European Journal of Operational Research 264 (2018) 813–829

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Time traps in supply chains: Is optimal still good enough?

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ARTICLE INFO

Article history:
Received 4 January 2016
Accepted 9 July 2016
Available online 16 July 2016

Keywords:
Optimality concepts
Online optimization
Look-ahead
Supply chain risk
Multi-period planning

ABSTRACT

Operations Researchers support Supply Chain Management and Supply Chain Planning by developing adequate mathematical optimization models and providing suitable solution procedures. In this paper we discuss what *adequate* could mean. Therefore, we may ask several questions concerning "optimality" in Supply Chain Planning under causal and temporal uncertainty: What is an optimal solution? When is it optimal? For how long is it optimal? How should the design of a supply chain be changed when conditions and requirements ask for new structures? In particular, we discuss new approaches to Supply Chain Planning in order to give an optimal transformation from an initial solution over multiple periods to a desired one rather than just specifying an optimal snapshot solution. Time and uncertainty are the factors triggering the whole discussion. In particular, several flaws often found when dealing with these factors result in so-called "time traps". We look at the impact of recent technological developments like the Internet of Things or Industry 4.0 on operational supply chain planning and control, and we show how online optimization can help to cope with real-time challenges. Moreover, we re-coin the concept of risk in the realm of Supply Chain Planning. Here the question is how to measure supply chain specific risks and how to incorporate them "adequately" into mathematical models.

1. Introduction

Supply Chain Planning—as an important subtask of Supply Chain Management—is the process of allocating resources over a network of interrelated locations with the goal to satisfy customer requirements. It spans all movements and storage of raw materials, work-in-process inventory, and finished goods from the point-of-origin to the point-of-consumption. Operations Researchers support Supply Chain Planning by developing mathematical optimization models and providing suitable solution procedures.

The concept of *optimality* describes the property of a solution which imposes the best feasible decision obtainable under specific conditions. These conditions need to be identified, gathered, and appropriately expressed by formulating mathematical models, which abstract from restrictions of the real world. If models do not capture the most relevant features and do not yield to applicable tasks or useful managerial insights, their solutions will never be regarded as good enough for practical implementation—although they are optimal from a strictly mathematical point of view.

Especially global supply chains have to face a rich variety of potential requirements. Not all of them can be considered within constraints, but some of them must be respected. Since Supply Chain Planning strongly depends on the ability to grasp future developments in order to balance supply and demand, the main challenge during the identification of important requirements is imposed by the weighting and the incorporation of characteristics that describe the future. Major components of the future are time and uncertainty. While the former refers to the "amount" of future to consider, the latter describes the degree and type of knowledge available about future developments. Ignoring an appropriate way of dealing with these two aspects—isolated or together–leads to what we call "time traps", which is a term indicating that the relevance of time is perceived but not adequately treated.

In this paper we claim that the existing optimization models for supporting Supply Chain Planning lack to address the future appropriately and thus, do not assure that optimal solutions represent applicable plans and provide intelligible benefits. We address three major topics that overlap with respect to their treatment of the future, namely: online optimization models, multi-period planning models, and risk-aware models.

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http://dx.doi.org/10.1016/j.ejor.2016.07.016
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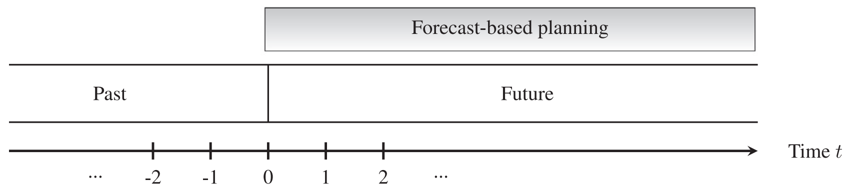

Fig. 1. Division of the time line under forecast-based planning methods in current APS systems.

Handling short-term future uncertainty can be accomplished by online optimization models (cf. Dunke, 2014). The discussion that we provide in the current paper regarding online optimization approaches gives a contribution to answering the following question: *What is an appropriate optimality concept with respect to a steady information inflow as facilitated by modern ICT (Internet of Things and Industry 4.0)?*

Multi-period planning models are of great relevance in the context of strategic Supply Chain Planning, e.g., in Supply Chain Network Design (see Alumur, Kara, and Melo, 2015a and Nickel & Saldanha-da-Gama, 2015). Related to this aspect, the relevant question that we aim at answering in this paper is the following: *How long can we consider a previously calculated solution for a snapshot of the overall problem as optimal? When should it be changed? To what extent? Which components of the solution should be modified?*

The consideration of unexpected mid- to long-term developments can be subsumed under the "family" of risk-aware formulations (Heckmann, Comes, & Nickel, 2015). Although risk-aware model formulations can be found in the literature, the definition of supply chain risk is most often treated in a cursory manner and leads to oversimplification and misestimation. By putting the focus on time, in the current work we answer the following central question: *How does supply chain risk evolve over time?*

The three previous paragraphs disclose a central aspect in the current work: time. Fig. 1 provides a simplistic view on how planning for future activities is currently integrated with time. In particular, we emphasize the fact that most of today's planning and scheduling systems rely on forecast-based approaches (Stadtler, Kilger, & Meyr, 2015). A major contribution of the current paper is to show that considering alternative views to this typical "approach" may render better solutions when dealing with time and uncertainty. We note that this does not mean that "forecast-based approaches" should be ignored. Our goal is simply to discuss possible alternatives.

It is important to point out that Fig. 1 and its variations presented throughout the paper are used schematically. For instance, in strategic risk-aware SC planning time buckets are different (e.g., months or years) from those in operational planning (e.g., days or hours). Nevertheless, it is worth noticing that Section 3 provides a tool for applying mathematical models irrespective of how a time bucket is defined.

In the following sections we discuss how the three model types mentioned above can handle time and/or uncertainty and also how, by doing so, they can help improving Supply Chain Planning decisions. We offer insights about common flaws as well as new concepts and definitions that may be of great help for achieving our goal. Furthermore, we provide appropriate illustrations to show the relevance of the aspects discussed.

This paper is not aimed at focusing specific aspects such as robustness, flexibility, stochasticity or resilience. Our focus is on Supply Chain Planning and what is necessary for that.

The remainder of this paper is organized as follows. Section 2 discusses limits of optimization paradigms and reveals how online optimization with look-ahead may be considered as an alternative. Section 3 uncovers inadequateness of single period planning models in the context of many Supply Chain Planning problems. Section 4 reveals how the flawed perception of supply chain risk leads to an imprecise and incomplete definition of this concept. In Section 5 we highlight the links between the major aspects discussed in Sections 2–4 and we present some conclusions drawn from the work done.

2. Online optimization with look-ahead

Operational tasks in Supply Chain Planning are often coined by data being received in a steady flow of information. Hence, optimization algorithms have to be employed repetitively and decisions have to be communicated on-the-line. For that reason, short-term decision making problems arising in environments with dynamic information flows are called online optimization problems (Fiat & Woeginger, 1998). While in the classical discipline of online optimization decisions are made only upon knowledge of the past and the current information, the field of online optimization with look-ahead additionally takes into account a preview of certain future information (Dunke & Nickel, 2016) which can be used in an event-based planning approach as indicated in Fig. 2. This information is made available through so-called look-ahead devices such as barcode scanners, RFID or GPS chips, or sensor modules.

Considering the transition from static to dynamic information provision in Supply Chain Planning through the mentioned standard devices, we realize that these technologies allow us to turn the uncertain future gradually into a certain one. In new application fields such as Industry 4.0 or Advanced Manufacturing it is even an essential prerequisite to know at each point what is currently going on Tassey (2014). Using information-transmitting devices, decision makers obtain more relevant data from different entities involved in their business processes. However, in order to make use of the data, suitable online methods and algorithms are required. Hence, bringing together the physical entities of a supply chain with data analytics and online optimization algorithms represents the methodological key to establishing the Internet of Things as an important part of Industry 4.0. Observe that the above technologies are mainly used in operational planning and control; nonetheless the use of information-transmitting devices (e.g., sensors) can help also on the tactical and strategic planning horizon to better anticipate future events and incorporate them in multi-period models (cf. Section 3) and risk-aware supply chain planning (cf. Section 4). However, only because technologies have matured, it does not imply that the scientific methods also did. Quite to the contrary, the theories of decision making in near real time and online optimization with look-ahead are still in a rather immature state, and a systematic approach to optimization under uncertainty in near real time is not yet established (Dunke, 2014; Grötschel, Krumke, & Rambau, 2001). The core reason for this can be traced back to the difficulties in finding a suitable concept of optimality that can be applied in sequential decision making under incomplete information. In Section 2.1 we discuss weak links of different optimality concepts when applied to online settings. Section 2.2 then shows that some of the issues can be resolved

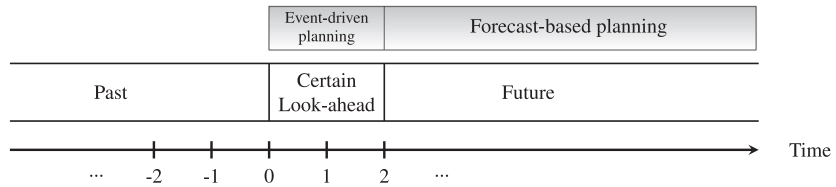

Fig. 2. Division of the time line under consideration of near-future data as transmitted by look-ahead devices.

in a general framework for online optimization with look-ahead. Lastly, Section 2.3 exemplifies the benefits of this approach.

2.1. Flaws

Real-valued key performance indicators (KPIs) are often used to evaluate performance. Hence, a straightforward approach would be to define a function $KPI(\sigma_1, \ldots, \sigma_m, x_1, \ldots, x_n)$ which gives the KPI value for given inputs $\sigma_1, \ldots, \sigma_m$ and selected decisions $x_1, \ldots, x_n$ with $m, n \in \mathbb{N}$. Because the $\leq$ -relation yields a total order on $\mathbb{R}$, this concept allows us to figure out under which inputs which decisions are needed to achieve the best value of *KPI*. The simplicity of the KPI concept with respect to "what is good" and "what is bad" is a major reason for its success both in industry and academia. However, it possesses several drawbacks concerning time and uncertainty.

