Process Transparency

Effects of a Structured Read Point Selection

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PROCESS TRANSPARENCY: EFFECTS OF A STRUCTURED READ POINT SELECTION

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Abstract

Modern supply chains, especially in the automotive industry, are prone to events that endanger their ability to deliver products on time. Comprehensive real-time tracking and tracing systems (e.g. RFID-based) can help in making them more robust by identifying events and enabling early responses that are capable of mitigating adverse effects. However, these systems are rarely realized and read points only placed in a few default locations (e.g. receiving and shipping) without further considerations. In this contribution weighted linear optimization models are used to assess the effect of including process characteristics such as variability and cycle times in this decision problem. Using an intuitive simulation setup in which the degree of transparency and system sensitivity are varied, the results indicate that locating read points in sensible places along a process rather than by chance can reduce false alarms by 31% while raising successful identifications by 2%.

Keywords: Supply chain event management, multi-criteria decision making, weighted linear optimization, RFID

1 INTRODUCTION

Globalization and lean production make supply chains (SC) increasingly complex and efficient but also prone to events (i.e. occurrences of different severity that certain SC actors regard as significant). One explanation for the instability of modern SC can be drawn from the Normal Accident Theory [1], which states that in complex, tightly coupled technological systems accidents (i.e. events of high severity) become inevitable. Similarly, an enlarged supply network and reduced time and stock buffers give rise to more uncertainty factors from which events result. As noted in [2], events are associated with a probability of occurrence and a severity of the resulting effects. They can manifest themselves in three forms of increasing severity: deviations, disruptions, and catastrophes [3]. In SC, deviations from target dates and with that the variability of order cycle times (*CT*) can partly be attributed to the severity of certain types of events (Figure 1).

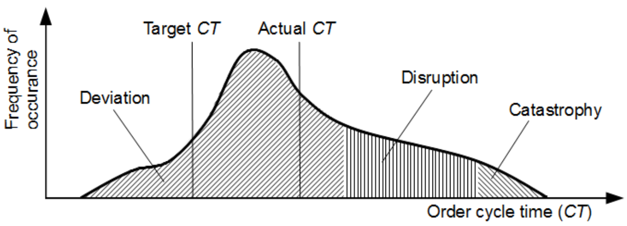

Figure 1: Variability of order cycle times (*CT*)

To address events, preventive and reactive measures exist [4]. The former aims at minimizing the probability of events, while the latter focuses on handling their effects. Now, [1] argued that '*redundancies and safety systems are the biggest single source of catastrophic failure in complex, tightly coupled systems*.' This statement implies and reality shows that preventive measures cannot exclude the possibility of events and thus, establishes a need for systems that address events and their effects once they unfold. One such system, supply chain event management (SCEM), aims at early, automated event recognition and communication to minimize the delay until the initialization of a reaction to ease their effects [4].

To realize this vision, events need to be identifiable along the SC, as long as effects are still small and scope for intervention still large. This makes SC transparency a critical success factor and real-time monitoring systems (e.g. RFID-based) a prerequisite for effective SCEM. For various reasons (e.g. data ownership, financial return, etc. [5]) these systems are rarely realized within companies and even less among SC partners. Also, read points are frequently limited to prominent processes (e.g. receiving and shipping). As observed in [6], the sparse implementation of information capture technologies is partly due to the difficulty associated with the quantification of their value and the extent of their benefits. However, on a sample of 519 publicly announced SC glitches, [7] found that shareholder value showed an abnormal decrease of 10.82%. Through early detection, monitoring systems can help in coping with some effects of SC glitches.

