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ADAPTION OF THE DISCRETE RATE-BASED SIMULATION PARADIGM FOR TACTICAL SUPPLY CHAIN DECISIONS

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ABSTRACT

The relative novel discrete rate-based simulation paradigm combines the advantages of the discrete event-based and the system dynamics simulation paradigms. Although its applicability is generally acknowledged in the context of supply chain management, no research works exist, that allow for a direct modeling and simulation of supply chain planning decisions within this paradigm. This paper therefore presents necessary adaptations of the discrete rate-based simulation paradigm for tactical supply chain planning decisions. Our main research contribution lies in extending the discrete rate-based simulation with modeling and material flow controlling mechanisms for enabling a simple implementation and simulation of tactical supply chain planning tasks. To evaluate different planning decisions in this context a multitude of simulation runs are necessary, creating a need for fast simulation approaches. Thus, we show formally, that discrete rate-based simulation models can generally be computed faster than commonly used discrete event-based simulation models.

1 MOTIVATION AND PROBLEM STATEMENT

Presently, supply chains operate in an increasingly complex, dynamic and uncertain business environment. Increased customer expectations, e.g. the demand for greater product choice and features, more responsive support services, and a higher product availability, drive market dynamics. The resulting higher product variety causes unstable or unknown demands due to a higher multitude of products, high rates of new product introductions and shorter life cycles (Bozarth et al. 2009). All of these factors contribute to increasingly complex planning tasks, such as the determination of capacity utilizations for manufacturing, transportation and storage facilities throughout the supply chain.

To evaluate the impact of different planning decisions in Supply Chain Management (SCM) regarding multiple use-cases, two simulation paradigms are most commonly used: Discrete event-based simulation (DES) and system dynamics (SD). These simulation paradigms are operating in a distinct matter by using different underlying principles. For example, the DES paradigm makes use of queuing theory. Changes of system states are occurring at irregularly distributed points of time, e.g. when an entity enters a waiting queue. Entities represent single logistical objects, e.g. individual products or machines. Furthermore, specific attributes can be assigned to each of the elements. These in turn are a determining factor for the future state changes (Semini, Fauske, and Strandhagen 2006). In contrast, individual entities are not explicitly modeled in the SD paradigm; they are modeled implicitly as continuous quantities instead. Changes regarding these continuous quantities occur only at predefined points of time, which can lead to a loss of information or to the creation of temporarily invalid system states, e.g. negative inventory amounts (Borshchev and Filippov 2004, Jain and Leong 2005).

A third simulation paradigm, the discrete rate-based (DRB) simulation paradigm, combines the key ideas and advantages of DES and SD. It encompasses the event handling at discrete points of times, likewise the DES paradigm, and the representation of entities as continuous quantities, likewise the SD paradigm. In particular, speed gains in comparison to DES can be achieved, when the simulation model deals with the flow of multiple goods instead of single ones, while a loss of information and the occurrence of invalid system states, as existing in SD, are avoided (Reggelin 2011). Figure 1 shows the different abstraction levels of the three simulation paradigms.

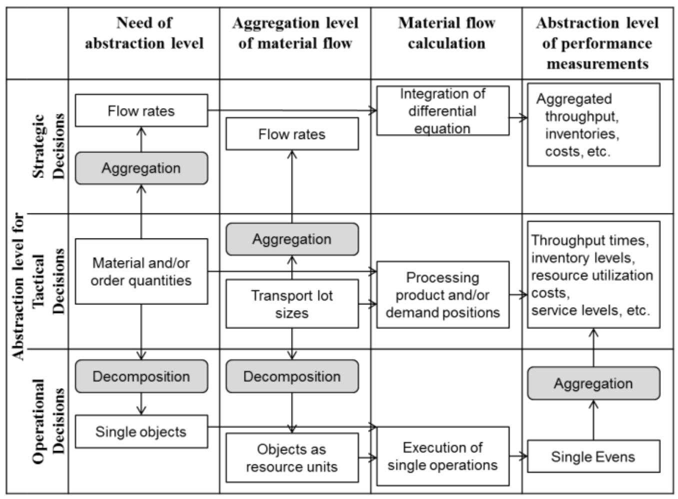


Figure 1: Different abstraction levels of simulation paradigms (c.f. Reggelin 2011).

The DRB simulation paradigm originates from Siprelle and Phelps (1997), who introduce an extension to the simulation software ExtendSim for modeling bulk, continuous batch and high speed operations. Their main research contribution is to model the material flow continuously linear. Furthermore, they represent value creation processes in a plant by using the basic modeling elements proposed by the SD simulation paradigm: Tanks, valves and conveys. These elements are used as an analogy to model and to steer the material flow, and thus need to be used when modeling a real supply chain.

