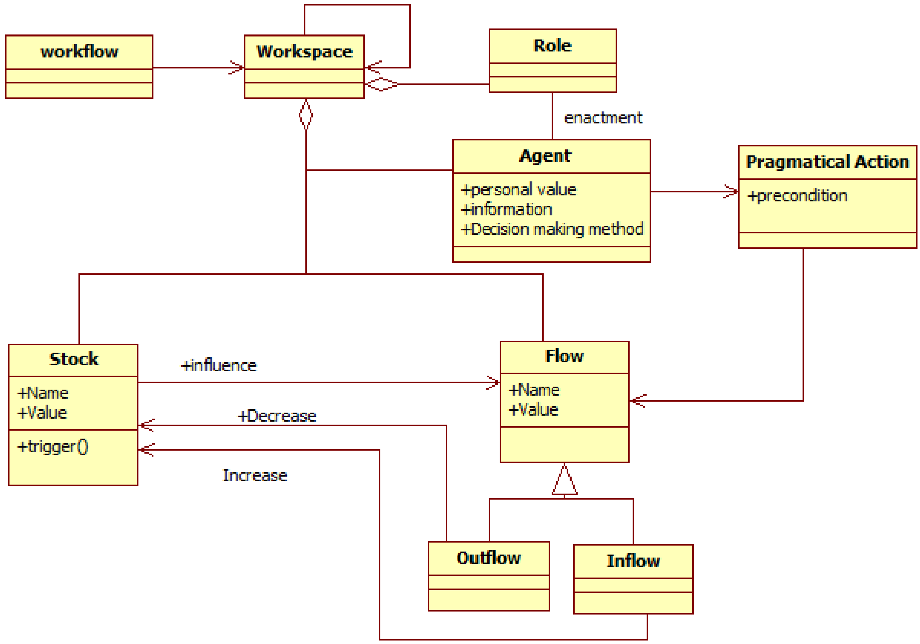


Figure 8.3 – The class diagram

8.5 Computer model for hybrid simulation: the challenge of differences in dealing with time

Although the value of hybrid simulation has been discussed in the existing literature (e.g., Schieritz and Grobler (2003)), - especially- ABM and SDM are rarely combined in a common simulation platform. A main difficulty is the difference in how time is dealt with in the modeling process (North, 2014). While ABM is a discrete-time approach, SDM is a continuous-time simulation method.

In most of literature, the practical method for combining SDM and ABM is connecting SDM software (e.g., Vensim) with a ABM software (e.g., Repast) using a common interacting interface. Therefore, in every time-step, the states of SDM sub-model are exchanged with ABM sub-model. This can be problematic because SDM uses differential equations to define the relationship between stocks and flows and consequently, the states of SDM sub-models change in every d_t. In Chapter 6 we have discussed that in cases that the flows in a system do not change in every d_t (e.g., decision making process of an actor), using differential equations enforces some approximation in the modeling process which may cause inaccuracy in the quantitative result. An alternative method to alleviate this limitation, using Discrete-time System Dynamics Modeling (DT-SDM) as discussed by in Chapter 6 and Hesan et al. (2014a). In this method, we use difference equations - instead of differential equations - to construct a system dynamics model. This method is more justified for modeling the dynamics at the operational level of a system in which flows do not change in every infinite short interval of time. In DTSDM, the amount of stock is calculated by Equation 8.1 considering the inflow/outflow and the previous quantity of that stock in every discrete point of time. Furthermore, the proposed method uses pure delay to model the time lags in a system (Equation 8.2).

$$stock[t] = stock[t-1] + [inflow - outflow] \tag{8.1}$$

$$\begin{aligned} outflow(t) &= inflow[t-D] \\ stock[t] &= \sum_{t=t-D}^{t-1} inflow(t) \end{aligned} \tag{8.2}$$

Since DT-SDM and ABM are both discrete-time modeling approach, they can be combined in a hybrid simulation platform. Agents, stocks, flows are the main element of our proposed hybrid approach. With the help of these three main elements and auxiliary variables we can construct a model.

8.6 An Illustrative Case

Supply chain system is a network of multiple actors (e.g., retailer, distributors,...) exchanging information, products, and money through the network. Making decision in such complex system which action of every actors influence the performance of other actors is challenging and calls for effective comprehensive tools.

The research in the field of supply chain simulation has been focused on the analysis of both long-term and short-term decision making. On the one hand, there are huge literature regarding inventory replenishment policy (e.g., Karimi et al. (2003), Ben-Daya et al. (2008)) which focus on finding optimum solution for actors at the tactical and operational level. On the other hand, there are some well-established lines of research on long-term behavior of actors at the strategic level such as supplier selection (e.g., De Boer et al. (2001), Ho et al. (2010)).

There are also several studies that are interested in studying both long-term and short-term decisions on the behavior of system. For more information we can refer to a review article by Minner (2003) which review some of these studies. Most of these studies try to analyze supply chain systems using analytical approaches. However, using analytical approach to study such complex systems is always along with some simplification and restriction which may limit the possibility to study the realistic aspect of a complex supply network.

Simulation techniques can provide a unique opportunity for researchers to study the effects and results of both short-term and long-term managers' decision making in the field of supply chain. We will use a supply chain example to explain different aspects of our proposed methods. As the following we describe our case-study in more details.

8.6.1 Description of systems

We will study the behavior of a two echelon supply using our proposed method. The supply chain consists of eight retailers and three suppliers. In addition, there are 150 customers who place orders in every time step. The demand for each customer is a random value in the range of 1 to 50. The average order placement by each customer is eight orders in a year.

Supplier selection

In this case, every supplier has some specific characteristics which make that supplier distinctive in the market. The retailers select the suppliers based on these characteristics. We consider three main characteristics here:

- Technological ability
- Price
- Financial stability

We assume that retailers are using a multi-criteria decision making method to choose their supplier based on the attributes of supplier and the weight which they give to each of them. For the aim of simulation, we assign the following values to the attributes of the suppliers and the weight that retailers consider for these attributes.

- Price = random number between 1 and 10.
- Technical ability = random number between 1 and 10.

Ordering Policy

All retailers and suppliers carry out their activity based on a plan that determines the sequence of their activities. We assume that in each period of time, the following sequence of events happen. First, every actor receives the products; then, the demand is observed and the shipment of products is arranged. Next, the actors check the state of system (e.g., the inventory level) and place an order to with an upstream actor in the chain. In the case that there are not enough products in the inventories since retailers do not have any backlog - they will lose their customer sales. For suppliers, there can be a backlog of unfulfilled orders which are satisfied as they receive enough products.

The lead-time between order placement by a retailer and receiving the products is 4 time steps. In the case of supplier, we assume that suppliers will receive their order after a 4 time step delay. However, retailers may receive part of their orders in the case of the shortage of products in the supplier stage. For the replenishment policy, we assume that they all will order in discrete points of time when the level of their inventory is lower than a reorder point. The amount of the orders is calculated using the EOQ formulation (Slack et al., 2010).

Retailers and suppliers can choose to perform different inventory replenishment policy and the quantity of the orders can be calculated through the use of EOQ formulation. For the sake of simplicity,

Shipping Policy

In every time step, the retailers check the list of demands and ship the products to the customers. Likewise, the suppliers keep track of unsatisfied demands and they fulfill them when there are enough products in their inventory. The sequence of process of shipping is as following. The suppliers first satisfy the backlogged demand. Then - if there are some products left in the inventory- they fulfill the new demands as well. At the end of a specific time point, all unsatisfied orders should be backlogged. In the case that part of order can be fulfilled, this part will be shipped to the retailer and the shortage of the products will be backlogged.

8.7 Supply Chain model

Figure 8.4 shows schematic of the system with two suppliers and four retailers. Figure 8.5 shows the structure of the system at the operational level using SFD diagram.