Although desirable, continuous SC monitoring is rarely technically and economically realizable. Thus, locations for suitable read points have to be identified. However, not all points along SC allow for equally important observances of critical effects on order *CT* as e.g. tasks performed before each possible point differ widely. These differences allow for the identification of a subset of read points that should be most sensible to monitor. This decision problem of a structured selection of read points and the assessment of the effectiveness of the choice is largely missing in the academic literature and therefore, represents the focus of this contribution. The research questions are as follows:

- Which points from a given set are most critical to monitor (i.e. where can it be expected to observe critical deviations from the order *CT*)?
- How does a structured selection of read points perform in a simulation setup against a set of points that was selected by chance?

To answer both questions, a serial process that is subject to minor, time-related events is assumed. The focus is put on deviations (Figure 1) because, in comparison to the other two categories, they are more frequent and subtle. Now, within this process, order progression can be monitored in intervals that can be separated by read points. By combining several criteria using weighted linear optimization models, the objective is to select a set of points that enables identification of critical deviations while minimizing false alarms. The performance of the models is compared against a benchmark model and through the usage of a static *CT* threshold above which a deviation is considered to be critical. In summary, this simulation study aims at effective identification of critical *CT* deviations by monitoring a sensible set of points that were selected in a structured way using weighted linear optimization models.

The study illustrates the effects of a structured approach to selecting the most appropriate monitoring points along a process. Furthermore, the impact of different levels of process transparency and system sensitivity on the performance of the approach are illustrated.

The remainder of the paper is structured as follows: Section 2 presents a literature review of possible models, including their respective advantages and disadvantages. In Section 3, details of the selected models and the employed criteria are presented. This is followed in Section 4 by an introduction to the simulation setup, its parameters and performance measures. The findings are summarized in Section 5. The last section is dedicated to some concluding remarks and next steps of research.

2 LITERATURE REVIEW

As stated earlier, the intention is to identify the most important read points among a certain selection, using their shared characteristics. Therefore, the literature review focuses on models that i) result in a single scalar measure, ii) are automatable and iii) intuitive. First, they need to be capable of combining several criteria (i.e. characteristics) of a single point into one measure of criticality. Second, they should be automatable as far as possible and third, they should be intuitive insofar that their application appeals to practitioners.

Among others, multi-criteria decision models (MCDM) are appropriate tools for this task because they assists *'a single decision maker to choose, rank, or sort alternatives within a finite set according to two or more criteria*.' [8] Recently it has undergone a rapid development with the application of several techniques to different problem areas; especially due to the popularity of artificial intelligence (AI) approaches [9]. The review focuses on methods used in inventory management as classifications of parts are a prime application area (e.g. [10, 11, 12]).

The first proposal in this regard, was a joint criteria matrix that combines two criteria [10]. Rather than resulting in a single scalar, the scheme places items in one of nine categories. A weighted or mechanical procedure then reclassifies them. Although intuitive, there is no obvious way of extending the methodology to more criteria.

The analytic hierarchy process (AHP) has also been applied to the problem [13]. Although the AHP is capable of combining many different criteria, it requires substantial subjective input from the decision maker for the preference matrices. The consistency index helps to judge the consistency of the user's preferences [14] but the AHP cannot be automated.

AI-based approaches have been applied to the problem. For instance, [15] used backpropagation (BP) and learning methods to develop an artificial neural network for inventory classification. More recently, [11] benchmarked AI-based classification techniques (support vector machines (SVMs), BP networks, and the *k*-nearest neighbor (*k*-NN) algorithm) against multiple discriminant analysis (e.g. AHP). They found that SVM enables more accurate classification than other AI-based techniques. However, their application is not as straightforward as that of methods based on multiple discriminant analysis.

[12] proposed a linear optimization model with an ordering constraint that allows decision makers to rank criteria according to their importance rather than specifying a precise degree (e.g. AHP). To avoid the usage of a linear optimizer, the model was simplified to be spreadsheet implementable. [16] extended the model such that it maintains the effects of the weights in the final solution.

