Logistics Research (2018) 11:5
DOI_10.23773/2018_5

Supply Chain Disruption Models: A Critical Review

Niels Bugert [1] · Rainer Lasch [1]

Received: 21 August 2017 / Accepted: 21 April 2018 / Published online: 20 June 2018

ABSTRACT

Enterprises affected by supply chain disruptions have reported adverse consequences and dramatic financial losses. Within the research area of supply chain risk management, researchers use simulation models and algorithms to analyze disruption risks and their potential effects on the supply chain. Supply chain disruption risk models focus on ways to quantify and assess disruption risks, study interdependencies between them, and explore the dynamic behavior of risks as they propagate through the network. So far, no review has covered and evaluated quantitative decision models which focus on these specific network-related risk characteristics. This paper derives a definition for supply chain disruption risk models and analyzes existing approaches on the basis of requirements derived from the literature. Its aims are to structure existing approaches, reveal their shortcomings, and guide future research efforts to improve prospective models systematically. This analysis reveals potential improvements regarding the simultaneous integration of dynamic and interdependent aspects of disruption risks in the supply chain model as well as their propagation through the network. More process steps of a supply chain risk management framework should be supported and more mitigation strategies should be incorporated to expand the scope and usefulness of the models.

KEYWORDS: supply chain disruption · supply chain risk management · simulation · risk management · risk analysis · modeling

Niels Bugert[1], (Corresponding Author)
niels.bugert@tu-dresden.de

Rainer Lasch[1]
rainer.lasch@tu-dresden.de

[1]Department of Business Management and Economics,
Chair of Business Management, esp. Logistics,
Dresden University of Technology,
Mommsenstr. 13, 01062 Dresden, Germany
Tel. +49-351-46333140
Fax +49-351-37779

1 INTRODUCTION

Supply chain disruptions are considered to be a combination of an unforeseen triggering event and the resulting consequences which jeopardize the flow of material and normal business activities significantly [138]. Disruptive triggers can be categorized into natural (earthquake, floods, fire, etc.) and man-made (terrorist attacks, accidents, supplier bankruptcy, etc.) triggers [27]. Well documented disruption triggers have been for example the 09/11 terrorist attacks, Hurricane Mitch, and the Taiwan earthquake of 1999. The resulting consequences of a disruption can be dramatic. In 2015, a series of explosions at a container warehouse for toxic chemicals at the Port of Tianjin caused heavy environmental damage (e.g. water cyanide levels 277 times the acceptable levels), destroyed 8,000 newly produced cars (causing a direct damage of an estimated 625 million USD), and provoked a shut-down of two manufacturing plants of Toyota for multiple days [39,68]. In 2017, Hurricane Harvey, with an estimated damage of over 125 billion USD the costliest tropical cyclone on record, not only knocked out 11% of US oil refining capacity and 25% of oil production from the US Gulf of Mexico, but also shut down 90% of the country's capacity to produce and ship base plastics [24, 109]. Among the many companies which had to close production plants were, for example, American Acryl, Braskem, Celanese, Covestro, Exxon Mobile, and Chevron Phillips Chemical [21].

These examples display the dramatic consequences and dependencies between supply chain entities and their vulnerability to disruptive triggers. The risk of supply chain disruptions has increased over the last decade due to the progress of globalization as well as outsourcing and an intensified focus on efficiency and lean management [114]. According to the 2017 Supply Chain Resilience Report from the Business Continuity Institute, which surveyed over 400 companies from 65 countries, 65% of the participants had experienced at least one supply chain disruption that year [1].

Companies are not defenseless against disruptions and can notably reduce the impact of a disruptive event with the right mitigation strategies. In 2000, Nokia and Ericsson were both affected by a fire in a supplier's semiconductor production facility, but

Nokia was able to handle the situation proactively by changing the design of their chips and making use of backup suppliers swiftly. Nokia even profited from the disruption and was able to steal market share from Ericsson due to their agility [57, 122].

Since the risk of experiencing supply chain disruptions has increased over the last decade and potential strategies are capable of decreasing risks, supply chain risk management (SCRM) has become a popular research area with a growing number of publications and an increasing interest from practitioners [16]. 41% of the organizations interviewed for the BCI Resilience Report acknowledged strong top management commitment regarding supply chain disruption risks in 2017. In contrast, only 37% of the companies use technology to analyze, track, or monitor supply chain risks with 41% thereof using Microsoft Excel. Integrated decision support models for identifying and analyzing disruption risks as well as for mitigation planning and risk control on a supply network-level should be provided by this field of research to assist practitioners.

Table 1 presents the methodologies and scopes of twelve review papers on SCRM which we were able to identify by using the scientific databases ScienceDirect, Emerald Insight, and Google Scholar. We have analyzed if quantitative models are presented, if the process steps of a standard SCRM framework, namely risk identification, risk assessment, risk mitigation, and control of risks, are considered to classify articles, if models are included that cover a network perspective, if the presented models consider multiple risks and at least three supply chain entities, and if the models are not just presented but also evaluated based on derived

			Scope							
Publication	**Including models up to**	**Methodology**	**Conceptual content**	**Quantitative models**	**Only models with at least three entities**	**SCRM framework perspective**	**Network-level view**	**Models concerning multiple risks**	**Interdependencies and propagation of risks**	**Model evaluation based on requirements**
Tang 2006 [122]	2005	- LR		✓			✓			
Khan / Burnes 2007 [50]	2005	- LR	✓							
Manuj/ Mentzer 2008 [67]	2007	- LR - GT	✓							
Rao/ Goldsby 2009 [92]	2008	- LR	✓							
Tang/ Musa 2011 [124]	2008	- LR - CNA	✓	✓						
Colicchia/ Strozzi 2012 [18]	2010	- SLR - CNA	✓							
Sodhi et al. 2012 [111]	2010	- LR - SV	✓							
Fahimnia et al. 2015 [27]	2013	- LR - CNA		✓						
Ho et al. 2015 [38]	2013	- SLR	✓	✓		✓				
Snyder et al. 2016 [110]	2014	- LR		✓			✓			
Rajagopal et al. 2017 [90]	2016	- SLR - CNA	✓	✓				✓		
Prakash et al. 2017 [84]	2014	- SLR	✓	✓				✓		
This review	2018	- SLR		✓	✓	✓	✓	✓	✓	✓

LR: Literature Review CNA: Citation Network Analysis
SLR: Systematic Literature Review GT: Grounded Theory

Table 1: Overview of literature reviews in SCRM

criteria. Tang [122] gives an overview of quantitative approaches and sorts the literature regarding the broad aspects supply, demand, product, and information management. The author further classifies these fields of interest in single supply chain planning problems under uncertainties like supplier selection, the construction of supply chain designs on a network-level, supplier contracting, etc. and gives an overview of insights of research areas that deal with management strategies like product substitution, postponement, and so on. Khan and Burnes [50] present general literature on risk definition as well as risk management frameworks before discussing risk and general risk mitigation in the context of supply chain management. Manuj and Mentzer [67] conduct a literature review combined with a grounded theory methodology to adapt the concept of risk and risk management strategies to the case of global supply chains. Rao and Goldsby [92] use the classification of business and organizational risks by Ritchie and Marshall [94], synthesize the SCRM literature accordingly, and develop risk factors for each risk group. Tang and Musa [124] review 138 research papers, summarize qualitative as well as quantitative mitigation strategies according to risks regarding the dimensions material flow, financial flow, and information flow, and use a keywords co-occurrence analysis to study research clusters in SCRM. Colicchia and Strozzi [18] use the systematic literature methodology of Denyer and Tranfield [23] combined with a citation network analysis to display the dynamic evolution of the SCRM literature. Sodhi et al. [111] choose a research field study to analyze the diversity of scope and research tools in the researcher's perception of SCRM. Fahimnia et al. [27] conduct a bibliometric analysis on 489 publications to define research clusters and top contributing organizations and authors of quantitative SCRM models. Ho et al. [38] undertake a systematic literature review and provide an overview of supply chain risk definitions, risk types, and risk factors as well as process steps of a standard SCRM framework by analyzing 224 research articles between 2003 and 2013. Quantitative approaches have been structured by the supported process steps of the SCRM framework and by defined risk types like demand risk, supply risk, etc. Models which cover more than two risks simulatenously have not been considered by the authors. Snyder et al. [110] give an overview of 180 quantitative models up until 2014 that deal with supply chain disruptions. The authors structure the literature by mitigation strategies and use the four sub-categories inventory, sourcing and demand flexibility, facility location, and interaction with external stakeholders. While the presented models on inventory management are for the most part variations of the economic order quantity (EOQ) model with a single supplier, the cited models for facility location problems deal with the construction of supply chain networks considering the risk of disruption or intentional attacks. The mitigation of disruptions through interaction with external partners deals with contracting. Prakash et al. [84] conduct a citation network analysis on 126 publications from 2005 to 2016 to identify research clusters, prominent articles, mitigation strategies, discussed risks, and modeling techniques used. Rajagopal et al. [90] identify 343 publications between 2004 and 2014 through a systematic literature search and classify the articles by general criteria like geographic locations, top contributing journals, etc. and more specific criteria like the research design, types of risks, and risk factors considered. Although both reviews do not cover network-level models, models with numerous risks are included.

The identified literature reviews differ in scope and methodology. Five reviews offer an emphasis on conceptual issues, while three solely focus on quantitative approaches. Citation network analysis has been used by five reviews to identify research clusters or identify the evolutionary aspects of the field of study. Other reviews aim to give a broad overview and classify the articles. Tang [123], Ho et al. [38], and Snyder et al. [110] contain a great amount of quantitative models, but the large majority of the models deal with specific planning problems under uncertainty and date back to 2014. All reviews consider also dyadic models that include only two entities which we do not consider to be a supply chain yet ([45, 69]). A number of the identified reviews ([18, 38, 84, 124]) express the need for more holistic and integrated decision models that deal with dynamic as well as interdependent and propagative risk behavior, but we find that the existing research efforts have been largely overlooked in existing reviews so far and have only been presented marginally. Only Snyder et al. [110] present a handful of models of a given supply network which aim to evaluate the impact of disruptions, but the authors do not consider interrelations between risks, risk propagation in networks, and the dynamic modeling of multiple risks.

In this paper, we aim to identify and present modeling approaches which possibly identify and analyze numerous disruption risks, consider their dynamic and interdependent behavior on a supply chain network level, and potentially integrate mitigating or risk control possibilities. We want to evaluate the usefulness of the identified models from the viewpoint of professional SCRM managers of an already operating supply network and assess how integrated and holistic these models are, what modeling techniques are used, and which process steps of a standard SCRM framework are supported. Therefore, we not only present, classify, and condense the literature like previous reviews, but derive requirements from the literature to critically assess the identified models to guide future research efforts by presenting what modeling aspects have been neglected so far and which modeling techniques could be combined to better cater to holistic, system level decision support. Although the term supply chain has been discussed in a multifaceted way by researchers, a consensus can be reached that a multitude of entitities are considered and at least three entities are included [26, 45, 69, 117]. We therefore analyze approaches with at least three supply chain entities and assume that a supply chain structure is already given. We exclude models which do not aim at specifically supporting the SCRM framework processes like, for example, quantitative models regarding supply chain design and facility location planning, models which focus on supplier selection, one or two-stage inventory models, and the research area of risk-related contracting.

The rest of this paper is structured as follows. Section 2 develops a first definition of supply chain disruption risk models as the foundation of subsequent sections. Section 3 describes the paper's research methodology by specifying the parameters of the conducted literature search and defining the criteria of the subsequent analysis. Section 4 presents the identified publications according to the modeling technique used and evaluates the models with the help of the described criteria. After interpreting the results of the evaluation and framing a future research guideline, the last section summarizes the findings and offers a general look at future research in this field of study.

2 DEFINITION OF SUPPLY CHAIN DISRUPTION RISK MODELS

Supply chain risk is predominantly defined in the literature as an event-oriented concept in which risk strongly relates to the probability and consequence of a potentially harmful event (e.g. [73, 124, 149]). Heckmann et al. [35] broaden this traditional risk perception and also consider characteristics which influence supply chain risks like supply chain goals, risk exposure, and risk attitude. Risk exposure is further segmented into the triggering event, time-based characteristics, and features of the supply chain like vulnerability and resilience. Heckmann et al. [35] define supply chain risk as "the potential loss for a supply chain in terms of its target values of efficiency and effectiveness evoked by uncertain developments of supply chain characteristics whose changes were caused by the occurrence of triggering-events". The potential loss of a supply chain can be categorized according to its magnitude. A disturbance is seen as a deviation from normal business activities which deteriorates the accomplishments of goals [118]. A disruption is considered to be more severe than a disturbance, but a clear distinction between these two concepts is missing.

The literature offers no consensual definition of SCRM, although there has been plenty of conceptual research in this area [27]. Jüttner et al. [46] define SCRM as "the identification and management of risks for the supply chain, through a co-ordinated approach amongst supply chain members, to reduce supply chain vulnerability as a whole". The concept of vulnerability is regarded as the susceptibility of the supply chain to specific or unspecific risk events [35]. Ceryno et al. [16] combine several definitions and describe SCRM as "the identification and management of risks for the supply chain through a coordinated approach amongst supply chain members to reduce supply chain vulnerability as a whole, to increase resilience". SCRM aims to minimize, monitor, and control the probability and impact of uncertain disruptive events and therefore guarantees high performance, profitability, and continuity [16]. The notion of resilience describes the system's ability to return to a stable state after experiencing disturbances [18].

The differentiation between supply chain risk and supply chain disruption risk (SCDR) is necessary since supply chains, in general, encompass plenty of companies dispersed across the globe and only risks which jeopardize normal business activities crucially are relevant. Following the definition of Heckmann et al. [35], SCDRs can be defined as the subset of all supply chain risks with potential consequences that impede the supply chain at least temporarily of achieving its operational goals and/or jeopardize the existence of one or more supply chain partners.

Conceptual models, in general, represent a real system which may or may not currently exist. A model is created through the process of abstraction in which specific features of a real system are embedded in the model depending on its purpose [96]. Therefore, conceptual models can be classified according to their objectives. Different quantitative models exist which deal with supply chain risk either explicitly or implicitly. Models which consider risks implicitly focus on specific supply chain decision problems, and the concept of risk is part of the problem. Risk is embedded in these models, for example, by using the variance or standard deviation of variables and different value-at-risk concepts [35]. Typical supply chain decision problems focus on the supply chain network design and facility location, supplier and vendor selection, pricing and contracting as well as concepts of information sharing regarding, for example, the bullwhip effect as well as collaborative planning, forecasting, and replenishment [27]. Models which consider supply chain risk explicitly focus on the analysis of various supply chain risks, their interdependencies, and propagation in the supply chain and therefore support the objectives of SCRM and risk analysis in particular (e.g. [30, 53, 121]). The aim is to understand the dynamic behavior of the supply chain facing risks of supply chain disruptions. These models are therefore not problem-specific and more abstract, but insights from supply chain disruption modeling can show vulnerabilities of supply chains and shift the attention to specific supply chain decision problems like considering the supply chain design as part of a mitigation strategy to optimize the supply chain.

Based on the previously mentioned definitions regarding SC risks, SCDR, SCRM, and conceptual models as well as the distinction between problemspecific decision problems under consideration of risks and explicit risk modeling, we define SCDR models as:

A SCDR model represents a supply chain and all relevant potential triggering events which can potentially impede the supply chain from achieving its operational goals and/or jeopardize the existence of one or more supply chain entities and includes all necessary static and dynamic features to describe potential losses for all supply chain partners in terms of the supply chain's target values in order to support the coordinated approach amongst supply chain entities to reduce supply chain vulnerability and to increase the supply chain's predicted ability to return to a stable state after experiencing disruptions in the real system.

3 RESEARCH METHODOLOGY

To attain this paper's objectives, it is necessary to conduct a critical review on SCDR models. A review is not based on new scientific insights primarily, but rather digests, classifies, and synthesizes already publicized research results to compare, integrate, and evaluate prior findings and give suggestions for future research activities [66]. A critical review aims to synthesize existing research articles and to evaluate them against criteria [20]. Its strength is the ability to constructively highlight discrepancies in the literature and stengthen new insights by giving a direction for further improvement [76]. Critical reviews focus on specific sections of a research area and rarely include an exhaustive look at a complete field of study [51]. Our literature search is based on the framework of Fink [28], who described seven steps aimed to ensure a systematic, explicit, and reproducible literature review. The first step of this framework (1) consists of formulating research questions to specify the target of the study. The next four steps design the literature search by (2) selecting relevant bibliographic databases, (3) defining appropriate search terms, and (4) applying practical as well as methodological screening criteria (5) in the form of exclusion and inclusion criteria. Practical screening criteria include factors like the articles' language and time-aspects, while methodological screening criteria cover the papers' scientific quality and adequacy for the purpose of the review. After abstracting information from the articles (6), the findings are synthesized descriptively and/or statistically (7).

The following research questions (RQ) specify the goals of this review:

RQ 1: What risk-specific modeling characteristics and evaluation criteria can be defined?
RQ 2: Which modeling techniques are used for supply chain disruption modeling?
RQ 3: How well do the identified models and modeling techniques take the identified risk-specific modeling characteristics into account?
RQ 4: What process steps of a standard SCRM framework are supported by the models?
RQ 5: What potential improvements can be formulated for prospective models and modeling techniques?

3.1 Literature search

An extensive literature search is the foundation of a review and aims to locate an exhaustive and problem-specific set of publications on the topic of interest [20]. A literature search should focus, according to vom Brocke et al. [137], on peer-reviewed articles to ensure credible and reliable information sources. The search should not be limited to a specific research method, a small number of journals, or a prearranged geographic region [142]. Our search therefore considers multiple scientific databases, namely ScienceDirect, Emerald Insight, Google Scholar, Inderscience, and Taylor & Francis. The mandatory keywords used for data collection are chosen to be "Supply Chain" or "Supply Network" as well as at least one of the following keywords in the publications' title, abstract, and keywords, combined with "OR" operators: "Risk", "Disruption", "Disturbance", "Simulation", "Interdependence", "Propagation", "Quantitative", "Optimization", "Optimisation", "Crisis", "Catastrophe", "Terror".

