Enabling Smart Manufacturing with Visual Analytics for Plant Workers

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Abstract: Smart manufacturing is increasingly making use of visual analytics to optimize production or to identify early problem signs [Su19]. However, current solutions and approaches require professionals, especially from the data science area, to make use of it, which is for most production companies not affordable. In this paper, we describe first a best practice to sensorize plants from the wood and beverage industry to enable smart manufacturing in general. Second, we describe a new approach that aims at providing easy-to-use visual analytics functionalities that are designed to be used directly by plant workers. Plant workers usually have encompassing experience in the production and the plant, but lack of computer experience and corresponding mathematical knowledge for data analysis. Through lowering the barriers for plant workers in performing data analysis of the IoT sensors with simplified and almost automated analysis functions would give them the ability to gain insights into the production and achieve similar production optimizations and problem preventions as data science experts could. The main contributions of this article are on the one hand the best practice of how production lines of the wood and beverage industry could be made ready for smart manufacturing, but also an approaches that enable non-data scientists, especially plant workers, to perform sufficient analysis about optimal production settings and early problem cause identification.

Keywords: Smart Manufacturing, Internet of Things, Visual Analytics, User-Centered Design, Human-Computer Interaction

1 Introduction

The manufacturing industry is currently facing many upheavals worldwide. Companies in Europe, in particular, are facing a unique set of challenges. In addition to global competition, companies are being challenged by issues such as sustainability, more efficient energy use, and a shortage of skilled workers. With the methods used to date, companies will hardly have any long-term market opportunities.

In particular the producing industry became in focus of attention, as IoT means that production lines can now be monitored completely digitally. This allows to detect and correct errors in production at an early stage, which avoids waste. Production lines can also be optimized in terms of the use of materials and, of course, energy. This allows an increasingly efficient and sustainable production.

With smart manufacturing, these optimizations of production are already established in a number of companies. However, there is a growing problem with the necessary specialists,

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doi:10.18420/BTW2025-33

especially in European countries. Data analysts and data science experts in particular are in short supply on the market and are often expensive experts. These are almost impossible for small and medium-sized companies to cope with.

In this paper, we therefore present an approach on how smart manufacturing, in particular the visual analysis of production, can also be made possible with normal production employees. We are developing and testing this concept in collaboration with manufacturing companies from the wood and beverage industry. Their systems were previously sensorized, which we also describe shortly as a best-practice approach in the paper.

2 Visual Analytics of IoT Data and Plants

The common and generic form of using visual analytics is using basic forms to analyze IoT data such as temperatures, pressures, speeds, or flow rates. Most of the available systems, such as Cumulocity [2], provide already basic visualization components to analyze the data. But also cross connections to advanced analytical systems such as Tableau or Microsoft Power BI are common. The main idea is to enable analysis close to the sensor data.

A less common approach for this type of visual analytics is the creation of specific visualizations that are usually not part of common platforms. One of these examples is LiveGantt [Jo14], which is a visual analysis approach used in analyzing large-scale manufacturing schedules consisting of numerous production tasks and resources. As the main features, it utilizes task aggregation and resource reordering algorithms to deal with schedule data at first and then uses a new Gantt chart to visualize the results of these algorithms. Another kind of approach is the visual analysis solution allowing test engineers to interactively steer ensembles generated in the performance test of automobile power system published by Matkovic et al. [Ma14].

