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STAY FLEXIBLE: A PRESCRIPTIVE PROCESS MONITORING APPROACH FOR ENERGY FLEXIBILITY-ORIENTED PROCESS SCHEDULES

Research Paper

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Abstract

The transition from fossil fuels to renewable energy sources poses major challenges for balancing increasingly weather-dependent energy supply and demand. Demand-side energy flexibility, offered particularly by companies, is seen as a promising and necessary approach to address these challenges. Process mining provides significant potential to prevent a deterioration of product quality or process flows due to flexibilization and allows for exploiting monetary benefits associated with flexible process operation. Hence, we follow the design science research paradigm to develop PM4Flex, a prescriptive process monitoring approach, that generates recommendations for pending process flows optimized under fluctuating power prices by implementing established energy flexibility measures. Thereby, we consider company- and process-specific constraints as well as historic event logs. We demonstrate and evaluate PM4Flex by implementing it as a software prototype and applying it to exemplary data from a heating and air conditioning company, observing considerable cost savings of 1.56ct per kWh or 34.35%.

Keywords: process mining, prescriptive process monitoring, energy flexibility.

1 Introduction

Mitigating climate change is one of the major challenges of our time. Treaties like the Paris Climate Agreement or the European Climate Law provide goals for reducing emissions, e.g., greenhouse gas neutrality of the EU by 2050. Germany, currently the largest emitter of greenhouse gases in the EU, is even aiming at national climate neutrality by 2045. The rapid phase-out of nuclear power generation and conventional fuels as well as the expansion of renewable energy sources (RES) are needed at once to achieve this goal (BMWK and AGEE-Stat, 2022; Die Bundesregierung, 2011). The volatility of power generation and corresponding power prices will increase as a result of the high dependence of RES on uncertain weather conditions. Ultimately, on the one hand, the energy system faces the challenge of balancing volatile generation and demand to ensure a reliable power supply for consumers, maintaining grid stability. On the other hand, companies face the challenge of adapting to and exploiting fluctuating power prices (caused by a weather-dependent power supply of RES), e.g., by consuming power when prices are low and when the RES share is high, to decrease energy procurement costs and CO_2 emissions.

Both challenges can be addressed by energy flexibility (EF), which describes the ability to exploit the described variations on the supply side. EF is an opportunity for energy consumers since the greatest EF potential is attributed to demand-side EF compared to, e.g., energy storages that are still too expensive to be widely used. Within demand-side EF, industrial companies account for a considerable share of energy consumption (Heffron et al., 2020), with an EF potential estimated at up to 3.98 GW in Germany. Especially short-term demand adaptations within 15 minutes are already relevant today to compensate for short-term energy supply fluctuations (Sauer et al., 2019). Some energy-intensive companies already optimize the energy procurement for their processes, thus, increasing their competitiveness with reduced energy costs and additional revenues from EF marketing (Alcázar-Ortega et al., 2015; Sauer et al., 2019).

Research has identified and discussed several options to exploit the EF potential (VDI, 2020). Many existing approaches flexibilize processes on highly simplified production systems (ignoring important characteristics of real-world processes) in a real-time manner or focus on control loads in buildings (Beier et al., 2017; Lu et al., 2020; Schultz et al., 2015; Sun and Li, 2014; Zhou and Li, 2013). Thus, they do not apply a sufficiently detailed process perspective and cannot be transferred easily to more complex processes as observed in practice. Power price developments are rarely considered for load control (Schultz, 2018; Nayak et al., 2019). Existing approaches further only regard a limited selection of available EF measures (EFM), potentially disregarding relevant EF (Schultz et al., 2015).

Concerning practical implementations of EFMs, many companies have not yet recognized, let alone exploited, their EF potential at all (Schott et al., 2019), since no sufficient insights into revenues or cost savings of EF are available (Alcázar-Ortega et al., 2015; Leinauer et al., 2022). Many fear that providing EF by implementing EFM deteriorates both product quality and production flow. Moreover, the complexity of the used IT systems is often perceived to increase markedly (Leinauer et al., 2022).

As we argue in this paper, the described concerns and challenges of EF can successfully be addressed with process mining. Process mining is a research area that focuses on data-based process insights and optimization and is already well-established in other fields of application (Eili et al., 2021). Hence, existing process mining applications can be extended by EF considerations without enlarging the IT landscape within a company. Further, due to a highly detailed process perspective, challenges regarding negative impacts on processes are inherently considered with process mining. In particular, process mining can be used for prescriptive process monitoring (PPM), which aims at triggering interventions to optimize processes (Shoush and Dumas, 2022a). PPM adds a recommendation perspective to the previously prevalent research focus on process predictions (Kubrak et al., 2022). Thus, it can be used in a recommender system (RS) that aims at process improvement. In PPM, the focus is mainly on the question of when and for which instances interventions can be applied rather than on the choice of interventions. Further, PPM is mainly used to optimize time-related key performance indicators (KPIs) and not to optimize energy consumption or cost (ibid.). For these reasons, it is worthwhile looking at the interface of PPM and EF to improve processes by exploiting the EF potential in processes.

