

Order Related Acoustic Characterization of Production Data

Michael Iber and Katja Windt

Abstract The conductor of an orchestra is able to distinguish not only between different instruments, but even among dozens of string players performing on instruments with similar sound qualities. Trained human ear not only is capable to highly differentiate between pitches and colors of sound, but also to localize the position, where the sound is coming from. This chapter presents a parameter mapping sonification approach on production data, which is based on these human perceptual skills. Representatively for other logistic parameters, throughput times of orders are sonified and allocated in a sonic space. Additionally to auditory representations of the established resource and order oriented views in logistics, a third perspective is introduced, which displays the complete workflow of an order simultaneously as a multi-pitched spatial sound. Thus, causes and impacts of high throughput times in the data set example could be identified.

Keywords Manufacturing · Parameter mapping sonification · Data mining · Logistic analysis

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1 Introduction

Profound analysis of actual and planning data and their correlation is an essential requirement for the adjustment of operating levers in production planning and control. Depending on the amount of work systems of a production shop, the number of product variants to be produced, and the quantity of restrictions caused by technical requirements or customer demands, the structure of manufacturing data easily reaches the complexity of NP-hard problems [1]. Whereas traditional methods [2] rely on averaging in order to reduce complexity, more recent approaches include advanced statistics and data mining [3] for a deeper understanding of production data. An important component of both, data mining and traditional statistic approaches as applied in logistic analysis, is exploratory data analysis (EDA). The term [4] comprises the participation of a human analyzer, who interactively explores the structure of data in recursive proceedings between generating and proving hypotheses. Well-established approaches are graphical statistics and data visualizations [5]. In the context of chronologically structured data such as production data, the acoustic equivalent to graphical display, the auditory display of statistical data (as provided by sonifications) is a promising method to gain knowledge about temporal fluctuations of bottlenecks in production workflows.

In natural science, auditory display still is widely disdained in comparison to its visual correspondent [6]. This might be caused by the visual alignment of human thinking per se including written language as the legitimate form to capture thoughts and scientific results. Still, the transfer of auditory cognition to a graphical representation meets a major challenge in most cases. But human ear has qualities that are literally complementary to the ones of the eyes. Whereas the latter tends to focus on singular events, the former is capable to perceive far more complex acoustic information. A conductor of an orchestra e.g. is able to distinguish not only between different instruments, but even among dozens of string players performing on instruments with similar sound qualities. Trained human ear is not only capable to highly differentiate between pitches and colors of sound, but also to localize the position, where the sound is coming from. Since sound only exists in temporal space, sonification of chronologically structured data such as production data is almost self-evident.

This chapter presents an approach on auditory display of production data, which is based on the human perceptual skills described. Exemplary for other logistically relevant parameters (such as work content, setup time, or schedule deviation), throughput times of orders were sonified and allocated in sonic space in order to reveal evident information about fluctuations in the overall workflow.

The following sections of this chapter depict the starting point of this research considering exploratory data analysis in logistic engineering (Sect. 2) as well as parameter mapping sonification in the scientific field of auditory display (Sect. 3). Section 4 describes the methodical approach of this research on the basis of the exploration of a data sample from sheet metal production. Finally, Sect. 5 presents a conclusion and a critical discussion.

2 Data Analysis in Logistics

The contradictoriness of logistic targets (low inventory, low throughput times, high schedule adherence, and appropriate utilization) as described by Gutenberg's scheduling dilemma [7] has comprehensively been treated in literature. Whereas there are practically approved solutions to balance inventory, throughput times, and utilization such as Logistic Operation Curves [2], schedule adherence and its impact on the overall workflow has not equally been investigated. Yu [8] criticizes an insufficient consideration of schedule adherence in production planning and control systems (PPC) and develops a scheduling operation curve in order to quantify the impact and causes of schedule deviations. As an extension of the Logistic Operation Curves, this approach is also based on averaging and not suitable for the identification of characteristic patterns in the chronological sequence of operations.

In order to enhance the level of detail in production planning and control as a first step, analysis methods need to be developed which provide a deeper understanding of the structure of logistic data itself. Therefore, novel approaches in logistic analysis increasingly rely on Knowledge Discovery in Databases (KDD) including artificial neural networks (ANN) and explorative data analysis such as the multi-stage quality information model (MSQIM), which reveals causal factors of quality defects [9]. Windt and Hütt [10] use cluster analysis and methods adapted from gene expression analysis to classify product variants that are the cause of lateness. Although classifications are capable to identify correlations between several qualities of orders and processes, in contrary to e.g. time series analysis they do not consider the serial impact of order sequences. Only [11] combines clustering with dynamically changing data.