Besides the generic visual analytics approaches, there are some production or plant-oriented analytical systems available. The intention is to offer an abstract visual view of the plant or production and apply analysis toward the root causes of problems or optimizations. Some recent visual analytics approaches, as presented by Xu et al. [Xu17], enable real-time monitoring of entire production lines with the help of a sophisticated interface. Their developed ViDX system (Visual Diagnostics of Assembly Line Performance for Smart Factories) is a dashboard that visualizes the manufacturing process. The interface is divided into five sections: the station map, histograms, an extended Marey graph, and a timeline with a calendar above it. The station map visualizes the sequence and connections of the individual stations. The histogram shows the utilization of the station. The extended Marey graph provides an overview of failures (gaps) or delays (converging graph with delayed further processing) by viewing all stations simultaneously. The timeline can be used to compare the production line scrap and anomalies can be found more quickly. The

[2] Website of the Cumulocity IoT platform: https://www.cumulocity.com/ (last accessed: 13/05/2024)

calendar aggregates the timeline monthly. In an advanced version, Xu et al [Xu19] monitors the physical layout and output of an entire factory historically, i.e. over time. Today's factories usually emit even more complex data sets, which will require even more specialized visualizations in the future. Data visualization thus forms an essential basis within smart manufacturing and ensures that very complex issues are presented in a meaningful way.

All of the mentioned system have in common, that they require substantial computer science knowledge to use them appropriately. These systems are not designed to be used by plant workers directly, who own an extensive knowledge and expertise about the plant and production but not about analysis with computer-based systems.

3 Plant Sensorization and Visual Analytics Infrastructure

Before any smart manufacturing is possible, the entire plant or at least the key machines and components need to be sensorized. In the E2COMATION project[3], we have three production partners from the wood and beverage industry, and as different as these industry sectors are also the sensorization strategies differ.

3.1 Approaches for Plan Sensorization

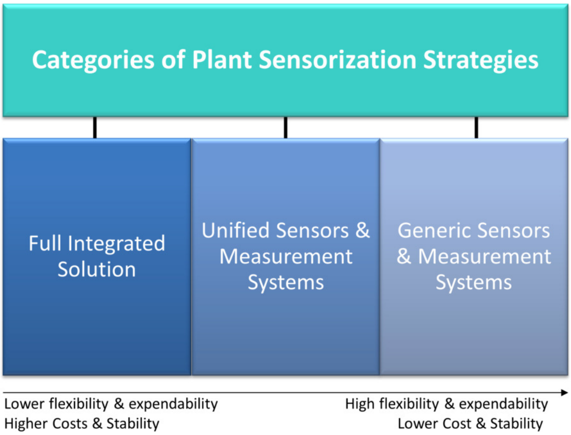

Fig. 1: Overview about the categorical types of plant sensorizing approaches

As a result of our work with the manufacturers, we could categorize the sensorization strategies into (1) generic sensors and measurement systems (e.g. [Xu20]), (2) unified sensors and measurement systems (such as [Li23]), and (3) fully integrated solutions (such as [NCB14]). While the first category makes use of a huge variety of sensors and systems

[3] Website of the E2COMATION research project: http://www.e2comation.eu (last accessed: 16/05/2024)

that could all be managed together, the third category makes use of full integrated systems, where most of the available components are installed and managed by almost just a single big supplier.

Generic Sensors and Measurement Systems

The advantage of this approach is its huge flexibility and the ability to always consider the costs for certain sensors and measurement systems. In general, any available sensor and own-created sensors can be used, which enables a lot of potential to reduce costs but also enables to use specific sensors, such as one with extreme sensitivity (such as [Xu20]). The challenge is the ability to harmonize the broad range of sensors and manage the sensor data on a central stage.

Unified Sensors and Measurement Systems

A more harmonized approach is to make use of unified sensors and measurement systems (such as [Li23]). Bigger IoT brands offer sensors and software solutions that are fully compliant with each other and offer lists with compliant sensors and systems of other market players that are also certified or tested and should be compliant with main supplier systems. On the one hand, flexibility is still given, but it is also ensured that harmonization can be realized with the offered software systems. The downside is often a higher price and often also a limited flexibility. For specific systems, it can also be hard to find sufficient sensors, because of the limited number of compliant alternatives.

