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ON AGENT-BASED MODELING IN SEMICONDUCTOR SUPPLY CHAIN PLANNING

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ABSTRACT

Supply chain (SC) planning in the semiconductor industry is challenged by high uncertainties on the demand side as well as a complex manufacturing process with non-deterministic failure modes on the production side. Understanding the complex interdependencies and processes of a SC is essential to realize opportunities and mitigate risks. However, this understanding is not easy to achieve due to the complexity of the processes and the non-deterministic human behavior determining SC planning performance. Our paper argues for an agent-based approach to understand and improve SC planning processes using an industry example. We give an overview of current work and elaborate on the need for integrating human behavior into the models. Overall, we conclude that agent-based simulation is a valuable method to identify favorable and unfavorable conditions for successful planning.

1 INTRODUCTION

The semiconductor industry is highly competitive with customers from heterogeneous industry sectors and high demand volatility. Rapidly changing environments as well as contracting product life cycles challenge the SC planning process (Geng and Jiang 2009). Manufacturing lead-times (months) are much longer than customer order lead-times (Ott et al. 2013). Products and processes increase in intricacy with every cycle. These market properties, amplified by globalization, diversity of variants, and declining manufacturing depth (Beinhocker 2007), result in highly complex SC. In addition, competitive pressure in the semiconductor market requires a continuous endeavor for cost reduction. Two common leverage points are technological enhancements and improvements of operational processes. Advancements in the operational processes seem to offer the most promising opportunities for cost reduction (Mönch et al. 2006). At the same time, flexible operational processes are a prerequisite to deal with the volatile characteristics of the semiconductor market and to manage its inherently complex structures.

The resulting uncertainty hampers a comprehensive digitalization of SC processes. On a shop floor level the semiconductor industry has mastered these challenges by making use of automation, robotics, statistical process control and other monitoring techniques. Visible examples of automation in today's fabrication are automated guided vehicles (AGV) and advanced material handling systems (AMHS). On the one hand this increases the importance of protecting such systems from unpredictable events and other uncertainties that cannot be handled by algorithmic automated decision making systems. On the other hand essential innovations have to be induced from outside the physical system, which replaces prior tasks of workers (e.g. supervisors or operators) who are directly in touch with products and the production system. Therefore, the increased agility in the manufacturing process shifted the challenges induced by the volatile and complex semiconductor market and the quest for innovation to the SC planning process, which now has to ensure stability and innovation in the uncertain and complex environment. Especially in the realm of SC planning processes, human planners remain important to mitigate the influence of uncertainties by their decisions, which cannot be achieved by automated decision making and furthermore, to seek for potential opportunities and innovations.

Current discussions of practitioners and academics (Chien et al. 2016) confirm that human decisions are crucial for planning and control. Although the planning process is supported by IT systems, human judgement is indispensable. The planning process includes different persons in the planning ecosystem and is characterized by complex interaction patterns. Human decision makers often decide both individually and intuitively within groups about capacity utilization, demand adjustments, wafer starts and options to realize opportunities or to mitigate risks. Due to the interactions of individual agents, emergent system properties arise, incorporating uncertainties caused by human behavior (Chien et al. 2016). As we desire and need the human decisions to mitigate risks and realize opportunities they are accompanied with effects such as overreactions as described in the prospect theory (Kahneman and Tversky 1979) or other cognitive biases that may distort successful planning.

Agent-based modeling (ABM) supports the analysis of heterogeneous human behavior on planning performance. This method allows for the specification of individual strategies by defining agent types representing individual planning types such as risk-averse behavior vs. risk-taking behavior. In simulation experiments, individual behavior can be varied and systematically analyzed. Therefore, ABM is an appropriate method to understand the behavior of human decision makers and their interactions. Simulation results may suggest improvements to avoid negative decision strategies and foster positive ones. Investigating SC planning with the method of ABM opens up the opportunity to design interaction processes more streamlined, efficient and less prone to error. This should improve overall planning performance. In this paper we introduce modeling approaches of a semiconductor company, show the experiences gained, and provide an outlook on planned activities.

