

# Optimization of Service Delivery through Continual Process Improvement: A Case Study

Kerstin Gerke<sup>1</sup>, Konstantin Petruch<sup>2</sup>, Gerrit Tamm<sup>3</sup>

<sup>1</sup>Institute of Information Systems  
Humboldt University Berlin  
Spandauer Strasse 1  
10178 Berlin, Germany  
mail@kerstin-gerke.de

<sup>2</sup>Deutsche Telekom AG  
T-Online-Allee 1  
64295 Darmstadt, Germany  
k.petruch@telekom.de

<sup>3</sup>SRH Hochschule Berlin  
Ernst-Reuter-Platz 10  
10587 Berlin, Germany  
gerrit.tamm@srh-hochschule-berlin.de

**Abstract:** In order to deliver services of high quality in a cost-effective manner, processes and their support through information technology (IT) play an increasingly significant role. We present an approach, which allows optimizing the service delivery through continual process improvement. This approach combines the 7-step improvement process recommended by ITIL with process mining. On the basis of suggestions derived from process mining, performance indicators of different services are determined and subsequently compared as part of an internal benchmark. The approach, which will be trialed in practice, enables the optimization of service delivery certainly, but it is also concerned with the most effective utilization of limited resources in terms of people and tools.

## 1 Introduction

Today IT service providers (ISPs) face the pressure to deliver high-quality IT services in a highly competitive and fast-moving environment. Quality enhancement and cost reduction, therefore, have become mainstream thinking. As a result of the pressures, ISPs are advancing the improvement of their IT service management (ITSM) processes and making use of reference models. ITIL, for example, is among the most used frameworks of service delivery [AS+08]; it provides guidance that enables organizations to create and maintain value for customers through better design and operation of services.

After the processes have been (re-)designed according to the reference model it is necessary to continuously check process execution. In order to identify possible quality problems, organizations commonly measure the efficiency and effectiveness of their ITSM processes with key indicators. Target value verification allows analyzing whether the reaching of a process goal might be jeopardized.

Building up such a measurement system involves a purposive definition of indicators. The definition, however, seems to be difficult for a variety of reasons. First, no organization knows the optimal set of indicators in advance and, with that, has difficulties in articulating them. Furthermore, such specification in advance results in a selective monitoring process, which appears to inevitably limit control and improvement opportunities (i.e., important relationships are left unmonitored and remain hidden). Second, as a reflection of the business strategy the metrics for process monitoring should adapt as the strategy and/or underlying goals change. Already Morgan and Schiemann (1999) [MS99] stressed that metrics, which are outdated or lack the alignment with organizational objectives, could even block the benefits.

The situation is further complicated by the fact that the degree of automation in the active handling of ITSM processes is still unsatisfying. Key sources of problems are missing or unexploited tools between the various perspectives and the various stages in the lifecycles of processes. The gap between normative modeling for compliance purposes and the actual execution of a workflow provides a pertinent example. In this context, process mining facilitates the automatic analysis of processes by deriving the process knowledge from event logs, which have been recorded during the execution of ITSM processes.

In view of the significance of ITSM processes, we have developed an approach for the purpose of continual process improvement (CPI) [GPT10]. The approach integrates process mining and the 7-step procedure recommended by ITIL into the ITSM process. In order to optimize the delivery of IT services to customers and users, two additional important topics need to be treated properly nevertheless: The first issue is the most efficient utilization of limited resources in terms of people, systems, and documents. The second issue arises from the fact that different services share the same IT process. Obviously, we need to prove if these processes hold for service-specific peculiarities.

Since process mining aims at revealing hidden process information, a further question emerges, namely whether this capability can be used to dynamically propose performance indicators, which hint at service improvement potential.

The contribution that our study makes is twofold. First, we present a case study of an incident management process of a German ISP, which enables us to verify the CPI approach with respect to the effectiveness of processes. Second, the case study enables us to theorize about the effects different services have on ITSM processes, resources, and tools. The result is a further development of the CPI approach.

In light of this background, the following section starts explaining the existing possibilities of process improvement based on ITIL and process mining. Section 3 reviews related work. Then, Sect. 4 applies the CPI approach in practice. Afterwards,

Sect. 5 describes the research implications reached from the case study. Finally, this contribution addresses central conclusions and future research directions.