Currently, RS utilizing process mining mostly rely on historic process data, similarity metrics, frequency, and KPIs to generate recommendations (Dees et al., 2019; Dorn et al., 2010; Petrusel and Stanciu, 2012; Schobel and Reichert, 2017; Schonenberg et al., 2008; Terragni and Hassani, 2018; Triki et al., 2013; van der Aalst et al., 2010; Weinzierl et al., 2020b; Yang et al., 2017). Some approaches base their recommendations on predictions (Dees et al., 2019; Weinzierl et al., 2020a; Weinzierl et al., 2020b). In many papers, only the next action is recommended, not the complete subsequent process flow like (Yang et al., 2017) do. There are only a few papers that consider time constraints (Barba et al., 2012; Dorn et al., 2010) or revise recommendations frequently (Barba et al., 2012; Petrusel and Stanciu, 2012). Thus, there is a research gap for KPI-optimizing, multi-activity recommendations using both process data and process-external prognostic data that trigger the review of generated recommendations. Enhancing EF-oriented scheduling of processes, we address the following research question: *How can process mining be used to exploit the energy flexibility potential of intra-organizational processes?*

To answer this question, we develop a PPM approach that uses integer linear programming (ILP) to recommend an optimal processing schedule for pending activities within a specific time horizon. We optimize overall energy costs under time-varying power prices by implementing EFM. We adopt the design science research (DSR) methodology as proposed by Peffers et al. (2007). Our artifact, called PM4Flex, uses event logs enriched with information about energy consumption and power price forecasts from the spot market. Based on this data input, PM4Flex provides a real-time recommendation on how to adapt underlying processes to a power price development to minimize energy costs. The approach is applicable to flexible processes with an execution period no longer than the time horizon of the price forecast. With this approach, we extend existing PPM approaches to tackle two major demand-side challenges in the energy system: adapting processes to volatile energy supply and prices.

The remainder of this paper is structured as follows. In Section 2, we provide the theoretical background and related work on EF, process mining, and RS. We explain our research method in Section 3. Then, we present our artifact in Section 4 and report on our evaluation in Section 5. Finally, in Section 6, we conclude our work with a short discussion of our contribution, limitations, and future research directions.

2 Theoretical Background and Related Work

2.1 Energy Flexibility

The dependence of RES on weather conditions induces volatility in power generation, which can be addressed by EF. The gap between decreasing supply-side EF and increasing levels of volatile RES is described by the so-called flexibility gap (Papaefthymiou et al., 2014; Papaefthymiou et al., 2018). This disparity in the power system challenges grid stability and supply security (Sauer et al., 2019). To close this gap, five main options for flexibilization have been identified. These options encompass supply-side EF, storage flexibility, transmission flexibility through grid expansion, demand-side EF, and inter-sectoral flexibility (Heffron et al., 2020; Tristán et al., 2020). Due to high costs for energy storage, slow progress on inter-sectoral flexibility, and a lack of acceptance of grid expansion, demand-side EF is a very promising option to address the flexibility gap (Heffron et al., 2020). Demand-side EF 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 EF, the energy-consuming system is constituted by an operational system that is capable of cost-effectively adapting to power market signals or the variable supply of self-generated power in a short period of time (Tristán et al., 2020).

There are two main options for marketing and, thus, economically exploiting demand-side EF in Germany: on the one hand, companies can market their EF on the power market, especially on spot markets. Both the day-ahead market and the intraday market in Germany are staggered and differ regarding the trading period and the length of the traded power products. Both spot markets enable short-term trading of power products and, thus, a flexible adjustment of power demand through the use of EF (Bachmann et al., 2021). For example, on the EPEX SPOT power exchange, the day-ahead auction takes place daily at noon with hourly and block bids for the following day. This day-ahead auction is followed by the auction of quarter-hourly products for the next day in the intraday auction. Afterward, continuous intraday trading takes place, where quarter-hourly products can be traded up to five minutes before the delivery time. On the other hand, EF can be capitalized on balancing energy markets, such as the control reserve market or the control energy markets. In these markets, the provision and implementation of load increase and reduction measures are auctioned. It is mandatory to implement auctioned measures in response to frequency changes or signals from the transmission system operator. In this way, EFM, which can be reserved accordingly, can be monetized (Bachmann et al., 2021).

The EF potential of a company's operating system can be realized and utilized by implementing EFM. Such EFM represent intentional actions to perform a specific change of state in the corresponding operating system to provide EF. A change of state can involve resources and process instances. It considers the related reciprocal effects in the operating system, e.g., interrupting an order impacts the possibility to adjust resource allocation given the fact that the currently used resource is occupied longer (VDI, 2020). The Association of German Engineers (VDI) has identified a set of 16 distinct generic EFM for production systems that can be structured along a temporal and an organizational axis. They distinguish (i) corporate management for the medium term, (ii) production control for the short term, and (iii) manufacturing for real-time EFM. (i) includes the adaptation of staff free time, working shifts, and order of execution sequence, defer 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 EFM within (ii). (iii) includes operation interruption, adjustment of operational sequence, adaptation of operation parameters, bivalent operation, and inherent energy storage.

Existing approaches for short-term or real-time planning and control of EF can primarily be assigned to the manufacturing industry (Beier et al., 2017; Lu et al., 2020; Schultz et al., 2015; Sun and Li, 2014; Zhou and Li, 2013). The central object and subject of EFM are machines of specific production systems. Adjustments of load profiles are mainly due to a (partial) shutdown of power-consuming machines, which means temporarily shifting these machines into different energy states and allocating resources. An exception is the approach of Bank et al. (2021) for the integration of EF into production planning and control based on the generic EF Data Model (EFDM) (Schott et al., 2019). Starting from an optimized production plan without flexibilities, applicable EFM are specified and integrated in a cost-efficient way. This requires precise knowledge and quantification of the inherent EF potential. While a production system only represents its different workstations (Schultz et al., 2015), a process depicts in detail which activities are actually executed on these working stations. However, none of the mentioned approaches considers a process perspective and, thus, process instances as the subject of EFM.

