A Framework for Enhanced Decision-Making Support in Production Planning through Event Data Analysis

Discussion Paper

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Abstract

This discussion paper presents the design and implementation of a decision-making framework for simulating production planning in manufacturing. The framework integrates techniques from Process Mining, Business Process Simulation, and Visual Analytics to analyze and interpret historical production event data. The business case centers on a manufacturing company specializing in sanitaryware production. The results highlight the potential of the framework to automatically generate production planning simulations, improving decision-making support.

Keywords

Event Data, Production Planning, Decision-Making, Process Mining, Business Process Simulation, Visual Analytics

1. Introduction

The era of *Industry 4.0* (I4.0) is characterized by the availability of a large variety of Internet-of-Things (IoT) devices that monitor the evolution of several real-world objects of interest and produce a massive amount of data and events [1, 2], which can be referred as Big Data. In this context, one of the primary objectives for companies is to leverage such data to establish autonomous smart solutions that encompass the digitalization of the entire *production process*, from the design to the testing phase [3]. This new industrial landscape demands a shift in *production planning* tools [4].

Production planning defines how products are manufactured, detailing production processes, dependencies, human and technological resources, and schedules to meet customers' demands (e.g., on-time delivery) and organizational needs (e.g., reduced process cycle time). Production planning is mainly performed with the support of Manufacturing Execution Systems (MESs),

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Product Lifecycle Management Systems (PLMSs), and Discrete Event Simulation tools (DESs). However, these solutions require a relevant manual effort performed by human experts to specify the potential production plans of a company. They typically rely on digital models developed during the design phase, thus representing outdated situations, and model obsolescence is a critical issue because it might lead to wrong decisions on production that can not be accurately predicted [5]. In these circumstances, the consequence is that decision-making is static, often relying on alarms set at the design stages. On the other hand, I4.0-driven production is becoming highly flexible, requiring an ever-increasing number of variants of a production plan to accurately perform decision-making by minimizing any imponderables [6].

To maximize their potential, production planning tools must take advantage of the Big Data from production processes by leveraging I4.0 technologies and adjusting automatically to the dynamic changes in production [7]. Nonetheless, integrating I4.0 into production planning remains in its early stages [8, 7, 4, 9]. Consequently, production planning activities and decisions are nowadays undertaken by expert users based on manual data collection and analysis techniques [10]. This is time-consuming, limits the degree of context-awareness to the experience and ability of the users involved in the production planning phase to capture up-to-date production-related data, and potentially leads to sub-optimal decisions that are poorly aligned with the production process requirements, as only a restricted subset of execution data and options are considered.

To mitigate this issue, in this discussion paper, we present a framework that integrates some techniques from the I4.0 realm, namely *Process Mining*, *Business Process (BP) Simulation*, and *Visual Analytics*, to address two research challenges for enhancing decision-making support in production planning, namely:

- (C1) the automated generation of up-to-date digital models of the production process from raw production event data;
- (C2) the elaboration of digital models for extracting insight-ready data to improve the quality of decision-making activities.

Specifically, *Process Mining* techniques [11] are used to analyze historical production event data recorded in dedicated event logs to extract a *digital model* that mirrors the production process along its lifecycle [12], reflecting the production phases, their frequencies and temporal behaviour, and for creating accurate *simulation scenarios* of the company's production planning. Simulation scenarios enable us capturing the *context* within which the production process is operating. In production planning, context is a multi-faceted concept encompassing production-related information such as the time and cost associated with each production phase, the workforce availability, the warehouse capacity, the priority of planned orders, etc. [13]. Such simulation scenarios are then executed through a *BP Simulation* tool [14]. BP Simulation involves accounting for the resources on hand and exploring ways to use them most effectively based on customer demand. Many potential production plans can be simulated to explore different strategies for optimizing the production process. Finally, *Visual Analytics* solutions provide interactive representations of the simulation results, thus allowing decision-makers to grasp essential patterns and trends for informed production planning.

In this paper, we summarize the key concepts discussed in [15] and present the most relevant details of the proposed framework, which aims to enhance context-awareness in production planning tools through event data analysis. The feasibility of the framework has been demonstrated through its implementation in the case of CER,[1] a leading I4.0 sanitary-ware manufacturer participating as a business case partner in the EU H2020 *DataCloud* project[2]. This project focused on developing solutions to support the life cycle of Big Data pipeline management [16].

