Bus Inf Syst Eng
https://doi.org/10.1007/s12599-024-00888-1

RESEARCH PAPER

Watt's Next? Leveraging Process Flexibility for Power Cost Optimization

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Received: 27 October 2023 / Accepted: 4 July 2024
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Abstract The transition from fossil fuels to renewable energy sources poses major challenges for balancing increasingly weather-dependent power supply and demand. Although demand-side energy flexibility, offered particularly by industrial companies, is seen as a promising and necessary approach to address these challenges and realize benefits for companies, its implementation is not yet common practice. Often facing highly complex process landscapes and operational systems, process mining provides significant potential to increase transparency of actual process flows and to discover or reflect existing dependencies and interrelationships of activities, instances or resources. It facilitates the implementation of energy flexibility measures and enables the realization of monetary benefits associated with flexible process operation. This paper contributes to the successful integration of energy flexibility into process operations by presenting a design science research artifact called PM4Flex. This is a prescriptive process monitoring approach that uses linear programming to generate recommendations for pending process flows optimized under fluctuating power prices by utilizing established energy flexibility measures. Thereby, event logs and corresponding company- as well as process-specific constraints are considered. PM4Flex is demonstrated and evaluated based on its implementation as a software prototype, its application to exemplary data from two real-world processes exhibiting power cost savings of up to 75% compared to the original execution, and based on semi-structured expert interviews. PM4Flex provides new design knowledge at the interface of prescriptive process monitoring and the energy domain providing decision support to optimize industrial energy procurement costs.

Keywords Process mining · Prescriptive process monitoring · Energy flexibility · Demand side management

Accepted after two revisions by the editors of the Special Issue.

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1 Introduction

Today, the world faces multiple crises, including wars, pandemics, and climate change (Kreuzer et al. 2020; Gross et al. 2021). Climate change is often considered one of the greatest challenges due to its far-reaching negative impacts (Hitz and Smith 2004; Tol 2018). A major and indispensable lever for reducing emissions is rapidly restructuring the energy system by simultaneously expanding renewable energy sources and phasing out conventional power plants (Heffron et al. 2020; Tristán et al. 2020). However,

Published online: 14 August 2024

renewable energy sources substantially increase the volatility of power generation and corresponding power prices. Such volatility causes continuously changing market and system conditions, e.g., intraday power price differences have risen to 250 €/MWh in Germany in 2022 (gridX 2023). Two main challenges arise: First, system operators must constantly balance volatile generation and demand to ensure grid stability for reliable power supply (Mohler and Sowder 2017). Second, especially energy intensive companies (Bank et al. 2021) must manage their power procurement and demand actively to stay competitive (Sauer et al. 2019). The incorporation of energy flexibility, i.e., the ability to adjust energy consumption in response to an external (price) signal (Eurelectric 2014), into the management and execution of (power-consuming) processes enables exploiting temporally changing power prices, limiting the exposure to power price volatility (Asadinejad and Tomsovic 2017). From a system's perspective, the collective adoption of demand-sided energy flexibility yields a faster and less costly transition from a carbon-intensive towards a renewable and carbon neutral power sector.

In many countries, industrial companies account for a substantial share of energy consumption (Heffron et al. 2020). Especially short-term demand adaptations are already relevant today to compensate for short-term power supply fluctuations (Sauer et al. 2019). Considering substantial savings potential and additional added revenues from energy flexibility marketing, decreasing energy procurement costs through active and continuous control of processes is a big lever for competitiveness (Eurelectric 2014; Heffron et al. 2020; Leinauer et al. 2022). It is already exploited by some energy-intensive companies (Alcázar-Ortega et al. 2015; Sauer et al. 2019) who have implemented energy flexibility measures to improve power cost efficient process scheduling and execution. However, due to lacking insights into revenues or cost savings associated with demand energy flexibility (Alcázar-Ortega et al. 2015; Leinauer et al. 2022; Rusche et al. 2023), most organizations have not yet recognized, let alone exploited, their energy flexibility potential (Schott et al. 2019). Many fear implementing respective energy flexibility measures deteriorates both product quality and production flow (Leinauer et al. 2022). Considering detailed process specifics in process control is vital to reach desired process outcomes and process quality as both can only be ensured if process execution adheres to essential control flow dependencies (Dumas 2008). Such specifics may relate to, e.g., cooling periods of welded metal before putting it into flammable packaging. Their detailed consideration in process planning significantly determines whether companies are actually willing to implement energy flexibility in practice. Thus, to ensure smoothly running processes despite implementing energy flexibility measures, basing decisions on process analyses alongside relevant data, e.g., power prices, is not only reasonable but of utmost relevance. Yet, although standardized instruments assisting companies in flexibilizing their power demand are much needed, there is a lack of decision support for exploiting process-inherent energy flexibility potential considering detailed process-specific characteristics and constraints. Considering these specifics is vital to maintain and facilitate the desired process outcomes and process quality that can only be ensured if process execution adheres to essential process and control flow dependencies (Dumas 2008).

Process mining techniques provide a valuable starting point for data-driven decision-making during process execution (Badakhshan et al. 2022). Building on historic process data, process mining can be utilized for both backward-looking (e.g., discovery and analysis) and forward-looking insights (e.g., predictions and recommendations) (Park et al. 2023). Especially the latter is relevant for prescriptive process monitoring (PPM), which bundles process mining methods that compile recommendations for subsequent process flows (Bozorgi et al. 2021; Kubrak et al. 2022). As PPM aims to trigger interventions at runtime (Kubrak et al. 2022; Shoush and Dumas 2022a), PPM methods can mitigate exogenous dynamics by providing recommendations, supporting data-driven business process management (BPM). It is worthwhile to investigate PPM in the context of energy flexibility potential (Kubrak et al. 2022).

To the best of our knowledge, there is currently no adequate PPM approach utilizing sufficiently detailed process data and corresponding planning constraints in the energy domain (Eili et al. 2021). On the energy side, most optimizing approaches are either too simplified (Zhou and Li 2013; Sun and Li 2014; Schultz et al. 2015; Beier et al. 2017; Lu et al. 2020) or too specific (Tan et al. 2017; Ramin et al. 2018) to allow for successful real-life application. A gap remains for cost optimizing, multi-activity recommendations using both detailed process execution data and external forecasted data that trigger the review of generated recommendations. To address this gap, it is worthwhile looking at the interface of PPM and energy flexibility measures to optimize processes to stay competitive despite volatile power prices, thereby supporting sustainable energy consumption. Thus, enhancing energy flexibility-oriented scheduling of processes, we address the following research question: *How can process mining be leveraged in a PPM approach to exploit energy flexibility potentials?*

To answer this question, we enhance PM4Flex (Hermann et al. 2023). PM4Flex provides a real-time, power-cost minimizing recommendation for process execution by implementing energy flexibility measures based on event logs enriched with power consumption data and power price forecasts from the spot market. It is especially useful for energy intensive processes, e.g., metal pipe or paper production, as it promises great savings potentials when energy is consumed in relatively cheap periods. We extend the PPM approach based on mixed integer linear programming to recommend a processing schedule for pending activities within a given period. Major advancements are the automation level, the artifact's efficiency, the considered process attributes, and its ability to work in dynamic environments. These changes enable a more responsive artifact than Hermann et al. (2023), increasing the suitability for highly volatile energy price environments and benefitting the target users by decreasing the need for manual input and computation times. To advance Hermann et al. (2023) we followed the design science research (DSR) methodology of Peffers et al. (2007). Thereby, we extend existing PPM approaches with an optimization model generating multi-activity recommendations to tackle a major demand-side challenge in the energy system: adapting processes to volatile power prices.

The remainder of this paper is structured as follows. In Sect. 2, we provide theoretical background on energy flexibility and PPM and present related work. We explain our research method in Sect. 3. Next, we present our artifact in Sect. 4, report on our evaluation in Sect. 5, and discuss our findings, contribution, limitations, and future research in Sect. 6. We conclude our paper in Sect. 7.

2 Literature Review

2.1 Energy Flexibility

The dependence of renewable energy sources on the weather induces volatility in power generation, addressable by energy flexibility (Heffron et al. 2020). The gap between decreasing supply-side energy flexibility and increasing levels of volatile renewable energy sources is described by the 'flexibility gap' (Papaefthymiou et al. 2014, 2018). This disparity challenges grid stability and supply security (Sauer et al. 2019). To close it, five main options have been identified (Table 1) (Heffron et al. 2020; Tristán et al. 2020). Due to high costs for energy storage, slow progress on inter-sectoral flexibility, and lacking acceptance of grid expansion, demand-side energy flexibility is very promising to address the flexibility gap (Heffron et al. 2020).

Demand-side energy flexibility describes the ability of an energy-consuming system to modify its energy consumption in response to an external trigger (Eurelectric 2014; Tristán et al. 2020). For corporate energy flexibility, the energy-consuming system is an operational system capable of cost-effectively adapting to power market signals or the variable supply of self-generated power in a short period (Tristán et al. 2020). In light of dynamic pricing based on the current demand–supply situation, the ability to adjust power consumption is decisive to maintain competitiveness (Dutta and Mitra 2017).

There are two main options for marketing and economically exploiting demand-side energy flexibility in liberalized energy markets (Buhl et al. 2019): On the one hand, companies can market their energy flexibility on energy-only-markets, especially spot markets, to monetize it (Bachmann et al. 2021). European spot markets, i.e., day-ahead and intraday markets, are staggered and differ regarding trading period and the length of traded power products (Pape et al. 2016). Both spot markets enable short-term trading of power products and a flexible adjustment of power demand through energy flexibility (Bachmann et al. 2021). On the other hand, energy flexibility can be capitalized as system services, e.g. control reserve, on balancing energy markets (Buhl et al. 2019). Here, the provision and implementation of load increase and reduction measures are auctioned as balancing power (Müsgens et al. 2014).

The energy flexibility potential of a company can be realized by implementing energy flexibility measures, which represent intentional actions to perform a specific change of state in the operating system to provide energy flexibility (VDI 2020). A change of state can involve

Table 1 Flexibility options, according to Heffron et al. (2020)

Flexibility option	Description
Supply-side flexibility	Adjustment of power output of plants
Storage flexibility	Shifting power supply or demand through time
Transmission flexibility	Power transport to balance local discrepancies of supply and demand
Demand-side flexibility	Temporal and spatial adjustment of power demand
Inter-sectoral flexibility	Interconnection and exchange of power and other sector's energy carriers, e.g., gas, heat, and mobility

resources and process instances. It considers the related reciprocal effects in the operating system, e.g., interrupting an order impacts the possibility of adjusting resource allocation given that the current resource is occupied longer (VDI 2020). The Association of German Engineers (VDI) has identified a set of 16 distinct energy flexibility measures for production systems that can be structured along a temporal and an organizational axis. They distinguish corporate management for the medium term, production control for the short term, and manufacturing for real-time energy flexibility measures. Medium term energy flexibility measures include the adaptation of staff free time, working shifts, and order of execution sequence, deferral of production start, and capacity planning adjustment. Interrupting the manufacturing order, adapting the order of production sequence or resource allocation, deferring the order start, as well as dedicating the energy storage and energy carrier exchange are energy flexibility measures for the short term. Real-time energy flexibility measures include operation interruption, adjustment of operational sequence, adaptation of operation parameters, bivalent operation, and inherent energy storage.