## **2 Continual Process Improvement in Concept**

This section provides a broad overview of the contribution of process mining and ITIL to service improvement for the remaining sections of this paper.

### **2.1 Service Improvement according to ITIL**

ITIL was originally developed on behalf of the British government by the Central Computer and Telecommunications Agency, which is now incorporated by the Office of Government Commerce. ITIL describes an integrated best practice approach to managing and controlling IT services. The content is depicted in a series of five books, which embrace the entire lifecycle of IT services: Service Strategy, Service Design, Service Transition, Service Operation, and Continual Service Improvement. Since we will adapt the procedural model of ITIL, we will introduce the processes within the lifecycle Continual Service Improvement in detail. For reasons of space, we refrain from presenting the remaining lifecycles and refer to the respective books<sup>1</sup>.

According to the book Continual Service Improvement it is essential to compare defined measurements with expected results. The comparison reveals those elements of process, which prevent from meeting the expected objectives effectively: The verification of key goal indicators (KGIs) determines whether process goals will be reached [IG07]. Key performance indicators (KPIs) display whether process performances endanger the reaching of a process goal. The ongoing confrontation between to-be and as-is condition is executed in seven steps [TCS07]:

- (1) Define what should be measured: Root objectives and success factors are defined.
- (2) Define what can be measured: In order to keep to the measurable points, organizations need to consider limitations (e.g., resources, budgets) on what can actually be measured.
- (3) Gather the data: The data is selected, which serves as the origin from which deviations can be identified and explained.
- (4) Process the data: The processing of the data refers to those operations, which are essential for the analysis (e.g., formalizing data).
- (5) Analyze the data: Measurements are compared with expected results to reveal those elements, which prevent from meeting the expected objectives effectively.

---

<sup>1</sup> [www.itil.org](http://www.itil.org)

- (6) Present and use the information: The information is communicated to business, senior management, and IT to derive corrective actions for implementation.
- (7) Implement corrective actions: The actions necessary to improve services are implemented.

## 2.2 Process Mining

Process mining is a method which automatically infers the general process knowledge from a set of individual process instances (i.e., cases). Generally, the execution of these instances is recorded by ISs and stored in event logs. The event logs are then formalized in the Mining Extensible Markup Language (MXML) format [DA05], which is required by the process mining algorithms [RVA08, MWA06] available in the process mining framework ProM<sup>2</sup>. These algorithms use the event logs as a starting point to derive the implicitly present knowledge in the form of a process model.

Process mining has many benefits. First, it reveals information as to what, how, when, and where something was done (i.e., process discovery). The primary goal strives for understanding what is actually happening in the organization. Second, process mining can be used for compliance checking, that is, comparing the current way of working with the way it was agreed upon [RJGA09]. Thus, as-is processes may be analyzed with respect to weaknesses and improvement potential. Finally, process mining supports the analysis of process performance (e.g., bottlenecks in the way of working).

A major drawback of process mining is that it can only be transposed to case-oriented processes. A case consists of a sequence of activities between which relations of dependence exist.