2 MODELING HUMAN DECISION MAKING IN SC PLANNING

Many researchers and decision makers have long recognized that simulation is a valuable tool for the analysis of complex dynamics in SC planning (Min and Zhou 2002; Terzi and Cavalieri 2004). Simulation allows for the analysis of large and complex logistics and SC systems, including stochastic elements and complex relationships between system components (Manuj et al. 2009). In particular discrete event simulation (DES) and system dynamics (SD) are widely applied decision support tools in logistics and SC management (Manuj et al. 2009), and also in semiconductor manufacturing (Sarjoughian et al. 2005; Chik et al. 2014). However, the use of DES to analyze business process design is scarce. So-called "soft" organizational aspects and human decisions are difficult to represent in a DES model (Semini et al. 2006).

2.1 Opportunities and Risks of Human Decision Making

From both a practical and a scholarly perspective, issues like human behavior, cooperation, and complexity are important future topics in SC management (Wieland et al. 2016). Humans in the SCs fulfill the requirements for adaptive process elements and provide the required agility in a rapidly changing environment and therefore endow the system with its necessary flexibility (Caridi and Cavalieri 2004). Brinkhoff et al. (2015) show that success of SC projects depends on the underlying relationship between SC partners, such as trust. Ali et al. (2017) discuss the relevance of information sharing within SCs for successful and efficient SC management, and implications for SCs where no information sharing takes place. Sun, Ponsignon, et al. (2015) show the effect of individual risk literacy on the performance of SC planning. Another typical example of human risk behavior properties is risk seeking or risk averse decision making behavior. This is exemplified by the utility function in Figure 1, which illustrates possible overreactions. Lipshitz and Strauss (1997) give evidence that human decision makers are able to distinguish among three types of uncertainty and develop five different strategies to cope with them.

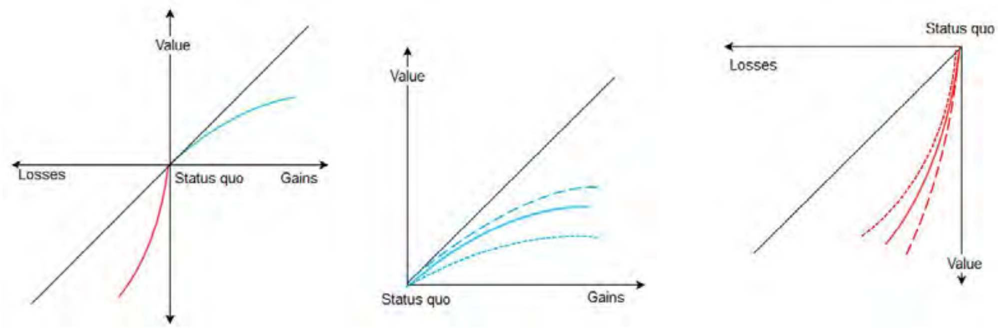

Figure 1: Utility function according to Kahneman and Tversky (1979); adapted from Plous (1993) and extended with corridors.

Integration of humans in a planning systems may result in a better performance compared to fully automated rule based systems. We exemplify three reasons for a performance increase resulting from human intervention. (1) Humans can hold (informal) information and domain knowledge that is not represented or representable in planning systems (e.g. information about the probability for acquisition of a new customer, or looming supplier-caused bottlenecks). (2) Human decision makers are agile, which enables the system to behave more flexibly in unusual situations (e.g. exogenous shocks like the financial crisis as well as internal events such as an abrupt production line shut down). (3) Human planners are able to initiate one-time sub processes by communication with other planners (e.g. to execute minor planning adaptions, which are yet impossible to implement in automated systems).

Process structures in the work environment of a human planner can impose sequential constraints that force the execution of certain tasks before others: Identifying an event X (e.g. drop in demand by 10%) triggers a reaction Y (e.g. demand adjustment by 5% for a certain customer or product group). Identifying such interlocking structures enables the automation of those process steps that do not require complex cognitive work and reduce the workload of human planner.

Nevertheless, human decision making also bears risks. Human decision making is not rational compared to algorithms and is susceptible to diverse cognitive biases (see e.g., Kahneman 2011). Research on judgmental forecasting stresses among others effects of overconfidence, optimism, recency, and hindsight bias (Lawrence et al. 2006). According to industry, experience overreactions of human planners, such as the bullwhip effect (Lee et al. 1997), are either triggered by out-of-stock situations, when demand is set too high, or by high stock levels when too few replenishments are ordered. Results of this overreaction can result in unused production capacities or scrapping of manufactured products.

