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DECISION SUPPORT VISUALIZATION APPROACH IN TEXTILE MANUFACTURING A CASE STUDY FROM OPERATIONAL CONTROL IN TEXTILE INDUSTRY

Abstract: *Decision support visualization tools provide insights for solving problems by displaying data in an interactive, graphical format. Such tools can be effective for supporting decision-makers in finding new opportunities and in measuring decision outcomes. In this study, was used a visualization tool capable of handling multivariate time series for studying a problem of operational control in a textile manufacturing plant; the main goal was to identify sources of inefficiency in the daily production data of three machines. A concise rule-based model of the inefficiency measures (i.e. quantitative measures were transformed into categorical variables) was developed and then performed an in-depth visual analysis using a particular technique, the categorical time series plots stacked vertically. With this approach were identified a wide array of production inefficiency patterns, which were difficult to identify using standard quantitative reporting - temporal pattern of best and worst performing machines - and critically, along with most important sources of inefficiency and some interactions between them were revealed. The case study underlying this work was further contextualized within the state of the art, and demonstrates the effectiveness of adequate visual analysis as a decision support tool for operational control in manufacturing.*

Keywords: *Decision making; Textile industry; Visual analysis.*

1. Introduction

In manufacturing, industrial production managers are responsible for continuously detecting and responding to problems in operational control, while also improving production by deciding how equipment, personnel, and planning are combined (Lim, 2014; Ruschel et al., 2017; Sánchez-Márquez et al., 2018) – increasing efficiency is a constant process of finding inefficiencies demanding intelligent action. Operational control in manufacturing offers several paradigmatic cases from equipment, personnel, and planning; typically, system components interact in non-obvious ways and frequently, only a subset of the whole system can be optimized (Pawlak, 2016; Lawrence, 1995). Further, most data is time-based and multivariate (e.g. multiple machines, daily or weekly perspectives).

Therefore, operational control in manufacturing can greatly benefit from using visual analytics tools for performing visualization and exploratory analysis. With advances in computer capabilities, visual analytics is emerging as a new science for data exploration supported by interactive visual interfaces (Thomas & Cook, 2006; Steiger et al., 2014). Moreover, appropriately

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designed decision support tools may also further improve collaborative practices in companies, which are becoming increasingly more important in the context of Industry 4.0 (Vafaei et al., 2019; Varela et al., 2019; Lu, 2017; Herter & Ovtcharova, 2016). Within computerized support systems, visualization tools are emerging as fundamental to support decision making because they support the tight feedback loops between system and decision maker, the open-ended analysis of results, and the testing of domain-specific models. Furthermore, any visual exploration process (Keim, 2002), should involve at least a three-step process: overview first, zoom and filter, and then details-on-demand; see also (Shneiderman, 2003). Good visualizations compress multidimensional data in a way that exploits the human visual system's superb ability to detect patterns in 2D, 3D, and 4D (e.g., with time), allowing the decision maker to focus their best cognitive skills in the problem at hand. There are already some visual exploration frameworks for spatial-temporal and multivariate proposed in the literature, see for example Keim (2002), Andrienko et al. (2010), Guo et al. (2006), and Rodriguez-Gonzálvez et al. (2017). Ware (2012) summarizes several advantages of visualization: it compresses data visualization reveals patterns without the need for an explicit model of all possible patterns – in line with the proposed visual system's natural abilities; it is useful to detect unexpected patterns; data quality issues become apparent – missing data and errors can be made salient; different scales can be understood in the same data – e.g. navigating between short and long time scales; and finally, it promotes hypothesis generation.

A central concern in this work is related to information visualization, specifically multivariate time series visualization, as a decision-support tool for improving operational control in textile manufacturing. For this purpose a suitable tool, denoted MUVTIME (Sousa et al., 2016), was used to discuss in detail a case study from a textile plant, where the main goal was visualizing plant production data in order to reveal sources of inefficiency, and the benefits of applying information visualization techniques over standard DSS reporting tools was clarified. Therefore, the present study found evidence of visualization benefits in a detailed analysis of a time series visualization for the daily production data.

The remainder of the paper is organized as follows: first briefly presents related decision support approaches in manufacturing; then the proposed approach is described, which is further illustrated through a case study, along with the used MUVTIME tool; followed by a detailed description of the main findings reached, within the state of the art, and finally main conclusions are summarized.

2. Decision Support Models and Approaches in Manufacturing

Theoretical models of decision-making as a process propose some form of enumerating or searching for alternatives as a starting point, or more generally, following Simon's (1960) seminal work, the first step of decision-making amounts to detecting a context in need of a decision. In manufacturing, industrial production managers are responsible for continuously detecting and responding to problems in operational control while also improving production by deciding how equipment, personnel, and planning are combined; efficiency is a constant process of finding inefficiencies demanding intelligent action.