[17] also proposed a weighted linear optimization model (R-model) that is similar to a class of linear programming models used in data envelopment analysis (DEA). The R-model enables each item to select its own weights for estimating its score. However, despite this advantage the R-model could lead to a situation where an item with a high value in an unimportant criterion is inappropriately classified [18]. Also, it allows for several items to have the aggregated score of 1, making further distinction impossible. Consequently, [18] proposed a revised model. Both models have the advantages that they are intuitive and, due to items selecting their own weights, can be fully automated. Since the models proposed in [17], and its extensions in [18], fulfill all of the requirements stated at the beginning of this section they are chosen for addressing the decision problem presented in this study.

3 STRUCTURED READ POINT SELECTION

This section introduces the basic problem formulation. This is followed by the presentation of the weighted linear optimization models that will be employed in the simulation. The section concludes with an introduction to the criteria and the reasoning behind their choice.

3.1 Problem formulation

Figure 2 shows that a generic, serial process is examined. It can be divided into M intervals of different, average cycle time $\overline{CT}_m$ and with each being subject to low variability (LV). As pointed out in [3], LV is the result of events that could delay or advance the arrival at a read point such as waiting time, set-up times, equipment failure, random noise, etc. Also, [19] stated that '*it is a characteristic of most LV processes to have a bell-shaped probability density.*' Thus, for simplification purposes it is assumed that processing time during each interval is normally distributed with mean μ_m (= $\overline{CT}_m$) and standard deviation σ_m – the latter leading to (critical) deviations in processing time due to their possible accumulation over time.

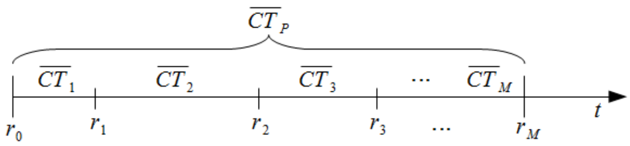

Figure 2: Problem setup

The M intervals are separated through M+1 possible read points (r_m). The scheduled target date is $\overline{CT}_P$, i.e. the time it takes on average to complete the process. Given this setup, the decision maker faces the constraint that not all possible read points r_m can be monitored. Thus, the most critical points within the process have to be selected.

3.2 Weighted linear models

In order to be able to choose the most important read points, each has to be evaluated in terms of N criteria (Table 1). The criterion score of the mth point in terms of the nth criteria is denoted as y_{mn}. Furthermore, all criteria are assumed to be positively related to the criticality level so they can be aggregated into a single score; the individual criticality c_m.

Table 1: Nomenclature

Read point	*Criterion (n=1…N)*				*Criticality*
m	*1*	*2*	…	*N*	c_m
1	y_{11}	y_{12}	…	y_{1N}	c_1
2	y_{21}	y_{22}	…	y_{2N}	c_2
…	…	…	…	…	…
M	y_{M1}	y_{M2}	…	y_{MN}	c_M

The R-model [17] is expressed as follows:

$$\begin{aligned} c_m^g = \max \quad & \sum_{n=1}^{N} w_{mn}^g y_{mn} \\ s.t. \quad & \sum_{n=1}^{N} w_{mn}^g y_{in} \le 1, \\ & i = 1, 2, ..., M \\ & w_{mn}^g \ge 0. \end{aligned} \tag{1}$$

With the objective to maximize the criticality of a specific read point c_m, this optimization problem tries to select the highest possible values for the decision variables (i.e. the weights w_{mn}). These are limited by the constraint that the weighted sum, computed using the same set of weights, for all read points (i=1,…,M) must be less than or equal to 1. Thus, if another read point has the combined value of 1, using the chosen set of weights w_{mn} in conjunction with its own specific scores y_{in}, the criticality value c_m of the point under concern cannot be raised further. In this way, each point tries to select the most favorable weights w_{mn} for its criterion scores y_{mn} to achieve the highest possible c_m.

