Design of an Ecological Visual Analytics Interface for Operators of Time-Constant Processes

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Abstract

In industrial applications where the physical parameters are highly interconnected, keeping the process flow steady is a major concern for the operators. This is caused by the sensitivity of system to the process dynamics. As a result, a slight adjustment to a control parameter can significantly affect the efficiency of the system and thus impact the financial gain. Paper pulp production is an example of such a process, where operators continuously investigate the potential of changes in the process and predict the consequences of an adjustment before making a decision. Process parameter adjustments prescribed by simulated control models cannot be fully trusted as the external disturbances and the process inherent variabilities cannot be fully incorporated into the simulations. Therefore, to assess the viability of a strategy, operators often compare the situation with the historical records and trends during which the processes in the plant ran steadily. While previous research has mostly focused on developing advanced control models to simulate complex pulp production process, this work aims to support operators analytical reasoning by provision of effective data visualization.

The contributions of our design study include a domain problem characterization and a linked-view visual encoding design, which aims to enhance operator’s mental models independent of particular users or scenarios. Finally, by reflecting on the advantages of our choice of task abstraction technique, inherited from the ecological interface design framework [5], we reason for the generalizability of our approach to similar industrial applications.

Keywords: Visual analytics interfaces, Design study, Focus+context techniques, Linked-view interfaces, Time-constant processes

Index Terms: Human-centered computing—Visualization—Visualization application domains—Visual analytics;
1 INTRODUCTION

Mining and cellulose pulp production are examples of industrial domains where operators are extremely cautious of unnecessary interventions with the process for two main reasons. First, the process parameters are tightly coupled, and it is challenging for an operator to understand the causal relationship between control parameters and predict the effect that changing one parameter can have on the whole process flow. Second, due to long dead times (the time at which the output first starts to respond to the change in the input [20, p. 101]) and time constants (the time it takes for the process to reach 63% of its final value after a change is introduced as an input [20, p. 100]) of the process, it may take several hours for an operator to observe the effect of an inapt intervention which could highly affect the final economic outcome. In such situations, an operator’s way of problem solving is highly affected by their mental model. Operators’ mental models are connected to their external representations as well as the actions they perform [21, 35]. In complex systems where connections between process parameters are hidden, the operators’ mental models could vary. As a result, different operators may operate the process plant differently throughout their shifts which may lead to unsteady and inefficient process flows.

This work aims to support steady operations by creating a clear understanding of the constraints and relationships between control parameters in an industrial process through visual representations. To this end, we present the design of an ecological visual analytics (VA) decision-support tool for operators of the delignification process (Section 2) in the paper pulp production industry. The contribution of this paper is threefold. First, in a close collaboration with industrial partners, a comprehensive field study has been conducted leading to knowledge elicitation on the domain problem. Second, operators’ analytical reasoning is supported through a novel linked-view VA interface, which can be applied to similar domains. The third contribution lies in our generalizable design to other time-series data [26]. With respect to the paper pulp production industry, previously designed decision-support systems have mainly focused on optimizing planning and scheduling tasks [10], predictive control [7, 18, 30] and analytics modelling [28].

The WDA technique, inherited from the ecological interface design framework [5], forms the foundation for our work on enabling operators to develop an accurate and effective mental model of the process. The technique describes the structure of the work domain, creating an understanding of the task characteristics [27]. The strength of the technique lies in specifying what functions need to be supported so that operators’ behavior is formed within safety and efficiency boundaries of the system. This is done by describing hierarchical means-ends relationships between process parameters. The approach has proven effective in shaping users’ behaviors within system boundaries (i.e., a range of actions within which system goals are not violated) in a variety of application domains such as energy efficiency monitoring [13, 14], maritime transport [9], aviation [4, 8] and medical engineering [19, 23]. In our previous work [40, 41] we applied the WDA to the design of two VA interfaces which improved experts and novices’ ability to understand complex situations in the domain of air traffic control.

A risk associated with the previously proposed models (where tasks are defined based on user needs), is that the resulting interface may work inefficiently if the user tasks are ill-defined. However, such risk is avoided in the WDA as the tasks are represented independent of specific users, scenarios, or system states. An additional benefit of such a domain-specific task-based approach is that the operators do not need to perform at a cognitive level higher than what the task requires. These characteristics make the WDA a robust task abstraction technique to design interfaces for operators of complex domains as well as identifying actions needed for making current interfaces work more efficiently.