Operational control in manufacturing offers several paradigmatic cases of Gorry and Morton (1971) semi-structured decision problems. Equipment, personnel, and planning combine in non-obvious ways; data is typically time-based and multivariate (e.g. multiple machines, daily or weekly perspectives). Although theoretically possible, a full detailed model of a manufacturing environment is often unfeasible (Pawlak, 2016) and in practice, sub-systems that can be optimized using a structured decision process, can only be optimized using simplifications and/or considering them as independent components (and frequently only in a subset of the whole system) (Pawlak, 2016; Lawrence, 1995). In many manufacturing plants, operational control is influenced by factors clearly outside the control of the most careful and quantitative planning, devised by an industrial production manager, for example if management accept urgent orders and demands rescheduling (Reddy et al., 2017). High-level operational control in manufacturing is thus highly conducive to Decision Support Systems (DSS) since all steps in Simon (1960)'s intelligence-design-choice sequence can be improved by computerized support.

Ware and Plumlee in 2013 describe several advantages of visualization tools: it compresses data – in a way that exploits human visual system's natural abilities; it is useful to detect unexpected patterns – visualization reveals patterns without the need for an explicit model of all possible patterns; data quality issues become apparent – missing data and errors can be made salient; different scales can be understood in the same data – e.g. navigating between short and long time scales; and finally, it promotes hypothesis generation.

The present study found evidence of those benefits to be further explored for enabling detailed analysis of a multivariate time series processing and visualization for supporting the daily setup data arising in the context of industrial systems, through a visualization decision support approach.

3. Background: Visualization Decision Support Tools

Time series and time series plots are particularly useful for determining correlations and causality relations between different variables. Historically, time series plots have been used at least since the seventeenth century for depicting economic data (Klein, 1997) and its use has since generalized specially during the twentieth century as the practice of systematically collecting time annotated data become common in almost every knowledge area.

The development of computer systems and computer graphics opened new possibilities for time series analysis and visualization, since the often-difficult process of digesting large time-series datasets and building visualizations, could now be automatized. Computer systems also facilitate the task of collecting data and consequently datasets are now becoming larger and increasingly multivariate. The added complexity requires visual exploratory tools than can manipulate the level of granularity and allow contrasting different visualizations when seeking insightful information.

A representative domain of application is health records, an important field of development of time-series visualization tools, as doctors often have to make critical treatment decisions based on individual patient histories or large epidemiological data. Early tools were meant for analysis of individual patient data (Bade et al., 2004, Shahar et al., 2006), with an emphasis on exploring different time granularities and identifying events. Other tools like CareGiver (Brodbeck et al., 2005), PatternFinder (Fails et al., 2006), Lifelines 2 (Wang et al., 2009), Similan (Wongsuphasawat & Shneiderman, 2009), CareCruiser (Gschwandtner et al., 2011) and VisuExplore (Rind et al., 2011) were devoted to exploration of multiple records. Common to all is an emphasis on temporal alignment of data, and identification of common sequences of events that translate, for instance, causal relations between treatment applications and physiological effects (Gschwandtner et al., 2011). These events can be extracted from data or result from annotations.

Other areas outside the medical domain place a large emphasis on exploring different temporal granularities for identification of both macro and micro temporal patterns. The TimeSearcher system (Buono et al., 2007; Hochheiser & Shneiderman, 2003) implements the "time box" concept, a sort of "magnifying glass" that allows zooming in on specific time windows. Somewhat similarly, the EventViewer developed by Beard et al. (2007) is a framework for exploring data acquired from multiple environmental sensors, manipulating time granularities. The ChronoViz (Fouse, 2013), and the BEDA software (Kim et al., 2015) shows similar concerns, but are applied to the field of behavioral science.

The already mentioned EventViewer (Beard et al., 2007) is also meant for exploring the geographical dimension of the data, allowing one to compare data of sensors placed in geographically distinct locations. This translates a concern with both temporally and spatially marked data that is common to many potential fields of application for visualization tools (Gahegan, 2005). For instance, the GeoTime software (Kapler & Wright, 2005; Kapler et al., 2008) uses a 3D view for showing both spatial (ground plane) and time (vertical) information while Andrienko et al. (2010) and Rodriguez-Gonzálvez et al. (2017) use different panel views for showing both the temporal evolution of variables and the geographical location of their origins. Guo (Guo et al., 2006; Mennis, & Guo, 2009) employ self-organizing maps (SOM) for data clustering and exploration of geo-tagged data.

3.1. The selected Visualization Tool: MUVTIME

To demonstrate the suitability of visualization tools for operational control in manufacturing textile, a visualization tool named MUVTIME was used. MUVTIME is a desktop application designed to assist in the process of multivariate time series data visual analysis. The first version is described in (Sousa et al., 2016). The current version, under development, was used in the present study.

This multimodal time series visualization tool provides four different visualization areas, each of them on a specific application panel: video playback, graphs, time brushing, and visualization of motion capture points. An extra panel, the playback controller, allows the user to navigate the data's time domain, maintaining synchronization across all the other panels. The user can load a time series collection and an associated video. This time series dataset is loaded from the user's file system in a CSV (Comma-separated values) format and the video file in a MPEG-4 format. All the features were designed to simplify the visual exploration and the analysis of large datasets.

