Process Mining in Dyeing Unit Using Organizational Perspective: A Case Study

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***Abstract*- The basic idea of process mining is to extract knowledge from event logs recorded by an information system. Until recently, the information in these event logs was rarely used to analyze the underlying processes. Process mining aims at improving this by providing techniques and tools for discovering process, organizational, social, and performance information from event logs. Hence to gain competitive advantage, dyeing unit try to streamline their processes. In order to do so, it is essential to have an accurate view of the workers work load under consideration. In this paper, we apply process mining techniques to obtain meaningful knowledge about these flows, e.g., to discover typical paths followed by particular groups of colors and assigned workers to do work. This is a non-trivial task given the dynamic nature of dyeing unit processes. The paper demonstrates the applicability of process mining using a real case of a worker work load process in Emerald Dyeing Unit, to discover the social network analysis. Using a variety of process mining techniques, we analyzed the dyeing unit process from three different perspectives: (1) the control flow perspective, (2) the organizational perspective and (3) the performance perspective. In order to do so we extracted relevant event logs from the dyeing unit information system and analyzed these logs using the ProM framework. This paper only deals about organizational perspective of the dyeing processes. Therefore the results show that process mining can be used to provide new insights that facilitate the improvement of existing workers work load.**

***Keywords*- process mining, organizational perspective, event log, ProM framework.**

I. INTRODUCTION

In a competitive world the business process is very tough to maintain and execute actions against other organizations. The business process system such as dyeing for a cotton yarn market, dyeing units have to focus on ways to streamline their processes in order to deliver high quality colors while at the same time reducing costs [1]. Furthermore, also on the governmental side and on the side of the pollution control organizations, more and more pressure is put on dyeing units to work in the most efficient way as possible, whereas in the future, an increase in the demand for care is expected.

A complicating factor is that dyeing unit is characterized by
highly complex and extremely flexible coloring processes, also referred to as “organizational flows”. Moreover, many disciplines are involved for which it is found that they are working in isolation and hardly have any idea about what happens within other disciplines. Another issue is that within dyeing unit or healthcare sector many autonomous, independently developed applications are found [2]. A consequence of this all is that it is not known what happens in a dyeing unit process for a group of colors with the same process. The concept of process mining provides an interesting opportunity for providing a solution to this problem. Process mining [3] aims at extracting process knowledge from so called “event logs” which may originate from all kinds of systems, like enterprise information systems or dyeing or hospital information systems. Typically, these event logs contain information about the start or completion of process steps together with related context data (e.g. actors and resources). Furthermore, process mining is a very broad area both in terms of (1) applications (from banks to embedded systems) and (2) techniques.

This paper focuses on the applicability of process mining in the dyeing unit domain. Process mining has already been successfully applied in the service industry [4]. In this paper, we demonstrate the applicability of process mining to the dyeing unit domain. We will show how process mining can be used for obtaining insights related to organizational flows, e.g., the identification of organizational paths and (strong) comparison between different workers to minimize workers to minimize the cost of production. We will use several process mining techniques which will also show the diversity of process mining techniques but in this paper we will discuss about organizational discovery.

In this paper, we present a case study where we use raw data of the Emerald Dyeing Unit in Nagari, a large dyeing unit in Andhra Pradesh, India. This raw data contains data about a group of four shades of color treated and for which all deep analysis and treatment activities have been recorded to analyze the workers works to decrease or increase the workers work efficiency. Note that we did not use any a-priori knowledge about the control process of this group of colors and that we also did not have any process model at hand.

Today's Business Intelligence (BI) tools [5] used in the dyeing unit domain, like Cognos, Business Objects, or SAP BI, typically look at aggregate data seen from an external perspective (frequencies, averages, utilization, service levels, etc.). These BI tools focus on performance indicators such as the number of tasks or operations of a color, the length of waiting lists, and the success rate of operations. Process mining looks “inside the process” at different abstraction levels. So, in the context of a dyeing, unlike BI tools, we are more concerned with the organizational paths followed by individual workers and whether certain procedures are followed or not.

This paper is structured as follows: Section 2 provides an overview of process mining. In Section 3 we will show the applicability of process mining in the dyeing unit. Section 4 discuss about social network mining of the dyeing process.