2 DELIGNIFICATION PROCESS IN THE DIGESTER

Delignification is the separation of wood fibers to allow formation of pulp [2]. Delignification takes place in a digester which is described in detail in Appendix A. In the digester, lignin is removed from wood chips to free the wood fibers by utilizing a thermo-chemical conversion process. The residual lignin in the pulp is quantified via the Kappa number, and operators aim for different Kappa levels depending on the desired quality of the end product. The process involves using an aqueous solution of sodium hydroxide and sodium sulfide, known as white liquor, at high temperatures to dissolve lignin. However, the white liquor also reacts with the fibers, degrading the physical properties of the pulp and reducing its yield.

Operators need to carefully control cooking conditions to achieve effective delignification without compromising yield. As lignin is removed, the white liquor loses its alkali strength and must be extracted. Monitoring the alkali levels is crucial because a complete reduction in alkali strength would render the liquor unusable, resulting in unusable pulp in subsequent sections of the plant.

The main parameter controlled by operators is the H-factor, which determines the temperature over time for the wood chips in the digester and directly affects the Kappa value. However, adjusting the H-factor poses a challenge as operators experience a several-hour delay in receiving feedback on the effect of their adjustments on Kappa. Therefore, they rely on their experience and exploration of historical trends to infer causal relationships between H-factor adjustments and resulting Kappa values, helping them make informed decisions in the absence of real-time feedback.

3 RELATED WORK

In the field of visualization, design of VA interfaces for industrial processes is challenging mainly due to the need for expertise in the field. Interactive dashboards have been designed for various industrial applications such as improving equipment condition monitoring [39], supporting identification of opportunities to improve production processes [36] and supporting plastic factory technicians’ understanding of time-series data [26]. With respect to the paper pulp production industry, previously designed decision-support systems have mainly focused on optimizing planning and scheduling tasks [10], predictive control [7, 18, 30] and analytics modelling [28].

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4 DESIGN PROCESS

Eliciting domain knowledge can be very challenging in application-oriented interface design. To overcome this challenge, we have collaborated extensively with domain experts, e.g., process technicians and engineers with long experience of the process. To understand operators’ task flows, six full days of data collection was conducted in two different paper pulp production factories in Sweden. Eight process operators were interviewed. The interviews were conducted during morning, afternoon and night shifts. The interview questions, listed in Appendix B, aimed at understanding the process, operators’ ways of problem solving and monitoring tasks, challenging situations they face and understanding the current systems they use to control the process. The interviews were recorded, transcribed, and analyzed. To derive the interface functions, an in-depth WDA was performed relying both on the interview data as well as on a detailed literature study on the delignification-specific tasks.
4.1 Task Abstraction Technique

This section describes derivation of interface functions through application of a WDA on the delignification-specific tasks. Figure 2 depicts how the WDA technique is applied to map the delignification-specific tasks to what needs to be supported by the interface so that operators’ performance and efficiency are enhanced.

The functional purpose level identifies goals of the delignification process. The first overarching goal of the pulp production process is to reach a desired production quality. A continuous process flow plays an important role in profitability of a pulp mill. Therefore, a decision-support interface should strengthen operators’ performance and enhance their efficiency in conducting the task processes.

The priority measures level defines the criteria to measure how well the interface is fulfilling the functional goals. The amount of lignin removed from the chipped wood in the digester as well as increasing pulp brightness are the criteria for measuring production quality. The sub-optimal flow behavior in the digester directly impacts the quality of the pulp and the production rate [32]. In addition, the time it takes for a change to be applied to the system affects the production quality as well. Therefore, to strengthen operators’ performance, the interface must support them in optimizing digester operation and predicting causal effects in time. Operators’ efficiency is affected by the historical data in which they explore the trends. Therefore, to help operators make decisions efficiently, the interface must be able to facilitate trends exploration process.

The purpose-related functions are identified based on the defined priority measures. To remove lignin, white liquor is used [31]. The Kappa number indicates the remaining amount of lignin content in the paper pulp. The amount of white liquor is specified based on effective alkali to wood ratio [30]. Adjusting digester’s cooking conditions is necessary to control the Kappa value. H-factor is used to describe the dynamics of lignin concentration depending on the temperature and time [34, 37]. To support optimizing the digester’s process flow, the interface must enhance operators’ understanding of the dynamics of the process at different stages and, to support operators in predicting causal effects on time, the interface must enhance their understanding of the complex casual relationships in the digester. To facilitate trends exploration process, the interface must support identification and comparison with a goal point.

