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Procedure For Hybrid Process Analysis And Design

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Abstract

Performing business processes are a critical asset for manufacturing companies operating on highly competitive markets. Conventional approaches to business process improvement, however, are vulnerable to subjectivity and high manual efforts in their execution. These challenges can be overcome with recent databased approaches that semi-automate process analysis and design. Those approaches formalize methodical knowledge on weakness detection, measure derivation and performance evaluation for business processes into a performance-related decision support. By enabling the databased automation of these tasks this formalization helps to reduce efforts and subjectivity in process analysis and design. However, practice lacks a procedure for applying this decision support in operative business process improvement. Moreover, this decision support only formalises methodological knowledge. Operative business process improvement in practice additionally requires the consideration of experts' contextual knowledge about the company and the business process itself. This paper presents a hybrid approach for the analysis and design of business processes using a databased decision support. First, existing phase models for business process improvement are consolidated into a reference model. Second, an expert-based assessment is conducted on how decision support extends, modifies or eliminates the conventional tasks of process analysis and design. In the third step, a hybrid phase model for process analysis and design is developed that integrates the formalised methodological knowledge of the decision support and contextual knowledge of experts.

Keywords

Business Process; Process Analysis; Process Design; Process Mining; Production

1. Introduction

Performant business processes are a critical necessity for success in a competitive economy [1]. Therefore, the continuous improvement of business processes constitutes an imperative for companies [2]. Business process improvement is defined as the continuous evaluation, analysis and improvement of business processes that are important to an organization's success. [3] Central tasks within business process improvement are process analysis and process design [2]. Within process analysis, process weaknesses are detected and quantified [2]. Process design identifies, evaluates and selects measures to eliminate process weaknesses [2]. Process design measures are semantically and structurally defined modifications to the business process to remedy identified process weaknesses and their related losses in terms of business process performance. Conventional approaches to business process improvement conduct process analysis and design manually in workshops [4]. Therefore, the risk of subjective influences is inherent to conventional approaches [5], as well as high costs and time effort [4].

These challenges can be overcome with recent event log-based approaches that semi-automate process analysis and design [6,7,8]. These approaches formalize methodical knowledge on weakness detection [6],

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measure derivation [7] and performance evaluation for business processes into a performance-related decision support [8]. By enabling the databased automation of these tasks this formalization helps to reduce efforts and subjectivity in process analysis and design. However, practice lacks a procedure for applying this decision support in operative business process improvement [8]. Moreover, this decision support only formalises methodological knowledge. Operative business process improvement in practice additionally requires the consideration of experts' contextual knowledge about the company and the business process itself [8]. Additionally, the consideration of human creativity can lever the effectivity in process design [9].

This paper presents a hybrid approach for the analysis and design of business processes using an event log-based decision support. First, the state of the art is reviewed in chapter 2. In chapter 3 the concept is developed and explained. Finally, the results are summarized and reviewed in chapter 4.

2. State of the art

Business process improvement, including process analysis and design, has been investigated in research and practice for many years. This results in a multitude of procedure models for business process improvement without the use of data. More recent, databased approaches are limited to the use of process mining in process discovery. Only few approaches describe data-based support in particular for process analysis and design.