The literature search includes published and not yet published but accepted papers from 2001 to early 2018. The year 2001 has been chosen since the 9/11 terrorist attacks dramatically shifted attention to the field of risk management. Tang and Musa [124] state that between 2000 and 2003, the number of articles in SCRM slowly started to increase, but the content was mainly qualitative. Since the topic of interest is focused on the concept of supply chain and risk and since our search string is relatively open, we concluded that relevant keywords would be part of the publications' titles, abstract, and keywords. We therefore could reduce the number of search results to a modest amount. The abstracts were used to evaluate the papers' relevance. Since we put ourselves in the shoes of SCRM managers of functioning supply networks facing a large variety of disruption risks simultaneously and suitable to the scope and aim of this review, exclusion criteria were determined to be:

- No risk mentioned,
- Approaches with a focus on contracting issues, supplier selection, inventory management (EOQ) models, and the construction of a supply chain design (facility location problems),
- Less than three supply chain entities considered,
- Review papers,
- Pure risk identification or risk ranking if there is no focus on risk interdependencies.

The identified publications were used as an input for a backward and forward reference search.

3.2 Evaluation criteria

One crucial aspect of this analysis, which has not been considered by any other of the prior reviews in the field of SCRM, is the formulation of evaluation criteria. These criteria should preferably include all critical evaluation dimensions and be clearly delimited from each other. In our case, main evaluation criteria are taken from the literature on conceptual modeling in operational research and business process modeling and are specified according to our definition of SCDR models as well as related statements of authors in the field of risk modeling.

According to Pritsker [85], the modeling process is difficult since there are no quantitative criteria for evaluating the value of a model. Teeuw and van den Berg [128] build an evaluation framework for business process models and introduce three external quality criteria for conceptual models which are used to evaluate the value of the model for the user or client: "completeness" (all essential aspects are integrated), "inherence" (the model focuses on essential aspects), and "clarity" (the model is comprehensible by the user and as objective as possible). Robinson et al. [95] summarize the quite manageable number of publications in the operational research field and identify four main requirements for an effective model: "validity", "credibility", "utility", and "feasibility". While the criteria "validity" is defined by Robinson et al. [95] as the perception of the modeler that the model is sufficiently accurate for the purpose at hand, the criteria "credibility" measures the same aspect but from the possibly different viewpoint of the client or user of the model. "Utility" describes the usefulness of the model and includes subcriteria like "ease-of-use", "flexibility", "visual display", and so on. The fourth criteria, "feasibility", refers to the amount of resources (time, data, etc.) necessary to build the corresponding computer model.

We focus, according to our first research question (RQ 1), on evaluation criteria specific to SCDR models. We therefore subdivide the content-specific main criteria "credibility" and "completeness", "inherence", and "clarity" by applying our definition of SCDR models and leave out risk-unrelated main criteria like the general "usefulness" and "feasibility" of the models. Measurable indicators for each subcriteria are defined so that criteria can be either not satisfied (denoted by ○), partially satisfied (denoted by ◑), or completely satisfied (denoted by ●).

According to our definition, a SCDR model should focus on relevant disruption risks. A focus on disruption risk is indicated by including at least one explicit disruption risk into the model (●). If no disruption risk is incorporated, this criteria is not satisfied (○). Relevant operational risks can be incorporated additionally into the models but should not be the complete focus. Various SCDRs can be distinguished. They can be classified according to the risk sources as external or internal risks. External risks, which emerge from outside the supply chain, are for example natural disasters like floods, earthquakes, or epidemics as well as political instability like wars, terrorism, and market uncertainty, which can come from price and exchange fluctuations as well as economic downturns. Internal risks can be caused by risks regarding the internal operations, such as quality issues or forecast inaccuracy, as well as risks regarding the information system and the available capacity, when for example a supplier files for bankruptcy [74]. Approaches which contain at least one and up to three risks satisfy this analysis criteria partially (◑), while approaches with more than three disruptions risks satisfy this criteria fully (●).

According to our definition of SCDR models, the anticipated losses due to SCDR need to be quantified. One possible way to quantify the losses consists of an integration of risks into model parameters by using standard deviations or value-at-risk concepts which statistically measure the maximum possible loss at specific percentiles [16]. Similarly, Spekman and Davis [112] define risk as the probability of variance in an expected outcome. A different, standard approach is the explicit risk quantification using the likelihood of occurrence multiplied with the expected impact of the risk event to obtain the expected loss [3]. To quantify the probability and impact of risk events, models can use historical data and/or expert knowledge. Knight [54] distinguished in his definition of risk between certainty, "measurable" uncertainty (quantitative), and "unmeasurable" uncertainty with no or partial knowledge of outcomes in the form of beliefs. According to this notion, Klibi and Martel [53] define three types of uncertainty. Randomness describes a business-as-usual fluctuation of random variables, while hazard is categorized by unusual situations with low probability and high impact. Deep uncertainty consists of a total lack of any information regarding the likelihood and outcome of future events. The latter two categories are relevant for disruption risks so that models should be able to handle uncertainty in the form of hazard and deep uncertainty. Models which use historical data as well as expert interviews to quantify risk fully satisfy this criteria (●), while models which use only expert knowledge or only historical data partially satisfy this criteria (◑).

Since a supply chain by definition is a system of multiple entities which are connected via material, monetary, and information flows, supply chain partners are influenced by connected companies and associated risks [5]. These interdependencies have increased due to trends such as outsourcing and globalization [22, 113]. Qazi et al. [86] identify holistic methods for capturing interdependencies between risk factors across the entire supply network as one important issue for future research in the field of SCRM. Modeling approaches should therefore take these interdependencies into account. This criteria is fully satisfied (●) if a model systematically analyzes and evaluates the existence and strengths of risk interdependencies. Partial satisfaction is present if a model takes risk interdependencies into account but does not consider their strength and does not use a systematic methodology to identify the interdependencies (◑).

Risk propagation is a consequence of existing risk interdependencies. It can be classified in upstream and downstream risk propagation. The propagation speed is dependent on the frequency of the information, material, and cash exchange in the supply chain. The impact of propagation can decrease along the network as buffers in the supply chain dampen the effect [121]. It is possible that overdependence of supply chain partners leads to an amplification of disruptions [119]. Understanding the propagation of disruptions helps to design mitigation strategies and reduce the impact of risks [145]. Several authors agree that there is a lack of quantitative models that compute propagation effects of disruptions at multiple stages of the supply chain [31, 82, 127, 134, 136]. Qazi et al. [86] also stress the importance of future research on risk propagation. Models which partially satisfy this criteria merely model the propagation of the risk impact (◑), while a complete satisfaction of this criteria is given if different propagation measures are used to quantify the propagation itself and if the likelihood as well as impact of propagation is modeled (●).

A system, in general, consists of an organized and an ordered finite set of variables and elements which interact with each other [29]. Strong interactions between a system's variables, time dependency, a complex causal structure, and delayed behavioral reactions characterize a dynamic system [6]. Therefore, supply chains can be regarded as dynamic systems. Since supply chains interact with their environment, they can also be viewed as open systems. External as well as internal risks are dynamic by nature and influence these systems [108]. To understand the temporal characteristics of risks, dynamic models are appropriate to describe the behavior of supply chains under the influence of risks. Elangovan et al. [25] as well as Colicchia and Strozzi [18] point out that more dynamic models are needed in risk management. This criteria can either be satisfied in the case of a dynamic model (●) or not satisfied in the case of a static model (○).

According to our definition, SCDR models should support the objective of SCRM by helping to reduce supply chain vulnerability and increase supply chain resilience. Supply chain vulnerability and resilience can be optimized by appropriate strategies if the future risk situation of the supply chain can be predicted well. Helbing et al. [36] state that due to the increased complexity of modern supply chains, it has become hard and even impossible to predict impacts of any events. Ghadge et al. [31] describe the behavior of supply chain risks as unpredictable and chaotic. Discrete events of low likelihood are often hard to be estimated due to lack of data. Some supply chain disruption triggers like hurricanes in the Gulf of Mexico or heavy snowstorms in the Alps can be estimated relatively well [132]. SCDR models should therefore not only predict the triggering event but also potential consequences of the supply chain (●). If probabilities cannot be quantified, the impact of disruptive events can be assessed as one important part of risk analysis (◑).

Evaluation criteria	Indicator of fulfillment
Focus on disruption risks	○: Only operational risk / risks included ●: Considering at least one disruption risk
Number of considered risks	○: Model contains one risk ◑: Model contains more than one and up to three risks ●: More than three risks considered
Data basis of risk concept	○: No data basis used ◑: Expert knowledge or historical data includable ●: Expert knowledge and historical data includable
Consideration of risk interdependencies	○: No risk interdependencies ◑: Model assumes specific risk interdependencies without analysis ●: Risk interdependencies systematically derived
Risk propagation	○: Risk propagation not considered ◑: Propagation of consequences considered ●: Propagation of risks considered
Dynamic modeling of risks	○: Static model ●: Dynamic model
Prediction of risks	○: No prediction included ◑: Prediction of risk consequences ●: Prediction of risks included
Risk optimization	○: No risk mitigation included ◑: Mitigation strategies included, but not systematically chosen ●: Numerous strategies considered, systematically chosen

Table 2: Derived evaluation criteria for SCDR models

According to Chopra and Sodhi [17], there is no silver bullet strategy to prevent or to completely reduce the impact and likelihood of disruptions singlehandedly. Mitigation strategies are calculated actions taken by a firm to lessen the risks of a disruption. These actions are proactive and are taken before a potential disruption occurs. Contingency plans are reactive and are implemented once a disruption has taken place [130]. Zsidisin and Ritchie [150] divided mitigation strategies into four categories: (1) eliminate the risk, (2) reduce the frequency and consequences of the risk, (3) transfer the risk by means of insurance and sharing, and (4) accept the risk. The specific actions taken by managers depend on the nature of risk, company's resources, their business strategy, and many more factors. Contingency plans are short-term measures taken like demand shifting to other not impacted products or increasing production at alternative suppliers [130]. In general, mitigation strategies come at the cost of less operational efficiency, but visibility across the supply chain is one example of a mitigation strategy that is believed to also boost efficiency, according to Stecke and Kumar [114]. Since there are so many potential disruptive triggers inside and outside the supply chain, the planning of a mitigation strategy is difficult and more than a single strategy needs to be implemented. Qazi et al. [86] emphasize the need for evaluating combinations of mitigation strategies. This criteria is fully satisfied if the SCDR model analyzes mitigation strategies and their expected consequences and comprehensively chooses the most effective strategy / strategies (●). The criteria is partially satisfied if the model incorporates mitigation strategies without a systematic selection procedure (◑).

This paper focuses on risk-related criteria and leaves out general criteria like the flexibility of the modeling approaches and the modeling complexity. Table 2 shows distinct and measurable indicators of the analysis criteria.

4 EVALUATION OF IDENTIFIED SUPPLY CHAIN DISRUPTION MODELS

With the previously described literature search, 57 papers were identified. Fig. 1 gives an overview of the temporal development of this field of research. It can be seen that in recent years publications have increased in general and it can be expected that prospective research output will further expand in the future. The identified literature contributions can be categorized according to the modeling techniques used. Table 3 shows that Petri Nets, System Dynamics, and Discrete-Event Simulation are the top three most popular modeling techniques in this field of study. Together these three modeling techniques make up a little more than 50% of all approaches. Bayesian Belief Networks are used in six publications, Agent-based Modeling in five, and Interpretive Structural Modeling, Monte Carlo Simulation, and Input-Output Modeling are applied three times each. Around 11% of all papers consist of approaches that have been utilized once so far (RQ 2).

Since different modeling approaches have characteristic features as well as advantages and drawbacks, it is useful to organize the following subsections according to the techniques applied. Each modeling approach is briefly introduced and each publication is presented. All papers of each group will be analyzed according to the criteria conceived above (RQ 3), and it will be shown which process steps of a standard SCRM are supported by the paper's models (RQ 4).

4.1 Petri Nets

Petri Nets (PN) are a graphical and mathematical modeling technique for describing and analyzing Discrete Event Systems [79]. A PN is a bipartite graph which consists of a set of places, a set of transitions, directed arcs that connect a place with a transition and vice-versa, and so-called tokens. Places represent

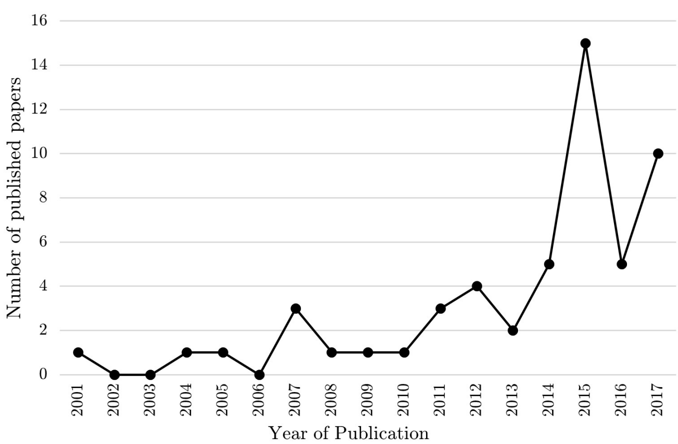


Fig. 1: Publishing trend of supply chain disruption risk models

Modeling techniques used	No. of instances	Quota
Petri Net	12	21%
System Dynamics	11	19%
Discrete-Event Simulation	8	14%
Bayesian Belief Network	6	11%
Agent-based Modeling	5	9%
Interpretive Structural Modeling	3	5%
Monte Carlo Simulation	3	5%
Input-Output Modeling	3	5%
Other approaches	6	11%
	$\sum$ 57	$\sum$ 100%

Table 3: Quantity of modeling techniques used

possible states or conditions of a system, whereas transitions visualize actions or events and display how states can potentially be transformed. The actual system state at a certain time is visualized by tokens. Tokens are depicted as small filled circles inside places and show if a condition is met to perform a transition in the system [14]. The main feature of a PN is that its state is a vector of nonnegative integers. PNs have been shown to be an effective modeling technique due to their ability to visualize parallelism, concurrency, synchronization, etc. [10]. E-commerce systems, agent-oriented manufacturing systems, production systems as well as enterprise resource planning systems have been modeled by PNs [55, 60, 146].

Blackhurst et al. [8] use a PN approach to model operative uncertainties in a four-tier supply chain. The authors develop a so-called Probability-based Trans-Net which symbolizes the manufacturing process of the finished process, subassembly parts, and raw material and incorporates historic data. The total costs of production and shipping as well as the lead time are used to assess supply chain activities. Four different probability-based transition functions are developed of which three are used for the case study. Two methods can be used for the total cost attribute of the Trans-Net, while the last method is helpful for the lead time attribute since the maximum lead time will be a constraint for the system. The Trans-Net is helpful when analyzing the supply chain with respect to specific attributes under the influence of uncertainty. Wu et al. [145] apply a PN to a four-tier supply chain and model the propagation of disruptions. The authors model production processes on an operative level and consider the cost and lead time increase of a disruption. The reachability set provides insight into the affected nodes of a disruption and simplifies the analysis since the affected subgraph of the so-called Disruption Analysis Network (DA NET) can be significantly smaller. A decision-making logic is incorporated into the model so that the initial order quantity affects where the parts are routed, the lead time of the orders, and the cost to run the order. The network is able to analyze different policies or different supply chain designs with respect to the lead time and cost effects.

Liu et al. [64] use a time colored PN to model cause and effect relationships of expected events and unexpected events (exceptions) and their effect on the system. A group of simple events occurring simultaneously may cause potential problems so that their interconnectedness needs to be studied. The authors display ways to model several event patterns in a PN connected by logic connectives as building blocks and ways to create new user-defined patterns by combining the patterns to exhibit more complex interactions. Dependency graphs are presented to be able to condense the cause and effect relationship between events and identify important exceptions. Reachability analyzing techniques for time colored PN are not feasible for large problems due to the complexity of the interrelationships between events. The authors simulate the operative processes of a two-tier supply chain with two alternative suppliers. The inter-arrival times of customer orders, the occurrence of production delays, as well as their resolution times are modeled stochastically. The effect of two mitigation strategies (reducing resolution time of production delays and increasing probability of finding alternative sourcing) on the base case performance measures are studied. The most important performance measures considered are the customer order fill rate and the average replenishment time of rush supply orders.

Blackhurst et al. [7] present a methodology which analyzes supply chain processes via PNs and systematically detects possible conflicts in the system as a source of supply chain disruptions. The authors dissipate the supply chain system in multiple so-called single system modules which are each modeled by a PN and subsequently synthesized into an integrated system using the synthesizing module. The single system module consists of multiple predefined components which can be linked together to enable easy customization of the model to individual needs. The single system modules are linked via AND and OR operators. More complex dependency types can be constructed through these simple operators. After each synthesizing process, conflict detection is conducted in order to cope with the size of the problem. Conflict detection is performed with the system conflict detection module, which uses matrix equations to detect possible conflicts. The model assumes that conflicts arise if final states of the system cannot be reached by the model's initial state. Tuncel and Alpan [133] study the effect of mitigation strategies on performance measures of a four-tier supply chain in the case of a medium-sized manufacturer in Turkey and its business partners. The authors use the Failure Mode, Effects and Criticality Analysis (FMECA) for risk identification. The data basis consists of expert interviews, brainstorming, crossfunctional teams, as well as historical statistical data. By ranking the possible disruption factors by their risk priority number, the model incorporates the three top-valued risks (quality failure of the supplier, transportation failure risk, system failure risk of the manufacturer) as well as corresponding mitigation strategies (decrease of risk occurrence probability). Nine different scenarios are simulated. For each risk the exposure level can be high (no mitigation), moderate, or low. If a mitigation strategy is implemented, a specific fixed cost is taken account of. Process times, customer order inter-arrival times, transportation times, etc. are incorporated as stochastic parameters. Performance measures like the total revenue, customer order fill rate, and percentage of orders fulfilled on time, delayed, and canceled are recorded.

Zegordi and Davarzani [148] extend the model of Wu et al. [145] by incorporating multiple disruption risks and considering the interdependencies of their risk impacts. The authors study the effects of sanctions on a five-tier supply chain situated in Iran with foreign sub-suppliers. A sanction changes supply chain processes and payment procedures depending on the specific case so that the procurement costs and lead times increase. In addition to a sanction, the model considers supplier financial inability, inflation, and fluctuation of exchange rate and their interdependencies. Experts' knowledge and experience are used to define the parameters.

John and Prasad [43] extend the model of Blackhurst et al. [7] and use a colored PN for conflict detection.