If, due to this model, a read point has the highest score y_{mn} for one criterion (i.e. dominating all other y_{in}), it would always receive a high c_m regardless of its values for other criteria. To avoid this drawback [18] revisited the issue and proposed an alternative approach. While the R-model helps in selecting weights which are most favorable, the Z-model does the exact opposite and is defined as follows:

$$\begin{aligned} c_m^b = \min \quad & \sum_{n=1}^{N} w_{mn}^b y_{mn} \\ s.t. \quad & \sum_{n=1}^{N} w_{mn}^b y_{in} \ge 1, \\ & i = 1, 2, ..., M \\ & w_{mn}^b \ge 0. \end{aligned} \tag{2}$$

Thus, the R- and Z-model represent two extreme, opposite cases which enabled [18] to propose a composite index. It combines the indexes of the models through the introduction of a control parameter λ (with $0 \le \lambda \le 1$) that may reflect the preferences of the decision maker. In the two extreme cases (λ=0 and λ=1), the normalized scores of the original models are obtained. If a decision maker is neutral about the indices, λ can be set to 0.5. This composite index allows for further distinction between the models:

$$\begin{aligned} c_m^c(\lambda) = {} & \lambda \frac{c_m^g - \min_{m=1...M}\{c_m^g\}}{\max_{m=1...M}\{c_m^g\} - \min_{m=1...M}\{c_m^g\}} \\ & + (1-\lambda) \frac{c_m^b - \min_{m=1...M}\{c_m^b\}}{\max_{m=1...M}\{c_m^b\} - \min_{m=1...M}\{c_m^b\}} \end{aligned} \tag{3}$$

3.3 Criteria

To apply the models, it is necessary to define the N criteria that are used to calculate the criticality c_m of each point. They can be selected from several dimensions (e.g. time, quality, reliability, costs, etc.). However, two constraints have to be considered. First, the selection of criteria is limited to those that are quantifiable. Second, criteria should be positively related, meaning a higher score indicates a higher criticality. For inversely related criteria [17] suggests to simply take the reciprocals of the scores.

Given the problem formulation of Section 3.1, time-related criteria are used. They are easy to determine and other criteria (e.g. quality issues) can be directly traced back to time-related effects (i.e. order has to be reworked). Thus, three guidelines for the criteria selection are formulated:

- *'Target Date'*: Read points closer to the target date are of greater importance than those further away.
- *'Visibility Gap'*: The longer preceding and succeeding intervals the higher the importance of a read point.
- *'Process Stability'*: More stable processes are of less importance than those that display a higher variability.

Target date

Read points further from the target date are less important than those closer to it. First, there is still time for an order to compensate its deviation without intervention. Also, it only becomes more certain towards the target date that a deviation is indeed 'critical'. Second, sensitive reactions to deviations in early stages of a process increase the amount of (suspected) events. Early monitoring and identification is desirable but given the principle of 'management by exception' [20], decision makers would find it difficult to handle a lot of suspected events. Also, the frequent revision of the original schedule would result in a nervous system. Third, time and scope for intervention are becoming limited as the target date approaches. In summary, the selection of read points should strike a balance between the ability of identifying critical deviations 'as early as possible and as late as necessary.'

The first criterion is the amount of remaining read points. It is inversely related to the criticality because the more future chances of intervention, the less critical are process deviations at this particular point in the process. In short, the process might still be able to correct itself so that intervention can be postponed. The second criterion is the remaining processing time from the monitoring point under concern to the target date and is also inversely related to criticality. Points closer to the target date are more critical as the available scope for speeding up or slowing down becomes increasingly limited. The two criteria are important because at a certain point a process might still be long but without further monitoring chances. If the remaining time were the only indicator, the importance of the monitoring point would be underestimated.

Visibility gap

If a process is not monitored, uncertainty about the state of an order increases with time. The "visibility gap" is expressed as the sum of the average *CT* of the two intervals that follow and precede one possible read point. The larger the gap, the more critical is the respective point.