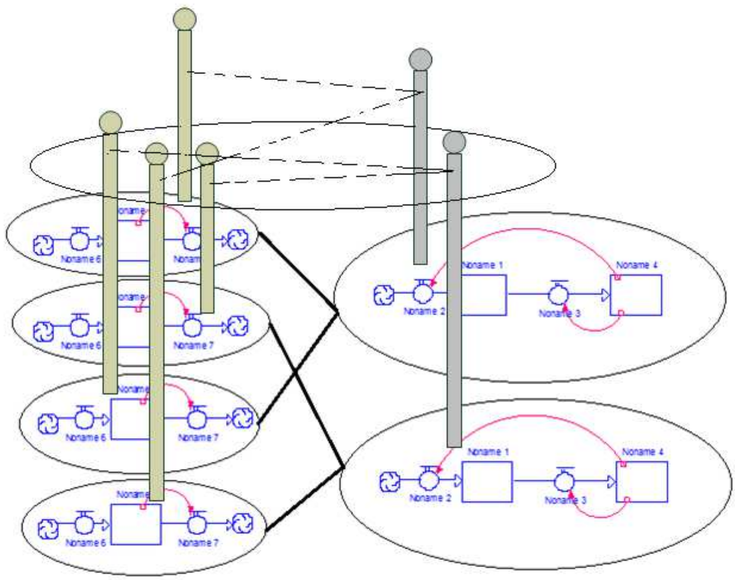


Figure 8.4 – Schematic of the Supply chain

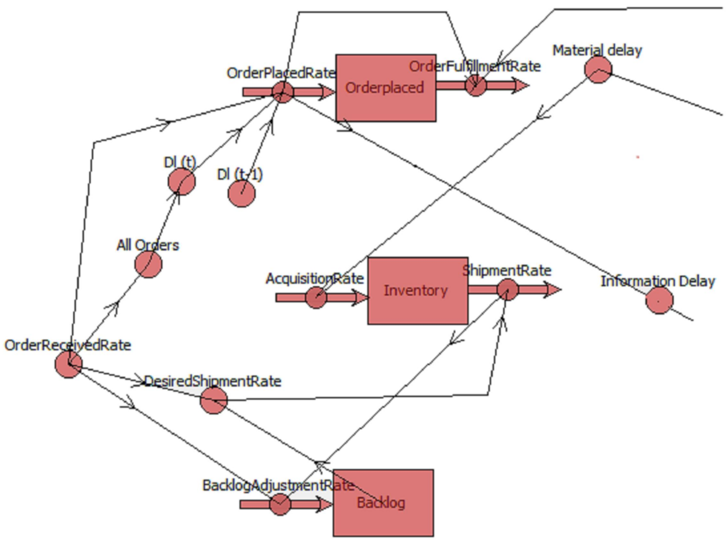
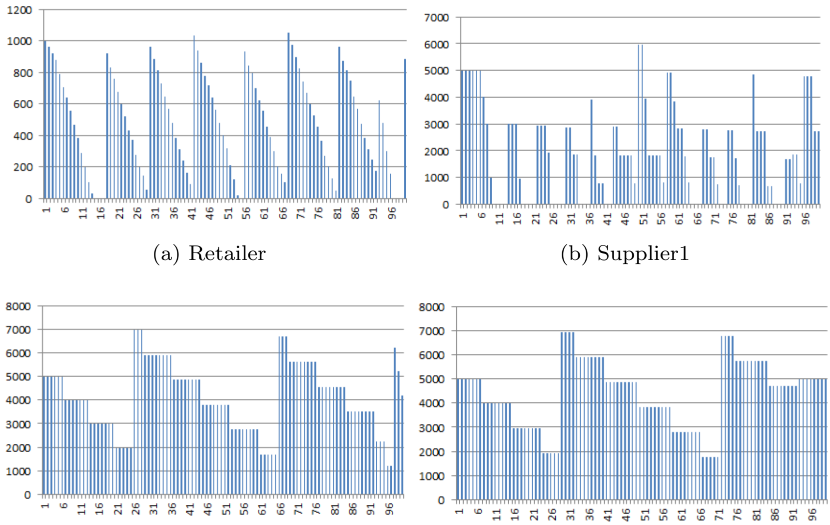


Figure 8.5 – Structure of the supply chain at the operational level

With multiple retailers and suppliers in the system, the behavior of all the elements involved in the case study cannot be shown in a figure. In the following, the behavior of inventory of the suppliers and one random retailer is presented and analyzed in different scenarios. In the first scenario, we assume that retailers select their suppliers at the starting point of the simulation and they would not change them during the simulation horizon. In the second scenario, we consider a case in which retailers will review their supplier selection every year.

As it is depicted in Figure 8.6, the behavior of the retailers inventory is the typical behavior of the discontinuous replenishment. At the reorder point, the retailer placed the predefined order and he receives the requested products before the depletion of its inventory. In this case, the majority of the retailers select the supplier-1 instead of other suppliers. Therefore, this supplier faces a lot of stock-outs and a big pile of backlogged orders. The behavior of the two other suppliers is different and their inventory is smoothly decreased during simulation

In the second scenario, we assume that the characteristics of suppliers change every year, and the retailers are going to select the new supplier based on their own criteria. Figure 8.7 shows the inventory pattern of the actors in the second scenario. In this case, although some suppliers do not have any demand at the beginning, they will receive that later as retailers have the choice to change their supplier. To interpret the behavior of inventories in the second scenario, we need to consider the dynamic of network formation and the changes in the retailer-supplier network. Furthermore, many different demand patterns are needed to be modelled before a generic conclusion can be made. In this section, of course, the goal is to introduce the hybrid simulation tool and therefore, the thorough analysis of case results is



(a) Retailer (b) Supplier1

(c) Supplier2 (d) Supplier3

Figure 8.6 – Inventory level of one random retailer and three Supplier applying first scenario

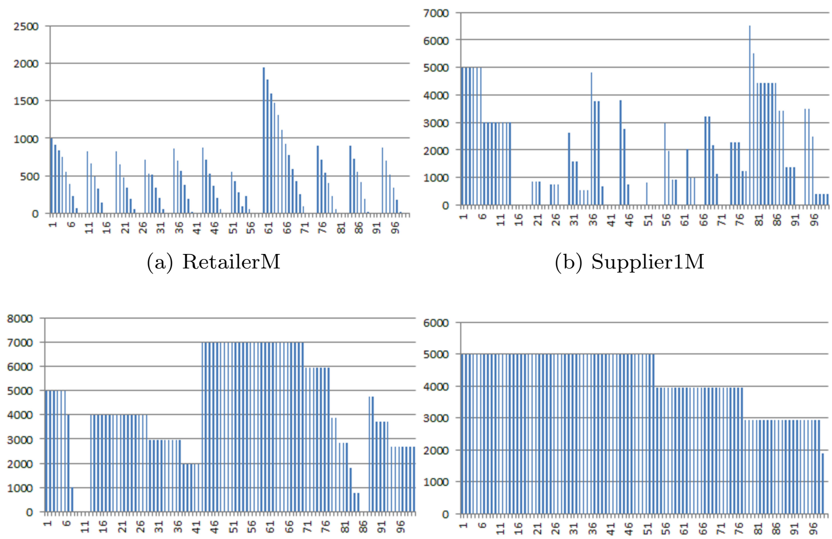
beyond the aim of this section.

8.8 Discussion and Conclusion

In this chapter, we presented how the complexity and computational usage of agent-based models can be reduced using a hybrid SDM and ABM approach. The meta-model of Chapter 5 is extended in order to merge ABM with SDM in a simulation study. We also explained how one can construct a hybrid simulation model using agent, stock, fow and auxiliary variable as the main elements.

As we discussed, in Section 3, the combination of SDM and ABM contributes to both ABM and SDM in several ways. It not only helps to decrease the complexity and computational usage of agent-based models but also provides an opportunity for modelers to apply the control theory principles in developing agent-based models. A hybrid simulation contributes to SDM in the way that facilitates having changeable structure in SDM models.

Furthermore, in this chapter the differences between ABM and SDM in dealing with time is discussed and to cope with this challenge- the DT-SDM approach is presented.



(a) RetailerM (b) Supplier1M

(c) Supplier2M (d) Supplier3M

Figure 8.7 – Inventory level of one random retailer and three Supplier applying second scenario

9

HybSim: Hybrid Simulation Software

9.1 Introduction

As part of our research we have developed a software called Hybrid Simulation Software (HybSimS) which provides an opportunity for modelers to combine ABM and SDM in one platform. Unlike many simulation tools which proposed their special modeling constructions (e.g., Netlogo in ABM and Ithink in SDM), HybSim is based on a universal programing language called Python. Using universal language for developing simulation has already attract some attention so that some simulation tools such as AnyLogic and Repast use another universal language called JAVA. However, Using Python has some advantage in comparison to other language like JAVA. For instance, python programs take much less time to develop. Besides, programming with python is much easier than JAVA. This can be a advantage for a simulation tool that its actual users are social scientist who are not expert in computer science.

Based on the meta-model presented in the previous section, Agent, Stock, Flow, and Auxiliary Variable are four main elements of HybSim for developing hybrid models so that Stocks and flows can be used at the operation level, social, and macro level. In order to construct hierarchy of the system, Hybsim provides an opportunity that the operational level can be constructed as internal part of social agents.

In this chapter we present different parts and feature of HybSim software. We start with exploring the GUI of the HybSim then we explain the characteristics of HybSim elements.

9.2 GUI

In this section we give a short description of every items in the GUI of HybSim. As it is depicted in Figure A.1, The GUI has four windows: Main (center), Elements (Left-Top), Element Setting (Right-Downn), and Running Result(Right-Down).

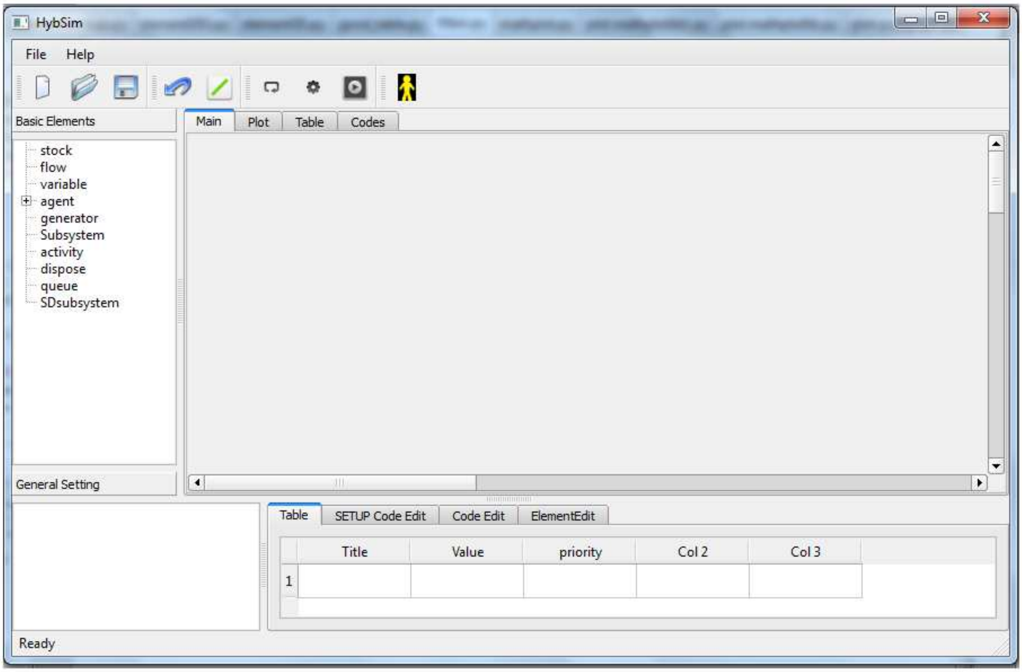


Figure 9.1 – HybSim GUI

9.2.1 Main Windows

The main window includes four Tabs: Canvas, Plot, Table, and Codes.