Kano et al. [47] use a PN to dynamically model the recovery of a supply chain after a disruption occurred. The authors consider a three-tier supply chain with safety stock and globally dispersed entities and assume that, after the material flow stops from the supplier to the manufacturer, the manufacturer looks for a new supplier and is able to start production with the new supplier after a certain time. The simulation consists of two scenarios (one without a disruption and one with a disruption of the supplier). To measure the impact of the disruption, the accumulated productivity regarding the simulation time span is analyzed.

Blos and Miyagi [10] combine Inoperability Input-output Modeling (IOM) with PN Modeling. IOM originally stems from Leontief 's Input-output Model [58], which is a useful tool to study consumption shocks on interdependent economic systems [99]. IOM attempts to foresee the resulting economic losses and inoperability suffered by different interdependent industry sectors [34, 100]. Wei et al. [143] use IOM to model the propagation and interdependencies of disruptions in supply chains, which will be discussed in section 3.6. Blos and Miyagi [10] formulate the model of Wei et al. [143] with the PN technique. So-called Encapsulated PNs (EPNs), which consist of a place node and a transition node, substitute the nodes in IOM modeling. Each EPN represents a function or supply chain entity and is combined with directed arcs that visualize the point of disruption, the transmissions of a disruption, and the recovery to a normal operating mode.

Zhang [147] models stock-outs occurring in a three-entity supply chain with two competitive products (with two different product sizes for each brand) with a high-level PN. The author analyzes the effect of five different customer behaviors and the effectiveness of information sharing on the inventory level, the backlog, and the bullwhip effect, quantified in this model by taking the variations of production and demand rate into account. Switching the store and delaying their purchase has a significant negative effect on the performance measures. Information sharing can have a positive impact but depends on the pattern of the customers' behavior.

Blackhurst et al. [9] combine a PN with a Triangularization Clustering Algorithm to identify the propagation path of disruptions and to find critical nodes in complex supply networks. After constructing a PN of the supply network, the structure of the PN is transferred to a Node Dependency Matrix, which contains the dependencies of places and transitions with a binary digit. The nodes and transitions are sorted by their strengths of dependency to define levels, and loops are identified to define cycles. If a disruption occurs at a node in a specific level, only subsequent levels will experience material outages. Cycles are vulnerable parts of the network and need to be monitored closely, according to the authors.

Liu et al. [63] use a colored PN to model the information and material flow of perishable products in a linear, five-entity supply chain and to control product quality risk based on sensor data. Environmental parameters, e.g. time-temperature data, processing parameters, e.g. the type of processing step, and quality parameters like the decay rate and quality grade of inspection are registered on sensors and transferred along the entities of the supply chain. A complex PN of all operating and information processes is built and analyzed together with the time-series data for risk identification, impact assessment, and risk control. Five risk grades range from perfect quality to inedible quality. Table 4 gives an overview of the modeling approaches with respect to the derived analysis criteria. The PN-based models generally focus on the impact of possible risk events in the form of what-if analyses. Liu et al. [64], Tuncel and Alpan [133], and Zhang [147] incorporate more than one and up to three risks in their models. Liu et al. [64] concentrate on the interdependencies of operative risk events, while Tuncel and Alpan [133] focus on the effect of mitigation strategies in the face of multiple disruption risks. Zhang [147] analyzes different possible customer responses to stock-outs and tests mitigation strategies.

Petri Nets	Focus on disruption risks	Number of risks	Data basis of risk concept	Risk interdependencies	Risk propagation	Dynamic modeling of risks	Prediction of risks	Risk optimization	Risk identification	Risk assessment	Mitigation of risks	Control of risks
Blackhurst et al. 2004 [8]	○	○	◑	◑	◑	○	◑	○	○	◑	○	○
Wu et al. 2007 [145]	●	○	◑	◑	◑	○	◑	○	○	◑	○	○
Liu et al. 2007 [64]	○	◑	◑	◑	◑	●	○	◑	○	◑	◑	○
Blackhurst et al. 2008 [7]	●	○	○	◑	◑	○	◑	○	◑	○	○	◑
Tuncel / Alpan 2010 [133]	●	◑	●	◑	◑	●	○	◑	◑	◑	◑	○
Zegordi / Davarzani 2012 [148]	●	○	◑	◑	◑	○	◑	○	◑	◑	○	○
John / Prasad 2012 [43]	●	○	○	◑	◑	○	◑	○	◑	○	○	◑
Kano et al. 2013 [47]	●	○	◑	○	◑	●	◑	○	○	○	◑	○
Blos / Miyagi 2015 [10]	●	○	◑	◑	◑	○	◑	○	○	◑	○	○
Zhang 2016 [147]	●	○	○	○	○	●	○	◑	○	◑	◑	○
Blackhurst et al. 2017 [9]	●	○	○	◑	◑	○	◑	○	◑	○	○	◑
Liu et al. 2017 [63]	○	○	◑	○	◑	○	◑	○	●	◑	○	●

Table 4: Comparison of Petri Net approaches to model supply chain disruption risks

John and Prasad [43] as well as Blackhurst et al. [7] aim to detect conflicts as a possible source of a disruption by using a PN technique. The model therefore does not use historical data or expert knowledge to quantify risks. Tuncel and Alpan [133] integrate historical data and expert knowledge simultaneously for risk identification, while other PN approaches use expert knowledge as a sole source of information. Some approaches model the interdependencies in the system dynamically but concentrate on the impact of risks and not on the risk interdependencies themselves. Kano et al. [47] focus on the recovery process after a disruption occurs and therefore model the risk propagation without considering interdependencies.

Four approaches in Table 4 use simulation studies to analyze the supply network dynamically. Basic risk prediction is mainly incorporated into the models since most approaches carry out what-if analysis, which helps to understand possible consequences. Proper risk prediction is not part of these studies. Liu et al. use sensor-based time series data to manually assess and partially predict quality risks of the considered products. This approach also supports risk control through sensor information. Liu et al. [64] as well as Tuncel and Alpan [133] partially optimize the risk situation of the considered supply chain. Both approaches test the mitigation strategies' effectiveness with respect to performance measures, but do not optimize risk itself.

The right part of Table 4 gives an overview of the supported framework steps of the articles. Most articles focus on risk assessment. The approaches of Blackhurst et al. [7] and John and Prasad [43] concentrate on risk identification and risk control since these approaches aim to detect conflicts in the supply chain which can lead to serious damage.

4.2 System Dynamics

System Dynamics (SD) is a modeling approach which aims to analyze complex and dynamic systems. In its essence, SD explains the dynamic behavior of a system as a consequence of the system's structure [93]. According to this approach, the structure of a system consists of elements that interact with each other through delayed cause-and-effect relationships and information feedback [116]. A model includes multiple causal loops which can either balance or reinforce fluctuations of variables. The relationship between elements is described with equations [52]. SD has been applied to various research areas such as supply chain management, biological and medical modeling, theory development in the natural and social science, and so on [2]. Nine models have been identified which use SD as the modeling technique of choice.

Wilson [144] uses SD to examine the effects of transportation disruptions on a five-echelon supply chain with fixed transit times. The author compares a traditional supply chain and a supply chain coordinated by a vendor managed inventory system (VMI). In the conventional arrangement only downstream demand information of the direct partners are known. In the VMI structure the retailer and the first-tier supplier receive direct customer demand information. A 10-day transportation disruption was simulated, and the effects on performance measures such as unfilled customer orders, maximum and average inventory levels, and maximum goods in transit are studied. All four possible disruption locations are considered.

In a similar approach, Sidola et al. [108] compare the effects of two transportation disruptions on a regular and a so-called visible four-tier supply chain. In case of the visible supply chain, all demand information is shared between the supply chain partners. The performance is measured by the number of stockouts of the retailer, the inventory variability, and average demand among all supply chain entities. Two consecutive disruptions are simulated in each of the two systems between the warehouse and the retailer.

Ghadge et al. [31] develop a SCRM framework which is supported by SD modeling. Qualitative and quantitative data of internal product development projects were used as a representation of a global supply chain. For risk classification, the "Process, Organisation and Location, Data, Applications and Technology" (POLDAT) model is used, which was originally applied for process improvement purposes in companies. Qualitative risk data is incorporated by using the Delphi method, while quantitative data is collected with the help of historic risk data. The average impact of the identified risk events on the performance measures (cost and duration) and their average probability of occurrence were analyzed with respect to the risk classification categories of the POLDAT model. It is therefore possible to define upper and lower limits for each risk attribute and gain understanding of the risk behavior. The risk modeling step itself starts with defining a risk as a set of attributes according to the POLDAT classification and initial parameters such as initial risk impact on time and costs as well as expected probability of occurrence. Subsequently, statistical modeling was conducted to find the best probability distribution for the set of data. The SD model considers the combination of these risk attributes and their behavioral pattern to simulate the overall impact within 200 iterations based on SD equations not explicitly shown. A sensitivity analysis of the two models is conducted to further analyze the system.

Bueno-Solano et al. [13] simulate the impact of a border shutdown on the inventory levels and total inventory costs of a four-tier supply chain due to a terrorist attack. The raw material supplier and supplier are located in Mexico, whereas the warehouse and manufacturer are situated in the US. Random border crossing times are used. Disruptions of different time spans are studied before, during, and after the disruption with respect to the performance indicators such as inventory level and service level.

Cedillo-Campos et al. [15] use the same SD model to simulate the impact of criminal acts on the inventory performance and total costs of the same fourtier supply chain used in the approach before, with a safety stock level of five days. The supplier is either located in Mexico or Brazil, resulting in different lead times. The consequences of a cargo robbery on the inventory level are similar to the findings of Bueno-Solano et al. [13].

Wang et al. [139] analyze a two-tier supply chain with one retailer and two independent suppliers. The authors use a SD approach to evaluate the risk mitigation strategy of having a more reliable but more expensive backup supplier in the form of a contingent supplier or standby supplier. If and only if a disruption occurs, the retailer will begin to place orders at the contingent supplier which then starts to produce and deliver the products. In case of using a standby supplier, the retailer reserves some products at the supplier and gets paid a specific ratio of the price per product by the retailer. If a disruption occurs, the retailer buys these products at the major supplier's regular price. If the order is higher than the standby quantity, a higher price needs to be paid by the retailer. Inventory levels, unsatisfied demand, and the retailer's total profit are used as performance measures.

Based on the basic four-tier manufacturing supply chain SD model of Sterman, Schuh et al. [104] develop and validate a SD model capable of assessing different disturbances in a supply chain. The basic model with its continuous replenishment was enhanced by defining reorder point variables for all material inventories to create discrete event points which describe real supply chain activities more accurately. The original time-based safety stock coverage variable has been changed into a target service level degree based on safety stock calculations. Furthermore, economic order quantity and lot size calculations are integrated based on cost parameters. Included cost parameters are material unit prices for each inventory level, stock holding cost per material unit, and fixed costs per material order as well as production setup. The disturbances are integrated by considering stochastic deviations. Disturbance parameters include customer demand, replenishment time, production lead time, and production output quantity. The authors also develop adjustment parameters to dampen the effect of the deviations. These mitigation strategies consist of the adjustment of the economic lot size or economic order quantity as well as the adjustment of reorder points and the safety stock level. The logistics costs, the supply service level, and the capital lockup are considered to evaluate the performance and usefulness of the adjustment strategies.

Guertler and Spinler [33] build an SD model to capture the internal dynamics of operational risks of an enterprise under the influence of supply risks. The authors define 14 operational risks and 10 risk categories to be able to compare different scales of original risk-related data. The data set includes data of two case companies, of over 3000 suppliers, expert interviews, and secondary data. The interrelationship between the modeled risks are quantified using in depth expert interviews via cross-impact analysis. The causal loop diagram contains only positive correlations since it is assumed that a risk increase does not lead to an improvement of the situation. The model is designed to consider disruptive shocks, but it also incorporates a degree of self-stabilization. The magnitude of a risk is therefore affected by the magnitude of interrelated risks (deviation from the equilibrium state), the presence of a disruptive shock, a random factor with a set standard deviation, and a stabilizing factor which is calculated as a constant flow towards the initial equilibrium of the system. Each simulation run consists of 500 iterations and is embedded in a Monte Carlo simulation to retrieve stable results from a sequence of 1000 simulation runs. Guertler and Spinler [33] follow a design of experiments approach with two independent experiments (a single factor and a multiple factor analysis). The single factor analysis studies the high impact occurrence of one operational risk and the multiple factor analysis studies the occurrence of multiple lowimpact operational risks. Li et al. [59] study the effect of 13 risk events, which are identified from existing literature, and two mitigation strategies (increasing transportation equipment capacity and increasing amount of transport vehicles) on the performance of a chemical supply chain transportation system. Risk is modeled by using four risk characteristics, namely the occurrence probability of a risk event, the probability that a risk event influences a variable, the likelihood of a consequence, and the severity of the consequence. The model focuses on one focal enterprise and consists of the inventory system and the dynamic capacity of the transportation system. The transportation time is dynamic and dependent on the infrastructure's capacity and the current volume of the products being transported. Expert opinion is used to generate input values and suggest risk mitigation methods. The performance of the system is evaluated by four measures, namely the transportation capacity, the transportation time, the inventory level, and the order fulfillment rate. Keilhacker and Minner [48] analyze five mitigation strategies (product substitution, recycling, increase of research and development, and mix of the previous four strategies) to cope with supply shortages of the critical commodity of rare earth elements due to export restrictions. With an extensive use of empirical data, an end-to-end supply chain model (including eight different supply chains) is developed, consisting of a great number of mining companies and raw material processors (modeled on country level), semi-finished goods and finished goods manufacturers, research and development labs (modeled on supply chain level), and consumers (modeled on industry level). The authors compare the model's output price of rare earth elements with the empirical price of Neodymium and the supply unavailability avoidance as performance values. Product substitution (especially for finished goods manufacturers) mitigates supply unavailability best. Recycling can be effective if the infrastructure and recycling technology is already present.

Shukla and Naim [107] build an SD model of the well known four-echelon supply chain of Sterman's Beer Game [115] and apply a cluster-based spectral analysis on time series profiles (amount of shipped goods and net inventory level) to detect disturbances due to capacity restrictions. In their first simulation scenarios, the mean customer demand per period is doubled halfway through the simulation run and the shipping capacity of one entity per scenario is designated to be the bottleneck of the system. The subsequent simulation

System Dynamics	Focus on disruption risks	Number of risks	Data basis of risk concept	Risk interdependencies	Risk propagation	Dynamic modeling of risks	Prediction of risks	Risk optimization	Risk identification	Risk assessment	Mitigation of risks	Control of risks
Wilson 2007 [144]	●	○	◑	◑	◑	●	◑	◑	○	◑	◑	○
Sidola et al. 2011 [108]	●	○	◑	◑	◑	●	◑	◑	○	◑	◑	○
Ghadge et al. 2013 [31]	○	●	●	●	○	●	●	○	●	●	○	○
Bueno-Solano et al. 2014 [13]	●	○	◑	◑	◑	●	◑	○	○	◑	○	○
Cedillo-Campos et al. 2014 [15]	●	○	◑	◑	◑	●	◑	○	○	◑	○	○
Wang et al. 2014 [139]	●	○	◑	◑	◑	●	◑	◑	○	◑	◑	○
Schuh et al. 2015 [104]	○	●	◑	◑	◑	●	◑	◑	○	◑	◑	○
Guertler / Spinler 2015 [33]	○	●	●	●	◑	●	◑	○	●	●	○	○
Li et al. 2016 [59]	●	●	◑	◑	○	●	◑	◑	◑	◑	◑	○
Keilhacker / Minner 2017 [48]	●	○	◑	○	○	●	○	●	○	○	●	○
Shukla / Naim 2017 [107]	○	○	◑	○	○	●	◑	○	○	○	○	●

Table 5: Comparison of System Dynamics approaches to model supply chain disruption risks

scenarios consider a capacity reduction of one entity per scenario, while the demand remains unchanged. In both simulation experiments the entity which limits the shipping capacity could be detected.

Table 5 provides an overview of the approaches with respect to the described requirements. The modeling approaches, for the most part, focus on disruption risks. Ghadge et al. [31] study risk in general and use project risk data as a representation of supply chain risks, while Schuh et al. [104] and Guertler and Spinler [33] focus on operative risks. It is debatable if project risk data can be used as a representative of supply chain risk data since multiple projects can be classified in different, recurring phases and supply chain activities are continuous. Shukla and Naim [107] study disturbances during which production capacity is limited but still available. Only four models incorporate more than one risk. Most SD approaches apply a what-if analysis where one specific risk is set as true and the consequences and behavior of the system are analyzed. The models therefore include only the impact as part of the risk concept, but are able to display interdependencies and propagation of the impact well. Guertler and Spinler [33] as well as Ghadge et al. [31] model risk explicitly and use qualitative as well as quantitative data so that these two models display a risk related modeling output. A few authors partly consider risk optimization. Wilson [144], Sidola et al. [108], and Wang et al. [139] compare different supply chain organization strategies (VMI, backup supplier) and therefore evaluate their usefulness. Schuh et al. [104] and Li et al. [59] change model parameters to study the effects of mitigation strategies, but only consider some mitigation strategies. The approach of Keilhacker and Minner [48] is an exception that solely concentrates on mitigation strategies to find ways to deal with scarce resources.

The right-hand side of Table 5 gives an overview of the supported process steps of each modeling approach. Although only the models of Ghadge et al. [31] as well as Guertler and Spinler [33] fully consider risk assessment, risk assessment with a concentration on the dynamic impact of risk events is the focus of the identified SD models. The only two approaches that considered systematic methods for risk identification were the models of Ghadge et al. [31] and Guertler and Spinler [33]. The data-driven monitoring approach of Shukla and Naim [107] integrates the control of risk indicators.

4.3 Discrete-Event Simulation

Discrete-Event Simulation (DES) models the system's dynamic behavior as a discrete sequence of events in time [40]. A wide range of supply chain planning problems have been modeled with DES models, such as supply chain design, inventory planning, production scheduling, and supplier selection [120]. Five models have been identified which use DES as the modeling technique of choice. Petrovic et al. [80] develop a DES tool to analyze uncertainty in a multitier, serial supply chain. Order-up-to-levels for all inventory stages are determined by using fuzzy sets regarding the customer demand, lead time, and supplier reliability. The control of the inventory levels is either decentralized or partially coordinated, which takes the uncertainty of the immediate predecessor into account. The fuzzy sets are used to calculate probability distributions of the SC parameters. The simulation analyzes various performance measures (total costs, holding costs, and fill rate) achieved by the SC under the specific parameters.