Process stability

Process intervals are not equally susceptible towards deviations. For instance, the likelihood of events with more serious effects is higher for just-in-sequence deliveries than for storage processes. Variability is one indicator of the potential magnitude of deviations that are possible during an interval. It can be expressed in different forms but is most commonly expressed through the (squared) coefficient of variation (*CV*); defined as the standard deviation of an interval m divided by its mean [19].

According to [19], processes display low variability (LV; i.e. deviations) in the case of *CV*<0.75. However, since the *CV* measure normalizes variability across intervals, the same *CV* for two intervals might represent two very different standard deviations σ_m. Since it indicates that an interval might have a severe impact on the ability of the order to make the target date, σ_m (rather than the *CV*) of the preceding interval will be used as an indicator of the importance of the following read point.

Summary

Depending on the requirements of the decision maker or the process, the composition of the final scores c_m can be easily adapted by adding or removing criteria. The four criteria that will be employed in the simulation study for ranking a read point r_m are summarized in Figure 3.

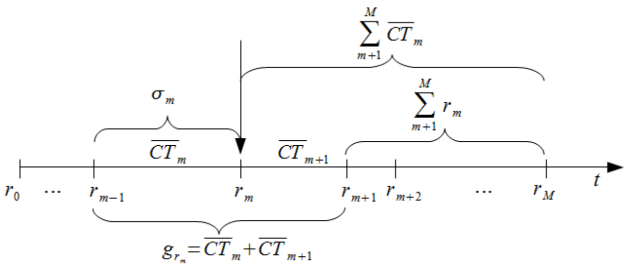

Figure 3: Employed criteria for read point ranking

4 SIMULATION SETUP

This section first addresses simulation related details, followed by an introduction to the performance indicators.

4.1 Simulation related details

As presented in Section 3.2, it is the intention to evalute the read point selections of three control parameters (λ=0, 0.5, 1) against a random selection of points. Figure 4 shows a schematic representation of the simulation procedure. First, the constants were defined. A process setup with 25 intervals (i.e. 26 possible read points) and a combined length of 5000 time units was employed.

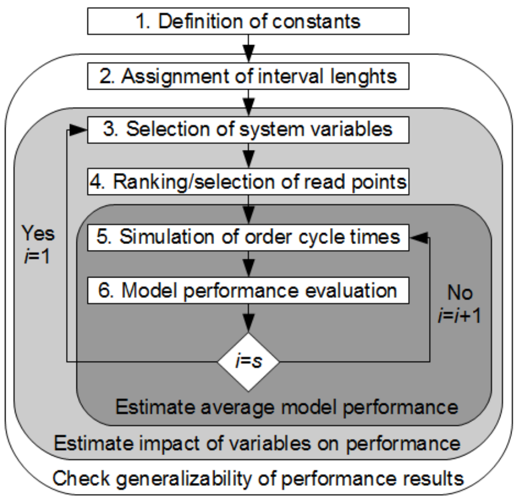

Figure 4: Schematic simulation procedure

Next (step 2), the 25 intervals were assigned random, average *CT* lengths (with a combined length of 5000 time units) and *CV* values in the range of 0.05 and 0.5, i.e. well within the range suggested in [19] for LV processes. The *CV* value was then used to infer the standard deviation. Then the variables were selected (step 3). The degree of process transparency is defined by the size of the selected subset of read points that are used for monitoring purposes. The subsets contained 4, 6, and 8 points. The system sensitivity, the second variable, is a factor v that is added and subtracted from the average, cumulated *CT* at point r_m (Equation 4). Thus, as long as the individual order CT^i at the respective point CT_m^i does not cross either threshold its current deviation is considered uncritical. The factor was chosen to be 0.1, 0.15, and 0.2.

$$\sum_{m=1}^{m} \overline{CT_m} \times (1-v) \leq \sum_{m=1}^{m} CT_m^i \leq \sum_{m=1}^{m} \overline{CT_m} \times (1+v) \qquad (4)$$

Afterwards (step 4) the read points were ranked according to the models and criteria presented in sections 3.2 and 3.3 respectively. Depending on the degree of transparency the most critical ones were then selected for order progress monitoring. Following this, *CT* for 5000 orders were simulated and deviations recorded. The procedure (steps 5 and 6) was repeated ten times (s in Figure 4) to be able to identify the model that, on average, performed best for the specific configuration of assigned interval lengths, variability values and system variables. After these simulations a new configuration with random interval lengths (step 2) was generated and the aforementioned procedure repeated.