4. Proposed Decision Support Visualization Approach and its Application

The proposed visualization decision support approach encompasses a set of five phases, varying from the initial knowledge elicitation with the domain expert and subsequent exploration of several different possible visualization solutions, down to in-depth interpretation of visualizations, and succeeding results compilation, analysis and validity discussion with the domain expert, as summarized view presented in Figure 1 and further detailed explanation provided below.

The proposed approach started with an initial knowledge elicitation phase with the domain expert (familiar with the textile plant and with the production data collected there). In this step were surveyed the available quantitative measures (mostly connected to total duration spent in production or in several types of unproductive times – this was part of periodic reporting at the plant) and critically, the domain expert was asked to transform the key measures into nominal variables; this resulted in a set of rules that indicate if the daily behaviour is poor, average, or good for the most important performance measures. The evaluation rules are crisp rules that transform one quantitative variable into another categorical variable, composed of mutually exclusive categories. In a second phase were devised several visualizations scenarios that varied in the degree of data compression; the dataset consisted of eight months of actual daily plant production data. In designing visualizations, Van Wijk's (2006) cost-benefit model for visualization was taken in consideration and to create visualizations with a low cost of development and a short learning curve was opted to use simple and common design options. For plotting multivariate time series, several commercial tools can be used; however, here, as mentioned above, was used MUVTIME, a custom-made application developed by some of the co-authors of this work: MUVTIME (Sousa et al., 2016). This choice is due to MUVTIME's capabilities for fast exploration of multiple stacked time series plots, specifically linking and brushing in the time domain – i.e. all plots are aligned with a single time axis and the user can select an arbitrary time window for the current view (the brushing component).

Next, the domain expert was asked to interpret the visualizations as in-depth as possible in a series of interviews. Based on this interviews it was quickly possible to discover that a particular visualization was the most potent – categorical time series plots, or tile maps; see (Aigner et al., 2011) – and the further meetings with the domain expert were focused on interpreting only those. Finally, were compiled all conclusions and discussed their validity with the domain expert in a final interview. The visualizations developed revealed multiple aspects of the plant's production inefficiencies demonstrating the visualization's value as a decision-support tool.

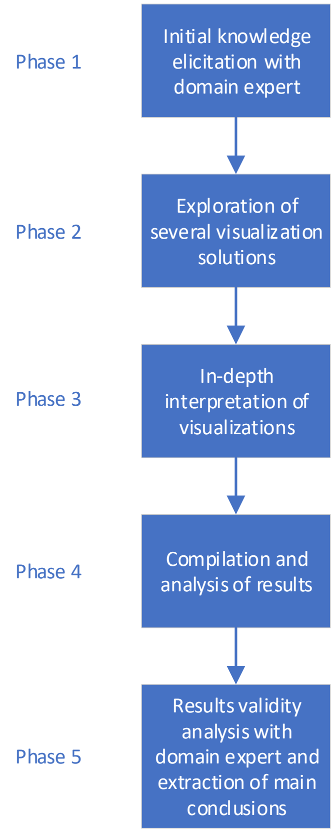

Figure 1. Proposed decision support visualization approach.

4.1. Case study description

The visualization tool was applied in a Company in the textile industrial sector, more specifically in the stamping business area, in order to further support its operational control regarding setup data processing, monitoring/visualization and analysis. In the referred Company a pattern consists of n colours, which give rise to n cylinders engraved with the intended design through holes, by which the respective ink colour passes and prints the fabric.

The Company had three machines, with two shifts each, where each shift recorded each day for each machine on a record sheet the following: production times, setup times, ink correction times, and times with other types of stops. This temporal data was analysed and treated by a technician, who prepared daily reports for management to discuss problems of the previous day with the head of the underlying production section.

The most notable problems of everyday life of the Company that contributed to inefficiencies were related to the times lost with changes of references related to setup times, to the rectification of colours, to changes introduced in the production planning, and to the existence of unregistered times, called as “invisible” times.

Every area of the Company, from warehouse, production, colour lab, recording cylinders, had access to daily planning, through which they managed their work. Often, urgent orders were introduced in the production plans, or due to deadlines changes, from the supplier side; production plans had to change frequently, sometimes two to three times a day, causing serious problems that were very noticeable in terms of delays in almost all departments, namely in material logistics, in the inks laboratory, and in production.

The Company used the terminology of *reference change*, that produced a full setup; this consisted of taking the cylinders from the previous stamping, taking them to wash and placing the cylinders for the next stamping, set machine parameters per cylinder and stamp the first sample. If the colours of the first sample did not match the customer's colour requirements, they would return to the colour lab again to be rectified. During this time, the workers and their production machine stood waiting for the colours to be corrected. After the correction, the inks returned to the respective machine and another sample was taken again. This process was repeated until all colours were in accordance with costumer requirements, proceeding to the shop floor for production.

Day-to-day in the Company passing through the problems mentioned above it was very unstable and problematic to deal with them and it was indispensable for the industrial manager to realize where the inefficiencies of the process were caused, on a daily basis.