Schmitt and Singh [101, 102] study DES to analyze the performance of a three-tier supply chain with two products (low-volume and high-volume), two raw material suppliers, three distribution centers, as well as predefined mitigation strategies. Monte Carlo Simulation is used to determine an aggregated distribution of the frequency and duration of disruptions per location. The data basis of the Monte Carlo simulation consists of historical disruption data and expert knowledge of future possible risk events. For each location a mitigation strategy (backup capacity at different locations) is defined which comes into effect after a set duration of a disruption. The authors analyze the effect of several inventory levels on the service level of the supply chain, in case of no disruption occurring and in case of disruptions occurring, and perform a stress test for various disruption scenarios.

Hishamuddin et al. [37] compare the impact of two different types of disruptions (supply disruption and transportation disruption) on the total recovery costs of a three-tier supply chain with three suppliers, one manufacturer, and one retailer. The total recovery costs include machine setup cost, inventory holding cost, penalty costs for late recovery, and shortage costs due to stock-outs. The supply disruption is analyzed at each location, whereas the transportation disruption is examined at each link of the supply chain. For simplicity, only one disruption can occur simultaneously. The authors compare the resulting eight different disruption scenarios.

Aqlan and Lam [4] combine a goal programming and a simulation model to find the best mitigation strategies, inventory levels, and production quantities under budget constraints in a high-end server manufacturing supply chain with four suppliers. The optimizing model determines the parameters (response strategy, production quantities, and inventory levels) for the subsequent simulation. It simultaneously maximizes total profit as well as total risk reduction and minimizes the total cycle time. The DES considers the parameters calculated by the goal programming approach and analyzes the performance values under stochastic features. The output of the simulation serves as input of the optimizing model and the deviation is calculated. This process is continued until convergence is achieved.

Discrete-Event Simulation	Focus on disruption risks	Number of risks	Data basis of risk concept	Risk interdependencies	Risk propagation	Dynamic modeling of risks	Prediction of risks	Risk optimization	Risk identification	Risk assessment	Mitigation of risks	Control of risks
Petrovic 2001 [80]	○	●	●	◑	○	●	○	○	○	●	○	○
Schmitt / Singh 2009 [101]	●	●	●	○	◑	●	◑	●	●	●	●	○
Schmitt / Singh 2012 [102]	●	●	●	○	◑	●	◑	●	●	●	●	○
Hishamuddin et al. 2015 [37]	●	◑	◑	○	○	●	◑	○	○	●	○	○
Aqlan / Lam 2016 [4]	●	●	◑	●	○	●	○	●	○	○	●	○
Ivanov 2017 [41]	●	○	◑	○	◑	●	○	◑	○	●	◑	○
Schmitt et al. 2017 [109]	●	○	◑	○	○	●	○	●	○	●	◑	○
Wang et al. 2018 [140]	○	●	●	○	○	●	◑	●	●	●	●	○

Table 6: Comparison of Discrete-Event Simulation to model supply chain disruption risks

Ivanov [41] builds a DES model of a four-echelon supply chain consisting of one manufacturer, one central distribution center (CDC), two regional distribution centers (RDCs), and ten customers in order to quantify the effects of two disruptive scenarios ((1) total disruption of CDC, (2) 50% capacity disruption at RDC and a full disruption of CDC) and corresponding recovery processes. Lead times and demand are modeled with a triangular distribution. Sales price, holding costs, fix facility costs, production time and costs, and transportation costs are defined to make monetary effects investigatable. Real transportation distances are used for the modeling of material flow and an order-up-to policy controls replenishment processes. Total revenue, cost, and profit as well as the customer service level and inventory holding costs are used for performance evaluation. The model shows that both disruption scenarios impact the performance values significantly, not every disruption leads to a propagative effects (ripple effect), and recovery processes can significantly alleviate the disruptive impact.

Schmitt et al. [109] implement a four-echelon supply chain (stage 3 and 4 containing two entities each) into a DES model to test the impact of 20-day disruptions ((1) close to the customer and (2) on the most upstream echelon) on the total supply chain inventory level and customer fill rate to evaluate the effect of expediting as well as dynamic cost-based ordering policies. Expediting is implemented by switching to airplane delivery in certain lowstock situations, which reduces lead times significantly. The simulations show that expediting increases the variability in order quantity and frequency, leads to significantly higher total inventory in the system, and reduces shortages slightly. A downstream disruption is shown to be more severe than an upstream disruption. Holding, backorder, lost sales, and transportation costs are subsequently added to find cost-based order-up-to levels across multiple echelons under the influence of the disruption. The authors vary the order-up-to levels of the first and second echelon, calculate the resulting total supply chain costs, and find highly volatile cost behavior. A genetic algorithm is designed and could outperform a regular line search algorithm.

Wang et al. [140] consider a two-echelon real-world precast supply chain in their DES approach to systematically analyze the uncertainty due to disturbances and the effects of precaution strategies on various operational (e.g. waiting time, lead time, etc.) and economic level measures (e.g. maintenance costs, inventory costs, etc.). The production and delivery process of ten different prefabricated molds is modeled with triangular distributions gained by on-site data collection. Possible disturbances are inserted in a database together with possible countermeasures. Cost attributes, the probability values of different disturbances, and the decrease in probability due to the countermeasures (low, medium, and high mitigation) are assessed by expert interviews. Four risks and their corresponding countermeasures are integrated into the model. By simulating 11 scenarios and subsequent sensitivity analysis, the authors conclude that machine breakdown is the most critical and risk countermeasures can significantly reduce lead times and total cost. By also considering cost variables for implementing the countermeasures, the optimal intensity of mitigation strategy can be defined.

Table 6 shows that the identified DES models predominantly incorporate a number of risks and have a strong focus on SC disruptions. Only the models of Petrovic [80] and Wang et al. [140] deal with general uncertainty and disturbances. A number of risks are incorporated, except for the DES models of Ivanov

[41] and Schmitt et al. [109] that concern generic disruptions. Hishamuddin et al. [37] conduct a what-if analysis on two different types of disruptions (supply and transportation disruption) so that this model is able to incorporate deep uncertainty without considering quantified likelihoods. Petrovic [80] analyzes uncertainty in general without any focus on disruption risk, but is able to incorporate linguistic and fuzzy data into the model. Wang et al. [140] rely on expert interviews and measured, quantified parameters. Schmitt and Singh [101, 102] incorporate historical disruption data and expert knowledge of future possible risk events. The main focus of these models is the dynamic description of the system's behavior. Schmitt and Singh [101, 102], Aqlan and Lam [4], Schmitt et al. [109], and Wang et al. [140] have a clear focus on risk optimization. Aqlan and Lam [4] aim to find the best mix of mitigation strategies to optimize the supply chain's risks with respect to different constraints. Schmitt and Singh [101, 102] focus on the optimal inventory level to face supply chain disruptions as well as the right backup supply strategy to cope with disruptions. Schmitt et al. [109] evaluate expediting and cost-based order-up-to policies. Wang et al. [140] analyze the effect of four mitigation strategies on the system's performance and aim to asses the most cost-efficient countermeasures. The DES models of Hishamuddin et al. [37], Wang et al. [140], and Schmitt and Singh [101, 102] display the relationship between disruption and potential consequences so that risk prediction is partially included. The only approaches which focus on risk propagation across the supply chain are the approaches of Schmitt and Singh [101, 102], since they study the time-aspects of disruptions regarding performance measures, and Ivanov [41], who analyzes the so-called ripple effect but without considering direct quantitative measures of this effect.

The right-hand side of Table 6 gives an overview of the supported process steps of each modeling approach. The models of Schmitt and Singh [101, 102] and Wang et al. [140] support risk identification, risk assessment, and mitigation of risks. Petrovic [80], Hishamuddin [37], Ivanov [41], and Schmitt et al. [109] focus mainly on risk assessment. The two latter approaches also partly consider risk mitigation. Aqlan and Lam [4] aim to optimize mitigation strategies. The control of risk is not included in the identified DES models.

4.4 Bayesian Belief Networks

A Bayesian Belief Network (BN) is a graphical model in the form of a directed acyclic graph which represents random variables and their conditional dependencies. It enables the computation of a joint probability distribution over a set of random variables [83]. It is widely used in statistics, machine learning, and artificial intelligence [49, 70]. Three applications of BNs have been identified, which will be outlined in the following.

Badurdeen et al. [5] use a BN to model risk interdependencies of an aerospace industry supply chain with 11 suppliers, one focal OEM, and 20 customers. The research group uses the risk taxonomy of Rao and Goldsby [92] and expands it to 94 risk drivers and 11 supply chain performance measures with the help of a literature search and expert knowledge. A risk network matrix was developed to identify risk interdependencies. An Excel-based prototype software tool transformed the matrix into a risk network map which visualizes how the identified risk drivers influence the performance measure. Data collection sheets were used to gather information regarding conditional probabilities, and a group of experts then estimated conditional probabilities used for the BN. Joint probabilities can be calculated and visualized for each producing entity of the supply chain by applying Bayesian theory. Further analyses are conducted by changing specific risks to 0% or 100% and studying the impact on other risks and performance metrics.

Garvey et al. [30] model the propagation of disruption risks in a supply chain. The authors identify multiple potential risk events at various nodes and arcs of the supply chain. These risk events are considered to be nodes of a so-called risk graph. A procedure based on a probability dependency model is developed to capture causal relationships between the occurrences of the identified risks without creating directed cycles. Due to this procedure, the arcs of the risk graph can be implemented. The BN is established by assessing conditional probabilities between these risk events. The impact of each potential risk event needs to be estimated and is captured by defining a cost function for each risk. Scenarios which cover all possible outcomes and corresponding probabilities of occurrence are assigned. The authors develop measures to study propagation effects of the considered risk events.

Qazi et al. [86] incorporate mitigation strategies into their BN approach and model the mitigating effects on the system. The conditional probabilities of each risk event can be reduced by implementing mitigation strategies, which results in extra mitigation costs. The authors define an objective function that rewards the saving of costs with respect to the costs of implementing all mitigation strategies and the reduction of expected loss in relation to implementing no mitigation strategies. The maximum weighted sum of these two normalized utility factors is considered to be the optimal combination of mitigation strategies.

Similar to Badurdeen et al. [5], Sharma and Sharma [106] develop a BN model to assess risk interdependencies of eight risks and 23 risk factors in an Indian textile supply chain to calculate the impact on three performance measures, namely cost, time, and quality. The structure and the conditional probability tables of the BN have been created with the help of six supply chain experts, historical supply chain data, and corresponding SCRM literature. To keep computing time manageable, the appearance state of risk factors,

Bayesian Belief Network	Focus on disruption risks	Number of risks	Data basis of risk concept	Risk interdependencies	Risk propagation	Dynamic modeling of risks	Prediction of risks	Risk optimization	Risk identification	Risk assessment	Mitigation of risks	Control of risks
Badurdeen et al. 2014 [5]	●	●	◑	●	◑	○	◑	○	●	●	○	○
Garvey et al. 2015 [30]	●	●	◑	●	●	○	●	○	○	●	○	○
Qazi et al. 2015 [86]	●	●	◑	●	●	○	●	●	○	●	●	○
Sharma/Sharma 2015 [106]	●	●	●	●	○	○	●	○	●	●	○	○
Qazi et al. 2017 [87]	●	●	●	●	○	○	●	●	●	●	●	○
Qazi et al. 2018 [88]	●	●	◑	●	○	○	●	●	●	●	●	○

Table 7: Comparison of Bayesian Belief Network approaches to model supply chain disruption risks

risks, and performance measures can either be "high" or "low". The Delphi method has been adopted to reach a consensus between experts. After calculating the state probabilities of the performance nodes, the probability of risk factors are individually set to 100% to identify the most critical risk factors as part of the sensitivity analysis.

Qazi et al. [87] combine a FMECA approach with a BN model in a Turkish supply chain, considering all immediate suppliers of a manufacturer of supplementary parts in the home appliance industry, to identify risk factors, risks, and possible losses and to assess the interdependencies between them. FMECA is used for the identification of risks, direct losses, and possible mitigation strategies. The BN calculates the resulting probabilities. The authors develop measures to assess the contribution of risks to the overall losses in case of a risk-neutral and risk-averse decision maker. Risk mitigation is also considered by prioritizing risk mitigation strategies based on the impact on the developed risk measures under a budget or a resource constraint. If no mitigation cost can be assigned, the budget is split fairly by considering the Shapley Value, a concept in Game Theory, and calculating the marginal contribution of each mitigation strategy.

In a similar approach, Qazi et al. [88] use Fault Tree Analysis (FTA), BN, and Expected Utility Theory to model 29 risks of a component manufacturing supply chain in the aerospace industry and their effect on the following performance values: quality, timeliness, market share, profit, and sustainability. FTA (conducted and validated by focus group sessions of experts) is used as a top-down way to identify the performance measures' potential risks as well as their underlying causal risk factors and to therefore determine the hierarchical structure of the BN. The experts subsequently determine the strength of interdependency between the risks by assessing conditional probabilities. After identifying potential risk mitigation strategies and estimating their costs and the overall budget constraint, the mitigation strategies and their effect on the risks are built into the BN. All possible combinations of mitigation strategies are analyzed by running the BN and calculating the performance values for each scenario. The final step is the selection of strategies that maximize the decision maker's overall expected utility and therefore considering their risk attitude.

Table 7 compares the six approaches with the requirements derived above. All six models focus on a number of SCDR and concentrate on modeling the interdependencies between them. Since conditional probabilities need to be defined, the models incorporate the risk categories "randomness" and "hazard". Deep uncertain risks are not considered. Four modeling approaches quantify risks by using experts without using historical data. Sharma and Sharma [106] and Qazi [87] also integrate historical data into their approach. Risk propagation is mainly studied by Garvey et al. [30] and Qazi et al. [86], who both develop propagation measures. Badurdeen et al. [5] briefly mention that risk propagation can be explored by setting specific risks as true and analyzing the impact. Qazi et al. [86–88] concentrate on risk optimization. The prediction of risks is considered in all approaches. Badurdeen et al. [5] only predict the probability of occurrence, while the other five models predict the probability of occurrence and the impact of risks. None of the approaches include dynamic aspects into their models.

The right-hand part of Table 7 shows which steps of the standard SCRM framework are modeled and supported by the publications. While the control of risks is not supported, all approaches cover risk assessment. On top of that, Badurdeen et al. [5], Sharma and Sharma [106], as well as Qazi [87, 88] extensively cover risk identification, and Qazi et al. [86–88] find ways of mitigating risks. The control of risk is missing in BN approaches, so far.

Agent-based Modeling	Focus on disruption risks	Number of risks	Data basis of risk concept	Risk interdependencies	Risk propagation	Dynamic modeling of risks	Prediction of risks	Risk optimization	Risk identification	Risk assessment	Mitigation of risks	Control of risks
Park 2014 [77]	●	○	○	○	○	●	○	○	○	◑	○	○
Blos et al. 2015 [11]	●	●	●	○	○	●	○	◑	◑	◑	◑	○
Seck et al. 2015 [105]	●	○	○	○	○	●	○	○	○	◑	◑	○
Otto et al. 2017 [75]	●	○	◑	◑	◑	●	○	◑	○	◑	◑	○
Ledwoch et al. 2018 [56]	●	○	○	○	○	●	○	◑	○	◑	◑	○

Table 8: Comparison of other modeling approaches to model supply chain disruption risks

4.5 Agent-based Modeling

Agent-based Modeling (ABM) is a modeling and simulation method in which multi-agent systems represent social, economic, and ecological systems, etc. [97]. Each system consists of a set of agents, a set of relationships, and the agents' environment in the boundaries of an overarching system. An agent is an autonomous, self-directed, individual entity which can function independently from other agents. It interacts with and reacts to other agents and their environment by having either a simple collection of if-then-else rules or complex artificial intelligence techniques integrated in their behavior [125]. ABM is particularly interesting because of its ability to represent self-organizing systems in which entities interact, influence each other, and are able to learn from their experience to be better adapted to their environment [65].

Park [77] combines ABM as well as SD modeling to study the behavior of a three-tier supply chain with two manufacturers of two different products, two retailers, and a customer. The customer chooses between the two products and waits a given time before consuming again. The customer's behavior is modeled by SD, whereas the production processes are described by ABM. The service level of the supply chain is used as a performance metric.

Blos et al. [11] describe a simulation-based methodology to assess and mitigate identified risk scenarios with a supply chain risk event database and ABM of the supply chain. Scenarios are generated by expert-based probabilistic description or by known historical risk events, and an SCRM specialist generates possible mitigation strategies. Simulation models of all scenarios need to be developed before the performance and effectiveness of the strategies can be quantitatively assessed. The authors adopted their methodology to a global supply chain of a manufacturing firm within the electronic industry in Taiwan but do not describe their simulation models in detail.

Seck et al. [105] present an ABM approach to study the effect of different risk scenarios on the fill rate of the supply chain system. The authors analyze a three-tier supply chain with two suppliers and two sub-suppliers. The first risk scenario consists of a perfect demand forecast with a planning horizon larger than the cumulative lead time and a capacity superior or equal to the demand. As expected, the fill rate is 100%. A minor forecasting error with no safety stocks results in a fill rate below 100%. The authors test a major forecasting error with enough safety stock to maintain a perfect fill rate. The last scenario consists of a disruption of one of the sub-suppliers with a set duration and a set time to recovery. This scenario shows the delayed drop of the fill rate and the slow replenishment of the safety stock.

Otto et al. [75] propose the ABM approach "acclimate" to assess the propagation of losses in global supply networks due to natural disasters of different sizes using the example of the Japanese automotive manufacturing industry. The authors consider the economic monetary input-output data table of 27 sectors and a large number of contributing countries including consumer demand in the form of household consumption, governmental spending, and private investments. The producing agents are capable of adjusting their production capacity, assessing future demand, receiving price-offerings of suppliers, and setting the ordering quantity to locally maximize their profit. During simulated disruptions of different time lengths (0 to 19 days) the production capacity of a specific regional sector is reduced by a certain variable degree. The authors find that indirect losses strongly depend on the duration and magnitude of the disruptions and can rise well after the disruption has ceased. The exogenous variable of buffer inventory serves as a mitigating component and is recommended to be increased due to the increase in the number of expected natural disasters.