## 2.3 Integration of ITIL and Process Mining

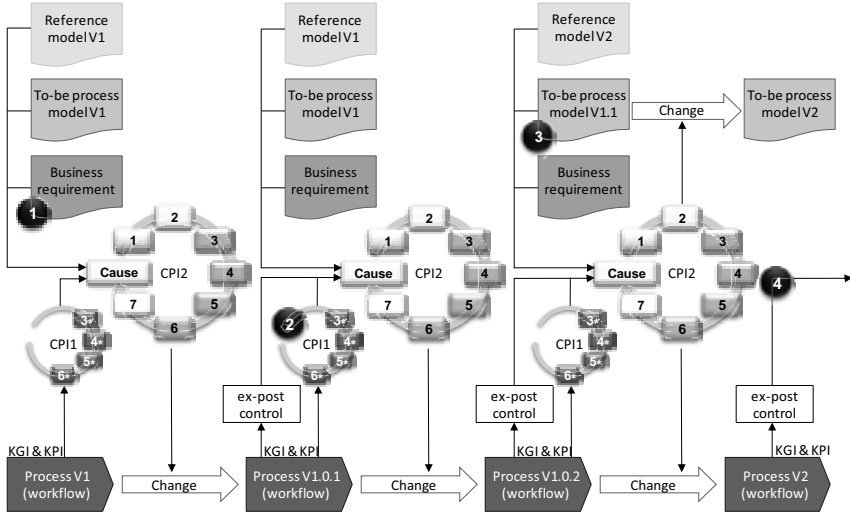
Figure 1 depicts an approach to continually improve ITSM processes as proposed by Gerke et al. [GPT10]. In the first phase, each ITSM process is continuously monitored as part of the processes execution. The role of operational monitoring is to ensure that the ITSM process functions exactly as specified. This is why the first control cycle (CPI 1) is primarily concerned with target verification and the compliance of the as-is processes with to-be processes. This control cycle inherits steps three to six of the 7-step procedure. All steps are supported by process mining techniques, which allow automatically measuring, comparing, and alerting the meeting of the to-be specifications.

Once the process identifies a likely deviation, the second phase is triggered. The second phase (CPI 2) can be continually applied in a semi-automated way. It passes through all steps of the underlying 7-step procedure. The phase is initiated by four types of changes. First, changing business requirements might entail adapting the design and the implementation of the to-be process model. Second, the changes can be initiated by the

---

<sup>2</sup> <http://www.processmining.org/>

identification of deviations between both key indicator values and their target values or between the as-is process and the to-be process model. Third, the further development of the reference model (i.e., a new version) can trigger the changes. Finally, the approach supports the ex-post control of measures taken according to the intended success.



\* Continuous process mining

Figure 1: Continual process improvement approach [GPT10]

### 3 Related Work

This section investigates views of other researchers into the discussion of process improvement. The existing sources can be grouped into three categories: analysis of event logs, process controlling, and data warehousing.

#### 3.1 Analyzing Event Logs

Our contribution can be related to the mining of processes in the business context. There is a growing body of knowledge, which reports on case studies in different application domains. They resemble in that they all describe reverse engineering with process mining from event logs. Mieke et al. [MLV08], for example, analyzed the procurement process for the purpose of internal fraud risk reduction. Rozinat et al. [RJGA09] investigated feedback loops and the idle times of a test process of scanning to identify concrete improvement suggestions. Mărușter and Beest [MB09] proposed a methodology comparing the mined model with a simulated model to predict potential performance gains for redesigning business processes.

This paper extends our previous work as presented in [GPT10]. Rather than only focusing on improving the effectiveness of processes, we broaden the approach with respect to resources and service-specific characteristics. Since only a few researchers

have investigated the question of how to integrate the continuous improvement process and process mining techniques into ITSM processes, this topic is little understood so far.

### **3.2 Process based Controlling**

Well-known controlling and performance measurement systems, such as the balanced scorecard [KN92], Six Sigma [BR06], etc. support the evaluation and the monitoring of processes in order to improve the processes. The process of building an objective indicator-based measurement system, however, requires a deep understanding about the relationship between processes, target values, maturity levels, and corporate goals. This is the reason why organizations face the challenge of determining relevant indicators. In contrast, our approach provides guidance on automatically selecting statistically significant KPIs.

### **3.3 Applying Data Warehouse Concepts**

Process improvement based on event logs can be seen in the context of business process intelligence. Few authors, such as zur Muehlen [MU01] or Casati et al. [CCDS07] discussed the design of data warehouses, which take advantage of event logs as an information source. It should be noted that due to challenges in storing and modeling the *process warehouse*, there are still open issues (e.g., the integration of business data) requiring further research. Because of the unresolved issues, the aforementioned works presented are limited to theoretical approaches or prototypical implementations.

## **4 Case Study**

In order to deepen our theoretical understanding of continual process improvement, we carried out a case study of the German telecommunication industry. The relations in question are twofold. First, we want to understand the effects that different process variants (i.e., services) have on ITSM processes, and second we want to comprehend the influence of people, systems, and resources.