Due to its practical relevance, Krahl (2008) as well as Damiron and Nasti (2008) have included this aforementioned extension into the core capabilities of the ExtendSim software framework. Krahl (2008) shows a practical case of a bottle production in his publication, applying the DRB simulation approach. He came to the conclusion that the DRB simulation approach can be used in a variety of applications, including chemical processing, pharmaceuticals, consumer product manufacturing, food manufacturing, mining, and oil and gas industries.

Two main drawbacks of the DRB simulation approach as employed in the ExtendSim simulation software can be identified: (1) Conceptual abstractions are required to create the mapping between real world supply chain facilities, like production plants and warehouses, to these model elements. (2) Furthermore, a model element can only handle a material flow of one product. A modelling of different product types being handled in parallel by one model element is not possible. Therefore, it is in turn not possible to model real world supply chain facilities, e.g. production facilities. In these, usually a multitude of end products are created using an even greater number of intermediate products.

These two drawbacks are compensated by the findings of the researchers Reggelin, Hennies, Schenk and Tolujew, who named their DRB simulation approach mesoscopic simulation (Reggelin and Tolujew 2011; Reggelin 2011; Hennies et al. 2014; Schenk, Tolujew, and Reggelin 2010). In the following sections we will only reference Reggelin (2011), where the major results of these works are presented in a condensed manner. The main research contribution of Reggelin (2011) is the extension of the previously introduced model elements, which are enabled to employ different product types in parallel in order to differentiate between flow objects with different characteristics. Further features are the ability to model predefined product routes for modeling value chain processes as well as the modeling of resource consumptions. In addition to linear continuous flows, the mesoscopic simulation introduced impulse-like flows which allow to model bundled movement of logistical objects like bundled transports. Further explanations of Reggelin's approach will be given in section 3.1.

Nevertheless, all aforementioned research contributions regarding the DRB simulation paradigm do not address the following three research questions at all. (1) How can supply chain facilities directly be mapped to the model elements used in the DRB simulation? (2) How can the information exchange be modeled and how can the material flow be controlled during a simulation run? (3) Can it be formally shown that DRB simulation models can generally be computed faster than commonly used DES models?

To address these three research questions, our paper is structured as follows: The requirements of tactical planning tasks for supply chains are elaborated upon in section two, where they are generally aligned with the most commonly used simulation techniques in this area, but also with the DRB simulation in particular. Afterwards, extensions to the mesoscopic simulation approach, addressing the first two research questions, are described in section three. To address research question three, we illustrate the runtime advantages of the adapted DRB simulation. We formally show that the computational complexity of the DRB simulation is smaller or equal compared to the DES. We conclude this paper with a discussion of our findings and an outlook towards further research in section four. Our findings enable users not being familiar with the characteristics of the DRB simulation paradigm to set up a corresponding simulation model in a simple manner.

2 TACTICAL SUPPLY CHAIN PLANNING TASKS FROM A SIMULATION PERSPECTIVE

According to Tako and Robinson (2012), supply chain planning tasks can be categorized into three groups regarding the frequency of their execution and the impacted timeframe. As such, Hellingrath and Kuhn (2002), among others, differentiated supply chain planning tasks into operational, tactical and strategic timeframes with different levels of information aggregation. Operational tasks, such as short term production and distribution planning, operate within a timeframe of minutes up to a few weeks. In these planning tasks, every single logistical object, i.e. physical goods, is considered and often detailed information of customer demands exist. This allows for an elaborate simulation using DES approaches (Kuhn 1998; Cimino, Longo, and Mirabelli 2010). On the other end of the information aggregation level, strategic planning tasks usually operate within a timespan of several months up to years and deal with long term goals, e.g. the network design. As commonly only rough estimates of demand and supply information exist for these planning tasks and due to the scope of the decisions, the used information is highly aggregated. Between the operational and strategic timeframe, the tactical timeframe deals with decisions concerning several weeks or months. Typical planning tasks on the tactical level are for example demand forecasting, network-wide master planning and company internal mid-term supply, production and distribution planning. All these tactical planning tasks make use of aggregated data, e.g. the aggregation of demands for certain products towards an overall demand for a product group. This is on the one hand necessary, because exact demands for a specific product might not be known yet and forecasts for product groups can be more exact than for specific products. On the other hand it is also sufficient, as the determination of demand allocations and rough lot-sizes is not affected negatively by not using the most detailed data (Hellingrath and Kuhn 2002).