One of the most cited conventional approaches is the business process management lifecycle of [2], a six-phase-approach for improving business processes. It incorporates the phases of process identification, process discovery, process analysis, process redesign, process implementation and process monitoring, before iterating into the process discovery again. It does not explicitly use databased support, but considers process mining as an event log-based possibility for process discovery. [10] uses a four-phased model for business process improvement. By participative integration of employees in workshops, the contextual validation of analysis results and a creative solution finding is ensured. Databased support is not considered. [11] also present a participative approach to business process modelling and improvement that integrates human creativity and validation in group discussions. As a databased support for business process improvement, [12] combines process analysis on the basis of key performance indicators with process mining approaches. The "KPI4BPI " (key performance indicators for business process improvement) approach enables users to quickly identify negative deviances for process KPIs like quality, costs, time and additionally proposes process improvement heuristics automatically. However, this approach lacks a distinct explanation of a procedure to improve business processes beyond the quantification and delta reporting. The approach of [13] integrates the technology of process mining into the DMAIC *(define, measure, analyse, improve, control)* cycle of Six Sigma. Within the DMAIC-cycle process related data is used to identify processes, determine the process performance, model the process and take further analysis and monitor the process execution. This approach provides an integration of conventional and databased methods, however with a focus on quality management due to the DMAIC method. [14] develops a databased decision support for process improvement, that provides applicable best practices to a process expert. Yet a detailed explanation of its applications is non-existent. The approaches of [7,8,9] develop a decision-support to automate a majority of the tasks in process analysis and design. However, its application in practice is still missing. The evaluation of the state of the art constitutes the need for an approach, that supports process analysis and design by means of event log data like [7,8,9] and at the same time is applicable in practice.

3. Concept

Within preliminary work, the authors developed event log-based support for process weakness detection [7], measure derivation [8] and a performance-based decision support for business process analysis and design [9] in manufacturing companies. This paper's concept describes how this decision support can be integrated hybrid with contextual expert knowledge to a new procedure for business process analysis and design.

Therefore chapter 3.1 consolidates existing phase models for business process analysis and design into a reference phase model considering the most relevant tasks within. Chapter 3.2 presents the functionalities of the performance-based decision support and evaluates to which extent it can automate the tasks in the reference phase model. Within chapter 3.3 a hybrid procedure for business process analysis and design using the performance-based decision-support is introduced.

3.1 Consolidation of a reference phase model for conventional business process analysis and design

Procedures for business process improvement are typically described as a sequence of several phases. A large variety of phase models for business process improvement have evolved over the past decades in literature and practice. The most relevant phase models are summarized in Figure 1.

