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Inspection Coming Due! How to Determine the Service Interval of Your Processes!

by

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Inspection Coming Due! How to Determine the Service Interval of Your Processes!

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Abstract. Just like cars, processes require a general inspection from time to time. As, in reality, process portfolio managers are in charge of many processes, they do not have enough resources to deeply inspect all processes simultaneously. Nor would this be reasonable from a process performance point of view. Process portfolio managers therefore require guidance on how to determine the service interval of their processes, i.e., when they should analyze which process in depth to find out whether to initiate redesign projects. Despite the profound knowledge on process improvement, monitoring, and controlling, existing approaches are only able to rank processes or redesign projects. They do not indicate when to conduct an in-depth analysis. To overcome this research gap, we propose the critical process instance method (CPIM) that analytically predicts after which number of executed instances a process should undergo an in-depth analysis. The CPIM combines ideas from process performance management, value-based business process management, and stochastic processes. It accounts for variations in process performance induced by the paths and tasks included in a process model as well as by the positive and negative deviance experienced during past executions. For demonstration purposes, we apply the CPIM to an approval process for loan applications from the banking industry including a scenario analysis.

Keywords: Business Process Management, Deviance, Process Decision-Making, Process Performance Management, Stochastic Processes

1 Introduction

Process orientation is an accepted paradigm of organizational design with a proven impact on corporate performance [21]. Business process management (BPM) therefore receives constant attention from industry and academia [13], [44]. Global surveys and literature reviews corroborate the interest in BPM in general and business process redesign in particular [27], [35]. As, during the last years, BPM has proposed many approaches to the design, analysis, improvement, and enactment of processes [17], [39], the BPM's focus is shifting towards managerial topics [43]. In this paper, we investigate a novel managerial research question, i.e., how to determine when processes should undergo an in-depth analysis to check whether they require redesign.

This research question bears resemblance to the car industry, as processes, just like cars, require a general inspection from time to time [18]. Whereas car inspections focus on technical issues, an in-depth process analysis needs an economic perspective as well. Process portfolio managers require guidance on how to determine the service interval of their processes, leveraging performance data like a car's mileage from process aware information systems [37], [47]. As process portfolio managers do not have enough resources to analyze all processes simultaneously and as processes should not undergo an in-depth analysis too often, providing such guidance is a worthwhile endeavor [7].

From a literature perspective, the BPM body of knowledge abounds in approaches to process redesign, monitoring, and controlling [35]. Approaches to process monitoring and controlling primarily focus on technically enabling the assessment of the state of a process, e.g., using complex event processing or modelling of control objectives [19], [22], [34]. Most redesign approaches take a single-process perspective, e.g., they propose redesign projects for single processes based on an identified need for redesign [41], [46]. The need for redesign is typically quantified via performance indicators [13], [24]. Very few approaches investigate how to select or schedule redesign projects for multiple processes [10], [23]. Bandara et al. [1] discuss approaches to process prioritization, classifying them as "either of very high level and hence not of much assistance […] or […] so detailed that it can take a significant effort to simply identify the critical processes." Some approaches to process prioritization help rank processes or redesign projects [10], [28], [30]. No approach, however, helps determine when processes should undergo the next in-depth analysis to check whether they require redesign.

To address the research gap, we propose the critical process instance method (CPIM) that analytically predicts after which number of executed instances a process should undergo the next in-depth analysis. An in-depth process analysis is a thorough and resource-intense means of identifying variations in process performance and respective root causes (e.g., including simulation and diagnosis, verification, and process mining) [13], [41]. The CPIM builds on knowledge from process performance management and value-based BPM using process cash flows as performance indicators [6], [25]. To predict the risky performance of future process instances in terms of their cash flows, the CPIM draws from stochastic processes, a tool commonly used in financial mathematics [8]. The CPIM is data- and model-driven as it accounts for two types of performance variation, i.e., variation induced by the paths and tasks included in process models and variation induced by positive or negative deviance experienced during past executions. That is, the CPIM uses historical performance data not only to analyze how a process currently performs, but also to forecast future performance. Our contribution is a new method that extends prior work on process performance management and value-based BPM via predictive components based on stochastic processes.

The paper is organized as follows: In section 2, we outline the background with respect to process monitoring and controlling, process performance management, value-based BPM, and stochastic processes. In section 3, we introduce the CPIM and illustrate how it fits into the BPM lifecycle by a general monitoring and controlling cycle. In section 4, we report the results of applying the CPIM to an approval process for loan applications from the banking industry including a scenario analysis. In section 5, we critically discuss results and limitations. We conclude by pointing to future research.

