Supporting Decisions in Production Line Processes by Combining Process Mining and System Dynamics

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Abstract. Conventional production technology is static by nature, developments in the area of autonomous driving and communication technology enable a novel type of production line, i.e., dynamic production lines. Carriers of products are able to navigate autonomously through a production facility, allowing for several different "production routes". Given such dynamic behavior, it is interesting for a production line manager to study in what type(s) of station(s)/resource(s) he/she needs to invest in. We can do so by analyzing the behavior of the autonomous production line, to calculate what change is most likely boosting performance. In this paper, we use historical event data, which are the actual execution of the process, to support the design of system dynamic models, i.e., a high-level predictive mathematical model. The purpose of our framework is to provide the possibility for production line managers to oversee the effects of the changes at the aggregated level in the production line, regarding different performance metrics. At the same time, we provide the freedom in choosing the level of detail in designing the model. The generated model is at a customized aggregated level. We evaluated our approach based on synthetic event logs in which we emulate the effect of policy changes, which we predict accordingly.

Keywords: Process Mining · Performance Analysis · System Dynamics · Production Line · Simulation · What-if Analysis

1 Introduction

In the area of modern products in the automobile industry, e.g., e-mobility and autonomous driving, production lines should be able to handle the changes as fast as possible. Flexible manufacturing system proposed different approaches in order to deal with disturbances in the production systems [6]. Providing an agile platform in which the production line managers are able to find the points to improve the performance metrics is important. At the same time, the effects and costs of changes need to be considered carefully. Production line managers have to make the changes with a certain level of confidence regarding the possible effects before applying them. A complete insight into the performance of the production line is a requirement for a production line manager, prior to evaluating the effect of changes. In modern organizations, information systems are playing a substantial role in the support of day-to-day operations.

These information systems become more and more intertwined with production processes. Process mining [1] is a collection of highly automated techniques that aim to increase process knowledge primarily based on the event data recorded in such information. For example, process mining techniques enable us to discover descriptive process models, purely on the basis of the recorded information. Furthermore, advanced techniques allow us to assess process conformity w.r.t. a given reference model, as well as bottleneck identification. Since the information system tracks what actually happens, process mining techniques allow organizations to increase overall process transparency as well as improved process performance. The real running processes in an organization, along with bottlenecks and performance metrics are a crucial step for an organization to identify its current performance as well as to improve their processes. Furthermore, several techniques exist, that aim to increase the overall view of the process [7, 8]. Undisputed, predicting the future behavior of a process, specifically with the aim of improving process performance, is of interest to many organizations. Within process mining, some work towards the prediction of future behavior w.r.t. performance of the process is proposed [9]. In [11] focuses on assessing the applicability of deep learning techniques for short-term prediction. None of the existing techniques provides the freedom of choosing the level of detail in prediction. However, a decision-maker in an organization is often interested in the prediction of process performance regarding different levels of detail, specifically, in production lines. Current predictive approaches use extensive knowledge of the process, and, in production lines, the large number and diversity of activities make use of current forward-looking approaches not feasible. In [5] a general framework is proposed which can be used for scenario-based analysis and prediction at an aggregated level. It uses system dynamics models based on the past data of the organization. Using this approach the environmental variables, which in reality affect the performance of a process can be included. At the same time, despite the discrete event simulation techniques, the freedom in the level of detail is provided. Therefore, in this paper, we adopt the main approach in [5] and propose a general framework based on process mining and system dynamics for production lines. It provides insight into the current status of the production lines and its future statues considering the upcoming changes. We extend the proposed framework in [5] by adding a different level of detail for the modeling. In addition, we perform a preliminary case study w.r.t. the applicability of the proposed framework in future dynamic production line settings. The remainder of this paper is organized as follows. In Section 2, we introduce background concepts. In Section 3, we present our main approach. We provide an evaluation as a proof of concept in Section 4. In Section 5, related work is mentioned. Section 6 concludes our work and discusses interesting directions for future work.