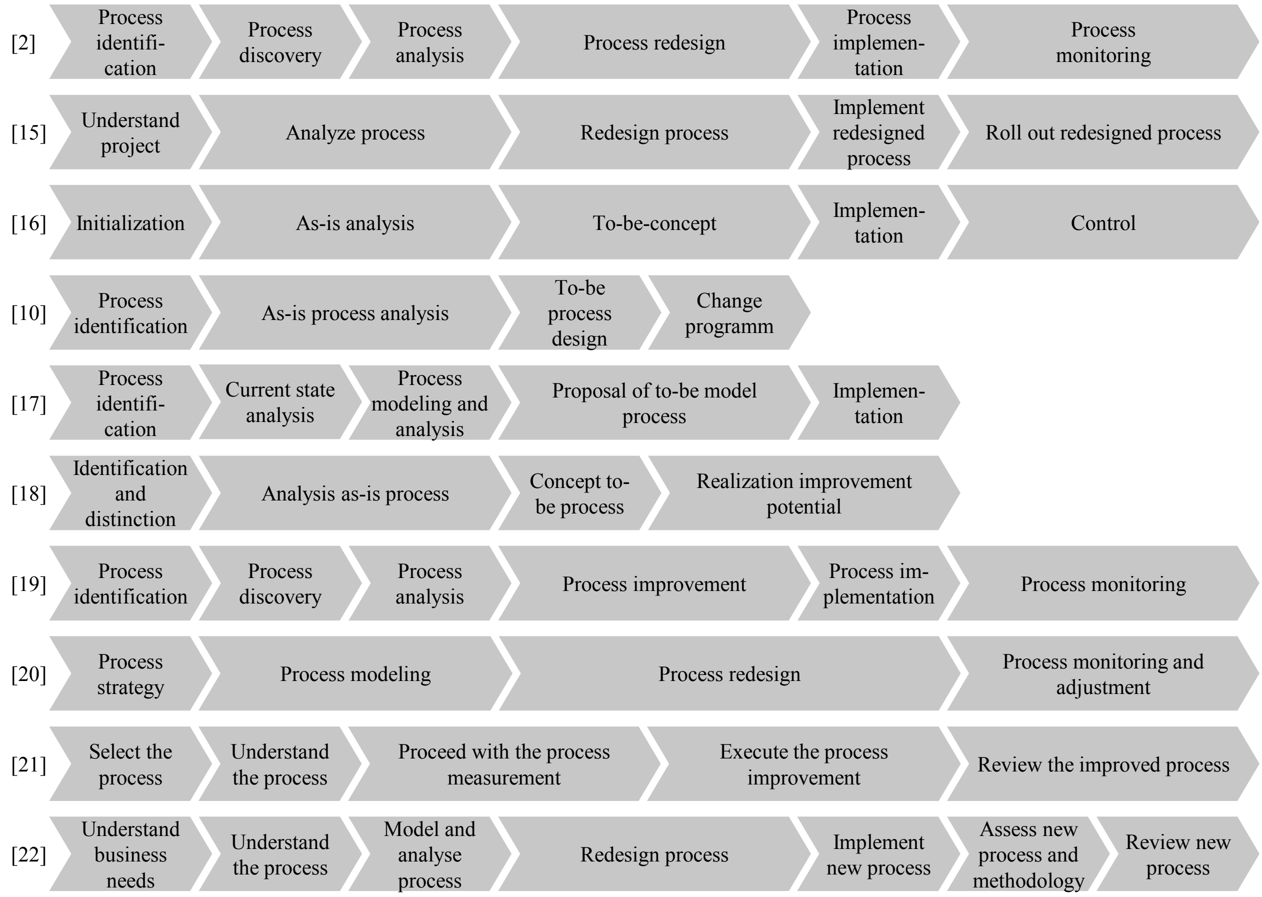

Figure 1: Overview of phase models for business process improvement

The length of the phases graphically illustrates the scope of the tasks contained and thus enables the phase models to be compared regardless of the labelling used. The phase models differ in the scope of the subtasks and the aggregation into main phases. However, their basic logic is similar. Figure 2 consolidates this basic logic of the relevant phase models to a reference phase model.

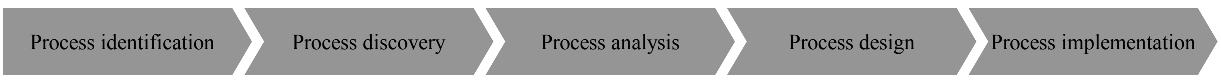

Figure 2: Reference phase model for business process improvement

The reference phase model shall serve as input for the evaluation of adaption needs in chapter 3.2. The consolidation logic and the reference phases are described subsequently. Typically, business process improvement projects are initiated with the **process identification**, e.g. the selection of one business process to be improved in the company. This is followed by the **process discovery**, in which the current as-is process is graphically modelled and documented. In the subsequent **process analysis**, this process model is examined for weaknesses and with regard to its process performance. In some phase models, process modelling and analysis are also combined into one phase and referred to as-is analysis. The process analysis is followed by the **process design**, during which measures to eliminate the process weaknesses and to design an improved to-be process are derived. The final phase following the process design is the **process implementation** of the improved to-be process, in some phase models followed by the monitoring of the implemented process.

For the scope of this paper, the two phases of process analysis and process design are examined more closely and their relevant tasks will be consolidated into a reference process for process analysis and design:

From the examined phase models, four referential tasks emerge for process analysis (cf. Figure 3): qualitative and/or quantitative analysis, validation, prioritisation and documentation. The analysis can be conducted via a variety of qualitative (e.g. value chain analysis, waste analysis) or quantitative (e.g. lead time analysis, queueing theory) methods and is used to identify weaknesses in business processes [2, 23]. Both [2] and [10] include a validation of the manually identified weaknesses. The third referential task within process analysis is the prioritisation of weaknesses according to e.g. their magnitude of impact or effort required to resolve them. Pareto analysis or the decision diagram are possible methods [2]. This requires an assessment of the problems in business processes and serves to concentrate resource allocation on the most severe weaknesses. The last step of the process analysis in the referential phase model is the documentation of the prioritised weaknesses, e.g. in a problem register [2].