Apparently, there have been no explicit researches using time series analysis, which in certain aspects is related to auditory display, for the identification of dynamic bottlenecks on planning and feedback data in manufacturing. The auditory analysis of production data therefore may also be considered as a first step to time series analysis in bottleneck analysis.

3 Auditory Data Analysis

Auditory Display has been established as a scientific discipline at the first Conference on Auditory Display at the Santa Fee Institute in 1992. The initiative, which led to the International Community on Auditory Display (ICAD),¹ aimed to bundle different activities in several scientific fields that examine the potential of information carried by sound. Auditory display therefore embraces a wide range of subcategories between the design of sound signals (e.g. for monitoring in medical environments or human computer interaction) and auditory data analysis.

¹ <http://www.icad.org>

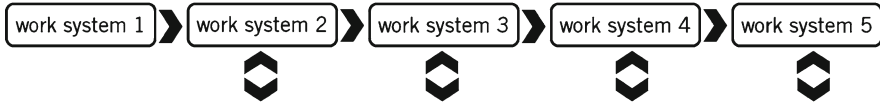


Fig. 1 Five linearly coupled work systems as an extract of a major manufacturing network. For detailed analysis only work systems 3, 4, and 5 were considered

Two key events demonstrated the potential of data sonification essentially. First, the detection of the consistency of the rings of Saturn [12]. Second, the final prove of the assumption that particle currents in weakly coupled macroscopic quantum systems would oscillate between the two systems [13]. Already in 1982, Sara Bly demonstrated in a case study including the sonification of six-dimensional data “that the auditory display was at least as effective as the visual display, and that the combined display outperformed them both” [14]. Numerous researches in fields such as neurology, theoretical physics, sociology, or psychology have refined the methodical approaches toward data sonification [15], including Parameter Mapping Sonification (PMS) and Model-Based Sonification (MBS) for exploratory data analysis [16].

4 Parameter Mapping Sonification of Production Data

In order to keep the information transfer (mapping) from a logistic datum to its representative sound event as immediate as possible, we chose Parameter Mapping Sonification (PMS) as method for the auditory exploration of manufacturing data. The target of this experiment was to identify the cause of high throughput times of production orders and their impact on successive work systems. The used data sample consisted of planning and feedback data of sheet metal production including all processes that had been completed within one year. Only orders in a linear work flow of five work systems (Fig. 1) were regarded.

Any order consisted of one or (mostly) several physically identical material pieces that were processed independently. The throughput time of an order n with k material pieces m consequently was calculated

$$TTP_n = t_{\text{end actual}}(m_k) - t_{\text{end previous}}(m_1), \quad (1)$$

whereas $t_{\text{end actual}}$ is the end of operation at the actual work system and $t_{\text{end previous}}$ is the end of operation at the previous work station.

In the following subsections of this chapter, it will be demonstrated how we mapped these orders and material pieces to auditory display. With the sonification software, developed within this research, we explored the data sample from three auditory perspectives in order to gain knowledge about its characteristics. Two of these perspectives represented the resource oriented and order oriented views [17] as established in logistics (Fig. 2). An additional third one (Fig. 3) displayed the

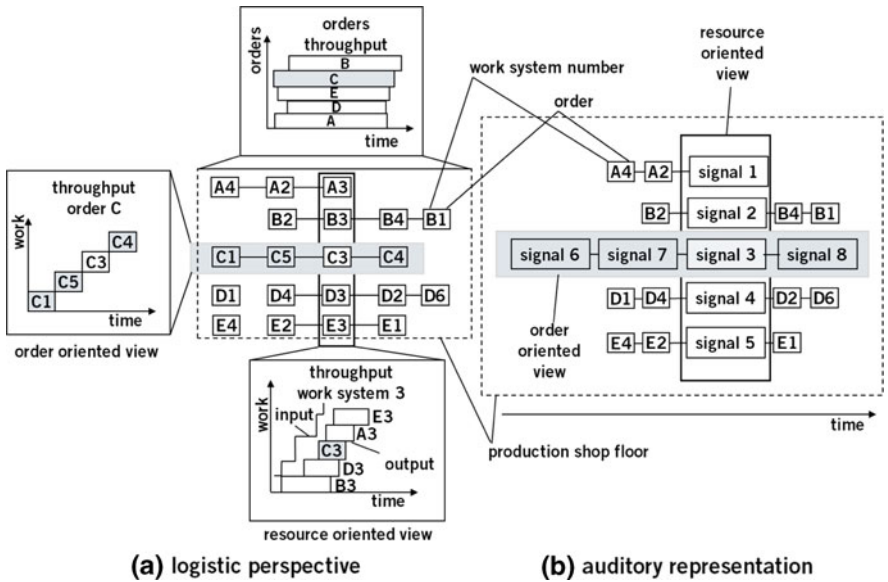


Fig. 2 Auditory representation (b) of order and resource oriented views (a) in logistics²

