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Measuring the performance-related effect of supply chain events on manufacturing operations

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Abstract
Today supply chain event management (SCEM) is an important research area because global and lean supply chains are prone to disturbances (i.e. events). SCEM systems identify these events early and mitigate their effects through counter-measures. The impact of common events like transport delays on scheduled manufacturing operations, however, is difficult to judge before effects have propagated through the production. Thus, to avoid an overly sensitive SCEM system that reacts to every event, an assessment of its probable performance-related effects is required. To this end, the paper proposes and evaluates two aggregated measures that capture the dynamics of system performance as an event’s effects unfold over time. The measures support the answering of the question of how and why one supply chain event would be more critical than another.

Keywords: Supply chain event management, performance indicators, production systems

Introduction
The increased integration of global supply chains (SCs) with a reduction in stock and time buffers has raised their vulnerability to events that erode efficiency and competitiveness by rendering original plans and forecasts obsolete. In this context, events can be defined as disturbances that impede, in various degrees, the execution of SC processes as they were originally scheduled. In recent years, supply chain risk management (SCRM) and preventive measures have done much to address the potential
of events. Theory states (Perrow, 1984) and ample examples from the literature illustrate (Guha-Sapir et al., 2011, Wagner & Bode, 2006), however, that preventive measures cannot completely eliminate events. Therefore, a company has to be capable of identifying events early and to quickly mitigate its effects with adequate countermeasures in such a way that event-related performance deterioration is avoided.

A promising approach to this end is the supply chain event management (SCEM) concept that refers to the practice of observing, prioritizing and reacting to events that occur during the operation of a SC (Tribowski et al., 2009). Already the early observation and prioritization of events through such a system, however, is inherently difficult because due to tightly coupled processes, subtle and obvious events alike lead to a cascade of amplifying knock-on effects that a causality analysis cannot always capture (Liu et al., 2007, Radjou et al., 2002). Furthermore, vulnerability factors and stochastic influences along the SC make it difficult to precisely judge the impact of an event’s effects on manufacturing operations in advance (Wagner & Bode, 2006). The decision about the ‘criticality’ of an event to a company’s operations is crucial, however, because it precedes the decision for enacting the set of counter-measures that mitigate the effects best. Consequently, (Craighead et al., 2007) stated that today a gap exists for the question how and why one supply chain event would be more severe than another.

This contribution intends to address this gap by quantifying the effect of an event on an affected production system. Thus, we focus on the prioritization component of an SCEM system. It judges the criticality of an event to manufacturing operations and estimates the effectiveness of possible counter-measures. To this end, two measures are proposed that link events to their performance-related effects. The remainder of this paper is structured as follows: Section 2 is dedicated to a literature review that introduces important concepts, terminology and recent advances in SCEM. Section 3 presents two measures that capture the dynamics of system performance as an event’s effects unfold over time. The following Section 4 illustrates and evaluates the applicability of the two concepts on a discrete-event simulation model of an event-prone production system. The paper concludes in Section 5 with a brief summary and an outlook on future research.

**Literature review**

This section first reviews event properties and draws a boundary between the application areas of SCRM and SCEM to narrow down the event types and application fields for which the developed measures are intended. Existing performance-based evaluations of an event’s effects are then examined to place the proposed measures into context.

The morphological analysis in Table 1 lists the most relevant event properties from the literature. According to (Jüttner, 2005) an event can affect a company from demand-side, supply-side and environmental risk sources. Demand-side risk covers outbound material flows and (erratic) product demand. Supply-side risk is the uncertainty connected with material inflows and can range from supplier failures to transport delays. Environmental risks are natural and civilization-based uncertainties. In order to capture the events that can stem from a company’s own operations (e.g. machine failure or strike), the internal risk category is added. Furthermore, events are associated with a probability of occurrence and a severity of the resulting effects (Kleindorfer & Saad, 2005). The former is generally assumed to be a three step classification that distinguishes between low, medium and high probabilities for the occurrence of an event (Thun & Hoenig, 2011). In
regard to the severity of effects (Gaonkar & Viswanadham, 2004) group events into deviations, disruptions and disasters. A deviation occurs when one or more parameters (e.g. supplier lead time, demand) stray from their expected or mean value and thus introduce instability into planned operations. Disruptions refer to a situation where the structure of the supply chain system is transformed through the non-availability of certain nodes and/or edges due to an unplanned, unanticipated occurrence (Craighead et al., 2007). Disasters describe a partial or complete system shutdown.