### **4.1 Methodology**

We chose the case study method as a qualitative research method because it enables us to analyze a contemporary phenomenon in its real word setting. In addition, it represents a means of collecting and analyzing data to gain a comprehensive and in-depth understanding of the situation present. Therefore, we believe that the case research method is well-suited to capturing the knowledge of practitioners and developing theories from it. As is true for any case-based analysis we cannot entirely overcome the inherent unreliability of generalizing from small samples, but the fact of having more depth in the analysis dominates on the positive side [Fly06].

## 4.2 Process Description

We analyzed the incident management process of a German ISP for its IT service production. The ISP manages incidents and service requests via a service desk. After a service request has been reported, a ticket is opened in the Workflow Management System (WfMS), which is initially handled through the incident management process. The ticket is passed through various processing steps until the incident is disposed or the problem is resolved and the ticket can be closed. In general, the processing consists of the steps *Receive Incident*, *Categorize Incident*, *Analyze Incident*, *Resolve Incident*, *Assure Quality*, and *Close Incident*. During the ticket flow, the WfMS stores information of the actual processing status as well as the corresponding time stamps in a history of action. In addition, the support groups involved with the incident handling will fully document all details of any actions taken, such as the originator of the action, the affected service, as well as the solution statements, and if applicable, cross references to master and slave tickets.

From a large set of services we selected the services to which we refer to as  $S_1$ ,  $S_2$ , and  $S_3$ . These services are not revealed due to nondisclosure agreements. The services embrace various aspects, henceforth referred to as differentiators. First, the routing of the incidents within the workforce involves different responsible support groups. Second, the complexity of the underlying ITSM process diverges significantly due to the collaboration to external supply chain partners. For example, the ISP engages the services of a carrier who provides the cable network to offer the service  $S_3$ . Instances can, therefore, be caused either by the ISP or the carrier. Consequently, we can classify service  $S_3$  as the most complex service.

## 4.3 Continual Process Improvement in Practice

Turning now to our use case we apply the CPI approach as described in Sect. 2.3.

Definition of what should be measured: The incident management poses a serious challenge to the ISP to restrain from having a negative impact on user experience. To ensure an effective incident management, the service operation follows ITIL. However, it needs to be analyzed whether the process implementation is effective for all services. Furthermore, the efficient utilization of resources is a precondition for successful cost control.

Definition of what can be measured: Incident management for each of the services  $S_1$ ,  $S_2$ , and  $S_3$  is implemented based on the reference process model. Statements on the efficiency and effectiveness are based on comparisons of the respective workflows as part of an internal benchmark. The histories of action recorded by the WfMS are the basis from which the as-is processes and a metric of performance can be derived. The processes and the performance values can subsequently be contrasted to each other.

Gathering of the data: We selected incidents, which were completed within a specified time interval according to the criteria, which we have already described in the use case description. The information about the incidents stems from the history of action.

Processing of the data: The gathered data was converted into the MXML format by a custom-built converter plug-in for ProMImport<sup>3</sup>. The event log of  $S_1$  was made of 1.816 cases, that of  $S_2$  consisted of 4.182 cases, and that of  $S_3$  comprised 6.070 cases.

These event logs serve as input parameter to the process mining algorithm Heuristics Miner [WAA06]. The resulting heuristic net uses rectangles to represent single activities, the current status, and the associated frequency of occurrence. The rectangles are connected via directed arcs visualizing the dependencies between activities. The upper numbers next to the arcs illustrate the absolute occurrence, whereas the lower numbers indicate how confident we are that the dependency exists. The closer the number is to 1, the stronger the relation is. As the event logs start and end with various events, two artificial events *ArtificialStartTask* and *ArtificialEndTask* indicate the start and end of the process. The left-hand side of Figure 2 shows model  $S_2$ ; the right hand side depicts model  $S_3$ . The models look different at first sight certainly, but a closer look shows that they have common ground: same activities, similar starting activities, and similar routing.