An open question is how to examine performance of a planning system composed of both human decision makers and IT systems. A major challenge is to quantify costs of unconsidered information by IT systems vs. costs of non-rational decisions by human decision makers. Even more challenging to answer is the question of how the planning performance is affected along the SC planning process if humans interact with others and with artifacts. Do interactions mitigate or reinforce planning errors? To investigate these questions and research how to mitigate negative influences of the indispensable human deciders we propose the use of ABM.

2.2 Using ABM to Model Human Decision Making

For the analysis of both human decisions as well as complex, adaptive systems, ABM is a valuable approach. Consequently, this methodology has attracted attention in many fields, such as political science, technology, economics, and business (Tesfatsion and Judd 2006; Macal and North 2014). The architecture of ABM is characterized by decentralized and distributed decision making entities, called agents. ABM is particularly relevant if heterogeneous behavior at agent level is observed or if networks and their structure matter. An agent may act autonomously, intelligently, and in a goal-oriented manner. System behavior emerges from individual agent behavior and the interactions among them.

Although ABM is applied in several studies of different domains, including manufacturing and SC decision making (Marik and McFarlane 2005; Hilletofth et al. 2016), few studies use ABM to address complex and adaptive traits (Li et al. 2010). In contrast to the widespread use of DES, only a limited number of agent-based manufacturing control approaches have been implemented to make production systems more flexible (Mönch et al. 2006; Wang et al. 2007; Macal and North 2014). This circumstance raises doubts of the applicability of distributed, intelligent agent-based control approaches for production optimization on the fab level (Leitão 2009).

Still, ABM has some modeling capabilities that make it particularly promising for the analysis of operational processes in SC planning. In general, the following reasons support (individually or collectively) choosing ABM instead of other modeling approaches (selection of Axtell 2000; Macal and North 2014): (1) Modeling individual behavior. The system consists of heterogeneous individual behavior and it is important to reflect on how individuals actually behave. (2) Modeling adaptive behavior and systems. Agents need to adapt and change behaviors to be successful. Learning and dynamic, strategic interactions are important. (3) Dynamic interactions and relationships between agents. Agents form, change, and decay interactions with others in the system or organizational process. (4) Organization formation. The process of how agents form organizations is important. (5) Changing emergent system behavior. The system structure is not determined only by the past, but new dynamic mechanisms may occur or emerge. Change may be an endogenous result of the agent interactions and not an input of the model.

3 INDUSTRY EXAMPLE OF SC PLANNING

In this section we introduce an industry example of a SC planning landscape and the humans and tools involved. We show where human decision making is associated with opportunities and might mitigate risks (cf. section 2.1). The description of the planning system also indicates that system properties are similar to those listed in section 2.2.

3.1 Planning Landscape

We use the description of the Supply Chain Operation Reference (SCOR) model to give an overview and to determine the scope of the case within the SC landscape. The SCOR model is the most commonly referenced standard for SCs (APICS Supply Chain Council 2015). SCOR is comprised of six primary processes: plan, make, source, deliver, return, and enable. As more and more processes in *make* are automated, we focus on the *plan make* process. Our case of plan make in the planning landscape is further subdivided according to SCOR as shown in Figure 2.

According to SCOR, capacity planning identifies, assesses, prioritizes, and aggregates the SC resources. Likewise, demand planning aggregates the SC requirements. Figure 2 shows that capacity and demand planning generate the input for supply planning. Supply planning balances demand with supply to generate a feasible production schedule that utilizes available resources efficiently. The output of the supply planning process provides the input for production and order management processes. Production and order management communicate and establish the generated SC plan on the production and customer sides.

The SCOR model illustrates the iterative nature of the planning process. Iterations of the process generate plans, which in turn influence future planning runs. Planning is executed on several different levels. Iterations on lower planning levels are initiated more often and change more frequently than on higher levels. Results of lower level planning activities provide information for planning on higher levels. Higher levels are characterized by higher product granularity and extended planning horizons. This differentiation leads to the typical categorization of SC management decisions into four decision tiers (Fordyce et al. 2011) as independently proposed by Kempf and Sullivan. However, excluding the dispatch level which is characterized by real-time responses, the planning landscape covers three planning levels in our industry example: strategic, tactical, and operational planning.