Simulation models are a sensible tool for an evaluation of the outcomes of the planning tasks for all of the aforementioned time horizons. According to Tako and Robinson (2012), no widely acknowledged and profound argumentation in scientific literature exists, to decide which simulation paradigm should be chosen according to a specific supply chain planning task. However, in their literature review they recognized the tendency that DES models are used to evaluate all planning levels, while SD models are overall used less often with a focus on the strategic level. Nevertheless, Tako and Robinson (2012) have not recorded any usage of DRB models in their literature review. From our perspective, a possible reason for the lower adoption of the SD and DRB simulation paradigms in research and practice is the conceptual effort needed to model the processes in a supply chain as continuous flows instead of using a one to one representation, as in the DES simulation paradigm.

Generally, just like the SD, the DRB simulation is based on the assumption that material flows can be modeled by linear flow rates, describing the throughput of products in production, transportation and storage facilities. Nevertheless, in the DRB simulation paradigm changes regarding these flow-rates are connected to certain events similar to events driving a DES. Three types of events exist in this simulation paradigm, which can alter the material flow: Predefined, model specific and control specific events.

Predefined events are used to model events that are known before executing a simulation run, e.g. the incorporation of new customer demands. Model specific events depend on the state of the model. These events occur for example if an inventory level of a product has been used up and the outbound flow needs to be adapted. Control specific events are used to model planning decisions and can be state as well as time dependent. One application is the automatic generation of restocking orders after accessing a reorder level in case of stocking processes.

Figure 2 illustrates the fundamental differences between the DES and the DRB simulation approaches, in particular the material flow calculation and the associated event generation procedure,. In this example, the production lots in three different manufacturing plants are shown. Each plant has a maximum throughput of 100 products per period, and the second and third plant require the products from the first and second plant using a one to one relationship. In the DES, events are needed to calculate the number of produced goods per period and manufacturing plant. To satisfy an end customer demand of 1,000 units, each plant has to operate for 10 periods at full utilization. With the exception of different starting times due to a one period lead time between the plants, their processes can operate in parallel. Thus, events for twelve time periods have to be created. In contrast, due to modeling the material flow as a linear flow rate, the DRB simulation only generates events in six periods, as the product flows can be propagated throughout the network. In consequence, an event only needs to be generated, whenever a flow rate has to be adjusted and computational savings can be gained.

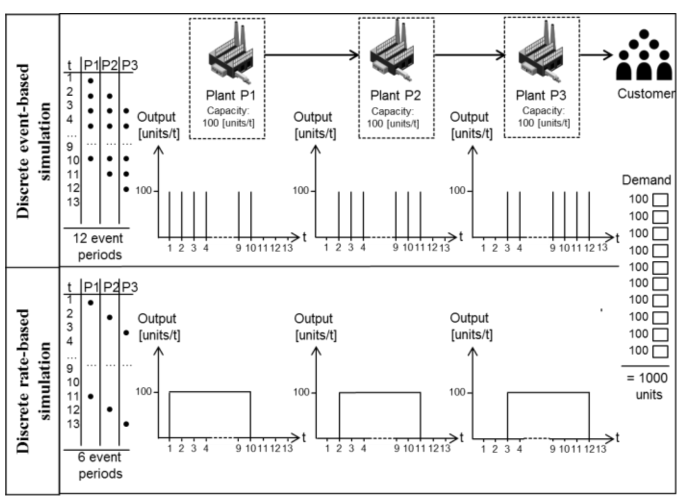
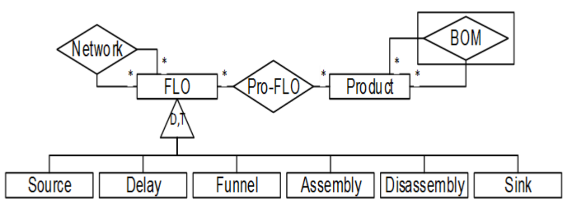


Figure 2: Discrete event-based vs. discrete rate-based simulation: Proceedings in event generation.

3 ADAPTION OF DISCRETE RATE-BASED MODELING APPROACH FOR TACTICAL SUPPLY CHAIN PLANNING PROBLEMS

3.1 Mesoscopic simulation approach

In order to be able to describe the extensions, which we have performed to transform the mesoscopic simulation approach proposed by Reggelin (2011) towards a demand-centric approach, we first describe further details of the mesoscopic simulation approach. This approach focuses on observing the changes of states in a given supply network over an investigated timeframe. For this reason, two different kinds of variables are used, namely steering and flow variables. (1) Steering variables are used to define the distribution of the material flow in the network and thus represent the main procedure of modeling planning decisions within this simulation approach, e.g. the maximum throughput capacity per supply chain facility. (2) Flow variables, which are calculated in dependence on the network structure and the steering variables, represent the material flows within the network, e.g. the transportation amounts between a warehouse and the end customer. In particular, the flow variables can be divided into input and output flow variables for each model element. Reggelin (2011) proposed six different model elements for representing a supply chain, which in turn make use of the two kinds of variables. Figure 3 introduces these model elements and gives examples for their practical application in supply chains.