2 Theoretical Background

2.1 Business Process Monitoring and Controlling

From a lifecycle perspective, BPM involves the identification, discovery, analysis, redesign, and implementation plus the monitoring and controlling of processes [13]. Continuous monitoring and controlling as well as adequate redesign are necessary to prevent process performance from degenerating over time. Reasons are the organic nature of processes and the evolving environment [13]. While people are bound in day-to-day operations, processes become more complex and lose performance. Multiple actors and resources influence one another, while being influenced themselves by the technological and organizational environment [3]. The unexpected behavior of employees as well as other kinds of unexpected change let emerge process instances that deviate from the process model [40]. Deviance becomes manifest in better or worse performance compared to the "normal" performance in case of positive or negative deviance. Deviance can be analyzed manually or automated, e.g., using sequence mining [29]. In sum, the organic evolution of processes over time allows for interpreting processes as a specific subset of organizational routines at drift [3].

The key part of process monitoring and controlling is to determine how well is the process performs with respect to defined performance indicators and targets as well as to identify bottlenecks, waste, and deviance [13], [33]. The monitoring and controlling phase can be considered from an operational and a strategic perspective [25]. Operationally, process managers and process-aware information systems continuously observe process performance regarding the target values and undertake corrective actions if necessary without changing the process model [22]. The operational perspective can be linked with each single process instance. The strategic perspective strives for novel process models through redesign, when the target can no longer be reached or critical performance thresholds are violated. In this case, processes must undergo an in-depth analysis whose results serve as input for a subsequent redesign.

2.2 Process Performance Management and Value-Based BPM

To assess the performance of a process, organizations use performance indicators together with desired target values (benchmarks) and admissible value ranges [25]. Process performance indicators can be grouped via the Devil's Quadrangle, a framework comprising a time, cost, quality, and flexibility dimension [32]. The Devil's Quadrangle is so-named because improving one dimension weakens at least one other, disclosing the trade-offs to be resolved during redesign. To resolve the partly conflicting nature of these performance dimensions via integrated performance indicators, the principles of value-based management have been applied to process performance management [6].

Value-based management is a paradigm where all corporate activities and decisions are valued according to their contribution to the company value [15]. A process-related performance indicator that complies with value-based management is the risk-adjusted expected net present value of the process cash flows [6]. This indicator can be decomposed into risky cash flows per process instance [5]. A process model consists of tasks and gateways that define the paths along which a model can be traversed. Each instance follows a distinct path. The instance cash flows result from the tasks included in the paths (e.g., outflows for wages) as well as independently from the paths (e.g., inflows for selling a product). The instance cash flows are risky, i.e., they are beset with variation, as it is unclear ex-ante which path an instance takes and because the cash flows of the tasks show variation themselves (e.g., consulting a customer takes different amounts of time, which causes different outflows) [5]. Task cash flows are risky as they depend on characteristics such as wages, material prices, time, or quality [13], [42]. In line with value-based management, instance cash flows are characterized in terms of their expected value and variance, capturing all path and task information [6]. Bolsinger [5] proposed a method for determining both figures for arbitrary process models. Using the expected value and the variance of instance cash flows is reasonable as, according to the central limit theorem, cumulated instance cash flows are approximately normally distributed for sufficiently many instances and independent from how the cash flows of single instances are distributed [5]. This property holds for the net present value of the process cash flows and the aggregated difference from a performance benchmark, which allows for providing analytical decision support. In sum, instance cash flows are a reasonable value-based performance indicator for monitoring and controlling purposes, whereas more complex value-based performance indicators such as the risk-adjusted expected net present value fit the preparation of investments in process redesign.

2.3 Predicting Process Performance Using Stochastic Processes

The performance data collected during process monitoring and controlling form an essential input for forecasting the performance of future process instances. While redesign projects can be initiated based on the insights from the last in-depth analysis, predicting when a process should undergo the next in-depth analysis requires information about future process executions, i.e., about the risky development of process performance. As this problem is similar to the assessment of risky price movements, we adopt the concept of stochastic processes from mathematical finance.

Stochastic processes are typically used to model the behavior of physical or mathematical systems [36]. This behavior is characterized by transitions among a finite or infinite number of states over time. At a distinct point in time, a system is in a distinct state. As transitions among states occur either at discrete points in time or continuously, there is a distinction between discrete and continuous stochastic processes. Mathematically speaking, a stochastic process is a family of random variables $\{X_t\}_{t\in T}$ denoting the transition probabilities for different states at time t. Stochastic processes are further classified according to the properties of the transition probabilities and the evolution of states. If transition probabilities do not change over time, the stochastic process is homogenous. If the evolution of a stochastic process is invariant to shifts in time, the process is stationary, i.e., it has a stationary distribution for being in certain recurrent states at time t, if $t \to \infty$ [36]. Otherwise, the stochastic process is non-stationary.

