Schedulater: Supporting Plant Operators in Scheduling Tasks by Visualizing Streaming Process Data and Model Predictions

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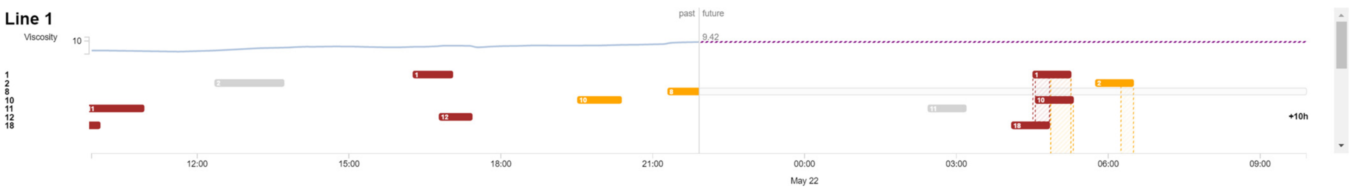

Figure 1: Schedulater showing a high-level overview of the recent 12 hours of operation and prediction for the next 12 hours for seven pressure filters in one of the production lines. Here, the tool shows a graph of filtrate viscosity and bars for periods where filters are off-line for cleaning, including predicted future periods of cleaning. A key use of the tool is to identify conflicts: periods where multiple filters are likely to be taken off-line at the same time (as seen here for filters 1, 10, and 18 around 05:00). Overlaps in filter state periods are thus emphasized by areas connecting the marks, for overlaps between and within production lines. Users can manipulate the predicted values and events to simulate different operation schedules that resolve conflicts.

Abstract

We introduce Schedulater: A tool that visualizes production data and predictions to help plant operators schedule their tasks. The tool visualizes streaming data from the production system and a predictive model based on first principles. We follow a design study approach, collaborating with engineers and operators. We describe the tool, key tasks of operators, design goals, and discuss challenges in integrating predictions in the context of streaming data.

Keywords: Design study, time-series data, predictive analytics.

Index Terms: H.5.2 [Information Systems]: Information Interfaces and Presentation—User Interfaces;

1 Introduction

We present research on introducing visualization to bio-based manufacturing (e.g., food ingredients and pharmaceuticals), which consists of a series of unit processes such as extraction, fermentation, filtration, and concentration. Bio-based processes involve organic raw materials and exhibits dynamic behaviors that are not fully understood (and thus hard to model). Humans thus need to continually monitor the processes and adjust production parameters. In this paper we focus on supporting operators of a single unit: pressure filtration in the production of food gelling ingredients. Here, current production systems seem to provide limited support for engineers and operators to explore their options in scheduling operations. This motivated the present work of developing visualizations for improving production (see Figure 1).

We present the results of on-going work following a user-centered approach of (1) meetings and interviews with stakeholders (production managers, engineers, and operators) and observations in the plant control room; (2) two iterations of designs including discussions of sketches and a formative prototype evaluation.

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2 Related Work

Our tool visualizes time-series data from the production system at a plant together with model-based predictions of key events and allows simulating different changes to production. Research has visualized time series data for manufacturing schedules in general [1] and for bio-based production in the case of beer production [2]. Whereas these works have focused on discrete events, our visualization integrates discrete process state data (e.g., filter off-line) and continuous data (e.g., filtrate flow or viscosity).

Our work relates to visualizing predictions in the context of streaming data. These are growing topics in information visualization [3]. Previous work has considered the visualizations reference model in relation to dynamic data and visualizations [4], and suggested visual metaphors for streaming data [5]. More recent work has considered visual forecasting which integrate historical data with predictions (e.g., [6]–[8]). In this endeavor, understanding uncertainties of predictions is important, and has been considered in several ways (e.g., [9]). Recently, quantile dotplots was presented as a technique that provides an intrinsic representation of uncertainty based on discrete visual marks [10]. However, visualizing predictions in the context of streaming data has yet to be explored. In our work, we aim to combine these areas, and integrate historical data and predictions in one visualization design.

3 Understanding Filter Scheduling

In the filtration unit which is the focus of our design study [11], operators oversee thirteen filters across three production lines. Each filter goes through a cycle of 1) preparation using a filter aid substance; 2) active filtration until pressure reaches a threshold level; and 3) cleaning, in which operators take the filter off-line in order to manually wash the filter and start preparation (to simplify in the following, we merge 1 and 3 in an off-line filter cleaning state). The operators' main goal is to keep the filters on-line as long as possible, thereby optimizing the filter capacity and consequently production yield. To do so, they observe current values for different production parameters (inflow, outflow, tank levels, pressure, viscosity) and react by adjusting parameters (flow, perlite, water intake).