2.2 Process Mining, Prescriptive Process Monitoring, and Recommender Systems

Process Mining aims at discovering, monitoring, and improving business processes. It combines data science and approaches based on process models to analyze data in the form of event logs. These event logs contain information about the sequential order of process activities and can be extended by additional information, e.g., about resources or social networks. The general goal is to improve processes with regard to set KPIs (van der Aalst, 2011). PPM does so by recommending interventions during the process flow (Kubrak et al., 2022; Shoush and Dumas, 2022a; Weinzierl et al., 2020a). It focuses mainly on interventions triggered by an incident presumably impacting the process outcome negatively (Fahrenkrog-Petersen et al., 2019; Kubrak et al., 2022; Shoush and Dumas, 2022a; Teinemaa et al., 2018; Weinzierl et al., 2020a). Thus, these approaches often neglect an opportunity-driven perspective. Since PPM provides recommendations, it can be performed by a recommender system (RS). RS are “software tools and techniques that provide suggestions for items that are most likely of interest to a particular user” (Ricci et al., 2022, p. 1). The basic goal of an RS is to provide a ranking of possible alternatives based on restrictions and preferences (Ricci et al., 2022). The specific type of knowledge-based RS requires specified requirements for the recommendation and is subject to temporal changes (Aggarwal, 2016). RS based on process mining represent an emerging research area (Yang et al., 2017) which can be seen in PPM.

RS based on process mining are not applied in the energy domain yet (Eili et al., 2021). All combined approaches, which we have found in the literature, are based on historic process data and disregard future developments. The approaches use different bases for their recommendations, which are KPI optimization (Barba et al., 2012; Petrusel and Stanciu, 2012; Terragni and Hassani, 2018; van der Aalst et al., 2010), similarity (Schobel and Reichert, 2017; Triki et al., 2013; Yang et al., 2017), predictions (Conforti et al., 2015; Dees et al., 2019; Weinzierl et al., 2020b), and combinations of these three aspects (Dorn et al., 2010; Schonenberg et al., 2008; Weinzierl et al., 2020a). Yang et al. (2017) provide multi-activity recommendations in the form of entire following process flows while all other approaches make only next activity recommendations (Eili et al., 2021). Only a few approaches allow explicitly for replanning previous recommendations (Barba et al., 2012; Petrusel and Stanciu, 2012). Temporal dependencies or other restrictions are rarely taken into account (Barba et al., 2012; Dorn et al., 2010).

3 Method

To answer our research question, we followed the established six-step DSR methodology by Peffers et al. (2007) (Figure 1). Our artifact is a PPM approach serving as RS, i.e., a method (Hevner et al., 2004; Hevner and Chatterjee, 2010; March and Smith, 1995) that generates recommendations for process flows optimized for energy costs. We have motivated our research (1) in Sections 1 and 2 and present design objectives (DOs) derived from the literature in Section 4.1 (2). For the design and development of PM4Flex (3), we applied situational method engineering (SME) (Ralyté et al., 2019). This entails setting the goal of the engineering task which we covered in (2) and constructing a suitable method for the problem at hand. We applied the method-driven strategy, particularly the assembly-based strategy by using justificatory knowledge from related work. SME evaluation is already included in DSR (5).

(1) problem identification and motivation	(2) definition of DOs	(3) design and development of an artifact	(4) demonstration	(5) evaluation	(6) communication
• Increased volatility through increasing integration of RES in the power system	• Derived DOs from the existing literature	• Design and development of PM4Flex using SME	• Instantiation of PM4Flex as software prototype	• Application of the PM4Flex software prototype to real world data	• Discussion of contribution • Publication of results

Figure 1: Structure of the used method

We demonstrated the feasibility of our artifact (4) using real-life data from a spiral pipe production process. Our evaluation (5) followed the framework for evaluation in DSR (FEDS), particularly the four steps of the *evaluation strategy choice process for DSR* (Venable et al., 2016) with a focus on the artifact itself (Cleven et al., 2009). First, we explicated the goal of the evaluation as demonstrating the efficacy and ensuring the rigor of our software prototype as an instantiation of our artifact. Second, we selected the *technical risk & efficacy* strategy (Venable et al., 2016) as we think the main design risk of our artifact is technical rather than social and a first artificial evaluation is sensible to avoid the risk of negatively influencing ongoing processes in a real-life setting. Third, we defined evaluation properties and criteria: approach-specific metrics like power cost savings, our DOs (Peffers et al., 2007), and the criteria *validity*, *utility*, and *efficacy* (Gregor and Hevner, 2013). The DOs are derived from a criteria-based analysis of existing approaches in both EF and process mining literature. In line with the technical risk & efficacy strategy, we used two evaluation episodes for our research. The first one is artificial as it analyses the existing relevant literature and performs a criteria-based assessment of comparable approaches, coupled with presenting the practical relevance of our work. It is classified as formative since it was instrumental in improving the outcome of the outlined research process. The DOs as the central output of this first episode are input to the second evaluation episode (Peffers et al., 2007). Herein, based on real data sets and historical power prices, we deployed PM4Flex in an isolated environment, also classifying it as artificial. Thereby, we investigate to what extent the results of the artifact application match the expectations, classifying it as summative.

4 PM4Flex Design Specification

4.1 Definition of Objectives and General Concept

Based on the relevant literature, we propose four DOs for PPM approaches for EF optimization:

DO 1: A PPM approach for EF optimization should be transferable to complex, flexible processes within an EF context (Beier et al., 2017; Lu et al., 2020).

DO 2: A PPM approach for EF optimization should allow for company- and process-specific constraints (Bahmani et al., 2022). Especially restrictions regarding time, energy, and sequence of activities are of importance. Therefore, a user-defined policy should be used to implement EF given the circumstances of the respective company and process (Kubrak et al., 2022).

DO 3: A PPM approach for EF optimization should recommend entire pending process flows instead of focusing on isolated activities due to inherent interdependencies (Bahmani et al., 2022).

DO 4: A PPM approach for EF optimization should be able to revise recommendations when circumstances change. For example, an external signal like new data triggers the artifact.