II. Process Mining

Process mining is applicable to a wide range of systems. These systems may be pure information systems (e.g., ERP systems) or systems where the hardware plays a more prominent role (e.g., embedded systems). The only requirement is that the system produces *event logs*, thus recording the parts of the actual behavior.

Interesting classes of information systems that produce event logs are the so called Process-Aware Information Systems (PAISs) [6]. Examples are classical workflow management systems (e.g. Staffware), ERP systems (e.g. SAP), case handling systems (e.g. FLOWer), PDM systems (e.g. Windchill), CRM systems (e.g. Microsoft Dynamics CRM), middleware (e.g., IBM's WebSphere), hospital information systems (e.g., Chipsoft), etc. These systems provide very detailed information about the activities that have been executed.

The idea of process mining is to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs. We consider three basic types of process mining as shown in the figure 1; that is Discovery, Conformance and Extension.

A. Discovery

Traditionally, process mining has been focusing on *discovery*, i.e., deriving information about the original process model, the organizational context, and execution properties from enactment logs. An example of a technique addressing the control flow perspective is the α-algorithm [7] which constructs a Petri net model describing the behavior observed in the event log. It is important to mention that there is no apriori model, i.e., based on an event log some model is constructed. However, process mining is not limited to process models (i.e., organizational flow) and recent process mining techniques are more and more focusing on other perspectives, e.g., the organizational perspective, performance perspective or the data perspective. For example, there are approaches to extract social networks from event logs and analyze them using social network analysis [8]. This allows organizations to monitor how people, groups, or software or system components are working together. Also, there are approaches to visualize performance related information, e.g. there is an approach which graphically shows the bottlenecks and all kinds of performance indicators, e.g., average / variance of the total flow time or the time spent between two activities.

B. Conformance

There is an apriori model. This model is used to check if reality conforms to the model. For example, there may be a process model indicating that purchase orders of more than one million Euro require two checks. Another example is the checking of the so called “four eyes” principle. Conformance checking may be used to detect deviations, to locate and explain these deviations, and to measure the severity of these deviations.

C. Extension

There is an apriori model. This model is extended with a new aspect or perspective, i.e., the goal is not to check conformance but to enrich the model with the data in the event log. An example is the extension of a process model with performance data, i.e., some a-priori process model is used on which bottlenecks are projected.

At this point in time there are mature tools such as the ProM framework [9], featuring an extensive set of analysis techniques which can be applied to real life logs while supporting the whole spectrum depicted in figure 1.

III. Dyeing Unit Process

In every process, there should be input to process, in this case the dyeing cotton yarn taken as input raw data to process the cotton yarn. The Cotton yarn of Weight of 4.5 kg is called one bundle. This cotton yarn bundle is first applied for boiling process to remove the impurities such as dust, small knots etc., and then this boiled yarn is sent to pre treatment; it is a treatment of converting the boiling yarn into pure white color yarn using bleaching process. After this bleaching process the real color mixing process is started, then after the coloring process post treatment is applied, it is a treatment to stabilize the color on the yarn called fixing. Finally the finishing process is for drying the colored yarn for better fastness; it is a property of getting pH value better.

In this section, we want to show the applicability of process mining in dyeing unit. However, a dyeing unit processes are characterized by the fact that several treatments can be involved in the coloring process of the cotton yarn and that these processes often have their own specific IT applications, it becomes clear that getting data, which is related to dyeing unit processes, is not an easy task.

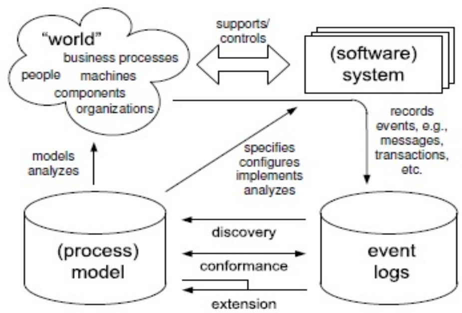


Fig1. Three types of process mining: (1) Discovery, (2) Conformance and (3) Extension.

