

Business Process Optimization: A Systematic Review of Combining Concepts from Business Process Management and Operations Research

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Abstract. Business Process Management and Operations Research are two research fields that both aim to enhance value creation in organizations. While Business Process Management has historically emphasized on providing precise models, Operations Research has focused on constructing tractable models and their solutions. This systematic literature review identifies and analyzes work that uses combined concepts from both disciplines. In particular, it analyzes how business process models have been conceptualized as mathematical models and which optimization techniques have been applied to these models. Results indicate a strong focus on resource allocation and scheduling problems. Current approaches often lack support of the stochastic nature of many problems, and do only sparsely use information from process models or from event logs, such as resource-related information or information from the data perspective.

Keywords: Business Process Optimization, Process Improvement, Business Process Management, Operations Research, Systematic Literature Review

1 Introduction

One major goal in Business Process Management (BPM) is process optimization and improvement [32]. Another research discipline targeting the operational performances of organizations is Operations Research (OR). OR “*is concerned with quantitative (mathematical) models and their solution*” [33]. [32] points out that OR “*is generally concerned with controlling an existing process without necessarily changing it, while BPM is often concerned with making changes to an existing process in order to improve it*” [32]. Nevertheless, “*many process improvement problems can in fact be traced back to typical problems investigated by OR*” [2]. Hence, BPM approaches such as [2,29] promote the idea of applying OR techniques on business processes.

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Despite the shared goal of improving the operational performance of organizations, so far, both disciplines have followed distinct optimization approaches. An OR project as described by [39] is a finite sequence of steps designed to serve a specific optimization goal. When a problem appears intractable for some solution method, an OR practitioner can either change the solution method (e.g., to a heuristic) or simplify the model [99]. In contrast, a key concept in BPM is the BPM lifecycle [32], which categorizes means to operationalize business processes into four recurring phases, i.e., the process (re-)design, system configuration, process enactment, and process diagnosis phase. The output of one phase is taken as input for the next phase and the cycle is continuously executed to reach ongoing improvement.

Existing surveys on Business Process Optimization focus on the improvement of the enactment phase of the BPM life cycle. [92] analyze methods of resource allocation and scheduling of business process in particular for the cloud computing domain. [84] analyze the BPM data sources that are used as input for resource allocation approaches of business processes. Here a specific focus is on the used process models and data for different allocation algorithms during enactment.

This work focuses on the model depicted in Fig. 1, which combines the OR-driven optimization project methodology presented in [39] with the BPM life cycle. By following this model, our survey enhances existing surveys by considering business process optimization as a holistic, continuous effort, which can affect the (re-)design and the enactment phase. The integrated model is based on the idea in [32], that *quantitative analysis* methods can be applied to the (re-)design and the enactment phase (①) and are based on data obtained during process diagnosis. We further enhance this definition by also looking at data gathered during enactment and (re-)design ②.

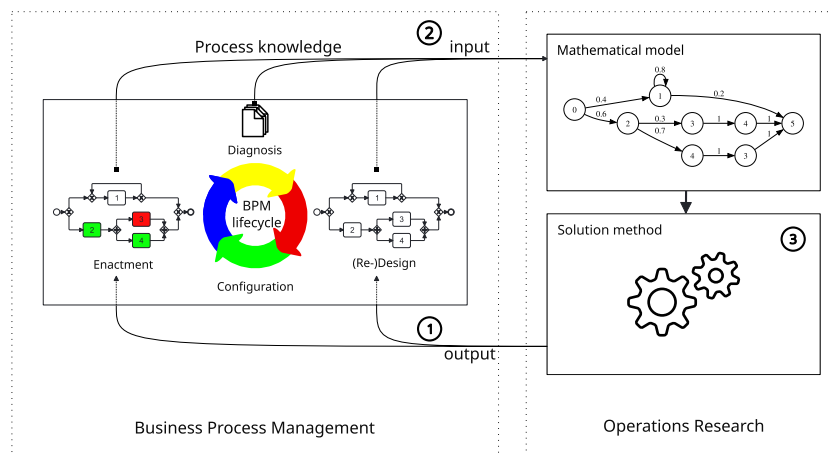


Fig. 1. Quantitative optimization of business processes using OR methods

We design the research questions for this systematic literature review in coherence with Fig. 1 and analyze the application of OR techniques in the context of business

process improvement. The first objective is to provide an overview of the targeted optimization phase, i.e., is the (re-)design or the enactment of a process optimized through the application of an OR method (see ①). We do not perceive the configuration and diagnosis phases as directly applicable to OR techniques, as the diagnosis phase is concerned with aggregating data post-ex, and the configuration phase with implementing a process model (see Fig. 1). The second objective is to survey how mathematical models are obtained from process data and in which form this data is structured. To this end, we distinguish data collected during process enactment, such as event streams/logs and runtime data, as well as during process (re-)design, i.e., process models. In particular, we are interested in which process mining techniques, which process modeling techniques, and which process perspectives are suitable or even required for the creation of an OR model (see ②). The third objective is to survey the solution methods used to solve the optimization problem, i.e., mathematical models obtained from process-related data (see ③).