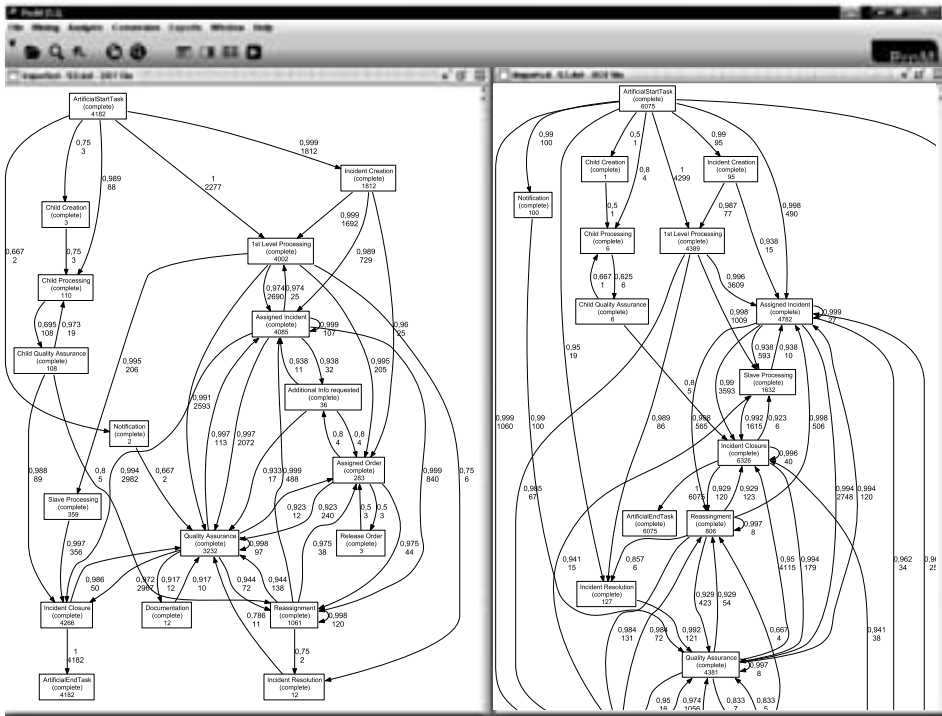


Figure 2: Process models derived by process mining

To assess the quality of the mined models, the continuous semantics fitness measure (CSF) [WAA06] calculates how precise the model actually covers the observed behavior in the event log. The measure results from replaying the activities in the event log. The

<sup>3</sup> <http://prom.win.tue.nl/research/wiki/promimport/start>



closer the value is to 1, the better the quality is. The CSF of the models yields high values of 0.97 (i.e.,  $S_1$ ), 0.72 (i.e.,  $S_2$ ), and 0.88 ( $S_3$ ), and with that a fairly well representation of the incident handling.

The event log further serves as input for a table where all process activities and their absolute (#) and relative (%) occurrences are listed. Condensing the information from  $S_1$ ,  $S_2$ , and  $S_3$  makes a statistical analysis of the data possible. The functions mean and standard deviation (SD) provide the statistical relevance. Table 1 shows an excerpt of the complete quality indicator list.

Activity	Occurrence						Mean	SD	Range	
	$S_1$		$S_2$		$S_3$				From	To
	#	%	#	%	#	%				
Assigned Incident	1,388	76.40	4,085	<b>97.70</b>	4,905	79.40	84.50	11.5	73.02	96.02
Incident Closure	1,815	99.94	4,182	100.00	6,172	99.95	99.90	0.0	99.94	100.00
Incident Resolution	8	0.40	12	0.30	129	<b>2.10</b>	0.97	1.0	-0.06	1.94
Reassignment	238	13.10	1,061	<b>25.40</b>	857	13.88	17.50	6.9	10.58	24.32
Quality Assurance	1,489	82.00	3,232	<b>77.30</b>	4,413	71.50	76.90	5.3	71.64	82.19

Table 1: Excerpt of the indicator-based measurement system

The information of this list is made comprehensible by gradually narrowing it down to a specific sample of KPIs. The selection process corresponds to the funnel method and is depicted in Figure 3.