2.1.1. Neglect of sequentiality

The function $KPI(\sigma_1, \ldots, \sigma_m, x_1, \ldots, x_n)$ suggests that *KPI* can be evaluated immediately once all of the arguments (inputs and decisions) are given. Unfortunately, this becomes real only when the planning horizon has expired. Contrarily, the entrepreneurial practice in the operational planning horizon is characterized by decisions $x_1, \ldots, x_n$ to be made successively without all of the inputs $\sigma_1, \ldots, \sigma_m$ known. Mathematically speaking, we seek for a sequential optimization method under imperfect information. Clearly, without overall knowledge on the inputs, we cannot expect to find decisions $x_1, x_2, \ldots, x_n$ one after another such that $KPI(\sigma_1, \ldots, \sigma_m, x_1, \ldots, x_n)$ is optimal retrospectively. Thus, there is neither a natural concept of optimality in online optimization nor is there any evidence that solving partial problems to optimality leads to an optimal overall solution (Dunke, 2014). Although we cannot expect optimality in terms of the overall decision vector $x_1, \ldots, x_n$, many members of the online optimization community use omniscience as the basis for their substitute concept of optimality—competitive analysis (cf. also Borodin & El-Yaniv, 1998): In a minimization problem, an algorithm is called c-competitive if for all input realizations, the decisions of this algorithm lead to a *KPI*-value at most c-times as large as the value of *KPI* that results from an optimal (hypothesized) offline algorithm.

According to competitive analysis, an optimal online algorithm then is a c-competitive algorithm with the smallest possible value of c among all online algorithms. It is easy to find numerous criticisms for this substitute concept of optimality (Dorrigiv, 2010; Fiat & Woeginger, 1998), e.g., the limited significance for practical applications due to exclusive worst case considerations or the reduction to a single number. In fact, the counterintuitivity of this measure has been observed in practice: for instance, in online variants of basic routing problems such as the traveling salesman problem, it is known from experiments that look-ahead improves the performance (Dunke, 2014) whereas in competitive analysis this can hardly be replicated (Allulli, Ausiello, Bonifaci, & Laura, 2008). Nonetheless, the real time character of many industrial planning problems (Ghiani, Laporte, & Musmanno, 2013) shows that there is a need for a comprehensive framework for online methods providing answers to the following questions: When should we solve a snapshot problem? Under which objective should we solve the snapshot problem? Which method (exact/heuristic) should we use to solve the snapshot problem? How does the solution type of the snapshot problem migrate to the overall problem, i.e., is the effort of generating an optimal partial solution justified? The modeling part of the framework in Section 2.2 will help in addressing these questions.

2.1.2. Oblivion to uncertainty

Part of the data input required by operational planning problems is generated by event occurrences which cannot be known in advance. Hence, one or another of the inputs $\sigma_1, \ldots, \sigma_m$ is afflicted with uncertainty. Mathematically, these inputs as well as *KPI* are random variables. Hence, what is needed for comprehensive decision making is more detailed information on the distribution of the *KPI* value and how it depends on the uncertain input data. Translated into mathematics, we need a stochastic model—although in many applications there is often no reliable stochastic information available.

In order to compare random variables, stochastic orders have been introduced (cf. also Müller & Stoyan, 2002). The simplest approach uses expectations: random variable KPI_1 is said to be stochastically smaller in expectation than random variable KPI_2 if and only if the expectation of KPI_1 is smaller than the expectation of KPI_2. An alternative is to consider stochastic dominance defined as follows: random variable KPI_1 is stochastically smaller than random variable KPI_2 if for all $p \in \mathbb{R}$ it holds that the probability for KPI_1 being smaller than p is larger or equal than the probability of KPI_2 being smaller than p, i.e., the $\leq$-relation is transferred to probabilities.

Unfortunately, in the expectation-based definition, variability and outliers are ignored; on the other hand, stochastic dominance does not admit a total order among random variables. To the best of the authors' knowledge, there is not a natural stochastic concept of optimality that allows us to compare arbitrary random variables. The evaluation part of the framework in Section 2.2 will present a possibility to evaluate the quality of algorithms without having to incorporate strong probabilistic assumptions.

2.2. New concepts and definitions

Based on Dunke (2014) and Dunke and Nickel (2016) we present a formal framework for online optimization problems with look-ahead. We subdivide it into two parts: a modeling part and a performance evaluation part. For compatibility with the related literature, we denote the sequence of input elements by $\sigma = (\sigma_1, \ldots, \sigma_m)$. Instead of using a function *KPI* we will denote the performance of an algorithm *ALG* on input σ by $ALG(\sigma)$.

2.2.1. Modeling

In offline optimization, σ is known in advance. In contrast, online optimization assumes that σ is not known entirely at the beginning of the planning horizon (Borodin & El-Yaniv, 1998). An

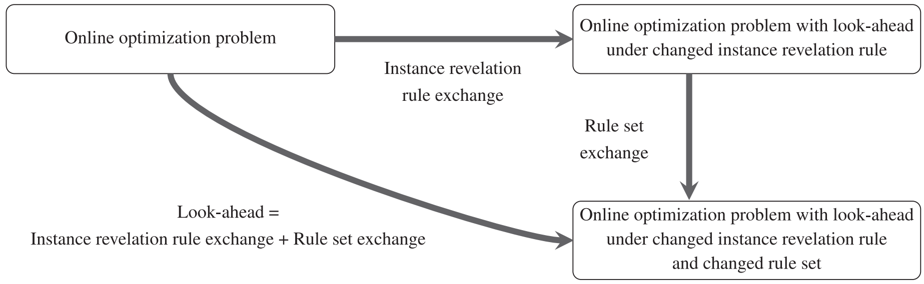

Fig. 3. Effect of look-ahead on a problem and its instances.

ONLINE OPTIMIZATION PROBLEM is characterized by the fact that partial decisions have to be made by *ALG* repetitively based on partial knowledge of σ. Hence, *ALG* has to be applied to several subsequences $\sigma_{\leq i} = (\sigma_1, ..., \sigma_i)$ with $i \leq m$ and monotonously increasing *i*. We refine these notions by introducing online optimization problems with look-ahead to obtain a smooth passage between online and offline optimization. To this end, we view an online optimization problem with look-ahead as an optimization problem that is derived from a reference online optimization problem (without look-ahead capabilities), but with an improved process of information release (Dunke, 2014).

In order to advance to a more formal definition of the look-ahead setting, we recall a general definition of an optimization problem (Ausiello et al., 2003): a single-objective OPTIMIZATION PROBLEM Π is a quadruple (*I*, *S*, *f*, opt) where *I* is a set of instances, *S* is a (multi-valued) function returning the set of solutions *S*(*i*) for any $i \in I$, *f* is a function returning the objective value for any pair (*i*, *s*) $\in I \times S(i)$, and opt $\in \{\min, \max\}$ is the optimization goal. This definition works well for offline problems, but since it does not address sequentiality, applying it to the online setting is cumbersome. To consider sequentiality explicitly, we refine this definition with two elements (Dunke & Nickel, 2016): first, we ascribe a so-called instance revelation rule to each instance; second, we ascribe a so-called rule set to each problem.

We define an INSTANCE REVELATION RULE as a rule that governs the temporal course of events in the release of information on the problem instance. Thus, it determines how information becomes known over time. We give four examples of general nature for an instance revelation rule:

- σ_{i+1} with $i = 1, 2, \ldots$ is revealed when σ_i is considered finished (processing-dependent online release).
- $\sigma_1, \sigma_2, \ldots$ are revealed at prescribed release times $\tau_1, \tau_2, \ldots$ (independent online release).
- $\sigma_1, \sigma_2, \ldots$ are revealed at prescribed release times $\tau_1 - D, \tau_2 - D, \ldots$ with fixed *D* (independent online release with time look-ahead).
- σ is known completely at time 0 (offline release).

On the other hand, once the information is known we may ask what we can do with it. Here the rule set comes into play. A RULE SET of a problem is a set of restrictions on the solution to an instance of the problem. Thus, it determines how information can be used when it became known already. We give three examples which may appear as elements of a rule set. Note that the first rule cannot be used in conjunction with the second or third rule, respectively.

- σ_i with $i = 1, 2, \ldots$ has to be finished before σ_j with $j > i$ can be processed (successive processing).
- The finishing order of the input elements in σ is arbitrary (arbitrary processing).
- At most $m \in \mathbb{N}$ input elements with $m > 1$ can be finished at the same time (limited processing).

The instance revelation rule and the rule set allow us to distinguish between the informational implications caused by look-ahead and the consequences on processing of the input elements inherent to look-ahead. For instance, in a packing problem it may be that boxes become known according to the independent online release with look-ahead. Then, in successive processing we can only make use of the information about the box specifications, whereas under arbitrary processing we may pack the box once its data is given. Summing up, an online optimization problem can be described as a quadruple (*I*, *S*, *f*, opt) along with a rule set and an instance revelation rule for each instance $i \in I$.

With these two extensions we define an ONLINE OPTIMIZATION PROBLEM WITH LOOK-AHEAD as an online optimization problem that arises from a reference online optimization problem through the instance-wise exchange of the instance revelation rule by an improved instance revelation rule. This ensures that at each point in time the information known in the problem with look-ahead is comprising the information known in the reference problem. Optionally, the rule set of the reference problem may be exchanged with another rule set which explicitly makes use of the look-ahead information. Fig. 3, taken from Dunke and Nickel (2016), summarizes the situation.

2.2.2. Performance evaluation

In order to depict algorithm quality in a comprehensive and differentiated way, we take on an approach which essentially consists of a distributional analysis of both the individual outcome of an algorithm as well as of the relative outcome of an algorithm with respect to a benchmarking algorithm (Dunke & Nickel, 2013; 2016; Hiller, 2009). The individual outcome of an online algorithm *ALG* provides an overall image of algorithm behavior over all instances whereas the outcome of *ALG* relative to that of a reference online algorithm ALG_{ref} yields a comparison to a suitable benchmark. We first provide definitions for the objective value and performance ratio. Given an optimization problem (*I*, *S*, *f*, opt), an instance $i \in I$, an algorithm *ALG*, and a reference algorithm ALG_{ref}, let $s_{ALG}, s_{ALG_{ref}} \in S(i)$ be the solutions selected by *ALG* and ALG_{ref}, respectively. We define

$$v_{ALG}(i) = f(i, s_{ALG}),$$

the OBJECTIVE VALUE of *ALG* on *i*, and

$$r_{ALG,ALG_{ref}}(i) = \frac{f(i, s_{ALG})}{f(i, s_{ALG_{ref}})},$$

the PERFORMANCE RATIO of *ALG* relative to ALG_{ref} on *i*.