PM4Flex generates multi-activity recommendations for pending process flows of active process instances, thereby optimizing the energy cost based on the load profile of potential following process flows and a power price forecast. We use a knowledge-based RS since the requirements of our recommendation, e.g., the price forecast that the load profile must be adapted to, are explicitly stated and our recommendations need to be adjusted over time due to changing conditions (Aggarwal, 2016). The optimization run is triggered whenever a new energy price forecast is available. The approach is subject to the following prerequisites: The process and associated activities that PM4Flex is applied to must inhere a utilizable level of flexibility. The 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 energy price forecasts from the spot market where ordering times are usually between one hour and 15 minutes before energy consumption respectively delivery. To enable the completion of all considered activities until their respective due dates, their duration should be considerably shorter than the time horizon of the forecast. As we consider short-term energy flexible planning and real-time process monitoring, PM4Flex only incorporates the following six EFM that can be deployed and are effective in the short term: interruption of activity, adjustment of activity sequence, interruption of instance, adjustment of instance sequence, deferral of instance starts, adjustment of resource (Tristán et al., 2020; VDI, 2020). In the following subsections, we describe the components of our RS, from input and data pre-processing to event log exploration, optimization, and output, which can be seen in Figure 2.

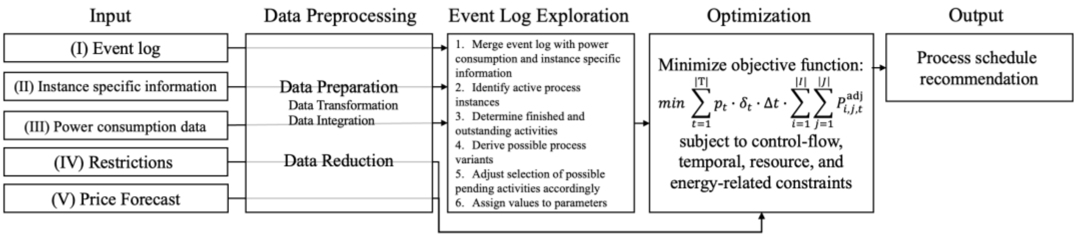

Figure 2: Structure of the PM4Flex approach

For explanatory purposes, we will use the assembly process of a radio throughout this paper. A corresponding process model is presented in Figure 3.

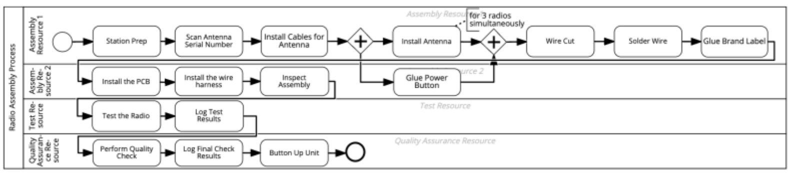

Figure 3: Radio assembly process (source: Software AG, figure adapted from ARIS Process Mining)

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 (ID) for respective instances, activity names, timestamps of the start and end time of each activity, and processing resources. Since not all relevant properties of process instances can be extracted from a standard event log, additional instance-specific information is considered (II). It includes relevant aspects like product type, customer, priority, or due dates which are necessary to, e.g., specify a suitable processing pattern 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, a technology that allows power consumption data from a central measuring point to be disaggregated for deriving reliable estimates of the consumption of individual resources (Klemenjak and Goldsborough 2016; Anderson et al. 2012; Schirmer and Mporas 2023). To allow for practical applicability, it is essential to incorporate company- and process-specific restrictions (IV). Such restrictions can 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 may be obtained from an external service provider. The time resolution of this forecast is determined by the length of the products traded and, thus, 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 re-scheduling of active process instances.

The subsequent step of pre-processing involves handling all input data types to provide an efficiently processable data set for both event log exploration and optimization. We did so 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 (García et al., 2015; García et al., 2016; Wirth and Hipp, 2000). Data preparation as the first step can be separated distinctly 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 and optimization 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. For example, for a temporal resolution of the forecast of 15 minutes (intraday market) and a temporal planning granularity of 5 minutes, each data point of the price forecast must be duplicated twice. Data integration refers to merging data from different sources (García et al., 2016; Wirth and Hipp, 2000). 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 the 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 ID to form instances. Data reduction as the second part of pre-processing aims at reducing the number of considered data records to the relevant ones only (García et al., 2015; García et al., 2016) to make the model more efficient. In PM4Flex, we select only the relevant columns as well as quite recent activities and instances from the given data sets to minimize processed data and, hence, computation time. The latter is especially relevant due to the frequency of optimization runs of our artifact.

4.3 Event Log Exploration

Within the event log exploration, we use the prepared data to extract all relevant process information for the optimization model. To do so, we first enrich the prepared event log with instance-specific information and power consumption data. Second, since the process variants are not known upfront, we manually specify end events such that each process instance that includes these events is automatically classified as finished and as active otherwise. Only the latter ones are considered in the optimization. Third, already finished activities within each active instance are identified automatically within the logged data. Based on already completed process instances, we determine a set of all possible future activities in the process, compare it to the list of already finished activities, and receive a list of all activities that potentially are still to be done. Fourth, depending on the already finished activities and, for instance, on different product types, it is specified which process variants are possible for the instance at hand. E.g., if the instance represents a radio of a certain model, only process variants for this model are relevant, not the ones for another radio model. Fifth, depending on the identified variants, the list of potentially pending activities is reduced to the ones which actually have to be done to finish the process of that specific product adequately. Depending on the prevalence of the variants, the approach prioritizes them for the optimization of the pending process flow. 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 Section 4.4 for the optimization model.