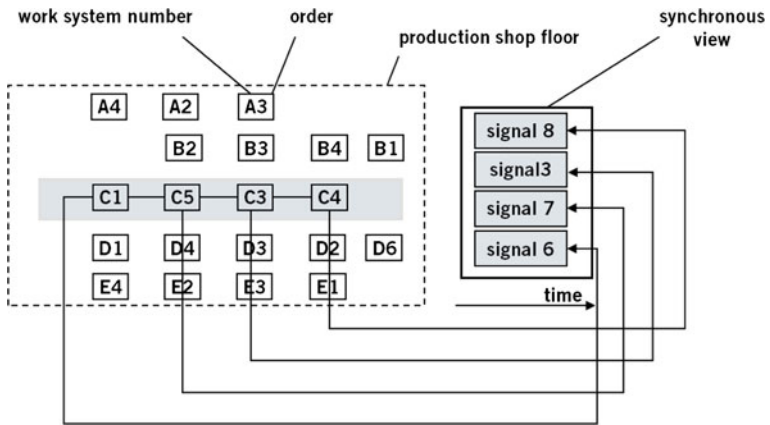


Fig. 3 In synchronous view sequential operations of an order were mapped to a multi-pitched signal

² Graphics according to Gläsner, J., Fastabend, H.: lecture presentation material of Institut für Fabrikanlagen (IFA), Leibniz University Hannover

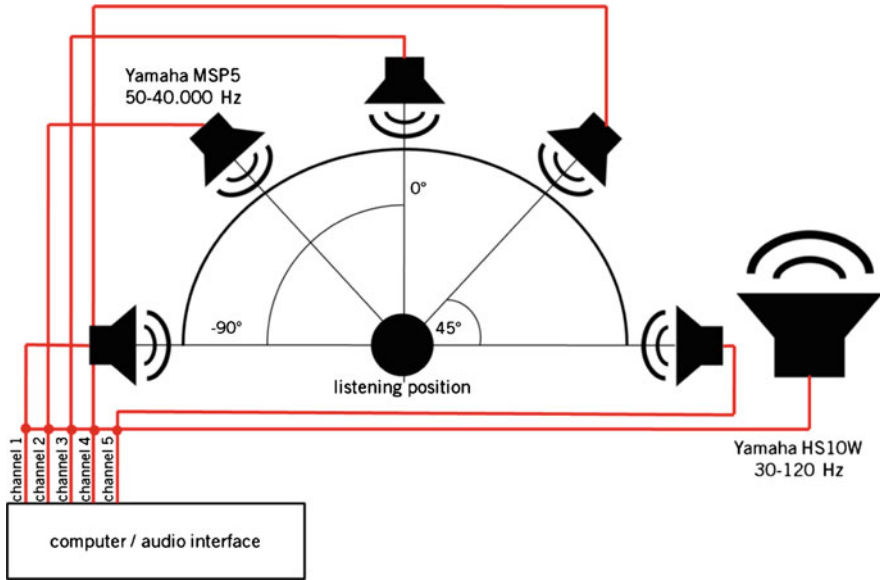


Fig. 4 Wiring of 5.1 surround audio system. In the described experiment, each work system was mapped to a discrete speaker in the upper frequency range (50–40.000 Hz) and merged in the low registers to a subwoofer channel

sequential processes of an order synchronously (synchronous view) in a single multi-pitched sound (Sect. 4.2).

4.1 Overview of Data Sample Using Resource Oriented View

Comparable to throughput diagrams [2], auditory displays in resource oriented view provide a general overview of processing at the monitored work systems. As a start-up of this research, we mapped average and accumulated throughput times ($TTP_{avg, acc}$) of all orders at each work system to sinusoidal sound signals (Fig. 5) with frequency $f(t)$ which is a function of time, e.g. for TTP_{avg} according to the equation

$$f_i(t) = f_{low} \times \left(\frac{f_{high}}{f_{low}} \right)^{\frac{\sum_{n_i=1}^N TTP_{n_i}(t) - TTP_{avgmin}}{TTP_{avgmax} - TTP_{avgmin}}} \quad (2)$$

whereas $f_{low, high}$ is the definable frequency range of the signal, i is the work system, n is the order, N is the number of orders, $TTP(t)$ is the throughput time at the selected time unit, $TTP_{avgmin, max}$ define the minimum and maximum of average throughput times of all orders and systems. This mapping logarithmically scales the TTP of an order to a definable frequency range, in our sonifications between 80 and 8.000 Hz.