2.2 Process Dynamics and Prescriptive Process Monitoring

Business processes are vital for organizations to accomplish work (Badakhshan et al. 2022). Processes are linked by temporal and logical dependencies that must not be violated to ensure the desired output and quality (Dumas 2008). Yet, the dynamics organizations face increase process complexity (Dumas 2008), complicating effective and efficient process execution. To handle this complexity, flexibility, i.e., the ability to adapt processes to dynamically changing circumstances, is a key concern for BPM (van der Aalst 2013) and one of the four traditional process performance dimensions in the devil's quadrangle among cost, time, and quality that must be considered for process design, adjustment, and execution (van Looy and Shafagatova 2016; Dumas et al. 2018). Hence, organizations need a profound set of dynamic capabilities that enable low-cost and high-flexibility adaptations (Teece et al. 1997). These dynamic capabilities are in line with the inherent dynamics of processes as depicted in the BPM lifecycle. According to van der Aalst (2013), the three iterative phases of the lifecycle are (re)designing, implementing, and running or adjusting business processes. The latter is supported by data-based analysis (van der Aalst 2013). Process mining provides techniques that support these analyses to make evidence-based decisions by analyzing process execution data on an instance level (van der Aalst et al. 2012). Within the scope of process mining are both predictive analyses and PPM (Kubrak et al. 2022).

PPM enables process optimization during runtime by prescribing certain actions, aiming at optimizing both outcome and efficiency (Fahrenkrog-Petersen et al. 2019; Kubrak et al. 2022). PPM approaches are sorted into the run and adjust phase of the BPM lifecycle (van der Aalst 2013), leveraging run time flexibility (van der Aalst 2011) and dynamically supporting process adjustments (Weinzierl et al. 2020b; Kubrak et al. 2022; Shoush and Dumas 2022a). They support flexibility by deviation, i.e., executing a process differently than designed without changing the process definition itself (van der Aalst 2013). Mainly, PPM provides recommendations as interventions triggered by an incident presumably impacting the process outcome negatively (Teinemaa et al. 2018; Fahrenkrog-Petersen et al. 2019; Weinzierl et al. 2020b; Kubrak et al. 2022; Shoush and Dumas 2022a). These interventions commonly pertain a control flow or resource perspective, e.g., prescribing the next activity or resource allocation, often optimizing time or cost performance (Kubrak et al. 2022).

In view of the accelerating environmental crises and the increasing awareness of organizations' impact on the environment, ecological sustainability has become an additional imperative for executing and adjusting processes (Couckuyt and van Looy 2020). Consequently, within the research area of Green BPM, sustainability as a process objective complements the so far purely economic focus of the devil's quadrangle as a fifth performance dimension (Seidel et al. 2012). This results in the devil's pentagon consisting of time, cost, quality, flexibility, and sustainability, additionally capturing environmental performance objectives such as minimizing energy consumption or reducing the carbon footprint (Seidel et al. 2012). This perspective helps to design, implement, and execute more sustainable business processes (Seidel et al. 2012), for instance, through PPM. While the minimization of related electricity costs as a process objective appears to primarily address the cost dimension at first glance, such a strategy simultaneously favors the (ecological) sustainability dimension of the devil's pentagon due to low marginal costs of renewable (and carbon–neutral) energy sources.

2.3 Related Work

Research in PPM so far mainly focuses on questions of when and for which instances interventions can be applied rather than on the choice of interventions (Kubrak et al. 2022). PPM is mainly used to optimize time-related key performance indicators and not to optimize energy consumption or cost (Kubrak et al. 2022). Recommendations are based on similarity metrics (Triki et al. 2013; Schobel and Reichert 2017; Yang et al. 2017), economic key performance indicators (van der Aalst et al. 2010; Barba et al. 2012; Petrusel and Stanciu 2012; Terragni and Hassani

2018), predictions (Conforti et al. 2015; Dees et al. 2019; Weinzierl et al. 2020a), and combinations of these aspects (Schonenberg et al. 2008; Dorn et al. 2010; Weinzierl et al. 2020b). Mostly, only the next action is recommended (Eili et al. 2021), not the complete subsequent process like in Yang et al. (2017). Only few papers consider temporal dependencies or other restrictions (Dorn et al. 2010; Barba et al. 2012) or revise recommendations (Barba et al. 2012; Petrusel and Stanciu 2012). Previous PPM approaches mostly rely on historic process data, disregarding predictive data on future developments (Kubrak et al. 2022).

From a Green BPM perspective, most PPM approaches do not operationalize sustainability as an explicit process objective in the devil's pentagon. Instead, they largely focus on purely economic objectives (Kubrak et al. 2022), even though it is meaningful to combine them with sustainability (Brooks et al. 2012). Approaches optimizing processes from an economic perspective can still support overarching sustainability efforts when applied in suitable use cases. For example, a cost-optimizing approach can support more sustainable energy consumption when considering renewable energy consumption (Seidel et al. 2012). In this context, among the few initial approaches considering energy flexibility measures and carbon-aware process execution are the works of Hehnle et al. (2024) and Hermann et al. (2023). However, Hehnle et al. (2024) present an approach to postpone energy intensive activities to time windows where green energy is available. They cover only one energy flexibility measure and optimize for carbon emissions, not considering trade-offs from a cost, time, or quality perspective in the objective function (apart from temporal service level agreements). Hermann et al. (2023) consider more energy flexibility measures and cost factors, still exhibiting various shortcomings, e.g., the level of automation, efficiency, considered cost, resource capacity, and handling dynamic environments.

Prevailing literature from the energy domain knows a large variety of planning and scheduling models for industrial energy flexibility (Zhang and Grossmann 2016b, 2016a). A wide range of underlying design alternatives is covered, reaching from stochastic programming (Mitra et al. 2014b, 2014a; Zhang et al. 2016) to multi-agent deep reinforcement learning (Lu et al. 2020). However, most existing approaches for short-term or real-time planning either flexibilize processes on highly simplified production systems, neglecting important characteristics of real-world processes (Zhou and Li 2013; Sun and Li 2014; Schultz et al. 2015; Beier et al. 2017; Lu et al. 2020), or are tailored to specific applications (Tan et al. 2017; Ramin et al. 2018). Those approaches are limited in their general applicability and transferability to varying processes and applications. Further, power price developments are not always a crucial factor for load control (Schultz 2018; Nayak et al. 2019). Research has focused on some of the most power-intensive production practices like aluminum and steel production, air compression, or electrolysis (Zhang and Grossmann 2016b, 2016a; Sauer et al. 2019). Existing approaches regard only a limited selection of energy flexibility measures, mostly (partial) shutdowns of machines, disregarding energy flexibility potential beyond that (Schultz et al. 2015). An exception is the approach of Bank et al. (2021) that cost-efficiently integrates discrete energy flexibility measures into pre-optimized production plans based on a generic data model for industrial energy flexibility (Schott et al. 2019). As this approach requires the identification and characterization of prevailing flexibilities (Schott et al. 2019) in the course of flexibility audits, conducting time- and cost-intensive analysis and evaluation procedures is mostly inevitable (Tristán et al. 2020; Bank et al. 2021; Rusche et al. 2023), still necessitating methods with low usage barriers. Especially the diverse spectrum of industrial processes not addressed by tailored approaches, without exceptionally high yet still significant energy consumption, lacks transferable and (investment) cost effective methods to utilize inherent energy flexibility potential. This goes hand in hand with the largely untapped potential of process mining to uncover previously hidden opportunities for improvement (Dreher et al. 2021).

3 Method

In our research, we followed the DSR methodology by Peffers et al. (2007) (Fig. 1). Our artifact is a PPM approach for process scheduling optimized for power procurement costs which support flexibility in the context of a more sustainable energy mix. Our approach primarily addresses 'cost' within the devil's pentagon while contributing to improved sustainability, as spot market electricity prices are positively correlated with associated emission factors (Förster et al. 2023). This shows that operations at low cost can be achieved simultaneously with low greenhouse gas emissions (Förster et al. 2023). The artifact is classified as a method offering guidance on rescheduling (March and Smith 1995; Hevner et al. 2004; Hevner and Chatterjee 2010). We report on our realization of the six DSR steps below.

3.1 Problem Space

We ground our research in the problem space defined according to (Herwix and Haj-Bolouri 2021). The scope of our targeted problem is global, because combating climate change and managing the respective changes in the energy system is a global matter. The problem situation must be

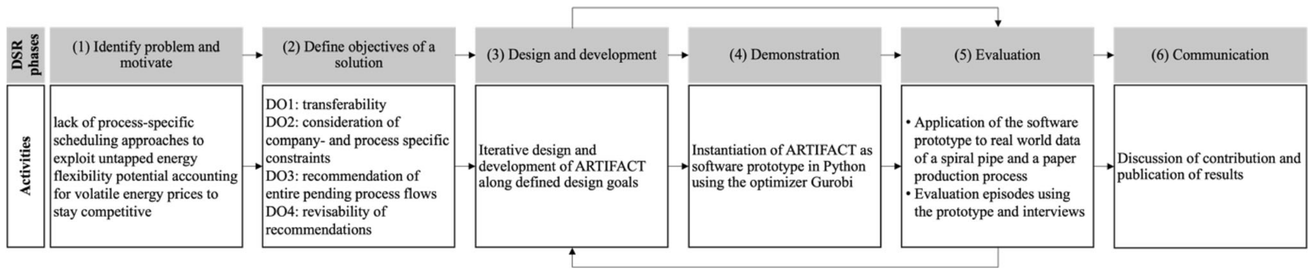

Fig. 1 Research design

tackled both from an academic and a practitioner perspective. We defined the problem by *needs, goals,* and *requirements* dependent on the respective stakeholders (Maedche et al. 2019): Regarding *needs*, the stakeholders are mainly companies requiring considerable amounts of energy to provide their products and services. They face the need of both minimizing their energy costs and their susceptibility to volatile energy prices while maintaining their usual quality by complying to complex constraints and interdependencies in their production processes. This emphasizes that our work addresses a (complex and relevant) problem faced by practitioners as demanded by DSR (Peffers et al. 2007). Existing approaches in PPM and production planning with energy flexibility being reinforcement learning based cannot be applied (Branchi et al. 2022; Donadello et al. 2023; Lu et al. 2020): Besides the inherent limitations of self-reinforcing learning, e.g., inability to guarantee quality of strategies and low sampling efficiency, aiming at recommending entire process flows leads to an extraordinarily large action space (Bozorgi et al. 2023; Branchi et al. 2022; Kotsias et al. 2023) and restrictions of varying complexity are difficult to capture in a loss function without information loss. Addressing the described needs of our target stakeholders, the *goal* is to maintain competitive prices of their products and services while maintaining or increasing process quality. The corresponding design objectives (DOs) as our *requirements* are detailed in Sect. 8. Boundaries of the problem are given by the focus on power instead of various forms of energy and the goal to provide recommendations instead of directly implementing changes.