The physical functions level identifies specific functionalities that the interface must have so that each purpose-related function is supported. The Kappa number measured at the end of the digester stage indicates the quality of the cooked pulp. However, the Kappa number variability at different stages of the digester is a major concern for the paper industry [30]. Therefore, the interface should visualize Kappa number profile across the digester’s length. To support steady operations and to enhance operators’ understanding of the process dynamics, the interface must visualize corresponding values as well as the acceptable change range for the control parameters. To support operators understanding of the causal relationships, the interface must visualize the consequences of various resolution strategies applied across the digester’s length. Finally, to support comparison with a goal point, the interface must detect, filter and then visualize the trends for the goal point.

5 Visualization Design

The physical form of the interface is outlined in a way that each individual function derived at the fourth level of the WDA is supported by visual representations on a separate coordinated view on the interface. Figure 1 depicts the VA interface, consisting of four linked views. The ideation, design, and implementation of the interface has been done by the first author.

The Topological View (Fig 1.A) aims to support the operator in identifying what historical data are relevant to look at and compare the trends with the current situation. The topological view allows the operator to interact with a K-nearest-neighbor machine learning (ML) classifier algorithm. The ML model analyzes the historical data and finds the data that are most similar to the current situation. These data points are mapped on a scatter plot where the y-axis represents the Kappa number, and the x-axis represents the process stages across the digester length (i.e., an indication of time). Depending on which stage of the process the operator wishes to control, they decide which data points are relevant to examine. The stage of interest can be selected by clicking on the x-axis buttons (highlighted in yellow). The main motivation for the choice of scatter plot is that previous studies have shown that users perform value retrieval and data exploration tasks better on scatter plots when working with high-dimension and high-density data sets [11, 16]. The scatter plot slider allows the operator to adjust the desired Kappa variability criteria for the selected process stage (e.g., here the criteria is set to a variation of 5-15 units at the cooking stage). The data points with Kappa variability within this range are filled in black. The operator may choose one of the black data points depending on which Kappa number they aim for. When a data point is selected it is designated by a yellow-filled circle and the data and time for the selected data point appear next to it in text format (here the operator aims for a Kappa number around 30 at the cooking stage). The similarity index is computed with respect to relevant features (H-factor, Kappa value, effective alkali and relevant temperature and pressure).

The interactive circle chart to the right visualizes feature weights (mapped on the radial axis) and accuracy (shown with color intensity) of the calculated similarity index with respect to each feature. The darker the colored area is, the higher the accuracy of the calculated index with respect to the corresponding feature. The main motivation for the choice of circle charts is that they are very helpful in identifying trends [1]. Based on this information, and also depending on the stage of the process that the operator is controlling, they can decide which features should be considered for similarity calculation. This is done by ticking the boxes next to each feature. In the depicted situation, among the selected features, the weight value of the H-factor is highest while the accuracy is lowest. Moreover, to improve the model’s robustness, the operator can increase/decrease...
the model weight values by clicking on the arc sections of the circle chart. Upon each click, new weight values are assigned, and the data points shown on the scatter plot will be updated. An alternative visual representation to show ML model performance with respect to individual features is depicted in the orange box bellow the circle chart. Here, features are denoted by colors and weights are denoted by the area of the pie chart. Accuracy is shown by distance from the radius of the pie chart. This visualization was rejected for the following reasons. First, for a constant weight value, depending on how many features are selected by the operator, the area of the pie chart would change, which could cause misinterpretation. Second, a low accuracy correspond to a feature with high impact (large weight) would have a bigger area, which could lead to a wrong understanding of the accuracy. For example, as depicted in the Figure, both the Kappa value (blue) and H-factor (green) have the same accuracy. However, due to larger weight value for H-factor, the green-dotted section has a larger surface area than the blue-dotted one.

The Situation View (Fig 1.B) aims to give the operators awareness and understanding of the Kappa number variability at the current process stage as well as predicting the Kappa number profile for the remaining stages of the process. The situation view serves the purpose of keeping the operator’s focus on the Kappa value profile while other views provide additional context. The situation view further enables the operator to compare the Kappa variability with the goal point that is selected from the topological view. As depicted by the figure, the operator has selected a data point which has had a Kappa number around 30 with variations within 5-15 units at the cooking stage. The situation display enables the operator to compare the current Kappa profile (solid line) with the goal profile (dotted line) and shows that the operator should aim for around 10 units reduction in Kappa number. The colored solid line emerges once the operator explores various resolution strategies on the Control View. This line shows the Kappa profile variations with respect to the changes of a parameter selected on the Strategy View.