Ledwoch et al. [56] build an ABM to quantitatively compare the consequences of different disruption frequencies and durations on the fill rate, backlog, and inventory holding costs of random and scale-free network topologies with a single original equipment manufacturer and 102 supplier nodes. In case of a random topology, a set number of links is randomly attached to a set of nodes. Scale-free networks consist of hub nodes with a large number of immediate suppliers. Producing agents can receive orders, forecast demand, ship product, and order supply, whereas logistics provider agents perform transportation between nodes. A specific random number of producing agents can perform two mitigation strategies. Contingent rerouting lets the agent transfer their orders from a disrupted node to one or more operational suppliers, while inventory mitigation increases the buffer inventory as a robust strategy. Simulation experiments with different risk and mitigation scenarios show that scale-free networks have higher disruption tolerance than random networks, inventory mitigation improves fill rates more effective than contingent rerouting regardless of the network topology, and inventory mitigation is cost effective only for frequent disruptions.

Table 8 shows that all ABM approaches focus on disruption risks and incorporate dynamic modeling. The identified models do not have a strong data basis for their modeled risk concepts and do not integrate risk interdependencies, risk propagation, and risk prediction. Blos et al. [11] is the only approach which considers numerous risks and focuses on historical data and expert opinion. Otto et al. [75] use historical data and study the interdependencies and propagative characteristic regarding the losses due to disruptions. Risk optimization has been slightly touched by the authors and only a single mitigation strategy has been tested. Otto et al. [75] and Ledwoch et al. [56] use buffer inventory for mitigation, while Blos et al. [11] conceptually integrates mitigation strategies but does not show numerical results.

A clear focus on risk assessment is visible in the approaches. Systematic risk identification methods have not been incorporated. Blos et al. [11] mention risk identification but do not go into detail. Risk mitigation has been partly integrated but not systematically supported. Seck et al. [105] indirectly show that nodes with backup supply or safety stock are less affected and accurate forecasting is beneficial. Approaches which emphasize the control of risks are still missing.

4.6 Interpretive Structural Modeling

Interpretive Structural Modeling (ISM) is a methodology which is used to transform unstructured graphical representations of a complex system into a well-structured directed graph with a hierarchy and relationships between elements [98, 141]. The basic procedure is as follows. The elements of the models need to be defined first. The structural self-interaction matrix (SSIM) contains the direct relationships between the elements. The relationships are determined by pairwise comparison of the risks. The SSIM, which includes four symbols to describe the interdependencies, is transformed into a binary reachability matrix. The final reachability matrix contains indirect relationships between the elements which are connected by intermediate elements. The elements are then put in a hierarchical order by level partitioning. The left part of Table 9 compares the ISM approaches. All of the models integrate a number of different SCDRs and have a high focus on risk interdependencies.

Pfohl et al. [81] as well as Vekantesh et al. [135] incorporate a fuzzy MICMAC analysis and are therefore able to evaluate the strengths of the interdependencies. ISM is suitable for all risk categories with the premise that it is possible to at least understand the consequences of deeply uncertain risk events on other risks and vice versa. The data basis of the described models stems from expert knowledge and literature reviews. Dynamic effects, the prediction of risks, risk propagation, and a risk-related optimization of the supply chain is missing.

The right-hand side of Table 9 shows which steps of the standard SCRM framework are modeled and supported by the publications.

Pfohl et al. [81] use ISM to identify interdependencies among supply chain risks and apply a MICMAC analysis to classify the risks according to their driving and dependence power. The authors study a supply chain consisting of a first-tier supplier, a focal company, and a third-party logistics provider which transports goods to the focal company as well as to the customer. 21 external and internal disruption risks are incorporated. A group of experts is suggested who then construct the structural self-interaction matrix (SSIM). After constructing the ISM-based model, the MICMAC analysis consists of calculating the sum along the rows and the columns of the final reachability matrix as an indicator for the driving power and dependence of each risk. Four groups of risks are defined (autonomous, dependent, linkage, and independent). A Fuzzy MICMAC analysis is applied to consider the strength of relationships on a scale from 0 to 1. The values are superimposed on the initial reachability matrix.

Vekantesh et al. [135] use the ISM approach to model the interdependencies of supply chain risks associated with the Indian apparel retail industry. The authors identified 12 risks with the help of experts through a Delphi study and a literature review. The Delphi methodology is an empirical tool to reach a consensus among a group of experts [61]. An expert-based fuzzy MICMAC analysis is used to describe the strength of relationships between the risks. A new risk prioritization number (RPN) is developed which replaces the occurrence probability in the classical formula (RPN = Occurrence x Severity x Detection) with the ratio of the driving power to the dependence power of a risk.

Interpretive Structural Modeling	Focus on disruption risks	Number of risks	Data basis of risk concept	Risk interdependencies	Risk propagation	Dynamic modeling of risks	Prediction of risks	Risk optimization	Risk identification	Risk assessment	Mitigation of risks	Control of risks
Pfohl et al. 2011 [81]	●	●	◑	●	○	○	○	○	◑	◑	○	○
Vekantesh et al. 2015 [135]	●	●	◑	●	○	○	○	○	◑	◑	○	○
Srivastava et al. 2015 [113]	●	●	◑	◑	○	○	○	○	◑	◑	○	○

Table 9: Comparison of Interpretive Structural Modeling approaches to model supply chain disruption risks

Srivastava et al. [113] focus on the Indian food retail industry and identify 24 supply chain risks with the help of experts. The authors also use a MICMAC analysis but do not apply a fuzzy-based evaluation of the strengths of the relationships.

Risk identification as well as the selection of elements to be examined are part of the ISM methodology. It is, however, not methodically supported. Literature or expert knowledge are named as the source of relevant risks. Interdependencies and the driving power of risks are one aspect of risk assessment. The quantification of risks is not considered in the ISM framework. Other process steps like the mitigation and the control of risks are not supported.

4.7 Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a simulation method based on repeated random sampling and statistical analysis to compute the simulation results. MCS usually considers a large number of stochastic parameters with known or assumed statistical distributions and generally depends on a great number of simulation iterations in order to be able to assess the detailed stastical features of the output parameters. MCS is used in a wide variety of application areas including Mathematics, Statistical Physics, Engineering, and Social Sciences [89].

Deleris and Erhun [22] combine MCS with a so-called flow model which calculates the loss of volume due to destroyed supply chain nodes to obtain the probability density function of the losses in the network. The likelihoods of the considered scenarios are estimated by experts.

Klibi et al. [53] use MCS to model the impact of random business-as-usual risk events as well as extreme events on the capacity of SC entities and on the demand of products. The authors propose a three-step modeling approach which consists of the definition of so-called multi-hazards (summary of different hazards with generic impact to improve quantification), geographic hazard zones, associated vulnerability sources (SC entities as well as infrastructure), and their exposure levels with respect to the defined multihazards. A stochastic process models the time and space characteristics of the risk events' occurrences as well as their intensity and the time for recovery regarding production capacity and demand of different product markets. It is recommended to use historical data and expert opinions to establish these parameters. The Monte Carlo Simulation creates a number of scenarios and calculates the number of hits and the number of unserved products within the planning horizon.

Mizgier et al. [71] quantify the direct and propagated losses due to both idiosyncratic (one node is directly impacted) and systemic (all nodes are directly impacted) disruptions of a two-stage converging network with a Monte Carlo simulation approach. The resulting loss distribution of the central manufacturer is considered by its mean, its value-at-risk (maximum possible loss up to a predefined quantile), and its expected shortfall (mean losses exceeding the predefined quantile). The disruption and recovery of nodes are modeled as a Renewal-reward process, in which hazard events disrupt the node according to a Poisson process with different intensities and the subsequent recovery time is identically distributed. Two idiosyncratic hazards per node and one systemic hazard, threatening all entities, are considered. The indirect losses are calculated based on a weighted adjacency matrix which contains the relative purchasing volume with respect to each direct customer. The nth power of the matrix describes the relative impact on the nth stage of the network. Indirect losses are immediately distributed and no buffer inventory is considered. The conducted simulation experiments quantify the effect of diversification as a mitigation strategy on the loss distribution of the manufacturer by adding one supplier in each simulation run to the network (starting with just a single supplier) and changing the intensity parameter of the hazards. In this model, the variance of the loss distribution is reduced with an increasing number of same-stage suppliers. This positive effect is diminished when suppliers on the second stage are added.

Monte Carlo Simulation	Focus on disruption risks	Number of risks	Data basis of risk concept	Risk interdependencies	Risk propagation	Dynamic modeling of risks	Prediction of risks	Risk optimization	Risk identification	Risk assessment	Mitigation of risks	Control of risks
Deleris / Erhun 2005 [22]	●	●	●	○	○	○	●	○	○	●	○	○
Klibi et al. 2012 [53]	●	●	●	○	○	●	●	○	○	●	○	○
Mizgier et al. 2015 [71]	●	●	○	○	◑	●	●	◑	○	●	◑	○

Table 10: Comparison of Monte Carlo Simulation approaches to model supply chain disruption risks

Table 10 compares the three MCS approaches regarding the fulfillment of the requirements derived above. All three MCS approaches focus on disruptions and incorporate numerous risks into their methodology. Historical data as well as expert opinions are used to assess the risk values, except in the methodology of Mizgier et al. [71], who have a more theoretic approach to risk modeling. Mizgier et al. [71] focus partly on risk propagation and aim at risk mitigation by a diversified sourcing strategy.

Systematic risk identification and the control of risks are not considered in the identified models. A strong focus on risk assessment is detectable, and all three models support this process step.

4.8 Input-Output Modeling

Input-Output Modeling (IOM) originally stems from Leontief 's Input-output Model [58], which is a useful tool to study consumption shocks on interdependent economic systems [99]. IOM attempts to foresee the resulting economic losses and inoperability suffered by different interdependent industry sectors [34, 100]. Wei et al. [143] use IOM to model the propagation and interdependencies of supply chain disruptions in a five-tier supply network with 11 members. The inoperability vector consists of continuous variables with values ranging from 0 to 1 which indicate the extent of inability of the system's member to perform its functions (perfect operable state is represented by 0). A so-called interdependency matrix displays the interdependencies between supply chain entities. Total inoperability is calculated by summing up the propagated inoperability passed on by dependent supply chain nodes and the direct inoperability of the node (direct effect of a disruption). The interdependency matrix can be calculated based on Ordered Weighted Averaging. The interdependency can be measured by determining multiple factors like trading volume, buffer capacity, and substitutability, etc. for each directly connected relationship to a node. Niknejad and Petrovic [72] combine Fuzzy Set Theory with a Dynamic IOM (DIOM) to measure the propagative effects of two disruptive scenarios in a supply chain with two suppliers, one manufacturer, and customers. Experts' knowledge is used to specify triangular fuzzy set numbers (TFSNs) of each entity's planned revenue and resilience as well as the dependencies between each partner. The disruption itself is also modeled with a TFSN. The exogenous disruption lasts for ten

Input-Output Modeling	Focus on disruption risks	Number of risks	Data basis of risk concept	Risk interdependencies	Risk propagation	Dynamic modeling of risks	Prediction of risks	Risk optimization	Risk identification	Risk assessment	Mitigation of risks	Control of risks
Wei et al. 2010 [143]	●	○	○	◑	◑	○	◑	◑	○	◑	◑	○
Niknejad / Petrovic 2017 [72]	●	◑	○	◑	◑	●	◑	○	○	◑	○	○
Brosas et al. 2017 [12]	●	○	○	◑	◑	○	◑	○	○	◑	○	○

Table 11: Comparison of Input-Output Modeling approaches to model supply chain disruption risks

time units, in which the disrupted entity is partially functional. The DIOM calculates the propagative effects for each time frame (50 time units in total) with respect to the dependencies between each partner and the resilience of each entity. The mean resulting inoperability is multiplied with the planned fuzzy revenue to calculate the fuzzy financial losses. A sensitivity analysis tests the impact of each input's value on the estimated fuzzy financial losses and on its ambiguity (a measure of uncertainty of TFSNs). The most critical input values should be reanalyzed more thoroughly until decision makers feel confident.

Brosas et al. [12] use a fuzzy supply-side IOM to assess the impact of price changes due to an occurring disruption. A Philippine herbal food supplement supply network which is exposed to devastating typhoons, consisting of five suppliers, two manufacturers, and three distributing pharmacies, is modeled. Unlike the standard IOM, the supply-side IOM models supply-side price perturbations. A typhoon is assumed to increase the prices of one supplier by 10%. The interdependency matrix consists of fuzzy supply costs in the form of TSFNs. The price increases are calculated for each partner to see the most affected nodes.

Table 11 compares the IOM approaches to the derived requirements. Although the approaches consider one generic disruptive event as a risk factor and do not have a strong focus on how to gather the input parameters, IOM is helpful for swiftly calculating the propagative effects with the help of the interdependency matrix. All approaches here partly fulfill the requirements of risk propagation and risk interdependencies because they focus on the impact of risks on the performance values. Risk mitigation is partly incorporated by one model. Wei et al. [143] increase the number of suppliers and evaluate the effects on the performance values. Niknejad and Petrovic [72] use a dynamic IOM and can therefore also provide temporal insights.

Risk identification as the first step of a standard SCRM framework is not supported by the IOM models. The control of risk has also not been incorporated so far. A clear focus lies on the easy assessment of risk impact.

4.9 Other approaches

Six approaches have been identified which could not be numbered alongside the simulation techniques described above. These approaches include Time-based Simulation, Static Simulation, Neural Networks, and models based on Graph Theory.

Thiagarajan et al. [126] develop a simulation-based risk analysis technique for large-scale military logistics planning. Simulation is used to evaluate the impact of unavailability of transport vehicles on the sequence of activities which form the logistics plan. The logistics plan contains the structural information about the available fleet of vehicles, required capacities, and time spans that the vehicles are needed. Some activities need to be fulfilled by specific transport vehicles so that unavailability can either cause the whole logistics plan to fail or has no effect. The static simulation calculates conflicts in the plan. The authors develop a simple so-called failure threshold and consequence metric to measure the relative criticality of transport vehicles observed in simulation and to enable large plans to be analyzed quickly. A risk matrix is used to combine the consequences with the likelihood of an unavailability, which needs to be assessed by experts, and to derive mitigation strategies.

Aqlan and Lam [3] develop a multi-objective mixed-integer linear programming model which looks for the best combination of different interdependent mitigation

	Miscellaneous Approaches	Focus on disruption risks	Number of risks	Data basis of risk concept	Risk interdependencies	Risk propagation	Dynamic modeling of risks	Prediction of risks	Risk optimization	Risk identification	Risk assessment	Mitigation of risks	Control of risks
SS	Thiagarajan et al. 2011	●	○	◑	○	○	○	◑	○	○	●	◑	○
MIP	Aqlan / Lam 2015 [3]	●	●	◑	◑	○	○	○	●	●	●	●	○
GT	Rajesh et al. 2015 [91]	○	●	◑	●	○	○	○	●	○	○	●	○
TBS	Tan et al. 2015 [121]	●	○	◑	●	●	●	○	○	○	●	◑	○
NN	Liu et al. 2016 [62]	●	○	◑	○	○	○	●	○	○	●	○	○
GT	Tang et al. 2016 [123]	●	○	○	○	●	●	○	○	○	●	○	○

GT: Graph Theory MIP: Mixed-Integer Programming NN: Neural Network
SS: Static Simulation TBS: Time-based Simulation

Table 12: Comparison of other modeling approaches to model supply chain disruption risks

strategies. Its aims are to minimize total mitigation cost and to maximize risk reduction under budget constraints and a minimum risk reduction constraint. Bow-Tie analysis is used to aggregate the likelihood and impact of multiple risk factors to form a single risk. To evaluate the interdependencies between different risk mitigation strategies, the authors use expert opinion and develop a so-called risk mitigation matrix which displays the effect of each mitigation strategy on the incorporated risks.

Rajesh et al. [91] combine Grey Theory with a Graph Theory Matrix Approach (GTMA) to find the most effective mitigation strategies with respect to various supply chain risks including the risk of disruption. Grey Theory is used to quantify the relative importance of risks as well as the positive and negative influence of each risk mitigation strategy over each risk by using linguistic expression of experts. The grey scales are converted into crisp values and the GTMA calculates the positive impact of each mitigation strategy in total as well as the negative impact of each mitigation strategy over all risks. The difference of these two values of each mitigation strategy forms the net positive influence value and enables the ranking of the strategies according to their effectiveness. 12 supply chain risk categories and 21 mitigation strategies with a focus on electronics manufacturing supply chains are considered.

Liu et al. [62] combine a grey prediction model with a Neural Network to predict the demand after the occurrence of a transportation disruption. Grey Prediction Modeling (GM) is based on Grey System Theory, which describes systems with partially unknown parameters. GM requires only a limited amount of data to estimate behavior of an unknown system compared to conventional statistical models and uses a so-called grey differential equation to explain and predict dependent variables [44]. Neural Networks are designed to estimate functions to explain large-scale nonlinear systems and predict their behavior based on a relatively large amount of training data [42]. The authors study the demand of one single supply chain enterprise which experienced transportation disruption after a snow disaster and could predict the demand with less error than the standard GM.

Tang et al. [123] analyze the dynamic effects of risk propagation in a supply network with 1000 nodes consisting of a physical-layer (material flow, directed graph) and a cyber-layer (information flow, undirected graph). Each node is given a specific initial load, a maximum capacity, and a maximum permitted propagable failed load. A proportion of nodes fail at the beginning of each simulation run, and the corresponding linkages of the affected nodes are removed. The initial loads of the affected nodes are distributed through a socalled priority redistribution strategy to the neighboring nodes and added to their load. If a node's maximum capacity is exceeded, the node fails and the propagated load as well as the load of the newly failed node are forwarded to the neighbors but are not allowed to top the maximum permitted failed load. The physical-layer and cyber-layer are linked by some nodes. The probability that the surviving network still belongs to the giant component of the graphs serves as a measure of robustness. The authors test the effect of a single-node disruption versus a multi-node disruption and vary input parameters regarding the maximum capacity and initial loads.