Full Integrated Solution

The easiest option to sensorize a plant is to use a fully integrated solutions (such as described in [NCB14]). Here a supplier offers a complete solution to the manufacturer and ensures that all sensors etc. will work in the specified ranges. However, this approach makes it hard to extend the plant with further sensors or with other sensors if maybe sensors need a higher sampling rate. In the worst case, no changes might be possible or only with high costs. On the other hand, the manufacturer can trust on a working infrastructure and support in case of problems.

In the E2COMATION project, we have representatives for the first two kinds of sensorization categories. To be able to offer similar visual analytics experiences on each plant, we had to consider abstraction layers to unify the provided data.

3.2 Data Abstraction and Unification

The data processing follows a 4-layer approach (see Fig. 2). It follows the principle of collecting the shopfloor data (layer 1), processing and aggregating the plant data (layer 2), and forwarding this data to advanced computing systems (layer 3), which process data that is finally being used in decision support systems (layer 4).

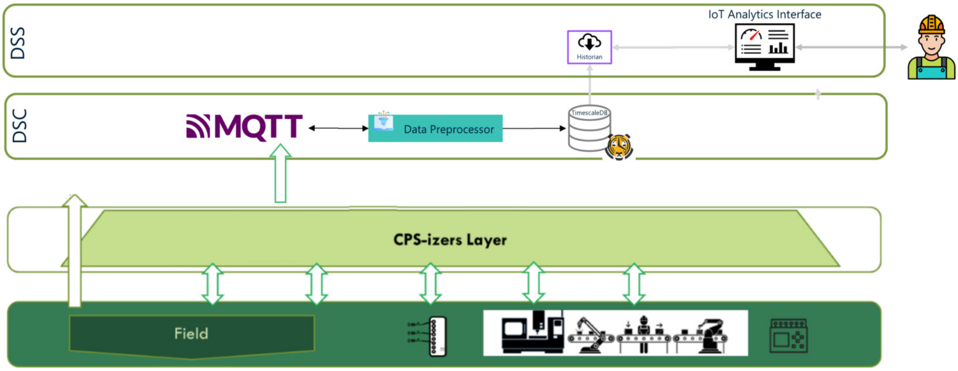

Fig. 2: Overview about the four processing layers to process the sensor data from the shopfloor to the final visual analytics system the user works with.

Processing Layer 1: Shopfloor

On the lowest layer, we have the *Shopfloor Layer*, where the plant machines and sensors are connected to one or many bus systems. At this stage, no data processing happens that is relevant for the final IoT analytics systems on top of the architecture. This level is only about data transmission of sensors and measurement systems. The wiring of the machines and sensors is almost individual for any plant but can be categorized as mentioned in the section before (see section 3.1).

Processing Layer 2: Cyber-Physical System (CPS)

The second layer is the *CPS Layer* which has the goal of processing and aggregating the data to a uniform data structure and providing the data in a harmonized, unified, and well-structured format. This means, that any sensor gets a unique sensor name or ID and is allocated to the plant structure. On this level, it can also be defined that some sensors will not be considered in further processing, e.g. because they just provide internal wiring status information.

Processing Layer 3: Distributed Data Streams Computing (DSC)

The third layer is the *DSC Layer*, which stands for Distributed Data Streams Computing.

The idea is that on this layer various systems could be set up to perform certain analytics, such as digital twin and simulations [Ga23], fault detection [KNH22], or data storage for later visual data analytics of the plant behavior [Su20]. The main component on this layer is the central MQTT broker, such as Eclipse Mosquitto. All processed sensor data from the CPS Layer is sent via the MQTT broker (see a message example in Fig. 3) so that any DSC system can receive any available data, but based on given topics any DSC system could filter the subscription to just to a subset of the available data.


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Fig. 3: Snapshot of MQTT messages with send sensor values from the shopfloor

Processing Layer 4: Decision Support System (DSS)

The most advanced systems that users work in production companies are aligned at the *Decision Support System Layer*. Decision support systems can address the optimization of the production but also support managers in a better price finding, to give two examples. So, the range of applications is pretty large.