3.2 Definition of Design Objectives

To define a possible solution (2), we refined the DOs presented in Hermann et al. (2023). DOs are derived from the defined problem and represent requirements for a possible solution (Peffers et al. 2007). The DOs are derived from a criteria-based analysis of existing approaches in energy flexibility and PPM. On the energy side, we searched for implemented rescheduling approaches based on energy flexibility. On the PPM side, we searched for applications in the energy domain and respective approaches. We defined four DOs covering the main gaps in the current literature and present them in Sect. 4.1.

3.3 Design and Development of PM4Flex

For design and development (3), we combined approaches commonly used in operations research, energy flexibility, and PPM, to construct use-case specific methods from existing method components (Harmsen 1997; Henderson-Sellers and Ralyté 2010). Design and development were conducted in three iterations (see Table 2). We refined the optimization model presented in Hermann et al. (2023) based on refined DOs and shortcomings of PM4Flex (Hermann et al. 2023). In each iteration, the design goal was implemented in a prototype after an in-depth analysis of its suitable translation into mathematical terms, evaluated with our real-world data sets, and design knowledge was derived. To evaluate the result of each iteration and identify the design goal for the next iteration, we applied logical reasoning and benchmarking (Sonnenberg and vom Brocke 2012) towards outcomes of prior iterations and the DOs.

In the first iteration, we aimed to instantiate an initial prototype that creates feasible process flows minimizing electricity costs within the scope of considered aspects and constraints, i.e. the artifact should embody the intended functionality. The outcome was the artifact presented in Hermann et al. (2023). While we pursued feasibility in iteration 1, we recognized inefficiencies in the chosen implementation approach. Thus, in iteration 2, we turned to the efficiency-oriented revision of the artifact, reducing the number of decision variables and constraints in the optimization model and increasing the share of parameters automatically derived from the event log. Further, in view of the first two episodes' results as well as the available data sets, we observed that we considered some aspects of processes in a highly simplified manner, e.g., the volumes of process instances and resource capacities and the costs caused by process interruptions or delays. In a third iteration, we advanced the artifact with the goal of more detailed and realistic modeling, resulting in adapting the

Table 2 Overview of our design iterations and resulting design knowledge

Iteration – design goal	*Changes*	*Evaluation results*	*Design knowledge*
01 – feasible solution	- Choice of energy flexibility measures -Mathematical formulation of optimization model -Implementation of optimization in Python	- Optimization model including six selected energy flexibility measures can be implemented and solved -Reasonable recommendations are generated	- Optimization models can be used for PPM -Energy flexibility measures can reasonably be integrated in process planning
02 – efficient computation	- Increased automation rate -More efficient structure of the linear program due to more effective pre-processing	Computation time decreases considerably	For efficient computation times, preprocessing and structure of optimization model must be chosen such that the number of decision variables and manually set parameters is minimized
03 – realistic representation	- Instance specific volumes -Additional costs	- Maximum completion time increases -Power procurement cost increases	Additional constraints worsen the results. Hence, the restrictions and included criteria should be limited to the essential ones
04 – dynamic adjustment	- Possibility to operate in dynamic environment -Use price forecasts on top of historic prices -Fixed observation horizon	- Computation time increases slightly -Maximum completion time decreases -Power procurement costs decrease	Even though dynamic environments cause higher computation times, they enable lower costs and completion times than static environments

optimization model and extending the event log exploration to newly added parameters. One aspect emphasized both in our own critical review and in the discussion of Hermann et al. (2023) is the adaptivity to changing electricity price forecasts. Hence, we initiated iteration 4 to enable the artifact to deal with dynamic external parameters, such as electricity price forecasts, and to react adequately to changes. This iteration is mainly reflected in changes of our artifact's deployment in the simulated environment used for evaluation episodes 2 and 3.

3.4 Demonstration and Evaluation

Aiming at demonstrating the functionality of PM4Flex (4), we implemented a Python software prototype as an instantiation (Sonnenberg and vom Brocke 2012). We deployed the prototype in an artificially constructed setting for two case examples based on real-world process data of two industrial manufacturing processes. Additionally, we included day-ahead power price forecasts used in the industry. These data sets are utilized for the demonstration of the artifact's functionality as well as for conducting the evaluation, especially evaluation episodes 2 and 3, as described below.

Our evaluation (5) follows the FEDS framework (Venable et al. 2016). First, we explained the evaluation goal as demonstrating the efficacy and ensuring the rigor of our instantiation. Second, we selected the technical risk & efficacy strategy (Venable et al. 2016), as the main design risk of our artifact is technical rather than social and a first artificial evaluation is advisable to avoid the risk of negatively influencing processes in a real-life setting. Third, we defined evaluation properties and criteria: approach-specific metrics such as power cost savings, our DOs (Peffers et al. 2007), and the well-established criteria for methods and instantiations: generality, operationality, efficiency, effectiveness, and usefulness (March and Smith 1995; Peffers et al. 2007; Sonnenberg and vom Brocke 2012).

Along the technical risk & efficacy evaluation strategy, we conducted four evaluation episodes on the final artifact after completing all four design iterations—an *ex-ante* episode prior to implementation and three *ex-post* episodes with the implemented artifact. The first is artificial as it evaluates if the designed artifact fulfills the DOs. It is formative since it is instrumental in ensuring high quality of the research outcome. The evaluated artifact regarding the DOs as the pivotal output of episode 1 is the input to the following evaluation episodes (Peffers et al. 2007). In episodes 2 and 3, we deployed the constructed artifact to one case example each. Each of these examples consists of an excerpt from a historic event log of a production process and associated energy and order data from a real manufacturing company. Because our prototype is used in isolated simulation environments that adapt to updates in power price forecasts, these episodes are also artificial. As we investigate to what extent the results of the artifact application match the expectations, it is summative.

In episode 4, we conducted eleven semi-structured expert interviews (Sonnenberg and vom Brocke 2012) in the energy and manufacturing domain, including experts from academia, consultancy, and manufacturing companies (Appendix A). Within their respective roles, they have gained expertise in both production processes and the energy domain, which is required domain knowledge for our artifact. This enables them to take ownership and guide the introduction and implementation of such a system in respective production processes. Interviewees 5, 8, 9, and 11 are representatives from the companies that provided the data for evaluation episodes 2 and 3. Reviewing the results, they could judge from experience whether PM4Flex can be operationalized at a reasonable effort for their company for the two processes we applied it to. Hence, they had the knowledge to judge whether the results were sufficiently efficient and effective to justify PM4Flex's usage. Interviewee 4 works in a company with energy intensive processes and evaluated the transferability of the approach to their processes in addition to the evaluations of the processes we have applied PM4Flex to. Interviewees 1, 2, 7 and 10 are researchers in the domain of energy-oriented production and manufacturing and evaluated whether the approach outperforms currently existing approaches with respect to the evaluation criteria. All of them were and are actively involved in a large, publicly funded research project investigating the adaptation of energy intensive production processes to a fluctuating power supply in practice. Hence, they understand the prevailing conditions, are experienced in the implementation of flexibilization approaches in practice and have sufficient knowledge in multiple production processes to transfer their experience to the evaluation of PM4Flex. Interviewees 3 and 6 have experience in energy consulting from an overarching perspective. Thus, they focused on evaluating the artifact's generality in addition to providing input from their experience with multiple energy-related processes. Hence, we consider all interviewees suitable, experienced interview partners.

We started the interviews with a brief introduction and explained the interview process. Then, we explained PM4Flex based on a simplified example of a production process. We focused on the artifact's general design and structure (Fig. 2) as well as notable restrictions of the optimization model (Sect. 4.4). Next, we asked several questions per evaluation criterion and DO (interview guideline see Appendix B). We focused on collecting qualitative answers to gain the richest insights possible and only complemented them with quantifiable results through answers on a 5-point Likert scale since we had too few interviewees for a large-scale quantitative evaluation. Regarding Interviewees 5, 8, 9, and 11, whose company data was used, we asked additional questions about the validity of the production schedule that PM4Flex recommends, evaluating whether the results are reasonably feasible and add value in practice. The results are displayed in Sect. 5.3.

4 PM4Flex Design Specification

4.1 Definition of Objectives and General Concept

The DOs characterize an artifact that supports companies in handling exogenous uncertainty through power price volatility. Based on literature, we tailored the DOs for PPM approaches for energy flexibility optimization by Hermann et al. (2023) to a more energy-focused context:

DO1: A PPM approach for energy flexibility optimization should be transferable to complex, flexible processes with an inherent energy flexibility potential (Beier et al. 2017; Lu et al. 2020).

DO2: A PPM approach for energy flexibility optimization should allow for company- and process-specific constraints (Bahmani et al. 2022), especially restrictions regarding time, energy, resources, cost, and sequence of activities. Thus, a user-defined policy should be used for energy flexibility given the circumstances of the respective company and process (Kubrak et al. 2022), especially regarding power consumption and feasibility.

DO3: A PPM approach for energy flexibility optimization should recommend entire pending process flows instead of focusing on isolated activities due to interdependencies (Bahmani et al. 2022). The recommendations should include time of execution as well as resource allocation and must ensure energy cost minimization over the whole process and not just for a single activity postponing cost to later activities.

DO4: A PPM approach for energy flexibility optimization should be able to revise recommendations when circumstances that influence energy intensive processes change. For example, an external signal like new energy price forecasts or just started process instances trigger the artifact.