4.2. Dataset and knowledge model

The dataset used in this case study, contained daily data per machine, for production efficiency analysis, regarding setup data relative to eight months, in which production times, setups times, colour correction times, invisible times, and efficiencies were recorded. Subsequently, the inefficiencies of the setups, the correction of inks and invisible times were calculated, in order to try to perceive the problems that contributed, in a more significant way, to a daily base real scenario, which was contributing to the total inefficiency of the machines in the underlying production environment.

The main objective in this industrial management problem is to understand the level of inefficiency (time stopped), in the daily life of the Company, and which sources contributed to the total inefficiency, so as to be able to perceive, in a timely basis typically daily and weekly, but also monthly or in any other desired time horizon, through an analysis carried out by the industrial manager, which are the worst and best production periods, which are the best and worst machines, which types of problems had the greatest influence on the overall inefficiency of the productive system and where the main improvement opportunities that could be prospected were centred, based on a system for supporting decision making based on an appropriate data visualization that could be favourable for carrying out this kind of data analysis. For the industrial manager, it was essential to be able to perform an efficiency/inefficiency analysis, when a "bad" level was reached in the factory, in order to try to understand why the day was “bad” and what were actually the underlying problems, when eventually the overall efficiency was either "good" or acceptable and the inefficiency of a given machine was "bad", i.e. the overall efficiency was within acceptable parameters, but the specific data of a particular machine or several ones did indicate the existence of many inefficiencies, becoming target problems that dictated fundamental improvement needs.

The key performance indicators (KPIs) are summarized in Table 1. The first and the most global measure is simply Efficiency corresponding to proportion of time spent in production (from the total available time considering the two shifts). Workers also logged the time they spent doing a setup or waiting for a colour correction; a third category is implicit here which is the remaining time after subtracting to the total available time the setup and colour correction time (thus was unaccounted, likely unlogged time, the "invisible" periods).

Table 1. Key variables used for modelling the textile stamping plant's efficiency and inefficiency

Variable Name	Description
Efficiency	Proportion of total time in production / total available time during a particular period
Class of Efficiency	Categorization of Efficiency in 3 categories: Low, Medium, and High
Inefficiency Due to Setup	Total time stopped because of setup related tasks / Total Time Stopped
Inefficiency Due to Inks	Total time stopped because of ink related tasks / Total Time Stopped
Inefficiency Due to Unaccounted Time	Total time stopped because of unaccounted time (not logged) / Total Time Stopped
Class of Inefficiency Due to Setup	Categorization of *Inefficiency Due to Setup* in 4 categories: "Good", "Tolerable due to planning", "Tolerable due to other sources", "Poor"
Class of Inefficiency Due to Inks	Categorization of *Inefficiency Due to Inks* in 3 categories: "Good", "Tolerable", "Poor"
Class of Inefficiency Due to Unaccounted Time	Categorization of *Inefficiency Due to Unaccounted Time* in 3 categories: "Good", "Tolerable", "Poor"

There were then three easily identifiable sources of inefficiency that were captured in equal number of inefficiency measures that took in consideration the time not in production: Inefficiency Due to Setup – proportion of time spent in setting up the machine divided by the time the machine was not in production, i.e. stopped; Inefficiency Due to Inks – proportion of time in ink correction related tasks divided by total time stopped; Inefficiency Due to Unaccounted Time – proportion of time spent in unaccounted time divided by total time stopped.

In a knowledge elicitation interview the domain expert was asked to categorize these four key measures (all proportions) in at least three levels.

The global measure of Efficiency was categorized as: "Low" (below 40%), "Medium" (between 40 and 60%), and "High" (above 60%). This definition may come as surprise (40 to 60% as acceptable) but production days with high efficiency were infrequent and this classification corresponded to the reality of what that manufacturing environment could realistically produce.

The inefficiency measures used additional knowledge. For the measure Inefficiency Due to Setup the domain expert defined four categories: "Good, likely source is orders"; "Tolerable, likely source is production planning"; "Tolerable, likely source is other delays inside the factory"; and "Poor, likely due to large number of reference changes". The rationale behind the levels used the number of setups per day to derive the classification:

- the category "Good, likely source is orders" was interpreted as "Things are ok, multiple orders are coming in". It was defined by more than 50% in Inefficiency Due to Setup but number of different daily setups higher or equal than 10 (typically this happened when many separated orders entered production).

- the category “Tolerable, likely source is production planning” was defined by more than 50% in Inefficiency Due to Setup and number of different daily setups between 5 and 10. The production planning was likely not going well.
- the category “Poor, likely due to large number of reference changes” was defined by higher than 50% in Inefficiency Due to Setup while number of daily setups was smaller than 5; this meant that some problem happened during a reference change in order to justify the high value for low number of setups.
- the category “Tolerable, likely source is other delays inside the factory” was related to the case exclusive of three previous cases where cannot be identified none of the previous scenarios, thus the problem could be related with some internal logistics problems, regarding the material to be supplied to the shop floor or to poor performance of some workers.