2 Background

Process Mining. Process mining is a collection of approaches, techniques, and tools, which provides a wide range of knowledge about the processes inside the organizations based on event logs. Using process mining, discovering and analyzing the processes executed in an organization is possible [1]. **Event Log**. Past data of the execution of the organization's processes provide the input for process mining. The execution of an activity, in the context of some process instances, identified by a unique case id at a specific timestamp by a specific resource is referred to as an event. For instance, an event in the production line is defined such as item 1 (case id) is cut (activity) by John (resource) at 10/1/2018 7:42:30 (timestamp). There are different events related to the different process instances, identified by different case ids. A set of events regarding the same case id forms a trace and multiple traces form the event log of the execution of the process. Note that, typically, an event log includes more data attributes related to the process, e.g., costs of an activity, account balance, customer id, etc.

System Dynamics. System dynamics is the collection of approaches, techniques, and tools, which is able to present the model of complex, dynamic systems, in a structured manner. In particular, it allows us to capture the factors affecting the behavior of a system [4]. Within system dynamics, we use a specific modeling notation, i.e. a stock-flow diagram that allows us to simulate possible future behavior of a system, e.g., a (business) process. **Stock-Flow Diagram**. A stock-flow diagram consists of three basic elements, i.e., stocks, in-/out flows, and variables [3]. A stock represents any entity that, in some way, is able to accumulate over time, e.g. the number of waiting items in the production line. An inflow increases the accumulated entity represented by a stock, whereas an outflow reduces the accumulated entity. Finally, any environmental factor that is able to influence the in-/outflow of a stock is modeled as a variable. Such a variable is able to influence other variables as well. Furthermore, the value of a stock, in turn, is able to influence w.r.t. a variable.

3 Proposed Framework

General key-performance metrics in production lines are resource management/utilization and throughput time. We adopt the framework presented in [5] and use the past execution of the processes in a production line in the form of event logs. Event logs and processes include track information on an activity level, i.e., they describe what activity is performed at what point in time, which makes the modeling complicated. In the proposed framework, as Fig. 1. shows, we extract the major process components, which are, in a production setting, the stations in the production line. In the newly discovered process model the level of stations is detailed enough to show the flow of cars being produced in the production line and at the same time aggregated enough to avoid unnecessary details. To do so, we extract activities and aggregate them into one single activity using [12]. The set of activities, which must be performed but may happen in different orders extracted, observing the traces in the event logs.

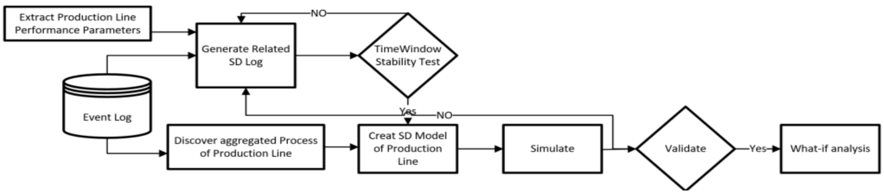

Fig. 1. The Proposed framework for the production line. It starts with discovering the process model of the production line at the station level. Generating SD-Log including the different performance parameters, which are used to design the model. After validation, the scenario-based analysis for the production managers is possible.

Considering the performance aspect, since all the parallel activities happen in any possible orders, we combine them into one single high-level activity. Using a module based on process discovery, the process model at the station level is discovered. In production lines, the tasks are distributed between stations, which can be handled by the same resources, we are able to get the performance of the process among the stations. We consider the following performance parameters exclusively in production lines: *average service time in each station, number of resources for each station, the arrival rate of items for production line, finish rate, the capacity of each station, and the number of items waiting in each station*. In the next step, we generate the SD-Log based on the performance parameters of stations for each time window. As shown in Fig.1. the similarity values of parameters in each time window are tested with the “Time Window Stability Test”. Exploiting the system dynamics modeling, the stock-flow diagram is being generated for the production line. We simulate the model populating the model with the values from SD-Log. This step is followed by a validation step, which provides the level of certainty, i.e., whether the model is acting similar to reality. In the final step, the general model can be refined by adding other parameters in the production line. We use the model to change the parameters and predict the different scenarios.

4 Proof of Concept

We use CPN tools[1] and ProM[2] to generate the event log based on the production line of an electric automobile company. The generated event log includes the execution of processes before and after applying the changes regarding performance metrics, e.g., the change in the number of resources. Our model includes multiple stations, which cars go into each in sequence. In our designed stock-flow model Fig. 2. the assembly of the doors including four other sub-activities takes two hours (station 210) and there is always a queue for this station. By increasing the number of resources in station 210, as we expected the number of cars in the queue for station 210 is decreased to zero in the second execution of the model with two resources. Therefore, the problem of waiting cars seems to be solved. However, the proposed framework represents the effect of changes in this station on the two next stations, which is the” window assembly” station.