In spite of this, systems used in dyeing units need to provide an integrated view on all these IT applications as it needs to be guaranteed that the dyeing unit process need to be compared between different shades of colors to minimize the processing time and to reduce the workers work load between each lot. Consequently, these kinds of systems contain process related information about dyeing unit processes and are therefore an interesting applicant for providing the data needed for process mining.

To this end, as case study for showing the applicability of process mining in dyeing unit, we use raw data collected by the dyeing the cotton yarn system of the Emerald Dyeing Unit. This raw data contains information about a group of four shades of color for which all steps of dyeing process have been recorded.

For this data set, we have extracted event logs from the Dyeing databases where each event refers to a different shade of color. As the data is coming from a treatment system, we have to face the interesting problem that for each shade of coloring the cotton yarn has similar treatment of dyestuff and little additional dyestuff is identified and recorded using the event logs. In this paper, the organizational relational ship that is social network between workers and experts such as dyer are identified. These event logs will show how these and process are undergone various steps or activities of same group of shades of a color. In additional we have some information about the actual similar works groups between workers are identified for each task or activity of dyeing process. Consequently, the processing of each processes need to be executed as per the event log generated by the system.

Nevertheless, as the log contains real data about the dyeing process delivered to dyer of the dyeing unit is still an interesting and representative data set for showing the applicability of process mining in dyeing unit as still many techniques can be applied. Note that the log contains 10 cases and 31 different events, which indicate that we are dealing with a non-trivial organizational flow process.

In the remainder of this section we will focus on obtaining, in an explorative way, insights into the treatment process of dyeing unit process. So, we will only focus on the discovery part of process mining, instead of the conformance and extension part. Furthermore, obtaining these insights should not be limited to one perspective only. Therefore, in section- IV, we focus on the discovery of paths followed by dyer with other workers. Also deals more about the organizational perspective that is the social network mining to know the details of workers more on working environment. The following section deals about the role of mining in dyeing process system to understand the coloring process.

A. Mining

In this section, we present some results obtained through a detailed analysis of the Dyeing process generated from the event logs of the treatment process. Hence, more specifically, we elaborate on mining results based on the organizational flow perspective in process mining.

1) Converting the raw data into MXML format: In dyeing process the color first applied to the sample of cotton yarn instead of lot of cotton yarn, because of failure of color matching, since the samples are tested by the dyer, an expert in dye stuffing. So, the sample process is recorded and fed into the system as a data. These data are stored in the form of database file format. Then this database information is converted into Mining Extensible Markup Language (MXML) file format using the ProM Import Framework. Finally this converted MXML file is sent as an input to ProM Framework to do different types of mining. In this paper we concentrated to deal with process or organizational flow of activities or tasks. Hence the view of organizational flow perspective deals about the social relationship among workers and organization structure of working environment. Hence, this helps to identify and minimize or maximize the workers work load of the production of colored yarn.

2) Organizational perspective: There are several process mining techniques that address organizational perspective, e.g., organizational mining, social network mining, mining staff assignment rules, etc. [8]. In this paper, we elaborate on social network mining to provide insights into the collaboration between different workers in the dyeing unit. The Social Network Miner [8] allows for the discovery of social networks from process logs. Since there are several social network analysis techniques and research results available, the generated social network allows for analysis of social relations between originators involving process executions. Figure 2, 3, 4 and 5 shows the derived social network. To derive the network, we used the *Work together, Handover of Work*, *Similar work without filter* and *Similar work with filter* [8] that measures the frequency of transfers of work among workers in the dyeing processing system. The network shows the relationships between originators above a certain threshold. Originators, for which all relationships are below the specific threshold, appear as low in-degree that is inward direction aero marks to a worker. The originators that were highly involved in the process appear as high in-degree. These results are useful to detect whether there are frequent interactions between originators that is workers, in our case.