4.4 Optimization Model

For the formulation of our optimization model, we assume perfect knowledge of all process-related parameters, e.g., processing duration or order of activities, as well as data given as time series, e.g., spot market prices for electricity or resource availability. This assumption infers that the scheduler knows the exact realizations of all parameters at the time of scheduling even if the actual realization of those parameters takes place in the future. Consequently, none of the considered parameters has a dynamic or stochastic nature. To reach a maximum, while striving for efficiency of computational effort, the optimization model is formulated as an ILP with all decision variables being expressed as *binaries*. The ILP finds an optimal processing schedule for the active process instances and their respective activities within a specific time horizon. Contrary to existing EF approaches, which focus on resources and their associated buffers (Beier et al., 2017; Lu et al., 2020; Schultz et al., 2015; Sun and Li, 2014; Zhou and Li, 2013), we adopt a process perspective. It includes constraints that ensure flexibilization within relevant boundaries. The majority of the input parameters can be determined through analysis of the event log. However, other parameters must be provided by human professionals or information systems (e.g., enterprise resource planning or energy management systems). Both input parameters and decision variables can have one or more indices, which refer to the four sets the model is based on: the active instances $I = \{1, \dots, |I|\}$, the possible activities $J = \{1, \dots, |J|\}$, the existing resources $R = \{1, \dots, |R|\}$, and the planning horizon $T = \{1, \dots, |T|\}$.

Our model entails several control flow, time, resource, and energy-related **parameters**. 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) restrictions, and (V) power price forecast. Parameters considering the **control flow** of the process are the following: The binary parameter $toBeDone_{i,j}$ (I) specifies whether an activity of an instance is still pending. Whether the two activities j_1 and j_2 can be parallelized is indicated by the binary parameter Prl_{j_1,j_2} (I). Dependencies between activities are indicated by the binary parameter Ord_{j_1,j_2} (I). The latter takes the value 1 if activity j_1 must be carried out without overlapping before activity j_2. If Ord_{j_1,j_2} has the value 0, there is no restriction regarding the order of the j_1 and j_2 in this direction, but Ord_{j_2,j_1} can 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, τ_j^{process}, 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 of periods for which j must be executed uninterruptedly $\underline{\tau}_j^{nonintr}$ (I). Further, we have to stick to the due date $DD_{i,j}$ (II) for each j and i 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. If this is the case, r can process j for $\#PrlInst_{j,r}$ (I) instances simultaneously. Whether two resources r_1 and r_2 can operate in parallel is indicated by the binary parameter $PrlRes_{r_1,r_2}$ (I). The following parameters depict the **energy**-related characteristics: $P_{j,r}^{\text{hist}}$ (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 in the network (Bahmani et al., 2022) or contractually regulated purchase quantities. The forecasted spot market price in t is denoted by p_t (V). The risk factor δ_t (V) incorporates the uncertainty of predicted p_t and typically increases with incrementing t, since the predictive accuracy of p_t forecasts decreases with decreasing temporal proximity to the time of fulfillment (Klobasa, 2007). 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**: $active_{i,j,r,t}$ indicates whether the processing of instance i, activity j on resource r actively takes place in period t. Likewise, $occ_{i,j,r,t}$

indicates whether j of i is assigned 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 j to r assignments and processing phases are signaled by the binary (auxiliary) decision variables $occStart_{i,j,r,t}$, $occEnd_{i,j,r,t}$, $actStart_{i,j,r,t}$ and $actEnd_{i,j,r,t}$. $Exe_{j,r,t}$ indicates whether r is performing j in t or is (at least) occupied to execute j.

Using all the introduced sets, parameters, and variables, our optimization model writes as follows: The **objective function of PM4Flex** minimizes power procurement costs.

$$\min \sum_{t=1}^{|T|} p_t \cdot \delta_t \cdot \Delta t \cdot \sum_{i=1}^{|I|} \sum_{j=1}^{|J|} \sum_{r=1}^{|R|} active_{i,j,r,t} \cdot P_{j,r}^{\text{hist}} \tag{1}$$

The specified objective function is subject to energy (Eq. (2)), control flow (Eqs. (4), (5), (6)), resource (Eqs. (7), (8), (9)), and temporal (Eqs. (10), (11), (12), (13)) **constraints**, ensuring feasibility. As an energy constraint, Eq. (2) ensures compliance with power supply limitations.

$$\underline{P_t} \leq \sum_{i=1}^{|I|} \sum_{j=1}^{|J(i)|} \sum_{r=1}^{|R|} active_{i,j,r,t} \cdot P_{j,r}^{hist} \leq \overline{P}_t \qquad \forall t \in T \tag{2}$$

The processing of an activity cannot be (re-) started and ended in the same period. Eq. (4.1) to Eq. (4.6) ensure that the logical relationships between the six activity-based decision variables are complied with.

$$occ_{i,j,r,t} - occ_{i,j,r,t-1} = occStart_{i,j,r,t} - occEnd_{i,j,r,t} \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{4.1}$$

$$active_{i,j,r,t} - active_{i,j,r,t-1} = actStart_{i,j,r,t} - actEnd_{i,j,r,t} \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{4.2}$$

$$actStart_{i,j,r,t} + actEnd_{i,j,r,t} \leq 1 \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{4.3}$$

$$occStart_{i,j,r,t} + occEnd_{i,j,r,t} \leq actStart_{i,j,r,t} + actEnd_{i,j,r,t} \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{4.4}$$

$$active_{i,j,r,t} \leq occ_{i,j,r,t} \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{4.5}$$

$$occ_{i,j,r,0} = occ_{i,j,r,T} = 0 \qquad \forall i \in I, j \in J, r \in R \tag{4.6}$$

Activities can be interrupted or paused while being executed. However, e.g., due to quality aspects (Leinauer et al), interruptions cannot take place arbitrarily and, thus, are restricted by Eq. (5.1) to (5.4). For example, when executing quality checks of the radio, there might be requirements that prevent from interrupting the process arbitrarily often and long such as testing the stable sound of the radio.