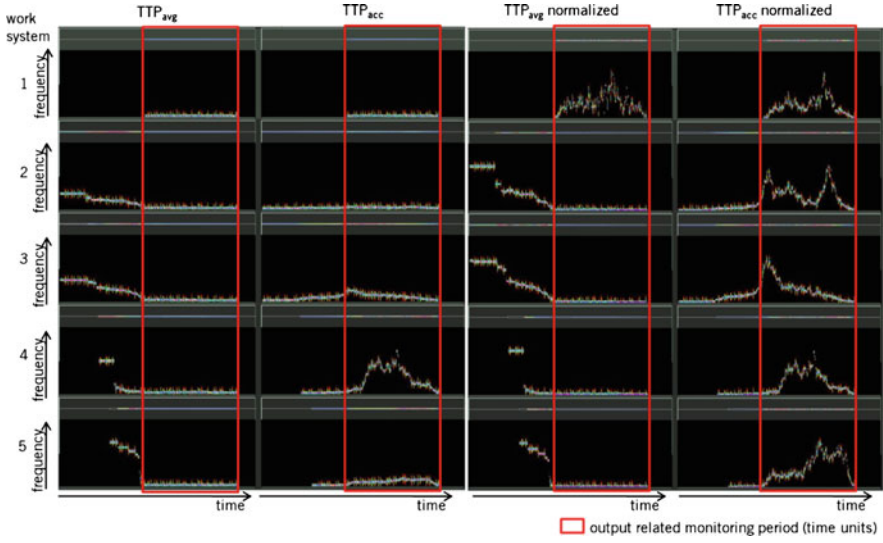


Fig. 5 TTP_{avg} , TTP_{acc} and normalized TTP_{avg} and TTP_{acc} of the five work systems

The mapping of accumulated TTPs was calculated accordingly, summing up TTPs of orders at work systems. The sum of these individual signals $f_i(t)$ representing work stations i resulted in an auditory display with signals:

$$s(t) = \sum_{i=1}^5 f_i(t) \quad (3)$$

The distribution of signal s in a 180° panorama (Fig. 4) facilitated the identification of the work systems.

The left half of Fig. 5 shows the spectrograms of the sonifications of TTP_{avg} and TTP_{acc} at the five work systems over the time span³ of the data sample. The red rectangles frame time units⁴ at which orders exited work systems (output). The auditory display embraced approximately twice this range since some orders had very high throughput times. The spectrograms of TTP_{avg} clearly show steady states of all work systems inside the red rectangle, while TTP_{acc} at work system 4 exhibited major fluctuations, which were subject to further investigations in Sect. 4.2.

To emphasize the individual fluctuations of each work system, we normalized the analyzed parameters (TTP_{avg} , TTP_{acc}) multiplying by:

$$f_{norm} = \frac{100}{TTP_{i,max}}, \quad (4)$$

³ Playback speed of sonification can be set arbitrarily in the software.

⁴ For confidential reasons, time-related information refers to neutral time unit.

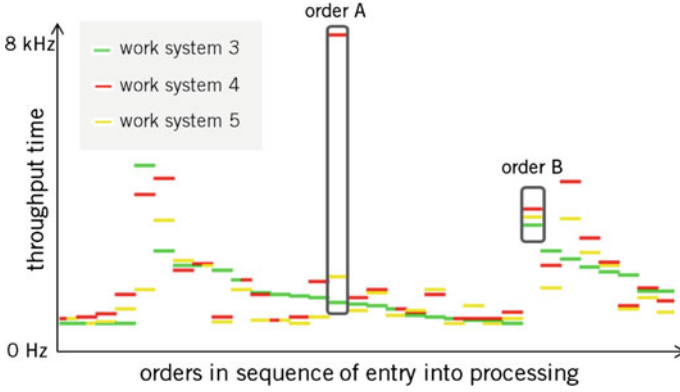


Fig. 6 Synchronous view of an extract of the data sample. Throughput times of all operations of an order were displayed as a synchronous sound. Highlighted orders A and B were subject to further analysis

whereas i is the work system, and TTP_{\max} is the maximum average (respectively accumulated) throughput time. Thus, fluctuations of each work system are independently displayed over the complete frequency range defined (80–8.000 Hz).

The normalized sonifications of TTP_{acc} (Fig. 5, right half) indicated potentially mutual (seasonal) impacts of fluctuations, particularly between work systems 3, 4, and 5, which we also further investigated by sonifications based on synchronous and order oriented perspectives.⁵

4.2 Order Characterization in Synchronous View

Contrary to sonifications in resource and order oriented view, which maintain the chronology of the data structure and therefore are related to time series analysis, synchronous view is based on a sorting of orders according to an arbitrary parameter.