The survey at hand contributes to the BPM community, as the results indicate which data baseline in the form of models is necessary for business process optimization from an OR perspective and discusses missing modeling standards. It contributes to the OR community, as the results indicate how mathematical models and solution techniques can be applied to business processes and, therefore, optimize meaningful real-world use cases.

The remainder of this work is structured as follows: In Sect. 2 we outline the search strategy of the literature review. The findings are presented in Sect. 3. In Sect. 4 we present identified challenges that should be considered by future research. Related work is presented in Sect. 5. Sect. 6 discusses and concludes the systematic literature review.

2 Research Method

The Systematic Literature Review (SLR) follows the guidelines by [51] and starts with defining research questions based on the integrated model depicted in Fig. 1. The first research question **RQ1** asks **which BPM life-cycle phase is addressed when applying optimization techniques from OR on business processes**. It seeks to provide insights into the types of optimization problems that have been predominantly proposed and addressed so far or present promising opportunities for future research. The second research question **RQ2** asks **how business processes are modeled or mined to deliver data for the application of OR techniques**. In detail, it aims to identify the most suitable business process modeling and mining techniques for creating mathematical optimization models, especially considering different process perspectives, i.e., control-flow, resources, time, and data. The third research question **RQ3** focuses on **which solution techniques are used to optimize business processes** and aims to identify mathematical solution approaches that align with business processes, including approximations or optimal solutions.

We search *Scopus* and *Web of Science* acknowledged as world-leading comprehensive databases [113]. The following search queries are designed to find relevant works for answering **RQ1–RQ3**.

For *Scopus*, we use:

```
TITLE-ABS-KEY (
  ("BUSINESS PROCESS MANAGEMENT" OR "WORKFLOW MANAGEMENT" OR "PROCESS MINING"
   OR "PROCESS ANALYTICS") AND
  ("OPERATIONS RESEARCH" OR "OPERATIONAL RESEARCH" OR "SCHEDULING"
   OR "ALLOCATION" OR "ROUTING" OR "OPTIMIZATION" OR "OPTIMISATION")
)
```

For Web of Science, we use:

```
TS=(
  ("BUSINESS PROCESS MANAGEMENT" OR "WORKFLOW MANAGEMENT" OR "PROCESS MINING"
   OR "PROCESS ANALYTICS") AND
  ("OPERATIONS RESEARCH" OR "OPERATIONAL RESEARCH" OR "SCHEDULING"
   OR "ALLOCATION" OR "ROUTING" OR "OPTIMIZATION" OR "OPTIMISATION")
)
```

In order to address the combination of BPM and OR fields, the search queries consist of keywords targeting the BPM field and the OR field, connected by a logical ‘AND’. For both fields, terms that are used interchangeably are included, such as *Business Process Management* and *Workflow Management*. Moreover, language bias is avoided by using, e.g., *Operations Research* and *Operational Research*. In a test run, the term *Business Process* yielded an infeasible amount of results, often unrelated to the BPM discipline, and is therefore disregarded from the search strings. The term *Process Mining* is included in order to address the process enactment phase.

The keywords are used to search within the title, abstract, and keywords of publications. The search was conducted in September 2025, resulting in 3 650 initial studies. After removing duplicates, 2 639 publications remain for the title, keywords, and abstract screening. The screening is based on inclusion and exclusion criteria. From a technical point of view, we consider peer-reviewed publications in English and exclude position papers. From a content perspective, we consider publications that regard formalized process models or event logs and are concerned with quantitative optimization techniques. Analogously, we exclude papers on manual optimization or manual re-engineering. Finally, we exclude papers on grid and cloud computing and scientific workflows as the corresponding optimization techniques are concerned with “the transportation and analysis of large quantities of data” [14]. The inclusion and exclusion criteria are applied to titles, keywords, and abstracts of search results and rated by the authors on a Likert-5 scale [62]. All publications that are ranked higher than 3 are chosen for reading the full text. Full-text copies are obtained for 179 publications, while the full text could not be obtained for six publications. After reading the full texts, 87 studies are excluded due to not meeting the inclusion criteria, resulting in 92 publications¹ put into further assessment.