$$\underline{\tau}_j^{intr} \cdot actEnd_{i,j,r,t} \leq \sum_{s=t}^{t+\underline{\tau}_j^{intr}-1} \left(1 - active_{i,j,r,s}\right) \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{5.1}$$

$$\left(occ_{i,j,r,t} - active_{i,j,r,t}\right) \leq \sum_{s=1}^{\overline{\tau}_j^{intr}} actStart_{i,j,r,t+s} \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{5.2}$$

$$\overline{\#Intr_j} + 1 \geq \sum_{t=1}^{|T|} \sum_{r=1}^{|R|} actStart_{i,j,r,t} \qquad \forall i \in I, j \in J \tag{5.3}$$

$$\underline{\tau}_j^{nonintr} \cdot actStart_{i,j,r,t} \leq \sum_{s=t}^{t+\underline{\tau}_j^{nonintr}-1} active_{i,j,r,s} \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{5.4}$$

Regarding the processing sequence and order of activities, it is necessary to specify dependencies between different activities as predecessor-successor relationships modeled by Eq. (6). As aforementioned, specific cables might need to be applied before the antenna can be screwed on the radio. In contrast, it might not matter whether you glue on the brand label or the model number first.

$$Ord_{j1,j2} \cdot toBeDone_{i,j_1} - 1 \leq \sum_{s=1}^{t} \sum_{r=1}^{|R|} occEnd_{i,j_1,r,s} - occStart_{i,j_2,r,s} \qquad \forall i \in I, j_1, j_2 \in J, t \in T \tag{6}$$

Eq. (7.1) ensures that processing only takes place if r is available in t. In our model, a resource is not per se limited to the processing of only one i at a time but instead, r can process j for $\#PrlInst_{j,r}$ instances simultaneously (Eq. (7.2)). In our radio assembly example, this could be a machine screwing antennas on several radios at the same time.

$$ResAv_{r,t} \geq \sum_{j=1}^{|J|} Exe_{j,r,t} \qquad \forall r \in R, t \in T \tag{7.1}$$

$$Exe_{j,r,t} \cdot \#PrlInst_{j,r} \geq \sum_{i=1}^{|I|} occ_{i,j,r,t} \qquad \forall j \in J, r \in R, t \in T \tag{7.2}$$

If more than one i can be processed simultaneously by r ($\#PrlInst_{j,r} > 1$), Eq. (8.1) and (8.2) ensure that processing of the corresponding i indeed takes place parallelly, time-congruently, and not staggered.

$$active_{i,j,r,t} \leq Exe_{j,r,t} + \left(1 - occ_{i,j,r,t}\right) \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{8.1}$$

$$active_{i,j,r,t} \geq Exe_{j,r,t} - \left(1 - occ_{i,j,r,t}\right) \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{8.2}$$

Our model allows for operating resources in parallel. For example, antennas can only be applied after the required cables are installed, so it is not sensible that the machine for adding cables and the one for adding antennas operate at the same time for one i. Also, several j of i can be allocated and processed parallelly. For instance, antennas and power buttons can be screwed onto the radio at the same time by the same machine. Eq. (9.1) and Eq. (9.2) limit parallelization to the technically feasible level.

$$Prl_{j_1,j_2} + 1 \geq \sum_{r=1}^{|R|} occ_{i,j_1,r,t} + occ_{i,j_2,r,t} \qquad \forall i \in I, j_1, j_2 \in J, t \in T \tag{9.1}$$

$$PrlRes_{r_1,r_2} + 1 \geq \sum_{j=1}^{|J|} Exe_{j,r_1,t} + Exe_{j,r_2,t} \qquad \forall r_1, r_2 \in R, t \in T \tag{9.2}$$

τ_j^{process} is estimated within the event log exploration and must be adhered to in the planning (Eq. (10.1)). Furthermore, the allocation of j of i can only occur once over the planning horizon and only for one r (Eq. (10.2)). For example, an assembly error at one cable of a radio can only be corrected by the one machine capable of installing it and, naturally, this specific error must be corrected only once.

$$\tau_j^{\text{process}} \cdot toBeDone_{i,j} = \sum_{t=1}^{|T|} \sum_{r=1}^{|R|} active_{i,j,r,t} \qquad \forall i \in I, j \in J \tag{10.1}$$

$$toBeDone_{i,j} = \sum_{t=1}^{|T|} \sum_{r=1}^{|R|} occStart_{i,j,r,t} \qquad \forall i \in I, j \in J \tag{10.2}$$

We further limit the total duration of allocating j to r, e.g., due to quality aspects or resource characteristics. Complying with this restriction is ensured by Eq. (11.1) and Eq. (11.2). In our exemplary process, the functionalities of a radio must be tested at least for a certain time to check all functionalities. However, testing it longer does usually not add value.

$$\underline{\tau}_j^{total} \cdot occStart_{i,j,r,t} \leq \sum_{s=t}^{t+\underline{\tau}_j^{total}-1} occ_{i,j,r,s} \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{11.1}$$

$$occ_{i,j,r,t} \leq \sum_{s=1}^{\overline{\tau}_j^{total}} occEnd_{i,j,r,t+s} \qquad \forall i \in I, j \in J, r \in R, t \in T \tag{11.2}$$

Practical rationales to constrain the time between two activities j_1 and j_2 exist. A minimum time span could be the consequence of a required transport or cool-down step. Exemplarily, a radio must be transported from the machine that finishes assembly to the manual testing station. An upper limit is reasonable for a case of sequential processing with j_1 transitioning i to a state necessary for executing j_2. After putting glue on a radio, the brand label can be applied for a limited time only before the glue is already dry. The required starting period of j_2 after j_1 is modeled by Eq. (12.1) and Eq. (12.2).