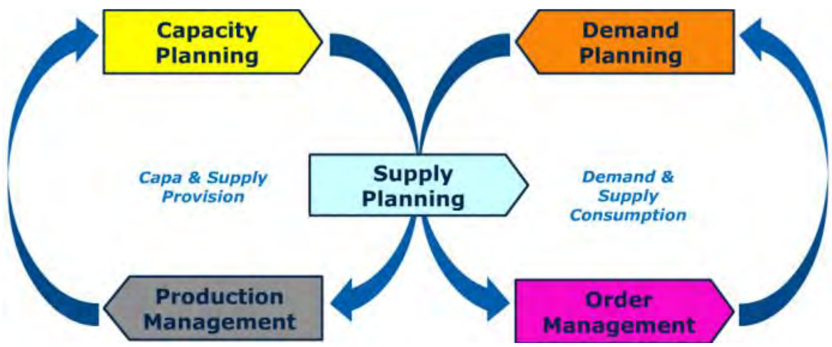

Figure 2: Overview of process elements in the plan make process as used in the industry example.

We focus on operational planning that reflects the aforementioned five step process as mentioned before. The process is operated by humans who are supported by an advanced planning and scheduling system (APS) (see Figure 3). A comprehensive description of the functionality of an APS is, for example, given by Leachman et al. (1996). Furthermore, we focus on the daily operational planning iterations that cover a planning horizon of six months.

3.2 Humans Involved in Planning

The five process elements in the plan make process consist of individual sub processes (cf. colorized elements of Figures 2 and 3). Heuristics, optimization algorithms, and human decisions constitute these processes. Theoretically, the operations could be fully automated, but specialized knowledge of humans is required to realize opportunities, mitigate risks, and stay competitive. Therefore, the sub processes are performed by several human specialists with the support of customized software tools. Certain operations are performed by software systems to reduce the workload for the planners. Consequently, successful planning processes require a frictionless interaction between human actors and software tools.

For operational capacity planning, capacity alignment planners (CAP) decide on the input for the available production resources to avoid capacity bottlenecks. Although various capacity optimization tools are used in industry (Brown et al. 2010; Ehm et al. 2011), the human control is presently indispensable to realize opportunities and mitigate risks. CAPs are responsible for the accurate representation of production capacities through the definition of capacity bottlenecks. Although actual capacity restrictions are automated, planners mitigate risks through flexible definition of bottlenecks, where needed.

On the demand side there are sales planners and demand planners. Sales planners estimate customer demand based on orders and forecasts; demand planners estimate total market demand including new products influence on production planning. This information is consolidated with time dependent, master data about production yield and work in progress (WIP) to define a production plan. A central role in the planning process is occupied by the supply chain planner (SCP). SCPs define requested stock levels at different disposition points which are either rule-based or based on experience. SCPs may include additional factors in their decision process, such as the estimated life time of products, the chances of new products to penetrate the market, or product alternatives. Production request decisions are made with different granularities concerning time and products. Granularity levels are useful to reduce the workload by aggregate planning of unproblematic products. In summary, the operational demand planning task requires three main decisions by SCPs: (1) Make to order or make to stock? (2) What demand forecast should be followed, and which granularity level to use to enter demand into the APS? (3) What stock targets to set in the APS, and for which disposition points?