DO1 accounts for the fact that processes are subject to a fast-changing environment and, thus, need to be flexible themselves. Hence, the opportunity to still handle processes when they must be adjusted to changed circumstances is crucial. To stay competitive, one has to adapt to the volatile environment within set boundaries of a company, ensured by DO2. By providing multi-activity recommendations (DO3), we reduce future planning uncertainty despite the dynamic changes, making sure that quality does not suffer from rushed decisions. Recommending whole process flows is required to account for cross-instance dependencies and constraints, e.g. multiple

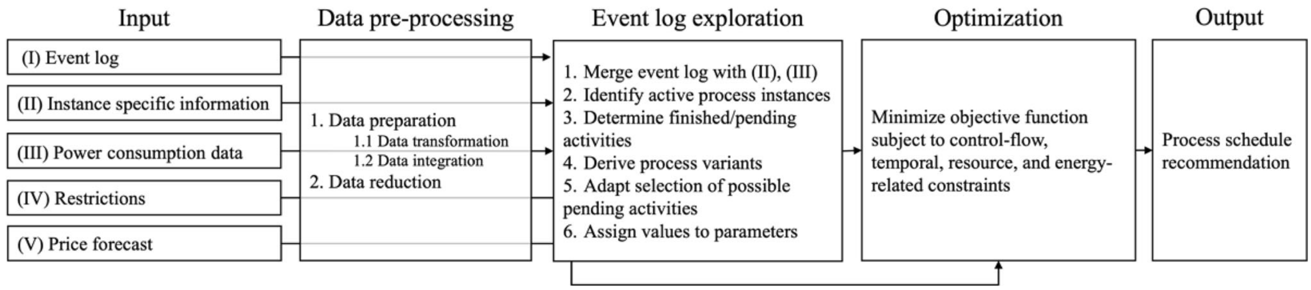

Fig. 2 Structure of the PM4Flex approach

instances can be processed simultaneously and influence the processing of other instances. DO4 accounts for the fact that price forecasts can reduce uncertainty but are still subject to volatile energy markets. To continuously adhere to the dynamics without prolonging process executions or increasing costs, the recommendations are revisable quickly.

Regarding the general concept, PM4Flex generates multi-activity scheduling recommendations for pending process flows of active process instances, thereby optimizing the power procurement cost based on the load profile of potential following process flows and a power price forecast (Aggarwal 2016). The optimization run is triggered whenever changes in the environment are observed, i.e., a new power price forecast is available, or a new process instance is created in the system.

The approach is subject to several prerequisites: The process must inhere a utilizable level of flexibility. The process activities must not be fixed immutably in time and order but must be reschedulable within a short time horizon. This is required since we use power price forecasts for the spot market where ordering times are usually between one day (day-ahead) and 15 min (intraday). To enable the completion of all activities until their respective due dates, their duration should be shorter than the time horizon of the forecast. As we consider short-term energy flexible planning and real-time process monitoring, PM4Flex only incorporates six energy flexibility measures that can be effectively deployed in the short term: interruption of activity, adjustment of activity sequence, interruption of instance, adjustment of instance sequence, deferral of instance starts, and adjustment of resource (Tristán et al. 2020; VDI 2020).

Our artifact keeps usage barriers low compared to, e.g., a machine learning approach. Thus, an extensive data basis is no prerequisite. Additionally, we chose an optimization model over a black box approach to generate replicable recommendations with higher user trust (Gunning et al. 2019) and account for the deficiencies of other approaches explained in 3.1.

We enhanced the previous version of PM4Flex (Hermann et al. 2023) as follows: we refined the pre-processing by deriving more parameters directly from the event log. We increased the efficiency of the artifact to reduce computation times by adapting the data structure and optimization model and shortening the observation period. Extra costs for missed deadlines or operation interruptions and instance-specific volumes that account for resource capacity are additionally included. Handling dynamic environments like periodically changing price forecasts is also enabled. In the following subsections, we describe the components of our approach summarized in Fig. 2.

For explanatory purposes, we will use the assembly process of a spiral pipe (Fig. 3) throughout this paper which is also used in the real-world evaluation episode 2. This process is especially energy intensive due to the processing of metal which makes it a suitable use case for our approach.

4.2 Input and Data Pre-Processing

PM4Flex incorporates five inputs. A current event log (I) of the as-is process containing at least a case identifier for respective instances, activity names, start and end timestamps of each activity, and processing resources is required. Since not all relevant process properties can be extracted from a standard event log, additional instance-specific information is considered (II). It includes relevant aspects like classifications and due dates which are necessary to, e.g., specify a suitable processing pattern for the product type at hand or provide relevant constraints for the optimization model. Power consumption data (III) represents how much power is consumed by a specific resource in a specific time interval of the monitoring period. Based on that, load profiles are assigned to activity executions. The collection of resource-specific power consumption data with a sufficiently high temporal resolution can be supported by non-intrusive load monitoring, which allows power consumption data from a central measuring point to be disaggregated for deriving reliable estimates of the consumption of individual resources (Anderson et al.

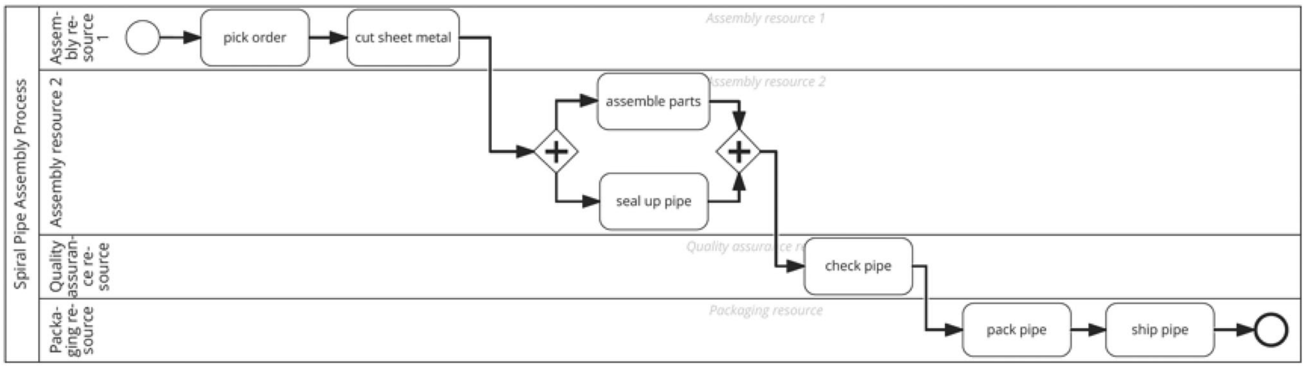

Fig. 3 Spiral pipe assembly process (source: own graphic based on real world event log)

2012). To allow for practical applicability, it is essential to incorporate company- and process-specific restrictions (IV). Such restrictions address control flow, temporal, resource, or energy-related aspects. A current power price forecast (V) for a relevant spot market covering a certain period of the near future can be obtained from an external service provider. The time resolution of this forecast is determined by the period length of traded products and depends on company-specific choices of and on the spot market. The lead time, i.e., the time between the provision of the forecast and the start of the forecast horizon, should allow for technically feasible and practically realizable rescheduling of active process instances.

The step of pre-processing involves handling all input data types to provide an efficiently processable data set for both event log exploration and optimization, as cleaning the data can improve the results of process mining considerably (Marin-Castro and Tello-Leal 2021). The pre-processing is structured along several data mining steps (Wirth and Hipp 2000; García et al. 2015, 2016).

Data preparation can be separated into data transformation and integration (García et al. 2016). In data transformation, raw data is converted into a manageable data format. First, the due dates provided in date format are converted into an integer value specifying the number of the period within the planning horizon corresponding to the respective due date. Second, the temporal resolution of the price forecast must be adapted to the temporal resolution of the process planning. E.g., for a temporal resolution of the forecast of 15 min and a temporal planning granularity of 5 min, each data point of the price forecast must be duplicated twice. Data integration refers to merging data from different sources (Wirth and Hipp 2000; García et al. 2016). We integrate the event log and power consumption data as follows: First, for each logged activity, the processing time is calculated as the difference between start and end timestamps. Second, a specific load profile is assigned to each activity according to logged timestamps, processing resources, and power consumption data for that time interval. Third, the activities are grouped based on their case identifier to form instance-specific sequences. Data reduction as the second part of pre-processing aims at reducing the number of considered data records to the relevant ones (García et al. 2015, 2016) to make the model more efficient. We select only the necessary columns to minimize processed data and computation time. The latter is especially relevant due to the frequency of optimization runs. Even though the general structure of the pre-processing in PM4Flex is fixed, its steps must be tailored to the data at hand, e.g., which columns need to be removed.

4.3 Event Log Exploration

Within the event log exploration, we use the prepared data to extract relevant process information for the optimization model. We first enrich the prepared event log with instance-specific information and power consumption data. Second, if no dedicated data on the status of process instances is available, it is necessary to (manually) specify a comprehensive list of end activities that indicate that a process instance is no longer active. The instance-specific sequences are then examined for occurrences of those activities. Accordingly, process instances are automatically classified as finished or active (Schobel and Reichert 2017). Naturally, only active instances are considered for optimization. Third, for these active instances, already completed activities can be obtained from the event log. Fourth, for each active instance, a list of all process variants of the same classification, e.g., the same product type (Dumas et al. 2018), sorted by frequency, is generated. Based on already completed activities, the most frequent variant that matches the given trace is determined (Schobel and Reichert 2017). Fifth, the difference between the most frequent matching variant and the trace of already completed activities determines the instance-specific list of activities that remain pending and need to be executed (Barba et al. 2012). Sixth, based on the information in the event log, values are assigned to the parameters needed for the optimization model. The parameters are described in Sect. 4.4 for the optimization model.

4.4 Optimization Model

We will first explain the nature of our optimization model. After clarifying the used parameters and variables, the whole optimization model including the objective function and constraints is presented.

Contrary to existing energy flexibility approaches, that focus on resources and their buffers (Zhou and Li 2013; Sun and Li 2014; Schultz et al. 2015; Beier et al. 2017; Lu et al. 2020), our optimization model adopts a process perspective, i.e., the control flow and resources. It is a mixed integer linear program that finds an optimal processing schedule for the active process instances and their respective pending activities within a specified time horizon. To reach a minimum while striving for efficiency of computational effort, all scheduling-related decision variables are expressed as binaries, and cost-related decision variables are represented as non-negative real numbers. The mixed integer linear program includes a set of constraints that enable flexibilization of process flows while ensuring adherence to existing boundaries. Both, parameters and decision variables can have one or more indices, which refer to the three sets the model is based on: all activities in the considered process $I = \{1, \ldots, |I|\}$, pending events (Bozorgi et al. 2021), i.e., one execution of a specific activity that still needs to be done for the instance at hand $J = \{1, \ldots, |J|\}$, resources $R = \{1, \ldots, |R|\}$, and the planning horizon $T = \{1, \ldots, |T|\}$.