Based on a full-text review of the 92 selected publications, we extract data in order to ensure a systematic approach in answering research questions **RQ1–RQ3**. The data set can be found in¹.

- **RQ1 – Targeted BPM life-cycle phase:** We assess whether the proposed process optimization approach affects the design phase, e.g., planning an optimal amount of resources prior to enactment, or the enactment phase, e.g., allocating resources to process activities during its enactment (life cycle phase \in {enactment, design}). Moreover, we assess the problem by categorizing it into category \in {Action rec

¹ https://github.com/Schlixmann/SLR_OR_BPM

ommendation, Resource planning, Resource allocation, Scheduling, Process navigation, Process model selection, Batching, Control-flow re-engineering, SLA Planning}. Initial categories were discussed during the review protocol design and refined after all relevant publications were read. OR categories are derived from [39], i.e., scheduling, batching, resource planning, and resource allocation. As BPM problems are typically concerned with changing the process model [32], we decide on the following categories from a process-driven perspective, i.e., selection of the best process model, control-flow re-engineering, process navigation, action recommendation, resource allocation (present in BPM and OR), and SLA planning.

- **RQ2 – Optimization input:** We assess the existence of (i) a process model \in {yes, no}, ii) an event log \in {yes, no}, iii) the workflow patterns \in {sequence, AND, XOR, deferred choice}, iv) multiple process instances \in {yes, no}, v) resource modeling \in {yes, no}, vi) resource performance indicators (RPI) \in {none, single, complex}, vii) resource grouping \in {pooled, individual, both}, viii) time profiles \in {yes, no}, and ix) data perspective \in {yes, no}. If, for example, a process model is available, we review which workflow patterns are supported in the optimization model. For the resource perspective, we extract how resources are represented, e.g., as individual resources and/or as pooled resource groups.

- **RQ3 – Solution method:** We assess x) which solution approach is applied and xi) optimality \in {yes, no}. Since publications often combine several algorithms to obtain a solution, we do not use a structured field to extract the proposed solution approaches. We extract whether the applied method finds an optimal solution to the mathematical model or an approximation and how this solution is found, e.g., by heuristics.

3 Results

This section presents the analysis of the included studies on the research questions **RQ1–RQ3** based on the categorizations presented in Sect. 2.

3.1 RQ1: Targeted BPM life-cycle phase

73% of the publications target optimization problems in the enactment phase and 27% the design phase. Fig. 2 shows the distribution of the publications on a timeline, grouped by *life cycle phase*. The majority of publications addressing quantitative optimization methods in BPM have been published since 2011. The number of publications that address optimization in the enactment phase peaked in 2016, while the number of publications that address optimizations in the design phase has been rather constant every year since 2017.

Fig. 3 shows the number of publications for each of the nine *problem categories*. The majority of publications are concerned with *scheduling* and *resource allocation* in the enactment phase, and with *control flow re-engineering* and *resource planning* for design time. In the following, a description of the individual problem categories and their publications is presented.