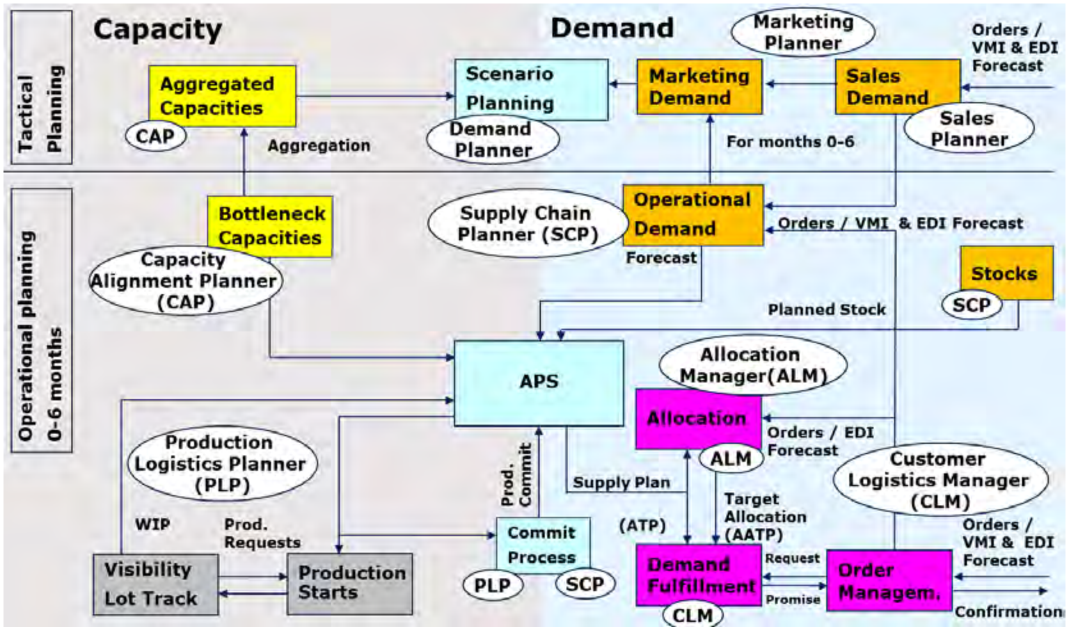

Figure 3: Interactions of planners and tools during operational planning.

The APS automatically performs the supply planning process based on the input of SCPs and CAPs who specify demand, stocks, bottlenecks, and auxiliary parameters for fine-tuning. The APS output consists of available-to-promise (ATP) information for the customer side and requests for manufacturing for the production side. These results of supply planning are established on the production and customer side. Production management is executed by the production logistics planner (PLP), and order management is conducted by the customer logistics manager (CLM).

3.3 Tools Involved in Planning

Understanding responsibilities and decisions of the planners is a necessary, but insufficient, condition to analyze and model the entire operational planning process. Deciders also interact with different software tools (cf. Figure 3) supporting them to cope with the complexity of work and to monitor organizational behavior (Hübner et al. 2010). Tools may perform sophisticated operations, such as optimization algorithms. For example, the APS uses such an algorithm to match supply and demand to generate the supply plan. Tools also support planners by housing, aggregating, sorting, and displaying information. One key differentiating factor between decisions made by humans and those made by tools is the ability of human decision makers to recognize opportunities faster and mitigate risks better than pre-defined algorithms. Automated decisions adhere to preprogrammed algorithms, heuristics or solvers. Any unforeseen input might result in (technically) correct, but unwanted outputs.

An example of human decision superiority is the acceleration of product ramp-ups due to regulatory requirements or geopolitical changes. These factors are very difficult to include in automated decision algorithms. Risk mitigation by humans involves the establishment of additional stocks for low risk products with unused capacities to increase flexibility in the future. All those actions require communication between two or more planners - often in a network.

3.4 Interactions of Humans and Tools

Complexity of the planning system is driven by interactions between different actors and the emerging behavior of the overall system. During operational planning several interactions among planners and tools take place (cf. Figure 3). For example, a CLM and a SCP may exchange information regarding customer acceptance of delivery dates for an important product which is not reflected in the tool. SCPs, PLPs and CAPs exchange information about possible, but unplanned and unlikely changes in production capabilities. Examples are the probability of unscheduled interruptions or the readiness of new equipment beyond the details already reflected in plans and schedules. These informal interactions make it possible to proactively make use of opportunities and mitigate risks in a sudden and unexpected event.

Our industry example shows, that humans are simply not replaceable by algorithms without sacrificing agility - a key competitive advantage. Although human involvement in decision making provides these benefits, acting on partial or vague information sourced from a network of distributed knowledge also bears the inherent risk of unwanted overreactions like the bullwhip effect. Human involvement in the steering of a SC therefore needs to be carefully planned, and measures to mitigate disadvantages must be installed. This necessitates research on the effects of human involvement and interaction on SC planning.

4 CURRENT RESEARCH AND MODELING APPROACHES REGARDING AGENTS IN A SEMICONDUCTOR COMPANY

A supply chain can be viewed as a "complex system consisting of a set of activities, agents, technological and physical infrastructures which interact with each other through information exchange and material flows in order to reach business goals" (Sun, Ehm, et al. 2015). To research the human involvement in this complex system, one possible approach is to conduct experimentation in a risk-free, controlled, simulation environment. The approaches presented in this section are those of a semiconductor company using the software tool AnyLogic (Anylogic 2017).