Our model entails several control flow, time, resource, cost, and energy-related parameters (Appendix C). Most of the parameters used in the constraints can be determined from the event log. However, parameters that cannot be inferred from process data must be provided by human professionals or information systems (e.g., enterprise resource planning or energy management systems), e.g., upper, and lower limits of power consumption characterized by a facility's grid connection point. Where the value of the parameter is derived from is indicated by: (I) event log exploration, (II) instance-specific information, (III) power consumption data, (IV) further exogenous restrictions, and (V) power price forecast. Parameters considering the control flow of the process are the following: The binary parameter $Assign_{j,i}$ (I) indicates which activity an event is associated with. Whether the j_1 and j_2 can be parallelized is indicated by the binary parameter Prl_{j_1,j_2} (I). A prescribed order of events is indicated by the binary parameter Ord_{j_1,j_2} (I). The latter equals 1 if j_1 must be carried out without overlapping before j_2. If Ord_{j_1,j_2} has the value 0, there is no restriction regarding the order of j_1 and j_2 in this direction, but Ord_{j_2,j_1} could still have the value 1. The maximum number of interruptions per j is given by $\overline{\#Intr}_j$ (I).

Temporal characteristics are captured by the following parameters: The processing time of j is given by τ_j^{process}, while the total period of allocation, i.e., the sum over processing time and all interruptions, must remain within the interval $\left[\underline{\tau}_j^{total}; \overline{\tau}_j^{total}\right]$ (I). $[\underline{\tau}_{j_1,j_2}^{btw}; \overline{\tau}_{j_1,j_2}^{btw}]$ (I) denotes the time interval after the end of processing j_1 in which the processing of j_2 must start. The duration of interruptions is bound to $\left[\underline{\tau}_j^{intr}; \overline{\tau}_j^{intr}\right]$ (I) and a lower limit defining the period for which j must be executed uninterruptedly $\underline{\tau}_j^{nonintr}$ (I). Each j has an associated due date DD_j (II) due to temporal requirements, commitments, and consequential costs from non-compliance.

The following parameters consider resources: The binary parameter $ResAv_{r,t}$ (I) indicates whether r is available in t. Whether r_1 and r_2 can operate in parallel is indicated by the binary parameter $PrlRes_{r_1,r_2}$ (I). While the parameter Vol_j (I) denotes the volume associated with j, measured e.g., in m^2, or pieces, the $Capacity_{i,r}$ indicates how much volume r can handle at once, e.g., maximum 20 pieces at a time.

The following parameters depict energy-related characteristics: $P_{j,r}$ (I) denotes the estimated power consumption of r while executing j. Lower and upper limits on power supply, indicated by $\underline{P}_t$ and $\overline{P}_t$ (III), might occur due to physical limitations at the grid connection point (Bahmani et al. 2022) or contractually regulated purchase quantities. The forecasted spot market price in t is denoted by p_t (V).

Additional costs for j due to exceeding the given due date or interrupting an event are quantified by C_j^{delay} and C_j^{break} which, in turn, result from the predefined cost rates c_j^{delay} respectively c_j^{break}. These costs summarize all potential additional costs which might for example result from idle machines or personnel during interruptions, higher costs for express shipping due to delays or increased costs for machine maintenance due to increased downtimes. For the formulation of our optimization model, we assume perfect knowledge of all parameters, i.e., we will not consider the stochastic or uncertain nature of parameters. Replanning frequently, we account for the inherent uncertainty of the predicted power price p_t. If there are any additional restrictions (IV) that cannot be obtained from the event log or other input data, the parameter values are set by process experts either based on their experience or information from other systems before the rest of the values are determined.

Our model further includes the following binary variables: $active_{j,r,t}$ indicates whether the processing of j on r actively takes place in t. Likewise, $occ_{j,r,t}$ indicates whether j is allocated to r in t. If no allocation is made and, consequently, no processing is performed, both decision variables are 0. The start and end of an assignment of j to r and its processing phases are signaled by the binary (auxiliary) decision variables $occStart_{j,r,t}$, $occEnd_{j,r,t}$, $actStart_{j,r,t}$ and $actEnd_{j,r,t}$. $Exe_{j,r,t}$ indicates whether r is executing j in t or is (at least) occupied to execute j.

Using all the introduced sets, parameters, and variables summarized in Appendix C, our optimization model writes as follows: The objective function of PM4Flex minimizes process costs related to power procurement and flexibilization (Eq. (1)).

$$\text{Min} \sum_{t=1}^{|T|} p_t \bullet \Delta t \bullet \sum_{j=1}^{|J|} \sum_{r=1}^{|R|} active_{j,r,t} \bullet P_{j,r} + C_j^{delay} + C_j^{break} \tag{1}$$

The specified objective function is subject to energy (Eq. (2)), control flow (Eqs. (3), (4), (5)), temporal (Eqs. (6), (7)), and resource (Eqs. (8), (9), (10)) constraints, ensuring feasibility. As an energy constraint, Eq. (2) ensures compliance with power supply limitations.

$$\underline{P}_t \leq \sum_{j=1}^{|J|} \sum_{r=1}^{|R|} active_{j,r,t} \bullet P_{j,r} \leq \overline{P}_t \quad \forall t \in T \tag{2}$$

The processing of an event cannot be (re-) started and ended in the same period. Equation (3) to Eq. (8) ensure that the logical relationships between the six event-related decision variables are complied with.

$$occ_{j,r,t} - occ_{j,r,t-1} = occStart_{j,r,t} - occEnd_{j,r,t} \quad \forall j \in J, r \in R, t \in T \tag{3}$$

$$active_{j,r,t} - active_{j,r,t-1} = actStart_{j,r,t} - actEnd_{j,r,t} \quad \forall j \in J, r \in R, t \in T \tag{4}$$

$$actStart_{j,r,t} + actEnd_{j,r,t} \leq 1 \quad \forall j \in J, r \in R, t \in T \tag{5}$$

$$occStart_{j,r,t} + occEnd_{j,r,t} \leq actStart_{j,r,t} + actEnd_{j,r,t} \quad \forall j \in J, r \in R, t \in T \tag{6}$$

$$active_{j,r,t} \leq occ_{j,r,t} \quad \forall j \in J, r \in R, t \in T \tag{7}$$

$$occ_{j,r,0} = occ_{j,r,T} = 0 \quad \forall j \in J, r \in R \tag{8}$$

Regarding the processing sequence and order of events, it is necessary to specify dependencies between different activities as predecessor-successor relationships modeled by Eq. (9). Considering our example, the material has to be cut into the right pieces before they can be assembled as the whole pipe. In contrast, it might not matter whether you cut the piece for the end of the pipe or the middle part first.

$$\sum_{s=1}^{t} occEnd_{j_1,r,s} + \left(1 - Ord_{j_1,j_2}\right) \geq \sum_{s=1}^{t} occStart_{j_2,r,s} \quad \forall j_1, j_2 \in J, r \in R, t \in T \tag{9}$$

Events can be interrupted or paused while being executed. However, inter alia to address quality concerns (Leinauer et al. 2022), interruptions cannot take place arbitrarily and, thus, are restricted by Eqs. (5). For example, when executing quality checks, there might be requirements that prevent from interrupting the process arbitrarily often and long such as testing the seal of the pipe. The duration of interruptions (Eq. (11)) and the execution time without interruptions (Eq. (12)) must not be violated to maintain a desirable level of processing quality. Interrupting events might result in extra costs, e.g., if additional human effort is required to shut down and power up a machine (Eq. (13)).

$$\overline{\#Intr}_j + 1 \geq \sum_{t=1}^{|T|} \sum_{r=1}^{|R|} actStart_{j,r,t} \quad \forall j \in J \tag{10}$$

$$actEnd_{j,r,t} - occEnd_{j,r,t} \leq \sum_{s=\underline{\tau_j^{\text{intr}}}}^{\overline{\tau_j^{\text{intr}}}} actStart_{j,r,t+s}. \quad \forall j \in J, r \in R, t \in T \tag{11}$$

$$\sum_{s=0}^{\underline{\tau_j^{\text{nonintr}}}-1} active_{j,r,t+s} \geq \underline{\tau_j^{\text{nonintr}}} \bullet actStart_{j,r,t} \quad \forall j \in J, r \in R, t \in T \tag{12}$$

$$c_j^{break} \left(\sum_{r=1}^{|R|} \sum_{t=1}^{|T|} actStart_{j,r,t} - 1 \right) = C_j^{break} \quad \forall j \in J \tag{13}$$

τ_j^{process} is estimated within the event log exploration and must be adhered to in the planning (Eq. (14)). A financial incentive to reach compliance with due dates is induced by Eq. (15). If delivering a certain number of pipes by a specified date is contractually agreed on, one must adhere to it to maintain customer satisfaction. Failing to do so might result in contractual penalty costs or additional costs, e.g., due to the resulting need for more expensive express shipping.

$$\tau_j^{\text{process}} = \sum_{t=1}^{|T|} \sum_{r=1}^{|R|} active_{j,r,t} \quad \forall j \in J \tag{14}$$

$$c_j^{delay} \sum_{r=1}^{|R|} \sum_{t=1}^{|T|} occEnd_{j,r,t} \bullet t - DD_j \leq C_j^{delay} \quad \forall j \in J \tag{15}$$

There are upper and lower temporal limits to the total execution time of an activity (Eq. (16)). In our exemplary process, the seal of a pipe must be tested at least for a certain time to check whether it is leakproof when used for a longer time. However, testing it longer might economically not be sensible. Practical rationales to constrain the time between two events j_1 and j_2 exist (Eq. (17)). A minimum time span could be the consequence of a required transport or cool-down. Exemplarily, a pipe must be transported from the machine that finishes assembly to the testing station. An upper limit is reasonable for a case of sequential processing with j_1 transitioning the instance to a state necessary for executing j_2. After the pipe is packed, it must be shipped within a certain time frame to avoid additional storage costs. The requirement of j_2 to start within a certain period after j_1's completion is modeled by Eq. (18).

$$occStart_{j,r,t} \leq \sum_{s=\underline{\tau_j^{\mathrm{total}}}}^{\overline{\tau_j^{\mathrm{total}}}} occEnd_{j,r,t+s} \quad \forall j \in J, r \in R, t \in T \tag{16}$$

$$\sum_{s=1}^{t} occEnd_{j_1,r,s} + \left(1 - Ord_{j_1,j_2}\right) \geq \sum_{s=1}^{t} occStart_{j_2,r,s} \quad \forall j_1, j_2 \in J, r \in R, t \in T \tag{17}$$

$$occEnd_{j_1,r,t} \leq \sum_{s=\underline{\tau_{j_1 j_2}^{\mathrm{btw}}}}^{\overline{\tau_{j_1 j_2}^{\mathrm{btw}}}} occStart_{j_2,r,t+s} \quad \forall j_1, j_2 \in J, r \in R, t \in T \tag{18}$$