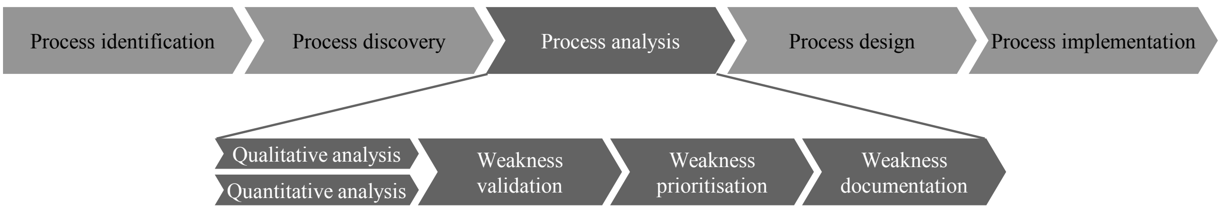

Figure 3: Referential tasks within process analysis

Process design exhibits six referential tasks in the examined phase models (cf. Figure 4): Measure derivation, measure validation, measure quantification, measure prioritization, to-be process design and measure documentation. In the process of measure derivation, creative (e.g. 7FE) or analytical (e.g. improvement heuristics) methods are used to identify measures that solve the identified problems and improve process performance [2]. By conducting workshops, the identified measures can be validated at the same time. In the second step, the identified improvement measures are evaluated (e.g. effectiveness, feasibility, effort) using methods like throughput time analyses, process simulations or cost-benefit matrices [2,4,10]. These and other methods like the Eisenhower matrix or the Pugh matrix enable the subsequent prioritisation of improvement measures [23,24]. The next step is the design of the to-be process. In this process, one or more to-be processes are modelled by application of improvement measures, to cleanse process weaknesses and ideally achieve the process goals. In the case of several to-be process variants, one to-be process model is selected after checking the feasibility, benefit or effort or by assessing through a process simulation. Finally, the last step in process design involves the documentation of the to-be process in a process model.

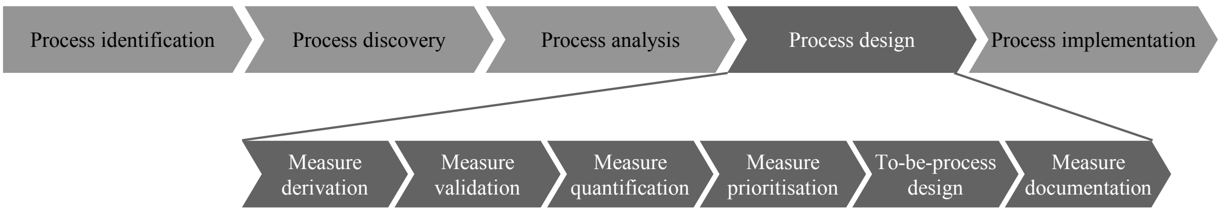

Figure 4: Referential tasks within process design

The reference phase model for process analysis (cf. figure 3) and process design (cf. figure 4) describe their basic tasks in a conventional, for example workshop-based, approach.

3.2 Evaluation on process changes due to decision support

The reference process describes the essential tasks to be executed in the analysis and design of business processes in a conventional, e.g. workshop-based, approach. With the availability of a performance-based decision support that was developed in preliminary work of the authors (cf. [9]) it needs to be examined, how those tasks need to be eliminated, automated, modified or extended. For this purpose, first the functionalities of the decision support developed in [7,8,9] are summarised in Table 1.

Table 1: Functionalities of the databased decision support for process analysis and design

Phase	Functionality
Process analysis	▪ Detection of process weaknesses based on weakness models ▪ Quantification of performance losses (absolute in time, relative in performance) on level of the process instances and the process model for detected weaknesses ▪ Quantification of process performance for process instances and process model ▪ Prioritized documentation of process weaknesses according to performance impact
Process design	▪ Derivation of suitable measures to solve detected process weaknesses ▪ Quantification of measures' performance potentials (absolute in time, relative in performance) on level of the process instances and the process model ▪ Prioritized documentation of measures according to performance potential