The existing production system shows current values for each production parameter. Operators can call up historical data for one filter at a time, which makes it hard for them to integrate the relevant data. The problem from the point of view of management, is that operators use their idiosyncratic strategies for controlling the process, thus causing a suboptimal filter cleaning schedule. To assist the operators, engineers at the plant developed a mathematical model to predict the filtration process. The model is derived from first principles, which describe the main phenomena (cause-effect) based on filtration theory. Additionally, a proportional estimator-predictor algorithm incorporates on-line data to adjust the prediction according to the current process conditions because the model cannot account for all variations in the biological raw materials. Initially, the engineers presented the predictions to the operators as isolated values in the production system. However, seeing the predictions out of the context of the related production data, made it difficult for the operators to use them in their work. We started our design studies based on these challenges.

From our domain inquiries, we identified three tasks. First, when arriving at a work shift, or when returning to the control room, operators need to obtain an overview of the current process conditions. Second, operators need to continuously monitor the filter states and identify potential periods of overlapping cleaning states. Third, in cases of overlaps, operators need to explore alternative schedules. To support these tasks, we designed Schedulater, which we describe in the following.

4 Scedulater

Schedulater presents data on horizontal time-lines (e.g., [12]) for each of three production lines and thirteen filters. We outline four design goals for the tool to support the tasks of the operators:

DG1: Provide a glanceable overview of the production state.
DG2: Emphasize filter overlaps to bring visual attention to potential problems.
DG3: Provide details about individual filters through interaction.
DG4: Support interactive exploration of alternative schedules.

From these design goals, we describe our chosen design:

Most important for the operators to gain an overview (**DG1**) is the filters' cleaning state periods: these periods are shown as bars on a separate timeline for each filter. The position and length of a bar encodes the starting time and duration of a cleaning period. Apart from showing the cleaning periods, the initial overview shows only filtrate viscosity, which is the key variable influencing filter cycles. Figure 1 shows this for a single production line.

The color of bars encodes whether the corresponding periods overlap (**DG2**), that is, filters being cleaned at the same time. Cleaning states with no overlap are gray, overlap across production lines are orange, and overlap within production lines are red. To indicate time intervals where cleaning states overlap, bars are linked by hatched rectangles colored similarly to the bars.

To see details (**DG3**), the operators can click on the production line label, expanding the view to show additional data: Separate time-series graphs are shown for each variable about the line (inflow, outflow, tank levels, viscosity) and for each of the filters (pressure, flow, perlite level).

Finally, the operators can explore alternative schedules (**DG4**). The graphs of production line data (e.g., viscosity) and filter data (e.g., flow) extrapolate current values to allow simulating changes to production. For example, operators can click on the line in the chart for flow, and drag up or down to increase or decrease the flow. All other variables and the predictions of cleaning state periods are updated accordingly, which allows operators to explore the effects of different changes on the production. Operators can then implement the changes that are most effective. Likewise, they can explore the effects of potential changes to variables that are beyond the operators' influence. For example, they can evaluate alternative schedules against potential fluctuations in filtrate viscosity.

5 Discussion and Conclusion

We are currently integrating the tool in the production environment for deployment in a longer term field study, which gives rise to several interesting challenges. First, Schedulater enable operators to explore alternative schedules and then implement the needed changes (e.g., changing the set point for a flow parameter) in the production system. A challenge is to reconcile the operators' what-if explorations with online data from the production system as changes take effect and scheduled events occur. We contemplate whether to transition from simulated schedules to online production data or to present both combined in one view: Would continually updating predictions amid the operators' what-if explorations distract or help understand the results of their actions? A second challenge concerns the uncertainty of the model predictions. While numerous techniques for visualizing uncertainty exist, an estimation that is stable over time might be more useful for the operators. As one possible approach, we consider leaving past estimates as gradually fading marks as a way to understand the uncertainty of the current estimates. Additionally, we find it important to increase our understanding of how to allow operators to annotate or adjust predictions they believe to be erroneous. Can we strike a balance between enabling operators to correct predictions and infer changes to other parameters due to these changes?

Finally, we partly see our design study, as a means to help the production company advance their understanding of their operation. In light of Sedlmair et al. [11], we see the tool as a way to increase *Task Clarity*. Further, we and our collaborators see our visualization work as a way to improve the predictive models and subtle suggestions as a way to move more information to computing systems, thus enabling more automatic production.

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