The rest of the paper is organized as follows. Section 2 describes the CER business case. Section 3 details the design of the proposed framework and its implementation in the context of CER. Finally, Section 4 concludes the paper by discussing lessons learned and future works.

2. Business Case

CER is a leading Italian company in the sanitaryware industry that targets innovating ceramic production by adopting advanced I4.0 automation technologies integrated with an IoT infrastructure to keep up with the ever-increasing demand for quality products.

CER experiences a continuous stream of purchase order requests, encompassing numerous ceramic-based sanitary items that need to be manufactured and delivered within a specific time frame. The CER production process relies on robotic arms to carry out the manufacturing phases. Specifically, starting from a CAD (Computer-Aided Design) 3D virtual prototype of a sanitary product, a *casting* phase generates its initial mould model, which is then manipulated by the subsequent steps of the production process (*drying*, *finishing*, *glazing* and *firing*) to obtain the final product as desired at design-time.

Given the high volume of daily requests, even if the company is equipped with some production lines to parallelize the manufacturing of different items, it can only fulfill a limited number of production orders each day. This limitation arises from the manual intervention of expert decision-makers required to schedule the production and delivery of new orders, considering the production queue, the history of previously approved orders, the stock availability, etc. This activity involves variable factors such as the time needed to set up the production process for a new order and the non-fixed duration for a robotic arm to handle a ceramic artifact depending on the specific item being produced.

In the following section, we show how the proposed framework was designed and implemented over the CER case to forecast the optimal timing for producing and delivering new orders automatically while meeting customer deadlines and minimizing the changes in the CER's production process. This is achieved by simulating different production plans and evaluating their insights through visual support.

3. Framework Design and Implementation

From a methodological perspective, the proposed framework has been conceptualized and designed for addressing the two research challenges (C1) and (C2) discussed in Section 1. The framework consists of 5 operational stages to be applied in sequence: *(i)* Event Log Extraction, *(ii)* Process Discovery and Parameters Estimation, *(iii)* Model Tuning and Context Management, *(iv)* BP Simulation, and *(v)* What-if Analysis, as shown in Figure 1.

[1]The name of the company is not disclosed due to confidentiality constraints.
[2]https://cordis.europa.eu/project/id/101016835

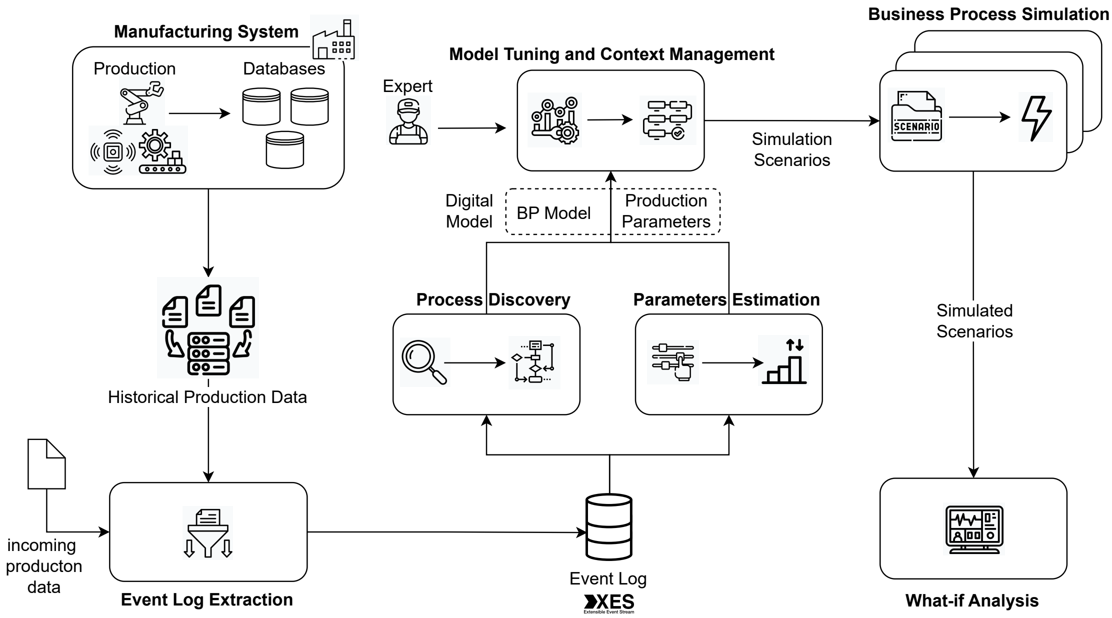

Figure 1: Design of the framework.