The Inefficiency Due to Inks measure was categorized in three levels: “Good” (below 30%), “Tolerable” (between 30 and 50%), and ”Poor” (above 50%). For Inefficiency Due to Unaccounted Time three categories were also defined: “Good” (below 30%), “Tolerable” (between 30 and 50%), and “Poor” (above 50%).

4.3. Visualizations performed for case study

Next, are described the main steps in deriving the visualizations for performing the visual exploration / analysis in the case study (see Figure 2).

In Figure 2, from the top, each block of four coloured lines represents Efficiency, Inefficiency Due to Setup, Inefficiency Due to Inks, and Inefficiency Due to Unaccounted Time. The last two rows represent week days/ weekends and the month. After loading the dataset from the csv file, were used mostly two components: a visualization panel, for selecting a variable for plotting, a modal window to define custom colour palette, and a timeline navigator to control the time scale, to choose the variables to be displayed in the timeline, and adjusting the zooming in the charts in the visualization panel for a given time prior to be further analysed.

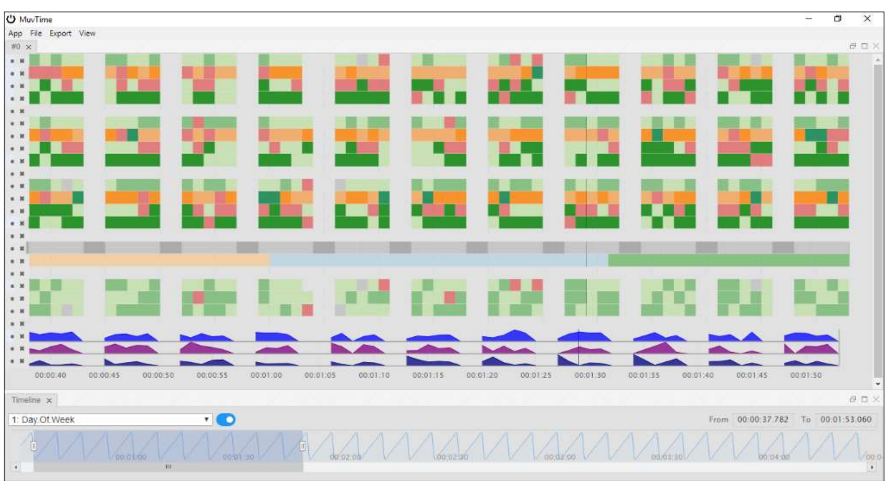

Figure 2. A screenshot of MUVTIME with the case study data loaded, showing two months of data for the three machines

4.4. Visual analytics/ exploration for the production data

After several interviews with the domain expert it became obvious that a visualization was the most useful one: categorical time series plots. Figure 3 shows an example of plotting the original quantitative measures of efficiency and inefficiency for machine 1 for two months. The quantitative data that was reported periodically by the industrial manager is present, but patterns are not straightforward to identify. The example shows two months of daily efficiency/ inefficiency data for machine one. From the top to bottom the rows represent: month, weekend (in orange), Efficiency, Inefficiency Due to Setup, Inefficiency Due to Inks, Inefficiency Due to Unaccounted Time. The last four rows correspond to the same variables but with an area plotted under the line. All rows have the same [0, 1] y-axis scale.

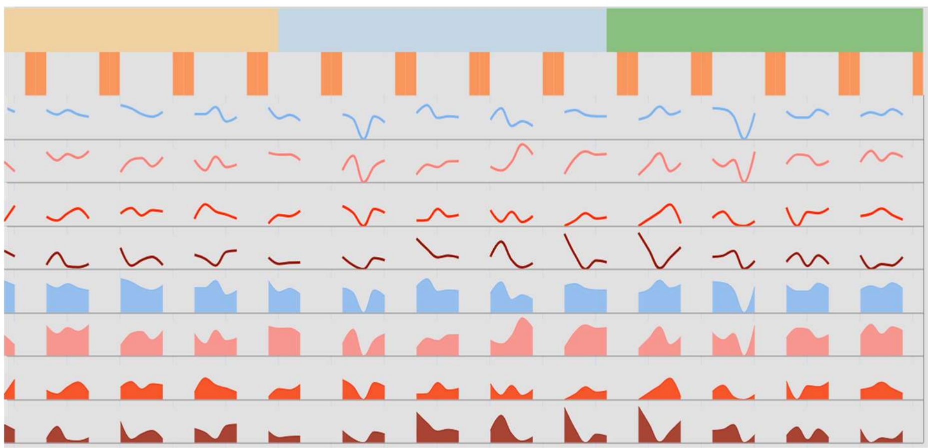

Figure 3. A representative example of plotting quantitative variables from the case study

The data as categorical time series plots was plotted following the knowledge elicitation step where the domain expert categorized the key measures. Data interpretation and conditions referred to above was based on a simple colour pattern. For the Efficiency and Inefficiency Due to Unaccounted Time variables, the colours of "dark green", "light green" and "red" were assigned to the categories: "Good", "Tolerable" and "Poor". Regarding the variable Inefficiency Due to Setup the ordinal colour order (from best to worst) was "dark green", "light orange", "dark orange", and "red". The situation underlying the "light orange" colour meant to identify a normal day-to-day situation of the factory, but with problems occurring that do indicate opportunities for improvements and the colour "dark orange" follows similar logic but represents a more serious problem. For *Inefficiency Due to Inks* variable the ordinal colour order was "dark green", "dark orange", and "red".