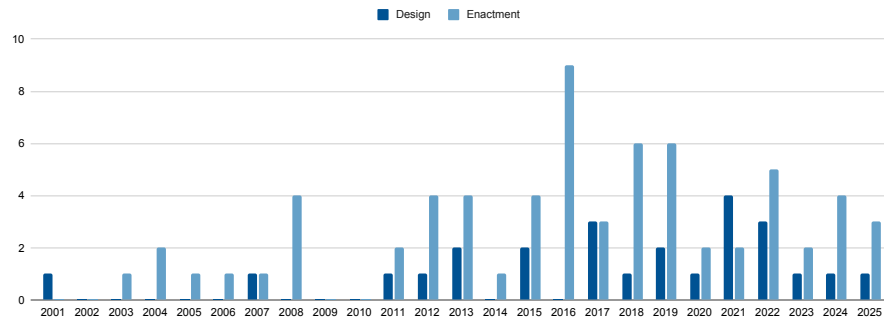


Fig. 2. Publishing year and life cycle phase

Design phase: *Process model selection* comprises [91,90], which are concerned with finding the best-performing process model from a set of feasible process models. *Control flow re-engineering* publications present quantitative optimization approaches for re-engineering the control flow of a process. In this category, [100,76] propose techniques to parallelize activities in an automated way to speed up the process execution. Conversely, [104] propose an automatic approach to sequentialize activities, such that an allocation algorithm is prevented from assigning an unsuitable or expensive resource to an activity when a well-suited resource is unavailable because it is executing a parallel activity. Two publications are concerned with (re-)engineering decision points: [16] aims to find optimal conditional values for exclusive choices, while [98] aims to move the decision points to the earliest possible points to enhance planning certainties. [1] investigates strategies to find an optimal task order in knock-out processes where the outcome is, e.g., to approve or disapprove a loan. [58] suggest splitting a process model into a subset of process models so that the process models have a minimal inter-process coupling. These smaller processes can be used individually for further scheduling or allocation techniques. Lastly, [97] presents an approach that finds the minimal number of change operations needed to transform a control flow model into another one. *SLA planning* in [18] is concerned with an automatic approach for proposing SLAs based on business processes. *Resource planning* publications aim to plan either the number of resources needed for process execution or the properties of resources, e.g., their locations. Finding the optimal number of resources is the goal of [78,82,5,60,66,15,73], while finding optimal properties is the objective for [50,35,87]. [20,68] propose approaches that can be used to evaluate the effect of replacing a resource with another one. [53] is concerned with identifying bottleneck resources. *Batching* addresses the problem of finding optimal batch sizes for activities. It is the only category considered in the enactment and design phases. [83] focuses on a static batch size determined during design time. In contrast, [79] introduces a dynamic method that adjusts the batch size during the enactment phase.

Enactment phase: *Action recommendation* refers to the execution of a next task in a process instance or for a resource or to initiate a new process instance. [12] recommend the most suitable next activity to a resource, i.e., a user. The pool of possible activities can stem from different process instances with different priorities or service-

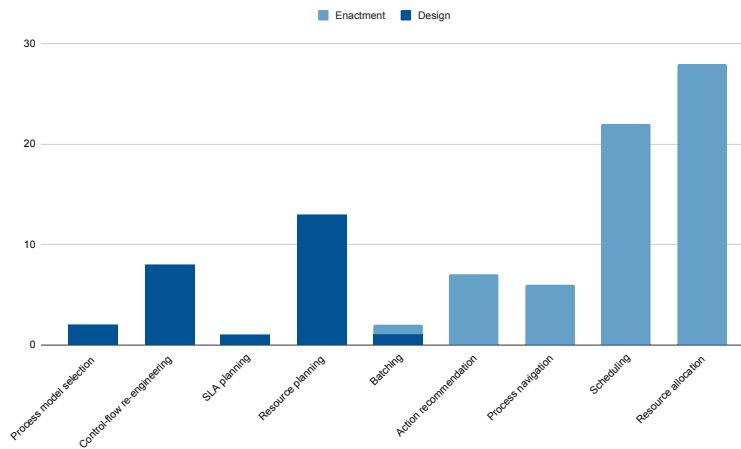


Fig. 3. Problem categories and life cycle phases

level agreements that must be obeyed. Similarly, [44] recommend the most suitable intervention for aggressive patients in a clinical process. [101] recommend skipping process activities, e.g., when a deadline can only be met if checking the credibility of a customer is skipped. [10] recommend whether a new process instance should be spawned or not, i.e., an offer be accepted or not. [56,89,88] focus on recommending time points for maintenance tasks. *Process navigation* proposes a viable process path, e.g., a set of activities required to complete a process instance. [72,49,48] are primarily concerned with (resource) deadlocks that might occur during the process executions and suggest identifying feasible execution strategies that are not exposed to deadlocks by using Monte Carlo simulation. [22,112] present approaches to select the optimal branch at deferred choices. Similarly, [11] conceptualizes robot movements as a process model and addresses the optimal navigation through the process model. *Scheduling* comprises approaches that schedule the execution of business processes in advance and, in doing so, typically also plan the allocation of resources to tasks. [106,103,96,55,23] focus on instance-level scheduling, i.e., planning the starting times of process instances. While [106] aims to balance the resource workload, [103] aims to maximize the number of instances that can be finished in a given timeframe. The other publications focus on scheduling at task level, i.e., they consider a process model for scheduling the execution of activities and propose either to solve constraint programming (CP) formulations [94,46,13,7], answer set programming (ASP) formulations [37,38,36], or (mixed) integer linear programming ((M)ILP) formulations [34,27,69,8,40]. [86] formulate the scheduling problem as a Markov reward process and propose to find an approximate solution via stochastic approximation methods. [75,69] propose to use metaheuristics, [42,41] multi-agent systems, and [93,19] propose to incrementally build schedules via heuristics. *Resource allocation*: In [31,30,9,73,54], resources are allocated to one specific type of activity. The other publications are concerned with allocating resources to tasks,

i.e., instantiated activities: In [64,108,59,6,45,102,65,107,67,110,111,85,28], allocation decisions are based on the best matching of properties of tasks to resources or resources to previous resources. Similarly, [105,21,109,63] propose allocation heuristics. [26,24] propose approaches to minimize resource conflicts and maximize the active resources. [80] propose an allocation approach based on multi-agent auction. Using reinforcement learning for training allocation policies is proposed in [74,43,73]. Finding the best match among the available resources and unassigned and future tasks by formulating the problem as a minimum-cost maximum-flow problem is presented in [77,54]. [6] propose two resource criteria driven allocation approaches, i.e., immediately allocating a task to the resource with the best resource criteria matching, and allocating a set of tasks (batch) to resources such that the best matching for all tasks is achieved.