Further, Eq. (19) ensures that processing only takes place if r is available in t. Resources have capacity limits restricting the volume of the product that can be produced at a time (Eq. (20)). For example, the unit of measure for capacity and volume in our spiral pipe process is the number of pieces. If the capacity of a resource is ten and the volume of a pipe one, the machine can process ten pipes at a time.

$$ResAv_{r,t} \geq \sum_{i=1}^{|I|} Exe_{i,r,t} \quad \forall r \in R, t \in T \tag{19}$$

$$\sum_{j=1}^{|J|} active_{j,r,t} \bullet Vol_j \bullet Assign_{j,i} \leq Exe_{i,r,t} \bullet Capacity_{i,r} \quad \forall i \in I, r \in R, t \in T \tag{20}$$

To ensure comprehensiveness of instance processing, the allocation and accompanying execution of an event must occur exactly once over the planning horizon and only for one resource r (Eq. (21)). For example, an assembly error at one piece of a pipe can only be corrected by the one machine capable of installing it and, naturally, this specific error must be corrected only once.

$$1 = \sum_{t=1}^{|T|} \sum_{r=1}^{|R|} occStart_{j,r,t} \quad \forall j \in J \tag{21}$$

Our model allows for parallelizing events and resources. If an activity can be processed simultaneously for more than one instance by r ($\#PrlInst_{j,r} > 1$), Eq. (22) ensures that the events take place parallelly, time-congruently, and not staggered. For example, a machine cutting sheet metal can do so for several parts simultaneously while a leak test can only be done for one pipe at a time. Several j of one instance can be allocated and processed parallelly, too. E.g., two parts of a pipe can be stuck together at the same time by the same r. Equations (23), (24) limit parallelization to the technically feasible level.

$$\sum_{j=1}^{|J|} active_{j,r,t} - occ_{j,r,t} \bullet Assign_{j,i} \geq Exe_{i,r,t} - 1 \quad \forall i \in I, r \in R, t \in T \tag{22}$$

$$Prl_{j_1,j_2} + 1 \geq \sum_{r=1}^{|R|} occ_{j_1,r,t} + occ_{j_2,r,t} \quad \forall j_1, j_2 \in J, t \in T \tag{23}$$

$$PrlRes_{r_1,r_2} + 1 \geq \sum_{i=1}^{|I|} Exe_{i,r_1,t} + Exe_{i,r_2,t} \quad \forall r_1, r_2 \in R, t \in T \tag{24}$$

4.5 Output

The optimization model derives an optimal schedule for pending activities of active instances. This schedule contains information about sequence, time, processing resources, duration, and interruption of activities. Periodic updates due to changing conditions enable energy-oriented real-time scheduling of instances. From a capacity planning perspective, a detailed occupancy schedule of considered resources is also obtained. This resource-specific schedule provides information about the time, duration, and type of activities processed by a resource. Based on this, e.g., break or setup times can be planned.

5 Demonstration and Evaluation

To demonstrate the feasibility and to evaluate PM4Flex (4), we instantiated our artifact as a software prototype[1] (Sonnenberg and vom Brocke 2012). The prototype is coded in Python, drawing from the *pm4py* package (Berti et al. 2019) for process-related aspects and *Gurobi*'s Python application programming interface for the optimization, i.e., specifying the proposed optimization model. The artifact was applied to two distinct scenarios based on real-world event logs, day-ahead power prices and price forecasts for the respective periods. An exemplary output of the artifact is depicted in Table 3. Since the artifact should be useful for its prospective users, we further evaluated the opinion of experts on the meaningfulness of the generated recommendations in semi-structured interviews (Sect. 5.3).

[1] https://www.dropbox.com/scl/fo/plarrsebagvlanydd8u0t/h?rlkey=27q3q38jtj1yj1c99pavdb5lr&dl=0

Table 3 Structure of the output of PM4Flex (excerpt)

Instance	*Activity*	*Resource*	*Start*	*End*	*Duration*	*Start interruption*	*End interruption*	*Power Cost*
Instance7	Activity1	Resource4	1	4	2	2	3	0.38255

5.1 Evaluation Episode 1 Considering the Design Objectives

Evaluation episode 1 examined whether PM4Flex fulfills the defined DOs. At this stage, this was evaluated artificially based on the conception and design of PM4Flex. Utilizing *Reasoning* and *Theoretical Arguments* for evaluation (Sonnenberg and vom Brocke 2012), we evaluated PM4Flex against each DO individually which yielded the following conclusions:

The artifact abstracts from the specific process structures and interdependencies by utilizing event logs, i.e., recorded execution data, as the basis for analyses and optimization. Specific relationships or dependencies in the processes are not explicitly modeled but are implicitly considered by deriving information from the event log. Accordingly, the artifact fulfills DO1. Process-specific constraints can be captured through event log analysis, assuming that the same constraints apply. This allows abstraction from the actual character and origins of restrictions and only considers measurable implications for past process runs. Hence, process- and company-specific restrictions can be taken into account, as required by DO2. Fulfilling DO3 is linked to the implementation and operationalization of the proposed approach. PM4Flex identifies the sequence of successive activities with the highest probability of occurrence for each active instance regarding comparable historical situations. Each activity is ultimately part of an optimal process flow recommendation, ensuring that DO3 is satisfied by the provided instantiation. DO4 requires the ability to automatically and regularly update recommendations to avoid suboptimal recommendations based on outdated environmental conditions. PM4Flex ensures a periodic adjustment of the optimal process flow, synchronized with obtaining a revised energy price forecast. In the instantiation, changes in environmental conditions apart from new energy price forecasts and incoming orders are out of scope. The prototype is, however, capable of reacting to changes in various conditions by adapting its recommendations, fulfilling DO4. In particular, the consideration of DO4 in the proposed approach constitutes a clear enhancement of the previous approach (Hermann et al. 2023).

To summarize, from an *ex-ante* logic, PM4Flex fulfils the defined DOs. This represents a promising starting point for the subsequent evaluation episodes.

5.2 Evaluation Episodes 2 and 3 Considering Distinct Case Examples

While the first process was already used to evaluate Hermann et al. (2023), the second one was added in our PM4Flex enhancement. Since the two process examples were considered at different stages in the research process and served a differing purpose, we distinguish two separate evaluation episodes. However, due to their analogue approach and structure, we will report on both episodes jointly in a single section, describing data input, setup, benchmarks, and results.

5.2.1 Data Input

The process considered in the second evaluation is a spiral pipe production of a German medium-sized heating and air conditioning company (Fig. 3). The process-related data contains the event log, power consumption data per workstation, and due dates as well as instance-specific information in the form of product types. The process includes several activities from cutting, grinding, bending, welding, and lacquering the metal, to assembling, checking, packing, and shipping the spiral pipe. The process is suitable to evaluate our artifact from a process perspective since the individual activities depend on prior activities' outcomes, making a process perspective that considers these dependencies inevitable. In addition, the process has a lot of variants which makes it more complex for scheduling activities. From an energy perspective it can evaluate the artifact reasonably since the machines used to process the metal for the pipes are quite energy intensive. We consider four business days, October 31st—November 3rd 2022, replanning with a three-day horizon and discrete periods of 30-min intervals.

For evaluation episode 3, we used process data from a paper production process of a large European company. It includes two activities—the production of the pulp and the final paper—executed by five resources. The process is suitable to evaluate our artifact from a process perspective since activity one is executed by three machines in a row separating it into three distinct activities in the event log. This increases the complexity of the process due to more dependencies and makes a process view considering these inevitable. Additionally, from an energy perspective the process is suitable to evaluate the artifact since it is highly energy intensive to process the materials so there are considerable energy saving potentials when applying our approach. We consider five days, 25th October—29th October 2021, and discrete periods of 30-min intervals with an observation horizon of four days.

While the characteristics of both processes justify that they can reasonably be used to evaluate our artifact from both a process and an energy perspective, the processes in episodes 2 and 3 differ in several aspects to achieve more comprehensive evaluation results (Appendix D). While episode 2 contains more distinct activities and resources which increase coordination demands, the process in episode 3 requires a considerably longer average execution time per activity which provides more room for the application of energy flexibility measures. In contrast, the resources in episode 3 are markedly more energy intensive than the ones in episode 2, and thus offer a higher potential for cost savings. In turn, episode 2 includes more human resources which increases cost for longer delays and interruptions.

5.2.2 Setup

We consider the six energy flexibility measures selected in Sect. 4.1. The valuation procedure of the parameters that define the constraints may differ between applications (Appendix E). For example, episode 3 requires different energy flexibility measures since the machines executing the last activity require long ramp up times and should be interrupted as little as possible, which, is no issue in episode 2 since the machines are stopped every night. Yet, the energy intensity of different product types differs more so the focus is on energy flexibility measures that rearrange the production of different product types. While PM4Flex comprises event-log based valuation of almost all flexibility characterizing parameters, users might want to set some parameters manually. This might be the case if parameters are unambiguously known, or a precise valuation is desirable or necessary. Considering episode 3, the process is carried out by a portfolio of highly automated and autonomous machinery. Therefore, parameters like resource capacity or power consumption result from technical characteristics and physical properties. In contrast, the process in episode 2 is run in a workshop-based production system with a high degree of human involvement, making a data-based valuation of parameters reasonable.

Since both processes are energy intensive due to the required high temperatures and mechanical processing, their costs highly depend on the dynamically changing power procurement costs which raises the need for adaptations to this dynamic environment. For both episodes, we used daily power price forecasts for the day ahead market used in practice, provided by a leading German software corporation. An appropriate size of the interval between forecast updates can be determined individually, depending on the power procurement model in place. Although the artifact allows for shorter update intervals in terms of technical feasibility (adaptive programming) and practical viability (computation time), the forecasts were updated daily in line with the interval between successive power price forecasts of the provided data. Hence, revising all recommendations in our evaluation happens once per day, taking the current state of the processes and the power prices into account. We evaluate the artifact's ability to revise recommendations based on the computation times. All computations were run on a machine with a 2.30 GHz 2-core CPU and 8 GB RAM using the *Gurobi* solver.