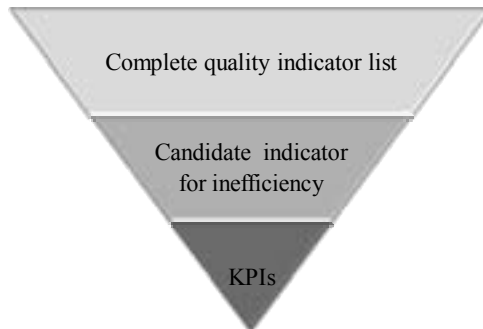


Figure 3: KPI selection process

The highlighted values in Table 1 propose those indicators, which hint at inefficiencies and with that, need further inspection. The values were highlighted because they are outside the range, which was computed by  $\text{mean} \pm \text{SD}$ . As a result of the selection process, the KPIs Assigned Incident, Incident Resolution, Reassignment, and Quality Assurance were selected.

The processing of the data as described in this section can be executed for all candidate service differentiators (e.g., support group), so that we extract a hierarchy of models and corresponding tables of performance indicators.

Analysis of the data: Upon inspection of the table it can be diagnosed that the performance values partially deviate strongly from those of different services. Limits of space only allow us a detailed description of three KPIs.

Take, as an example, the beginning of the incident processing. We refer to this example to as DEV1. We consider the indicator *Assigned Incident*, which expresses that the service desk staff was unable to resolve the operational problem themselves and assigned the incident to the next appropriate level for further inspection. The only slight increase in the frequency in  $S_3$  compared to  $S_1$  (79.4% as against 76.4%) indicates the similarity of the two services. Unlike  $S_1$  and  $S_3$  the activity is observed with 97.7% in  $S_2$  and, with that, exceeds the average 1.14 standard deviations.

It is interesting to note that the indicator *Assigned Incident* influences the KPI 1<sup>st</sup> kill rate, measured in the traditional measurement systems of the ISP. Just as the number of incidents which are released by the service desk increases, so does the 1<sup>st</sup> kill rate. Depending on the complexity of the service, however, it is possible that the organization is not striving for the highest possible 1<sup>st</sup> kill rate. One possible reason is that it is too expensive to build up the necessary knowledge among the employees. As this is the case for  $S_2$ , the ISP accepts a lower 1<sup>st</sup> kill rate for service  $S_2$ .

Now let us consider the indicator *Incident Resolution*. The activity represents the resolution of incidents in which a third party is involved. In services  $S_1$  and  $S_2$ , the activity is present with relatively low frequencies (0.4%, 0.3%) – as against 2.1% in  $S_3$ . Statistically spoken,  $S_3$  differs from  $S_1$  and  $S_2$  by 1.15 standard deviations. To put this into perspective, we look at the underlying collaboration in  $S_3$ . As above mentioned a telecom carrier is additionally involved in the delivery of service  $S_3$ . Since the resolution of incidents is more complex, the deviation, hereafter termed DEV2, has its origin in the complexity of service  $S_3$ .

The activity *Reassignment* is designed to redirect wrongly assigned incidents. According to specification this activity is, therefore, provided only by exceptions. It is noteworthy that the execution of this activity in  $S_2$  exceeds the average 1.15 standard deviations. To understand the deviation, hereafter abbreviated DEV3, we fell back upon the process models and drilled down to the group specific models. The table of these models revealed that the infringement of working procedure was prompted by a couple of support groups. This fact induces us to judge that this deviation results from resources, notably missing knowledge.

Summarizing, we found deviations particularly in  $S_2$  and  $S_3$ . We identified deviations, which are either inherent to the nature of the service, that is DEV1 and DEV2, or stemmed from improvable resources, namely DEV3. The services under observation are distinct in terms of resources and complexity. The factor resource in DEV1 and DEV3 differs in the way that the former is a suboptimum, which the ISP accepts when looking

at the service in its entirety, and the latter needs to be improved to optimize the service delivery.

Presentation and utilization of the information: We determined the measures necessary to optimize the service delivery in a series of workshops within the organization. In view of the increased transparency of service-specific characteristics, the ISP considers the utilization of the CPI approach in further process domains.

Implementation of corrective actions: The corrective actions are twofold: first, closing the gap of knowledge, and second a change in the comparison base of process mining. The former will be sealed with training for the users. The latter is required since the ISP accepts the service-specific characteristics in the process.