- Canvas: is the the main window of HybSim dedicated for construction of the models.

- Plot: this window is used for plotting the graphs (See Figure 9.2). We can easily choose the name of the property that we are willing to plot form the list (Data Series) and use the button of *show* to plot it. There is a table beneath of the plot which provide a opportunity to zoom, save, etc. the graphs.

- Tables: The result of the simulation can be shown in the form Tables in this window. Data which depicted in the tables can be selected and saved for the reason of transforming to another software such as Microsoft Excel.

- Codes; This windows is used to present the programming code of the model. Python code of the programs is presented in this windows

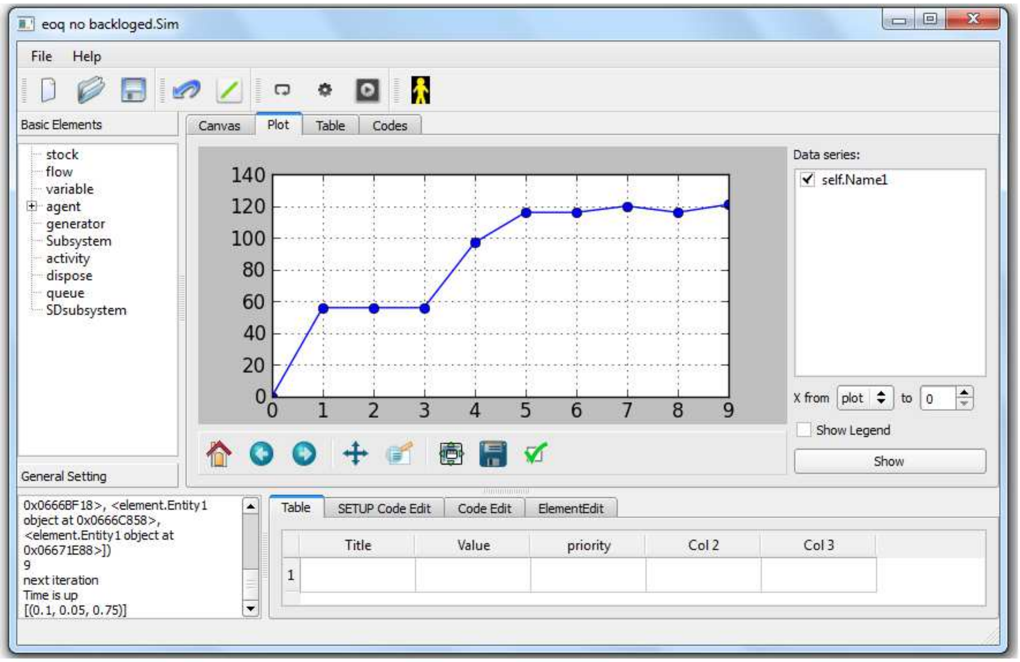


Figure 9.2 – plot

9.2.2 Elements and Running Result

The left-up window has two tab: Basic elements, and General Setting. Basic elements of the system can be added to the main canvas through the drag and drop. Figure 9.3 depicts the General Setting tab which can be used to configure the time and speed of the simulation.

Running Result (Left-down) windows is used primarily for testing and tracking the models. When we use the construction of *Print* in python program to test or see the result the output of the program is depicted in this windows. Beside, The message of the python program such as errors is presented in this windows.

9.2.3 Setting of Elements

In HybSim we construct a model with the help of four elements while each of them has different characteristics and setting panel. Setting-element window has four tabs (table, Setup Codes, Code Edit, Element Edit). the Element Setting windows is updated by pressing the left button of the mouse over the elements. For example, Figure 9.4 depicts the setting panel of an agent with name of Supplier.

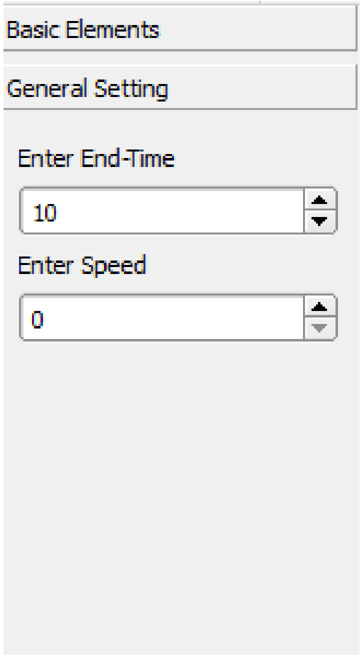


Figure 9.3 – General Setting Tab

- Table: this tab is used for changing the initial setting of each elements of the model.
- Setup Code: Sometimes to model a agent we need different functions or variables be defined before running the simulation. This tab is designed for this purpose.
- Code Edit: What agents and flows do in a model is defined though the programming code by using this tab.
- Element Edit: this tab is used to change the internal element of subsystems(e.g., internal system of social agents).

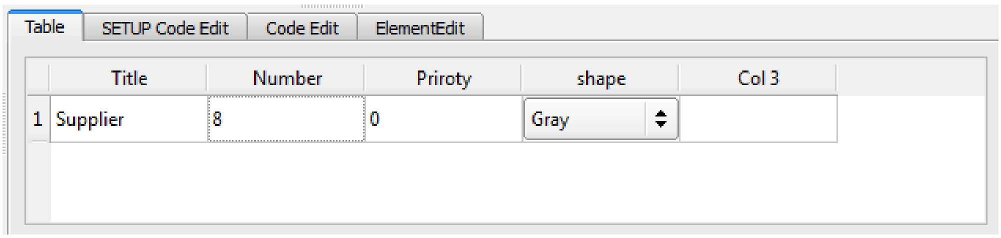


Figure 9.4 – Element Setting Windows

9.2.4 Toolbar

Figure 9.5 depicts the toolbar of the HybSim which has nine tab. Forst three tabs are dedicated to build a new model, open the file of the models which have already been saved, and save the new models.

- Exit: is used to change the main windows from the Submodel to Canvas.
- Sequence: is used to show the sequence between different element of the system.
- Line: is used for connecting different element of the model by arrows.
- Setup: is used to setup the model by running the setup codes and initialization of the elements of the model.
- Run: is used to run the model.
- Draw; Is used to show the position of the agents and their movement (See Figure 9.5)

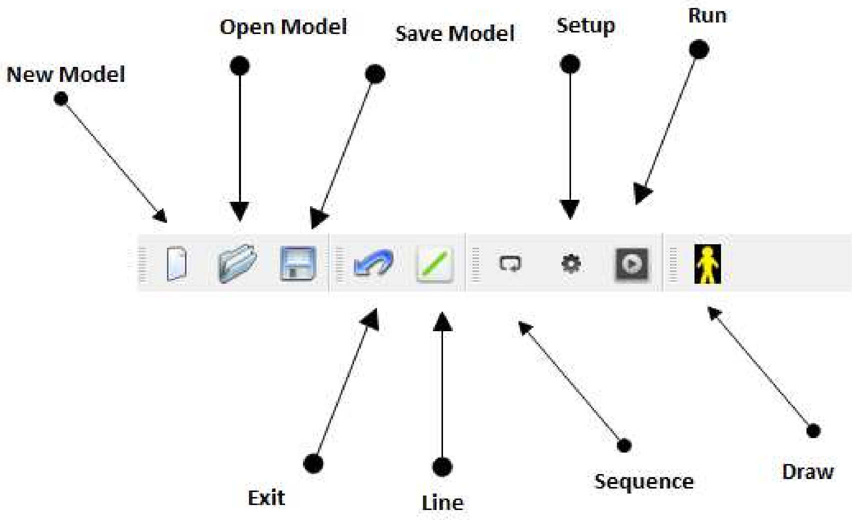


Figure 9.5 – Toolbar

9.3 Characteristics of HybSim Elements

10
Discussion and Conclusion

10.1 Overview

This thesis started with considering the challenging task of policy design and decision making in socio-technical systems. It is argued that due to increasing complexity and dual nature of socio-technical systems, decision makers often rely on model and simulation to get insight into the dynamics of these systems. ABM is one of the modeling methods which has received considerable attention recently. The power of ABM in providing a natural representation of socio-technical systems proposing agents as the main element of the simulation is one of the reason that make ABM an attractive modeling method. However, to increase usability of ABM, it is essential to overcome conceptual and practical limitations of this modeling method. We proposed that using SDM as complementary approach can help to overcome the limitations of ABM. This argument motivated us to define our research question as following:

> How can we decrease the complexity of agent-based modeling process while increasing the explanatory power, and considering the effect of feedback from macro-properties on agents behavior in agent-based models using system dynamics modeling as a complementary approach?

Furthermore, Additional research questions were formulated:

- What is the role of feedback in social systems and how it influences the modeling in ABM?
- How can we capture and explain the causal mechanisms (processes) involved in agent-based models?

- How can we simplify an agent-based model without losing the main dynamics driving the system?

In the next section we address these questions by presenting the outcomes and key findings of this thesis.

10.2 Research Outcomes

10.2.1 Emergence in ABM

In the first part of the thesis (chapter 2, 3), we addressed the first sub-question of this research investigating the role of feedback in ABM. One of the issues with ABM which is argued by many researchers is that due to bottom-up approach of ABM, considering the feedback from emergence features of systems on the behavior of agent is not part of design steps of agent-based models. However, in order to account fully account of social phenomena, the feedback from the emergent features should be considered.

To deal with this issue, we proposed to classify properties of systems at the emergent level to quantitative and qualitative type. We provide some evidence from the some well known social theories (e.g., Bystander theory) which prove the existence of feedback from quantitative properties. We explained though in normative agents the downward causation is modeled through the norms (qualitative properties), however, norms often are implemented as built-in mental object so that they are not emerged through the simulation. Besides, this approach of normative agents is not applicable in other type of agent-based approaches such as Agent-Based Generative social simulation (ABGSs) where agents are not cognitive agents.