As shown in Fig. 6, all sequential processes of an order are displayed as synchronous multi-pitched sound signals $s(n)$ representing the throughput times of operations according to the equation:

$$s(n) = \sum_{i=1}^N f_{n_i} \quad (5)$$

with

$$f_{n_i} = f_{\text{low}} \times \left(\frac{f_{\text{high}}}{f_{\text{low}}} \right)^{\frac{TTP_{n_i} - TTP_{\min}}{TTP_{\max} - TTP_{\min}}} \quad (6)$$

⁵ Fluctuations of work system 1 and 2 at least partly depended on incomplete data and therefore were not further considered.

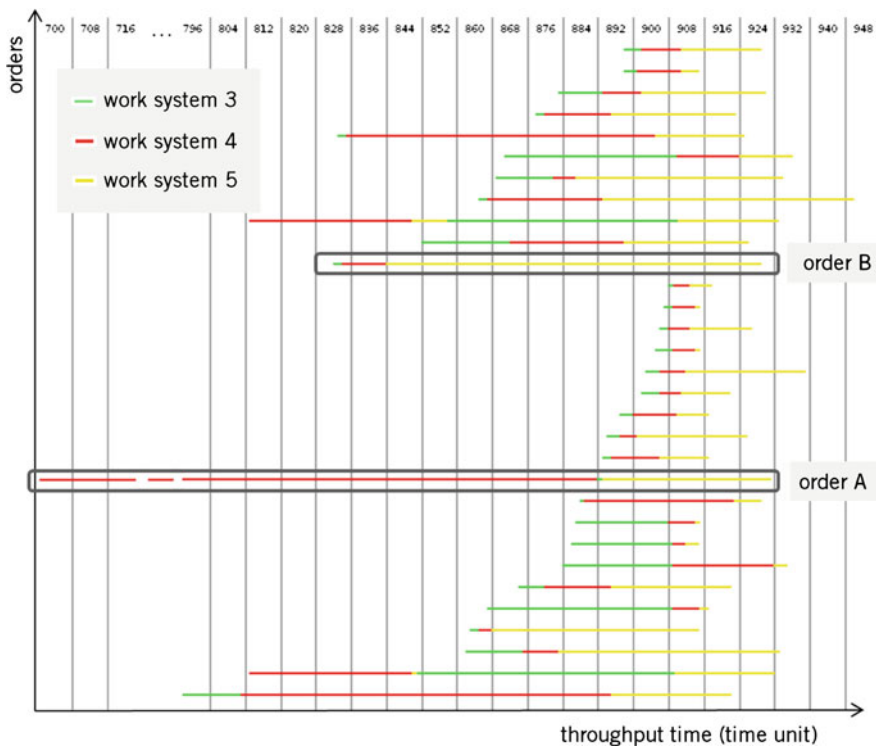


Fig. 7 Screenshot of the schematic graphical display integrated into the sonification software displaying an extract of the data sample. It should be noted that in case of overlapping throughput times in one order the graphical representations will also overlap and mask each other. The sonification displays the situation correctly

whereas $f_{low, high}$ is the definable frequency range of the signal, i is the work system, n is the order, TTP is the throughput time, $TTP_{min, max}$ is the range of throughput times over all orders and systems.

Signals s representing orders n create a set A , whereas

$$A = \{s(n_1), s(n_2), s(n_3), \dots s(n_n)\} \quad (7)$$

The sonification sequentially displays all elements of A (Fig. 6) in a speed adjustable by the listener. Through the spatial distribution of work systems (Fig. 4), the listener can attribute sound events to the corresponding work system also in synchronous view. Thus, orders are precisely characterized by the frequency distribution of the representing sounds.⁶ In the auditory display of TTPs in synchronous view, we found two evident patterns of orders: One, with