Mathematical finance is a typical application domain of stochastic processes. As financial products can be traded at virtually each point in time such that the value of these products changes continuously, continuous stochastic processes are used to enable riskneutral assessments of options or other derivatives based on interest rates [4], [9]. Stochastic processes also enable trading strategies based on volatility forecasts or risk management according to the value-at-risk approach [12], [26]. Even portfolio investment strategies are based on stochastic processes [14].

Since the development of process performance is driven by process instances, continuous stochastic processes do not fit the BPM context. Rather, discrete stochastic processes are appropriate, such as shown in the field of stochastic process control, a fundamental concept of six sigma [2]. As all instances of a process follow the same process model, the transition probabilities do not change over time. The stochastic process is homogenous. The number of states depends on the used performance indicator. It is finite for qualitative, ordinally scaled performance indicators (e.g., a customer satisfaction index). In case of quantitative, metrically scaled indicators, such as the risky instance cash flows, the number of states is infinite. Considering stationarity, both cases are possible as shown in stochastic process control [45]. A stochastic process that models aggregated performance (e.g., aggregated difference from a performance benchmark) does not have a stationary distribution as the value range of the aggregated performance increases with an increasing number of executed process instances.

3 The Critical Process Instance Method

3.1 General Setting

The CPIM predicts after which critical number of executed process instances (CPI) a process should undergo the next in-depth analysis. As it is neither possible nor reasonable to work on all processes simultaneously, the CPIM uses an individual process as unit of analysis. The central input of the CPIM is the related process model annotated with cash flows [41]. If available, the CPIM also considers historical process data (e.g., from event logs) to achieve better predictions by catering for deviant behavior. Depending on the available performance data, the risky instance cash flows $\widetilde{CF}$ can be determined based on real values from past executions or be estimated based on process simulation or experts [13], [39], [42]. As discussed in section 2.2, the expected value and the variance of the instance cash flows can be calculated based on Bolsinger [5]. We make the following assumptions:

(A.1) The processes included in the organization's process portfolio can be analyzed independently. Sufficient performance data is available or can be estimated for the process in focus. The CPIM does not consider external events that may trigger an extraordinary, potentially earlier in-depth analysis (e.g., price changes, new competitors).

(A.2) The expected values and variances of the cash flows associated with process tasks are finite and known (or can be estimated). The cash flows of single process instances are independent, i.e., the expected value $E[\widetilde{CF}]$ and variance $Var[\widetilde{CF}]$ of the instance cash flows can be calculated based on Bolsinger [5].

Besides the performance indicator $\widetilde{CF}$, the organization must provide a process-specific performance benchmark β [25]. This benchmark could be any target value set by the management or just the expected value of the instance cash flows.

3.2 The Role of Variation and Deviance

Comparing the cash flows of a specific instance with the performance benchmark provides no information about future process instances. It only shows the difference between that instance and the benchmark, not a trend in process performance. To determine the CPI, the organization must be able to predict process performance. Thus, it should account for two types of performance variation, i.e., variation induced by the tasks and paths included in the process model and variation induced by positive or negative deviance from the process model experienced in the past.

Although handling process instances in a compliant way, the first type of variation results from the process model itself depending on the process paths as discussed in section 2.2. Thus, the planned model-induced cash flows of a process instance $\widetilde{CF}_{\text{Model}}$, i.e., the cash flows that result from executing the process according to its current model, are a random variable whose distribution depends on the control flow of the process model as well as on the risky cash flows that relate to tasks. The expected value and the variance of the model-induced cash flows are shown in Formula (1) and (2).

$$\mu_{\text{Model}} = \mathrm{E}\left[\widetilde{CF}_{\text{Model}}\right] \quad (1) \qquad \sigma_{\text{Model}}{}^2 = \mathrm{Var}\left[\widetilde{CF}_{\text{Model}}\right] \quad (2)$$

The second type of variation results from positive or negative deviance experienced during past executions, i.e., behavior not covered by the process model as used in the past. In fact, process users sometimes run a process in a way not intended by the process owner [3]. As, for instance, more or fewer tasks are executed and new process paths emerge, this type of variation results in deviance-induced cash flows $\widetilde{CF}_{\text{Dev}}$. Deviance-induced cash flows take positive or negative values in case of positive or negative deviance, respectively. We consider deviant executions that largely comply with the process model. Deviance can, for example, be identified by analyzing event data from past executions using sequence mining [29]. To use the deviance experienced during past executions as a predictor for future deviance, we make the following assumption:

(A.3) The historic model-induced cash flows $\widetilde{CF}_{\text{Model,hist}}$ and the actual cash flows recorded from past executions $\widetilde{CF}_{\text{Log,hist}}$ feature a strong positive correlation $0 \ll \rho < 1$. Although the process model may have changed over time (e.g., due to the implementation of redesign projects), the process model used in the past only slightly differs from the process model to be used as foundation of future executions. Further, the current process users are about the same as in the past.