The main findings are in **Error! Reference source not found.** and Figure 5. **Error! Reference source not found.** shows an overview of the eight months of the dataset while Figure 5 shows a two and a half months zoom-in of the data. Each day is represented by a coloured square; a set of five squares refers to a week, and the grey blocks intermediate represent the weekends. The history of a machine is organized by line, i.e., the first four coloured lines refer to machine 1 and the following sets to machine 2, and 3 respectively. The first line, from each set of four, allows us to examine *Efficiency*, the second line to *Inefficiency Due to Setup*, the third to *Inefficiency Due to Inks,* and the last one to *Inefficiency Due to Unaccounted Time*.

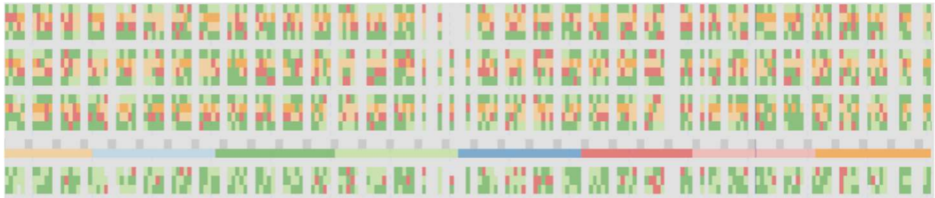

Figure 4. Overview of the dataset for the entire eight months of available daily production data

From top to bottom the visualization shows: (1) first four rows regard machine 1 and show *Efficiency, Inefficiency Due to Setup, Inefficiency Due to Inks, Inefficiency Due to Unaccounted Time;* (2) second set of four rows are the same but for machine 2, (3) likewise for machine 3; (4) weekend day plus month; (5) last three rows show the variable Efficiency for machines 1 to 3 – this shows the most compressed view of a week possible.

Examining **Error! Reference source not found.**, in general, the industrial manager can realize that during the eight months period dataset, machine 3 had a better performance and was less problematic. All machines show opportunities for improvement in setup times, ink correction periods, and in terms of production planning. The lack of planning compliance and frequent planning changes due to urgent orders entry are notorious. On the other hand, it is still possible to verify that the lack of coherence of a suitable planning significantly affects the setups times and the time of correction of inks. In summary, the industrial manager is able to get a global view of the performance of each machine and the most significant problems that may contribute to the overall inefficiency in the factory.

With a view for a specific period, as shown in Figure 5, the industrial manager is able to focus his/her analysis in more detail. A colour that repeats itself for more than two days, with the exception of green was considered by the domain expert as a bad symptom. This problem is easily detected for "red", "light orange", and "dark orange". For machines 1, 2 and 3, it can be verified that what is unfavourable to the efficiency of the machines is the production planning, a problem that is reflected individually or collectively in the inefficiencies of setup and ink.

Figure 5. Zoom-in to two-and-a-half month period in the daily production data

The order of variables from top to bottom is the same as described in Error! Reference source not found..

The domain expert also noticed that there is a possible temporal correlation when the same problem affects two distinct areas of the factory, in this case the factory floor, at the level of the reference change, and the paint laboratory, at the paint correction level, when the inefficiency of the setup is dark orange and the ink inefficiency is red. One hypothesis was that priority was not given to the fulfilment of planning, but to the entry of urgent orders.

On the other hand, the lack of fulfilment of customers' requirements with colours, a priori, is another problem, visualized by the "red" colour in the inefficiency of the inks and the "light orange" colour in the inefficiency of the setups. Here the domain expert identified a problem in the correct recipe of the colours of the customers, which affects the production time and contributes in some way to the inefficiency of the setup. In addition, it can be noticed that, in general, the data recording by the operators of the machines was fulfilled during this two-and-a-half months period under analysis. In conclusion, it is possible to refer that through a more focused analysis, in a given period, it is possible to perceive more in detail the specific causes that are the origin of concrete problems, as well as the existence of correlations between data and, therefore, of concrete problems and prioritize actions for their resolution.

5. General discussion and analysis of contribution in the state of the art

The existence of visual and intuitive means to effectively and efficiently support and guide an industrial manager analyse inefficiency, and identify its causes, is an important tool for appropriate and timely decision-making, and of fundamental importance for supporting an industrial manager in his/her daily based decision making process.