We proposed that in the normative agents models in which norms are not emerged through the simulation, and in non-normative agents based models which feedback from qualitative are not modeled, the feedback from quantitative properties of system should be modeled. In Chapter 3, we took advantage of the opinion dynamics model case to present the challenge of considering feedback from emergent properties: The way they would be perceived by the agents and how they get involved into the decision making process of the agents.

10.2.2 Mechanism in ABM

In the second part of the thesis (Chapter 4,5), we address the second issue with ABM regarding the explanatory power of ABM. We argued although mechanisms are modeled and implemented in the agent-based models, they are implicit in the models. When building an agent-based model, the modeler specifies the behavior of the agents and their interactions that bring about the macro-behavior of the system. However, the mechanisms which are driving the system are not often explained and they are implicit in the programming code. What is often explained by the modelers is "what agents do" which are the causes in the system. However, the effects of these causes and the chain of cause and effects are implicit in the programming codes.

In Chapter 4, we showed how we can use system dynamics tools to capture and explain the dynamics involved in the agent-based models. We present a conceptual model for modeling the global environment of agents using stock and flow diagram (SFD). In this chapter we take advantage of a consumer lighting example to illustrate our conceptual model. In the Chapter 5, we extended our work by looking at all the possible mechanisms involved in the agent-based models. We presented a meta-model for explaining these mechanisms. We distinguish between three level of a system (operational, social, and macro) then we introduce the mechanisms involved in each of these levels and the inter-level mechanisms. Furthermore, we showed how SFD, can be used to describe some of these mechanisms. Using SFD, in the one hand, help to do abstract the mechanisms through the applying aggregated approach of SDM, and on the other hand, it helps to describe the mechanisms visually.

The presented meta-model and the classification of mechanisms facilitate the conceptualization phase and the process of explaining the mechanisms involved in of agent-based model of socio-technical systems. Furthermore, using SFD to depict the mechanisms in ABM visualizes conceptualization of socio-technical systems models through the stock, flow, and auxiliary variable. SFD is the means of communication between the modeler and other stakeholders involved in the simulation study. Highlighting mechanism through the SFD, produces a structured representation of the perception of modelers regarding the system which can be presented to different stakeholders and experts for verification before implementation phase.

10.2.3 Complexity of ABM

The third part of the thesis is dedicated to address the last sub-question of the research regarding the complexity of agent-based models. We discussed that the high complexity of agent-based models may make it impossible for researchers to deduce any understanding from these models. To solve this problem we propose using SDM tool (SFD)in combination with ABM which lead to a hybrid simulation method. We argued that the aggregated approach of SDM which is applied through the SFD diagram reduce the complexity of agent-based models.

In Chapter 6, we developed Discrete-time System Dynamics Modeling (DTSDM). Similar to traditional SDM, in DTSDM, we use stock, flow, and auxiliary variable to construct a model. However, On the contrary to SDM which use differential equations as mathematical operation defining the relationship between stocks and flows, the basic mathematical operator in DTSDM is difference equation. DTSDM lead to the more accurate results where flows of the system subject to study are discontinuous and when there are not many items in delay. In Chapter 7, we take advantage of a supply chain example to illustrate the difference between quantitative results of SDM and DTSDM in such cases. DTSDM is a prerequisite for combining SDM with ABM. The difference between SDM and ABM in dealing with time is one of the main barriers for combining these two approaches in one platform. In Chapter 8 We addressed this problem discussing that this can be tackled by using DTSDM.

In Chapter 8, we extended the meta-model presented in chapter 5 to be used for combining SDM and ABM in practice. The extended meta-model is a general meta-model which not only can be used for combining ABM with SDM but also it can be applied to study socio-technical systems using only ABM as well. While currently the social and technical part of socio-technical systems are studied as two separate network interacting with each other, this meta-model provide a opportunity for researchers to merge both social and technical part of the socio-technical systems in one model. We took advantage of a supply chain example to illustrate different aspects of our proposed meta-model and hybrid simulation method.

Chapter 9, is dedicated to introduce the HybSimS simulation software. HybSimS is developed as part of this research to provide a opportunity for modelers to combine ABM and SDM in one platform. There are two main differences between HybSimS and other simulation hybrid software simulation such as Anylogic. First, HybSimS is based on the meta-model presented in chapter 8. Second, In HybSimS, we use DTSDM instead of SDM which can lead to more accurate quantitative results.

10.3 Future Work

In this section, we will propose several topics for future work.

Studying more case-study Although we have used multiple case studies and example to develop the presented multi-methodology approach, more case would help further improve of it. Conducting more case studies also will help to develop the generic library for HybSimS as well which can be shared between different models.

Advancing tool support Advancing the HybSimS can further ease the use of the hybrid simulation. HybSimS can become more user friendly by providing automated code generation and providing tips when constructing a model. The ability of importing and exporting models form other simulation tools would increase the usability of HybSimS.

Extend the frame work Although in this thesis we focused on the combination of SDM with ABM, there is a possibility to combine Discrete Event Simulation(DES) with these modeling approaches as well. Using DES will facilitate modeling the processes at the operational level of systems when we are aimed to model the processes in detail.

Appendices

A
Case Study Result

A.1 introduction

In Chapter 9, we take advantage of a two echelon supply chain model to explore different aspects of our proposed hybrid simulation. However, we did not get into the details of its programming codes. This appendix is aimed to present different aspects of HybSim using the supply chain case study. This appendix will help those who are interested to use HybSim.

A.2 Model Description

As we discussed earlier, we model a two echelon supply chain case comprising one hundred and fifty customer, eight retailers, and three suppliers. The structure and different policies that we used to model them have already been discussed. In this section we explain how we can implement this model in HybSim.

To construct the model, as it is depicted in Figure A.1, we add four agents to the canvas: customers, retailers, suppliers, and dummy agent. Since the role first three agents have been discussed earlier. We just need to explain what the role of dummy agent is. Dummy agent is used to model the delay between the time that suppliers place order and when they receive their products. It is assumed that supplier receive their products after 4 weeks so we use a dummy agent to receive their orders and send product to them after the delay.

In the next step we use the Element characteristics table to determine the number of agents involved in the model. We should determine the sequence between these agents using the Priority. For example, it is assumed that firs customer place an order, then retailer and finally suppliers. Elements will be sorted based on the their priority numbers so that the code of elements with lower number will be run before those with higher number.

The next is to define the structure of the agents at the operational level. By double clicking each of the agent we can reach their operational level canvas. For the sake of simplicity, we do not define any new agent at the operational level.