In the next step, we compute the so-called counting distribution of both the objective value and the performance ratio. A counting distribution is a distribution where each possible realization of the random variable under consideration (in our case the random variable describes the instance from set *I*) is weighted equally such that no (possibly biased) prior information or preferences are required. The resulting distribution hence objectively

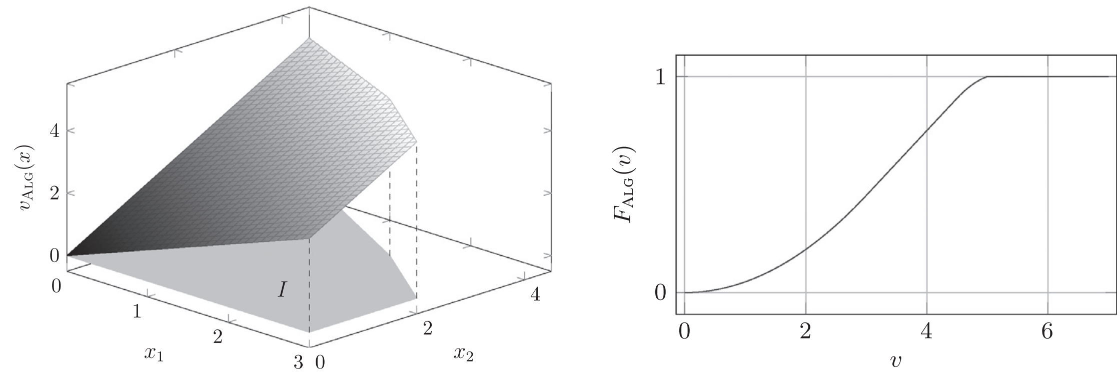

Fig. 4. Objective value of Alg over instance set I and corresponding counting distribution function plot.

counts how many out of all realizations would lead to a certain objective value or performance ratio, respectively. Fig. 4 schematically shows how the information about the objective values attained over the instance set I can be translated into the corresponding counting distribution function. On the left of the figure, the plot of the objective values attained by algorithm *ALG* over the instance set I is displayed; on the right of the figure the relative frequencies of the attained objectives are illustrated by means of the corresponding counting distribution function $F_{ALG}(v)$. Considering that in ad-hoc decision making it is often impossible to make any prediction on what an algorithm will have to cope with next, this approach presents a natural way of displaying the range of upcoming uncertainty that is inspired by maximum entropy considerations (Jaynes, 1957a,b).

Formally, we can define the counting distribution function of the objective value of *ALG* over I by

$$F_{ALG}(v) = \frac{|i \in I \mid v_{ALG}(i) \le v|}{|I|}.$$

The counting distribution function of the performance ratio of *ALG* relative to ALG_{ref} over I is defined as

$$F_{ALG,ALG_{ref}}(r) = \frac{|i \in I \mid r_{ALG,ALG_{ref}}(i) \le r|}{|I|}.$$

We can provide *ALG* and ALG_{ref} with different levels of look-ahead in order to examine the value of additional information.

2.3. Examples and results

The general framework of online optimization with look-ahead has been instantiated in a number of theoretical problems and practical applications (Dunke, 2014; Dunke & Nickel, 2015). Along with the outlined performance measurement approach it facilitated an evaluation of the value of look-ahead and the identification of promising algorithms and control strategies.

2.3.1. Truck entrance control

Dunke and Nickel (2015) examine how the arrival process of trucks at the main gate of a factory site can be coordinated by the gate operators in order to ensure that the raw materials loaded on the trucks are delivered to the production sites in time. To this end, it is assumed that the gate consists of four check-in counters where the trucks coming from the road have to enqueue in one of them and be served first before accessing the factory site. The leading research goal was to check whether the operator decisions can be improved by additional data collection and transmission technologies as considered in Industry 4.0 and Advanced Manufacturing settings. To this end, six different technology scenarios were considered which could equip the decision maker with different types of real-time and look-ahead data:

1. No additional data, i.e., drivers choose the lane themselves (baseline scenario).
2. Additional data about the lane occupations (in terms of the number of trucks), e.g., through a camera system.
3. Additional data about the current check-in counter statuses, e.g., through electronic data interchange.
4. Additional data about the expected (remaining) workloads for gate service of all trucks in a lane, e.g., through status protocols.
5. Additional data about the types and amounts of loaded raw materials and about the production demands at factory site, e.g., through forwarding truck load information.
6. Additional data about the geographical position of the trucks, e.g., by track and trace technology.

Observe that Scenarios 2–4 are concerned with gate data, Scenario 5 considers load and demand data, and Scenario 6 takes into account spatial truck data which can be translated into a time look-ahead. For each scenario, simple rule-based heuristics were applied that make use of the provided information in a straightforward manner to minimize the penalty costs that would result from stopped production due to missing raw materials. The simulation study comprised 100 simulation replications of a 14-hour work day with 300 trucks arriving randomly. Gate service is assumed to take between 2 and 5 minutes, but breakdowns of lane counters with a duration ranging from 15 to 100 minutes may occur. In case of a lane breakdown, the corresponding counter is out of service for the duration of the disturbance which may severely reduce the truck throughput at the gate.

The simulation results (depicted in Fig. 5) show that the company should refrain from using the baseline policy where drivers decide themselves on the queuing process rather than the gate operators.

It can be observed that simple structured information such as number of trucks currently in some lane leads to an average reduction of daily penalty costs of approximately 3 percent. Also in a distributional analysis the benefit of this type of additional information is clearly visible from a stable left-shift of the counting distribution function corresponding to Scenario 2 when compared to Scenario 1. Moreover, all strategies making use of gate data (Scenarios 2–4) lead to average reductions at a similar level of roughly 3 percent. The negligible differences in the average case analysis is confirmed by the counting distribution functions. Since for all three scenarios, the plots intersect with each other, there is no point in declaring any of the three technological scenarios to be superior.

When factory demand data and truck loading information can also be used, supply and demand information are better matched leading to another penalty cost reduction of around 4.5 percent on average. On the other hand, there is no substantial surplus from additionally using positioning data of the trucks (corresponding to

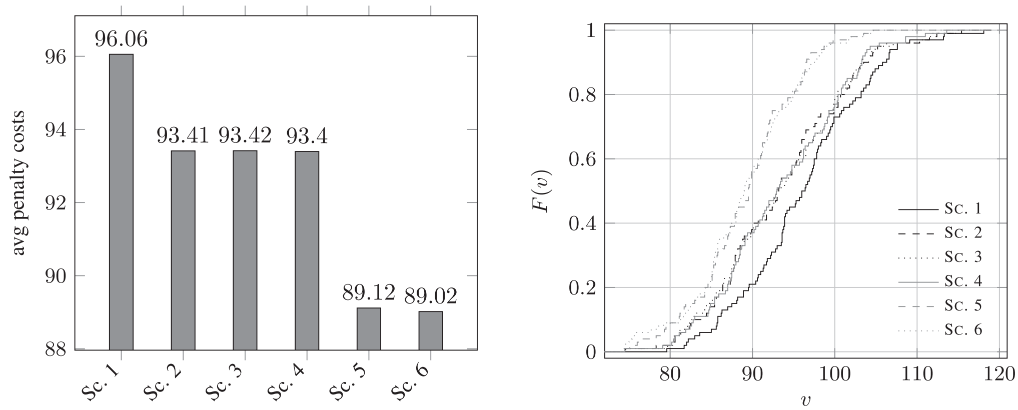

Fig. 5. Average penalty costs (left) and empirical counting distribution functions of penalty costs (right) in 10,000 monetary units (case study investigated in Dunke & Nickel (2015)).

time look-ahead) as they are still approaching the gate on the road. Given that the gate plays the role of a bottleneck in the entire production system, there are always enough trucks with a requested load available in the immediate vicinity of the gate such that the information about what happens on the road becomes nearly irrelevant. This is also confirmed by the counting distribution functions corresponding to Scenarios 5 and 6 whose plots are intersecting permanently making it impossible to claim that one of the technologies is better than the other. Summing up, Scenario 5 (where truck loads and factory demands as well as the lane statuses are forwarded to the operators) represents the most recommendable control strategy. For further details, see Dunke and Nickel (2015).

2.3.2. Benefit of look-ahead

Considering the increased usage of data collection and transmission devices, we can tackle short-term uncertainty by utilizing look-ahead devices, which turn parts of the previously uncertain future into certain. To describe the structure of an online problem directly, a classification scheme $\alpha\,|\,\beta\,|\,\gamma\,|\,\delta$ was proposed in Dunke (2014) and Dunke and Nickel (2016). In this scheme, α describes the look-ahead type (indicating the instance revelation rule, e.g., request look-ahead, time look-ahead, property-based look-ahead); β gives the processing mode and order (indicating handling aspects of the rule set); γ yields the processing accessibility (indicating temporal aspects of the rule set); finally, δ indicates the algorithm execution mode. Using this classification scheme it is then possible to organize literature on applications of online optimization with look-ahead. In particular, it becomes apparent that different authors consider look-ahead differently.

The classification scheme is then used as a starting point for the analysis of look-ahead effects in applications. Depending on the complexity of the problem setting, different approaches were used in Dunke (2014). The authors carried out an exact distributional analysis of algorithm performance in rudimentary versions of academic problems such as the traveling salesman problem (TSP) and the bin packing problem (BPP). The analysis reproduced an exact image of algorithm behavior over all input sequences (including competitive analysis). Already in very simple problem settings it is observed that the magnitude of the look-ahead effect depends strongly on the problem itself. Improvements in the BPP are small and hard to obtain, whereas in the TSP additional look-ahead immediately helps. As a result of an increased usage of geographic information systems (GIS) and global positioning systems (GPS), the research focus in routing has in fact shifted from the static to the dynamic version of the problem (Psaraftis, 1995); the latter also refers to the online version of vehicle routing. Given the fact that in traditional worst-case analysis only minor improvements were found for different types of look-ahead (Allulli et al., 2008; Jaillet & Wagner, 2006), our results strongly support observations from practice that additional information allows to create better routes. Complementing the theoretical results, the authors followed an experimental approach and conducted numerical experiments on several standard problems (TSP, BPP, machine scheduling, and paging). Again, significant differences were observed depending on the problem settings. Based on the results, an information pool delivering quick explanations for look-ahead effects in different problem classes was built. An important result was that over all problem classes, sophisticated re-optimization algorithms outperformed simple methods only in case of large look-ahead. For small to medium look-ahead, simple heuristics often even fare better. Finally, the effect of look-ahead in two real world applications (manual order picking system, pickup-and-delivery service) was analyzed by simulation. These systems exhibit a higher complexity due to additional random events, realistic restrictions upon operations, and relevance of multiple performance criteria. For explaining the observed behavior of performance criteria over time, it was possible to make use of the information pool that was built up before in the theoretical and experimental approach for elementary problems.