The tool used in this case study was based on an essentially qualitative analysis of data regarding inefficiencies, and their potential causes, given the importance of achieving a minimally realistic perception of the scenarios that occur in the factory's given period of time. Therefore, although a quantitative analysis is usually useful in a process of analysis and decision making for an industrial manager, sometimes the excess of data, originated by a vast set of factors or variables makes these processes of analysis with the appropriate need for decision-making, a process that is too complex and even ambiguous and therefore challenging to carry out in a minimally objective and precise way (Pawlak, 2016; Lawrence, 1995; Reddy et al., 2017). Consequently, a tool such the one used in this work is clearly beneficial, by allowing, in a more or less "friendly", and "intuitive" way, and without great effort, for a minimally trained industrial manager, to acquire a perception of the behaviour of the production environment. It is possible to switch from a more general to a more detailed perspective, for instance, per machine, allowing to analyse, with a minimum of clarity and precision, which are the main reasons or causes associated to the occurrence of the main inefficiencies in the factory. In more detail, it is possible to examine which machine(s) is(are) the most problematic one(s), in terms of inefficiency and which should be given more attention, at each moment along the decision making process, varying from a more long term down to a shorter time horizon.

The proposed visualization approach provided a global view on efficiency and sources of inefficiency and allowed a better, therefore, more effective and efficient assistance to the industrial manager in identifying the most serious problems and its further prioritization for being solved or at least minimized. Furthermore, it allows essentially a hierarchical analysis, i.e. a global versus more localized overview on given datasets, because it is possible to switch between a whole dataset view and any zoom-in of the time axis, such as a monthly or weekly based vision, or even a more general and historic perception about the efficiency/inefficiency of the machines in the factory. On the other hand, it increases the level of decision support to industrial managers because visual exploration facilitates to achieve the compaction or level of abstraction versus detail, i.e. it contributes to a more attractive, intuitive and quick way for an appropriate level of data analysis. This allows the industrial manager to act in an appropriate and timely way, conversely to a quantitative analysis purely based on weekly or daily detailed reports, which would turn the data analysis process more cumbersome.

In addition, the visualization data underlying this work is not merely retrospective as it enables daily production data exploration. For instance, one can analyse previous day data, i.e. a current situation, alongside a more extended historical analysis. Through the analysis of colour standards, it is possible to achieve the main objectives inherent to this work, of carrying out an analysis of the performance of a set of machines and to identify the most problematic one(s), to categorize the kind of underlying inefficiency and the main cause(s), which may be related to one or more of the following: lack or deficient production planning, correction of inks, changes of reference/entrance of urgent orders, lack or deficient registration of data by the operators, among other problems that condition the efficiency of the setups.

Next, in Table 2 is presented a summarized description of the main contributions put forward by the corresponding authors of the sources analysed, based on a set of six main criteria considered for comparative analysis with the proposed visualization decision support approach. In general, and according to the information presented in Table 2, it is possible to realize that a range of five varying contributions or approaches is being put forward (A1 (Stadnicka, 2015), A2 (Mayr et al., 2018), A3 (Gonnermann & Reinhart, 2019), A4 (Vinodh et al., 2011), and A5 (Wu et al., 2018)), for instance during the last decade varying in terms of type of approaches, methodologies or methods and underlying tools that have been used, concerning setup data representation, processing, analysis and visualization or monitoring, for different industrial sectors and manufacturing environments, with several distinct specificities and requests, for accomplishing differed purposes and by considering different manufacturing systems' performance measures and setup variables.

Table 2. Resume of contributions from the literature and proposed approach

Main criteria	**A1**	**A2**	**A3**	**A4**	**A5**	**A6 (proposed)**
1. Supporting methodology/ tools	SMED, bottleneck, Pareto and FMEA analysis	Lean management (LM) oriented methodologies and tools (SMED, Visual management, Value Stream Mapping - VSM, digital twins)	Skill-based approach for an automatized setup of process monitoring in reconfigurable assembly systems	Lean principals (LM: 5Ss, VSM) and simulation in Matlab	Simulation and queueing models, with JIT and TPS	Multi-variate time series based approach/tool
2. Applicable industrial sector/ environment	Small to medium enterprises (Machining – CNC Turning)	General manufacturing application scenarios versus I4.0 oriented ones (with Additive Manufacturing – AM and Augmented Reality – AR, etc.)	Automated Assembly lines, in context of Cyber Physical Systems (CPS)	Automotive industry – automobile valve manufacturing industry	Flexible Manufacturing System (FMS) – production lines in semiconductor industry	Textile industry – stamping factory (applicable and extensible to other industrial sectors and manufacturing environments)