⁶ So to speak “acoustic fingerprints” of orders

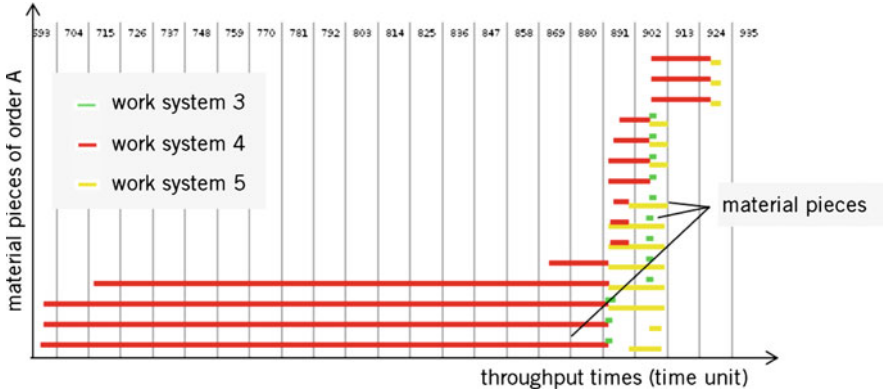
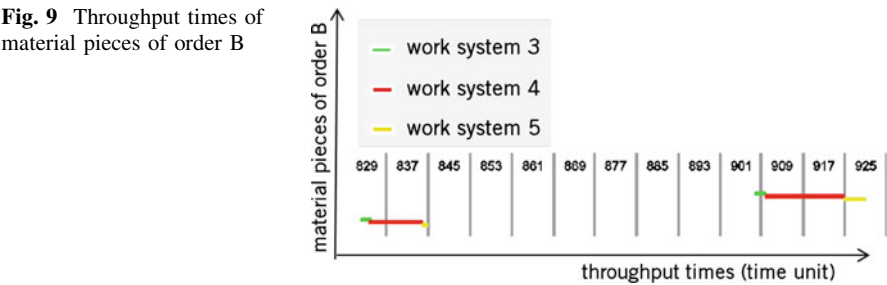


Fig. 8 Throughput times of material pieces of order A



extremely high throughput times at only one of the work systems and another one with above-average throughput times synchronously at work systems 3, 4, and 5.⁷ We selected two orders, order A and order B (Fig. 6) representing either of these two patterns for an exemplary detailed analysis in order oriented view. Order A exhibits extremely high TTP at work system 4. TTPs of order B are not as high, but above average at the three work systems taken into account.

4.3 Detailed Analysis with Order Oriented View

Figure 7 shows order A in the auditory representation of order oriented view (Fig. 2) which was mapped

⁷ The operation times (TOP) at the work systems were of comparable length and, given the overall duration of TTPs, negligible.

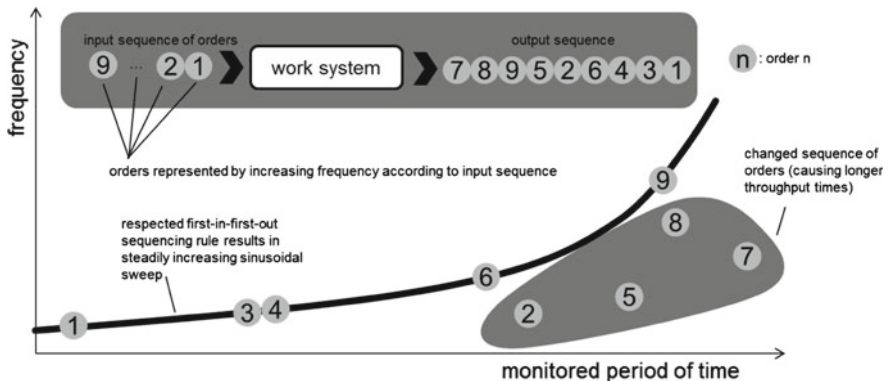


Fig. 10 Deviations of FIFO sequencing rule, represented by an increasing sinusoidal sweep

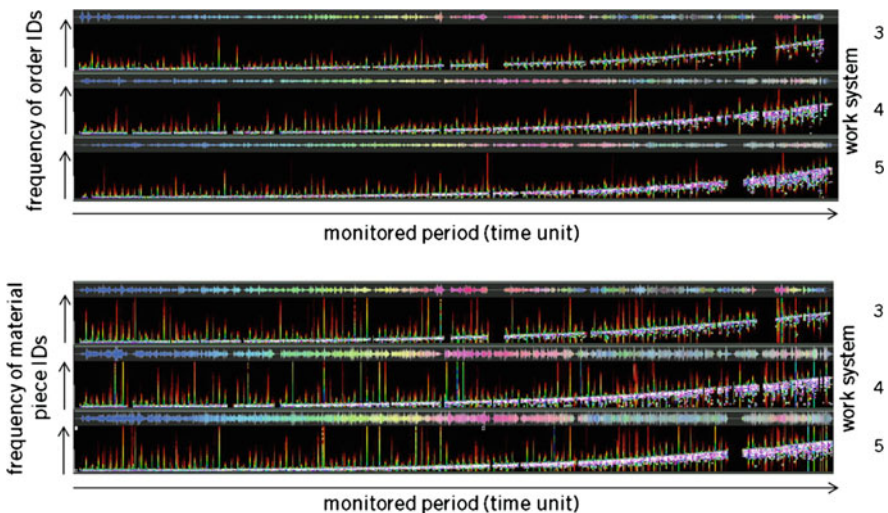


Fig. 11 Sonification of data set using statically attributed frequency to orders or respectively material pieces