4.2 Model evaluation

The evaluation was based on the hit and miss rates, i.e. the effectiveness of a model in selecting a set of points that are superior in identifying critical deviations while minimizing false alarms. They are calculated as follows (Figure 5): At the chosen monitoring point (r_m), a critical deviation of the order can be identified (y_1) or not (n_1). Then the same order can exhibit a critical (y_2) or uncritical deviation (n_2) at the end of the process (r_M).

		Critical at point r_M	
		y_2	n_2
Critical at point r_m	y_1	$y_1 y_2$	$y_1 n_2$
	n_1	$n_1 y_2$	$n_1 n_2$

Figure 5: Classification of order cycle times

The hit rate (*HR*) is then defined as the ratio of orders that were correctly identified as exhibiting a critical deviation divided by the total amount of orders that showed a critical deviation at the end of the process (i.e. r_M). The larger the *HR* for a model the more effective was the selection. Using the notation of Figure 5, it is defined as follows:

$$e_1 = \frac{y_1 y_2}{y_1 y_2 + n_1 y_2} \qquad (5)$$

The miss rate (*MR*) is defined as the ratio of orders that were wrongly identified as critical at r_m divided by the total amount of orders that arrived on time at r_M, i.e. within the given *CT* window (Equation 4). In short, these orders were considered critical at the respective monitoring point but compensated for their deviation over the remainder of the process. A large *MR* shows that a given selection of read points produced more false alarms. Using the notation of Figure 5 again, it is defined as follows:

$$e_2 = \frac{y_1 n_2}{y_1 n_2 + n_1 n_2} \qquad (6)$$

5 CONCEPT ILLUSTRATION AND EVALUATION

This section first discusses detailed results for one interval configuration before presenting the general evaluation of the models across several configurations.

Figure 6 shows the criticality values across one set of read points. Since these are normalized scores they can be used to rank the points and to identify a subset of the most important ones. Those can be used for monitoring purposes in the simulation. It is apparent that the different models result in different subsets and thus, it can be expected that the resulting accuracy in identifying critical deviations will vary. The coming paragraphs address the findings of the effects of transparency and system sensitivity before presenting the general effectiveness of the read point selection procedure employed in this study.

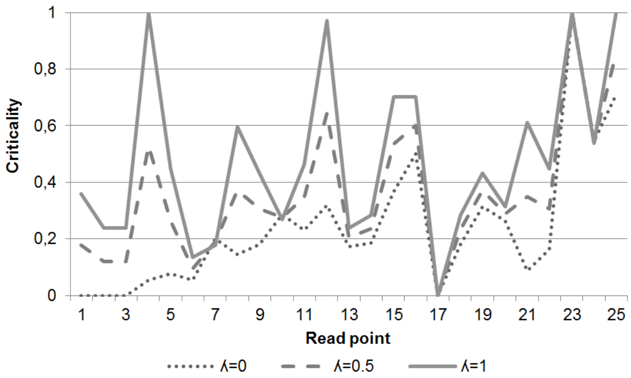

Figure 6: Criticality of read points

Figure 7 illustrates the effect of holding the *CT* threshold fixed while increasing the degree of transparency, which can be equated with increasing the possibility of early detection of critical deviations. It can be observed that more read points (RP) lead to a higher *HR* for the weighted linear models. However, while the increase from 4 to 6 read points results in gains in the *HR* and relatively minor changes in the *MR*, the opposite occurs when the degree of transparency is raised from 6 to 8 read points. In this case the increases in the *MR* are disproportional to gains in the *HR*. This indicates that enlarging the subset with points that are not very critical decreases the effectiveness of the approach as more uncritical deviations are falsely identified as important. The random read point selection shows no apparent pattern and, due to very high *MR*, exhibits the worst performance.