3.3 Visual Analytics Infrastructure

The main setup of our IoT Visual Analytics solutions starts at the DSC layer with the sensor data consumption coming from the *MQTT broker* (see Fig. 2).

First, we need to store the sensor data to have the principal opportunity to analyze the historical data. As main storage, we use a *TimescaleDB* which is optimized for time series data with features for automated data aggregation, downsampling, and retention. To be able to consider the shopfloor data of all involved use-case production companies via *MQTT*, we developed a *Data Preprocessor* that can parse, verify, correct, unify, and normalize the data coming from the *MQTT*. This is necessary since the structure of sensor data in the body of *MQTT messages* is not strictly specified and therewith we have to define specific parsers for each manufacturer in the project. We also need to verify the data for measurement errors as they can sometimes happen e.g. due to transmission errors. The correctly parsed and verified data will be stored in the *TimscalDB*.

The frontend of our IoT Visual Analytics system uses a so-called *Historian* to retrieve the data from the database. Besides the connection to various other possible data source types, the Historian also manages the performant data access to the *TimescaleDB*.

As frontend solution we use our TrendMiner solution [Tr22]. TrendMiner is based on a high-performance analytics engine for data captured in time series. TrendMiner as industrial analytics software that allows process engineers and operators to search easily for trends and question their process data directly.

4 IoT Analytics for Plant Workers

While usual smart manufacturing applications require data analysts and data science experts, our approach focuses on plant workers, who should be able to use the system. The main benefit is that production workers already know the plant and the entire plant's behavior so that it might be easier for them to identify faults and problems during production. Furthermore, this approach reduces costs by saving those data analysts and data science experts, who are nowadays also rare resources on the market. However, to enable plant workers to perform a similar analysis and gain insights as data science experts, particularly from a quality perspective, the analytical software has to provide powerful functions but at the same time, they must be simple to use as well. Particularly advanced analysis capabilities which usually require extensive parametrization need to be simplified and automized as far as possible.

4.1 User Model and User Behavior

The important point that needs to be considered is the human, including his behavior and profession, in the work with a computer [Jo93]. As already mentioned, IoT analytics is usually performed by IT experts and data science specialists, which build a different stereotype than plant workers who usually have less contact with a computer. To better classify the weaknesses and strengths of these two user groups, we classify them by the user experience model of Nielson [Ni93][Bu12]. The typical data analyst and data science expert usually has moderate knowledge about the production domain but has extensive computer experience and advanced expertise in using the system at the plant. In contrast, the typical plant worker has an encompassing knowledge about the domain, but has minor computer experience and is expertized in using the system at the plant. The biggest impairment for plant workers is the lack of computer experience which needs to be compensated in a potential visual analytics system, which includes appropriate visualization capabilities. Therewith visualizations stay in demand to the user, task and the given data to analyze [Bu13].

4.2 An Optimized IoT Analytics Interface for Plant Workers

For the practical testing, the most important analysis scenarios that the plant workers can analyze were first defined with the partners (see Fig. 4). The focus here is on common problems that occur during production and whose evaluation helps to assess the consequences, for example in terms of regularity or potential (root-)causes.

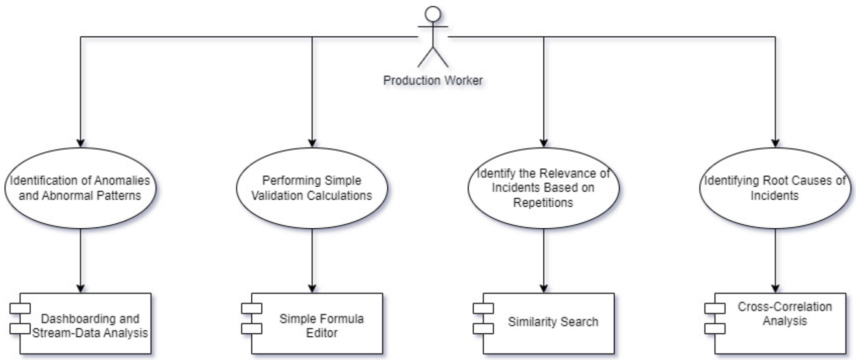

Fig. 4: Use-case diagram about the identified most relevant actions for IoT Analytics for the most important production events.