3.2 RQ2: Optimization Input

Finding a mathematical model that precisely depicts reality and maintains computational tractability is key to solving an OR problem. In the following, we investigate for which process representations and process perspectives mathematical optimization models are currently obtained that are later solved through various techniques.

Information sources, Workflow Patterns, and Multiple Instances: 53 of the publications formalize the *process model (i)* in an imperative and 3 in a declarative way. 38 publications do not specifically mention the usage of a process model. 13 publications mention an *event log (ii)* as information source and 43 publications describe the discovery of a process model from an event log. 30 publications use/mention both process model and event log as an information source. Assessing the expressive power of the proposed models and associated mathematical formulations is based on selected *workflow patterns (iii)* used in the process models, i.e., sequence, parallel split and synchronization, exclusive split, and merge, as well as deferred choice. Workflow patterns are conceptualized in OR problems in two distinct ways. One option is to formalize them as constraints into mathematical models directly. Solutions are then obtained from the mathematical model by using *analytical optimization* techniques. The sequential pattern, for example, can be formalized as a constraint in a constraint programming formulation such that no activity may be scheduled before its predecessor has been finished. The second approach is to conceptualize workflow patterns in simulation models, where only the simulation model is aware of the workflow constraints. The optimization model itself then learns a policy based on the outputs of the simulation model, e.g., by using reinforcement learning techniques. This approach is known as *simulation optimization* [4]. Of the 56 publications that formalize the control-flow perspective for optimization, 23 use *simulation optimization* techniques, and 33 use *analytical optimization* techniques.

Table 1 summarizes the workflow patterns for the 53 publications using an imperative modeling approach, differentiated by life cycle phases design and enactment. All 53 publications incorporate the sequential pattern in their analytical or simulation models. 44 publications additionally conceptualize and consider information from

	Design	Enactment	Σ
Sequential	15	38	53
AND	12	32	44
XOR	10	11	21
Deferred Choice	1	10	11

Table 1. Workflow patterns

parallel splits and their synchronizations. 21 publications consider exclusive choices and their merges, and 11 publications consider the deferred choice pattern, with a focus on the enactment phase.

Exclusive choices are interesting because, unlike AND-splits, where all subsequent branches are executed, the branch chosen at an exclusive choice can typically not be foreseen during design time or at model instantiation, consequently creating *uncertainty* for OR models. In [98], data-flow analysis is conducted to move decision points to the earliest possible points to reduce the number of possible paths of a process as early as possible. [16] optimize the conditions of exclusive choices themselves to maximize the value contribution of a process. In the context of scheduling and planning, 10 publications conceptualize exclusive choices for the application of *analytical optimization* techniques and 10 for *simulation optimization* techniques. For exclusive choice gateways, analytical approaches most commonly use probabilistic techniques such as transition probabilities to handle individual branches [37,78,38,16,25,9]. [13] schedule the execution of a business process until an exclusive choice is reached. [38] combine the idea of rescheduling and using transition probabilities. They propose considering the most likely branch of an exclusive choice when it exceeds a predefined threshold. In resource planning for emergency processes, the work of [60] considers the worst-case branch for estimating the maximal number of simultaneously required resources. Another non-probabilistic approach is presented in [20]. Under the assumption that resources affect the data perspective of processes, their approach finds associations between resources and the control flow path. Exclusive choices in *simulation models* are considered in the works of [106,63,68,20,30,66,34,15,73,70], but only [30,73,70] describe in detail how they set up their simulation model or provide an artifact.

Another dimension in which the performance of business processes can be improved is through optimization across multiple process instances. A multi-instance view is known in simulation approaches as multi-entity simulation. In process mining, a comparable multi-case approach is rare [71]. 52 publications claim to consider *multiple instances (iv)* for the optimization, but most works do not further describe how information from multiple instances is formalized.

Process Perspectives: A key approach to quantitative business process improvement is to optimize a process not only over the control-flow, but also over other perspectives. Intuitively, the focus is often set on the planning, allocation, and modeling of *resources (v)* that execute process tasks. 78 papers model resources and use them as input to solve their mathematical model. For the 78 publications, we investigate in detail how resources are modeled, including *resource performance indicators (RPI) (vi)*, e.g., execution time. Moreover, we analyze if resources are considered as individual instances or groups, e.g., as (*resource grouping (vii)*), if their availability schedules (*time profiles (viii)*) are modeled, e.g., following a shift plan.