Table 1 – Morphological analysis of event properties and applicable counter strategies

<table>
<thead>
<tr>
<th>Category</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source</td>
<td>Supply</td>
</tr>
<tr>
<td>Probability</td>
<td>Low</td>
</tr>
<tr>
<td>Severity</td>
<td>Deviation</td>
</tr>
</tbody>
</table>

Table 1 illustrates that SCRM and SCEM are complementary concepts that address events but differ in their respective focus and application. SCRM aims at reducing the potential for the occurrence of events by addressing their ultimate cause with preventive strategies. These strategies, however, are costly and time consuming because they frequently involve a supply chain redesign (Blackhurst et al., 2005). Thus, (Thun & Hoenig, 2011) propose that only highly severe and likely events with network-wide consequences justify mitigation strategies. These typically have a tactical or strategic time horizon of months to years (e.g. dual and/or local sourcing to prevent supplier failure). The majority of events, however, are deviations (e.g. transport delay) and minor disruptions (e.g. 1-day strike) where the SC remains fully operational but variation is introduced so that plans become inherently unreliable and less optimal. Here SCRM is of limited use because i) the ultimate cause of an event is not always identifiable, ii) preventive measures are too costly and iii) the occurrence of minor events cannot be excluded. A SCEM system fills this gap by addressing deviations and minor disruptions of the SC after their occurrence through e.g. a reactive amending of operations (Otto, 2003). This concept requires an IT system that is coupled with monitoring (e.g. RFID-based tracking) and business systems (e.g. ERP, MES). It is then capable of identifying deviations (and disruptions) by comparing plan data with real-time status data from SC material flows (Straube et al., 2007). A frequent approach for deriving an event from RFID-based observations is complex event processing where several primitive readings are combined through their causal relationship to derive higher knowledge (Zang et al., 2008). After an event is identified but before the SCEM system triggers operational, proactive reactions like a rescheduling of the planned production sequences (Lamparter et al., 2011), i) the effects of an event to the planned manufacturing operations have to be estimated and ii) the effectiveness of possible reactions evaluated.

This is precisely the task of the prioritization component of a SCEM system that uses information from the supply chain and the production to predict the effects on planned manufacturing operations. It enables a distinction between critical events and uncritical situations, which is crucial for two reasons. First, its sensitivity determines the overall effectiveness of a SCEM system by avoiding high false-negative and false-positive rates – the latter refers to a system that frequently misjudges situations as critical and
consequently triggers unnecessary reactions. Second, the earlier a situation is identified in the SC, the more uncertain becomes the estimation of its effects on an affected company. Consequently, the relationship between a certain observation in the supply chain and its most likely impact (e.g. financial and/or operational) has to be established.

Petri nets are an effective tool for modeling complex and dynamic systems due to its ability to illustrate precedence, concurrent and asynchronous events, its mathematical foundation and ability to represent a system graphically (Wu et al., 2007). (Liu et al., 2007) used Petri nets extended with time and color as formalism for managing events. They designed seven basic patterns to capture modeling concepts that commonly arise in SCs and showed how to combine the patterns to build a complete Petri net. (Wu et al., 2007) presented a network-based approach to model a SC and the performance-based effects of a disruption and perturbation on it. In an example it was shown that a machine disruption either increased lead time or unit costs. More recently, (Zegordi & Davarzani, 2012) extended this study to include dependencies between different disruptions – e.g. that import/export sanctions increases the likelihood of price decreases. (Wilson, 2007) used system dynamics (SD) in order to investigate the effect of transport disruptions on performance. Besides a mathematical foundation and an intuitive graphic notation, SD is capable of considering complex structures and feedback. Using several performance measures (unfilled customer orders, inventory levels, and goods in transit), it was shown for a traditional retail supply chain that a transport disruption between the 1st tier supplier and the warehouse or distributor creates the most problems. A vendor managed inventory counters these problems through sharing of customer demand information and inventory positions at retail and warehouse level with the supplier. Rather than focusing on the logistics perspective, (Heinecke et al., 2012) proposed a SD approach that links events with company-internal effects that manifest themselves in the operational performance indicators of Figure 1. Consequently, (Köber & Heinecke, 2012) applied the SD model to an industrial case, showing that disruptions severely affect performance of manufacturing operations and that costly capacity flexibility is of limited use to mitigate effects.