The examples presented above show that the framework of online optimization with look-ahead along with the presented approach of performance measurement offers a tool for identifying look-ahead effects and successively designing control strategies for logistics systems.

These developments are of relevance as a means for capturing short-term uncertainty and thus obtaining solutions that can better anticipate the near future. Accordingly, this can be of use when planning for operational tasks in SCM. However, when we focus on strategic decisions, we often need to go further into the future namely when the decisions have a long lasting effect such as some locational decisions that are typically part of Supply Chain Network Design (SCND). In such a situation, Fig. 2 may no longer provide a correct representation of the time line and online optimization with look-ahead may no longer render the best approach for supporting decision making. This is what we discuss in the following section.

3. Multi-period planning

The simplest and most common way for embedding the future into a model consists of forecasting the relevant parameters and then assuming the entire future as a single static block (online optimization with certain look-ahead goes in this direction).

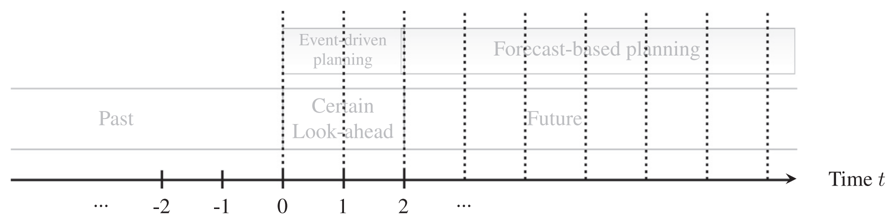

Fig. 6. Division of the time line into multiple periods setting the time frame for multi-period planning methods.

This leads to a so-called *static model*: a decision is made here-and-now—no recourse is possible, i.e., no further decision can be made that is able to "correct" in some way decisions already made and implemented. An alternative is to explicitly consider time in the models. In this case, we may either complement the online optimization models with the future that is beyond the one defined by the short-term look-ahead or we can simply consider the future starting from the present setting. The former case is often tackled by means of hierarchical planning since it calls for the decomposition of the overall planning problem into partial plans. The reader should refer to Stadtler et al. (2015) for further details. In this paper we do not focus on hierarchical planning since we are putting the emphasis on elements required by individual optimization models supporting Supply Chain Planning and not in the way several different complementary models may be used.

As we discuss later in this section, embedding time explicitly into optimization models gives the possibility of capturing many features of practical relevance and thus, of making the models more comprehensive and realistic. The need for explicitly including time into a model calls for some changes in Fig. 2 such as those conveyed by Fig. 6. In particular, we emphasize the situation in which time is no longer looked at as a static block. In this section we discuss in detail this re-designed time line. In particular we focus on different aspects related to time-dependent optimization models in the context of Supply Chain Planning. A particular emphasis is given to the case in which decisions related to the network structure (e.g., locational decisions) have to be made. As we will observe, the contents of this section turn out to be crucial for the uncertainty issues discussed in Section 4.

The current section is organized as follows. In Section 3.1 we discuss different issues that if neglected may easily lead to misleading or at least not so realistic models. In Section 3.2 we discuss several relevant concepts and definitions in terms of multi-period planning models. Finally, in Section 3.3 we use an example for illustrating some of those concepts and definitions.

3.1. Flaws

When time is not explicitly included in optimization models supporting Supply Chain Planning we often oversimplify the reality and overlook several important decisions that may be relevant in the decision making process.

3.1.1. "Collapsing" the future

For many years (e.g., in the 1970s and 1980s) available technology (computational resources, software, etc.) was still much limited. Nonetheless, the scientific community early realized the relevance of explicitly considering time in optimization models used for supporting locational decisions within the context of production/distribution decisions (see, e.g., Nickel & Saldanha-da-Gama, 2015). This called for more complex and comprehensive models to be developed and thus more difficult to tackle. This difficulty (together with the lack of technology) is possibly the reason why for several decades static location models were prevalent in the literature.

Nowadays, in the context of Supply Chain Network Design, a static model is looked at as an oversimplification of the reality since it misses many features of practical relevance (see, e.g., Melo, Nickel, & Saldanha-da-Gama, 2006). When future is collapsed into a single "block", a here-and-now decision is to be made and implemented. As a result, relevant changes in the underlying conditions are ignored. This may render a solution too much insensitive to changes in relevant parameters such as demand levels or transportation costs, just to mention a few. In other words, a static model may completely overlook changes that could be predicted *a priori* and thus anticipated. In fact, the major motivation for considering time explicitly in an optimization model for Supply Chain Planning is exactly that: to better anticipate the future. Even if we are facing a "deterministic future" (i.e., the values for underlying parameters and their changes can be accurately predicted for a reasonable amount of time using some forecasting method), this often calls for a forecast-based time-dependent model.

Finally, it is important to point out that collapsing the future into a single "block" is often not feasible namely when it comes to making decisions involving large structures. For instance, the full operational capacity of a large manufacturing plant is often not attained in a single step but in different phases over the future (see, e.g., Melo, Nickel, and Saldanha-da-Gama, 2008 for a deeper discussion). In this case, we talk of a progressive phase-in of a facility.

3.1.2. Inability to adapt

By ignoring time as a dimension to explicitly account for in a planning tool for strategic Supply Chain Planning, we are typically led to a single-step phase-in problem. This can be observed in the literature (see, e.g., Alumur et al., 2015a) and means that a new system is to be built in a single step from scratch or an existing system is to be expanded also in a single step (which can be converted—for mathematical modeling purposes—into the first case). However, reality may call for something totally different. In many situations, companies have a supply chain already operating and wish to plan for adapting it to predictable changes in the underlying conditions (or simply to modernize it). This may call, for example, for some structures to be removed (e.g., relocation of a production plant to an area with lower labor costs). Accordingly, in terms of SCND we find phase-in/phase-out problems in which some new facilities are opened throughout time while some others are removed (possibly as the result of relocation).

Related to the previous aspect it is worth noticing that decisions associated to capacity changes cannot be captured by a static model. Due to technological or customer behavior changes, production capacity has often to be adapted. This does not necessarily mean installing a new facility or removing an existing one. A trade-off is to consider capacity adjustments (expansion, reduction, or transfer) within a time-dependent modeling framework.

Last but not the least, additional constraints such as those related to the available budget or "project management constraint" may call for a time-dependent model to be considered. In the former case, we note that budget limitations may easily emerge since shareholders' interests have to be taken into account. Concerning the latter, it is important to point out that implementing a large project at once can be difficult (or even impossible) for organizational reasons or lack of resources. The reader should refer to Nickel, Saldanha-da-Gama, and Ziegler (2012), Alumur et al. (2015a), Melo et al. (2006), and Melo, Nickel, and Saldanha-da-Gama (2009) for further details.

3.1.3. Length of a planning horizon

Nowadays, we can find much literature embedding future in optimization models within the context of Supply Chain Planning (see, Alumur et al., 2015a; Arabani and Zanjirani Farahani, 2012, and Melo et al., 2009 as well as the references therein). Interestingly, we find no discussion neither about the appropriate length of the planning horizon nor about the length of a single time bucket (i.e. the discretization width). Moreover, even the concept of *planning horizon* is not properly discussed in the literature. Most of the authors (not to say all) simply assume that some plan should be developed for a time frame given in advance.

In the context of Supply Chain Network Design, several decisions may last for far more time than the planning horizon during which they were made and implemented. Furthermore, in many cases there is no “end” planned for some system or structure, which means that in principle, the system should be planned for working over an “infinite” planning horizon. Nevertheless, much of the work found in the literature assumes models built based upon finite planning horizons; the obvious question emerges: what exactly is an optimal solution for such a model? Without a proper answer to this question, the usefulness of many modeling frameworks become questionable.

In Section 3.2 we give a contribution for the clarification of these aspects.

3.1.4. Errors in the data

Supply Chain Planning is well-known as a very practical-oriented topic. Many optimization models can be found in the literature for solving different problems in this area. In most cases, particular emphasis is put on solving models to optimality (see Arabani and Zanjirani Farahani, 2012 and Melo et al., 2009). What is the relevance of doing so? In other words, what is the meaning of an “optimal solution” if the model does not properly represent the problem? The issue emerges because even if correctly describing the problem on hands, a model must be loaded with data. Such data often suffers from errors (e.g., typos or forecasting errors). Cordeau, Pasin, and Solomon (2006) argue that solving a real-life problem to optimality is usually not meaningful due to errors contained in the data estimates. Since the error margin tends to be larger than 1 percent, those authors claim that it is adequate to run a mathematical solver until a feasible solution within 1 percent optimality has been identified. We note that this discussion is motivated by a static problem—the one investigated in that paper. If we consider a time-dependent model that obviously should be loaded with data associated with a large time frame, then the issue may become even more relevant; easily the 1 percent error mentioned above increases. In particular, the larger the length of the planning horizon the more likely it is to observe an increase in the data errors. Accordingly, does it make sense to solve such a model to optimality? Even if the model gives a perfect description of the problem to be solved (we recall that many models represent in fact a simplification of the reality) is the data trustworthy? Is the setting reliable?

Again, these questions need a proper answer without which the optimization models used for supporting decision making can be questioned.

3.1.5. International facilities

Nowadays, large companies think “globally” when it comes to designing and managing their supply chains. Accordingly, modern supply chains often span several countries across the globe and thus across different time zones. This makes international operations very hard to formulate realistically.

The relevant aspect for our discussion is that in a global supply chain, we have so-called international facilities (a company installs facilities in countries different from the one in which the company is registered). The location of international facilities is not a recent topic. This is a situation in which a static model may totally overlook practical aspects.

Issues such as taxes, duties, tariffs, exchange rates, transfer prices, local content rules, transportation modes, etc., become of relevance and can hardly be neglected. This fact has been recognized by some researchers who have proposed time-dependent models for better capturing the problems’ features. The reader can refer to Canel and Khumawala (1997), Canel and Khumawala (2001), Gutierrez and Kouvelis (1995), and Syam (2000) for examples of time-dependent models which focus on advanced decision making in the area of international facility location. These models take into account some of the aspects discussed above.

3.2. New concepts and definitions

When the parameters underlying a Supply Chain Planning problem are variable and can be predicted, we can think of using a deterministic time-dependent model. For instance, if we have predictable but variable demand, it makes sense to embed this information into a time-dependent model.