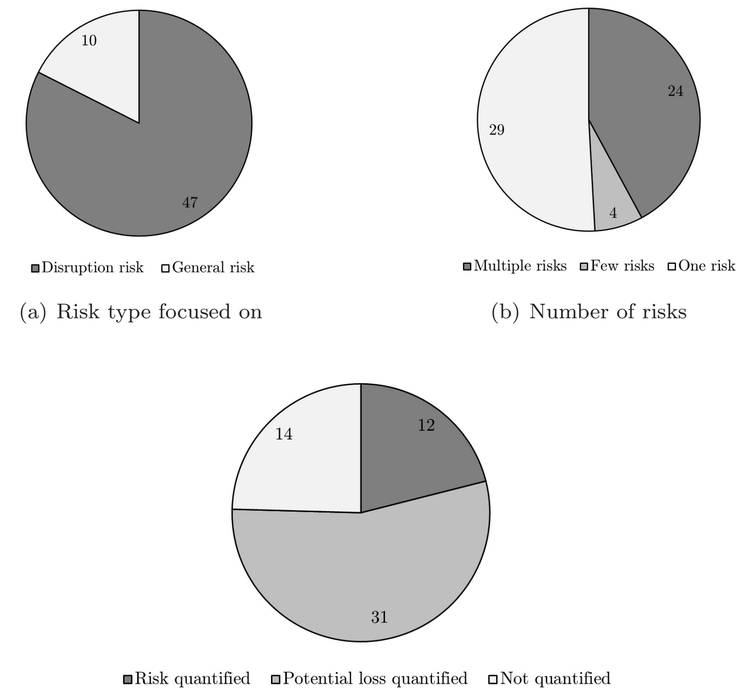
Table 12 compares the remaining modeling approaches and shows their corresponding modeling techniques. All approaches except the model of Rajesh et al. [91] focus on disruption risks, but only two of the models incorporate multiple risks. The variety between the models is relatively high, since different simulation techniques are used. Each technique has its own field of attention. The Neural Network approach of Liu et al. [62] emphasizes risk prediction based on historical data, while the multi-objective optimization model of Aqlan and Lam [3] and the Grey Theory approach of Rajesh et al. [91] aim to minimize risks with an adequate risk mitigation mix. The time-based simulation approach of Tan et al. [121] gives insight into the dynamic nature of risk propagation. Table 12 shows that all models contain a form of risk assessment except Rajesh et al. [91], which focus solely on risk mitigation.

The models of Rajesh et al. [91] as well as Aqlan and Lam [3] consider the process step risk mitigation explicitly, while Thiagarajan et al. [126] and Tan et al. [121] suggest risk mitigation strategies and indirectly show that nodes with backup supply or safety stock are less affected and accurate forecasting is beneficial.

4.10 Interpretation of results

The previous subsections have presented the 57 approaches with the corresponding modeling techniques which are used to model SCDR on a network-level. Each of these simulation techniques as well as specific approaches possess different characteristics. This section compares the eight techniques regarding the previously derived requirements and displays the strengths and weaknesses of these methods. The analysis of the requirements regarding the data basis and the risks integrated into the model can be conducted independently from the simulation techniques used.

Regardless of the simulation techniques used, most of the identified models focus on disruption risks. Fig. 2a displays that more than 80% of all contributions have a direct focus on disruption risks, while ten publications consider disruption risks among general supply chain risks. Fig. 2b presents the fact that around half of the models incorporate only one risk, while 24 models (around 40%) include more than three various risks simultaneously. This indicates that a good proportion of researchers have recognized the importance of analyzing disruptions and have developed extensive models which include a multitude of strategic risks.



(a) Risk type focused on (b) Number of risks

(c) Data basis of risk concept

Fig. 2: Overview of papers with respect to the focus on disruption risk, the number of risks considered, and the data basis of risk concept

One important aspect of risk modeling is the data basis of the approach. Fig. 2c shows that more than three-quarters of the identified SCDR models consider the potential losses of the risk without integrating the probability of occurrence to their risk concept. This is suitable for considering deep uncertainty where events happen rarely and have a high impact. Only 12 models (around 20%) have risks quantified with their probability of occurrence by historical data and expert knowledge. The approach of Klibi et al. [53] is the only one which considers hazardous as well as deeply uncertain events explicitly. This aspect indicates that more extensive work on the data basis of the developed models could be done.

The types of disruptions modeled by the identified models can be seen in Fig. 3. Disruptions have been modeled by 29 publications, modeled in a generic way by impairing entities and/or links between supply chain partners independently of the risk cause. While 20 models create disruptions by letting nodes fail, seven

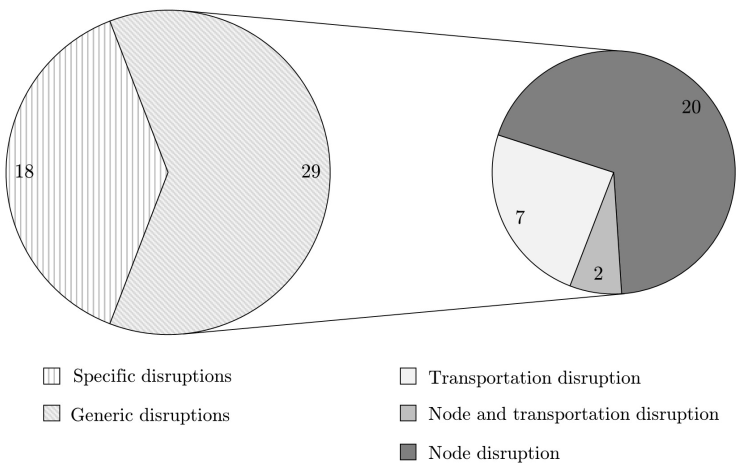


Fig. 3: Types of disruptions modeled

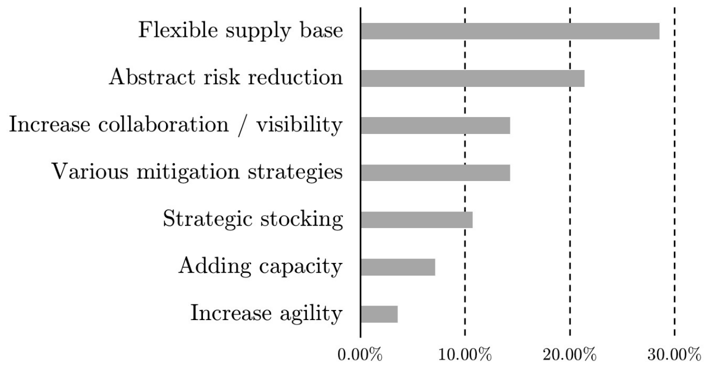


Fig. 4: Mitigation strategies incorporated by models

models focus on generic transportation disruptions. Two of the models consider both transportation and node disruption. The most frequent specific disruption risks included by the 18 approaches are natural disasters, machine breakdowns, political risk, strikes, material shortages, financial instabilities, alignment conflicts, criminal activities, and IT breakdowns.

Fig. 4 shows the proportion of each risk mitigation strategy with respect to the models which include some kind of risk mitigation. The largest portion of the risk mitigation strategies (nearly 30%) concern the supply base in the form of establishing backup supply. Around 20% reduce risks by lowering their value in an abstract way without integrating the cause-effect relationship of strategies in the model itself. Increasing visibility and information sharing have been considered by around 15% of the models which have some kind of risk mitigation implemented. The same ratio of papers have various mitigation strategies implemented in their approach. Buffer inventory in the form of strategic stocking has been tested by around 10% of the models. Increasing transportation capacity has been used by around 7% and agility in the form of expediting deliveries has been implemented by 3% of the models.

The risk behavior of the identified models is characterized by the evaluation criteria "interdependency", "propagation", as well as "dynamic modeling". The output and the aim of the model, respectively, are defined by the criteria "risk prediction" and "risk optimization". We study how the eight identified techniques satisfy each of these criteria independently before regarding how the criteria are satisfied jointly to learn more about the strengths and weaknesses of the techniques (RQ 3). Other approaches are not considered at this point since their quantity is too low to give insight into their characteristic features. Fig. 5 shows the proportion of instances of each technique and their fulfillment of the evaluation criteria.

PN approaches have a focus on interdependent and propagative characteristics. Around 90% of the models include propagative aspects. The structure of this simulation technique, namely the alternating behavior of place and transition nodes, helps to model propagative effects. The approaches measure the propagation of the effects of a disruptive event or, in the case of stochastic and dynamic models, calculate the effects of risks. Interdependencies of different risk events are included in around 75% of the publications. No PN approach considers the propagation and the interdependencies of risks itself. Only around 30% of PN approaches display a dynamic model with stochastic features regarding, for example, process time or demand. 70% of the models are static and deterministic. The presence of risk prediction is twofold: PN and its reachability matrix can be either used to discover inconsistencies in intra and cross-company processes and is therefore able to detect the risk of coordination problems early on or the PN can be applied to better understand the system and the effects of SCDR. The prediction of risks itself is partly considered by 75% of the identified PN models but the effects of the supply chain system are measured by analyzing lead time and total disruption cost of the system. As part of risk optimization, around 25% of PN models are used to test the effects of individual mitigation strategies on the performance of the system.

In comparison to PN, SD captures the dynamic behavior of its systems very well. All models integrate dynamic risk behavior. This factor can be ascribed to the equation structure of SD modeling as well as the use of causal loop diagrams. Closely linked to the aspect of dynamic modeling is the risk propagation behavior. It focuses on the transfer of risks to upstream and downstream supply chain entities. Around 60% of the instances exhibit either the propagation of detrimental consequences of risks and do not model the risk propagation itself or model risks explicitly but only focus on the direct supply chain partner. Around 90% of all models implement some form of interdependency since the cause-effect relationship expands over more than one supply chain entity. 60% of the SD models merely consider the interdependency of resulting potential losses of a risk, while the approaches of Guertler and Spinler [33] as well as Ghadge et al. [31] address risk interdependencies explicitly. Risk prediction is part of around 90% of all identified approaches. These models

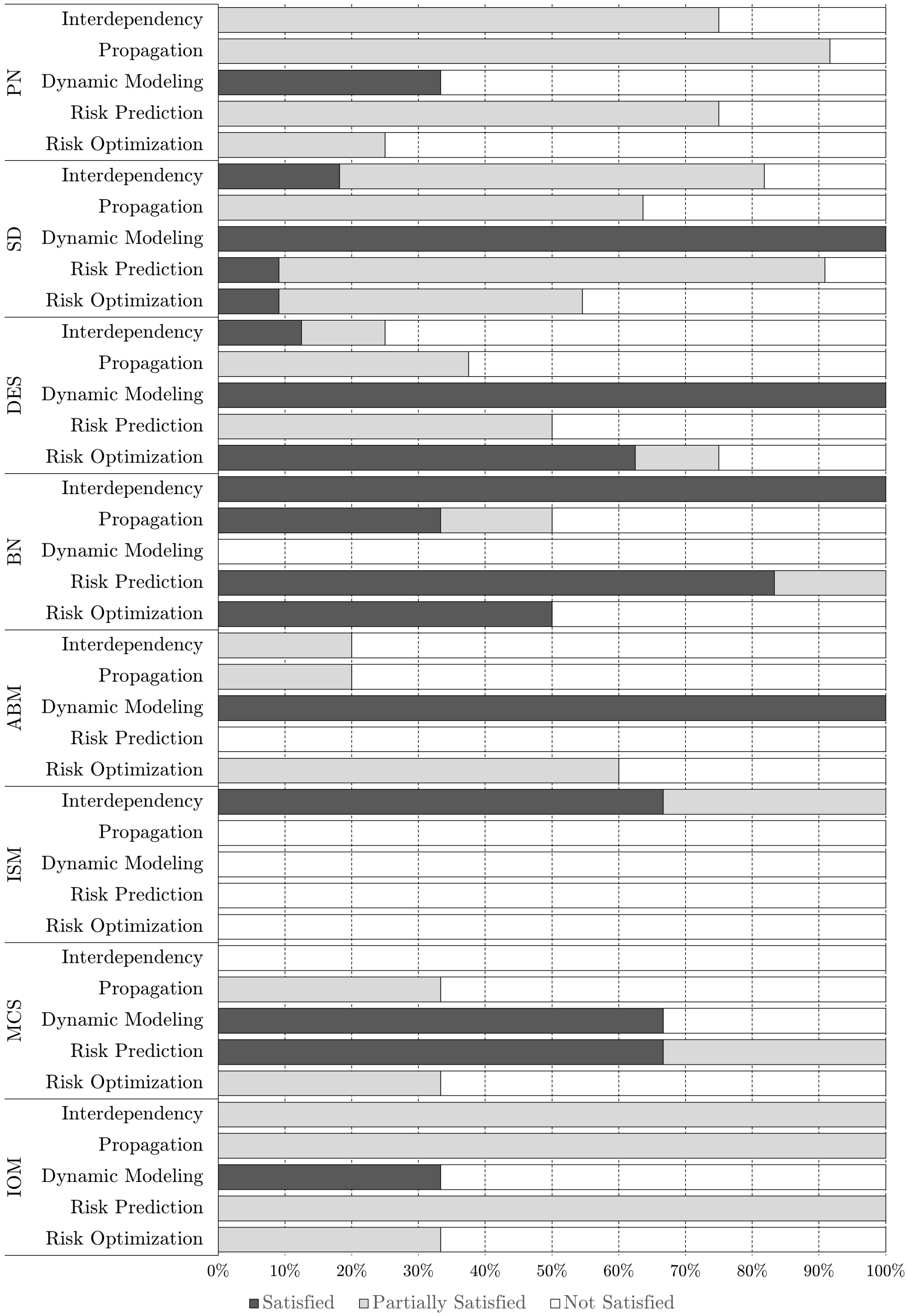


Fig. 5: Evaluation of the simulation techniques used for SCDR modeling

give insight into how the system would behave in case a risk event actually occurs. The model of Ghadge et al. [31] predicts risk explicitly by using project risk data as a representation of supply chain risk which is hard to transfer to general supply chain activities. Around 50% of the approaches partially aim to optimize the risk situation of the system. The authors compare the effects of one mitigation strategy on the performance indicators of the system in case of a disruption, but do not systematically optimize the system with various mitigation strategies at hand. The approach of Keilhacker and Minner [48] is an exception that completely focuses on risk mitigation.

Discrete-Event Simulation as a dynamic and simulative modeling approach is mostly concentrated on risk optimization of the supply chain system. All models display dynamic charateristics. More than 60% of the models incorporate a number of mitigation strategies and quantify their effect on the system's performance. The approach of Ivanov [41] considers recovery processes as an abstract way of risk mitigation. Risk interdependencies have not been the focus of the identified studies so far. Only around 25% include a consideration of interdependencies. Aqlan and Lam [4] use a goal programming approach to find the best mitigation strategies and test their effects with DES. The optimizing model takes risk interdependencies into consideration and makes sure that mitigation strategies do not increase correlated risks. Petrovic [80] tests the effect of various uncertainties on the performance of the system, so the model partially satisfies the interdependency criteria. Risk propagation itself is not fully considered, but the propagation of the effects of SCDR is integrated similarly to SD and PN models. Over 30% take propagative features of disruptive events into account. The prediction of risks is so far only considered indirectly by the models of Schmitt and Singh [101, 102], Hishamuddin et al. [37], and Wang et al. [140] in the form of a basic analysis of cause-effect relationships regarding the potential impact of disruptive events.

Bayesian Belief Networks by nature model risks explicitly and are predestined to calculate interdependencies between risks. All of the six identified SCDR models manage to display risk interdependencies. The definition of conditional probabilities is mandatory for this modeling technique, so it is difficult to use for deeply uncertain risk events which can only be studied in a what-if analysis. Due to its directed graph representation, it is suitable to model propagative system behavior. Two out of six models address the spread of different risks through the supply chain network and develop specific propagation measures. The model of Badurdeen et al. [5] partly measures risk propagation because it sets risks as true and analyzes the impact as a form of sensitivity analysis but does not consider the propagation through the network. In opposition to DES, the BN models concentrate less on risk optimization and more on risk prediction. Risk prediction is fully considered by five approaches, while the approach of Badurdeen et al. [5] considers the probability of occurrence without estimating the impact. Risk mitigation strategies can be integrated by reducing the probability of occurrence of a specific risk or risks and capture the difference on the overall risk situation. None of the BN models display dynamic effects.

Due to the nature of ABM modeling, every approach displays dynamic features of risk assessment. Other risk characteristics have not been thoroughly captured yet. Only one out of five models, namely the model of Otto et al. [75], analyze the direct and indirect effects of the disruptions and models the interdependent and propagative aspects of the resulting losses. 60% include some kind of risk optimization. Buffer inventory is used by Otto et al. [75] as well as Ledwoch et al. [56], who also incorporate contingent rerouting as a mitigation strategy. Bloss [10] discusses various strategies but does not present a detailed, concrete inclusion.

Interpretive Structural Modeling is used to cover interdependencies between risks, and two out of three models are combined with a fuzzy MICMAC analysis to capture the strengths of the interdependencies. This modeling technique does not integrate any other risk behavior aspects, so that the field of application is more narrow than the other described techniques but can be easily combined with other techniques.

The emphasis of MCS approaches lies in risk prediction. All three models incorporate risk prediction since they calculate the loss distribution due to various disruptive scenarios of different probabilities. Two out of three models include temporal aspects of the disruptive scenarios, while the model of Deleris and Erhun [22] calculates the losses by summing up the volume loss of each disruption. Risk optimization has not been modeled thoroughly yet. One of the three models, namely the one of Mizgier et al. [71], tests risk diversification through a multi-sourcing approach. The interdependencies of risks have not been considered by MCS approaches yet.

IOM have a strong emphasis on loss interdependencies and loss propagation. All three models integrate the propagative and interdependent features through the interdependency matrix. The matrix is used to calculate the effects of the inoperability so that all models also incorporate the prediction of losses. IOM lacks a consideration of probabilities so far, so that it can only be used for deep uncertain risk events in the form of swift what-if analysis. The model of Niknejad and Petrovic [72] uses a dynamic IOM approach so that temporal aspects can be analyzed as well. The only model that considers one mitigation strategy is the model of Wei et al. [143], which focuses on redundant supply as a countermeasure for disruptive events.