$$f_{n_i}(t) = f_{low} \times \left(\frac{f_{high}}{f_{low}} \right)^{\frac{TTP_{n_i}(t) - TTP_{min}}{TTP_{max} - TTP_{min}}} \quad (8)$$

whereas $f_{low, high}$ is the definable frequency range of the signal, i is the work system, n is order, $TTP(t)$ is the throughput time at the displayed time unit, $TTP_{min, max}$ is the range of throughput times of all orders and systems. The resulting signal s equated to the sum of non-stationary signals f of orders n at work systems i (Fig. 7):

$$s(t) = \sum_{n_i=1}^N f_{n_i}(t), \quad (9)$$

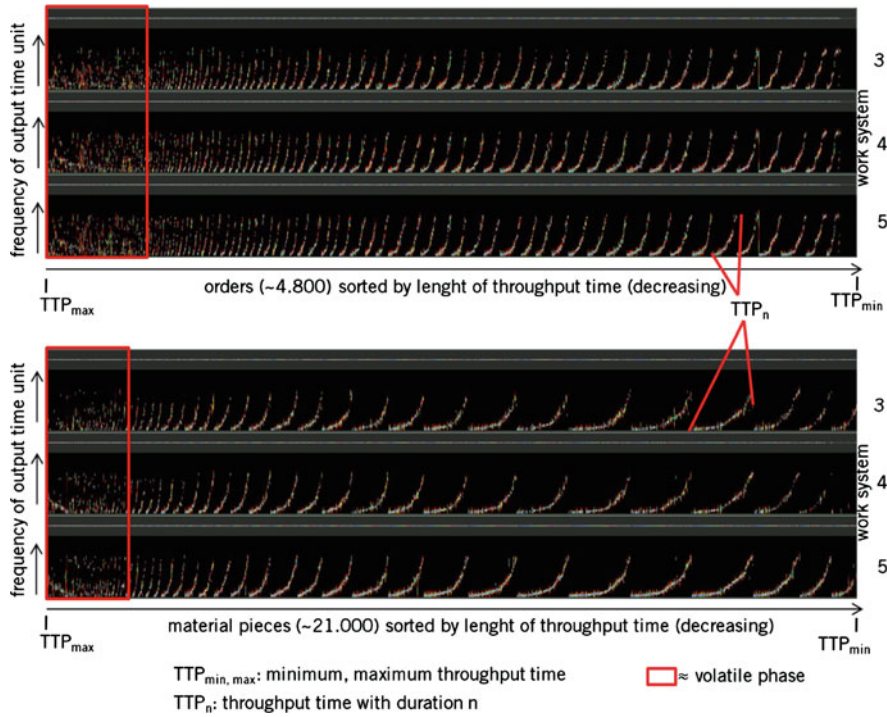


Fig. 12 Orders and material pieces sorted decreasingly (from left to right) by their largest throughput time (TTP) displaying the output time unit (increasingly) as pitch (first time unit ≈ 200 Hz, last time unit ≈ 8.000 Hz). After a short unstructured period (extreme TTPs) both sonifications adjusted to a more or less consistent distribution between output days and TTPs

whereas N is the number of orders.

The sonification of order A (Fig. 7) revealed overlapping of processes not visible in the graphical representation and changes of the operational sequence. Noticeable was the early start (at time unit 699) and the long duration of the throughput time (TTP) at work system 4, which we further tracked down by a sonification of the discrete material pieces, the order consisted of (Fig. 8). The sonification of the material pieces of order A supported our findings revealing major deviations of the expected sequence of operations.

The analysis of order B (Figs. 6, 7, 9) was exemplary for another cause of high TTPs as we confirmed by further spot samples. Individually, both material pieces (Fig. 9), order B consisted of, were produced within average TTPs. Only their combination as an order caused above-average TTPs at the regarded work systems. Our findings resulted from the re-allocation of material pieces to orders, which is characteristic to sheet metal production.

In order to quantify the amount of orders with high TTPs (as an indicator for the degree of re-allocation applied) and to analyze their distribution over the three work