3.2.1. Planning horizon

When time is to be explicitly embedded in an optimization model within the context of Supply Chain Planning, a first aspect to look at is the so-called *planning horizon*; but then, a natural question emerges: what exactly is the planning horizon?

We first note that a plan devised for some time frame does not necessarily mean that at the end everything is “shutdown” and the system comes to an end. This is particularly true in Supply Chain Planning where the planning horizon may simply be an indication of how far into the future a decision maker can go in terms of collecting meaningful information.

In a time-dependent supply chain optimization model, the PLANNING HORIZON can be defined as the time frame corresponding either to the available data (meaningful/trustworthy information) or to the time span defined by a decision maker for having the system fully operational and/or appropriately adapted to the circumstances. This may be dependent on a specific industry/product. For instance, in Fleischmann and Koberstein (2015) the authors exemplify with the specific case of the automotive that the planning horizon for strategic decision making typically covers up to 12 years. This is closely motivated by the life-cycle of many car models.

The previous definition makes it clear that a planning horizon may simply result from a time frame previously defined by a decision maker for implementing a new system or adjusting an existing one. However, it may be industry- or product-dependent.

A planning horizon is a fundamental element in a time-dependent model. Therefore, by using such type of model, we can avoid collapsing the future into a single block. In this case, the focus changes from “what should be done” (static setting) to “what should be done and when” (time-dependent setting).

From a practical point of view, a time-dependent model can be of great relevance since it allows embedding other decisions, such as those related with (i) inventory management, (ii) progressive phase-out of existing facilities, (iii) progressive phase-in of new facilities, (iv) adjustment of the operating capacities (which, from a cost point of view may be preferable to opening new facilities), etc.

Even if the underlying parameters (e.g., consumer preferences, demand levels, transportation costs, etc.) do not induce a time-dependent model, some other conditions may do so. Above we have already mentioned the possibility of having to deal with an exogenous budget constraint, which may impose the development of a time-dependent plan for building/adjusting a system.

3.2.2. Discrete- versus continuous-time models

When working with a time-dependent model we can distinguish between continuous- and discrete-time models. In the first case, there are no specific moments for implementing the decisions; the best moment for performing changes in the system may be endogenous or exogenous. In the former situation, these moments are themselves a decision to make; in the latter, we fall in the field of even-driven planning: some event triggers a change in the system. The reader should refer to Stadtler et al. (2015) for a deeper discussion of even-driven planning in the context of Supply Chain Management. Some works in line with endogenous moments for performing changes in the system are Drezner and Wesolowsky (1991), Orda and Rom (1991), Puerto and Rodríguez-Chía (1999), and Zanjirani Farahani, Drezner, and Asgari (2009). These works also discuss typical decisions in the strategic scope of Supply Chain Planning, e.g., decisions on facility locations.

A large majority of the literature assumes a discrete-time model, i.e., it is assumed that the planning horizon is divided into several time periods. It is possible to enumerate a few reasons justifying the use of such a type of model.

1. The models are easier to handle. Typically, decision variables can be associated with the different periods of the planning horizon and thus, a mixed-integer mathematical programming model can often be derived.
2. Looking more into the future, we possibly face more uncertainty (less accurate information is available) that nonetheless is typically gathered using a discrete time scale (e.g., weekly, monthly, yearly).
3. The length of a time period is primarily determined by the decisions to be planned. Nevertheless, depending on the information we have, the length of a time period can be easily adjusted if the decision maker wishes so: if we have more information we can consider a daily planning; otherwise we can go into a monthly or yearly planning, for instance.
4. The organization of the data makes multi-period models more natural. For instance, we often find or look for daily, weekly or monthly demand levels. This is also connected to a large extend with forecasting systems that typically work with time periods no matter their length.
5. In nowadays planning systems, multi-period is the minimum time consideration that is possible.

When considering a discrete-time model for a Supply Chain Planning problem we simply partition the relevant time frame into several "slices"—time periods as illustrated in Fig. 6. The time periods do not have to be of the same length; it is the available data and the goals set by the decision makers that will define them. Furthermore, a discrete-time model can also be looked at as a means for aggregating continuous time intervals into single time points. Somehow, what we are considering is the possibility of taking into account the look-ahead (short-term uncertainty) discussed in the previous section and "enlarge" the future time frame to be embedded into the model.

3.2.3. The value of the multi-period solution

When we consider a multi-period optimization model, we are considering one extra dimension in the problem—time. The corresponding optimization models tend to become much larger than the static ones. A relevant question is whether it is worth considering such a larger model (and thus possibly more difficult to tackle). In other words, is it not possible that a solution obtained using an appropriate static model represents a good approximation to the multi-period problem? A first answer to this question was given by Alumur, Nickel, Saldanha-da-Gama, and Verter (2012) in the context of a reverse logistics network design problem. Later, this aspect was formalized by Nickel and Saldanha-da-Gama (2015) in the general context of multi-period facility location problems.

A central concept for evaluating the relevance of considering a multi-period model is that of a STATIC COUNTERPART PROBLEM. It can be defined as a problem that takes into account the information available for the entire planning horizon and looks for a static (time-invariant) solution that holds for every period.

This concept is very easy to capture within the context of SCND. In that case, decisions have to be made regarding the network structure; these are typically strategic decisions that once made will influence the more tactical and operational decisions (e.g., shipment of commodities through the network). In a multi-period SCND problem, several parameters such as transportation costs and demand levels are assumed to change over time. A static counterpart is a problem obtained from the original one that allow us to define a network design that can be implemented at the beginning of the first period and remains unchanged until the end of the planning horizon.

One possibility for building a static counterpart is to somehow aggregate the information available for all periods. For instance, suppose that we are dealing with time-varying demands. If facilities (e.g., manufacturing plants, central distribution centers) are uncapacitated, then several possibilities emerge for aggregating that information: (i) the demands can be averaged over the planning horizon, or ii) a reference value can be determined (e.g., the maximum value observed throughout the planning horizon). If additional constraints exist (e.g., capacity constraints), then choosing a reference value may render the resulting static solution infeasible in some periods. In this case, one possibility for building a static counterpart is to define the (time-invariant) demand of each customer according to the maximum value observed across all periods. In any case, the adequate aggregation of multi-period data is very much problem-dependent.

Once a static counterpart is defined, we can finally evaluate the relevance of using a multi-period modeling framework. We define the VALUE OF THE MULTI-PERIOD SOLUTION as the arithmetic difference between two other values: (i) the (multi-period) value of the optimal solution to a static counterpart (when that solution is feasible for the multi-period problem), and (ii) the optimal value of the original multi-period problem.

When the value of a multi-period solution is obtained by aggregating the data for all periods, it is referred to as a WEAK VALUE OF THE MULTI-PERIOD SOLUTION (see Alumur et al., 2012 and Nickel & Saldanha-da-Gama, 2015). On the other hand, a STRONG VALUE OF THE MULTI-PERIOD SOLUTION is obtained if no aggregation is performed in the data. This is a possibility in some cases, namely when we can add a set of constraints to the multi-period problem stating that some or all decisions are to be the same in all periods of the planning horizon (the reader should refer to Nickel and Saldanha-da-Gama (2015) or further details and for an example).

3.2.4. Rolling horizon planning

Many multi-period models in the context of Supply Chain Planning can be used in later periods exactly as in the beginning, as far as the decisions already implemented are fixed, i.e., as far as we "freeze" the periods already in the past. In such a case, the model is used to plan for the "remaining" future but the decisions to be made should take into account what has already been implemented. By doing so, we obtain a model which is able to "react" to the decisions already implemented considering new or more accurate information made available in the meanwhile. This is a typical situation in which new technologies (e.g. sensors) can be used to fine-tune the available information and thus turn the uncertain future gradually into a certain one. When only operational decisions are involved, this procedure is well-known as rolling horizon planning (see Stadtler et al., 2015 for further details). There is no reason for not using the same term when strategic decisions are involved. In particular we can formalize these concepts, which we do next.

In a time-dependent supply chain optimization model involving strategic decisions (e.g. locational decisions), a RECOURSE MODEL is the model that we obtain from the original one when in some future period we fix the decisions already made (and implemented), thus aiming at finding a plan for the remaining future. The periods whose decisions are fixed in the recourse model are referred to in Heckmann (2015) as *frozen periods*. The process of solving a series of recourse models is called ROLLING HORIZON STRATEGIC PLANNING. This aspect is explored by Alumur et al. (2012) and Alumur, Nickel, Saldanha-da-Gama, and Seçerdin (2015b) and we refer the reader to those references for further details and examples.

3.3. Examples and results

The use of discrete-time optimization models in the context of Supply Chain Planning is not new (the reader can refer to Melo et al. (2009) as well as to the references therein). In this section we refer to a more recent application namely, the case study inspired by a real-life problem in Germany in the context of reverse logistics network design for washing machines and tumble dryers (see Alumur et al., 2012).

In that study, the authors investigate the collection of washing machines and tumble dryers. In particular, 40 collection centers are considered, namely those installed by the municipalities in the 40 most populated cities within Germany. Initially, a 5-year planning horizon was considered. The reverse logistics network studied includes: collection centers, inspection/disassembly centers, remanufacturing plants, and secondary markets. Decisions are to be made concerning: (i) the location and capacity of inspection centers, (ii) the location and capacity of re-manufacturing plants, (iii) the flow of materials through the network, (iv) the procurement at the re-manufacturing plants, and (v) the inventories to hold at re-manufacturing plants. Capacities are modular both in the inspection centers and in the re-manufacturing plants. These capacities can be expanded throughout the planning horizon if necessary. This is accomplished by the installation of a set of additional modules in the corresponding facility.

The authors proposed a multi-period planning model that was loaded with real data (when available). In order to evaluate the sensitivity of the results to variations in the data, the authors built 18 instances that differ in set-up costs and capacities. This is justified by the lack of real data associated with those parameters.

In this section we summarize the analysis performed in that paper concerning both the length of the planning horizon and the value of the multi-period solution.

After developing an appropriate static counterpart Alumur et al. (2012) evaluated the value of the multi-period solution for each of the 18 instances considered. The results are replicated in Fig. 7, where we observe that the percentage difference between the optimal solution to the multi-period problem and the multi-period solution derived from a static model can be up to approximately 11 percent of the optimal cost.

The largest differences (percent) were reported for instances 13 and 14 with 11.56 percent and 11.40 percent, respectively. These values are associated with a gain in the profits of about 5.6 million Euros. Those instances differ from the other ones in terms of the fixed set-up costs for the facilities which are the highest tested and in terms of the capacity configurations that are the tightest analyzed. This resulted in instances for which a multi-period modeling framework clearly outperforms the static counterparts considered.