Event Log Extraction. Starting from the historical production data stored in the company's databases (DBs), e.g., those data keeping track of the evolution of production over the years, as well as incoming data related to new products to be manufactured, the first stage of the framework is to generate an *event log* that encapsulates all the information about the production phases involved in the end-to-end execution of the production process. Specifically, an event log is a collection of *traces*. A trace represents the execution of an instance of the production process. Each trace contains a sequence of *events*, each related to a step of the production process. Events are associated with an activity label, a timestamp, and a trace identifier. The IEEE standard for storing, exchanging and analysing event logs is XES[3] (eXtensible Event Stream).

In the case of CER, the event log was obtained by analyzing the three core relational databases (DBs) of the company, namely the Production DB, Warehouse DB, and Orders DB, together with the reception of a new order made by a customer. An order consists of the desired product types (e.g., washbasin of type 'A' and water closet of type 'X'), the number of items for each product type (e.g., 300 items of type 'A' and 500 of type 'X'), and an expected deadline for delivery. With this input at hand, an event log reflecting the historical production data of the product types included in the order was generated. In a nutshell, each trace in the event log encapsulates the information about the manufacturing phases involved in the end-to-end execution of the production process for a single item belonging to an ordered product type (e.g., looking at the previous example, the event log contains only data related to products of type 'A' or 'X'). The procedure to obtain the event log from the company's databases followed traditional event log extraction techniques [17, 18].

[3]https://xes-standard.org/

Process Discovery and Parameters Estimation. Once the event log is obtained, well-established Process Mining techniques can be leveraged to reveal fact-based insights into how the production process transpires. Specifically, the objective of this stage is twofold: *(i)* learning the sequencing of production phases to reproduce the behaviour observed in the log; and then, *(ii)* extracting the relevant time and cost information associated with each production phase (e.g., the total and average time of the production process, processing time and cost of each phase, average arrival times between traces, waiting time, etc.), together with an estimation of the human and technological involvement (e.g., cost of the involved resources, human resource calendars, etc.). Thus, the output of this stage consists of defining a *digital model* of the production process, which includes two elements: *(i)* a *Business Process (BP) model* detailing the control flow of the production process to be emulated, and *(ii)* the estimated *production parameters*, that are passed to the next stage of the framework.

In the case of CER, we relied on the *Inductive Miner* algorithm implemented in PM4PY[4] to discover the BP model of the CER production process. Of course, for different orders, the possibility exists that slightly different BP models are discovered from the log. Then, we translated the event log into a relational DB through the *RXES* schema [19]. We used it to feed a customized version of the Process Mining technique described in [20], which enabled us to extract the relevant time and cost information associated with each manufacturing phase of the historical production of a product type included in the order, with an estimation of the human and technological involvement. When no historical information about a product type was available in the company's DBs (e.g., for novel products to be manufactured), we employed its default production parameters.

Model Tuning and Context Management. To build realistic simulation scenarios, the BP model can be customized by expert users to comply with the technological and physical limits of the current production process. This includes incorporating in the model those contextual information not directly observable in the execution of the production process (e.g., market demand, financial constraints, etc.), or removing complexities that may hinder the correct interpretation of the model developed. Through a proper customization of the production parameters computed in the previous stage, this stage enables us to generate many *simulation scenarios* required to perform BP Simulation.