IV. Social Network Mining in Dyeing Unit Process

One of the most promising mining techniques is social network mining which automatically derives process models from process logs. The generated process model reflects the actual process as observed through real process executions. If we generate process models from dyeing unit process logs, they give insight into most responsible and less priority paths for dyeing color process. Till now, there are several process mining algorithms are used to generate process models such as the α-mining algorithm, heuristic mining algorithm, region mining algorithm, etc [7][10][11] for control flow perspective mining, but for organizational perspective mining mostly only one algorithm is used, that is social network miner algorithm. In this paper, we use the Social Network Miner algorithm, since it can deal with noise and exceptions, and enables users to focus on the main process flow instead of on every detail of the behavior appearing in the process log [8].

Since, processes in the dyeing unit domain do not have a single kind of flow but a lot of variants based on different shades of the colors. Therefore using the figure 2, 3, 4 and 5, we can understand the similar workgroups and handover work and similar work process by comparing all log events. It is surprising that the derived process model is spaghetti-like and convoluted. One of the methods for handling this problem is breaking down a log into two or more sub logs until these become simple enough to be analyzed clearly. We apply clustering techniques to divide a process log into several groups that is clusters, where the cases in the same cluster have similar properties. Clustering is a very useful technique for logs which contain many cases following different procedures, as is the usual case in dyeing unit process systems.

A. Social Network Miner of Work Together Type Model

In dyeing units there are many dyeing treatments such as pre treatment, process treatment and post treatment that interact and work together. The mining result shows that the general dyeing unit is highly involved in the process and interacts with many workers. The dyer is often involved, but is not directly connected to all other workers. In figure 2 shows the worker "*kumar*" has highest in-degree, that he is the main person has the unity and work together property, so from this, we come to know that he is the person has highest responsibility to lead the team and work. This also represented in the form of table in Table I.

TABLE I

WORK TOGETHER TABLE

	Arun	Dyer	Guru	Kiran	Kumar	Rajan	Ramesh	Saran	Suresh
Arun	0.1495...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dyer	0.0	0.2242...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Guru	0.0	0.0	0.0747...	0.0	0.0	0.0	0.0	0.0	0.0
Kiran	0.0	0.0	0.0	0.0	0.1682...	0.0	0.0467...	0.0467...	0.0467...
Kumar	0.0	0.0	0.0	0.1682...	0.2990...	0.0560...	0.0841...	0.1401...	0.0841...
Rajan	0.0	0.0	0.0	0.0	0.0560...	0.0	0.0	0.0093...	0.0
Ramesh	0.0	0.0	0.0	0.0467...	0.0841...	0.0	0.0093...	0.0	0.0
Saran	0.0	0.0	0.0	0.0467...	0.1401...	0.0093...	0.0	0.0093...	0.0
Suresh	0.0	0.0	0.0	0.0467...	0.0841...	0.0	0.0	0.0	0.0093...

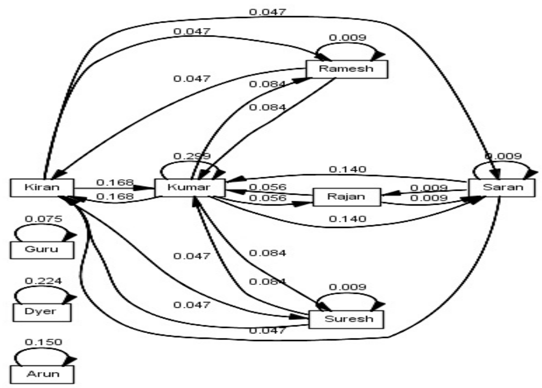


Fig 2. Social Network Miner of Work Together Type Model

B. Social Network Miner of Handover Work Type Model

In dyeing units there are many processes are involved to complete a coloring process, so that many workers are involved to dye the color on the cotton yarn. Hence each activity can be handed over to others to complete a sequence or cycle of process. The mining result shows that the general dyeing unit is highly involved in the process and interacts with many workers. The dyer is often involved, but is not directly connected to all other workers. In figure 3, it shows that always "*Kiran*" handover work to "*Kumar*" through "*Ramesh*", "*Saran*" and "*Suresh*". The same is also represented in the form of table in Table II.