We consider three metrics for comparison. First, *power procurement cost* which is calculated by summing up the products of power price and power consumption over all instances and periods. Savings in power costs demonstrate the effectiveness and the impact of our artifact. Second, *maximum completion time* relates to the completion time of the last activity over all resources considered within the optimization run. A reasonable maximum completion time ensures that energy flexibility measures do not impede process execution negatively. Third, *computation time*, is the time required to reach an optimal solution. Short computation times provide evidence for the efficient replanning possibility of PM4Flex. The more complex a process gets, i.e., the more dependencies and constraints, the longer the computation time. Especially the number of activities, the length of the considered time horizon, and its granularity of periods e.g., 15 min or one-hour intervals, increase the computation time. However, this can be offset by higher computation capacity and more efficient solvers. Since the processes used for evaluation are already quite complex, we can observe whether the approach is applicable to complex processes. Depending on the frequency of replanning, the need for fast optimization, and the computation capacity, the possibility to extend the optimization model is, however, limited.

5.2.3 Choice of Benchmark

For evaluation episode 2 and 3, we searched for a suitable benchmark. Comparing existing scheduling approaches from the energy domain (Sect. 3), we found that none can serve as a direct quantitative benchmark, but rather as a qualitative one given our experimental setting and data. Energy-focused approaches either handle only simple processes from a resource perspective (Sun and Li 2014; Schultz et al. 2015; Beier et al. 2017) or require comprehensive and detailed knowledge of energy flexibility measures' properties (Schott et al. 2019; Tristán et al. 2020; Bank et al. 2021; Bahmani et al. 2022). Since our data contains complex control flow dependencies of non-linear processes, we cannot apply approaches that account only for simple process flows. Additionally, our approach extracts knowledge from event logs to require markedly less precedent analysis, making a comparison with complex pre-analysis approaches unsuitable. On the PPM side, most approaches account for only one constraint, e.g., resources or time (Barba et al. 2012; Weinzierl et al. 2020b; Bozorgi et al. 2021; Shoush and Dumas 2022b, 2022a), neglecting e.g., costs and adjust themselves step by step (Dorn et al. 2010; Yang et al. 2017), however, not simultaneously. Many of them use machine learning (Barba et al. 2012; Weinzierl et al. 2020b; Bozorgi et al. 2021; Shoush and Dumas 2022b) which we did not do intentionally to keep the procedure of how the recommendation is generated clear, understandable, and trustworthy (Gunning et al. 2019) and to achieve reasonable results independent of the size of the data base (Dorn et al. 2010). Due to all of these drawbacks and the fact that none of the existing approaches optimizes the recommendations subject to changing price forecasts, a direct comparison is inadequate (Li et al. 2015).

Due to the lack of a benchmark fulfilling the same requirements as PM4Flex apart from its previous version, we use an approach widespread in the industry for production process optimization (Li et al. 2015) for comparison. This approach is an optimization model minimizing the maximum completion time to generate a process schedule. Both the benchmark and PM4Flex account for control flow dependencies among activities and were tested with the same data, enabling a reasonable comparison. Since the chosen benchmark is the most common optimization objective discussed in literature (Ruiz and Maroto 2005), we can realistically evaluate the cost savings when using our approach. Additionally, we can show whether the maximum completion times of our approach are competitive with the industry standard and whether the cost savings justify potentially longer execution times. In summary, the chosen benchmark helps us to reasonably evaluate whether our approach is an improvement to the current industry standard. Further, to evaluate the replanning functionality of our artifact explicitly, we also compare it to results without replanning in the same approach, represented as static PM4Flex.

5.2.4 Results

In episode 2, we receive the following results (Table 4). All approaches lead to an average power consumption of 481.04 kWh within 4 rescheduling runs. PM4Flex identified a solution with minimal power costs of 14.57 € saving procurement costs of 0.29 € (1.95%) compared to the static version of the artifact, 3.96 € (21.37%) compared to the processing according to benchmark scheduling, and 74.51 € (83.46%) compared to the original data using no interventions. In contrast, PM4Flex yields a greater maximum completion time than the benchmark approach (+ 18.5 h) and the original log (+ 24 h). However, the results are still compliant with the due dates, ensuring timely production and, hence, not representing a relevant issue. Additionally, we show that the dynamic nature of PM4Flex adds value in terms of reducing the maximum completion time by 6 h compared to the static version. Regarding the computation time, PM4Flex exceeds the benchmark by 93.83 s and the static version by 101.33 s. Although both maximum completion time (+ 8.5 h) and power procurement cost (+ 3.46 €) increased compared to Hermann et al. (2023), we show that our enhancements regarding efficiency of PM4Flex improved its performance as the computation time is reduced by 31.10%.

episode 3 shows similar results (Table 5). Within five rescheduling runs, an average power consumption of 3,264,375 kWh is optimized. PM4Flex yields power cost of 58,474.83€, enabling savings of 21,744.89 € (27.11%) compared to the static version, 22,673.32 € (27.94%) compared to the previous version, 30,423.17 € (34.22%) compared to the benchmark, and 122.658,17 € (67.72%) compared to the actual process execution. The maximum completion time of PM4Flex exceeds the benchmark by 8.5 h. However, it we can show again that adding the dynamic aspect of rescheduling frequently may have a considerable effect on the execution and its associated maximum completion time, in this case 47.5 h compared to the static version, 49 h compared to Hermann et al. (2023) and 116.5 h compared to the original execution, which are almost five days. Evaluation episode 3 shows as well that the efficiency improvements that we conducted reduce computation time markedly by 37.79% compared to Hermann et al. (2023). This is notable since multiple optimization runs are added to replan the process schedule triggered by changed price forecasts or diverging realization of prices.

Both episodes show that enhancing Hermann et al. (2023) by efficiency improvements and the possibility to handle dynamic environments leads to reduced computation and significantly different maximum completion times. This improves agility and the ability to frequently reschedule when circumstances change. Additionally, the dynamic nature and flexible adaptions of recommendations to changing power prices, enables considerable power cost savings which is shown by the comparison of PM4Flex and the static version. The fact that the optimization of Hermann et al. (2023) and PM4Flex lead to contradictory results within the two episodes can likely be traced back to the additional constraints referring to instance-specific volumes and resource-specific capacities. Those constrains may shrink the solution space and therefore increase the

Table 4 Results of evaluation episode 2

	PM4Flex	*Static PM4Flex*	Hermann et al. (2023)[a]	*Benchmark*	*Original log*
Power procurement cost [€]	14.57	14.86	11.11€	18.53	88.08
Maximum completion time	Period 81	Period 93	Period 64	Period 44	Period 33
Computation time [s]	278.30	176.97	403.86	183.47	–

[a]https://www.dropbox.com/scl/fo/o9mppdugo3cn62tle4luq/h?rlkey=hda2wu1oksltn7unx5k9cy4u2&st=0xnys436&dl=0

Table 5 Results of evaluation episode 3

	PM4Flex	*Static PM4Flex*	Hermann et al. (2023)	*Benchmark*	*Original log*
Power procurement cost [€]	58,474.83	80,219.72	81,148.15	88,898.00	181,133.00
Maximum completion time	Period 97	Period 192	Period 186	Period 83	Period 330
Computation time [s]	78.47	166.08	126.13	98.83	–

value of the optimal solution (as seen in episode 2). However, the constraints increase the feasibility of the recommendation which is approved by the interviewees. The output of PM4Flex for both process examples is depicted in Appendix F.

5.3 Results of Evaluation Episode 4

In addition to the benchmark evaluation, we evaluated PM4Flex qualitatively in expert interviews referring to both episode 2 and 3 to cover a broader range of use cases. The interviewees evaluate PM4Flex regarding DO1, DO2, and the well-established evaluation criteria generality, efficiency, operationality, effectiveness, and usefulness (March and Smith 1995; Peffers et al. 2007; Sonnenberg and vom Brocke 2012). They were asked for detailed, qualitative feedback on these criteria for comprehensive insights. Results of a supplementary quantitative assessment can be found in Appendix G. DO3 and DO4 cannot be evaluated reasonably in an artificial setting.

Regarding *DO1,* the interviewees confirmed that PM4Flex is scalable with reasonable effort and not limited to specific production systems or workshops. Interviewee 1 highlighted that "*an advantage of your approach is the automation preventing that I have to pay for services tailoring it to my processes' complexity*." Regarding *DO2,* the interviewees confirmed that a great number of relevant restrictions and especially the most important aspects occurring in real life processes are included. However, most companies face restrictions that cannot be represented in general terms. Parameters derived from historical data can be more restrictive than actually acceptable limits.

Concerning the *generality* of PM4Flex, the experts agreed that it can be applied to various degrees of process flexibility and complexity, not limited to the processes in our evaluation. It was highlighted that the automated parameter derivation from historic data makes the approach reasonably scalable.

The instantiation for two different processes shows that our approach can be *operationalized.* The experts confirm that the approach itself does what it is intended to and can be implemented with reasonable effort in practice. Some concerns were raised about the data base required for the approach, not yet available in many companies. Interviewee 5 added: "*The more automated a process is, the easier it is to implement PM4Flex in productive operations.*" emphasizing the added complexity in episode 2 due to primarily manual activities.

PM4Flex can exceed the *efficiency* of current standards. This was confirmed by a lower computation time in episode 3 than the benchmark, Interviewees 8 and 9 appreciating the considerably shorter computation time than their current approach, and Interviewee 7 mentioning advanced planning approaches with a couple of minutes of optimization time. Hence, PM4Flex computing 1–4 min is competitive especially if the replanning frequency is moderate: "*I don't see any issues if you reschedule daily*" (Interviewee 5). Most experts confirmed that daily replanning is sufficient. Other comments revealed that acceptable computation times depend on the process and its execution time.

Regarding *effectiveness,* almost all experts agreed that the savings are sufficient to implement the approach in their processes. The implementation effort was considered as *"marginal compared to the utility generated by*

PM4Flex" (Interviewee 11). The interviewees working in our exemplary companies validated the generated recommendations of process flows, approving that the results are effective in practice. Thus, PM4Flex supports users in easily and effectively saving power cost and contributing positively to their environment, particularly to grid balancing and stability.

Regarding the *usefulness* of our approach, the great majority of experts considered our artifact as very useful in practice. Interviewee 10 stated: "*You have used process mining not as a standalone tool but to directly generate added value, which is very good*". Interviewee 7 added that "*the approach itself is extremely interesting. Our audits are primarily limited to technical systems which is why it is sensible to add the process mining perspective.*" The interviewees mentioned that PM4Flex is especially useful in practice since it generates recommendations using a replicable approach and involves humans to validate the recommendations which is more accepted in practice than full automations.