A.3 Related Codes

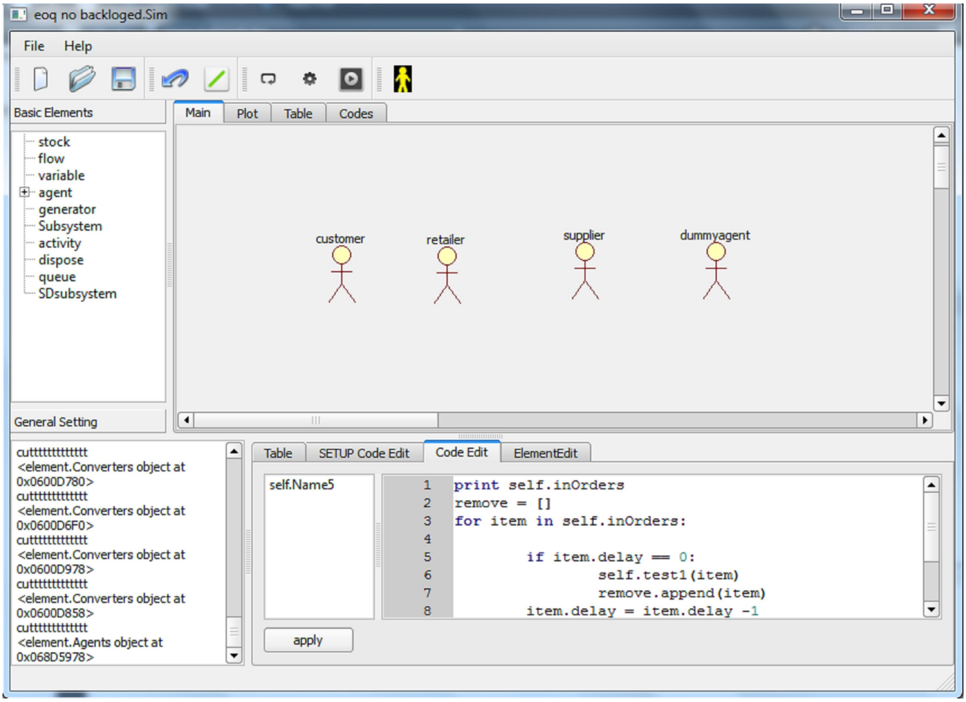


Figure A.1 – Overview of the Supply Chain Case

A.3.1 Retailer

```

entity = self.indelay.popleft()
self.receiver.inOrders.append(entity)

#start OrderFulfillmentRate
self.OrderFulfillmentRate = 0
removed = []
for item in self.inProduct:
    self.OrderFulfillmentRate=self.OrderFulfillmentRate+item.amount
    removed.append(item)
```

```
self.Orderplaced = self.Orderplaced - self.OrderFulfillmentRate
for item in removed:
  self.inProduct.remove(item)
#end OrderFulfillmentRate

#start AcquisitionRate
self.AcquisitionRate=self.OrderFulfillmentRate
self.Inventory = self.Inventory + self.AcquisitionRate
#self.OrderFulfillmentRate = 0
if self.AcquisitionRate > 0:
  self.trigger = 0
#end AcquisitionRate

#start DesiredShipmentRate
self.DesiredShipmentRate=self.OrderReceivedRate+self.Backlog
#end start DesiredShipmentRate

#start orderreceived
self.OrderReceivedRate =0
for item in self.inOrders:
  self.OrderReceivedRate = self.OrderReceivedRate+item.amount
#end orderrecived

#start shipmentRate
removed = []
removed1 = []
if self.Inventory > 0:
  for item in self.backlogOrders:
    if self.Inventory >= item.amount:
      self.test1(item,item.amount)
      self.Inventory = self.Inventory-item.amount
      removed1.append(item)

  for item in self.inOrders:

    if self.Inventory >= item.amount:
      self.test1(item,item.amount)
      self.Inventory =self.Inventory-item.amount
      removed.append(item)
    else:
      self.test1(item,self.Inventory)
      item.amount = item.amount -self.Inventory
      self.Inventory  = 0
      self.backlogOrders.append(item)
      self.newbackloged =self.newbackloged+item.amount
      removed.append(item)

else:
  for item in self.inOrders:
    self.backlogOrders.append(item)
    self.newbackloged =self.newbackloged+item.amount
    removed.append(item)

for item in removed:
  self.inOrders.remove(item)
for item in removed1:
  self.backlogOrders.remove(item)
#end shipmentRate
```

```
#start backlog
self.Backlog = 0
for item in self.backlogOrders:
  self.Backlog = self.Backlog + item.amount
if self.Backlog <= 0: self.Backlog =0
#end backlog

#start OrderPlacedRate
self.DesiredInventory=self.OrderReceivedRate*self.InventoryCoverage
if self.Inventory <= 60 and self.trigger == 0 :
  self.OrderPlacedRate= 80 + self.newbackloged
  self.trigger = 1
  self.newbackloged = 0
else:
  self.OrderPlacedRate= 0
if self.OrderPlacedRate <= 0:self.OrderPlacedRate = 0

entity = Entity1(self, self.transporter, self.receiver, self.
    OrderPlacedRate)
self.indelay.append(entity)
#end OrderPlacedRate
```

A.3.2 Supplier

```
#start OrderFulfillmentRate
self.OrderFulfillmentRate = 0
removed = []
for item in self.inProduct:
  self.OrderFulfillmentRate = self.OrderFulfillmentRate+item.amount
  removed.append(item)
self.Orderplaced = self.Orderplaced - self.OrderFulfillmentRate
for item in removed:
  self.inProduct.remove(item)
#end OrderFulfillmentRate

#start AcquisitionRate
self.AcquisitionRate=self.OrderFulfillmentRate
self.Inventory = self.Inventory + self.AcquisitionRate
if self.AcquisitionRate > 0:
  self.trigger = 0
#end AcquisitionRate

#start DesiredShipmentRate
self.DesiredShipmentRate=self.OrderReceivedRate+self.Backlog
#end start DesiredShipmentRate

#start orderreceived
self.OrderReceivedRate =0
for item in self.inOrders:
  self.OrderReceivedRate = self.OrderReceivedRate+item.amount
#end orderreceived

#start shipmentRate
if self.DesiredShipmentRate < self.Inventory:
```

```
  self.ShipmentRate = self.DesiredShipmentRate
else: self.ShipmentRate = self.Inventory
removed = []
removed1 = []

if self.Inventory > 0:
  for item in self.backlogOrders:
    if self.Inventory >= item.amount:
      self.test1(item,item.amount)
      self.Inventory = self.Inventory-item.amount
      removed1.append(item)

  for item in self.inOrders:

    if self.Inventory >= item.amount:
      self.test1(item,item.amount)
      self.Inventory = self.Inventory-item.amount
      removed.append(item)
    else:
      self.test1(item, self.Inventory)
      item.amount = item.amount-self.Inventory
      self.Inventory  = 0
      self.backlogOrders.append(item)
      self.newbackloged=self.newbackloged+item.amount
      removed.append(item)
else:
  for item in self.inOrders:
    self.backlogOrders.append(item)
    self.newbackloged=self.newbackloged+item.amount
    removed.append(item)
for item in removed:
  self.inOrders.remove(item)
for item in removed1:
  self.backlogOrders.remove(item)
#end shipmentRate

#start backlog
self.Backlog = 0
for item in self.backlogOrders:
  self.Backlog = self.Backlog + item.amount
if self.Backlog <= 0: self.Backlog =0
#end backlog

#start OrderPlacedRate
self.DesiredInventory=self.OrderReceivedRate*self.InventoryCoverage
if self.Inventory <= 80 and self.trigger == 0 :
  self.OrderPlacedRate= 80 + self.newbackloged
  self.trigger = 1
  self.newbackloged = 0
else:
  self.OrderPlacedRate= 0
if self.OrderPlacedRate <= 0:self.OrderPlacedRate = 0

entity=Entity1(self, self.transporter, self.receiver, self.OrderPlacedRate
    )
self.receiver.inOrders.append(entity)
# end OrderPlacedRate
```

A.3.3 Dummy agent

```
remove = []
for item in self.inOrders:
  if item.delay == 0:
    self.test1(item)
    remove.append(item)
  item.delay = item.delay -1
for item in remove:
  self.inOrders.remove(item)
```

A.3.4 Customer

```
if self.parent.currentTimes >=3:
  self.OrderPlacedRate = randint(1,15)
entity = Entity1(self, self.transporter, self.receiver ,self.
    OrderPlacedRate)
self.receiver.inOrders.append(entity)
removed = []
for item in self.inProduct:
  self.OrderFulfillmentRate = self.OrderFulfillmentRate + item.amount
  removed.append(item)
for item in removed:
  self.inProduct.remove(item)
```

Bibliography

Abbott, A. (1998). The causal devolution, *Sociological methods & research* **27**(2): 148–181. 52

Afman, M. R., L., C. E. J., Wander, J. and J., D. G. P. (2010). Agent-based model of transitions in consumer lighting, *3rd World Congress on Social Simulation, Kassel, Germany.* 40, 46

Ajzen, I. and Fishbein, M. (1977). Attitude-behavior relations: A theoretical analysis and review of empirical research., *Psychological bulletin* **84**(5): 888. ix, 26, 28

Akkermans, H. (2001). Emergent supply networks: System dynamics simulation of adaptive supply agents, *System Sciences, 2001. Proceedings of the 34th Annual Hawaii International Conference on*, IEEE, pp. 11–pp. 102

Allen, L. J. (1994). Some discrete-time epidemic models, *Mathematical biosciences* **124**(1): 83–105. 69

Amblard, F. and Mailliard, M. (2007). Review of e4mas 2004-2005 proceedings. 39

Andrighetto, G., Conte, R., Turrini, P. and Paolucci, M. (2007). Emergence in the loop: Simulating the two way dynamics of norm innovation, *Normative multi-agent systems* **7122**. 20

Aronson, E., Wilson, T. and Akert, R. (2005). *Social Psychology*, Prentice Hall.
URL: *http://books.google.nl/books?id=Y4hhQgAACAAJ* 21, 27

Asch, S. E. (1956). Studies of independence and conformity: I. a minority of one against a unanimous majority, *Psychological monographs: General and applied* **70**(9): 1–70. 2, 21, 27

Aström, K. J. and Murray, R. M. (2010). *Feedback systems: an introduction for scientists and engineers*, Princeton university press. 45

Axelrod, R. (1997a). Advancing the art of simulation in the social sciences, *Simulating social phenomena*, Springer, pp. 21–40. 8

Axelrod, R. (1997b). Advancing the art of simulation in the social sciences, *Complexity* **3**(2): 16–22. 52

Bandini, S., Manzoni, S. and Vizzari, G. (2005). A spatially dependent communication model for ubiquitous systems, *Environments for Multi-Agent Systems*, Springer, pp. 74–90. 39

Bandini, S., Manzoni, S. and Vizzari, G. (2009). Agent based modeling and simulation: An informatics perspective., *Journal of Artificial Societies & Social Simulation* **12**(4). 25

Bandini, S. and Vizzari, G. (2007). Regulation function of the environment in agent-based simulation, *Environments for Multi-Agent Systems III*, Springer, pp. 157–169. 38, 39

Barlas, Y. (2007). System dynamics: systemic feedback modeling for policy analysis, *SYSTEM* **1**: 59. 69

Barlas, Y. and Gunduz, B. (2011). Demand forecasting and sharing strategies to reduce fluctuations and the bullwhip effect in supply chains, *Journal of the Operational Research Society* **62**(3): 458–473. 69

Barlas, Y. and Özevin, M. G. (2001). Testing the decision rules used in stock management models, *Proceedings of the 19 th International Conference of the System Dynamics Society 2001*. 69

Bedau, M. (1997). Weak emergence, *Noûs* **31**: 375–399. 17

Bedau, M. A. (2008). Is weak emergence just in the mind?, *Minds and Machines* **18**(4): 443–459. 17

Ben-Daya, M., Darwish, M. and Ertogral, K. (2008). The joint economic lot sizing problem: Review and extensions, *European Journal of Operational Research* **185**(2): 726–742. 109

Bobashev, G. V., Goedecke, D. M., Yu, F. and Epstein, J. M. (2007). A hybrid epidemic model: combining the advantages of agent-based and equation-based approaches, *Simulation Conference, 2007 Winter*, IEEE, pp. 1532–1537. 3, 101, 102, 104

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems, *Proceedings of the National Academy of Sciences* **99**(suppl 3): 7280–7287. 6

Bond, R. and Smith, P. B. (1996). Culture and conformity: A meta-analysis of studies using asch's (1952b, 1956) line judgment task., *Psychological bulletin* **119**(1): 111. 30

Borshchev, A. and Filippov, A. (2004). From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools, *Proceedings of the 22nd international conference of the system dynamics society*, number 22. 5, 102, 104

Boschetti, F., Prokopenko, M., Macreadie, I. and Grisogono, A.-M. (2005). Defining and detecting emergence in complex networks, *Knowledge-based intelligent information and engineering systems*, Springer, pp. 573–580. 17