Model element	Description	Examples of practical application
Source	System boundary – Entry point(s)	External suppliers – not under supply chain control
Sink	System boundary – Exit point(s)	Customer / customer groups
Funnel	Buffer processes at resources of objects	Warehouses, distribution centers, inventories
Assembly	Convergent object flows	Production, packaging
Disassembly	Divergent object flows	Dismantling, unpacking
Delay	Time delays at object flows	Production time, transportation time

Figure 3: Structural model and model elements of the mesoscopic discrete rate-based simulation.

A [Funnel] is one of the core model elements in the mesoscopic simulation. This model element can be used to buffer material flows, e.g. as occurring in warehouses or distribution centers. The main steering variable of a [Funnel] is the maximum throughput capacity. If the input flow is higher than the throughput capacity, the output flow equals this capacity and inventory amounts are created.

The model element [Assembly] is used to transform all incoming flows of several products into one or more outgoing flows of other products. In contrast, the model element [Disassembly] is applicable to model the separation of an input flow in one or more output flows. Both model elements contain steering variables determining the ratio from input and output flows. As such, a combination of a [Funnel] and an [Assembly] / [Disassembly] is used to model real world manufacturing resources.

The model element [Delay] is used for time-dependent delays during a simulation. Input flows are only send out as output flows again, after the delay time has passed. The delay time itself is a steering variable. In the context of SCM time-dependent delays are used to model waiting times or transportation times.

Furthermore, the model elements [Source] and [Sink] represent the beginning and the end of a supply chain. This allows to model real world actors like suppliers, not belonging to the actively observed members of the supply chain, and end-customers. A [Source] is used to generate flows, which will later on be propagated throughout the whole network. The [Sink] model element receives all incoming flows. It contains no steering mechanisms and simply aggregates all incoming flows into inventory amounts. Therefore, it can be used to model the customer demands in a supply chain.

The findings by Reggelin (2011) mark an important milestone in the applicability of the DRB paradigm for tactical supply chain planning tasks. Summarizing, within the mesoscopic simulation, two factors regulate the material flows through a network: (1) The initial material flow, set at the entry point of the network and (2) the material flow distribution ratio at the different facilities within the network. However, for simulating different supply chain planning decisions, it is necessary to calculate the material flow distribution ratio based on demands during a simulation run and not in advance. For example, it is only then possible to evaluate different inventory policies featured by demands generated during a simulation run for stock replenishment. In consequence, it can be stated that the mesoscopic simulation does not support the evaluation of different supply chain planning decisions directly.

In case of applying the mesoscopic simulation, it is the general procedure to calculate the steering variables in advance before a simulation run. At any time, when a material flow is processed at a model element, it is distributed in a predefined ratio, as no information exchange is modeled within this approach. For example, no customer demands are communicated. In consequence, supply chain planning tasks, which commonly operate by allocating such demands to the facilities within a supply chain, cannot be easily implemented and simulated. This can be regarded as the main drawback of the mesoscopic simulation approach, as it is necessary to make material flow steering decisions based on demands during a simulation for the application of tactical supply chain planning tasks (Kreipl and Pinedo 2004). Furthermore, Reggelin (2011) only describes the required modeling elements for some supply chain facilities. Therefore, the potential user has to invest further conceptual efforts, when creating a simulation model. Combined, these drawbacks directly lead to the first two research questions mentioned in section one.

3.2 Demand-centric discrete rate-based simulation approach

As described in the former section, the mesoscopic simulation requires the transformation of planning decisions by means of predefining values of the steering variables before a simulation run. With the overall objective of easing the creation of simulation models to evaluate planning decisions in mind, we implement new steering mechanisms automatically adjusting the material flow during a simulation run. Besides, we provide commonly used key performance indicators in the context of SCM as proposed by Kleijnen and Smits (2003), enabling a performance and cost assessment of different parameterizations.

Figure 4 shows our extensions of the mesoscopic simulation, mainly composed by (1) simplified model elements ("Supply Chain Structure") and (2) the introduction of an upstream information flow, i.e. the propagation of final customer demands ("Demand"). Although the core model elements used by Reggelin (2011) remain mostly unchanged, adaptations and additions to them were needed. We substituted the delay element, by modeling the time usage of processes through a parameterization of the other model elements.