Assumption (A.3) implies that the cash flows recorded from past executions result from many instances with compliant and very few instances with deviant behavior. Assuming a strong positive correlation is a reasonable compromise between assuming independence, which would heavily overestimate the variance of the deviance-induced cash flows, and assuming a perfect correlation, which would underestimate the variance of the deviance-induced cash flows. If the recorded cash flows were indeed independent of the historic model-induced cash flows, all process instances would have shown deviant behavior. Perfect correlation would imply that all instances had perfectly complied with the process model. Both options seem unrealistic. We investigate the sensitivity of the CPIM with respect to this parameter in the demonstration section.

On this foundation, the deviance-induced cash flows can be calculated as difference between the cash flows actually recorded for past process executions and the historic model-induced cash flows that should have been recorded based on the process model used in the past [36]:

$$\mu_{\text{Dev}} = \mu_{\text{Log,hist}} - \mu_{\text{Model,hist}} \tag{3}$$

$$\sigma_{\text{Dev}}^{2} = \sigma_{\text{Log,hist}}^{2} + \sigma_{\text{Model,hist}}^{2} - 2 \cdot \rho \cdot \sigma_{\text{Log,hist}} \cdot \sigma_{\text{Model,hist}} \tag{4}$$

As it is not possible to determine the exact correlation ρ mathematically, it must be set outside the CPIM. If an organization cannot access recorded data from event logs at all, only the first type of variation can be used for predicting the development of process performance. The prediction results then are less precise compared to the case where the deviance-induced variation is included as well. Based on this information, we can formulate the risky cash flows of a single instance via a compound random variable:

$$\widetilde{CF} = \widetilde{CF}_{\text{Model}} + \widetilde{CF}_{\text{Dev}} \tag{5}$$

Thus, the performance of a single instance can be predicted based on past and planned cash flows. As the organization is interested in determining the CPI, it must be able to identify trends in process performance. Therefore, the organization needs aggregated information about future process instances. We therefore calculate the aggregated difference $\delta(n)$ from the process benchmark β, shown in Formula (6), as a discrete stochastic process where n refers to the number of executed instances. Remember that the cash flows of instances from the same process are identically distributed as they share the same process model. Thus, the aggregated difference is a sum of independent and identically distributed (iid) random variables and can be treated as a normally distributed random variable for sufficiently many process instances according to the central limit theorem [36]. In addition, the property of identically distributed cash flows results in homogenous transitions. In contrast to many homogenous stochastic processes, the distribution of $\delta(n)$ will be non-stationary as the value range of the aggregated performance increases with the number of executed instances.

$$\delta(n) = \sum\nolimits_{1}^{n} \left(\widetilde{CF} - \beta\right) \tag{6}$$

Hence, the aggregated difference serves as central indicator for determining the CPI.

3.3 Determining the Critical Process Instance

As the instance cash flows follow Formula (5), the value range of the aggregated difference from the process benchmark is cone-shaped, as illustrated in Figure 1 [11]. The cone represents the upper limit $UL(n)$ and the lower limit $LL(n)$ of the aggregated difference's value range after a distinct amount of executed instances n and at a distinct probability. As the aggregated difference is a sum of random variables, the upper and the lower limit increase and decrease with an increasing number of executed instances. That is, the cone is small in the near future after and broadens in the farer future expressed in terms of executed instances.