These functionalities can be executed for an event log of a business process which serves as input for the databased decision support. Due to their automation in the decision support, the following related tasks from the reference phase model (cf. chapter 3.1) can be automated: process weakness detection in qualitative process analysis, process weakness quantification in quantitative process analysis, process weakness prioritization, process weakness documentation, measure derivation, measure quantification, measure prioritization, measure documentation. The functionality *Quantification of process performance for process instances and process model* extends the tasks of the reference model, since this was typically not possible in non-databased approaches. The remaining delta between the functionalities of the decision support and the reference process for process analysis and design is in the weakness validation and the measure validation. These tasks are not automatable due to the required context knowledge (e.g. about the company and the specific business process) and remain to be conducted manually. Additionally the prioritization of measures can only be semi-automated as the decision support only considers time-based performance. In practice, however, potential measures for process design need to be assessed with regard to additional criteria such as effort, costs, implementation time, etc. Due to the extensive automation of process analysis and design through the decision support, the general structure of existing phase models is no longer appropriate. For this reason, a completely new approach to the analysis and design of business processes is required.

3.3 Hybrid procedure for data-supported business process analysis and design

Following the conclusion of chapter 3.2 a completely new procedure for process analysis and design in manufacturing companies is developed in this chapter. Due to their extensive automation the two phases of process analysis and design are merged into one phase, in which detected weaknesses and suitable measures are examined simultaneously. Within this common phase, the procedure also differs considerably from the reference process. Whereas the reference process was structured sequentially according to the tasks of process analysis and design, the new procedure is structured around the decision support in preparatory, executing and processing-decision phases. This results in a procedure including the four sub-phases

Configuration of the decision support*,* **Execution** of the decision support, the **Process Exploitation** and **Process Exploration** (cf. Figure 5). The **Execution** is fully automated by the decision support, the other phases require preparatory actions or decisions by users. In the following, the tasks within these four sub-phases are detailed.

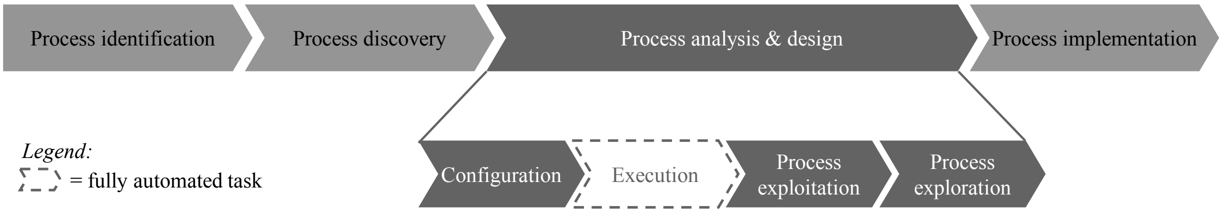

Figure 5: Phase model for hybrid process analysis and design

The sub phase **Configuration** serves to pre-process the data of the event log and to configure the decision support for the application context of the company and the business process to be examined. First, an event log with the attributes process instance, activity, start time and end time is extracted for the business process to be analysed. If in a business process improvement project, the process mapping was conducted with process mining, this event log can be used. Further, the execution time and the upstream transition time are added for each event in order to detect non-realistic outliers (e.g. due to incorrect bookings) via statistical scatter measures. These outliers could influence the detection of the process weakness types *unsuitable scope* and *transition time* (cf. weakness types in [7]) and need to be eliminated from the event log to be examined. In each individual case, a decision must be made whether to eliminate the entire process instance or - if possible - to correct the time. This concludes the data pre-processing as the first task within the configuration phase. Subsequently, the configuration of the data-based decision support for the process analysis and design is conducted for the given context of company and the business process to be analysed. The configuration is ideally carried out in collaboration between an internal process expert and an external method expert. The internal process expert can decide, which of the weakness types shall be applied to the event log. Additionally, he can configure the weakness types developed in [7], e.g. the upper limit of the variation of execution times for the weakness type unsuitable scope or the list of unwanted activities to be detected. If required, the process expert is also able to define new, context dependent weakness types that shall be detected in the event log in accordance to the formalization logic of [7]. Analogously, the measure types are configured. In particular it is defined, to which extent the measures are capable of reducing the performance loss of the related process weakness. This applies to the measure types *reduction of transition time* and *acceleration* (cf. measure types in [8]) that use historic process times to calculate their performance potential. By setting a quantile value, the internal process expert can determine which quantile of historical best times should be considered as realistic and permanently achievable for a to-be process. If required, new, context dependent measure types can be modelled in accordance to the formalization logic of [8]. After this step, the data-based decision support is fully configured for application to the event log of the business process.