18 of the 78 publications target the optimization of the design phase. A resource is modeled as an individual instance in 6 of these publications. In [68], the difference between modeling resources as individuals and modeling resources as groups is assessed for simulation models and finds that the individual modeling of each resource leads to simulation models closer to actual event logs. In terms of modeling RPIs, 5 publications model multiple RPIs, and 4 publications model a single performance mea-

sure. 9 publications fully disregard the performance of resources. 11 publications, where optimization affects the design phase model resources in a grouped manner, [68] uses a hybrid model. In terms of time profiles, only [5] models a notion of a schedule for the design phase. Here, the waiting times in an emergency department are optimized by improving the overall schedule design.

60 publications consider resources as input for an optimization model to improve the enactment phase of business processes. 24 approaches model a single RPI. The resource performance is fully disregarded in 15 publications. Different modeling approaches for the RPIs are chosen. An advanced modeling is described in [6]. The authors employ the structure of resource process cubes, where each dimension represents one RPI of a resource. These cubes enable the usage of online analytical processing (OLAP) operations to obtain insights into resource performance. When targeting the enactment phase, 45 approaches use individually modeled resources. In 11 publications, resources are pooled, and 4 publications combine individual and pooled modeling. E.g., [36,63] enable an aggregation of RPIs for a group, if not enough information for an individual resource is present. 13 publications model time profiles as part of their resource modeling. Many of those publications are concerned with scheduling, especially in the healthcare domain, e.g. [27,34,19]

The *data perspective (ix)* is (partly) modeled by 28 approaches. [98] models data dependency graphs. In [16], information from the data perspective is used to improve the decision at XOR-Gateways. [38] uses the data perspective to decide if a fragmentation for better allocation should be done at a decision point or not.

3.3 RQ3: Solution Method

Some publications set up a simple formal model on which the application of optimal solution techniques is tractable. Other publications present complex mathematical models to which only approximate solution methods can be applied. Optimal solutions are preferred when the search space is small, mostly due to a small number of input variables from the model or due to a small number of objective variables with a small value range. The first is the case when information is strongly aggregated. [9], for example, use risk and cost information of each task as input for allocating control resources that reduce overall costs, to tasks. The latter is the case when, e.g., only starting times of instances are to be scheduled, instead of scheduling all tasks from all instances [106]. Some publications propose optimal solutions, even when the algorithmic complexity is NP-hard. [37,36] propose to use logic programming and [94] constraint programming to find optimal schedules for imperative process models. Similarly, [13,46] suggest using constraint programming for scheduling on descriptive process models.

Approximate solutions are the preferred solution method when the search space is intractably large or when the problem is subject to uncertainties under which searching for an optimal solution seems to be infeasible. Approximate solutions are especially present in publications that relate to resource allocation and scheduling, resource planning, or process navigation. Linear programming relaxation is used for resource allocation in [24,25]. [102] argue against scheduling allocations in business processes due to the problem complexity and that “various unpredicted factors” can occur during the execution. Therefore they propose to conduct on-the-fly resource allocation by matching

resource properties to task properties. Other approaches propose the use of metaheuristics; [22,75] propose ant-colony optimization for process navigation and scheduling. [31] proposes a genetic algorithm for planning the number of resources for each activity. [16] proposes an evolutionary algorithm to find good conditional values for decision points. Overall, metaheuristic approaches find their solution by using simulation-optimization techniques that require a simulation of the process. However, most approaches do not describe in detail how complex the simulation models become.

Overall, data provided from process models and from event logs is only sparsely used: In particular, fundamental workflow patterns like XOR gateways are often not considered in optimization models or are only abstracted in a very simple fashion. As of today, no publication explicitly aims at scheduling tasks by considering different scenarios that can occur when taking either of the XOR branches. Similarly, no publication addresses that transition probabilities of XOR gateways might change depending on data attributes and leverages this information for further planning. Moreover, resource-related information such as their performances or availabilities is rarely modeled or learned from event logs.

4 Open challenges and research directions

This section discusses research gaps when combining BPM and OR identified by the literature review.

4.1 Targeted BPM life-cycle phase

Challenge: Existing optimization approaches affect either the design or the enactment phase of the BPM life cycle. Some resource planning approaches test if adding a resource enhances the process performance by employing a simulation model that uses an allocation algorithm [5]. However, during enactment, neither the quality of the found plan is determined, nor the simulation model is updated. Future holistic approaches should combine optimizations in the process (re-)design phase, e.g., by providing optimized process models, and the enactment phase, e.g., by providing an optimized process execution.