$$1 - \sum_{r=1}^{|R|} occEnd_{i,j_1,r,t} \geq \sum_{s=t}^{t+\underline{\tau}_{j_1,j_2}^{btw}-1} \sum_{r=1}^{|R|} occStart_{i,j_2,r,s} \qquad \forall i \in I, j_1, j_2 \in J, t \in T \tag{12.1}$$

$$toBeDone_{i,j_2} \cdot Ord_{j1,j2} \cdot \sum_{r=1}^{|R|} occEnd_{i,j_1,r,t} \leq \sum_{s=t}^{t+\overline{\tau}_{j_1,j_2}^{btw}-1} occStart_{i,j_2,r,s} \qquad \forall i \in I, j_1, j_2 \in J, t \in T \tag{12.2}$$

Compliance with due dates is necessitated by Eq. (13). If delivering a certain number of radios by a specified date is contractually agreed on, one has to adhere to it to maintain customer satisfaction.

$$DD_{i,j} \geq \sum_{r=1}^{|R|} \sum_{t=1}^{|T|} occEnd_{i,j,r,t} \cdot t \qquad \forall i \in I, j \in J \tag{13}$$

4.5 Output

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

5 Demonstration and Evaluation

First, we evaluate whether and to which extent PM4Flex fulfills the DOs presented in Section 4.1. PM4Flex fulfills DO1 as will be presented in this section by being applied to a flexible but complex process from a real-life production. PM4Flex allows for company- and process-specific constraints and satisfies DO 2 since they can be integrated by instantiating the input parameters, either derived from the event log or set manually, or by adding specific constraints. PM4Flex fulfills DO3 as it can recommend entire process flows including the pending activities, which is proven in our instantiation. Addressing DO4, PM4Flex can quickly adapt its recommendations to changes like a new price forecast or a change in the availability of a resource by automatically adjusting its input parameters.

To demonstrate the added value of our artifact, we implemented an instantiation of PM4Flex[1] as a software prototype in python. We used the *pm4py* package (Berti et al., 2019) for the event log exploration and the *gurobipy* package to create the proposed optimization model that we applied to a scenario based on a real-world event log and historical power spot market price data. To quantify the added value of the developed PM4Flex approach, we considered a benchmark approach.

Comparing existing scheduling approaches from the energy domain (cf. Section 2.1) to PM4Flex, we found that there are no approaches that can serve as a direct quantitative benchmark, but rather as a qualitative one given our experimental setting and the used data. In comparison to PM4Flex, two classes of energy-oriented scheduling approaches can be distinguished in current literature: The first class relates to approaches for simple processes only, taking a resource-centric perspective and aiming at adjusting the power consumption according to external variables (spot market prices, self-generation, etc.) by changing the operational state of machines (Beier et al., 2017; Schultz et al., 2015; Sun and Li, 2014). Since our data set contains complex control flow dependencies of a non-linear process, we cannot apply them to our evaluation setting. The second class of approaches (Bank et al., 2021; Bahmani et al., 2022) considers power consumption and process-inherent EF on a higher level of abstraction, where comprehensive and detailed knowledge of the EFM properties (Schott et al., 2019) is needed. This requires extensive analysis of the relevant processes, involved resources, and historical power consumption in the form of an industrial EF audit (Tristán et al., 2020), which can be a considerable temporal and financial effort. For this reason, our partnering company could not provide such extensive insights, making a comparison infeasible.

On the other hand, there are also no PPM approaches to quantitatively compare our artifact to. In fact, some approaches aim to optimize cycle times (Bozorgi et al., 2021), take resource constraints into account (Shoush and Dumas, 2022b, 2022a), recommend next best actions (Weinzierl et al., 2020a; Barba et al., 2012), and do so self-adjustedly (Dorn et al., 2010) and step by step similar to our approach (Yang et al., 2017). Many of them use machine learning (Barba et al., 2012; Bozorgi et al., 2021; Shoush and Dumas, 2022b), e.g., neural networks (Weinzierl et al., 2020a). However, we did not do so intentionally to avoid a black box, making the procedure of how the recommendation is made clear and replicable. This is important for users to understand and trust the recommendation and to evaluate whether they want to follow it. In contrast to learning algorithms, PM4Flex should be applicable to and achieve reasonable results with any kind and size of event log data basis. We lack a sufficiently large database for a reasonable utilization of learning algorithms as a benchmark. One approach in PPM is based on sequence graphs and process models (Dorn et al., 2010), which we could also derive from our data. However, this approach makes recommendations with regard to possible next activities only without considering cost, making a direct comparison impossible. We could overcome all of these

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

drawbacks, however, none of the existing approaches optimizes the recommendations subject to a changing price forecast, which makes a direct comparison infeasible as well.

Due to this lack of a reasonable benchmark, we use a widespread approach for production process optimization in the industry (Li et al., 2015) as our point of comparison. This approach is an optimization model that minimizes the maximum completion time and generates a process schedule from that. For a reasonable comparison, both the benchmark and PM4Flex account for control flow dependencies among activities and were tested with the same data set. Below, we present the investigated process and input parameters in more detail.

The considered process is essentially based on the event log of a real-world process for spiral pipe production of a German medium-sized heating and air conditioning company. The corresponding process-related data contains the event log, power consumption data per workstation, and due dates as well as product allocations as instance-specific information. The process includes several activities from cutting, grinding, bending, welding, and lacquering the metal, to assembling, checking, packing, and shipping the spiral pipe. For the electricity price forecast, we used actual historic market data from the European power exchange (*EPEX SPOT*) for the German intraday market of 2022. It is important to note that we assume perfect knowledge of the realizations of electricity spot market prices, i.e., the forecasted prices used for the optimization equal actual realizations. Furthermore, we consider two business days, Monday, October 17th, and Tuesday, October 18th, 2022. The ILP considers discrete periods of 30-minute intervals.