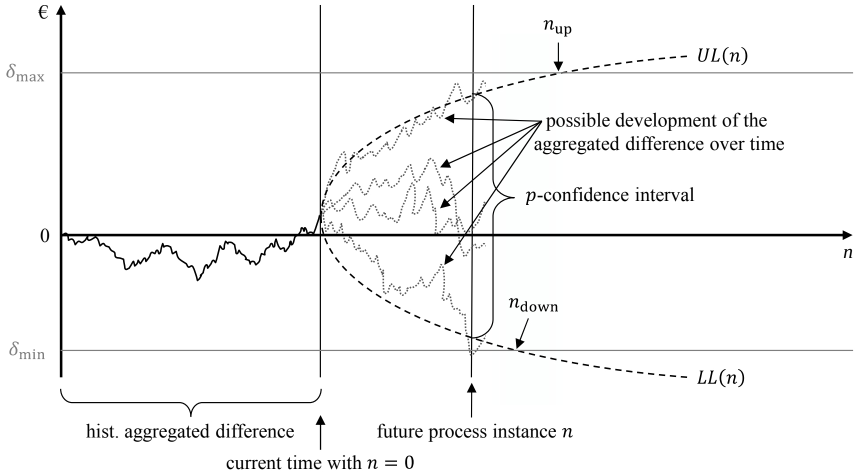


Fig. 1. Determination of the process instances n_{down} and n_{up}

As the aggregated difference from the performance benchmark is risky, it may take any value. Therefore, we use a confidence interval in which the true value of the aggregated difference lies with the probability $p \in]0; 1[$, also known as the confidence level. Consequently, the value of the aggregated difference is outside the confidence interval with a probability of $(1 - p)$. The confidence level must be set by the management. A confidence level p of 95% is typically used in statistics [11]. Transferred to the CPIM, the factual aggregated difference from the performance benchmark then lies outside the upper and lower limits with a probability of 2.5%, respectively. The larger the confidence level, the broader the confidence interval.

The upper limit $UL(n)$ and the lower limit $LL(n)$ of the confidence interval are calculated as shown in Formula (8) and (9) [11]. Based on assumption (A.3), the variables $\widetilde{CF}_{\mathrm{Model}}$ and $\widetilde{CF}_{\mathrm{Dev}}$ feature the correlation ρ as well because the current process model is very similar to the historical process model. Further, the function $\phi^{-1}(p)$ is the inverse function of the normal distribution for the chosen confidence level. We use this function as the aggregated difference, as specified in Formula (5) follows a normal distribution. Formula (7) represents the diffusion of the stochastic process ξ.

$$\xi = {\sigma_{\mathrm{Model}}}^2 + {\sigma_{\mathrm{Dev}}}^2 + 2 \cdot \rho \cdot \sigma_{\mathrm{Model}} \cdot \sigma_{\mathrm{Dev}} \tag{7}$$

$$UL(n) = n \cdot (\mu_{\mathrm{Dev}} + \mu_{\mathrm{Model}} - \beta) + \phi^{-1}(p) \cdot \sqrt{\xi \cdot n} \tag{8}$$

$$LL(n) = n \cdot (\mu_{\mathrm{Dev}} + \mu_{\mathrm{Model}} - \beta) - \phi^{-1}(p) \cdot \sqrt{\xi \cdot n} \tag{9}$$

Besides the performance benchmark, we need thresholds concerning the aggregated difference from the performance benchmark to determine the CPI. The process in focus should undergo an in-depth analysis if the aggregated difference violates one of the thresholds at the given confidence level to check whether the aggregated difference factually violates a threshold. According to [20], [31], and [3], the organization must balance two conflicting goals: Staying competitive by conducting redesign projects earlier vs. avoiding resistance by conducting redesign projects later. Thus, the organization must define two thresholds for the aggregated difference, one upper $\delta_{\max}$ and one lower $\delta_{\min}$ threshold. The upper threshold represents the value at which the organization has gathered enough information about positive deviance that could be used to realize first mover advantages or to reflect on a reallocation of resources currently assigned to the process. The lower threshold represents the value at which a negative development of process performance endangers the profitability or competitiveness of the process.

Based on the thresholds and the information about the future development of the aggregated difference, we can determine the CPI after which the aggregated difference falls short of or exceeds the thresholds at the given confidence level. We calculate the number of instances for which the upper and the lower limit of the confidence interval intersect the upper and lower threshold following Formula (10) and (11).

$$n_{\text{down}} = \left\lfloor \min\left\{\left(\frac{+\phi^{-1}(p)\cdot\sqrt{\xi} \pm \sqrt{\phi^{-1}(p)^2\cdot\xi - 4\cdot(\mu_{\text{Dev}}+\mu_{\text{Model}}-\beta)\cdot(-\delta_{\min})}}{2\cdot(\mu_{\text{Dev}}+\mu_{\text{Model}}-\beta)}\right)^2\right\}\right\rfloor \tag{10}$$

$$n_{\text{up}} = \left\lfloor \min\left\{\left(\frac{-\phi^{-1}(p)\cdot\sqrt{\xi} \pm \sqrt{\phi^{-1}(p)^2\cdot\xi - 4\cdot(\mu_{\text{Dev}}+\mu_{\text{Model}}-\beta)\cdot(-\delta_{\max})}}{2\cdot(\mu_{\text{Dev}}+\mu_{\text{Model}}-\beta)}\right)^2\right\}\right\rfloor \tag{11}$$