We asked the interviewees working at the two companies providing event logs on the exemplary processes further questions about the validity of the generated recommendations referring to their processes. Interviewees 5 and 11 approved the generated recommendations (of episode 2) to be valid and feasible in practice. *"I see the approach as definitely implementable. The result is something the employees understand for sure"* (Interviewee 11). Interviewee 5 expressed that the free capacity of employees due to implemented energy flexibility measures, e.g., interruptions, must be used. It is especially important in the context of this process as process execution is primarily manual. If the number of orders that can be flexibly scheduled is large enough, he agreed that rearranging orders can realistically mitigate the vacancies of employees. Interviewees 8 and 9 approved the recommendations (of episode 3) as they comply to an almost full-time operation of the machines executing the final activity of the process, which is desirable due to high ramp up costs. Other machines in the process and switching differently energy-intensive product types as energy flexibility measure provides more energy flexibility than the machine that needs to run uninterruptedly.

Judging from their own processes, the four experts from our exemplary companies mentioned that PM4Flex adds most value if a process has mainly control-flow and resource constraints, e.g. if a machine must operate uninterruptedly, while constraints of process parameters, e.g., temperatures, require specific attention in other processes. The more automated a process is, the less dependencies from human work need to be considered in PM4Flex's implementation. Computation times are in line with the execution duration of the activities, e.g., in episode 3 an activity requires on average of approximately 6 h, so that 1:20 min computation time are reasonable, similarly for episode 2. However, the evaluation does not provide insights into PM4Flex's applicability for processes consisting of activities with short execution times, e.g. only 5 min. All four experts agree that the cost savings are significant but might decrease due to ramp-up costs, fixed costs, risk premiums, license costs for PM4Flex, employee vacancies etc.

Possible concerns about the feasibility of implementing PM4Flex pertain insufficient data availability and the relevance of energy costs in companies' overall cost, which lead to the following preconditions. First, it is necessary to collect electricity consumption data of the considered operational system in an appropriate temporal and spatial-structural resolution is necessary. The electricity consumption should be collected for each resource independently or obtained by subsequent decomposition of the total load profile (e.g., non-intrusive load management). The temporal resolution should reflect the usual magnitude of processing times and downtimes. For resources with highly asymmetric load profiles, a higher resolution can be advisable. Second, the collection of process data is just as essential. In addition to the collection of integral attributes of activity execution, the (automated) collection of actual process events in real time is essential for our artifact. Focusing on the end timestamp of an activity or process substantially impedes the application of our artifact. Third, the IT and database infrastructure of companies should allow for the assignment of process instances to relevant entities of the company's data model, such as customer orders. Fourth, access to reliable and updated electricity price forecast data is crucial for successful application.

Briefly, episode 4 shows that, despite several preconditions, our artifact is perceived to be useful and value-adding in practice.

6 Discussion

6.1 Theoretical Contribution

We have developed a PPM approach which recommends process schedules with optimized power costs. Our approach comprehensively accounts for control-flow as well as resource dependencies and provides recommendations in a reasonable time frame for daily replanning. Through PM4Flex, we contribute to theory by creating design knowledge in the form of a PPM approach for energy flexibility for both the energy and the PPM domain. Integrating both domains opens a new research field and stimulates the academic discourse to answer research questions for critical problems in times of the climate crisis. In particular, PM4Flex contributes to the research stream on Green BPM, combining domain-specific economic process performance objectives to support an overall more sustainable energy mix, thereby directly addressing the cost perspective of the devil's pentagon, but also supporting sustainability objectives on a rather global level. To the best of our knowledge, it is the only approach to date which incorporates several energy flexibility measures. Going beyond the scope of existing work, e.g., Hermann et al. (2023) and Hehnle et al. (2024), PM4Flex marks a significant advancement with respect to the integration of real-time, proactive, data-informed decision making and power cost optimization into process scheduling, broadening the methods applied in PPM in the literature by using a non-black-box approach. A high degree of automation, handling dynamic energy environments more efficiently, and explicitly addressing relevant aspects like additional cost or resource capacity make PM4Flex a more comprehensive PPM approach compared to Hermann et al. (2023) with low barriers of usage. Nevertheless, as aforementioned specifics such as much manual execution or vital constraints not considered in our approach must be considered upon implementation (see limitations below). When we evaluate our contribution to the existing design knowledge base using Gregor and Hevner's (2013) knowledge contribution framework, we classify it as an improvement. Fluctuating power prices and the resulting need for demand side energy flexibility is a known problem although it is a new use case in BPM. PM4Flex constitutes a novel solution, constructed by drawing on various existing methods and design knowledge from mixed linear integer optimization and PPM. Providing both a method and its instantiation, PM4Flex is a valid DSR artifact covering contribution levels 1 and 2 (Gregor and Hevner 2013).

The design knowledge inherent in PM4Flex on the one hand builds on existing approaches (Sect. 5) by aggregating poorly researched PPM considerations, e.g., revising recommendations, recommending whole pending process flows, as well as using more than historic data (Dorn et al. 2010; Barba et al. 2012; Yang et al. 2017). On the other hand, it adds new aspects and perspectives to existing approaches, e.g., key sustainability aspects to PPM approaches (Kubrak et al. 2022), a process perspective (Zhou and Li 2013; Sun and Li 2014; Beier et al. 2017; Schultz 2018; Lu et al. 2020), and additional resource prices in the form of energy prices (Schultz et al. 2015; Nayak et al. 2019) to enable an energy-oriented scheduling, which have all been disregarded until today. Additionally, our approach decreases the need for manual assessment of energy flexibility measure suitability and automatically considers multiple measures (Bank et al. 2021).

6.2 Practical Relevance

There are various practical implications of our work for different stakeholders. The provided artifact enables companies not only to implement energy flexibility measures faster and more efficiently, but also to acquire an active control over their power cost and achieve considerable savings. Thus, if processes have inherent flexibility potentials, e.g., in episode 3 some machines are flexible while others must run uninterruptedly, they can realize important competitive advantages leveraging today's dynamic environment. This increases their resilience towards volatile power prices. As PM4Flex accounts for vital constraints within processes, it supports companies in maintaining product quality and desirable process flows despite the implementation of energy flexibility measures. Especially if process inherent constraints are primarily control-flow and resource related, as it is the case in our exemplary processes, PM4Flex considers them comprehensively. Additionally, the economic benefits of these measures are immediately apparent from the optimization's output and support decision making after they have been prepared in a user-friendly way.

Our open-source software research prototype serves as an inspiration and proof-of-concept for further domain-specific software development, e.g., by process mining and scheduling vendors. In individual companies, it can already be applied for decision support on power cost optimization. Using PM4Flex in a company contributes to the power system's rising need for energy flexibility which supports a sound and accelerating transition towards a carbon neutral electricity sector based on renewable energies.

6.3 Limitations and Future Work

Our research is subject to limitations. Given the assumptions described in Sect. 4.1 and the relevant specifics described in Sect. 6.1, we cannot claim exhaustiveness. Excluded from the scope are, e.g., energy flexibility measures for longer time horizons, machine ramp-up costs, energy types other than electricity, such as heat or cooling, and energy generated by own solar panels. Also, our approach is not fully automated due to the tradeoff between data-based deduction of constraints on the one hand and human expertise and domain knowledge on the other. We cannot provide knowledge regarding the artifact-in-use but focus on the method itself in our solely artificial evaluation. Additional challenges that may arise in real-world implementations, e.g., concerning the interaction between system and human decision-makers, are neglected.

A further limitation concerns the informative value of the quantitative comparison of the developed artifact in evaluation episodes 2 and 3. Besides the original log and the chosen benchmark we compare our final artifact with a static implementation (iteration 3) and Hermann et al. (2023) (iteration 1), both of which are the results of this research effort from previous design iterations and therefore do not reflect PM4Flex's positioning within existing literature. Nevertheless, we argue that, in the absence of comparable and competing approaches, those early versions of the artifact are the only feasible reference points with the same inherent intention. They not only verify but also quantify the enhancements of the artifact achieved by individual iterations.

In our approach, the dynamic environment is primarily represented by the changing price forecast and the ability to replan frequently, neglecting other dynamic influences on process scheduling like changing priority or due dates of orders and further aspects related to power procurement. As a first step, it is perceived as sufficient by the interviewees. Hence, we consider PM4Flex as an initial step towards the exploration of PPM for energy flexibility and a starting point for further research.

Future work can focus on increasing the generalizability of our approach, extending the environmental aspects considered, e.g. on-site generation, energy storages, charging profiles of electric vehicles, price forecasts for other energy forms. Further process-based optimization models can be developed by building on design knowledge by PM4Flex for optimization, or other PPM approaches for cost optimization could be examined. With a sufficient database, it is reasonable to compare the performance of machine learning based approaches to our mixed integer linear programming. For this reason, future research could focus on data collection, data quality of event logs, and power data to ensure reliable outcomes from the artifact, which is according to the interviewees a current deficit in practice. A more comprehensive evaluation of our approach in a real-world setting is advisable to assess its practical feasibility and usefulness, and to discover areas for improvement, including specific design knowledge for the artifact-in-use. In line with this, it would be interesting to create more abstract and mature design knowledge, e.g., in the form of design principles (Gregor et al. 2020), to provide more prescriptive guidance for the design and development of related approaches. In general, future research should investigate more broadly how process mining techniques can address urgent issues in the energy domain, e.g., crisis management for outages or CO_2 reduction. Our work provides a valuable starting point for the described extensions.

7 Conclusion

Companies operate in a dynamic environment and must tackle multiple crises (Kreuzer et al. 2020; Godoy and Filho 2021; Gross et al. 2021; Röglinger et al. 2022). One of the most impactful and devastating is climate change (Hitz and Smith 2004; Tol 2018). Addressing and minimizing its impact will require fundamental changes in the energy sector, e.g., an increasing share of renewable energy sources (Heffron et al. 2020; Tristán et al. 2020), which will lead to more volatile power generation. Power prices fluctuate accordingly, requiring companies to adapt their processes. Energy flexibility is an effective means to do so, but requires support from a process perspective. To address this demand, we enhanced PM4Flex (Hermann et al. 2023) to help companies exploiting the energy flexibility potential of their processes through PPM, following a DSR approach in our research. We demonstrated the method as a software prototype and evaluated it in four episodes, including prototype application and expert interviews.

As a result, PM4Flex helps companies adapt flexible processes to volatile power supply on short notice by implementing energy flexibility measures in an energy-cost minimizing manner, thereby adapting to a more sustainable energy mix by enhancing process flexibility and reducing process cost. Our evaluation episodes show that the approach meets the DOs. Our artifact generates considerable cost savings, adds value to process scheduling in practice, and is perceived as such by practitioners when prerequisites such as data availability are met. The basis for future research is to combine the energy and process domains and to propose a new PPM approach to address climate change.

Acknowledgements Supported by PayPal and the Luxembourg National Research Fund FNR (P17/IS/13342933/PayPal-FNR/Chair in DFS/Gilbert Fridgen).

Funding Open Access funding enabled and organized by Projekt DEAL.

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