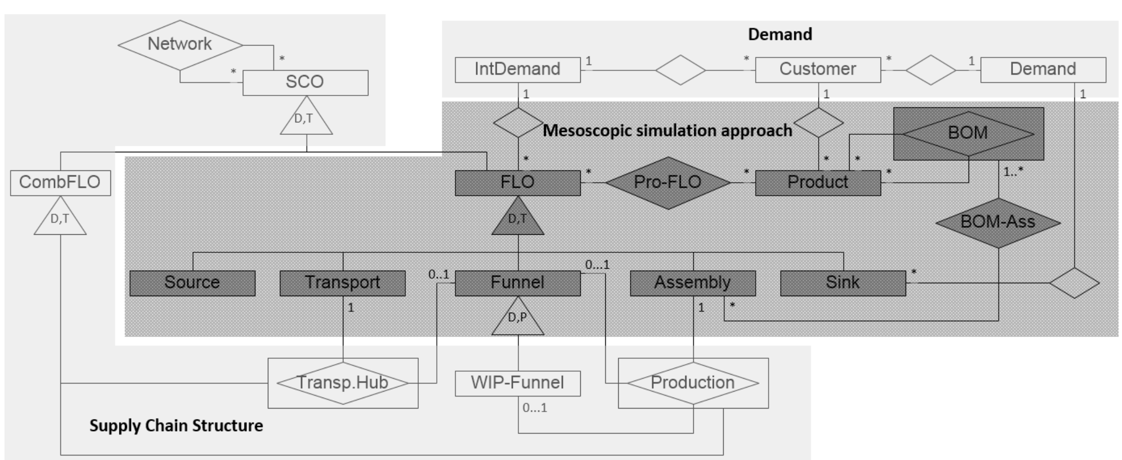


Figure 4: Structural model and model elements of the demand-centric rate-based simulation.

Furthermore, we introduced new elements to incorporate demands and structural supply chain model elements. Demands are either entering the system from end customers [Demand] or are generated by the system internally [IntDemand], and can be exchanged between model elements. The new structural supply chain model elements are used to model important supply chain activities like temporal restricted inventories, so called work-in-progress inventories [WIP-Funnel]. These inventories are used to buffer products in cases, where the transportation lot size of production facilities exceeds demands. See Chopra (2010) for further details on such temporal restricted inventories.

To reduce the conceptual effort needed to model a supply chain by means of the DRB simulation, we introduce a mapping of the three main facility types in supply chains (production, transportation and storage) to the according DRB model elements. Depending on the parameterization of these three main facility types, e.g. whether they operate customer order dependent (BTO) or independent (BTS), the appropriate underlying model elements of the DRB simulation are automatically chosen and parameterized as well. For further explanations, how BTS and BTO planning tasks differ we recommend e.g. Gunasekaran and Ngai (2009) or Simchi-Levi (2008). Figure 5 shows the supply chain modeling elements and the according modeling elements as proposed by Reggelin (2011) (c.f. Figure 3) as well as the corresponding structural composition elements (c.f. Figure 4).

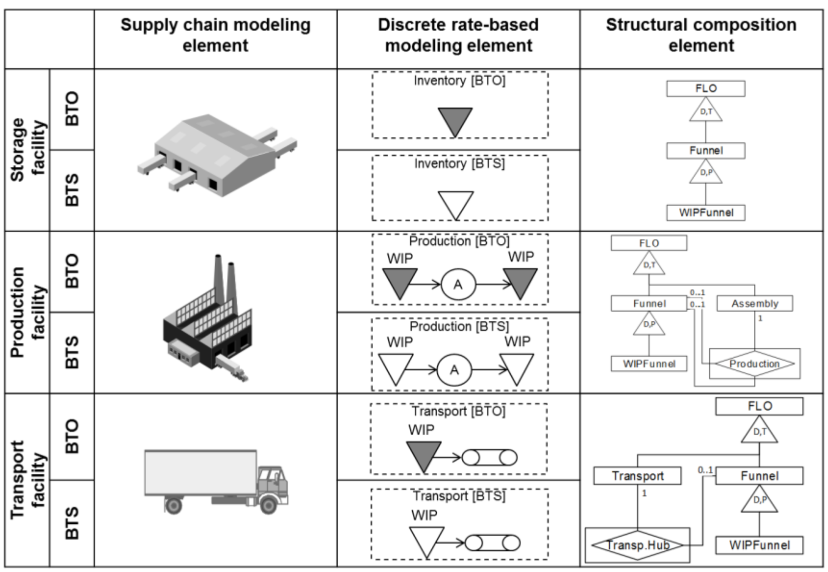


Figure 5: Mapping between supply chain model elements and discrete rate-based model elements.

At the three different facilities, the material flow is restricted by means of volume-based and flow-rate based capacities. For storage facilities, the maximum storage capacity is limited by the available volume. In case of production facilities, the throughput rate is limited by the maximum flow capacity. Transportation facilities are restricted by volume capacities to limit the transportation amount regarding the capacity of the transportation vehicle and by flow capacities to limit the transportation amount regarding the handling capacities for loading and unloading the transportation vehicle.