TABLE II
HANDOVER WORK TABLE

	Arun	Dyer	Guru	Kiran	Kumar	Rajan	Ramesh	Saran	Suresh
Arun	0.0952...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Dyer	0.0	0.1428...	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Guru	0.0	0.0	0.0476...	0.0	0.0	0.0	0.0	0.0	0.0
Kiran	0.0	0.0	0.0	0.0	0.0	0.0	0.0476...	0.0476...	0.0476...
Kumar	0.0	0.0	0.0	0.1428...	0.1904...	0.0476...	0.0	0.0	0.0
Rajan	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ramesh	0.0	0.0	0.0	0.0	0.0476...	0.0	0.0	0.0	0.0
Saran	0.0	0.0	0.0	0.0	0.0952...	0.0	0.0	0.0	0.0
Suresh	0.0	0.0	0.0	0.0	0.0476...	0.0	0.0	0.0	0.0

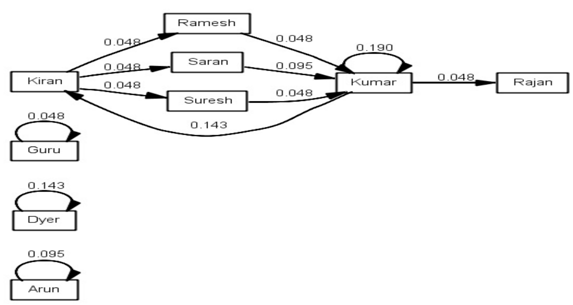


Fig 3. Social Network Miner of Handover Work Type Model

C. Social Network Miner of Similar Work Type Model

The Similar work progresses of different workers are shown in the figure 4 and 5. The figure 4 has the dyer that is expert in the dyeing unit has the major role to allot the work to each end workers, so that no filter is used. But in figure 5, we also experiment the work progress without the dyer involvement that is work between end workers similarity. The same is also shown in the Table III for without filter. The figure 5 has both table and resultant model. Hence, this knowledge will provide the dyer or expert in the dyeing unit to allocate the better work load to end workers in the forthcoming schedules. So that mining of event logs is helpful to the dyeing unit and workers in the dyeing unit to minimize and maximum the work.

TABLE III
SIMILAR WORK WITHOUT FILTER TABLE

	Arun	Dyer	Guru	Kiran	Kumar	Rajan	Ramesh	Saran	Suresh
Arun	0.0	4.2426...	3.1622...	3.8729...	6.1644...	2.6457...	3.1622...	3.3166...	3.1622...
Dyer	4.2426...	0.0	4.0	4.5825...	6.6332...	3.6055...	4.0	4.1231...	4.0
Guru	3.1622...	4.0	0.0	3.6055...	6.0	2.2360...	2.8284...	3.0	2.8284...
Kiran	3.8729...	4.5825...	3.6055...	0.0	6.4031...	3.1622...	3.6055...	3.7416...	3.6055...
Kumar	6.1644...	6.6332...	6.0	6.4031...	0.0	5.7445...	6.0	6.0827...	6.0
Rajan	2.6457...	3.6055...	2.2360...	3.1622...	5.7445...	0.0	2.2360...	2.0	2.2360...
Ramesh	3.1622...	4.0	2.8284...	3.6055...	6.0	2.2360...	0.0	3.0	2.8284...
Saran	3.3166...	4.1231...	3.0	3.7416...	6.0827...	2.0	3.0	0.0	3.0
Suresh	3.1622...	4.0	2.8284...	3.6055...	6.0	2.2360...	2.8284...	3.0	0.0