The IoT Analytics interface consists of five main areas as are marked in Fig. 5. Area 1 is the selection area for the analyzed sensors. Area 2 is the functional area, where the main function category can be chosen and the aligned available functions will be shown in area 3. Area 4 is the main view and analysis area of selected indicators or analysis functionalities. In area 5 the time range of interest can be chosen.

Fig. 5: Structure of the IoT Visual Analytics Interface for Plant Workers

4.3 Effective but Simple to Use Analysis Features

To allow the use of IoT Visual Analytics for less professional computer science users, such as plant workers, the functions must be easily usable and almost automated. In the following, we describe three simplified functions in detail that were most relevant to the project.

Dashboarding and Stream-Data Analysis

As fundament for any data analysis is the availability of all relevant sensors of the machines at the plant, which can be selected for data view and analysis for normal operation. In behalf of the plant worker experience critical sensors can also be added and observed via a dashboard (see Fig. 5) to keep track if they run into a critical stage. In case of identification of an abnormal behavior, the following further analysis functions are essential to identify the criticalness, regularity and root cause.

Simple Formula Editor

Analyzing only the existing data from sensors is sometimes not sufficient enough. Sometimes you need to create e.g. a sum when you want to calculate the sum of the consumed energy of all plant components to analyze the total energy consumption of the entire plant. In our IoT Analytics solution we use virtual sensors and the formula editor is graphically oriented on Office products like Spreadsheet or Microsoft Excel. In difference to these office products, our systems perform the calculation as a stream so that it can be analyzed like a normal sensor from the shopfloor (see Fig. 6).

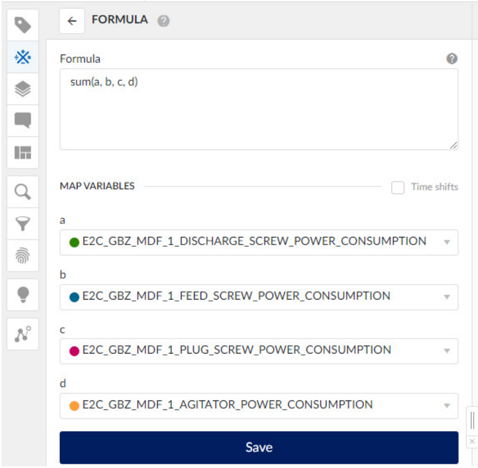

Fig. 6: Simplified formula editor on time series data streams

Similarity Search

To rate if a detected incident occurs often, a similarity search is essential to rate it as an exception or regular incident. The integration of this feature is realized in an interactive style and requires just a minimum of parameters. Therewith it is only necessary to mark the behavior of interest in the sensor's line chart and as parameters, the user can set if it should consider the absolute numbers or the signal shape and minimum similarity score. Afterward, the user gets the result listed in similarity groups by its percentage and can view it as an overlay to the current chart (see Fig. 7).

Cross-Correlation Analysis

Certain behaviors in the data lead to impacts on other parts of the production and therewith sensor data. For example, if the wood for the MDF plate (medium-density fibreboard) production is not dry enough, it could cause trouble in the form of anomalies in the entire production line. To identify these impacts, cross-correlation analysis could be used.

If cross-correlation is used on retrospective data, the root cause of an identified behavior could be analyzed. In particular, the root cause analysis is a powerful feature, because most often an abnormal behavior could be noticed, but it is not clear what the reason was. In our application (see Fig. 8), you just need to mark the abnormal behavior and select the option "search only early indicators" and the max. upstream shift to get a list of potential root cause incidents in the form of specific sensors.