Due to the scale of the system, we divide simulation efforts according to a four level hierarchy (cf. Figure 4). The levels reach from modeling single pieces of equipment on Level 1 to models of the whole end-to-end SC on Level 4. Typical questions on Level 1 are related to tool designs, process sequences inside work centers, or estimation of lot completion dates. Level 2 models are concerned with mimicking production sites. The evaluation of control strategies and the prediction of fabrication performance are examples of Level 2. Level 3 SC simulation models address the internal SC. The aim on this level is to better understand emergent network effects and to support the planning and decision making processes. The main purpose of Level 4 simulation is to understand the interactions among the players of the end-to-end SC; an example of a SC coordination problem is known as the bullwhip effect (Lee et al. 1997).

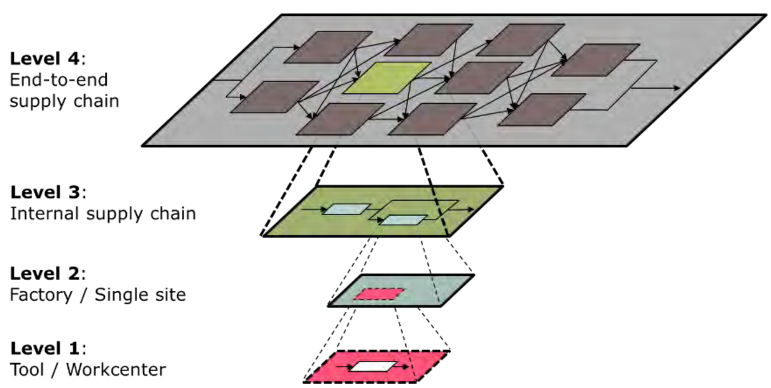

Figure 4: Hierarchy of four simulation levels (Fowler et al. 2015).

In the recent past, DES was successfully applied to simulate machines, work centers, and sites (Levels 1 and 2) to better understand and improve the manufacturing process. ABM has already been applied to model behavior of agents within the end-to-end SC on Level 4. In a first attempt, Sun, Ponsignon, et al. (2015) applied ABM to mimic overreactions in the ordering behavior along the SC using the example of the beer game. Although this is still an area for future research (e.g. by investigating other types of overreaction or the influence of decision frequency), ABM proved to be a practicable method for modeling and understanding interactions in end-to-end SC. To continue this path we decided to use the ABM approach to capture the human-system interactions on Level 3 as well. This enables research regarding the influence of interactions to understand and mitigate the negative effects of human decision maker in planning. For this approach it was necessary to first identify the agents (as shown in Section 3) and then investigate their tasks, responsibilities, decisions, and interactions.

4.1 Modeling of Human Decision Makers as Agents

Applying the definition from section 2.2 we treat human decision makers as agents in simulation models, acting autonomously, goal oriented, and intelligently (which does not necessarily mean rationally). Agents decide independently based on heterogeneous behavior rules, adapt to different system states, and form changing relationships through interactions. We identify different groups of agents depending on the planning level and planning process (cf. Figure 3). All agents act in a decentralized and distributed manner, contributing to planning decisions on different levels.

The SCP is chosen as the central agent because of the high involvement of the SCP in the planning process on an executional and operational level and because of the many interactions with other agents involved in the process. The first ABMs regarding the SCP in the semiconductor company of the industry example focused on the investigation of individual planning tasks and decisions. From this starting point one key decision, the stock target setting, was investigated in more detail. Since it was found to be difficult and insufficient to study SCP decisions in isolation, a map of the decision process and the interrelations of decision consequences to other agents was created. In addition, the impact of SCP decisions on KPIs and general SC behavior were examined. This enables the validation of SCP models with empirical data on decisions and planning performance. Currently, we combine detailed analyses of individual decisions and the existing SCP agent model into one model. This model allows for simulation experiments to identify decision triggers and decision patterns. To accurately model the difference between heuristic decisions and decisions drawn from experience, special recursive simulation techniques are used. For other agents such as the CLM and PLP, descriptive work has commenced regarding inputs, tasks, and outputs.

The modeling process of an agent needs to go from the agent in reality to a fully implemented model including all relevant tasks and interactions. Therefore, each agent is treated as an individual modeling project, which is divided into working packages of collecting task descriptions, interface definitions, and the implementation of risk behavior, learning abilities, and decision behavior. The modular nature of agent-based models enables an iterative refinement of individual model parts over time by different modelers. This enables the ability to adapt to increasing system understanding and process changes.