If the benchmark equals the expected performance of the process, i.e., $\beta = \mu_{\text{Dev}} + \mu_{\text{Model}}$, Formulas (10) and (11) can be simplified as follows:

$$n_{\text{down}} = \left\lfloor\left(\frac{\delta_{\min}}{\phi^{-1}(p)\cdot\sqrt{\xi}}\right)^2\right\rfloor \tag{12}$$

$$n_{\text{up}} = \left\lfloor\left(\frac{\delta_{\max}}{-\phi^{-1}(p)\cdot\sqrt{\xi}}\right)^2\right\rfloor \tag{13}$$

The CPI then equals the smaller number of instances:

$$n^* = \min\{n_{\text{down}}; n_{\text{up}}\} \tag{14}$$

3.4 Integration into the BPM Lifecycle

As mentioned, the BPM lifecycle covers the phases identification, discovery, analysis, redesign, implementation as well as monitoring and controlling. A vital part of monitoring and controlling is "to determine how well is the process performing with respect to its performance measures and performance objectives" [13]. Since the CPIM identifies the critical number of instances, it belongs to the monitoring and controlling phase. We therefore investigate how the CPIM can be integrated into this phase.

First, the CPIM determines the next CPI of a specific process. Therefore, our proposed monitoring and controlling cycle follows an iterative approach, as shown in Figure 2: In the beginning, the expected value and the variance are calculated based on the current process model. If available, the performance data gathered in a preceding in-depth analysis can serve as input. For instance, performance data can be extracted from event logs [38]. These performance data fit past process executions, if the process model has not changed. Otherwise, the performance data from past executions must be collected separately. After that, the process benchmark and the thresholds must be set. Then, the CPI is calculated based on past and planned cash flows, following three steps: First, the past deviance and, second, the intersections between the thresholds and the confidence interval are determined. Third, the CPI is selected. Now, the process is executed until the CPI is reached, before an in-depth analysis is conducted to assess whether the process required redesign. If the in-depth analysis concludes that the process performance is uncritical, the CPIM is applied again. The organization may also adapt the thresholds or the benchmark in response to changes in the corporate environment. Otherwise, a redesign project should be started. No forecast is needed until the redesign is finished.

In cases of IT-supported process performance management or business activity monitoring, the CPIM can be applied continuously, i.e., after each finished process instance. As the performance forecast also grounds on data from past executions, each instance provides knowledge about process performance and deviance. As the deviance-induced cash flows affect the intersection between the thresholds and the confidence interval, they can be used to continuously adjust the scheduling of the next in-depth analysis.

Finally, the CPIM can be used as a tool for process portfolio management, taking a multi-process perspective. When applying the CPIM to multiple processes, the process portfolio manager receives information about the CPI for each process. Hence, the process portfolio manager is not only able to prioritize processes such as already supported by existing approaches, but also to schedule several in-depth analyses, taking into account possible resource restrictions.

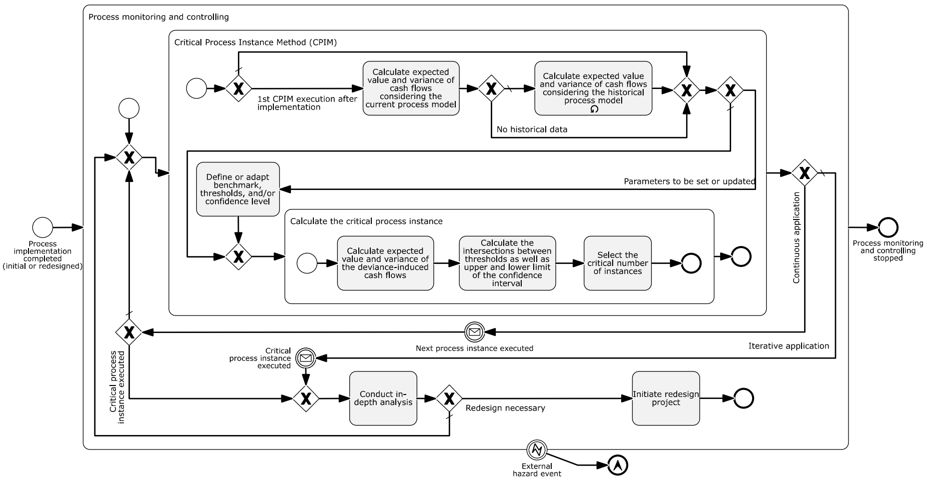


Fig. 2. Monitoring and Controlling Cycle

4 Demonstration Example

For demonstration purposes, we apply the CPIM to an exemplary approval process for loan applications from the banking industry. We first present the process models that contain the information needed for the calculation, including the properties of the deviance-induced cash flows. We then determine and analyze the CPI using a scenario analysis to discuss the sensitivity of the CPIM.