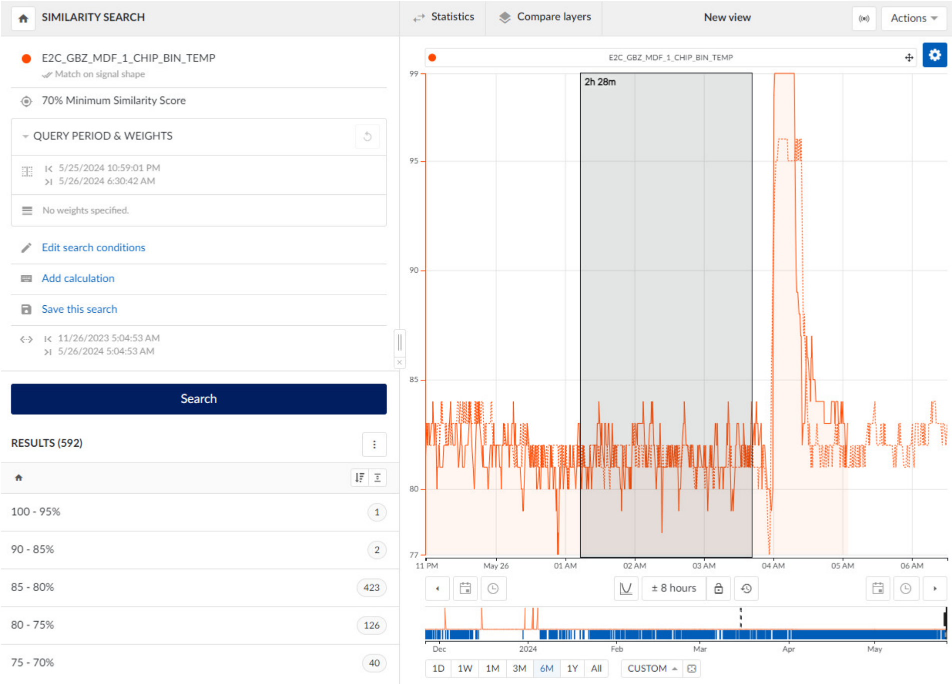

Fig. 7: Simplified similarity search based on time series data streams

5 Discussion

The system was deployed in the project and introduced with a small training for the plant workers for a few months. The feedback we have got so far is in general positive since the intended goal of an easier analysis even for non-analysts is achieved. However, setting up a real evaluation is difficult since we have to deal with two constraints. First, before using our system, the company already had a command stand that observed the production for incidents, but only in a very basic setting such as observing parameter ranges. The approach of identifying an anomaly and investigating the root cause, e.g. to create automatic warnings in case of repetition, was never made before. Secondly, on the command stand some more computer-related workers were placed, but in the project, we involved especially the plant workers on the different machines in production who also tried to figure out the root causes of incidents. Due to this massive change in the usual operation, the impact cannot be limited to our system approach, but introducing a comparable tool is not possible.

Fig. 8: A cross-correlation analysis performed on early indicators to identify potential root causes

6 Conclusion

In this paper, we described how the production companies from the wood and beverage industry could be sensorized to enable smart manufacturing. Smart manufacturing is nowadays the foundation to enable efficient production and therewith reduce the waste of materials but also resources, especially energy. The second part faces the challenge of rare experts on the market in data analysis and data science that would be required for effective smart manufacturing through analyzing the IoT shopfloor data. In the paper, we outlined an approach how plant workers as non-data science experts could also be enabled to perform similar qualitative analysis just through smart visual IoT analytics systems. The analytical systems consider the specific behavior of plant workers, in particular the lack of computer science expertise and related mathematical foundations, and offer them a simplified, but for the tasks optimized analyzing features. In the project, we could already see the first achievements at the involved companies where plant workers do make use of optimizing the production with this approach.

Acknowledgement

This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 958410.

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