Together with the responsible process manager, we also verified that the use of the CPI approach clearly enables a growing maturity of the ITSM processes and, with that, an optimized service delivery.

## 5 Research Implications

One important conclusion we can draw from the use case is that one deviation is not like the other. Some deviations can be justified by peculiarities inherent to the services, whereas others stemmed from deviant working behaviors. Therefore, we distinguish between deviation patterns, which are led back on weak points either in the process or in the process implementation. We refer to the former as *Reference Non-Adherence* (RNA) and the latter as *Reference Adherence* (RA). As the CPI approach is only aware of structural deviations, that is pattern RNA, it has to be extended as depicted in Figure 4.

Step five of the control cycle CPI 1 includes a pattern analysis for making the appropriate determination of whether a problem lies within the process or within the process execution. In case of pattern RNA the process deviates from specification as a result of which the CPI approach is continued as originally developed.

The determination of pattern RA, however, triggers the control cycle CPI 2b. The rationale behind this cycle is that the process still optimally supports the business but has to be improved service-specifically with respect to the actual implementation. The semi-automated analysis is done by control cycle CPI 2b, which consists of all steps of the 7-step procedure. It is important to note that the analysis of the deviation (i.e., step three to five) is carried out in an automated way; it is supported by means of process mining and results in a measurement system, which in conjunction with the process model supervises the complete process course and identifies statistically relevant KPIs. It is, therefore, not necessary to determine KPIs in advance.

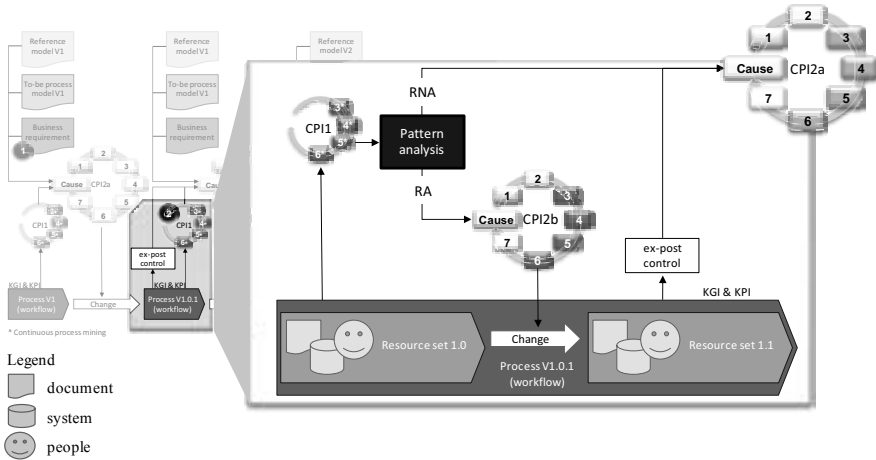


Figure 4: Extended CPI approach

The analysis of the KPIs can be particularly made with respect to distinctive features of the process in order to detect the sources of the deviations. Examples of possible differentiators are services, spheres of responsibility, cooperation models, or resources. If a deviation is due to process execution, two candidate solutions are available. First, it is not necessary to change the process itself but rather initiation of a resource or service-specific improvement activity (e.g., additional training etc.) might be more recommendable. The activity changes the resource set in terms of people, systems, or documents. Cycle CPI 2b continually repeats itself until the performance indicator is within the normal range again, that is, an efficient resource set with respect to the internal benchmark is found.

Second, the alternative decision is to accept the deviation because the supposed outlier is specific to the differentiator. In this case, the comparison base (i.e., to-be model) for process mining has to be adjusted or supplemented.

## 6 Conclusions and Future Research Directions

Based on our experiences in the telecommunications industry [GPT10], we have proven the validity of our approach to continually improve processes with respect to structural deviations from reference processes. The use case, however, confirmed that further deviations occur. Here are two examples: Services of different complexity require different knowledge levels. Depending on the complexity of the collaboration mode, working procedures can diverge within a process.

Because of the results from practice, we extended the CPI approach so that it provides guidance not only to comply with reference models but to identify and correct service-specific weaknesses of the process implementation. The extension integrates ITSM processes, people, and resources into the CPI approach.