The approval process for loan applications is an internal back-office process. The planned – historical and future – process model, shown in Figure 3, starts with a request of the bank agency. First, an employee of the loan approval department gathers the necessary customer data. Before the internal assessment, an external rating agency assesses the customer's creditworthiness. If the customer is creditworthy, the application comes to a decision based on the four-eyes-principle. Two independent and positive assessments are required for specifying the contract conditions and accepting the loan application. Otherwise, creditworthiness is denied and the application is declined. As it is for internal use only, we consider a transfer price as cash inflow in addition to cash outflows induced by task processing when calculating the process cash flows.

As it is part of the CPIM, we also include information about the process model and the associated deviant behavior extracted from log data (differing parts are presented in gray and where appropriate with dashed lines in Figure 3). The main difference is that internal creditworthiness assessors consolidate their information before the final judgment and may ask for further customer information one time. Furthermore, the factual task cash flows as well as the particular path probabilities differ from the planned ones.

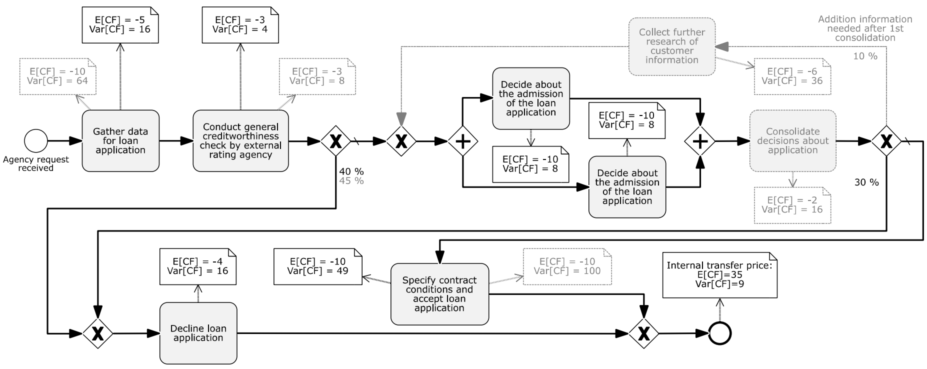
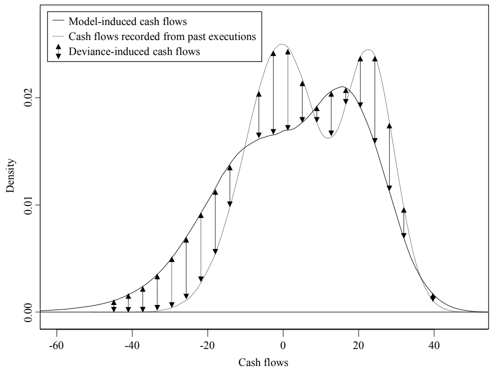


Fig. 3. Process model based on design and log data (deviant tasks and properties in gray)

We analytically calculate the expected values and variances of both process models. As this is a fictitious example, we estimate the distribution properties of the past executions. To visualize the deviance-induced cash flows, we determined the density functions of the process instance cash flows for both process models using simulation. The results in Figure 4 show that simple distributions such as the normal distribution typically do not fit the instance cash flows. It can also be seen that the planned process model overestimated the expected value and underestimated the variation of the instance cash flows. Based on these insights, the model-induced as well as the deviance-induced variation can be calculated and included in the CPIM.



	μ	σ
Model	8.48	213.55
Log	2.83	298.60
Dev	-5.65	512.15 – 505.04·ρ

Fig. 4. Density functions of the process instance cash flows

Besides the parameters gathered from process models or logs, the management must set the critical thresholds, the performance benchmark, and the confidence level. It must also determine the correlation between the model-induced cash flows and the cash flows recorded from past executions (e.g., approximating by the fraction of instances adhering to the historical process model or the quotient $\sigma_{\text{Model}}/\sigma_{\text{Log}}$ as it explains the variance of the cash flows recorded from past executions that cannot be explained by the process model). Since estimation errors can occur in real-world applications (e.g., when reconstructing an event log), we consider different scenarios to evaluate the sensitivity of the CPIM. Table 1 summarizes the results.