In general, every transport or production process starts with a [WIP-Funnel] element, in order to buffer incoming material flows. It passes the demand to the preceding model elements and gives the material to succeeding elements. If the successional elements do not have free flow or enough volume capacities to handle the material flow, the material flow stops. In contrast to a [WIP-Funnel] model element, a [Funnel] model element influences the material and information flow. In case of customer order independent supply chain parts, it can be used to model a storage facility. In this case, it does not directly pass the demand to preceding model elements. If it receives a demand, it will try to fulfill the demand, using its' stored products first. Only if the stored product volume reaches an inventory level under a certain threshold, an [IntDemand] will be generated by the [Funnel] element to refill its' inventory level.

A production facility is modeled by combining the three DRB modeling elements [WIP-Funnel]-[Assembly]-[WIP-Funnel]. The purpose of the successional [WIP-Funnel] element is to buffer the material flow after the [Assembly] element has finished the production process. The material flow is controlled by the [Assembly] model element. The [Assembly] model element checks if the preceding [WIP-Funnel] element holds sufficient amounts of intermediate products in its inventory to fulfill the demand or at least to fulfill partially the demand of the product manufactured by the [Assembly]. Besides, it checks if the three elements contain sufficient flow capacity to produce the demand and if the successional [WIP-Funnel] element has enough free volume capacity.

Transport facilities are modeled by combining the DRB modeling elements [WIP-Funnel] and [Transport]. The material flow is controlled by the [Transport] element. The element checks if the preceding [WIP-Funnel] element has sufficient inventory levels to fulfill the demand of the successional model elements. Furthermore, the [Transport] model element checks if it and the preceding [WIP-Funnel] element as well as the successional element own sufficient flow capacities. It also checks whether the successional funnel element contains sufficient volume capacities for storing the material output flow.

Each of these model elements contains its own list of demands. The setting of the steering and flow variables of the corresponding model element is then automatically derived from the current demands during the runtime of a simulation. In our demand-centric approach, output flows are only calculated, when a demand for the given product exists. In consequence, the path of the material flow through the supply chain is not predefined as in the mesoscopic simulation approach, instead it is determined at runtime by the successional model element, which has created the current demand.

3.3 Assessment of the computational savings

After the introduction of the DRB simulation paradigm in general and the adapted simulation approach in particular, this section deals with the question of how the aforementioned conceptual thoughts about the computational savings can be explained mathematically when applying the DRB simulation instead of the DES. These computational savings are the main advantage for employing the DRB simulation, as it allows for the efficient evaluation of multiple scenarios, i.e. concrete planning decisions, especially in the case of tactical supply chain planning.

A supply chain can be modeled as a directed graph representation $G = (N, E)$, consisting of nodes $n \in N$ and directed edges $(n_1, n_2) \in E$. Nodes represent the DRB modeling elements for the supply chain facilities production, storage as well as transport. Edges represent connections between these facilities. Besides, direct predecessor model elements of element n can be defined as $m \in \cdot n \mid \exists (m, n) \in E$. Consequentially, direct predecessor products of product p can be defined as $q \in \cdot p \mid \exists (q, p) \in BOM$, with BOM being the set of bill of material relations. See Ahuja, Magnanti, and Orlin (1993) for further information about suchlike graph representations of supply chains. In accordance to the DRB simulation paradigm's recalculations of material flows, a resulting event is needed, if either the corresponding variables (both steering and flow variables) in one model element n for a product p or the variables of an intermediate product ($q \in \cdot p$) of one of the predecessor model elements ($m \in \cdot n$) has to be changed. Only when neither an incoming flow variable nor a control variable for the model element n is changed, no event is generated.

The probability of an occurrence of the cases, in which an event generation has to be performed, can be calculated by (1). Hereby, $\rho_{n,p}$ describes the probability of an event generation for one product in one node. The probability of an event generation in one of the preceding nodes is calculated by the complementary probability (cf. first summand in brackets of (1)). The second summand of (1) describes the probability, that the focused model element but not the preceding model elements requires an event generation. The probability for a general recalculation in the model can be calculated by (2). The minuend represents the probability that no need of event generation exists in the simulation model.

$$\nabla_{n,p} = (1 - \prod_m^{:n} \prod_p^{\cdot p}(1-\rho_{n,p})) + \prod_m^{:n} \prod_p^{\cdot p}\left(1-\rho_{n,p}\right) * \rho_{n,p} \tag{1}$$
$$\widehat{\nabla} = 1 - \prod_n^{N} \prod_p^{P}(1-\nabla_{n,p}) \tag{2}$$