We support practitioners in their evaluation of the potential of process mining. Process mining allows an objective and automated determination of the as-is condition, notably process models. The capability to reveal hidden information is particularly useful for the dynamical suggestion of performance indicators pointing to potential efficiency problems. It has to be stressed that the composition of the indicators is dynamic rather than static. These indicators contribute to an optimization of the IT service delivery as perceived by the user.

In summary, we identified various benefit potentials: First, service-specific characteristics of the incident management process are transparent. Second, the process quality can be measured and controlled through quantifiable information. Third, measurement is reproducible, repeatable, and comparable as base for improvement measures and the corresponding ex-post control. Finally, the high level of automation contributes to a good cost-benefit ratio.

In future, we will account for process variants when checking process compliance with to-be processes. A to-be model, which embraces the service inherent peculiarities, needs to be derived. It then serves as the process model against which the as-is process will be checked. We also aim to learn if it is possible to build a knowledge base as input for the pattern analysis. Information about former deviations, such as solution, type, or reason can flow in the knowledge base from which the pattern analysis can automatically classify deviations and present suggestions simultaneously to solve the deviations.

## List of Literature

- [AS+08] Ampe, F.; Steuperaert, D.; Peeters, B.; Hamilton, M.; Mcllwaine, R.; Maguire, C.: IT Governance Global Status Report IT Governance Institute. 2008.
- [BR06] Brooks, P.: Metrics for IT Service Management. Van Haren Publishing, Zaltbommel, The Netherlands, 2006.
- [CCDS07] Casati, F.; Castellanos, M.; Dayal, U.; Salazar, N.: A Generic Solution for Warehousing Business Process Data. In Proc. 33rd Int. Conf. on Very Large Data Bases, 2007; pp. 1128-1137.
- [DA05] van Dongen, B. F.; van der Aalst, W. M. P.: A Meta Model for Process Mining Data. In (Castro, J.; Tentiento, E. eds.): Proc. 2nd CAiSE Workshop-Proceeding, Portugal, Porto. 2005; pp. 309-320.
- [Fly06] Flyvbjerg, B.: Five Misunderstandings about Case Study Research. Qualitative Inquiry, 2006; pp. 219-245.
- [GPT10] Gerke, K.; Petrucci, K.; Tamm, G.: Continual Process Improvement based on ITIL and Process Mining. In (Spath, D.; Praeg, C.-P. eds.): Management for IT Services Quality. IGI Global, to be published in 2010.
- [IG07] The IT Governance Institute: COBIT 4.1. <http://www.isaca.org>, 2007.
- [KN92] Kaplan, R.; Norton, D.: The Balanced Scorecard – Measures that Drive Performance. Harvard Business Review, 70(1), 1992; pp. 71-79.
- [MB09] Märušter, L.; van Beest, N.: Redesigning Business Processes: A Methodology based on Simulation and Process Mining Techniques. Knowledge and Information Systems, Springer Verlag, London, 2009.
- [MLV08] Mieke, J.; Lybaert, N.; Vanhooft, K.: Business Process Mining for Internal Fraud Risk Reduction: Results of a Case Study. In Proc. Induction of Process Models, 2008.

- [MU01] zur Muehlen, M.: Process-driven Management Information Systems - Combining Data Warehouses and Workflow Technology. In Proc. 4th Int. Conf. on Electronic Commerce Research, 2001, pp. 550-566.
- [RJGA09] Rozinat, A.; de Jong, I. S. M.; Günther, C.; van der Aalst, W. M. P.: Process Mining Applied to the Test Process of Wafer Steppers. In IEEE Transactions on Systems, Man, and Cybernetics, IEEE Computer Society, 2009; pp. 474-479.
- [TCS07] Taylor, S.; Case, G.; Spalding, G.: Continual Service Improvement. Stationery Office Books, London, UK, 2007.
- [WAA06] Weijters, A.; van der Aalst, W. M. P.; Alves de Medeiros, A. K.: Process Mining with the Heuristics Miner Algorithm. BETA Working Paper Series, WP 166, Technical University of Eindhoven, The Netherland, 2006.