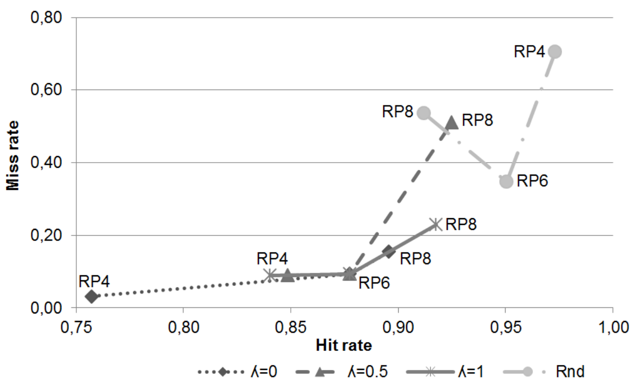

Figure 7: The effect of transparency

Similar observations can be made for changing the system sensitivity while keeping the degree of transparency fixed. Figure 8 illustrates that lower thresholds lead to increases in the *HR* as well as the *MR*. This illustrates the trade-off between the robustness and sensitivity of a monitoring system. The more sensitive a system reacts to deviations, regardless of where the monitoring points are located, the more suspected events are raised, although they really were uncritical. Again, the random selection behaves counter-intuitive and exhibits the worst performance.

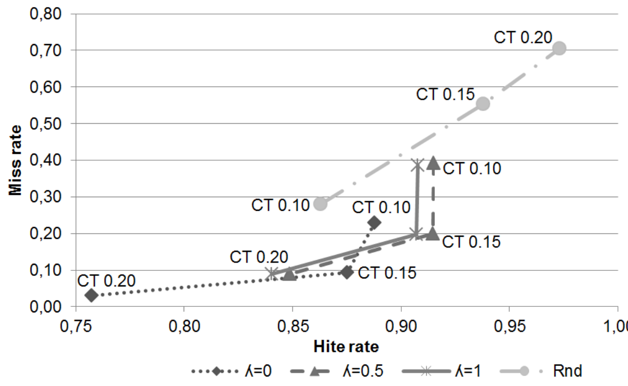

Figure 8: The effect of system sensitivity

While the effects of transparency and sensitivity are straightforward, the determination of the most effective model is somewhat more difficult. Figure 9 displays the best-performing models for a given parameter configuration. Arguably, it should be the objective to choose the system parameters in such a way that a high *HR* is combined with a low *MR*. Using this argument, the overall superior model should have the least distance to the lower right corner. Using the Pythagorean theorem it can be calculated that the parameter configuration RP6_CT20 and the R-model (=1) is on average the best-performing combination as it has the smallest distance to the lower right corner. However, this result accounts for a decision maker with the intention of identifying only the most severe deviations. A more careful decision maker would decide for the combination of RP4_CT10 (=0.5), which is the best-performing model for a low threshold. However, since only four points are monitored in this case, deviations are detected rather late in the process.