Burns, J. F. and Sivazlian, B. (1978). Dynamic analysis of multi-echelon supply systems, *Computers & Industrial Engineering* **2**(4): 181–193. 69

Cannella, S., Barbosa-Póvoa, A. P., Framinan, J. M. and Relvas, S. (2013). Metrics for bullwhip effect analysis, *Journal of the Operational Research Society* **64**(1): 1–16. 88

Chalmers, D. J. (2002). Varieties of emergence, *Department of Philosophy, University of Arizona, USA, Tech. rep./preprint* . 17

Chappin, E. J. L. (2011). *Simulations of Energy Transitions*, PhD thesis, Delft University of Technology. ISBN: 978-90-79787-30-2. 40

Chen, F., Drezner, Z., Ryan, J. K. and Simchi-Levi, D. (2000). Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information, *Management science* **46**(3): 436–443. 92

Chen, F. and Samroengraja, R. (2000). The stationary beer game, *Production and Operations Management* **9**(1): 19–30. 91

Cialdini, R. B. and Goldstein, N. J. (2004). Social influence: Compliance and conformity, *Annu. Rev. Psychol.* **55**: 591–621. 20, 21, 27

Cialdini, R. B., Kallgren, C. A. and Reno, R. R. (1991). A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior, *Advances in experimental social psychology* **24**(20): 1–243. 30

Coleman, J. (1986). Social theory, social research, and a theory of action, *American journal of Sociology* pp. 1309–1335. 38

Conte, R. (2009). From simulation to theory (and backward), *Epistemological aspects of computer simulation in the social sciences*, Springer, pp. 29–47. 2, 16, 19, 50, 53

Conte, R., Andrighetto, G. and Campennl, M. (2013). *Minding Norms: Mechanisms and dynamics of social order in agent societies*, Oxford University Press. 20

Conte, R., Gilbert, N. and Sichman, J. S. (1998). Mas and social simulation: A suitable commitment, *Multi-agent systems and agent-based simulation*, Springer, pp. 1–9. 6

Crutchfield, J. (1994). The calculi of emergence, *Physica D* **75**: 11–54–. 16

Cvitanovic, P., Artuso, R., Mainieri, R., Tanner, G., Vattay, G. and Whelan, N. (2005). Chaos: classical and quantum, *ChaosBook. org (Niels Bohr Institute, Copenhagen 2005)* . 69

Darley, J. M. and Latane, B. (1968). Bystander intervention in emergencies: diffusion of responsibility., *Journal of personality and social psychology* **8**(4p1): 377. 21

Davidsson, P. (2001). *Multi agent based simulation: beyond social simulation*, Springer. 6

De Boer, L., Labro, E. and Morlacchi, P. (2001). A review of methods supporting supplier selection, *European Journal of Purchasing & Supply Management* **7**(2): 75–89. 109

De Bruijn, H. and Herder, P. M. (2009). System and actor perspectives on socio-technical systems, *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on* **39**(5): 981–992. 1

Deffuant, G., Neau, D., Amblard, F. and Weisbuch, G. (2000). Mixing beliefs among interacting agents, *Advances in Complex Systems* **3**(01n04): 87–98. 16, 26, 34

Deguet, J., Demazeau, Y. and Magnin, L. (2006). Elements about the emergence issue: A survey of emergence definitions, *Complexus* **3**(1-3): 24–31. 17, 18

Dejonckheere, J., Disney, S., Lambrecht, M. and Towill, D. (2004). The impact of information enrichment on the bullwhip effect in supply chains: A control engineering perspective, *European Journal of Operational Research* **153**(3): 727 – 750. {EURO} Young Scientists.
URL: *http://www.sciencedirect.com/science/article/pii/S0377221702008081* 82

Dejonckheere, J., Disney, S. M., Lambrecht, M. R. and Towill, D. R. (2003). Measuring and avoiding the bullwhip effect: A control theoretic approach, *European Journal of Operational Research* **147**(3): 567–590. 84, 91, 95

DeLoach, S. A. and Valenzuela, J. L. (2007). An agent-environment interaction model, *Agent-Oriented Software Engineering VII*, Springer, pp. 1–18. 53

Deutsch, M. and Gerard, H. B. (1955). A study of normative and informational social influences upon individual judgment., *The journal of abnormal and social psychology* **51**(3): 629. 21, 27

Dignum, V. (2004). *A model for organizational interaction: based on agents, founded in logic*, PhD thesis, University of Utrecht. 107

Disney, S. M. and Towill, D. R. (2002). A discrete transfer function model to determine the dynamic stability of a vendor managed inventory supply chain, *International Journal of Production Research* **40**(1): 179–204. 69, 82, 84, 91

Disney, S., Naim, M. and Potter, A. (2004). Assessing the impact of e-business on supply chain dynamics, *International Journal of Production Economics* **89**(2): 109 – 118. Supply Chain Management.
URL: *http://www.sciencedirect.com/science/article/pii/S0925527302004644* 82

Doyle, J. C., Francis, B. A. and Tannenbaum, A. (1992). *Feedback control theory*, Vol. 1, Macmillan Publishing Company New York. ix, 85, 86

Drogoul, A. (1995). When ants play chess (or can strategies emerge from tactical behaviours?), *From reaction to cognition*, Springer, pp. 11–27. 6

Drogoul, A., Vanbergue, D. and Meurisse, T. (2003). Multi-agent based simulation: Where are the agents?, *Multi-agent-based simulation II*, Springer, pp. 1–15. 6

Duggan, J. (2008). Equation-based policy optimization for agent-oriented system dynamics models, *System Dynamics Review* **24**(1): 97–118. 102

Eagly, A. H. and Chrvala, C. (1986). Sex differences in conformity: Status and gender role interpretations, *Psychology of Women Quarterly* **10**(3): 203–220. 30

Edmonds, B. and Moss, S. (2005). *From KISS to KIDS–an anti-simplisticmodelling approach*, Springer. 3, 8, 101

Epstein, J. (2006). *Generative social science: Studies in agent-based computational modeling*, Princeton Univ Pr. 2, 5, 16, 19, 52

Epstein, J. M. and Axtell, R. (1996). *Growing artificial societies: social science from the bottom up*, Brookings Institution Press. 18

Ferber, J. (1999). *Multi-agent systems: an introduction to distributed artificial intelligence*, Vol. 1, Addison-Wesley Reading. 53

Ferber, J., Dessalles, J.-L. and Phan, D. (2008). Emergence in agent based computational social science: conceptual, formal and diagrammatic analysis, *Intelligent complex adaptative systems* pp. 255–299. 16, 17

Ferber, J., Gutknecht, O. and Michel, F. (2003). From agents to organizations: an organizational view of multi-agent systems, *Agent-Oriented Software Engineering IV* pp. 443–459. 107

Ferber, J., Michel, F. and Baez, J. (2005). Agre: Integrating environments with organizations, *Environments for Multi-agent Systems* pp. 48–56. 56

Forrester, J. W. (1961a). *Industrial dynamics*, Vol. 2, MIT press Cambridge, MA. 7, 39

Forrester, J. W. (1961b). *Industrial dynamics*, Vol. 2, MIT press Cambridge, MA. 83, 85

Fowler, M. (2004). *UML distilled: a brief guide to the standard object modeling language*, Addison-Wesley Professional. 51

Galam, S. (2002). Minority opinion spreading in random geometry, *The European Physical Journal B-Condensed Matter and Complex Systems* **25**(4): 403–406. 27

Galam, S., Gefen, Y. and Shapir, Y. (1982). Sociophysics: A new approach of sociological collective behaviour. i. mean-behaviour description of a strike, *Journal of Mathematical Sociology* **9**(1): 1–13. 27

Gambetta, D. (1998). 5. concatenations of mechanisms, *Social mechanisms: An analytical approach to social theory* p. 102. 53

Garro, A. and Russo, W. (2010a). ¡ i¿ easyabms¡/i¿: A domain-expert oriented methodology for agent-based modeling and simulation, *Simulation Modelling Practice and Theory* **18**(10): 1453–1467. 37

Garro, A. and Russo, W. (2010b). easyabms: A domain-expert oriented methodology for agent-based modeling and simulation, *Simulation Modelling Practice and Theory* **18**(10): 1453–1467. 56

Gendre, M. F. (2003). Two centuries of electric light source innovations, *URL: http://www. einlightred. tue. nl/lightsources/history/light_history. pdf* **143**. 32, 40

Ghaffarzadegan, N., Lyneis, J. and Richardson, G. P. (2011). How small system dynamics models can help the public policy process, *System Dynamics Review* **27**(1): 22–44. 8

Ghorbani, A., Bots, P., Dignum, V. and Dijkema, G. (2013). Maia: A framework for developing agent-based social simulations, *Journal of Artificial Societies and Social Simulation* **16**(2). 3, 37, 39, 41, 42, 46, 56, 57

Ghorbani, A., Dechesne, F., Dignum, V. and Jonker, C. (2014). Enhancing abm into an inevitable tool for policy analysis, *Journal of policy and complex systems* **1**. 46

Gilbert, N. (2002). Varieties of emergence, *Agent 2002 Conference: Social agents: ecology, exchange, and evolution, Chicago*, pp. 11–12. 15, 16, 19

Gilbert, N. and Ahrweiler, P. (2009). The epistemologies of social simulation research, *Epistemological aspects of computer simulation in the social sciences*, Springer, pp. 12–28. 52

Gilbert, N. and Conte, R. (1995). *Artificial Societies: the computer simulation of social life*, Taylor & Francis, Inc. 15, 17, 18

Gilbert, N., Schuster, S., den Besten, M. and Yang, L. (2005). Environment design for emerging artificial societies, *MPRA Paper* . 17, 52

Gilbert, N. and Terna, P. (2000). How to build and use agent-based models in social science, *Mind & Society* **1**(1): 57–72. 37, 38, 39, 41