Fig. 6 displays the supported process steps of each simulation technique of a standard SCRM framework (RQ 4). BN models show a high focus on risk assessment with 65% risk identification and

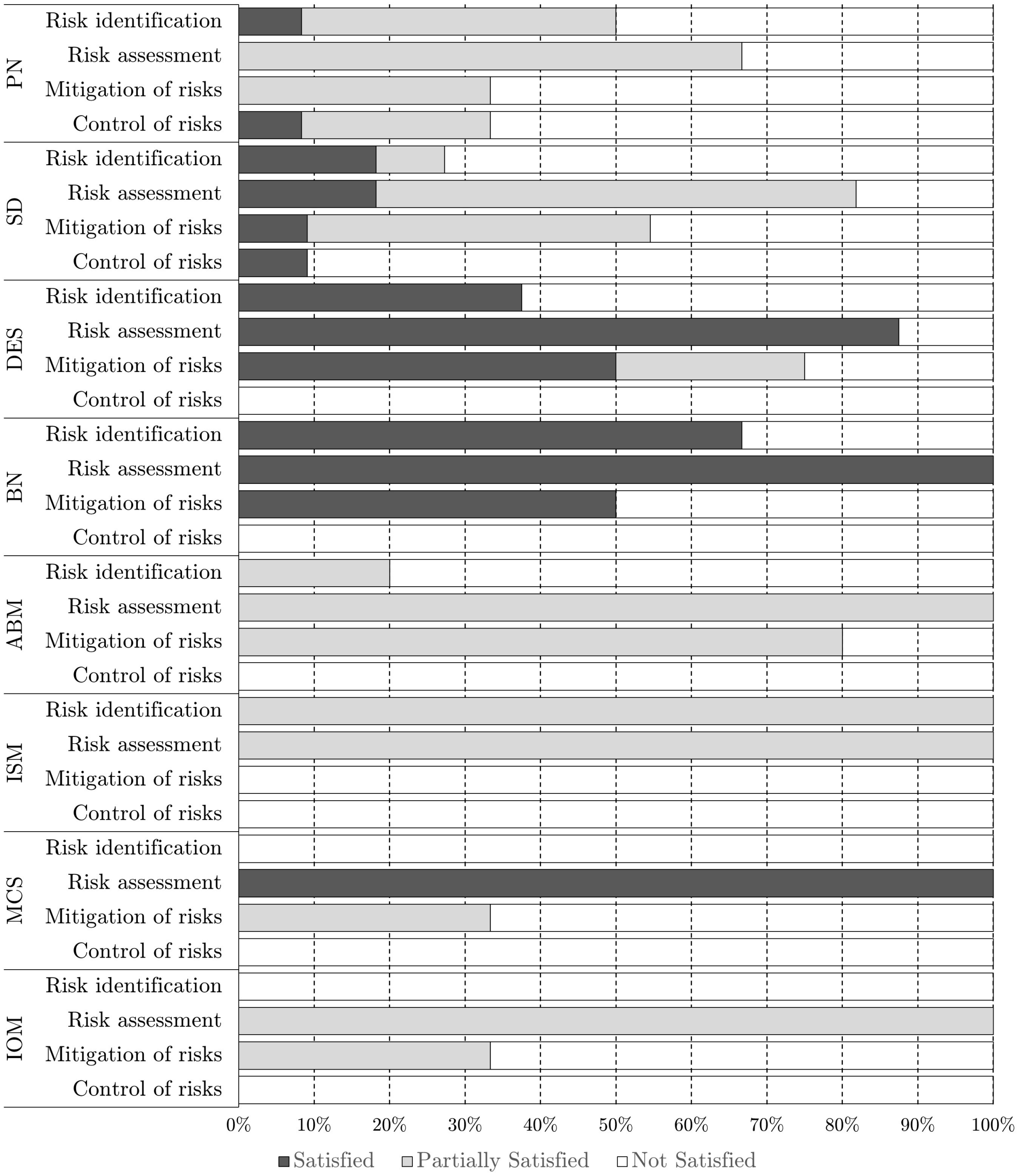


Fig. 6: Comparison of supported process steps of SCRM

another 50% also fully including risk mitigation. DES displays a slightly higher concentration on risk mitigation with 50% completely fulfilling this criteria and another 25% of the approaches partially fulfilling it. The control of risks is only completely present in one PN and one SD model. Two further PN approaches, namely the approaches of Blackhurst et al. [7] as well as John and Prasad [43], partially consider control of risk, since they address the detection of process related risks in the system. ISM is primarily used for risk identification and risk assessment. It does not support the risk identification itself, but identifies risk interdependencies and therefore supports risk assessment partially, too. ABM models concentrate on assessing the consequences of disruptive events and 80% of the models support risk mitigation partially. With their specific design, MCSs have a strong focus on risk assessment and all approaches completely support this SCRM process. Only a third of the MCS models also consider risk mitigation. IOM approaches demonstrate a swift way to assess the consequences of disruptive scenarios. The IOM models lack a focus on risk identification and quantification, which decrease their usefulness. One of the three IOM models partially supports risk mitigation.

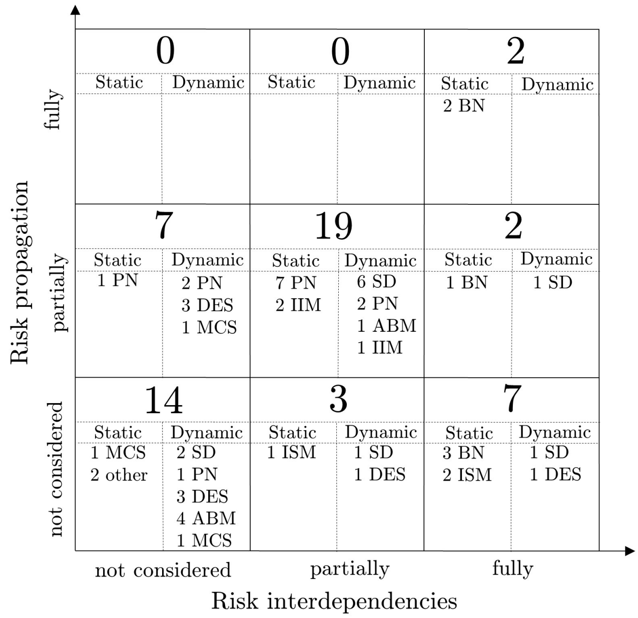


Fig. 7: Comparison of identified simulation techniques

After analyzing the evaluation criteria separately, we now shift the attention towards the simultaneous satisfaction of the requirements. Fig. 7 displays the simulation techniques with respect to risk interdependencies, risk propagation, and dynamic risk modeling. The previously discussed features of the identified modeling techniques can be seen in the illustration. Only two models which use Bayesian Nets for modeling fulfill risk interdependencies and risk propagation requirements completely, but do not consider dynamic aspects. The majority of PN approaches and all IOM models consider risk propagation and risk interdependencies partially. The majority of SD approaches also cover these two aspects partially, with the exception of two SD models that fully cover risk interdepedencies. All ISM, DES, MCS, and the majority of ABM models only consider either risk propagation or risk interdependency. It is discernible that no approach covers all three important risk behavior characteristics totally. Since we now have analyzed the characteristics of the identified models and have also extended the view of the characteristics of the modeling techniques, we now want to focus on identifying possible improvements for prospective models (RQ 5). The prior analysis displayed that the identified models lack the simultaneous consideration of the three important features of risk behavior on a network-level: risk propagation, risk interdependencies, and dynamic behavior. We also revealed that not all SCRM processes are supported yet. The inherent strength of the BN modeling technique is the consideration of risk interdependencies and the possibilities to also take risk propagation into account. It lacks the portrayal of dynamic features. To accomplish modeling this aspect, BN models can be combined with dynamic techniques like SD, PN, ABM, or DES. The BN model could focus on calculating probabilities of occurrences for risk events and consider their interdependencies. The dynamic simulation techniques can be used to assess the consequences and losses of the networks, and the effect of mitigation strategies. The identified BN approaches have considered risk mitigation mainly by reducing the risk in an abstract way. Therefore, a combination with other simulation techniques could provide more valid insights.

The strength of MCS consists in the inclusion of a large number of potential scenarios with stochastic distributions, so that the output of MCS models not only calculate a crisp value but develop a more differentiated stochastic view of potential damages. So far, the MCS approaches lack considering risk propagation and interdependencies. Since MCS consists of a large number of experiments and combining it with computation-intensive techniques would be impractical, they can be greatly combined with an IOM model to swiftly calculate risk impact on a network level.

The ABM approaches have not yet lived up to their full inherent potential yet. ABM is useful for mimicking the complex behavior of entities and integrating rule-based or complex decision making into the independently acting agents. The identified models do not display decision making of the agents. In the context of SCRM, agents could be equipped with multiple mitigation possibilities and even complex ways of anticipating the consequences of risk countermeasures for the network. With other techniques like SD or PN this behavioral logic would be very complex and time-consuming to integrate, but ABM models allow a compact way of incorporating individual decision making. Even a BN can be integrated into the agents' decision process and it could assess the impact of decisions on a network level. We therefore point out that prospective ABM models in SCRM should concentrate on more complex risk mitigation behavior.

ISM can be easily combined with different modeling techniques and is useful in structuring information in the face of a large and complex system such as a supply network. None of the identified BN models have integrated ISM into their methdology even though it addresses risk interdependencies and can be used to build the structure of a BN systematically. ISM can also be combined to a great extent with IOM, since the interdependency matrix of the IOM approach is often not derived in a systematic way.

As Fig. 4 has shown, a number of mitigation strategies have been implemented and around 15% of the models that include some form of risk mitigation have used various of mitigation strategies simultaneously. Still, there are plenty of further risk reduction techniques that could be modeled on a network-level. The strategies could be more thoroughly tested on their effectiveness. The mitigation strategies implemented are for the main part proactive strategies.

Reactive strategies like responsive pricing, revenue management, or shifting demand over time have not been implemented by the identified models yet but can also be useful, as seen in the case of Nokia [57, 122]. The interdependencies between multiple mitigation strategies could be analyzed in prospective models and optimal mixes of proactive and reactive strategies would be helpful for practitioners.

The effects of disruptive events have been mainly captured with measures like inventory stock, customer fill rate, and cost measures like lost sales, etc. Some approaches have developed more risk-specific measures which take propagative aspects into account. What is still missing in the identified models is the perspective of measuring the resilience and robustness of the considered system. It would be interesting to analyze how long entities or the total network need to get back into balance. Therefore we want to motivate researchers to define specific metrics to measure disruption propagation as well as the degree of robustness and resilience of the system.

Regarding the process steps of supported SCRM, it can be summarized that no approach supports all SCRM processes to date. Risk identification can be integrated by using specific systematic tools and techniques which also increases the validty of the whole risk assessment process. Risk assessment is the main focus of the majority of the identified models, also considering risk mitigation partly. The control of risks is only supported by a few models so far. Considering the recent trend in digitization and sensor-based data capture, processing, and intelligent behavior of cyber-physical systems, prospective decision making models need to capture this aspect more thoroughly. A key contribution would be to aggregate measurable risk indicators that can be tracked by modern sensors for a multitude of risks and integrate the data with the decision making models. The new trend in digitization could lead to a stronger symbiosis between SCRM and supply chain event management system.

5 CONCLUSION

This review has identified 57 SCDR models and the corresponding modeling techniques between 2001 and early 2018. Unlike prior reviews, we have not only presented the corresponding literature but also have derived relevant risk-specific criteria from the literature and from our introduced definition of SCDR models. All models have been evaluated based on these requirements. Subsequently, modeling techniques have also been analyzed. Our analysis indicates that the modeling approaches fulfill a great number of important risk-specific requirements, but still a lot of progress needs to be made. Especially on the main network level, risk characteristics, namely risk propagation, risk interdependency, and dynamic risk behavior, should be given more emphasis by future research efforts. Also the data basis of the approaches could be given a more central role to increase the models' validity. We could also detect the individual strengths and weaknesses of the modeling techniques and proposed numerous ways of combining and expanding the techniques to cover more risk characteristics synchronously. In addition to that, prospective models should put more emphasis on resilience and risk control. The trend of sensor-based digitization will connect prospective decision models to real-time information more and increase their consideration. We therefore expect the research field of SCRM to further grow, expand, and play a more decisive role for academics and practitioners.

REFERENCES

1. Alcantara P, Riglietti G, Aguada L (2017) BCI Supply Chain Resilience Report 2017. Retrieved from: https://www.riskmethods.net/resources/research/BCI-Resilience-Report-2017.pdf
2. Angerhofer BJ, Angelides MC (2000) System Dynamics Modelling in Supply Chain Management: Research Review. In: Joines JA, Barton RR, Kang K, Fishwick PA (eds) Proceedings of the 2000 WSC, pp 342-351
3. Aqlan F, Lam SS (2015) Supply chain risk modelling and mitigation. Int J Prod Res 53: 5640-5656
4. Aqlan F, Lam SS (2016) Supply chain optimization under risk and uncertainty: A case study for high-end server manufacturing. Comput Ind Eng 93: 78-87
5. Badurdeen F, Shuaib M, Wijekoon K, Brown A, Faulkner W, Amundson J, Jawahir IS, Goldsby

TJ, Iyengar D, Boden B (2014) Quantitative modeling and analysis of supply chain risks using Bayesian theory. J Manuf Technol Manag 25: 631-654
6. Bérard C (2010) Group model building using system dynamics: an analysis of methodological frameworks. The Electron J Bus Res Meth 8: 35-45
7. Blackhurst J, Wu T, Craighead CW (2008) A systematic approach for supply chain conflict detection with a hierarchical Petri Net extension. Omega 36: 680-696
8. Blackhurst J, Wu T, O'Grady P (2004) Network-based approach to modelling uncertainty in a supply chain. Int J Prod Res 42: 1639-1658
9. Blackhurst J, Rungtusanatham MJ, Scheibe K, Ambulkar S (2017) Supply chain vulnerability assessment: A network based visualization and clustering analysis approach. J Purch Supply Manag, in press.
10. Blos MF, Miyagi PE (2015) Modeling the Supply Chain Disruptions: A Study based on the Supply Chain Interdependencies. IFAC-PapersOnLine 48: 2053-2058
11. Blos MF, da Silva RM, Miyagi PE (2015) Application of an Agent-based Supply Chain to Mitigate Supply Chain Disruptions. IFAC-PapersOnLine 78: 640-645
12. Brosas ME, Kilantang MA, Li NB, Ocampo L, Promentilla MA, Yu KD (2017) Novel approach for manufacturing supply chain risk analysis using fuzzy supply inoperability input-output model. Manuf Letters 12: 1-5
13. Bueno-Solano A, Cedillo-Campos MG (2014) Dynamic impact on global supply chain performance of disruptions propagation produced by terrorist acts. Transport Res E-Log 61: 1-12
14. Cassandras CG, Lafortune S (2008) Introduction to Discrete Event Systems. 2nd edition. Springer, New York
15. Cedillo-Campos MG, Pérez-Salas G, Bueno-Solano A, González-Ramírez RG, Jímenez-Sánchez E (2014) Supply Chain Disruptions Propagation Caused by Criminal Acts. J Appl Res Technol 12: 684-694
16. Ceryno PS, Scavarda LF, Klingebiel K, Yüzgülec G (2013) Supply Chain Risk Management: A Content Analysis Approach. Int J Ind Eng Manag 4: 141-150
17. Chopra S, Sodhi MS (2004) Managing Risk to Avoid Supply-Chain Breakdown. MIT Sloan Manage Rev 46: 52-61
18. Colicchia C, Strozzi F (2012) Supply chain risk management: a new methodology for a systematic literature review. Supply Chain Manag 17: 403-418
19. Cooper HM, Hedges LV (1994) Research synthesis as a scientific process: The handbook of research synthesis. Russel Sage Foundation, New York
20. Cooper HM, Hedges LV (2009) The Handbook of Research Synthesis and Meta-Analysis. 2nd edition. Russell Sage Foundation, New York
21. Dang T (2017) Harvey prompts force majeures, more US plant shutdowns. ICIS News. Retrieved from: https://www.icis.com/resources/news/2017/08/29/10137419/harvey-prompts-force-majeures-more-us-plant-shutdowns/
22. Deleris LA, Erhun F (2005) Risk Management in Supply Networks using Monte-Carlo Simulation. In: Kuhl ME, Steiger NM, Armstrong FB, Joines JA (eds) Proceedings of the 2005 WSC, 1643-1649
23. Denyer D, Tranfield D (2009) Producing a systematic review. In: Buchanan DA, Bryman A (eds) The SAGE handbook of organizational research methods. Sage Publications, London, pp 671-689
24. DiChristopher T (2017) Harvey has 'paralyzed' a critical part of US manufacturing supply chain. CNBC: https://www.cnbc.com/2017/09/06/harvey-has-paralyzed-a-critical-part-of-the-us-manufacturing-chain.html
25. Elangovan D, Sundararaj G, Devadasan S, Karuppuswamy P (2010) Development of futuristic supply chain risk management pilot strategies for achieving loss reduction in manufacturing organisations. World J Entrepreneurship Manag Sustain Dev 6: 39-51
26. Ellram LM, Cooper MC (2014) Supply Chain Management: It's all about the journey, not the destination. J Supply Chain Manag 50: 8-20
27. Fahimnia B, Tang CS, Davarzani H, Sarkis J (2015) Quantitative models for managing supply chain risks: A review. Eur J Oper Res 247: 1-15
28. Fink A (2014) Conducting Research Literature Reviews: From the Internet to Paper. 4th edition. SAGE Publications, Los Angeles
29. Forrester JW (1994) System dynamics, systems thinking and soft OR. Syst Dynam Rev 10: 245-256
30. Garvey MD, Carnovale S, Yeniyurt S 2015. An analytical framework for supply network risk propagation: A Bayesian network approach. Eur J Oper Res 243: 618-627
31. Ghadge A, Dani S, Chester M, Kalawsky R (2013) A systems approach for modelling supply chain risks. Supply Chain Manag 18: 523-538
32. Ghadge A, Dani S, Roy K (2012) Supply Chain Risk Management: present and future scope. Int J Logist Manag 23: 313-339
33. Guertler B, Spinler S (2015) Supply risk interrelationships and the derivation of key supply risk indicators. Technol Forecast Soc 92: 224-236