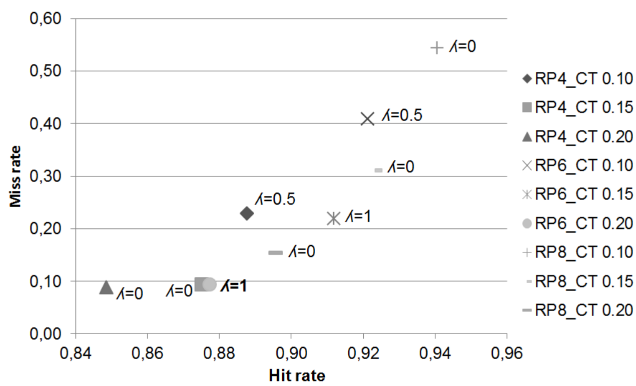

Figure 9: Parameter configurations and superior models

Table 2 compares the average performance of the best weighted linear model (WLM) against the naïve (random) selection across all parameter configurations (i.e. sensitivity and degree of transparency) for eight configurations of different interval lengths and variability values. It shows that the structured selection of read points is generally superior to the naïve selection. Using the simulation setup, the structured read point selection raised over eight configurations the hit rate on average by 2% while reducing the miss rate by 31%. Both approaches successfully identify critical deviations well. However, there are substantial differences for deviations that were wrongly identified as being critical. This is partly due to the fact that the WLM approach selects read points for monitoring that are closer to the end of the process, where there is increased certainty about the criticality of a deviation.

Table 2 : Performance comparison of the read point selection approaches (naive and weighted linear model)

#	Hit rate			Miss rate		
	Naive	*WLM*	*Δ*	*Naive*	*WLM*	*Δ*
1	96,0%	96,2%	-0,2%	60,6%	18,5%	42,1%
2	97,4%	98,1%	-0,8%	54,0%	14,7%	39,4%
3	93,5%	99,0%	-5,6%	41,4%	16,9%	24,5%
4	97,6%	98,9%	-1,3%	33,0%	12,6%	20,5%
5	91,6%	96,9%	-5,3%	47,0%	38,6%	8,4%
6	92,1%	100,0%	-7,9%	44,9%	10,9%	34,0%
7	95,1%	93,0%	2,1%	62,9%	12,1%	50,8%
8	91,9%	88,7%	3,1%	51,3%	23,1%	28,2%
Ø	**94,4%**	**96,4%**	**-2,0%**	**49,4%**	**18,4%**	**31,0%**

6 CONCLUDING REMARKS AND NEXT STEPS

Complex and efficient supply chains and production processes, especially those in the automotive industry, demand a comprehensive monitoring system for early event identification in order to be able to meet customer requirements. Therefore, the decision problem of selecting appropriate read points for monitoring purposes deserves close attention. This study examined the effect of a structured read point selection along a process as well as the effects of system transparency and sensitivity by using an intuitive simulation setup. The results indicate that a structured selection of read points achieves superior results to those selected by chance, given that meaningful criteria are employed. On average, it raised successful identifications by 2% while reducing false alarms by 31%.

Both variables, system sensitivity and the degree of transparency, had an ambiguous effect on the performance of the models. The more read points are selected (i.e. the higher the degree of transparency), the more critical deviations are identified. However, at the same time the process is monitored at increasingly earlier stages when the true consequences of deviations are less predictable. Thus, the false alarm rate also rises. Also, the performance of the monitoring system is heavily influenced by system sensitivity. The more sensitive a system reacts to deviations, the less effective is any set of selected read points and thus, any given monitoring system.

SCEM is a relatively novel research area and offers many opportunities for further scientific enquiry. First, research into criteria (others than time-related ones) that affect the presented decision problem would be of value. For instance, it would be a valuable contribution to weight financial gains from additional transparency against additional costs (e.g. more false alarms).

Furthermore, the study is confined to order deviations rather than more severe events (e.g. disruptions). Thus, the assumption of normality could be relaxed to include (skewed) distributions that better resemble real-world processes by allowing exceptional events. This could be done by modeling them in a more sophisticated simulation software and re-evaluate the approach in this setting.

The approach formulated in this contribution represents only a first step in addressing the decision problem of a more structured selection of read points within supply chains and production processes. It is a decision making tool to help planers decide in advance where transparency within a process would be most sensible. Thus, it should be beneficial to integrate an approach similar to the one presented in this study in existing engineering tools.

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