Table 1. Results of the scenario analysis

No.	ρ	p	β	$\delta_{\min}$	$\delta_{\max}$	n_{down}	n_{up}	n^*
1	0.70	0.80	8.48	-1,000	1,000	133	n.d.	133
2	0.70	0.80	5.65	-1,000	1,000	238	n.d.	238
3	0.70	0.90	5.65	-1,000	1,000	194	n.d.	194
4	0.70	0.90	2.83	-1,000	1,000	966	1,249	966
5	0.70	0.90	2.83	-500	250	241	78	78
6	0.80	0.90	2.83	-500	250	269	74	74
7	0.80	0.90	1.41	-500	250	n.d.	42	42
8	0.80	0.99	1.41	-500	250	n.d.	18	18
9	0.80	0.99	1.41	-500	1,000	n.d.	191	191

The results can be interpreted as follows (with corresponding scenarios in brackets):

1. The variation of the benchmark confirms that a benchmark close to the actual performance increases the CPI and postpones the next in-depth analysis (3 & 4). Larger differences between the benchmark and the performance lead to unilateral solutions, i.e., one threshold will never be reached (1 & 7). As there is no solution for the calculation of the second intersection, one CPI is not defined ("n.d."). In this case, the process heavily under- or over-performs.
2. The results show that the thresholds have a higher impact on the CPI, if the actual process performance is close to the benchmark, i.e., the process executions meet the

process target (4 & 5 and 8 & 9). As the cone of the confidence interval is a concave curve, this is not a counterintuitive observation, but must be remembered by process managers when defining the thresholds.

3. Just like the thresholds, the breadth of the confidence interval expressed by the confidence level influences the CPI (2 & 3 and 7 & 8). An increased confidence level heavily reduces the CPI. A higher confidence level increases the probability that the predicted process performance matches with the real future one.
4. Finally, the demonstration example contains statements about the influence of the correlation between the model-induced cash flows and the cash flows recorded during past executions (5 & 6). A higher correlation implies a lower variance of the deviance-induced cash flows and, therefore, a more distant CPI. It can be seen that the CPI is less sensitive to the correlation compared to other parameters such as the confidence level. The effect of a differing correlation on the CPIM is very limited.

The scenario analysis provides insights into the sensitivity of the CPIM against estimation errors. The assumption of a strong positive correlation between the model-induced cash flows and the cash flows recorded from past executions has a small effect on the CPI. The thresholds and the confidence level affect the CPI much more strongly. Determining these parameters thus requires special care. The process-specific performance benchmark has the greatest effect on the CPI. Therefore, process targets should be very clear and set very mindfully – not just because of the application of the CPIM.

5 Discussion

As the CPIM is beset with limitations, we compile noteworthy discussion points that, e.g., arise from the CPIM's assumptions. The most important point relates to the assumed independence of process instances (A.2). This simplification has weaknesses compared to techniques from time series analysis (e.g., autocorrelation, asymmetric effects), particularly when using deviance-induced cash flows. Deviance-induced cash flows, however, are only an optional input of the CPIM. As event logs are not available for all processes, the CPIM is content with model-induced cash flows that can be estimated by process experts. Thus, the CPIM also applies to processes where no historical data is available, which is not the case for techniques from time series analysis. Moreover, assumption (A.2) enabled building on Bolsinger's results [5]. It cannot be easily assessed how (A.2) influences the results of the CPIM. Thus, a thorough comparison between the CPIM and time series analysis should be conducted in future research.

Further, the CPIM focuses on single processes and abstracts from interactions among processes. In reality, however, we find portfolios of interacting processes. Hence, the CPIM should be extended such that the critical number of instances accounts for interactions among processes. Moreover, the CPIM only incorporates performance data that results from deviance experienced during past executions as well as performance data that can be expected to occur based on the current process model. The CPIM neglects external events that may cause an extraordinary, potentially earlier in-depth analysis. To overcome this drawback, the CPIM may be coupled with complex event processing systems, which already account for external events.

As for the evaluation, the CPIM was applied to only a small example. The sensitivity analysis aimed at testing the CPIM with respect to varying input parameters. Therefore, the results must be critically examined when applying the CPIM in reality. Furthermore, organizations use different process variants in different contexts. According to a higher amount of routing constructs, the variance of the instance cash flows increases and influences the CPI substantially. Conducting in-depth analyses would be impossible. In such cases, it might help split the process model into smaller groups of similar paths regarding a limited set of executed instances.

6 Conclusion

We investigated when a process should undergo an in-depth analysis to check whether it requires redesign. As a first answer, we proposed the critical process instance method (CPIM) that analytically predicts the critical number of executed instances after which a process should undergo the next in-depth analysis. We also sketched how to integrate the CPIM in the process monitoring and controlling phase of the BPM lifecycle, depending on whether a process runs in an automated execution environment. Finally, we demonstrated the CPIM using a sample process from the banking industry.

Future research should address the limitations discussed in section 5 and conduct real-world case studies. Our long-term vision is to extend the CPIM accordingly and to implement it in an automated process execution environment such that it can be applied continuously and simultaneously to multiple interdepending processes to provide process portfolio managers with adequate support for process decision-making.

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