The subsequent sub-phase **Execution** begins with the application of the selected, configured and potentially added weakness models to the pre-processed event log to detect process weaknesses. These are added to the event log at the associated event. Transition times are noted to the event following the transition time. The weakness quantification adds the absolute influence of each process weakness on the process time and affected OPE loss type in the process performance key figure OPE[1]to the event log (cf. performance-based decision support in [9]). Single events and their inherent execution and transition times can be affected by several process weaknesses. A multiple consideration of single times would incorrectly reduce the process performance OPE. To avoid this multiple consideration, a weakness hierarchy defines the process performance relevance of detected process weaknesses. Subsequently, the relative OPE performance losses

[1] OPE = Overall Process Efficiency, a holistic key figure for process performance as defined by [9]

at process instance level and process model level are quantified for each process weakness added to the event log. In parallel, a list with all process weaknesses as well as supplementary information (e.g. affected event, loss type, absolute loss, relative loss) is generated. In addition, the total loss time is quantified at the levels of process instance and process model. Furthermore, the absolute and relative values of the loss types (e.g. continuity, linearity and performance loss) are calculated at level of process instance and process model based on the loss type assigned to each process weakness. The performance evaluation of the business process concludes with the calculation of the process performance OPE per process instance and for the entire process model. The functions and calculations presented so far concern the data-based decision support for the process analysis. The data-based decision support for process design starts with the allocation of measures to detected process weaknesses according to process weakness-measures matrix [8]. These measures are added to the extended event log and the process weakness list. After the measure assignment, the measure quantification is done as absolute time values as well as relative OPE potentials on levels of process instance and process model. This information is shown in the extended event log and the process weakness list. The extended event log only serves as a data basis for decision support. The process weakness list serves as a basis for decision-making in the subsequent sub-phase of exploitative process analysis and design. To enable prioritization, the process weakness list is sorted in descending order according to the magnitude of the OPE loss caused by detected process weaknesses at overall process level. This allows limited resources to be focused on particularly serious problems in practice. It is noteworthy that the execution phase fully automates the described tasks so that they are executed almost simultaneously in a very short time. Therefore, despite the numerous tasks, the execution phase substitutes high-efforts for conducting process analysis and design in workshops.

After the automated execution of decision support, all information about process weaknesses, measures and process performance is available for the as-is process. In **Process exploitation**, the decision-relevant information is validated and decisions are made regarding the analysis and design of business processes. Due to its characteristic of incremental process improvements through weakness elimination this phase is called *exploitative* following the logic of [25]. The automated decision support allows an iterative procedure in exploitative process analysis and design, in which single process weaknesses are examined individually. Thereby, the weakness list enables to examine process weaknesses with major impact with priority. This iterative approach allows a flexibly extensive process analysis and design depending on the availability of resources. As a first step in exploitative analysis, the process expert selects any process weakness from the prioritised weakness list (e.g. the process weakness with the highest OPE loss at the overall process level) for detailed analysis. Further, it needs to be validated whether the detected process weakness is actually a process weakness in the context of the investigated business process. Invalid process weaknesses are excluded from the OPE calculation and marked as processed and non-valid in the process vulnerability list. In the case of overlapping process vulnerabilities, the process vulnerability next in the process vulnerability hierarchy becomes OPE relevant. After successful validation of the process vulnerability, potential measures to remedy the process weaknesses are presented to the user including their OPE potential. On this basis, the process expert can assess whether and which measure to select for the process weakness under examination. In addition to the OPE related information in the decision support, the process expert must consider contextual factors for the operationalisation of the measures (e.g. effort, investment, implementation time). The decision on measures in process design therefore involves multiple criteria, of which the data-based decision support automatically quantifies and provides the criterion *benefit for process performance*. When a measure is selected, this measure is transferred into a list of action measures, which serves as the basis for the process implementation. In addition, the event log is manipulated, so that the changes caused by applied measures (e.g. activity elimination) become visible in all process instances. Additionally, the OPE at process instance and overall process level is also increased. This iterative procedure of process weakness examination is repeated at the discretion of the process expert until a satisfactory OPE level is reached, all process weaknesses have been examined or the process analysis and design needs to be terminated due to resource constraints (e.g. time). At the end of this iteration, the process instances of the process model are manipulated by the application of measures and the theoretical OPE of these process instances are known. Among all process instances of the examined business process, the manipulated (historic) process instance with the highest OPE is proposed as the basis for the to-be process. The final selection remains with the process expert, who can display the process model for each process instance.