The respective computational efforts are calculated by (3) for the DES and by (4) for the DRB simulation paradigm. The computational savings applying the DRB simulation paradigm in contrast to the DES simulation paradigm are calculated by (5). It is assumed that the material flow calculations are in both simulation paradigms comparable in their complexity. Furthermore, the model is assumed to be in full utilization, requiring material flow handling in regards of every node and product. In consequence, the following conclusion can be drawn: The computational complexity of both simulation paradigms is only equal, if material calculations are necessary in every time period in both simulation paradigms. Thus, in a simulation model applying the DES simulation paradigm, material flow calculations have to be performed in every time step ($\rho_{n,p}^{DES} = 1$). If the need for an event is not given at every material flow element, which is usually the case, the DRB simulation paradigm outperforms the DES simulation paradigm regarding the computational complexity. In consequence, computational savings can generally be achieved by applying the DRB simulation paradigm.

$$\lambda_{DES} = |N| * |P| \tag{3}$$
$$\lambda_{DRS} = \sum_n^N \sum_p^P \nabla_{n,p} \tag{4}$$
$$\lambda_{Sav} = \lambda_{DRS}/\lambda_{DES} \leq 1 \tag{5}$$

The following example illustrates the computational savings applying the DRB simulation paradigm. Figure 6 depicts a multi stage supply chain with convergent and divergent material flows. The supply chain produces only one product and on average, the corresponding material flow for the product at each model element remains constant for five periods ($\rho_{n,1} = 0.2$). Although the overall probability for recalculating the material flow is 96.4%, computational savings can be achieved by 43.18%. The potential of computational savings is thereby dependent of the graph structure $G = (N, E)$ and the BOM relations. Finally, please note that although the equations in this section are only applied to a small and abstract example of supply chain models, they can be easily extended to account for other, eventually more complex, supply chain models.

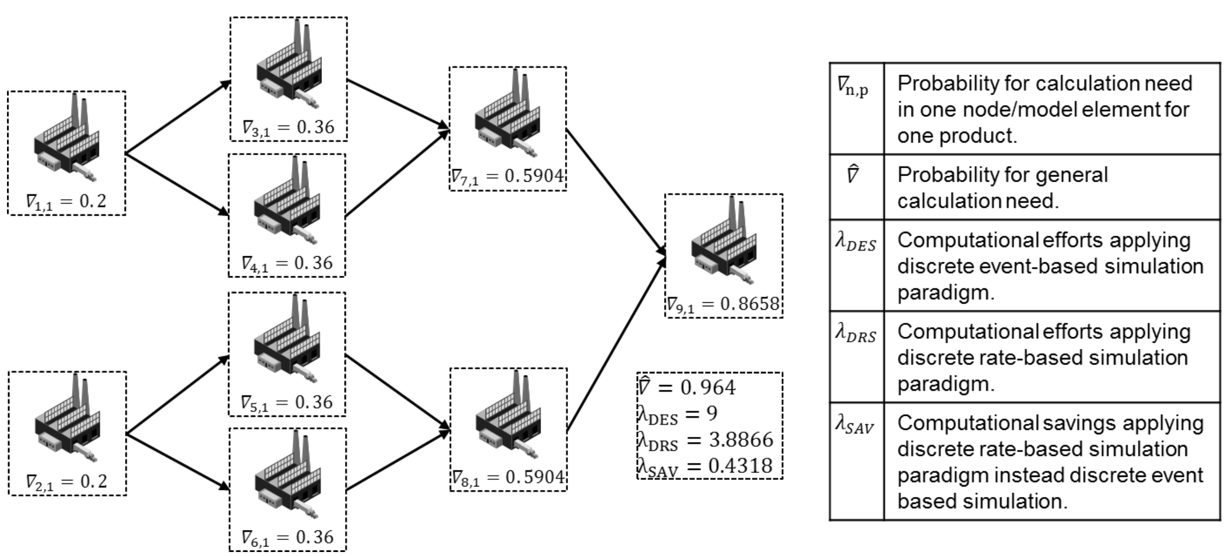


Figure 6: Achievement of computational savings applying the discrete rate-based simulation paradigm.

4 DISCUSSION AND OUTLOOK

Especially in situations where the environment of a supply chain is characterized by a high uncertainty, e.g. regarding customer demands, it is necessary that practitioners make use of a simulation paradigm empowering them to run multiple simulation scenarios in a fast manner. When undertaking attempts to simulate the information and material flow as well as measuring the resulting service levels and costs in a supply chain in dependence of concrete planning decisions, an appropriate simulation paradigm needs to be chosen. It should fit in regards to the needed abstraction level, affected by the given circumstances and objectives. In addition to the commonly used simulation paradigms DES and SD, the relative novel DRB simulation paradigm can be used, which combines key ideas and advantages of DES and SD. In particular, it is generally stated in previous scientific publications that speed gains in comparison to DES can be achieved, while a loss of information and the occurrence of invalid system states existing in SD are avoided (Reggelin 2011).