Research Direction: A holistic approach creates an optimization cycle that covers both the enactment and design phase and serves multiple optimization purposes successfully along the BPM life cycle. This also requires the development of a feedback strategy between the design and enactment phases.

4.2 Process models

Challenge: Information provided by the process model currently finds only limited use for decision making. Especially in the context of resource allocation and scheduling, 38 of 66 publications consider information from process models, but only 17 consider the basic workflow patterns, exclusive choices, and merges. From the 17 publications that consider exclusive choices, 7 conceptualize them in analytical models. Of these, only [37,38] propose to build schedules beyond the points of exclusive choices. However, these schedules are only built when a branch is expected to be selected with a likelihood that

surpasses a predefined threshold. Existing optimization approaches disregard exclusive choices in process models and, hence, the stochasticity of the problem.

Research Direction: Full support of conceptualizing exclusive choices in optimization approaches supports the application of stochastic optimization techniques for an analytical solution approach, e.g., stochastic linear programming. Moreover, simplifying the transfer from process models to optimization models offers the opportunity to embed optimization during process execution.

Challenge: Conceptualizing the control-flow perspective as a simulation model is another approach pursued in some publications that can be used, e.g., for what-if analysis or to find solutions to combinatorial optimization problems via simulation optimization techniques. Most surveyed publications that use simulation models do not describe in detail how a simulation model is built from a process model or an event log. Creating simulation models is generally considered complex and time-consuming [47]. If a simulation model does not depict reality, a solution based on the simulation model will never be applicable in reality. Some approaches circumvent the issue by, e.g., suggesting to replay event logs instead of building complex simulation models [3].

Research Direction: Precise simulation models should be discovered automatically. Recent approaches combine log-replay methods (e.g., [17]) with simulation methods to build hybrid simulation models. This appears to be a promising research direction to ease the simulation model-building process and should be further studied for simulation improvement. Other recent approaches have suggested using event log data to improve the modeling of resources in simulation models, such as capturing the availability of human resources [68]. Further research should additionally focus on process performance aspects, such as learning the processing and waiting times of activities, to simulate more than only control-flow aspects.

4.3 Resource modeling

Challenge: When modeling a resource perspective, existing work mostly relies on data tailored to the specific optimization use case, resulting in a variety of performance data representations. A structure named in multiple works is the resource profile, e.g., [6], but the structure of resource profiles is not clearly defined. A generally agreed-upon resource representation is missing. A common approach to mining and modeling resource data cannot be identified among the publications. Following this, the optimization and simulation approaches become highly specialized to the given problem, and general solutions, which can be easily adapted and reused, are non-existent. Further, current process optimization approaches lack a sophisticated analysis of the interaction between resources, resource and task performance, and, even further, resource and process performance.

Research Direction: A standardized modeling approach for resources, which connects resource data and process execution data, fosters the creation of general optimization and simulation models. Resource performance can be analyzed during process runtime. This could enable on-the-fly optimizations based on resource usage adaptations. Moreover, resource and process performance should be analyzed, mined, and optimized in a combined manner. If BPM wants to become more proactive [81], a more general resource model is needed that is linked to the control-flow to improve forecasting, optimization,

and simulation models. This can enable advanced allocation algorithms from the OR field to outperform reactive approaches.

Challenge: [68] shows that an individual representation of resources can lead to improved resource allocation. Often, data on individual resources is missing, and such an individual consideration of resources becomes impossible. When using a pooled approach, no direct connection of resource performance and process performance is possible and the outcome of optimization approaches suffers.

Research Direction: Hybrid approaches combine individual and pooled resource data to address the challenge of missing data. The pooling of resources can be used to extrapolate missing data. Two existing approaches propose and evaluate a hybrid format between pooled resource representation and individual resource representation [25,63]. A fluid approach between treating resources individually or in a pooled way can address the trade-off between performance and missing data. AI approaches can also support the generation of missing data.

4.4 Solution techniques

Challenge: Current approaches often do not model stochastic properties sufficiently due to two reasons. Firstly, the set of tasks required for finishing a process instance is often assumed to be known upfront. Model-induced uncertainty, e.g., due to exclusive choices, is often not considered. Secondly, task durations are often assumed to be deterministic, and solution methods work only with their expected values. As real-life problems often have stochastic properties and uncertainties, it appears worth exploring the potential for applying stochastic optimization methods. Currently, only approaches that use simulation-optimization (metaheuristic) techniques have considered stochastic task durations. Whether finding optimal solutions, e.g., via stochastic linear programming, can practically be applied is questionable, as incorporating stochastic properties into the problem formulation will likely increase the problem complexity. As, e.g., the benchmarking results from [37] revealed that solving a deterministic scheduling problem for a process instance with 64 activities and 32 resources could already not finish within 2 hours of time, one can expect that for a stochastic formulation only small problem types will be solvable in a feasible amount of time. Recent advancements in deep reinforcement learning have shown remarkable results for different kinds of optimization problems [61]. Future work could explore how deep reinforcement learning approaches can be applied to solve optimization problems in the context of business process management.