In the case of CER, we customized the behaviour of the BP model to make it compliant with the specific constraints of CER. Indeed, while some steps of the production process of CER involve robotic arms and machineries that can manipulate ceramic items associated with any kind of sanitary product (e.g., *drying*, *glazing*, and *firing*), other steps such as *casting* and *finishing* are constrained by technological and physical limits that must be considered in the BP model to build a realistic simulation scenario. For example, concerning the *casting* step, the CER plant is equipped with N machineries configured with the specific mould stamp of the product the company will produce in a certain period. Switching mould stamps requires not only the direct and time-consuming involvement of human resources but even interrupts the working of some lines of the production process temporarily. To mitigate this issue, CER tends to produce sanitary items of a certain type in batches before changing the stamps. Consequently, based on the different product types in an order, the machineries available for the casting step

[4]PM4PY is a suite of state-of-the-art Process Mining algorithms for Python: https://pm4py.fit.fraunhofer.de/

must be wisely assigned to the different product types. For example, if an order includes only products of type 'A' or 'X', we may customize the BP model allocating $N/2$ casting machineries to 'A' and the others to 'X'. This is reflected by modeling two distinct BP activities for the casting phase in parallel branches, namely (for example) "*Casting_A*" and "*Casting_X*", each one associated with $N/2$ machineries. Another possible (more drastic) solution is to assign all the N casting machineries to 'A', meaning that products of type 'X' can start to be produced only after all products of type 'A' completed the casting phase. Additional valid combinations can be implemented, allowing the creation of diverse BP models to simulate order production using various strategies. The point is that the BP model reflecting the CER's production process can be structured in many variants based on the nature of the order being received by combining the sequencing and the number of the casting and finishing phases. These constraints represent an example of contextual information not available in process execution data but owned by CER domain experts that must be incorporated in the BP model before simulating the scenarios. In the context of CER, this task was performed automatically by a dedicated software component that generates suitable BP model variants considering their combination as realized in the historical production of orders of similar kind.

BP Simulation. It is the pivotal aspect of the framework. While traditional production planning requires a consistent involvement of human decision-makers to manually compute an optimal production strategy based on historical data, we rely on BP Simulation techniques to mimic the execution of the production process for specific product types. This allows us to automatically estimate the effectiveness of several potentially valid production plans that would require much human effort to be obtained manually. Once the computation of the multiple instances of the BP Simulation is completed, the results of the *simulated scenarios* are aggregated and visually presented to the decision-makers.

In the case of CER, we emulated independently each simulation scenario using the engine running behind BIMP.[5] We opted to use BIMP due to its wide range of simulation features and lightweight performance that align perfectly with our specific needs. The simulation of a single scenario configuration was repeated a fixed number of times (from 3 to 5, depending on the size and complexity of the order); this is a common practice to minimize the potential outliers that may arise from random factors during BP Simulation [14]. The negative side effect was that if, for example, 50 distinct simulation scenarios were generated for a specific order, repeating them 5 times each required running 250 instances of the BP Simulation step, a time-intensive activity requiring several hours or even days to be completed, which is a time not acceptable for CER and very close to the current timing needed by the decision-makers to manually developing a production plan that accomplishes the order. To mitigate this issue, within the scope of the DataCloud project, we enhanced performance scalability by parallelizing the processing of multiple BP Simulation instances, obtained by distributing the workload of the BP Simulation across the distributed resources of Cloud Computing.

What-if Analysis. It is an approach for estimating the impact of changes to a production process in terms of time and cost measures. This stage facilitates informed decision-making by providing visual insights into the potential consequences of adjustments to a production plan according to the simulated scenarios.

[5]https://bimp.cs.ut.ee/simulator

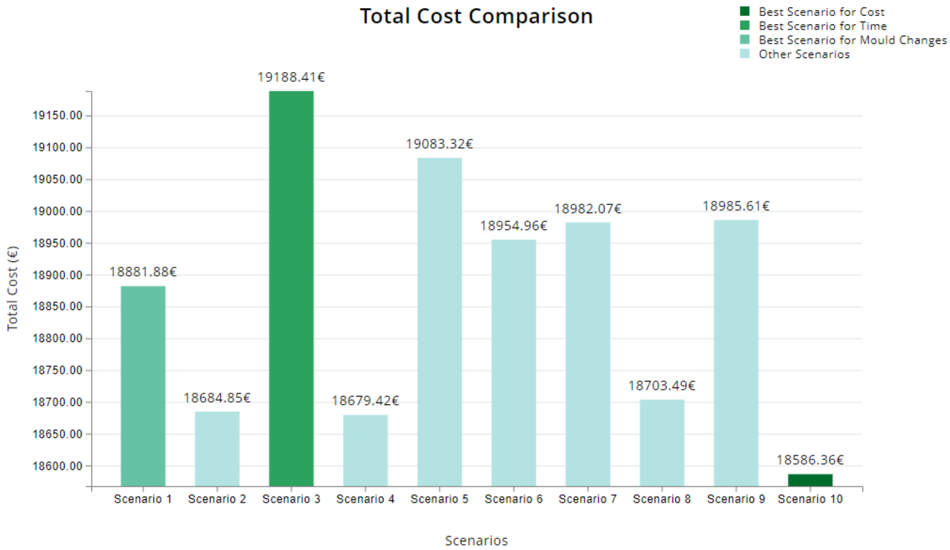

Figure 2: The scenarios comparison page.