The case study we are mentioning is also a good example that the extra dimension induced by time can still lead to models tractable by means of a general purpose solver. This is particular relevant for practitioners who often do not master advanced methodological skills for integer and combinatorial optimization problems but can easily use a commercial solver for solving a model.

To the best of the authors' knowledge, Alumur et al. (2012) was the first to evaluate the impact associated with the length of the planning horizon and also to find its appropriate size for modeling purposes. The authors considered what they called a base instance (the instance from which all the other instances were generated by varying some parameters) and for that instance they considered planning horizons ranging from 1 to 7 years. The authors concluded that the additional computational effort when using a 5-year model instead of a single-period model is negligible (although in the latter case a more comprehensive and realistic model is considered and a clear financial benefit is achieved as we observed above). The extra computational effort required by an off-the-shelf solver for planning horizons with a larger number of periods can be significant. In Fig. 8 we depict the corresponding CPU times obtained in Alumur et al. (2012) . This figure shows that a trade-off may have to be considered between the comprehensiveness of a multi-period model and the effort necessary to solve it. Furthermore, Alumur et al. (2012) emphasize that given the amount of assumptions that may have to be taken regarding the problem data, the computational effort associated with the multi-period model may be reduced by allowing a gap in solving the problem instance. This stays in line with the discussion about errors in the data presented in Section 3.1.

4. Risk-aware supply chain planning

In the previous section we have seen that multi-period models play a major role in Supply Chain Planning. However, a model capturing a medium or long planning horizon has some uncertainty inherent which has to be adequately considered.

Usually decision makers are aware of the uncertain development of some information required for making decisions. For example expectations about customer demand deviate in most cases from the initial outlook. Means for predicting uncertain information may include historic data or expert knowledge. Nowadays, proprietary planning tools still restrict uncertainty to demand fluctuations and encapsulate volatilities in demand forecasts (Melo et al., 2009).

Over the last decades supply chains evolved into highly complex, internationally-acting systems and are since then caught in a crossfire of additional environmental influences. This evolution led to an increase of uncertain information and to a broadened range of uncertainty. In particular, incidences that lead to sudden and unexpected modifications at different locations within the supply chain attracted the attention of decision makers. Natural disasters such as earthquakes can easily destroy production facilities or roads, thus forestalling the possibility of satisfying customer needs as promised. Besides these so-called disruptions, unpredictable and slightly aggravating deviations also affect a supply chain's goals achievement. Exchange rate fluctuations, variability of oil prices, or

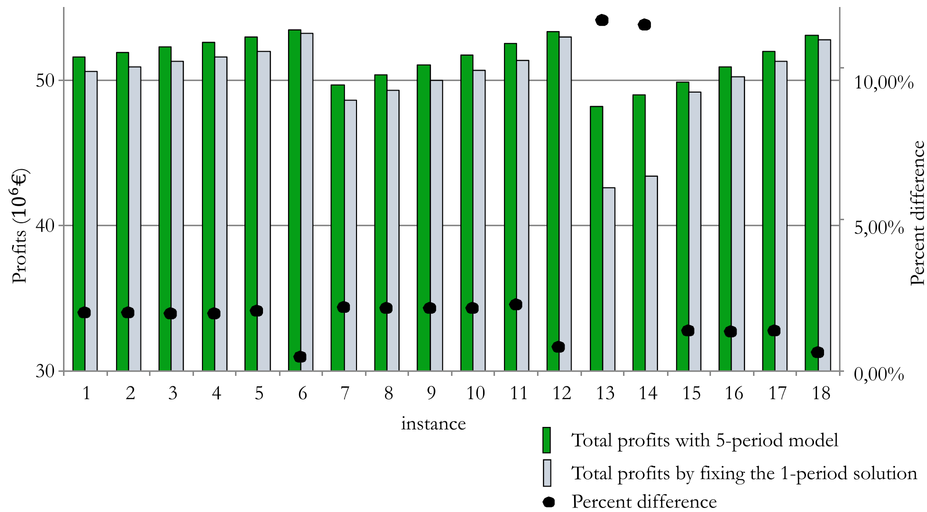

Fig. 7. The value of the multi-period solution illustrated (case study investigated in Alumur et al., 2012).

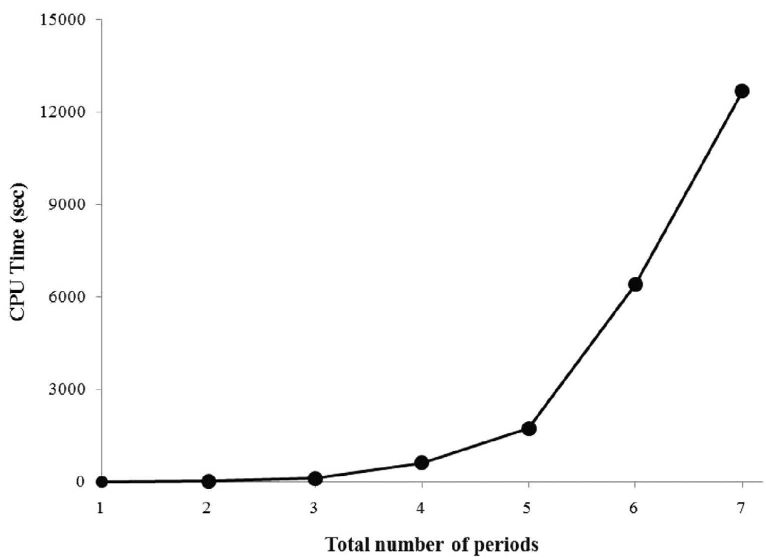

Fig. 8. Length of the planning horizon—CPU time (case study investigated in Alumur et al., 2012).

increased labor costs have the potential to reduce the profit margin and hence the competitive advantage of supply chain partners. Thus, unexpected deviations and disruptions—subsumed under the notion of *supply chain risk*—impede the availability of resources, the realization of the devised plans, the satisfaction of customer demand, and consequently the achievement of global supply chain objectives. Taking these aspects into account, the time line that has been used throughout this paper can now be refined according to Fig. 9.

The perils that have the potential to derogate the supply chain are accounted under the research topic known as *supply chain risk management* (Waters, 2007; Zsidisin & Ritchie, 2008). Over the last decade there has been a growing interest concerning the inclusion of risk aspects in supply chain optimization models. This development has led to the adoption of risk concepts, terminologies and methods that have been defined and applied in a broad variety of related research fields and methodologies. However, for the purpose of supply chain risk management the suitability of risk, as it is coined in these domains, is up for discussion, see Heckmann et al. (2015).

In this section we highlight the importance of time aspects underlying uncertain developments. Additionally, we discuss their effects on the extent of supply chain risk. We follow the same structure already used in Sections 2 and 3. Therefore, we start by presenting and discussing common flaws in terms of supply chain risk perception and the way(s) they aggravate a reliable supply chain risk assessment. Next, we present new concepts related with time-dependent risk consideration. Finally, we provide some logistics insights.

4.1. Flaws

Most of today's supply chain risk definitions start from the assumption that events are *the* decisive factor determining risk (Waters, 2007). Supply chain risk evaluation and assessment, therefore, focus on an event-by-event analysis and assume that the consequences of an initial triggering event can be uniquely determined. However we believe that this event-focused perception, definition and assessment of supply chain risk is flawed since it leads to misinterpretation and oversimplification. Next, we briefly embrace the essence of this definitional fiat and then we focus on flaws that result from ignoring time as a relevant dimension in the planning process.

Global supply chains are exposed to many potential threats. Hardly is it possible to consider and manage *each and every* risk.

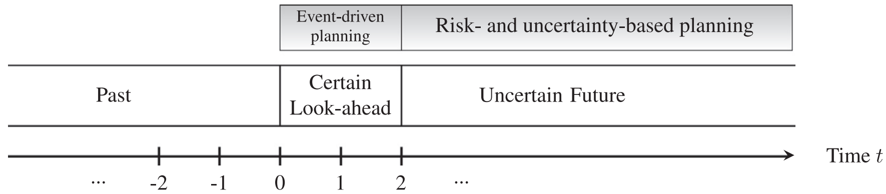

Fig. 9. Division of the time line under additional consideration of risk and uncertainty measures.

Accordingly, supply chain managers apply *heuristics thinking* and try to focus on managing the "most important" risks. In order to determine what actually is "most important", the product of probability of an event and the related severity is commonly accepted and used as a risk measure. However, this can be misleading. For illustrative purposes consider the example of a meteor strike. Since the risk of a meteor striking the Earth affects not only specific communities or countries, but imposes a threat for the entire mankind, its assessment is a very sensitive topic. Only recently is it possible to accurately detect the frequency of such strikes. A dependable statistic is therefore missing. Accordingly, a probability estimation for meteor strikes is especially difficult to obtain. Additionally, an estimation of the impact of such an event is quite hard because the magnitude of severity is strongly related to the geographic point of impact. On February 15, 2013, for example, an asteroid entered Earth's atmosphere over Russia and exploded above the city of Chelyabinsk. The impact was considerably low when compared to the potential results had this meteor not exploded miles over the surface but hit a major city like London, New York or Paris. Hence, the risk of a meteor strike depends not only on probability and severity, but also on numerous aspects that have not been considered, respected or even modeled so far. One of these essential characteristics is time. For instance, the point in time a meteor enters the atmosphere has an influence on the geographic point of its impact and consequently on the severity of the event. In the particular case of supply chain risk, time—having influence on the "degree" of uncertainty—is often ignored or neglected. We denote this biased practice as the TIME TRAP OF SUPPLY CHAIN RISK.

Next, we focus on describing different settings that uncover the lack of considering distinct aspects related with time. Note that while we discuss these flaws, we claim that their common and ultimate source is the oversimplified but still prevailing definition of supply chain risk.

4.1.1. Ignorance of dynamics

As it was emphasized in Section 3, most existing approaches for Supply Chain Planning are based on a problem environment, where certain parameters are treated as constant over all time. In those cases, it is assumed that supply chain structures (including resource allocation) are established and remain constant over years. However, product portfolio, production technology as well as international price politics change over time together with other parameters such as transportation costs, supplier reliability, and lead time. The dynamics of uncertainty associated with the evolution of supply chain parameters is usually neglected—especially when it comes to the assessment of supply chain risk. Following the prevalent supply chain risk understanding, the extent of a risk is calculated by the product of probability of an occurring event and the severity of its consequences. Since the "degree" of uncertainty associated with a situation and its evolution may evolve over time (new information becomes available), the probabilities associated with some risk may change, as well. This can lead to misjudgments of risk relevance or even to its ignorance: if the probability of a highly ranked risk decreases over time, the risk becomes less prominent and should have been rejected from the priority list. If the probability of a low-ranked risk increases, the risk becomes more relevant and it would have been better to have considered this risk in the priority list. Instead, initial risk assessment is considered to be valid for the entire time horizon of the decision level.