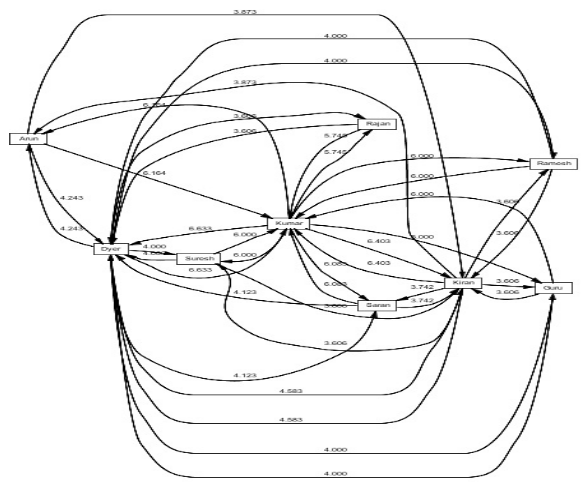
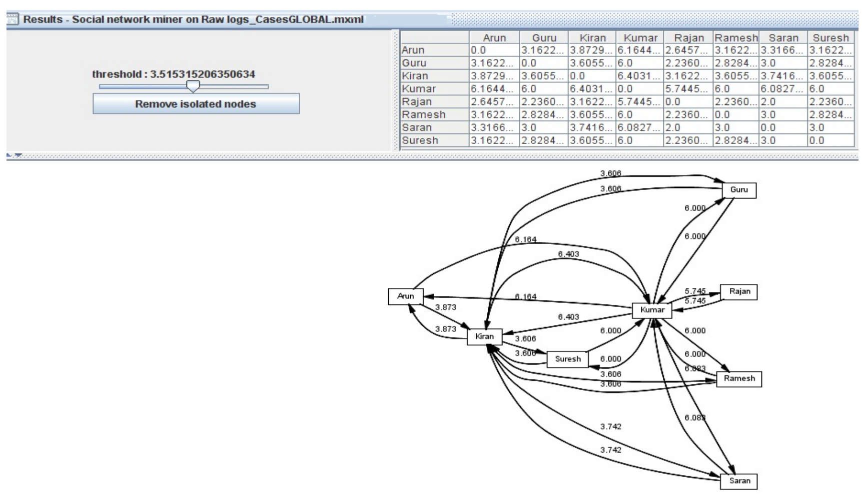


Fig 4. Social Network Miner of Similar Work without Filter Type Model



	Arun	Guru	Kiran	Kumar	Rajan	Ramesh	Saran	Suresh
Arun	0.0	3.1622...	3.8729...	6.1644...	2.6457...	3.1622...	3.3166...	3.1622...
Guru	3.1622...	0.0	3.6055...	6.0	2.2360...	2.8284...	3.0	2.8284...
Kiran	3.8729...	3.6055...	0.0	6.4031...	3.1622...	3.6055...	3.7416...	3.6055...
Kumar	6.1644...	6.0	6.4031...	0.0	5.7445...	6.0	6.0827...	6.0
Rajan	2.6457...	2.2360...	3.1622...	5.7445...	0.0	2.2360...	2.0	2.2360...
Ramesh	3.1622...	2.8284...	3.6055...	6.0	2.2360...	0.0	3.0	2.8284...
Saran	3.3166...	3.0	3.7416...	6.0827...	2.0	3.0	0.0	3.0
Suresh	3.1622...	2.8284...	3.6055...	6.0	2.2360...	2.8284...	3.0	0.0

Fig 5. Social Network Miner of Similar Work with Filter Type Model

V. CONCLUSION

In this paper, we have focused on the applicability of process mining in the dyeing unit domain. For our case study, we have used data coming from non-trivial shades of dyeing process of the Emerald Dyeing Unit. We focused on obtaining insights into the organizational flow by looking at the Organizational perspective. For this perspective, we presented some initial results. We have shown that it is possible to mine complex dyeing unit processes giving insights into the process. In addition, with existing techniques we were able to derive understandable models for large groups of workers and colors to identify the work together, work handover and similar work among various activities. The results are not derived by human thinking, it goes as per the recorded information and hence the automated process for further necessary measures for the dyeing expert called dyer is well sufficient for the better dyeing process.

Furthermore, we compared our results with a flowchart for the same color of dyeing unit process, and where a top down approach had been used for creating the flowchart and obtaining the logistical data [12]. With regard to the flowchart, comparable results have been obtained. However, a lot of effort was needed for creating the flowchart and obtaining the logistical data, where with process mining there is the opportunity to obtain these kind of data in a semi automatic way.

Unfortunately, traditional process mining approaches have problems dealing with unstructured processes such as can be found in Dyeing unit environment. Future work will focus on both developing new mining techniques and on using existing techniques in an innovative way to obtain understandable, high level information instead of "spaghetti-like" models like in the figure 5, showing all details. Obviously, we plan to evaluate these results in dyeing unit organizations such as the Emerald Dyeing Unit.

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