Gilbert, N. and Troitzsch, K. (2005). *Simulation for the social scientist*, McGraw-Hill International. 3, 6, 18

Gouaïch, A., Michel, F. and Guiraud, Y. (2005). Mic*: a deployment environment for autonomous agents, *Environments for Multi-Agent Systems*, Springer, pp. 109–126. 55

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S. K., Huse, G. et al. (2006). A standard protocol for describing individual-based and agent-based models, *Ecological modelling* **198**(1): 115–126. 53

Grüne-Yanoff, T. (2009). The explanatory potential of artificial societies, *Synthese* **169**(3): 539–555. 2, 52

Guizzardi, G. and Wagner, G. (2012). Tutorial: Conceptual simulation modeling with onto-uml, *Simulation Conference (WSC), Proceedings of the 2012 Winter*, IEEE, pp. 1–15. 50

Hannoun, M., Boissier, O., Sichman, J. and Sayettat, C. (2000). Moise: An organizational model for multi-agent systems, *Advances in Artificial Intelligence* pp. 156–165. 107

Heath, B., Hill, R. and Ciarallo, F. (2009). A survey of agent-based modeling practices (january 1998 to july 2008), *Journal of Artificial Societies and Social Simulation* **12**(4): 9. 50

Hedströ m, P. (2008). Studying mechanisms to strengthen causal inferences in quantitative research, *The Oxford Handbook of Political Methodology. Oxford University Press, Oxford* pp. 319–335. 50, 52

Hedstrom, P. and Swedberg, R. (1998). Social mechanisms: An introductory essay, *Social mechanisms: An analytical approach to social theory* pp. 1–31. 50, 58

Hedström, P. and Ylikoski, P. (2010). Causal mechanisms in the social sciences, *Annual Review of Sociology* **36**: 49–67. 3, 52, 53

Hegselmann, R. and Krause, U. (2002). Opinion dynamics and bounded confidence models, analysis, and simulation, *Journal of Artificial Societies and Social Simulation* **5**(3). 16, 26

Hesan, R. and Behdani, B. (2015). Supply chain simulation: A hybrid approach combining system dynamics and agent-based modeling, *6th International Conference on Computational Logistics Delft, The Netherlands, Sept. 23-25, 2015 – http://realtimelogistics.info/*. 101

Hesan, R., Ghorbani, A. and Dignum, M. (2014a). Using difference equation to model discrete-time behavior in system dynamics modeling, *32nd International Conference of the System Dynamics Society, Delft, The Netherlands, 20-24 July 2014; Authors version*, System Dynamics Society. 67, 84, 85, 86, 109

Hesan, R., Ghorbani, A. and Dignum, V. (2014b). Modeling the influence of multiple social groups on agents behavior, *European Conference on Social Intelligence (ECSI-2014) Barcelona, Spain, November 3-5, 2014*. 25

Hesan, R., Ghorbani, A. and Dignum, V. (2015). Modelling environments in abms: A system dynamics approach, *Multi-Agent-Based Simulation XV*, Springer, pp. 41–52. 37

Ho, W., Xu, X. and Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review, *European Journal of Operational Research* **202**(1): 16–24. 109

Holland, J. H. (2000). *Emergence: From chaos to order*, Oxford University Press. 17

Holley, R. A. and Liggett, T. M. (1975). Ergodic theorems for weakly interacting infinite systems and the voter model, *The annals of probability* pp. 643–663. 27

Jadbabaie, A., Lin, J. and Morse, A. S. (2003). Coordination of groups of mobile autonomous agents using nearest neighbor rules, *Automatic Control, IEEE Transactions on* **48**(6): 988–1001. 26

Jennings, N. R. (2000). On agent-based software engineering, *Artificial intelligence* **117**(2): 277–296. 6

Jiang, Y. and Ishida, T. (2006). Concurrent agent social strategy diffusion with the unification trend, *Agent Computing and Multi-Agent Systems*, Springer, pp. 256–268. 26

Jiang, Y., Jiang, J. and Ishida, T. (2009). Compatibility between the local and social performances of multi-agent societies, *Expert Systems with Applications* **36**(3): 4443–4450. 25

Jonassen, D. H. and Ionas, I. G. (2008). Designing effective supports for causal reasoning, *Educational Technology Research and Development* **56**(3): 287–308. 22

Karimi, B., Ghomi, S. F. and Wilson, J. (2003). The capacitated lot sizing problem: a review of models and algorithms, *Omega* **31**(5): 365–378. 109

Klügl, F. and Davidsson, P. (2013). Amason: Abstract meta-model for agent-based simulation, *Multiagent System Technologies*, Springer, pp. 101–114. 55, 57

Klügl, F., Oechslein, C., Puppe, F., Dornhaus, A. et al. (2004). Multi-agent modelling in comparison to standard modelling, *Simulation News Europe* **40**: 3–9. 6

Lalwani, C. S., Disney, S. M. and Towill, D. R. (2006). Controllable, observable and stable state space representations of a generalized order-up-to policy, *International journal of production economics* **101**(1): 172–184. 69

Lättilä, L., Hilletofth, P. and Lin, B. (2010). Hybrid simulation models–when, why, how?, *Expert Systems with Applications* **37**(12): 7969–7975. 102

Laugesen, J. and Mosekilde, E. (2006). Border-collision bifurcations in a dynamic management game, *Computers & operations research* **33**(2): 464–478. 81

Lee, H. L., Padmanabhan, V. and Whang, S. (1997). The bullwhip effect in supply chains, *MIT Sloan Management Review* **38**: 93–102. 81

Lee, H. L., Padmanabhan, V. and Whang, S. (2004). Information distortion in a supply chain: the bullwhip effect, *Management science* **50**(12_supplement): 1875–1886. 81, 82, 92

Little, D. (1991). Varieties of social explanation: An introduction to the philosophy of social science. 50, 52

Little, D. (1996). Causal explanation in the social sciences, *The Southern journal of philosophy* **34**(S1): 31–56. 52

Lorenz, T. and Jost, A. (2006). Towards an orientation framework in multi-paradigm modeling, *Proceedings of the 24th international conference of the System Dynamics Society, Nijmegen*. 4

Macal, C. M. and North, M. J. (2005). Tutorial on agent-based modeling and simulation, *Proceedings of the 37th conference on Winter simulation*, Winter Simulation Conference, pp. 2–15. 6

Maes, P. (1995). Artificial life meets entertainment: lifelike autonomous agents, *Communications of the ACM* **38**(11): 108–114. 54

Marchionni, C. and Ylikoski, P. (2013). Generative explanation and individualism in agent-based simulation, *Philosophy of the Social Sciences* **43**(3): 323–340. 2, 53

Meadows, D. H. and Robinson, J. M. (2002). The electronic oracle: computer models and social decisions, *System Dynamics Review* **18**(2): 271–308. 4

Menanteau, P. and Lefebvre, H. (2000). Competing technologies and the diffusion of innovations: the emergence of energy-efficient lamps in the residential sector, *Research policy* **29**(3): 375–389. 32, 40

Mingers, J. and Brocklesby, J. (1997). Multimethodology: towards a framework for mixing methodologies, *Omega* **25**(5): 489–509. 4, 5

Mingers, J. and White, L. (2010). A review of the recent contribution of systems thinking to operational research and management science, *European Journal of Operational Research* **207**(3): 1147–1161. 64

Minner, S. (2003). Multiple-supplier inventory models in supply chain management: A review, *International Journal of Production Economics* **81**: 265–279. 109

Miragliotta, G. (2006). Layers and mechanisms: A new taxonomy for the bullwhip effect, *International Journal of Production Economics* **104**(2): 365–381. 82, 88

Moris, M. U., Ng, A. H. and Svensson, J. (2008). Simplification and aggregation strategies applied for factory analysis in conceptual phase using simulation, *Proceedings of the 40th Conference on Winter Simulation*, Winter Simulation Conference, pp. 1913–1921. 101

Mosekilde, E. and Laugesen, J. L. (2007). Nonlinear dynamic phenomena in the beer model, *System Dynamics Review* **23**(2-3): 229–252. 81

Mosterman, P. J. (1999). An overview of hybrid simulation phenomena and their support by simulation packages, *Hybrid Systems: Computation and Control*, Springer, pp. 165–177. 103

Myrtveit, M. (2000). Object-oriented extensions to system dynamics, *Proc. 18th Intl. System Dynamics Conference*. 104

Neubert, M. G., Kot, M. and Lewis, M. A. (1995). Dispersal and pattern formation in a discrete-time predator-prey model, *Theoretical Population Biology* **48**(1): 7–43. 69

North, M. J. (2014). A time and space complexity analysis of model integration, *Proceedings of the 2014 Winter Simulation Conference*, IEEE Press, pp. 1644–1651. 108

North, M. J. and Macal, C. M. (2007). *Managing business complexity: discovering strategic solutions with agent-based modeling and simulation*, Oxford University Press. 6

Nowak, A., Szamrej, J. and Latané, B. (1990). From private attitude to public opinion: A dynamic theory of social impact., *Psychological Review* **97**(3): 362. 27

Odell, J. J., Parunak, H. V. D., Fleischer, M. and Brueckner, S. (2003). Modeling agents and their environment, *Agent-oriented software engineering III*, Springer, pp. 16–31. 54

Okuyama, F. Y., Bordini, R. H. and da Rocha Costa, A. C. (2005). Elms: An environment description language for multi-agent simulation, *Environments for Multi-Agent Systems*, Springer, pp. 91–108. 55

Olaya, C. (2009). System dynamics philosophical background and underpinnings, *Encyclopedia of complexity and systems science*, Springer, pp. 9057–9078. 7, 60

Omicini, A., Ricci, A. and Viroli, M. (2008). Artifacts in the a&a meta-model for multi-agent systems, *Autonomous agents and multi-agent systems* **17**(3): 432–456. 55