These and other studies (Hendricks & Singhal, 2005) focus on the analysis of severe disruptions and, with the exception of (Heinecke et al., 2012), evaluate performance on a supply chain level. SCEM systems, however, are proprietary systems that operate within a company and consequently aim at optimizing local objectives rather than global ones on a supply chain scale. As illustrated by Figure 1, these objectives can be summarized as maximizing machine utilization and the customer service rate while minimizing inventory levels and the production lead time (Nyhus & Wiendahl, 2006). These indicators are further grouped by either targeting market or operational performance.
(Wiendahl & Breithaupt, 2000). This set of conflicting and supporting optimization objectives result in an ambiguous effect of events on manufacturing operations since positive effects may outweigh or balance negative ones for some events (i.e. deviations) and make a reaction obsolete. Thus, (Heinecke et al., 2012) stated that further research is required into “the combined effect of events when conflicting optimization goals are pursued.” To this end, the following section proposes two aggregated measures that capture the dynamics of system performance as an event’s effects unfold over time.

**Measuring event criticality**

Based on the four optimization targets in Figure 1, the next two subsections present the weighted sum and cost function approaches that allow a comprehensive judgment about the impact of an event on a production system and the effectiveness of counter-measures.

**Weighted sum approach**

Considering the optimization targets in Figure 1, this approach measures the performance oscillation when a system moves from its steady state when the event is first noticed into the state when its effects propagate through the production system. To this end, the indicators need to be calculated and monitored at every point \( t \in T \) over a finite time horizon of total length \( T \). In order to have an accurate picture of system performance, the distance between two time steps needs to be sufficiently small. Thus, given a time step \( t \in T \), the total inventory \( I_{tot} \) at a company is determined by the sum of the raw material inventory \( I_{mat} \) and finished product stock \( I_{prod} \):

\[
I_{tot}(t) = I_{mat}(t) + I_{prod}(t)
\]  

(1)

The average utilization of a single machine \( m \in M \) in a system with \( M \) machines is determined by the number of time steps which it was working during the observation period (time steps 1 to \( t \)). This can be achieved through a binary variable \( z_{ki} \) that obtains the value 0 when the machine was idle during a specific time step and the value 1 if it was working. The summation of the resulting values gives the number of time steps during the observation period that the machine was actually working. This value is then divided by the total possible working time of a machine until time step \( t \). The average system utilization is then given by summing the individual utilization rates of all \( M \) machines and dividing them by the total number of machines:

\[
U(t) = \frac{\sum_{k=1}^{M} \left( \sum_{i=1}^{t} z_{ki} / t \right)}{M} \text{ with } z_{ki} = \begin{cases} 
0, & \text{if } k \text{ in } i \text{ idle} \\
1, & \text{if } k \text{ in } i \text{ working}
\end{cases}
\]  

(2)

Given \( J \) customer orders that arrived during the observation period, \( j \in J \) orders have already finished production and have been assigned a production end time \( t_{end,j} \in T \). By subtracting the order-specific production start time \( t_{start,j} \in T \) from the end time \( t_{end,j} \in T \), the order lead time is obtained. This calculation is repeated for all \( j \in J \) orders that were assigned an end time \( t_{end,j} \) and the resulting values are summed up. The average system lead time in \( t \) is obtained through the division by \( j \):
The average customer service rate of a system is given by the ratio of on-time deliveries until time step $t$. To this end, all $J$ orders are associated with a specific due date $t_{\text{due}j} \in T$ and all $j \in J$ finished orders have an actual delivery time $t_{\text{del}j} \in T$. All unfinished orders $J - j$ are then checked through a binary variable $z_k$ whether their due date has already passed. All finished orders are analyzed through $z_i$ whether their due date surpassed the delivery time. The summation of the number of on-time orders divided by the total number of orders $J$ results in the average customer service rate of the system in $t$:

$$
\bar{L}(t) = \frac{\sum_{j=1}^{J} (t_{\text{end}j} - t_{\text{start}j})}{J}
$$