Research Direction: Stochastic approaches better represent real-world scenarios, but can often not be solved sufficiently. Deep reinforcement learning can be employed to address this trade-off [61]. Stochastic approaches could also address incorporating uncertainties introduced by XOR-Gateways in process models. Additionally, incorporating information from the process model into *simulation optimization approaches* might help improve their performance.

5 Related work

Multiple surveys have focused on the topic of business process optimization [52,84] taking a specific method from BPM and analyzing how it has been used to improve business processes. This SLR offers a broader scope in terms of optimization techniques since it is not limited to approaches prevalent in the BPM world. By incorporating OR into the research questions, the optimization-driven research area of OR as a whole is analyzed for possible optimization approaches that could advance automated business process optimization in the future. In the following, we discuss further research directions that are related but beyond the scope of this SLR.

Prescriptive Process Monitoring is defined as “*a family of techniques to optimize the performance of a business process by triggering interventions at runtime*” [95]. [52] find that prescriptions can i.a. refer to the resource perspective, e.g., which resource to choose from the pool of possible resources to execute a task. In contrast to our work, [52] focus on optimization during process enactment, but not during design. Further, the focus is on the BPM field and does not consider the combination with OR optimization approaches.

Resource allocation strategies for business processes during the enactment phase have been surveyed in [84]. The strict focus on resource allocation emphasizes the importance of resources for business process optimization. Yet, important factors for resource allocation, such as the modeling of resources, have been excluded. In contrast, this SLR investigates how multiple different optimization approaches can contribute to quantitative business process improvement and provides insights on typical solution methods.

6 Conclusion, Discussion, and Outlook

This SLR aims at providing a holistic picture of the current state of research in process optimization at the intersection of BPM and OR. We examined the targeted life-cycle phase of optimization approaches in existing literature (**RQ1**), how the control-flow, resource and data perspective of business process models and event logs have been conceptualized as mathematical models (**RQ2**), and which solution techniques have been applied for finding optimal or near-optimal solutions (**RQ3**). **RQ1**: Existing works address optimization problems in either the design or enactment phase, with the majority addressing the enactment phase and, in particular, resource allocation and scheduling problems. No approach has yet investigated a holistic approach concerned with both phases, mutual goals of both phases or carrying information from one phase over into the optimization of the other. Furthermore, most works focus on a single optimization objective. Future work should consider multi-objective optimization with interaction among all life-cycle phases. **RQ2**: Important information from process models or event logs is often disregarded when constructing an optimization model. Results show that in the control flow perspective, most works do not consider complex workflow patterns, such as the exclusive choice pattern. From the resource perspective, information on the effect of resources on the execution performance of tasks or processes is often missing. While the event log is mainly used to structure control-flow data, no such consensus is

found for the resource and data perspective. To combine several perspectives into one model a standardized data structure would be helpful. **RQ3:** Optimization techniques strongly depend on their mathematical model. As many approaches set up simplified mathematical models, optimal solution techniques have been widely used. However, as simple models often neglect implications from the control flow, resource, and data perspective, solving larger, more holistic models with optimal algorithms is infeasible.

Discussion and Limitations: First, BPM and OR are both broad fields with rather specific terms that were not explicitly part of the search strings. [57], for example, list the top 40 keywords used in the European Journal of Operations Research. However, as using all keywords was not feasible for this research, this study is limited to a subset that the authors deemed most relevant. Further, the nomenclature between the two fields differs. We addressed this by identifying and including interchangeable terms in the search strings (see Sect. 2). Secondly, optimization approaches from cloud computing might be applicable to business process management. However, due to the size of the research field and the potential bias that could be introduced by that, the authors decided to exclude the field.

This SLR shows that a better specification of the interface between OR and BPM is required. Since many optimization approaches focus on allocating processes and process tasks over resources, a more general representation of resources, their availabilities, and performance implications is required from BPM. The same accounts for the data perspective. Future optimization approaches should focus on developing solution techniques that can better handle the complexity represented in process models and stochasticity created during process execution. Even if an optimal solution can not be found for these more complex models, a better representation of real-world use cases can be achieved.

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