Oppenheim, A. V., Willsky, A. S. and Nawab, S. H. (1983). *Signals and systems*, Vol. 2, Prentice-Hall Englewood Cliffs, NJ. 69, 83, 85

Ortega, M. and Lin, L. (2004). Control theory applications to the production–inventory problem: a review, *International Journal of Production Research* **42**(11): 2303–2322. 83

Ossimitz, G. and Mrotzek, M. (2008). The basics of system dynamics: Discrete vs. continuous modelling of time, *Proceedings of the 26th International Conference of the System Dynamics Society], System Dynamic Society, Wiley-Blackwell (July 2008).* 72

Ottens, M., Franssen, M., Kroes, P. and Van De Poel, I. (2006). Modelling infrastructures as socio-technical systems, *International Journal of Critical Infrastructures* **2**(2-3): 133–145. 1

Özgün, O. and Barlas, Y. (2009). Discrete vs. continuous simulation: When does it matter, *Proceedings of the 27th International Conference of The System Dynamics Society,(06)*, pp. 1–22. 69

Papanagnou, C. and Halikias, G. (2005). A state-space approach for analysing the bullwhip effect in supply chains, *Proceedings of ICTA* **5**: 79–84. 69

Parunak, H. V. D., Savit, R. and Riolo, R. L. (1998). Agent-based modeling vs. equation-based modeling: A case study and users guide, *Multi-agent systems and agent-based simulation*, Springer, pp. 10–25. 103

Pavón, J. and Gómez-Sanz, J. (2003). Agent oriented software engineering with ingenias, *Multi-Agent Systems and Applications III* pp. 1069–1069. 56

Pavon, J., Gomez-Sanz, J. and Fuentes, R. (2005). The ingenias methodology and tools, *Agent-oriented methodologies* pp. 236–276. 37

Pavon, J., Sansores, C. and Gomez-Sanz, J. (2008). Modelling and simulation of social systems with ingenias, *International Journal of Agent-Oriented Software Engineering* **2**(2): 196–221. 3, 56

Pidd, M. (1998). *Computer simulation in management science*, John Wiley. 5, 49

Rahmandad, H. and Sterman, J. (2008). Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models, *Management Science* **54**(5): 998–1014. 103

Ricci, A., Viroli, M. and Omicini, A. (2006). Programming mas with artifacts, *Programming multi-agent systems*, Springer, pp. 206–221. 39, 54, 55

Ricci, A., Viroli, M. and Omicini, A. (2007). Carta go: A framework for prototyping artifact-based environments in mas, *Environments for Multi-Agent Systems III*, Springer, pp. 67–86. 39, 54, 55, 105

Richardson, K. et al. (2003). On the limits of bottom-up computer simulation: Towards a nonlinear modeling culture, *System Sciences, 2003. Proceedings of the 36th Annual Hawaii International Conference On*, IEEE, pp. 9–pp. 2

Robinson, S. (2006). Conceptual modeling for simulation: issues and research requirements, *Proceedings of the 38th conference on Winter simulation*, Winter Simulation Conference, pp. 792–800. 49

Robinson, S. (2008). Conceptual modelling for simulation part i: definition and requirements, *Journal of the operational research society* **59**(3): 278–290. 49

Rossiter, S., Noble, J. and Bell, K. (2010). Social simulations: Improving interdisciplinary understanding of scientific positioning and validity, *Journal of Artificial Societies and Social Simulation* **13**(1). 51

Sansores, C. and Pavón, J. (2005). Agent-based simulation replication: A model driven architecture approach, *MICAI 2005: Advances in Artificial Intelligence* pp. 244–253. 50

Sarimveis, H., Patrinos, P., Tarantilis, C. D. and Kiranoudis, C. T. (2008). Dynamic modeling and control of supply chain systems: A review, *Computers & Operations Research* **35**(11): 3530–3561. 84

Savarimuthu, B. T. R., Cranefield, S., Purvis, M. and Purvis, M. (2007). Norm emergence in agent societies formed by dynamically changing networks, *Proceedings of the 2007 IEEE/WIC/ACM international conference on intelligent agent technology*, IEEE Computer Society, pp. 464–470. 20

Sawyer, R. K. (2001). Simulating emergence and downward causation in small groups, *Multi-agent-based simulation*, Springer, pp. 49–67. 2, 16, 17, 19

Sawyer, R. K. (2004). Social explanation and computational simulation, *Philosophical Explorations* **7**(3): 219–231. 15, 52

Schelling, T. C. (1971). Dynamic models of segregation, *Journal of mathematical sociology* **1**(2): 143–186. 19

Schieritz, N. and Grobler, A. (2003). Emergent structures in supply chains-a study integrating agent-based and system dynamics modeling, *System Sciences, 2003. Proceedings of the 36th Annual Hawaii International Conference on*, IEEE, pp. 9–pp. 5, 102, 103, 104, 105, 108

Schieritz, N. and Milling, P. M. (2003). Modeling the forest or modeling the trees, *Proceedings of the 21st International Conference of the System Dynamics Society*, pp. 20–24. 5, 103

Scholl, H. J. (2001). Agent-based and system dynamics modeling: a call for cross study and joint research, *System Sciences, 2001. Proceedings of the 34th Annual Hawaii International Conference on*, IEEE, pp. 8–pp. 4, 5, 103

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J. and Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms, *Psychological science* **18**(5): 429–434. 20, 30

Shannon, R. E. (1998). Introduction to the art and science of simulation, *Proceedings of the 30th conference on Winter simulation*, IEEE Computer Society Press, pp. 7–14. 49

Shanthikumar, J. and Sargent, R. (1983). A unifying view of hybrid simulation/analytic models and modeling, *Operations research* **31**(6): 1030–1052. 103

Sheppard, B. H., Hartwick, J. and Warshaw, P. R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research, *Journal of consumer Research* pp. 325–343. 31

Sherif, M. (1936). The psychology of social norms. 2, 21, 22, 27

Simon, H. A. (1952). On the application of servomechanism theory in the study of production control, *Econometrica: Journal of the Econometric Society* pp. 247–268. 83

Slack, N., Chambers, S. and Johnston, R. (2010). *Operations management*, Pearson Education. 111

Sterman, J. (1984). Instructions for running the beer distribution game (d-3679). sloan school of management. 81, 83, 95

Sterman, J. (2000). *Business dynamics*, Irwin-McGraw-Hill. 7, 8, 38, 39, 67, 69, 70, 73, 86, 99, 105

Sterman, J. D. (1989). Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment, *Management science* **35**(3): 321–339. 70, 82, 96, 99

Sznajd-Weron, K. and Sznajd, J. (2000). Opinion evolution in closed community, *International Journal of Modern Physics C* **11**(06): 1157–1165. 27

Tesfatsion, L. (2003). Agent-based computational economics: modeling economies as complex adaptive systems, *Information Sciences* **149**(4): 262–268. 6

Tignor, W. W. and Myrtveit, M. (2000). Object-oriented design patterns and system dynamics components, *Proceedings of the International System Dynamics Society, Bergen: System Dynamics Society* . 104

Towill, D. R. (1982). Dynamic analysis of an inventory and order based production control system, *The international journal of production research* **20**(6): 671–687. 84

Towill, D. R. (1996). Industrial dynamics modelling of supply chains, *Logistics*

Information Management **9**(4): 43–56. 84

Turner, J. C. and Oakes, P. J. (1986). The significance of the social identity concept for social psychology with reference to individualism, interactionism and social influence, *British Journal of Social Psychology* **25**(3): 237–252. 28

Urbig, D. (2003). Attitude dynamics with limited verbalisation capabilities, *Journal of Artificial Societies and Social Simulation* **6**(1): 1–23. 27

Van Dam, K. H., Nikolic, I. and Lukszo, Z. (2012). *Agent-based modelling of socio-technical systems*, Vol. 9, Springer Science & Business Media. 6

Van der Zee, D.-J., Pidd, M., Tolk, A., Kotiadis, K., Tako, A. A., Balci, O. and Elder, M. (2010). Panel discussion: education on conceptual modeling for simulation-challenging the art, *Proceedings of the Winter Simulation Conference*, Winter Simulation Conference, pp. 290–304. 49

Vassian, H. J. (1955). Application of discrete variable servo theory to inventory control, *Journal of the Operations Research Society of America* **3**(3): 272–282. 83

Verhoog, R. (2013). *Exploring biogas stakeholder interaction in the Netherlands: an Agent Based Modeling approach to explore location specific biogas system performance under different scenarios*, PhD thesis, TU Delft, Delft University of Technology. 62

Vincenot, C. E., Giannino, F., Rietkerk, M., Moriya, K. and Mazzoleni, S. (2011). Theoretical considerations on the combined use of system dynamics and individual-based modeling in ecology, *Ecological Modelling* **222**(1): 210–218. 104

Wakeland, W. W., Gallaher, E. J., Macovsky, L. M. and Aktipis, C. A. (2004). A comparison of system dynamics and agent-based simulation applied to the study of cellular receptor dynamics, *System Sciences, 2004. Proceedings of the 37th Annual Hawaii International Conference on*, IEEE, pp. 10–pp. 5, 103

Warburton, R. D. (2004). An analytical investigation of the bullwhip effect, *Production and operations management* **13**(2): 150–160. 81

Weyns, D., Omicini, A. and Odell, J. (2007). Environment as a first class abstraction in multiagent systems, *Autonomous agents and multi-agent systems* **14**(1): 5–30. 37, 38, 39, 54

Wooldridge, M. and Jennings, N. (1995). Intelligent agents: Theory and practice, *Knowledge engineering review* **10**(2): 115–152. 6, 54

Yücel, G. (2010). *Analyzing transition dynamics: the actor-option framework for modelling socio-technical systems*, TU Delft, Delft University of Technology. 3, 102