We consider several metrics (power procurement cost, maximum completion time, computation time) for our comparison. The first metric is calculated by summing up the products of electricity price and electricity consumption over all instances and time periods. The maximum completion time relates to the completion time of the last instance over all resources considered within the optimization run. Computation time is the time required to reach an optimal solution. The more complex a process gets, i.e., the more dependencies and constraints, the longer the execution time. Since the process we used for the evaluation is already quite complex with regards to dependencies, however, it can be said that the approach is applicable to complex processes. Depending on the frequency of replanning and the resulting need for fast optimization, the ability to extend the optimization model is, however, limited. Our evaluation results are summarized in Table 1. Both implemented approaches were run on a virtual machine with a 2.25 GHz 32-core CPU and 16 GB RAM using the Gurobi solver.

As an output for our artifact and the benchmark, we obtain for each active instance and its pending activities a start and an end period, its duration, the resource on which it should be processed, as well as the associated electricity procurement cost (Table 1).

Table 1: Output of PM4Flex (excerpt)

Instance	*Activity*	*Resource*	*Start*	*End*	*Duration*	*Electricity Cost*
Instance127	Activity13	Resource14	5	6	1	0.385255
Instance133	Activity07	Resource10	41	46	5	2.706225
…	…	…	…	…	…	…

From the experimental setting and its outcomes, we receive the following results for the comparison of PM4Flex and the benchmark (Table 2) that enable us to quantify the added value of PM4Flex. As aimed for, PM4Flex yields lower power costs than the benchmark. Both approaches lead to a power consumption of 650.61 kWh for ten processed instances. However, PM4Flex identified a solution with minimal electricity costs of 19.36 € saving procurement costs of 10.13 € which equals 34.35 % compared to the processing according to benchmark scheduling. In contrast, PM4Flex yields a greater maximum completion time. However, the results are still compliant with the due dates, ensuring timely production and, hence, representing no issue for applying PM4Flex in practice. Regarding the computation time, PM4Flex exceeds the benchmark by 197.5 seconds. Nevertheless, it is still within a reasonable time span to be used with a 30 min replanning frequency.

Table 2: Comparison of PM4Flex and a benchmark

approach	*power procurement cost*	*maximum completion time*	*computation time*
PM4Flex	19.36€	period 48	221.85s
Benchmark	29.49€	period 21	24.37s

Based on these results, we evaluate PM4Flex with respect to *validity*, *utility*, and *efficacy*. Comparing the recommendations with the actual process flows in the event log, it can be observed that PM4Flex indeed provides valid recommendations under the given circumstances and restrictions ensuring its *validity* (Gregor and Hevner, 2013). An isolated demonstration environment ensures that other factors besides PM4Flex do not influence and modify the recommendations and resulting savings guaranteeing the *efficacy* of the artifact (Gregor and Hevner, 2013). As PM4Flex outperforms the benchmark approach in terms of power costs, it achieves its set objective and, hence, adds value to the process it is applied to ensuring the *utility* of our artifact (Gregor and Hevner, 2013).

6 Discussion and Conclusion

Due to a high weather dependency on RES, power generation is becoming more volatile. Both the energy system and companies need to ensure a reliable energy supply and adapt to fluctuating energy prices. To support companies in exploiting the EF potential of their processes, we developed PM4Flex, following the DSR paradigm. PM4Flex helps companies to adjust flexible processes in the short term to volatile energy supply by implementing EFM in an energy-cost minimizing manner. For demonstration and evaluation, we instantiated PM4Flex as a software prototype and applied it to real-world data from a spiral pipe production process. We compared it to a throughput time minimizing benchmark proving that PM4Flex outperforms this benchmark in terms of power costs.

With PM4Flex, we contribute to research by creating descriptive design knowledge for both the energy and the process mining domain. On the one hand, we extend PPM with specific EFM as interventions as well as with a non-black box approach. PM4Flex focuses on energy consumption and energy-cost minimization rather than on time-related KPIs which is paired with power price data. Entire pending process flows rather than only one next activity are recommended. Hence, we add a new perspective to PPM. On the other hand, PM4Flex also allows for the exploitation of EF from a process perspective, extending established EF-oriented planning approaches. It considers power prices in the optimization which was rarely done in existing EF approaches. Overall, PM4Flex helps to exploit the potential of process mining for EF optimization, thereby addressing several research gaps.

Our research, of course, is subject to limitations. First, given the assumptions described in Section 4.1, we cannot claim exhaustiveness. For example, due to PM4Flex’s focus on short-term adaptations of processes, not all EFM are considered. Moreover, the more requirements and circumstances are considered, the more complex the model gets, and, thus, the execution time increases. Additionally, we only considered power but did not take other kinds of energy like heat or cold into account. Further, due to growing complexity, we did not look at prosumers, energy storage, or other possibilities to adjust the energy consumption from the grid. Also, our approach is not fully automated. It is still necessary to manually adjust the constraints according to the company-specific requirements, resulting in the requirement for human expertise. On top of that, our evaluation is limited as we focused on artificial evaluation activities and a specific process. Therefore, we consider PM4Flex as an initial step towards the exploration of process mining for exploiting EF, opening the possibility for further research.

Future work could, for example, focus on automating the derivation of constraints from past event logs. To increase its generalizability, our approach could also be extended by price forecasts for other forms of energy. Since the number of both prosumers and energy storages is rising, it would be interesting to consider their specific restrictions and potentials as well. Special attention could be paid to the extended demand-side EF potential when, e.g., owning energy storage. Additionally, a more comprehensive evaluation of our approach, especially in a real-life setting (i.e., not only with extracted real-life data), is sensible to assess the practical feasibility and utility further.

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