In the case of CER, this stage was implemented through a visual analytic tool (cf. Figure 2) that offers a comprehensive range of visual comparisons among production scenarios. These comparisons focus on metrics such as total cost/time, and the total number of mould changes needed on machines required to implement the chosen production plan. Particular emphasis was put on the presentation of the top three scenarios for the aforementioned metrics. In general, the best scenario for cost, time, and mould changes depends on the configuration of the scenarios in terms of the quantity of production lines used to parallelize the manufacturing of different items, the order in which products are realized and the number of mould changes performed. Furthermore, this user interface provides the opportunity to analyze individual scenarios and get an overview of their relevant metrics and KPIs achievement. From a technological point, the development of the visual analytic tool followed a User-Centered Design[6] approach, leveraging the well-established front-end Web stack (HTML, CSS and JavaScript) to ensure that the implementation process does not require any additional local installation of dependencies or frameworks. This aspect holds great significance as it reduces CER's effort to seamlessly integrate the tool into their existing information system. A preliminary user study evaluating the usability and effectiveness of the What-If analysis component is presented in [15].

4. Conclusion

In this paper, we presented the design and implementation of a context-aware framework to simulate the production planning of a manufacturing company. Specifically, by leveraging historical and incoming data of production, our framework enables predicting the optimal

[6]ISO 13407:1999

timing for fulfilling new requests and meeting customers' time requirements based on different simulated scenarios. By relying on the capabilities of Process Mining, BP Simulation and Visual Analytics, we analyzed and extracted valuable insights from historical production data towards building a proactive approach to support decision-making for production planning, allowing for the simulation of different production scenarios before their execution. Implementing the proposed framework for CER has demonstrated its ability to transform production data into digital models to simulate the effects of potential changes in the production process (C1), and improve predictive order forecasts, enabling more accurate decision-making (C2).

Despite the positive outcomes and advancements achieved through the implementation of the framework, there are certain limitations to acknowledge:

(i) the effectiveness of the framework heavily relies on the quality and availability of historical production data. Incomplete or inaccurate data may lead to suboptimal predictions and recommendations. Therefore, ensuring data quality and integrity is crucial for maximizing the benefits of the framework [21];

(ii) our framework enables production planning tools to become automatically "aware" of the contextual information recorded in process execution data, while further contextual information not strictly related to the execution of the production process must be incorporated (if needed) by expert users into the BP model during the Model Tuning and Context Management stage;

(iii) the complexity and variability of production scenarios make it challenging to generate realistic simulation models employing mainstream approaches to BP Simulation, which treat resources as undifferentiated entities grouped into resource pools. We have shown an example of this issue in Section 3 and the ad-hoc solution we found for properly managing the casting phase in a BP model. However, this limitation calls for novel BP Simulation techniques to capture the full complexity of manufacturing operations.

As future work, we would like to assess not only the entire framework's effectiveness, including the accuracy of simulation scenarios and their alignment with real-world outcomes but also a comparative analysis with respect to alternative tools or approaches to production planning providing concrete performance metrics or objective measures.

This work could play a key role in the context of AI-augmented Business Process Management Systems (ABPMSs), that is, an emerging class of process-aware information systems empowered by AI technology for autonomously unfolding and adapting their execution flow [22]. Indeed, we envision extending this work in two different directions. Firstly, since the prominence and versatility of Large Language Models (LLMs) [23, 24, 25] have reached unprecedented heights, an additional future work could be to embed LLMs into the What-if Analysis stage to assist decision-makers in the selection of the optimal simulated scenario. Secondly, we envision leveraging the concept of *process framing* [26] to predict new possible production scenarios that break the boundaries imposed by the current production constraints, thus deviating from what is expected and ensuring process resiliency [27] and adaptation [28].

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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