The last phase of **Process exploration** consists of three tasks. In the first step, a to-be process needs to be generated from the selected manipulated (historic) process instance with the highest OPE. Its process structure is derived from the event IDs or the time sequence of the selected process instance. The to-be execution and transition times can be derived from the manipulated event log. On this basis, a synthetic event log for the target process model can be generated by setting a calculatory start time stamp of the first event to a *zero time*, e.g. 01.01.1900 at 00:00:00 and modelled with process mining discovery algorithms. In the second step, parallelization potentials become visible by discovering the synthetic event log and using the weakness information from the decision support. Contrary to the OPE, the calculation of throughput times in this step enables the quantification of the time potentials through parallelization. In the third step, the actual exploratory improvement of the synthetic process instance to a to-be process model takes place. Here, the process expert can improve the business process beyond the standard improvements of the decision support by applying individual contextual knowledge about the process or creative solution approaches. An example would be the elimination of several activities through a novel technological solution or outsourcing. The implementation in the process model is done by shifting or eliminating activities with adaption of the associated execution and transition times. The implementing software solution should enable intuitive adaptations directly in the process model for both parallelisation and exploratory process analysis and design. These changes in the user interface then need to alter the event log of the underlying synthetic process instance. Thus the effects of the explorative improvements by the process expert on OPE and the throughput time can be calculated and made available to support decision-making.

4. Conclusion

The performance of business processes is a critical success factor for manufacturing companies on competitive markets. Available methods for business process improvement are driven by high efforts and subjective influences, why business process improvement projects regularly fail to fulfil their expectations. In previous research the authors have developed a databased decision support which semi-automates process analysis and design. Together with process mining discover methods for process mapping this decision support is the key lever for reducing efforts and subjectivity in business process improvement. For its application in practice, however, the databased decision support needs a procedure. Conventional phase models for business process improvement are no longer applicable after the significant automation of the included tasks.

This paper provides an approach, how the databased decision support for business process analysis and design can be applied for business process improvement in practice to reduce efforts and subjectivity. For this purpose, existing phase models for business process improvement are consolidated into a reference model in a first step. A second step examines to which extent the functions of the decision support substitute, modify or extend the tasks of business process improvement. On this basis, a hybrid procedure for process analysis and design using the decision support is designed. This paper's approach makes the preliminary developed decision support applicable for business process improvement in practice. Thereby it levers objectivity and methodological efficiency, while at the same time integrating formalized methodological knowledge, context-specific expert knowledge and creativity to improve business processes.

Future research should address the development of user interfaces to enable technical applicability of the databased decision support in practice. Based on the procedure developed in this paper, requirements for a user interface can be derived, that leads the user through the hybrid process analysis and design. Furthermore, future research can investigate in the integration of process mining discovery and the decision support to offer a holistic event log-based solution for business process improvement. Lastly, it could be examined if modern process mining solutions enable process simulation to further enhance the functionalities of the databased decision support.

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