(3)

After the indicators are estimated for a time step $t$, the weighted sum $c_{\text{ws}}(t)$ is calculated by weighting each indicator with a factor $\lambda_i$:

$$
c_{\text{ws}}(t) = \lambda_1 \left(1 - U(t)\right) + \lambda_2 \left(1 - \bar{S}(t)\right) + \lambda_3 \frac{\bar{L}(t)}{\max(\bar{L}(1), ..., \bar{L}(t))} + \lambda_4 \frac{I(t)}{\max(I(1), ..., I(t))}
$$

(5)

The measure reflects the performance oscillation of the system when it evolves from its steady state into the period where it is affected by a specific event. In order to make its interpretation more intuitive, its value should be close to 0 on the y-axis if the system performs well. An event’s ‘criticality’ is then the distance of the $c_{\text{ws}}$-value from 0. To this end, the optimization targets of the performance indicators from Figure 1 need to be recalled. Considering Equations 2 and 4, it is apparent that the utilization and service rate are bounded between 0 and 1, which makes normalization obsolete. Furthermore, due to the maximization objective, both scores are considered ‘better’ when they are closer to 1. Thus, both indicators simply have to be subtracted from 1 in order to be considered ‘better’ when they are closer to 0 (compare Equation 5). The minimization objectives of inventory levels and lead time are unbounded in their present form and require normalization. Since we require small values to be considered better than large ones, the values are normalized by dividing them through the respective maximum that was recorded during the observation period (time steps 1 to $t$). Finally, the weighting factor $\lambda_i$ reflects the preference of the decision-maker of one indicator over another and is often an arbitrary choice. Thus, rather than weighting each individual indicators, we propose to either place more or less emphasis on the overall target, which means that either the operational or market indicators are more significantly incorporated into the analysis.
Cost function approach

The approach of a cost function is an alternative to the weighted sum method. It translates the aforementioned performance indicators into widely used cost concepts. By building on the supporting and conflicting optimization objectives, it also aims at capturing and quantifying the interrelationships between the four indicators. Both approaches differ in that the weighted sum averages system performance across the observations period (time steps 1 to \( t \)), whereas the cost function is a snapshot of company profit in one time step.

Inventory levels are easily converted by simply charging a fixed amount \( x \) for each item that was in inventory during time step \( t \). This results in the inventory holding costs \( c_I \):

\[
c_I(t) = x \times I_{it}(t)
\]

(6)

Utilization can be transformed intuitively. If a machine was idle in \( t \), the opportunity is lost to process raw material instead. Thus, similarly to Equation 2, a binary variable \( z_{kt} \) takes the value 1 if machine \( m \) was idle in \( t \). This analysis is repeated for all \( M \) machines in the system. The opportunity costs \( c_U \) are then calculated by proportionately allocating the profit \( p \) from selling one order to the \( M \) machines in the system and multiplying the result with the overall lost capacity units in \( t \):

\[
c_U(t) = \frac{p}{M} \sum_{k=1}^{M} z_{kt} \quad \text{with} \quad z_{kt} = \begin{cases} 0, & \text{if } k \text{ in } t \text{ working} \\ 1, & \text{if } k \text{ in } t \text{ idle} \end{cases}
\]

(7)

A final cost factor that is affected by the effects of an event is the penalty costs for late product deliveries. Literature often assumes that costs are also connected to a finishing of production before the due date (Pinedo, 2008). These costs are explicitly accounted for through the inventory holding costs, which include costs for finished products (compare Equation 1). The tardiness costs \( c_s \) are calculated using all finished orders \( j \in J \) that are delivered in \( t \) (\( t_{del,i} = t \)) by summing their individual number of time steps that they are delivered late and then multiplying with a fixed cost factor \( y \):

\[
c_s(t) = y \sum_{i=1}^{J} (t_{del,i} - t_{due,i}) \quad \text{for all } i : t_{del,i} = t
\]

(8)