However, so far three important research questions have not been answered yet, but have been addressed in this paper: (1) How can supply chain facilities directly be mapped to the model elements used in the DRB simulation? (2) How can the information exchange be modeled and how can the material flow be controlled during a simulation run? And finally: (3) How can it be formally shown that DRB simulation models can generally be computed faster than commonly used DES models?

To answer the first research question, we created a mapping from the three facility types found in supply chains (production, storage and transportations) towards the model elements used in the DRB simulation, as seen in Figure 5. In response to the second research question, we implemented an information exchange and a material flow steering mechanism based on demands. To address the third question, we illustrated with the help of mathematical reasoning that the complexity assessment of the adapted demand-centric DRB simulation approach outperforms the complexity assessment of the DES. The overall differences between the mesoscopic simulation approach described by Reggelin (2011) and the adapted, demand-centric approach introduced by us, are shown in Figure 7.

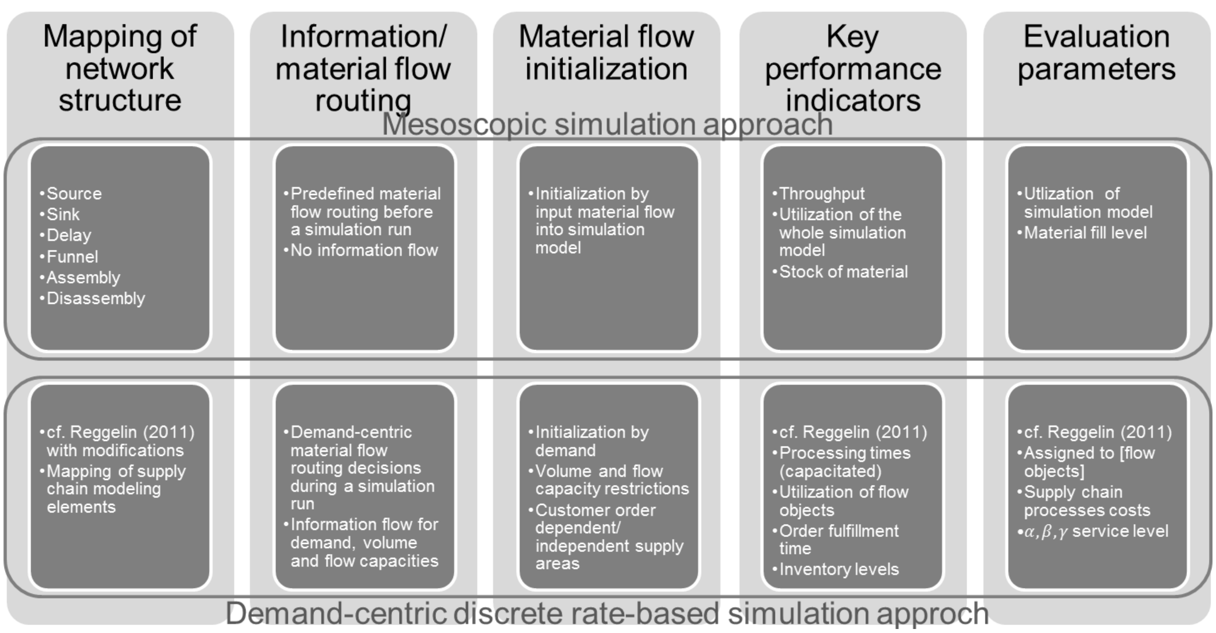


Figure 7: Comparative functionality overview between the mesoscopic and the demand-centric discrete rate-based simulation approach proposed in this paper.

In general, the three research contributions constituting our demand-centric DRB simulation approach enable an easy modeling and simulation of tactical supply chain planning decisions. Furthermore, the shown computational advantages in comparison to DES allow for a quicker evaluation of several alternative decisions. Combined, these two factors ensure that the DRB simulation paradigm is the appropriate choice when performing tactical supply chain simulations.

There are however two limitations that apply to our contributions. (1) First, the expressiveness of the findings is partially restricted to theoretical considerations and the evaluation of our proposed DRB simulation approach by means of practical use-cases is missing so far. Although the effects reducing the complexity of the DRB simulation could be revealed theoretically, they will likely vary from case to case. Further investigations are required to show that the DRB simulation paradigm is generally applicable for tactical supply chain planning tasks as well as for other simulation purposes, where the information aggregation level of the material flow is reasonably aligned. (2) Second, the mapping of supply chain model elements was set up for a simple supply chain modeling language not comprising all aspects that can be focused on in the problem domain of tactical supply chain planning. As other modeling languages can be used in accordance of the modeling purpose, we will conduct further investigations, proofing that the mapping is applicable in general.

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