What is clear when we look into risk assessment considered nowadays is that the dynamics of uncertainty evolution is simply ignored.

4.1.2. Neglect of preparation time

The complexity of modern supply chains together with the uncertain evolution of important parameters and the unknown propagation of disruptions through the networks (see, e.g., Ivanov, Sokolov, and Dolgui, 2014 on the ripple effect in supply chains) make the management of supply chain risks awkward. Accordingly, most decision makers accept the recurrent appearance of disruptions and come together in a so-called war-room right after a disruption occurs. This approach has the potential of yielding far worse consequences namely if relevant events are not considered appropriately. This may occur if the relevance of an event is neglected either explicitly or implicitly, which easily happens in case of unprecedented events that have not yet been identified. Most supply chain disruptions are declared to have an earthquake momentum: they appear suddenly without any warning. However, there are many events, such as labor strikes, price changes, and even natural catastrophes evolving over time, which provide early warnings and which can be anticipated prior to their occurrence. The volcanic ash cloud that affected Europe in April 2010 (that is estimated to have caused losses of US$4.7 billion in global GDP (Oxford Economics, 2010)) is an example of unused preparation time. Although this event has been frequently called unprecedented and unexpected (Lynch, 2012; Rogers, Pawar, & Braziotis, 2012), it was neither. Volcanic activities in Iceland comparable to the 2010 eruption occur on average every 20–40 years (Sammonds, McGuire, & Edwards, 2010). This volcanic activity only becomes a problem for air traffic in Europe when it coincides with rare north to north-westerly wind movements (Leadbetter & Hort, 2011). While the ash cloud can be considered unusual, it was far from unprecedented and unexpected: the volcano had been in eruption for four weeks before the ash cloud reached the airspace of the United Kingdom on April the 15th, which was more than enough time for launching contingency plans—had these existed.[1]

A conclusion is clear from the above discussion: the extent of supply chain risk can increase significantly by neglecting the preparation time available prior to the occurrence of a disruption.

4.1.3. Non-sub-additivity of supply chain risk over time

Financial risks are quantified by the evaluation of risk measures. Financial risk measures must satisfy certain axioms, including sub-additivity, which refers to the diversification potential of several

[1] A phenomena closely related to the neglect of available preparation time is formulated within the Black Swan Theory (Taleb, 2007). It defines an event to be a *Black Swan*, when it is unexpected, has major impact and is rationalized in hindsight. The latter means that the information and data available before the event are re-interpreted in the light of the new insights. A *Black Swan*, therefore, is an event that could have been anticipated.

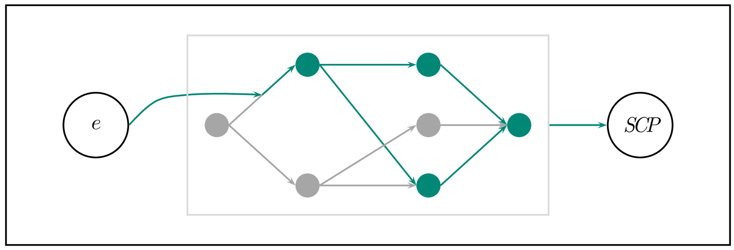

Fig. 10. Event *e* triggers malfunction of a supply chain process, which propagates through the entire network and affects supply chain's performance, *SCP*, in terms of functionality and/or efficiency.

portfolios compared to a single one. Mathematically, a sub-additive function is a function for the sum of two elements that returns something less than or equal to the sum of the function's values at each element.[2] Especially when considering the duration of unexpected changes the sub-additivity axiom does not hold for evaluating supply chain risk. An example is the West Coast Port lockout: after weeks of negotiations between the international long-shore and warehouse union on one side and the pacific maritime association on the other, workers of all ports of the US West Coast went on strike for 10 days. The incident was not totally unexpected, and led New United Motor Manufacturing Incorporated (NUMMI) to increase stock levels. Increased inventories, however, can overcome supply shortages only for a limited time. The duration of the labor strike was too long for the inventory to compensate late goods. For this reason, NUMMI installed an additional supply channel via air freight.

The duration of relevant changes has tremendous influence on the extent of supply chain risk. Thus, supply chain risk metrics need to reflect the effect of time aspects, such as the duration of unexpected changes. From the above it is obvious that a good supply chain risk function cannot be separable in time, since this would very likely lead to a violation of the sub-additivity axiom. Another indicator for the importance of time in supply chain risk.

4.1.4. Biases of mitigation planning

The aforementioned time aspects, which if overlooked at result in time traps of supply chain risk, usually need to be respected while designing and planning supply chains. However, modeling and assessing of supply chain risk are oversimplified, as it is the planning of proper mitigation measures, also referred to as recovery planning and business contingency planning (Tang & Tomlin, 2008; Tang, 2006a; 2006b; Tomlin, 2006).

Decision models for Supply Chain Planning problems consider risk at distinct planning levels. Traditionally, a hierarchical planning scheme is employed such that strategic supply chain decisions are the first ones to be made. Afterward, they are used as an input for consecutive, e.g. tactical and operational decision levels. Often, decision makers argue that risks yielding to *huge* performance deteriorations should be handled on a strategic level whereas *medium* and *small* risks should be accounted for at tactical and operational decision levels, respectively. Due to the nature of most supply chain risks (including the type of uncertainty and its future development), it might be necessary to split this decision process. Consider as an example a Swiss chemical producer trying to limit the loss evoked by a breakdown of its production process (Logistik Heute, 2010). Typically, companies strive to limit the loss they might encounter by closing insurance contracts. However, in the case of the above mentioned Swiss company, the major re-insurer refused to insure the production breakdown since the replacement time of the batch reactor was estimated to be over 1 year (the reader should refer to Logistik Heute, 2010 for further details). The producer had to identify another mitigation alternative in order to be prepared for disrupted production: the company established an agreement with a major competitor to share production capacity in case of a production breakdown. The mitigation for the huge disruption of reactor destruction was handled via strategic contract negotiation. In contrast to increased safety stock (which is effective over the whole planning horizon), the aforementioned measure becomes effective on an operational level (right after a disruption occurs). Contrary, increased inventory levels supported some of the major European automotive manufacturers when supply shortages occurred during the (short-term) events that surrounded the European ash cloud.

The belief that distinct types of supply chain risks can be assigned to different planning levels is naive—especially since decision makers do not know how the disruption's severity may evolve over time. In order to offer reliable mitigation options or even robust and flexible supply chain designs and plans, it is necessary to overcome the time traps of supply chain risk described above. In the next section we introduce important concepts and definitions that facilitate the modeling of relevant time aspects.

4.2. New concepts and definitions

The exclusive probabilistic and event-related understanding of supply chain risk leads to an incomplete and insufficient perception of risk and impedes its appropriate and effective management. Next, we present some key elements and concepts that are needed to understand the dynamics of supply chain risk and to design appropriate risk-aware decision models. For further reading we refer to Heckmann (2015).

4.2.1. Causalities

The biases discussed in the previous paragraphs are based on an analysis of supply chain risk that focuses on the simplified evaluation of the disruptive trigger and the performance deterioration. Nevertheless, triggering events can yield different outcomes. Moreover, distinct performance deteriorations may result from different events. Accordingly, a triggering event can be assumed only as the "root" cause of performance deterioration. In fact, a single event or a sequence of consecutive events only becomes an issue if they negatively affect one or several supply chain processes and if their consequences propagate through the entire supply network—see Fig. 10. We define a SUPPLY CHAIN PROCESS as an individual activity involved in procuring, producing, storing, and distributing goods as well as services for the sake of goal achievement of the underlying supply chain. Supply chain processes can result from different types of operations like transportation, production, manufacturing, storage, handling, shipment, engineering design functions, or even legal processing (Hopp, 2008). Once an event occurs it is irrelevant whether it has arisen internally or externally to the supply chain. It is the interplay of all supply chain processes and their actual states of supply chain characteristics that determine if a supply

[2] $f(x+y) \leq f(x) + f(y)$.

chain is able to absorb modifications. This interaction determines whether the first impact of an initial event on the supply chain provokes the inefficiency or/and ineffectiveness of consecutive processes, propagates through the entire network and finally results in a performance deterioration—see Fig. 10.

We define a POTENTIAL TRIGGER as an event that has the potential to negatively affect the efficiency and effectiveness of a supply chain process, which may result in a performance deterioration.

The eruption of the Icelandic volcano is considered to have evoked a perfect storm of consequences such as ash cloud, aircraft grounding, lead time increase, delays, halt of production and delayed customer orders. European supply chains were only hit by air transportation starting or ending in Europe. Nevertheless, for some of them, the increase in the lead time of air-shipped goods was large enough to result in supply chain disruptions.

A potential trigger is called a DISRUPTIVE TRIGGER when its occurrence results in the deterioration of supply chain performance.

A potential trigger along with a vulnerable supply chain (i.e., a supply chain that is not able to handle modifications in its characteristics) uncover the existence of one or several supply chain risks. However, inefficiency or ineffectiveness can be evoked by any known or unknown disruptive trigger. Instead of starting risk analysis by the identification, gathering and assessment of potential events that may serve as a disruptive trigger, we consider that the main task of supply chain risk analysis is to evaluate the potential effect of modifications of supply chain characteristics and assess their influence on key performance indicators.

4.2.2. Uncertainty profile

The occurrence of triggering events may affect the actual status of supply chain processes. The status of a process is determined by attributes that further describe its use and capacity. The effectiveness and efficiency of supply chain processes such as transportation, production, storage, handling, or shipment can for example be characterized by attributes like costs, capacity and time. In what follows we denote these attributes of supply chain processes as SUPPLY CHAIN FACTORS.

We define a supply chain factor (SCF) as the quantitative description of a specific attribute of a certain supply chain process.