The profit \( P(t) \) during time step \( t \) is then calculated by multiplying the profit per order with the number of orders that were delivered to the customer in \( t \). From the resulting value the aforementioned costs are then subtracted to obtain the overall profit \( P(t) \):

\[
P(t) = p \sum_{i=1}^{J} z_i \{ c_I(t) + c_U(t) + c_s(t) \} \quad \text{with} \quad z_i = \begin{cases} 0, & \text{if } t_{del,i} \neq t \\ 1, & \text{if } t_{del,i} = t \end{cases}
\]

(9)

Evaluation

This section illustrates the estimation of an event’s ‘criticality’ by applying the proposed measures. They both return the performance oscillation before and after the effects of an event have rippled through a system. To this end, a production system is modeled with
the discrete-event simulation tool Matlab Simulink. The model is based on an actual production test facility at Siemens AG in Nuremberg, Germany. The scenario is a recurring transport of raw material from a supplier to the OEM in Nuremberg where the material is stored, processed and shipped to the customer. During the simulation time of 80,000 time steps, a deviation event (traffic jam) at $t=20,000$ delays several truckloads of raw material deliveries to the production. Performance is recorded at every simulation time step as described in Section 3. Figure 2 depicts the results for the weighted sum approach. As suggested in Section 3 and shown by the legend in Figure 2, the weights are varied between market targets (MT) and operational targets (OT) in the range of 25 to 75 percent respectively. The two indicators within each target set are weighted equally.

![Figure 2 – Criticality of a deviation event using the weighted sum method](image)

Figure 2 shows a discrepancy between the occurrence of the event and the appearance of its effects in production that results from i) remaining inbound stock and ii) arriving transports that were not affected by the event. The unanimous rise in the weighted sum measures when the effects ripple through the production system, regardless of the employed weights, suggests that the event has an overall negative impact on the four indicators and consequently overall system performance. Furthermore, with emphasis shifting towards the MT the weighted sum increase becomes most clear, which suggests that they are more strongly affected by an event than the OT. Over the remaining simulation time the performance-related effects of the event wear off slowly because i) measures are averaged across time and ii) the production system operates close to its capacity limit. The latter causes a backlog of production orders that are processed late and have long lead times. The question of whether a reaction to this event is required can be answered in two ways. First, the maximum tolerated performance oscillation from the steady state is defined as a threshold. Second, the effectiveness of potential counter-measures in reducing the oscillation is estimated. If for instance a rescheduling of production orders is successful in retaining the steady state, a reaction is preferable.

Figure 3 depicts the average profit per sold unit and time step for the same event by utilizing the cost function method. After the calibration period the company is profitable until the event’s effects reach the system when it starts to make frequent loses. Both measures agree in the delay between events and effects since they comprise similar indicators. If the cost function would be equal to the service rate, the effects would show
later. Also, the recovery of the system is sluggish due to the backlog of orders that have long lead times and often miss their due dates. This supports the finding of (Heinecke et al., 2012) and (Köber & Heinecke, 2012) that an event lowers company performance when production operates close to capacity limits. In comparison to Figure 2, however, the performance oscillation is less distinct in Figure 3. Nevertheless, since the company now operates close to its operating costs a reaction to the event is required.

![Figure 3 – Criticality of a deviation event using the cost function approach](image)

**Conclusion**

Trends like just in sequence deliveries and build-to-order have made production systems prone to events. Supply chain event management (SCEM) systems counteract the resulting instability through early identification of events and mitigation of their effects through reactions. The prioritization component of a SCEM system hereby distinguishes between critical events and uncritical situations by estimating an event’s effects on a production system. To enable this distinction, this paper presents two measures that are each based on several optimization objectives and thus, comprehensively capture the dynamics of system performance as an event’s effects unfold over time. The evaluation shows that the weighted sum and cost function approaches also effectively capture the effect of small events like transport delays. Since both are aggregate measures, they facilitate the assessment of an identified event and support an informed judgment about its ‘criticality’ to manufacturing operations. Further research is required in regard to possible reaction strategies that are offered by a rescheduling in just in sequence supply chains. The decision that triggers a reaction depends just as much on the performance-related impact of an event as it does on the effectiveness of available reaction options.

**Acknowledgments**

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**References**