The Strategy View (Fig 1.C) aims to support operators’ decision-making by visualizing the safe ranges within which different control parameters can be adjusted. The colored boxes specify the minimum and maximum values selected by other operators in the historical data as filtered on the topological view. The yellow-colored band inside each box, illustrates the change range applied by the operators for different control parameters of the goal data point. Depending on which stage of the process is being controlled, a specific strategy may be of interest. Furthermore, the strategy view visualizes the corresponding values for process parameters shown as a parallel coordinates plot. This enables the operator to quickly find the corresponding value for other parameters in the historical data when they explore a particular value for a control parameter. The motivation for the choice of parallel coordinates is their effectiveness in outlier and change detection [15, 33].

The Control View (Fig 1.D) consists of line graphs which allow the operator to compare multiple time series [17]. The graphs enable the operator to visualize the consequence of a resolution strategy across the digester length. They further enable the operator to explore possible resolution strategies and visualize how they can change the current situation to the goal situation. Upon clicking on a strategy on the strategy view (here, temperature is selected), the solid line graph visualizes the prediction of the temperature profile across the digester length. The profile of the selected value (temperature) for the goal data point is also visualized in a dotted line. In the example shown in the Figure, the temperature in the heating phase is equal to the goal point. However, without operator’s intervention, the temperature will drop in the next phases leading to a decrease in the Kappa number after the cooking phase. A potential strategy is to increase the H-factor which would increase the temperature. The horizontal control bars to the right on the control view allow the operator to explore what will happen if they change H-factor or white liquor. On the control bars, the current values are denoted by a black-filled button while the explored value is denoted by a white button. Upon moving the white button, a prediction for the selected strategy is visualized on the line graph showing the operator how the selected strategy affects the profile of the selected parameter (in this example, temperature). As depicted in the example Figure, the operator can see increasing H-factor will lead to temperature rise from the middle of the cooking stage which will result in improvement in the Kappa profile as depicted on the situation view which is denoted by the colored solid line in Fig 1.B. This enables the operator to visualize to what extend different strategies can lead to the Kappa number recovery. The color of the solid lines emerging on the Control View and the Situation View is the same as the color of the parameter selected on the Strategy View (here, red for the temperature).

6 Expert’s Review and Lessons Learned
An expert review session with our industry collaborator, the third author of this paper, was held during which he stated that “when an operator is in a situation where (s)he is not sure which strategy will lead to minimum deviation from optimal Kappa, (s)he would want to know how other operators resolved a similar situation.” He also mentioned that “operators want to know how they can relate to an ideal Kappa value and what can be done to reach those values. How would the process deviate from the optimal Kappa value?” When we asked him to explain his opinion about the interface and how it may affect operators’ workflow, he stated that “I find the linked-views very useful, especially the visualization of operators’ taskflows has a great potential to improve their decision-making process.”

Transferable Contribution
Even though our design study addresses the important but narrow problem of supporting decision-making for the operators in the paper pulp production industry, we foresee that our main contribution, a linked-view interface to make hidden relationships between coupled parameters explicit, transfers to a broad range of time-constant industrial domains.

Linked-View Interface
Consistent linked-view interfaces are commonly used as “explicit encoding” to support users’ decision-making, allowing users to explore large complex data sets efficiently and compare multiple aspects of data simultaneously [3, 6, 29]. The design is unique in that its layout was derived from a hierarchical task abstraction technique which has proven to be promising in shaping operators’ behavior aligned with domain-specific goals.

7 Discussion and Future work
In this paper, we demonstrated how the WDA technique is applied to the design of VA interfaces for operators of paper pulp production. The outcome of the WDA revealed the need for visualization of five sets of information: relevant historical data points to study, the key production quality parameter, correspondence of process parameters values to each other, acceptable change ranges for process parameters, and consequences of various resolution strategies. This information set is generic in the sense that it can be applied to other time-constant industrial domains where process parameters are tightly coupled, and production quality relies on a key performance parameter. Through our strong collaboration with the industry, similar characteristics were identified in the mining industry where production relies heavily on the foam quality produced during the flotation process (also a time-constant process). Therefore, one future direction is to apply the design approach and the interface presented in the current work to a sustainable mining case. We further plan on conducting human-in-the-loop quantitative studies to evaluate the extent to which various aspects of the linked-view design improves operators’ mental models and decision-making tasks.
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