Production capacity, transportation lead time, customer demand, or detailed inventory levels for finished goods at some distribution center are all examples of supply chain factors. In order to evaluate the potential effects of supply chain factor modifications, it is necessary to anticipate how their values may develop over time. A deviation may lead to specific supply chain risks when it takes positive (e.g., lead times, prices) or negative values (e.g., capacities). Considering a single potential trigger, the development of a supply chain factor over time can be described by temporal and quantitative aspects. Important aspects are: time interval between two distinct deviations, duration of a deviation (includes duration of peak-moment and time for the deviation decay), speed to maximum deviation and speed to full recovery, point in time of information availability or deviation detection (this may coincide with the start of change, lie before or after the beginning of changing factors), time to respond, magnitude of deviations over all affected time periods.

Note that the relation between time and performance deterioration as introduced in Sheffi (2007), Sheffi and Rice (2005) and discussed by several further authors (e.g., Asbjornslett, 2009; Behdani, 2013; Craighead, Blackhurst, Rungtusanatham, & Handfield, 2007; Lynch, 2012; Melnyk, Rodrigues, & Ragatz, 2008; Snyder et al., 2012) is referred to as a disruption profile. In this paragraph, we highlighted the uncertainty development referring to the relation between time and value deviation of supply chain factors. Depending on the type of supply chain factors, uncertainty profiles look different and can be described by statistical moments like expected

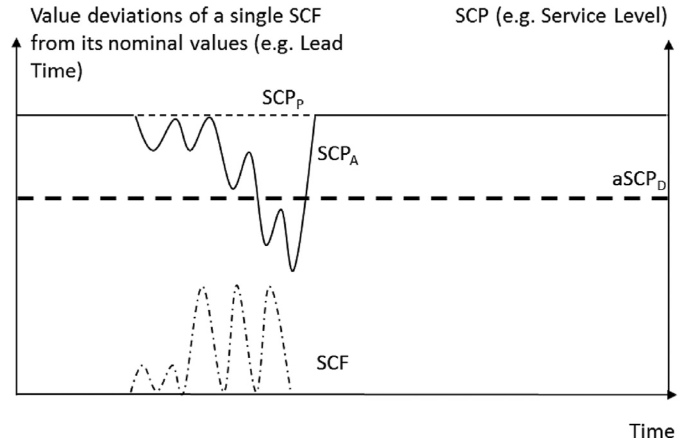

Fig. 11. Exemplary uncertainty profiles of supply chain factor values and related level of supply chain performance.

value, variance, skewness, and kurtosis. The use of new technologies (e.g. seismic sensors) is a means for improving the accuracy of the forecasts and consequently of the above mentioned measures. In particular, more information about uncertain developments can be gathered.

4.2.3. Performance deterioration

There is a vast amount of literature available that discusses both the importance of performance measurement (cf. Akyuz & Erkan, 2010; Beamon, 1999; Li, Ragu-Nathan, Ragu-Nathan, & Rao, 2006) and the difficulty of choosing the "appropriate" measures (cf. Eccles, 1991; Lapide, 2000). Due to the complexity of globally operating supply chains, the variety of activities within a supply chain system as well as the subjective assessment of goal achievement of supply chain partners, the choice of supply chain performance measures is a critical task (Elrod, Murray, & Bande, 2013). In particular, choosing the appropriate measure might be difficult to accomplish; if there are several such measures their relative importance must be taken into account as well (Sawik, 2015).

Having identified the performance measures that best reflect and assess supply chain strategy and the related objectives with respect to efficiency and effectiveness, it becomes necessary to determine the target level for these performance measures as well as the acceptable degree of level deterioration. Quite often managers know what they can bear. A service-level reduction of 2 percent might be acceptable, while an increase of overall logistics costs by 50 percent may simply be unacceptable. A POTENTIAL SUPPLY CHAIN PERFORMANCE DETERIORATION, SCP_D, is defined as the difference between the planned or targeted supply chain performance value, SCP_P, and the actual performance value, SCP_A. A performance deterioration becomes CRITICAL if it exceeds the acceptable value of performance deterioration $aSCP_D$. The evaluation of the performance deterioration is a subjective concept and depends on the preferences of the decision maker (French, Maule, & Papamichail, 2009). The importance of a (potential) loss depends on both organizational and individual goals and constraints. Some decision makers accept only small deviations from the planned supply chain performance while others allow higher changes.

4.3. Examples

After having set the basis for a new and time-dependent supply chain risk perception, we give strength to our definitions through examples.

Consider the case of a labor strike that affects the lead time between a core supplier and the major production site. At the

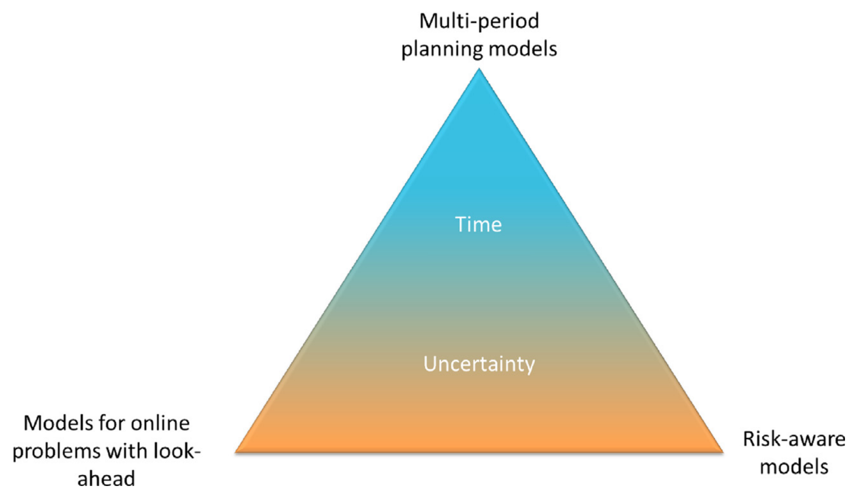

Fig. 12. Interaction between the different types of models discussed and the main “future” components.

beginning the strike yields only minor but recurrent lead time increases, because emergency supplies are still delivered. After a few days, however, the staff of the major supplier carrier starts a general strike that results in a large lead time increase. By means of temporal and quantitative concepts introduced above the uncertainty profile of the supply chain factors involved can be modeled.

Fig. 11 highlights an exemplary development of such a factor modification. Additionally, this figure shows how the factor change affects the supply chain performance, which can be described for example through the overall service level. The effect of a factor change becomes visible when the planned or targeted supply chain performance cannot be met. The deviation of the target performance level only becomes critical if the acceptable level of performance is deteriorated.

As it can be observed in Fig. 11, if a supply chain ships only small amounts by the transportation link associated to the lead time fluctuations (as exemplified above) or is endowed with sufficient back-up inventory units, overall supply chain performance might not be affected. The potential loss is acceptable, which refers to the non-existence of supply chain risk. This is reflected by the fact that the first minor to moderate changes can be handled or compensated by the supply chain. If the transportation link is, however, used more frequently, back-up inventory units are too few or used up too early, and thus performance deterioration grows up continuously over time. This development could take place slightly or with up-and-down movements. Within the figure this situation is reflected after the third lead time increase, when the supply chain cannot adhere to the acceptable level of performance deterioration. The associated loss is not acceptable and uncovers the existence of supply chain risk.

Due to the limits of explanatory power provided by the supply chain risk definition and the methodology deduced from this definition, numerous biases emerge. The assessment of risk as the product of event-related probability by impact may lead not only to faulty identifications, but also to deficient conclusions. Statements about the future are difficult and have to be handled carefully. Besides prospective developments, it is the understanding of how changes affect the supply chain that need to be thoroughly evaluated. For many years it has been difficult to get access to a sufficient amount of information necessary to describe supply chain complexity and interactions. Nowadays, due to technical innovations, data acquisition and preparation are easier. What is still missing is the understanding of the supply chain dynamics that cause the existence of supply chain risk. The missing consideration of relevant interactions forestalls the possibility to understand, model and analyze *all* potential disruptive triggers, *all* available countermeasures, and their interaction with enough detail. Having understood the dynamics that affect the goal attainment of underlying supply chains, the formulation and solution of optimization models should resume the determination of risk-aware supply chain designs and plans. Commonly used countermeasures such as additional suppliers, safety stocks, and capacity fall back positions would still be used but should be determined by the mathematical model formulation.

5. Discussion and conclusion

When we review the findings analyzed in Sections 2–4, we observe two central underlying aspects: time and uncertainty. Each of those sections was built around the need for handling at least one of these aspects. As a result, we were led to different classes of models depending on the features captured. In particular, we observed that the time line from the introductory section was too simplistic and had to be refined or adapted progressively depending on the emerging circumstances analyzed. Furthermore, uncertainty is often present in the re-designed time lines.

In synthesis, the contents of Sections 2–4 are strongly linked to each other by time and uncertainty. This is illustrated in Fig. 12 with those two (central) aspects in the interior of the triangle. Then, we observe online models with look-ahead when capturing short-term uncertainty is the goal. In this case, time is not the main driving aspect and thus we locate “models for online problems with look-ahead” in the lower-left corner of the triangle. Nevertheless, we observe a common edge between online models with look-ahead and multi-period models. This makes clear the fact that when considering online models we are already capturing time (future) although in the short term. In this situation we have to be aware that we are talking about a “deterministic” future (the *look-ahead*). It is crucial for planners to be able to determine which look-ahead is still feasible. On the other hand, when time is the driving aspect we need to consider time-dependent models: we move up and right in the triangle. All the ingredients are gathered by risk-aware models. In this case, we look far into the future and thus we have to deal with stochasticity in an explicit way. A big challenge is to bring such models into Advanced Planning Systems (which is obviously needed). In Fig. 12 the risk-aware models are represented in the right corner of the triangle and have a common link with multi-period models (the multi-period setting) and also with online models (uncertainty as a key driving aspect).

In this paper we discussed the relevance of time and uncertainty in the context of Supply Chain Planning. We observed that depending on the driving aspect we should consider a different type of model. We identified several flaws in the existing knowledge or, in other words, we enumerated some issues that have not been appropriately accounted so far. In particular, we discussed new approaches to Supply Chain Planning. We looked into the impact of recent technological developments like the Internet of Things or Industry 4.0 on supply chains, and we showed how online optimization models can help coping with real-time challenges. Finally, we re-coined the concept of risk in the realm of Supply Chain Planning and we answered to the questions of how to measure supply chain specific risks and how to incorporate them into mathematical models.

We strongly believe that the findings of this paper will lead to interesting new OR models, both for academic research and for integrating realistic planning tools suitable for practitioners.

Acknowledgments

The authors thank the three anonymous reviewers for their useful insights that helped improving the manuscript.

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