Only after these steps can a meaningful experimentation on the behavior of agents be conducted. In the future, the models of two or more agents will be combined into a single model to simulate interactions and to investigate the expected emerging behavior. The modular nature of ABM enables an iterative refinement of individual model parts over time by different modelers. Therefore, models can be adapted to increased system understanding and process changes during the modeling process.

4.2 Modeling of Software Tools and the SC Environment

The interaction between planners and tools is an important aspect to consider (see section 3.4). Consequently, software tools used in SC planning have also been examined as artifacts in models. The main research question is the impact of automated decisions. Existing DES models of different tools are reused and modified to interface with the agents in development to reduce the modeling workload.

Regarding the environment of the planning system in simulations, different approaches have been taken for the production side and the customer side. To accurately represent the production side, several elements of already existing DES libraries (Yuan and Ponsignon 2014) may be reused. The customer on the other hand can be modeled as an agent as well. Only in conjunction with sufficiently accurate models of artifacts and the SC environment can models of human agents be used to their full potential.

4.3 First Results of ABM Application to Semiconductor SC Planning

Modeling of the specific agents from the example is still ongoing. Nevertheless, we already generated valuable results by utilizing ABM with simpler agents. The model developed to investigate the bullwhip effect is actively used in planner training to illustrate its internal and external ramifications. The internal bullwhip effect could be decreased through this training. For a special SC disruption case, a study using ABM investigated information flow and the effects of (non-)collaborative behavior of actors. The results give advice regarding the decision on a leader or follower strategy. Another model, focused on interaction of agents, shows the impact of human behavior and agent interactions on forecast accuracy. From this model it can be concluded that interaction patterns and communication channels are needed from the beginning of modelling, instead of connecting models developed in isolation.

5 OPPORTUNITIES, CHALLENGES AND OUTLOOK

Introducing ABM as a tool for modeling the SC planning landscape of a global semiconductor manufacturer provides a promising path towards improved operational processes in an increasingly digitalized and automated SC environment. Good progress has been made towards a comprehensive model which includes crucial human decision makers. Furthermore, we have gained many insights regarding the advantages and disadvantages of this method.

The theoretical properties of ABM as described in section 2.2 make it a good fit for the existing real-world structure and challenges of SC planning. As shown in the industry example and reviewed literature, SC planning ideally involves human decision makers and their interactions. The resulting complex network is well represented through agents. The modular nature of ABM enables the development and iterative refinement of individual parts of the complete model by several modelers. This allows modeling of large scale systems, such as the presented internal SC, in acceptable time frames. The fact that ABM can be combined with existing elements from a DES library further reduces modeling effort. This advantage is additionally exploited by the use of the AnyLogic software, which combines both modeling approaches (as well as others) in one simulation tool.

However, it takes considerable effort to accurately capture tasks, decisions and interactions of SC planners. DES modelers must first readjust to the ABM approach to effectively use it. The benefit of ABM also emerges in a late phase of the modeling process when large parts of a system are modeled and experimentation involves interaction of agents, artifacts and the SC environment in one simulation. Overall we identify three main challenges when applying this method to the described problem: (1) Large scale systems demand substantial modeling efforts. These efforts need to be coordinated well. Abstraction levels as well as system borders need to be defined precisely in advance. (2) Discovering human interactions and understanding their intricate nature introduces a new field of study different from traditional operations and supply chain research. Current modelers benefit from exchange with researchers with other educational backgrounds (e.g. social science, cognitive science or psychology). (3) Modeling success depends on a well-defined interaction framework. Model parts developed in isolation need to fit together. Significant effort is required to adjust misaligned models. To support this process we suggest to use the distributed cognition perspective (Hutchins 1995) as a framework. This means guiding the modeling of interconnected agents and artifacts by the question “What information goes where, when and in what form?”

When these challenges are overcome, ABM can display its full potential. We expect ABM to help gain an understanding of human decision making in SC planning beyond the current level. Furthermore, we expect ABM to help foster the understanding of interactions between humans and systems. The knowledge gained can be used subsequently to redesign SC planning processes for optimal human involvement. The human ability to recognize and use changes can be enhanced, while the negative impact of human overreactions can be reduced or even marginalized. At the same time, workloads for planners can be reduced by automating SC planning where algorithmic decisions are applicable, thus further supporting the endeavor of a full digitalization of the SC.

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