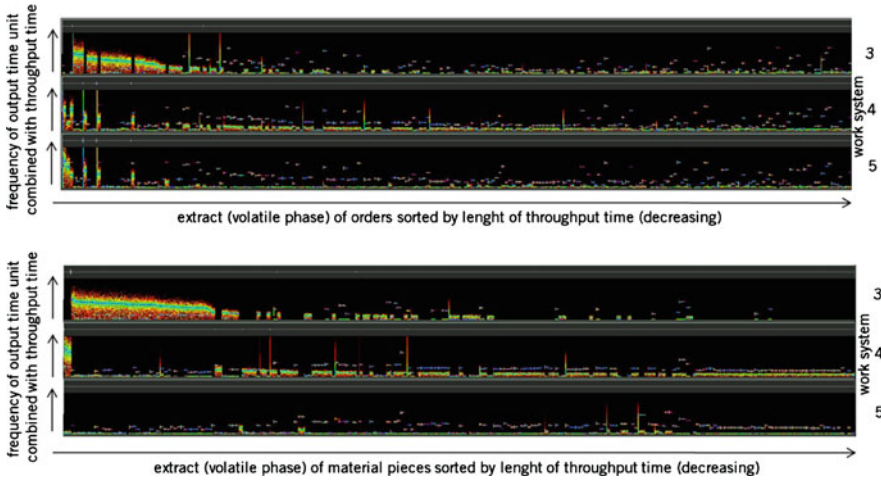


Fig. 13 Auditory display (\approx volatile phase of Fig. 12) of throughput times (represented as band-passed noise) and output days (sinusoidal sounds). The predominance of the band-pass filtered noise in the spectrograms does not reflect the auditory results, where the sinusoidal sounds were in the foreground

systems during the monitored period, we generated auditory displays, where each event was sonified at its respective output time unit only. According to the equation

$$f_n = f_{low} \times \left(\frac{f_{high}}{f_{low}} \right)^{\frac{n}{N}} \quad (10)$$

whereas n is the order (respectively material piece), and N is the number of orders (or material pieces), a static frequency was attributed to each order according to its first entry into the monitored scenario.

For a linear workflow respecting first-in-first-out sequencing rules (FIFO) this mapping would result in a constantly increasing sweep (Fig. 10) at each work system.

The sonifications of orders and material pieces (Fig. 11) indicated an increase of deviations to the main sweep during the course of time. While there was a common tendency in both sonifications, it was noticeable that particularly the material pieces at work system 4 were affected by extended TTPs, which can also visually be identified by the high amount of low frequencies in the spectrogram, but the listening results were much more detailed. The sonification of material pieces at work system 5 displayed a similar trend containing a high amount of dispersing frequencies. However, the amount of low frequencies toward the end of the sonification was clearly less. Considering the large amount of high TTPs of these results, it seemed surprising that the average throughput time (TTP_{avg}) of all work systems was at a more or less constant level (Fig. 5).

In order to get a more refined understanding of the distribution of TTPs over the monitored production period, we applied further sonifications using synchronous view. Orders and material pieces were sorted by their respectively highest TTP. The output time unit at the respective work system was correspondingly mapped as pitch (frequency). Except for orders with extremely high TTPs (about 8 % of data sample, which exhibited a volatile behavior), the spectrograms (Fig. 12) show periodically increasing sweeps. This means that most values of TTPs were consistently distributed over the monitored period and explains the quite stable average TTPs stated before.

For the volatile phase of this sonification (Figs. 12, 13) we found quite different structures of the distribution of TTPs between orders and material pieces. A sonification using band-passed noise to additionally sonify the corresponding TTPs showed that, after a burst of extreme TTPs at work system 4, high TTPs of material pieces mostly were attributed to work system 3, whereas compound to orders, TTPs considerably contributed to work systems 4 and 5.

5 Conclusion and Discussion

For the chosen data sample of sheet metal production, we demonstrated that high throughput times were concealed by a relatively consistent distribution. We also revealed that high throughput times resulted from inappropriate re-allocations of material pieces to orders. Considering that around 8 % of orders were affected by very high throughput times and given the synchronous distribution of orders with long and short throughput times mentioned above, we expect that there is reasonable potential for improvements by reducing re-allocations to a minimum level.

Particularly in combination with traditional and advanced statistical methods [2, 10], auditory data analysis becomes a powerful addition that e.g. distinctly indicates seasonal fluctuations of processes and allows to partition data samples into expedient segments for further analysis.

At this stage of our research on auditory data analysis of production data, it can be said that the questions, which arose during the experiments, differed from the ones usually asked using only established analysis approaches. These questions finally revealed results, which had not been analyzed by traditional methods performed beforehand. Analogue to the function of an engineer as a “hypotheses generator” in a recursive data-mining process [9], in its approach to data itself lies a major benefit using auditory display.

Auditory data analysis requires specialized expertise and experience that make it unsuitable for internal company use. Hence, an application would be well embedded in logistic consultancy projects as an additional analysis tool in order to re-adjust production planning and control strategies in industry.

One of the major problems of the introduced approach is a meaningful graphical transformation of auditory displays in order to fulfill scientific standards. Up to now,

graphical representations and written descriptions can only be understood as hints toward the far more detailed information sonifications provide.

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