34. Haimes YY, Jiang P (2001) Leontief-based model of risk in complex interconnected infrastructures. J Infrastruct Syst 7: 1-12
35. Heckmann I, Comes T, Nickel S (2015) A critical review on supply chain risk Definition, measure and modeling. Omega 52: 119-132
36. Helbing D, Hendrik A, Kühnert C (2006) Disasters as extreme events and the importance of network interactions for disaster response management. In: Albeverio S, Jentsch V, Kantz H (eds) Extreme events in nature and society, the frontiers collection. Springer, Berlin, pp 319-348
37. Hishamuddin H, Sarker R, Essam D (2015) A Simulation Model of a Three Echelon Supply Chain System with Multiple Suppliers subject to Supply and Transportation Disruptions. IFAC-PapersOnLine 48: 2036-2040
38. Ho W, Zheng T, Yildiz H, Talluri S (2015) Supply chain risk management: a literature review. Int J Prod Res 53: 5031-5069
39. Inagaki K, Mitchel T, Hornby L (2015) Companies feel effect of Tianjin blasts as $625m of cars wrecked. Financial Times https://www.ft.com/content/ad62904c-44ce-11e5-b3b2-1672f710807b
40. Insua DR, Ruggeri F, Wiper MP (2012) Bayesian Analysis of Stochastic Process Models. UK: John Wiley & Sons, Chichester
41. Ivanov D (2017) Simulation-based ripple effect modelling in the supply chain. Int J Prod Res 55: 2083-2101
42. Jevsenak J, Levanic T (2016) Should artificial neural networks replace linear models in tree ring based climate reconstructions? Dedrochronologia 40: 102-109
43. John FR, Prasad PSS (2012) Supply chain conflict detection with coloured petri nets. J Adv Manag Res 9: 208-216
44. Julong D (1989) Introduction to Grey System Theory. Journal Grey Syst 1: 1-24
45. Jüttner U (2005) Supply chain risk management Understanding the business requirements from a practitioner perspective. Int J Logist Manag 16: 120-141
46. Jüttner U, Peck H, Christopher M (2003) Supply Chain Risk Management: Outlining an Agenda for Future Research. Int J Log 6: 197-210
47. Kano CH, Blos MF, Junqueira F, dos Santos Filho DJ, Miyagi P E (2013) Modeling and Analysis of Global Supply Chain Disruption Based on Petri Net. In: 22nd International Congress of Mechanical Engineering, pp 382-390
48. Keilhacker ML, Minner S (2017) Supply Chain risk management for critical commodities: A system dynamics model for the case of the rare earth elements. Resour Conserv Recy 125: 349-362
49. Kenett RS Harel A, Ruggeri F (2009) Controlling the Usability of Web Services. Int J Softw Eng Know 19: 627-651
50. Khan O, Burnes B (2007) Risk and supply chain management: creating a research agenda. Int J Logist Manag 18: 197-216
51. Kirkevold M (1997) Integrative nursing research – an important strategy to further the development of nursing science and nursing practice. J Adv Nurs 25: 977-984
52. Kirkwood CW (1998) System Dynamics Methods: A Quick Introduction. Arizona State University
53. Klibi W, Martel A (2012) Scenario-based Supply Chain Network risk modeling. Eur J Oper Res 223: 644-658
54. Knight FH (1921) Risk, uncertainty and profit. Boston: Houghton Mifflin Company
55. Kwon OB, Lee JJ (2001) A multi-agent intelligent system for efficient ERP maintenance. Expert Syst Appl 21: 191-202
56. Ledwoch A, Yasarcan H, Brintrup A (2018) The moderating impact of supply network topology on the effectiveness of risk management Int J Prod Econ 197: 13-26
57. Lee HL (2004) The Triple-A Supply Chain. Harvard Bus Rev 82: 102-113
58. Leontief WW (1951) Input-output economics, Sci Am 185: 15-21
59. Li C, Ren J, Wang H (2016) A system dynamics simulation model of chemical supply chain transportation risk management systems. Comput Chem Eng 89: 71-83
60. Lin F, Norrie DH (2001) Schema-based conversation modeling for agent-oriented manufacturing systems. Holonic Manufact Syst 46: 259-274
61. Linstone HA, Turoff M (1975) The Delphi method: Techniques and applications. Addison-Wesley Publishing Company, Reading
62. Liu C, Shu T, Chen S, Wang S, Keung Lai K, Gan L (2016) An improved grey neural network model for predicting transportation disruptions. Expert Syst Appl 45: 331-340
63. Liu L, Liu X, Liu G (2017) The risk management of perishable supply chain based on coloured Petri Net modeling. Info Proc Agr: In press
64. Liu, R, Kumar A, van der Aalst W (2007) A formal modeling approach for supply chain event management. Decis Support Syst 43: 761-778
65. Macal CM, North MJ (2014) Tutorial on agent-based modeling and simulation. In: Taylor S (ed), Agent-based Modeling and Simulation. Palgrave Macmillan, London, pp 11-31
66. Manten AA (1973) Scientific literature reviews. Scholarly Publ 5: 75-89
67. Manuj I, Mentzer JT (2008) Global supply chain risk management strategies. Int J Phys Distrib Log 38: 192-223

68. McDonell S (2015) Thousands of dead fish wash ashore in Haihe river near Tianjin. ABC. Retrieved from: http://www.abc.net.au/news/2015-08-21/thousands-of-dead-fish-washed-ashore–in-tianjin/6716108
69. Mentzer JT, DeWitt W, Keebler JS, Min S, Nix NW, Smith CD, Zacharia ZG (2001) Defining Supply Chain Management. J Bus Logist 22: 1-25
70. Mittal A, Kassim A (2007) Bayesian Network Technologies: Applications and Graphical Models. IGI Publishing, Hershey
71. Mizgier KJ, Wagner SM, Jüttner MP (2015) Disentangling diversification in supply chain networks. Int J Prod Econ 162:115-124
72. Niknejad A, Petrovic D (2017) Analysis of impact of uncertainty in global production networks' parameters. Comput Ind Eng 111: 228-238
73. Norrman A, Janson U (2004) Ericsson's proactive supply chain risk management approach after a serious sub-supplier accident. Int J Phys Distrib Log 34: 434-456
74. Olson DL, Wu DD (2010) A review of enterprise risk management in supply chain. Kybernetes 39: 694-706
75. Otto C, Willner SN, Wenz L, Frieler K, Levermann A (2017) Modeling loss-propagation in the global supply network: The dynamic agent-based model acclimate. J Econ Dyn Control 83: 232-269
76. Palvia P, Leary D, Mao E, Midha V, Pinjani P, Salam AF (2004) Research Methodlogies in MIS: An Update. Commun Associat Inf Syst 14: 526-542
77. Park K (2014) Effect of Destruction and Disruption of an Enterprise Network Using Agent-Based Simulation and System Dynamics. Adv Sci Technol Letters 62: 13-16
78. Peng M, Peng Y, Chen H (2014) Post-seismic supply chain risk management: a system dynamics disruption analysis approach for inventory and logistics planning. Comput Oper Res 42: 14-24
79. Petri CA (1962) Kommunikation Mit Automaten. PhD Thesis, University of Bonn, 1962
80. Petrovic D (2001) Simulation of supply chain behavior and performance in an uncertain environment. Int J Prod Econ 71: 429-438
81. Pfohl HC, Gallus P, Thomas D (2011) Interpretive structural modeling of supply chain risks. Int J Phys Distrib Log 41: 839-859
82. Pfohl HC, Köhler H, Thomas D (2010) State of the art in supply chain risk management research: empirical and conceptual findings and a roadmap for the implementation in practice. Logist Res 2: 33-44
83. Pourret O, Naim P, Marcot B (2008) Bayesian Networks: A Practical Guide to Applications. John Wiley & Sons, Chichester
84. Prakash S, Soni G, Rathore AP (2017) A critical analysis of supply chain risk management content: a structured literature review. J Adv Manage Res 14: 69-90
85. Pritsker AAB (1987) Model evolution II: An FMS design problem. In: Thesen A, Grant, H, Kelton WD (eds) Proceedings of the 1987 WSC, pp 567-574
86. Qazi A, Quigley J, Dickson A (2015) Supply Chain Risk Management: Systematic literature review and a conceptual framework for capturing interdependencies between risks. In: 5th International Conference on Industrial Engineering and Operations Management, pp 1-13
87. Qazi A, Quigley J, Dickson A, Ekici S (2017) Exploring dependency based probabilistic supply chain risk measures for prioritising interdependent risks and strategies. Eur J Oper Res 259: 189-204
88. Qazi A, Dickson A, Quickley J, Gaudenzi B (2018) Supply chain risk network management: A Bayesian belief network and expected utility based approach for managing supply chain risks. Int J Prod Econ 196: 24-42
89. Raychaudhuri S (2008) Introduction to Monte Carlo Simulation. In: Mason SJ, Hill RR, Mnch L, Rose O, Jefferson T, Fowler JW (eds) Proceedings of the 2008 WSC, pp 91-100
90. Rajagopal V, Vekatesan SP, Goh M (2017) Decision-making models for supply chain risk mitigation: A review. Comp Ind Eng 113: 646-682
91. Rajesh R, Ravi V, Venkata Rao R (2015) Selection of risk mitigation strategy in electronic supply chains using grey theory and digraph-matrix approaches. Int J Prod Res 53: 238-257
92. Rao S, Goldsby TJ (2009) Supply chain risks: a review and typology. Int J of Logist Manag, 20: 97-123
93. Richardson GP, Pugh AL (1981) Introduction to System Dynamics Modeling. Productivity Press, Portland
94. Ritchie B, Marshall D (1993) Business Risk Management, Chapman & Hall, London
95. Robinson S (2011) Conceptual Modeling for Simulation: Definition and Requirements. In: Robinson S, Brooks R, Kotiadis K, van der Zee DJ (eds) Conceptual Modeling for Discrete-Event Simulation. CRC Press, Boca Raton
96. Robinson S (2014) Simulation: The Practice of Model Development and Use. Palgrave Macmillan, New York
97. Sălamon T (2011) Design of Agent-based Models: Developing Computer Simulations for a Better Understanding of Social Processes. Tomas Bruckner

98. Sage AP (1977) Interpretive Structural Modeling: Methodology for Large-Scale Systems. McGraw-Hill, New York
99. Santos JR (2006) Inoperability input-output modeling of disruptions to interdependent economic systems, Syst Eng 9: 20-34
100. Santos JR, Haimes YY (2004) Modeling the demand reduction input-output (i-o) inoperability due to terrorism of interconnected infrastructures. Risk Anal 24: 1437-1451
101. Schmitt AJ, Singh M (2009) Quantifying supply chain disruption risk using Monte Carlo and discrete-event simulation. Rossetti M, Hill RR, Johansson B, Dunkin A, Ingalls RG (eds) Proceedings of the 2009 WSC, pp 1237-1248
102. Schmitt AJ, Singh M (2012) A quantitative analysis of disruption risk in a multiechelon supply chain. Int J Prod Econ 139: 22-32
103. Schmitt TG, Kumar S, Stecke KE, Glover FW, Ehlen MA (2017) Mitigating disruptions in a multi-echelon supply chain using adaptive ordering. Omega 68: 185-198
104. Schuh G, Schenk M, Servos N (2015) Design of a simulation model fort the assessment of a real-time capable disturbance management in manufacturing supply chains. Procedia Manufact 3: 425-432
105. Seck M, Rabadi G, Koestler C (2015) A Simulation-based Approach to Risk Assessment and Mitigation in Supply Chain Networks. Procedia Comput Sci 61: 98-104
106. Sharma SK, Sharma S (2015) Developing a Bayesian Network Model for Supply Chain Risk Management. Suply Chain Forum: An International Journal 16: 50-72
107. Shukla V, Naim M (2017) Detecting disturbances in supply chains: the case of capacity constraints. Int J Logist Manag 28: 398-416
108. Sidola A, Kumar P, Kumar D (2011) System Dynamic Methodological Approach for Design and Analysis of Risk in Supply Chain. Proceedings of 2011 IEEE International Technology Management Conference, pp 495-500
109. Schneider E, Seba E (2017) Harvey throws a wrench into U.S. energy engine. Reuters. Retrieved from: https://www.reuters.com/article/us-storm-harvey-energy/harvey-throws-a-wrench-into-u-s-energy-engine-idUSKCN1B70YQ
110. Snyder LV, Atan Z, Peng P, Rong Y, Schmitt AJ, Sinsoysal B (2016) OR/MS models for supply chain disruptions: a review. IEE Trans 48: 89-109
111. Sodhi MS, Son BG, Tang CS (2012) Researchers' Perspectives on Supply Chain Risk Management. Prod Oper Manag 21: 1-13
112. Spekman RE, Davis EW (2004) Risky business: expanding the discussion on risk and the extended enterprise. Int J Phys Distrib Log 34: 414-433
113. Srivastava SK, Chaudhuri A, Srivastava RK (2015) Propagation of risks and their impact on performance in fresh food retail. Int J Logist Manag 26: 568-602
114. Stecke K, Kumar S (2009) Sources of Supply Chain Disruptions, Factors that Breed Vulnerability, and Mitigating Strategies. J Mark Channels, 16: 193-226
115. Sterman DJ (1989) Modeling managerial behaviour: misperceptions of feedback in a dynamic decision making experiment. Manage Sci 35: 321-339
116. Sterman JD (2000) Business Dynamics. McGraw-Hill, New York
117. Stevenson M, Spring M (2007) Flexibility from a supply chain perspective: definition and review. Int J Oper Prod Man, 27: 685-713.
118. Svensson G (2002) Dyadic vulnerability in companies' inbound and outbound logistics flows. Int J Logist-Res App 5: 81-113
119. Swierczek A (2014) The impact of supply chain integration on the snowball effect in the transmission of disruptions: An empirical evaluation of the model. Int J Prod Econ 157: 89-104
120. Tako AA, Robinson S (2012) The application of discrete event simulation and system dynamics in the logistics and supply chain context. Decis Support Syst 52: 802-815
121. Tan CS, Tan PS, Lee SS (2015) Quantifying disruptions propagation in a supply chain. 2015 IEEE International Conference on Industrial Engineering and Engineering Management, pp 1668-1672
122. Tang CS (2006) Perspectives in supply chain risk management. Int J Prod Econ 103: 451-488
123. Tang L, Jing K, He J, Stanley HE (2016) Complex interdependent supply chain networks: Cascading failure and robustness. Physica A 443: 58-69
124. Tang O, Musa SN (2011) Identifying risk issues and research advancements in supply chain risk management. Int J Prod Econ 133: 25-34
125. Taylor S (2014) Introducing agent-based modeling and simulation. In: Taylor S (ed) Agent-Based Modeling and Simulation. Palgrave Macmillan, London, pp 1-10
126. Thiagarajan R, Kwok HW, Calbert G, Gossink D, Shekh S, Allard T (2011) A simulation-based risk analysis technique to determine critical assets in a logistics plan. In: Chan F, Marinova D, Anderssen RS (eds) 19th International Congress on Modelling and Simulation, pp 503-509
127. Thun JH, Hoenig D (2011) An empirical analysis of supply chain risk management in the German automotive industry. Int J Prod Econ 131: 242-249

128. Teeuw WB, van den Berg H (1997) On the Quality of Conceptual Models. In: Liddle SW (ed) Proceedings of the ER'97 Workshop on Behavioral Models and Design Transformations: Issues and Opportunities in Conceptual Modeling
129. Terry-Armstrong N (2016) The Volkswagen Scandal – The high cost of corporate deceit. Busidate 24: 9-13
130. Tomlin B (2006) On the Value of Mitigation and Contingency Strategies for Managing Supply Chain Disruption Risks. Manage Sci 52: 639-657
131. Treece JB (1997) Just-too-much single sourcing spurs Toyota purchasing review. Automotive News (March 3)
132. Trkman P, McCormack K (2009) Supply chain risk in turbulent environments A conceptual model for managing supply chain network risk. Int J Prod Econ 119: 247-258
133. Tuncel G, Alpan G (2010) Risk assessment and management for supply chain networks: A case study. Comput Ind 61: 250-259
134. Vakharia AJ, Yenipazarli A (2009) Managing Supply Chain Disruptions. Found Trends Technol Inf Oper Manag 2: 243-325
135. Vekantesh VG, Rathi S, Patwa S (2015) Analysis on supply chain risks in Indian apparel retail chains and proposal of risk prioritization model using Interpretive structural modeling. J Retailing Consumer Serv 26: 153-167
136. Vilko JP, Hallikas JM (2012) Risk assessment in multimodal supply chains. Int J Prod Econ 140: 586-595
137. vom Brocke J, Simons A, Niehaves B, Riemer K, Plattfaut R, Cleven A (2009) Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process. 17th European Conference on Information Systems, pp 2206-2217
138. Wagner SM, Bode C (2006) An empirical investigation into supply chain vulnerability. J Purch Supply Manag 12: 2877-2891
139. Wang Y, Huang M, Chen J (2014) System Dynamics Modeling of Backup Purchasing Strategies under Supply Disruption Risks. Int J ue-Serv Sci Technol 7: 287-296
140. Wang Z, Hu H, Gong J (2018) Simulation based multiple disturbances evaluation in the precast supply chain for improved disturbance prevention. J Clean Prod 177: 232-244
141. Watson R (1978) Interpretive Structural Modelling A useful tool for worth assessment? Technol Forecast Soc 11: 165-185
142. Webster J, Watson RT (2002) Analyzing the Past to Prepare for the Future: Writing a Literature Review. MIS Quart 26: xiii-xxiii
143. Wei H, Dong M, Sun S (2010) Inoperability Input-Output Modeling (IIM) of Disruptions to Supply Chain Networks. Syst Eng 13: 324-339
144. Wilson MC (2007) The impact of transportation disruptions on supply chain performance. Transport Res E-Log 43: 295-320
145. Wu T, Blackhurst J, O'Grady P (2007) Methodology for supply chain disruption analysis. Int J Prod Res 45: 1665-1682
146. Xu H, Shatz SM (2001) An agent-based Petri net model with application to seller/buyer design in electronic commerce. 5th IEEE International Symposium on Autonomous Decentralized Systems, pp 11-18
147. Zhang X (2016) A Petri net based simulation to study the impact of customer response to stock-out on supply chain performance. Cogent Eng 3: 1-16
148. Zegordi SH, Davarzani H (2012) Developing a supply chain disruption analysis model: Application of colored Petri-nets. Expert Syst Appl 30: 2102-2111
149. Zsidisin GA (2003) A grounded definition of supply risk. J Purch Supply Manag 9: 217-224
150. Zsidisin GA, Ritchie B (2009) Supply chain risk: A handbook of assessment, management, and performance. Springer, New York