Table 2. Resume of contributions from the literature and proposed approach

Main criteria	**A1**	**A2**	**A3**	**A4**	**A5**	**A6 (proposed)**
3. Variety of setup data	Setup time and number of setups	Digital versus physical setup time (downtime) and setup cost	Data related to production of different product variants, and thus enable to automatically identify devices and their process abilities, and relevant production data	Setup time, along with other kind of wastage and cost (e.g. non-value added time, lead time, and travelling time)	State-induced setup and product-induced setup data (changeover setup or a replacement)	Varying set of considered most setup and general inefficiency measures and further relations among setup data (measures)
4. Varying time horizon (per month, day, etc.)	Monthly data, based on daily setup information	Varying time horizon, but mostly focused on short term time periods, i.e., per day, hour, etc.	Continuous and adaptable process monitoring system focused on considered relevant process data gathered through RFID	Analysis of a set of manufacturing lines and its machines in a monthly to daily basis for several different products (valves) through SMED and Kanban techniques	Varying time horizon analysis based on queuing model and setup time distributions according to production lines and corresponding products information	Data visualizations and analysis by month, day, etc. for enabling integrated and diverse analysis from overall system perspective to specific analysis on each machine
5. In-depth visual data analysis (per production system, per machine, etc.)	Data analysis (graphs) on given CNC turning machine	LM versus I4.0 oriented visual management based on 5S, zoning and andon, along with AR and digital twins	Communication interfaces and intelligent data processing, automated installation for monitoring processes	Non-value added time, lead time, and travelling times are calculated and further checked if the value are within corresponding ranges or not	Quantification of the impact of setup reduction in scope of manufacturing system's productivity analysis based on overall mean queue time of all products	Data visualization and analysis (graphs) per production system down to work station or machine, based on multivariate time series
6.Categorization of quantitative variables (performance measures/KPI)	SMED based internal and external setup data categories	Digital versus physical setup categories	Setup data categorized based on skill based model	SMED based internal and external setup	Setup data categorized as state-induced setup and two types of product-induced setups, i.e. changeover and replacement setups	Rule-based model (KBS) of the performance measures (KPI) for being transformed into categorical variables

Legend: A1 (Stadnicka, 2015), A2 (Mayr et al., 2018), A3 (Gonnermann & Reinhart, 2019), A4 (Vinodh et al., 2011), A5 (Wu et al., 2018), A6 (proposed decision support visualization approach and underlying tool).

Thus, it becomes out to be quite a hard task to carry out a more precise and objective and clear comparative analysis among such different proposals, which are have quite disperse focuses regarding each different scope. Although, and focusing on the purpose or the proposal of the contribution put forward in this paper, and due to the impossibility of being able to come across any more closely related contribution to this one within the literature, it becomes out to be possible to state that this contribution brings some novelty regarding a setup data visualization decision support approach, based on multivariate series analysis, intending to enable to identify a widened range of production inefficiency patterns, which were difficult to identify using more standard quantitative reporting, along with a critical identification of most important sources of inefficiency regarding setups, and some interactions between them. Moreover, the proposed approach permits an integrated analysis regarding overall efficiency versus specific analysis, on individual machines of a production system, in a varying time basis.

6. Conclusion

Visualization decision support approaches play a crucial role in improving automatic production and management systems, in the context of the nowadays Industry 4.0 era. In order to provide a contribution in this direction, this paper proposed a visualization decision support approach for setups processing and analysis in a stamping factory.

The proposed visualization approach enabled to analyse setup data varying from a long term down to a short-term time horizon, as well as real-time data exploration and analysis. It identified most problematic or critical areas, regarding the setup data, and categorization of the underlying inefficiencies and their main causes.

Concluding, through the use of the proposed visualization approach a contribution was put forward to improve the decision making process by production managers in stamping factories.

Planned future work includes work in several dimensions. The first dimension is related to the further satisfaction of the factory's actual requirements which consist of: 1) the extension of the proposed approach to a fully interoperable system for further enabling automatic data acquisition from the shop floor of the stamping factory; 2) the integration of the used MUVTIME visualization tool with other systems, including data bases to further extend the data analysis though appropriate algorithms, for instance, in the scope of data science, and machine learning is also intended.

The second dimension is oriented to applications to other domains such as: 3) embedding the MUVTIME tool into a Cyber-physical systems (CPS) for visualization of time series for data collected from machine and environment sensors, such as resources availability, machine elements states, CO_2 emissions, forecasted data, to visualize the output of simulations, which are usually raw data, into a “visible" data, all in order to facilitate the process of decision making; 4) to extend the use of the visualization tool to other manufacturing environments and industrial sectors, also in the context of cyber physical systems.

The third dimension is oriented to advanced approaches and theoretical developments towards visualisation as disruptive technology including approaches such as: 5) Context Aware visualisation meaning visualising data not only of machines but also production plans, operators (humans), etc. as all these elements influence the behaviour; 6) Customer experience (CX) (considering that the products are much less produced in mass but as a personalised products aligned with the personal interests of each customer individually); 7) predictive, meaning that it is not possible anymore to base only on the historical data but considering all the socio/business context; 8) Crowd Computer Vision and Analysis, including pattern recognition and Artificial Intelligence, with co-construction and co-decision. Also, future research will address 9) evolution of the visualisation tools towards infra-structures for supporting it and other services; 10) emergent interfaces with VR/ÇAR/etc which role will be to integrate various tools and those that will emerge.

In conclusion, concerning the third dimension for the future research, the evolution of the actual tools will be in direction not only towards purely applications for improvement of the existing processes, but towards the change of the processes.

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