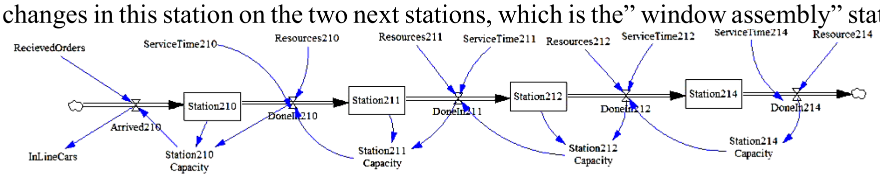

Fig. 2. Part of the designed stock-flow diagram for the production line based on synthetic data of automobile company. This model is populated with the data from SD-Log in the time window of one day at the station level.

[1] http://cpntools.org/
[2] http://www.promtools.org/

As Fig. 3. shows the cars which are waiting for station 210 are decreasing at the same time the number of cars waiting for station 211 is increasing. Since in the production line all the cars after station ”door assembly” go through ”window assembly”, we chose two involved stations and all their possible performance parameters generated from the aggregated process model and the event log. This evaluation as a proof of concept shows the effectiveness of the approach in demonstrating the effects of one change through the whole production line. We can pragmatically deduce the detailed knowledge of the process and performance aspects from an event log in the scenario-based analysis of processes. Using the proposed approach, we are able to predict any further changes in the production line by changing one part, such as adding more resources to one of the stations. As the example demonstrates, the proposed approach is able to predict the consequence of changes/decisions in the process.

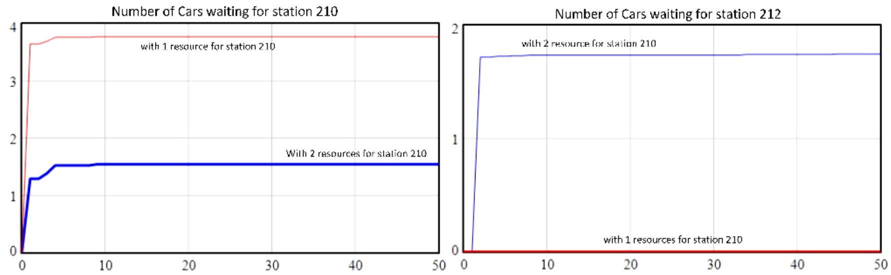

Fig. 3. Number of cars waiting for station 212 and station 210 before (red) and after (blue) adding one resource to station 212 in 50 days.

5 Related Work

An overview of process mining and system dynamics is provided in [1] and [4], respectively. In the field of system dynamics, different work toward simulation and prediction are done. There are different research conduct on the basis of using system dynamics in different contexts such as business process management, e.g. using both Petri net models and system dynamics to develop a model for the same situation [2]. According to [13] system dynamics among the simulation techniques in the manufacturing and business is an effective technique, however, the used techniques did not use the provided insight into the process by process mining techniques. In process mining, prediction and simulation approaches are mainly at a detailed level and they are at the case level [10]. In [5] the possibility of addressing the aggregate level of models are addressed using both process mining and system dynamic.

6 Conclusion

In this paper, the necessity of providing a platform to support the decisions in the modern production lines is discussed. Establishing flexible production lines for modern products such as autonomous cars is the goal of the new products. Our framework provides the ability to oversee the new decisions and changes for a production line to be agile. It employs process mining techniques, specifically processes discovery at a

higher level of abstraction along with performance analysis. We use the outcome of process mining techniques to generate an SD-log. We design the general system dynamics model based on the discovered knowledge from process mining and related parameters in the production line. General stock-flow diagram for the production line at an aggregated level can be improved and changed regarding different situations. We evaluated our framework based on a synthetic event log, which is generated using a CPN model. This evaluation serves as a proof of concept showing the efficiency of our generated model. As future work, we focus on identifying the underlying relationships between the parameters of the production line. Extending our approach in the field of performance analysis and resource management for the process to meet the requirements of the business is another practical approach.
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