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Integrating a data analytics system in automotive manufacturing: background, methodology and learned lessons

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Abstract

Integrating and exploiting a data analytics system in manufacturing is a complex task that involves different skills and most of the times requires to handle a brownfield scenario. Under this context, this paper aims to act as a guide to study the background and justification to industrialize a data analytics system in manufacturing, providing a methodology, learned lessons and potential use cases. As application of this methodology, the digitalization case of an automotive manufacturing factory is shown, which includes scenarios dealing with improvement of quality, process optimization and early detection of deviation of parameters. Even in an early stage of implementation, it has been demonstrated that these actions provide an economical advantage for the factory, in terms of productivity improvements and efficiency increasings. This methodology can be useful not only in automotive, but also in other manufacturing domains.

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1. Introduction

Car manufacturing industry has traditionally acted as a lighthouse regarding innovation in process and implementation of new technologies [1]. In the era of digitalization, data analytics and business intelligence, automotive industry has been leader in the adoption of this kind of solutions.

Due the digitalization efforts in the last years, standard automotive companies usually use many different information systems in their daily routine, to approach diverse functions. However, these systems normally have their data confined, so data sharing, data accessibility, and especially interoperability, are complex. This happens nowadays in most of manufacturing industries worldwide [2].

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The concept of a centralized data analytics system is not new, but it is nowadays more valid than ever, thanks to the last technological advances. The idea is to relate every production variable (temperatures, energy, etc) with the produced part (for instance, a car), to build the instance of the part, thus forming a feature vector with every involved variable during the manufacturing process. However, this variable agglutination process is not obvious at all, since data sources are diverse, heterogeneous, and coming from different technologies and generations.

Under this context, Stellantis (former Groupe PSA), one of the biggest car manufacturers worldwide, has been working in a digitalization project in its factory in Vigo, Spain, in the last years. This paper presents the background and circumstances that influence the process of integration of data analytics in manufacturing, as well as a series of learned lessons that illustrate this process. We have previously presented a related list of specific success stories and use cases [3], meanwhile the current paper is focused on the integration process.

In this paper, Section 2 will present Background and related aspects of the factory environment. In Section 3 the technology aspects such as Architecture and Methodology will be commented. Section 4 will present the importance of measuring economical impact. Finally, Sections 5 and 6 will summarize the discussion, learned lessons and conclusions.

2. Background

2.1. State of the art

The new tendencies in automotive industry of lot–size–one (each unit is potentially different to any other), high variability in the product (short life cycle and speed–to–market) [4], and mass customization [5], are forcing automotive companies to look for state-of-the-art solutions to improve their reconfigurability capabilities [6], and their already excellent levels of quality, efficiency and productivity [7]. Other global trend is taking into account the impact of the carbon footprint of processes [8] in order to collaborate in the global challenge of circular economy. This means that hyperflexibility, and the calculation of the energy usage during every step of a manufacturing process, although partially monitored nowadays, will be more and more important in the next decades [9].

The last years have boosted the concept of Industry 4.0, as the combination of Information and Communication Technologies (ICTs) and Manufacturing [10], as a new approach of achieving a proper information sharing in the factory, in contrast with the historical division of different subsystems with diverse objectives [11]. Industry 4.0 means more connectivity, which acts as a solution to these reconfigurability and hyperflexibility needs, now that technology allows new approaches not possible before.

The main function of a data analytics system is supporting the decision making in the factory with more reliable data [12], i.e. data with better quality, more recent, structured, aggregated, etc. The main applications deal with optimization of parameters of a process [13], process control [14], quality prediction [15], among others. These analytics capabilities are based on having an automatic parallel system collecting data from different data sources and translating them into information [16], which is presented to the factory expert either in simple or complex ways, so the best process or quality decision can be made [17].

There are plenty of software-based data mining and big data solutions in the market nowadays [18], allowing sophisticated ways to monitor and set-up the production based on semi-supervised tools [19]. However, the implementation and successful integration of such systems is not obvious and forces to face complex challenges, especially in large companies [20]. Presenting the difficulties and details of their implementation in a large manufacturing company can be useful as a guide and methodology to perform this same action in other companies and sectors. The problems and learned lessons can be applicable worldwide.

A key aspect is the economical impact and return of investment of a data analytics system. Although some studies estimate annual efficiency gains between 6% and 8% [21], every case needs to be studied in detail. The economical aspect should guide the implementation of incremental pilots [22], allowing to obtain partial success stories to maintain the faith of the organization in the project, and to orient the priority of the use cases to consider, instead of monolithic developments with benefits only in the last step.

2.2. The factory environment

Automotive manufacturing is fed by two main approaches, each one covering a different aspect of the process: Information Technology (IT) and Operational Technology (OT), i.e. software-based information systems and automation. OT layers handle automatisms, Programmable Logic Controllers (PLCs), robots, conveyors, etc., meanwhile IT layers are composed by diverse interconnected information systems. Both visions are usually confined, managed by different departments and designed with different purposes.

Nowadays, automation is still the basis of manufacturing, using PLCs, robots, conveyors, as the main control tools, as can be seen in Table 1. However, the data that we can find in OT layers have not usually been designed to be exploited, but to have the manufacturing process alive and working correctly [23]. Additionally, these data are usually volatile, and not stored in any database. This is very relevant when implementing a data analytics system.

For example, a robot does its cycle only knowing the current reference, creating and consuming data from that point of view. A robot does not need the car reference (Vehicle Identification Number, VIN) to operate. The PLC handles that the process is being correctly performed, registering only the strictly necessary data, since speed, determinism, and real-time behaviour is crucial. Supervisory Control And Data Acquisition systems (SCADA) see data with the main objective of visualizing and alerting, but these data are usually volatile. Enterprise Resource Planning systems (ERP) has trace of part of the manufacturing process, but it does not know manufacturing data. In case there is a Manufacturing Execution System (MES) or Product Lifecycle Management system (PLM), manufacturing data can be stored and exploited, but most of the times the situation is that there are multiple systems collaborating, coming from different technological generations, designed for different purposes, and important parts of the manufacturing process are still non–digitalized, especially those ones involving operators.

Table 1. Stack of layers in industrial IT and OT systems. The higher the layer in this table, the farther from the physical devices.

Layer	Purpose
ERP	Financial
MES	Manufacturing execution
SCADA	Visualization and alerts
PLC	Process governance
In/Out, Drives, Sensors	Physical activity

This automation–based manufacturing has some consequences. First, manufacturing lines are mostly rigid. This means that, once a project is industrialized, only minor changes can be made, and the line usually operates for years. The alternative is the hyperflexible approach, allowing more customization in the product, more variety in the process, and less restrictions to update the factory. However, this requires a huge effort in digitalization, both to handle the production complexity, and to exploit the data which are produced during manufacturing. Additionally, many processes still use paper or non-exploitable electronic formats (such as quality controls, production summary, etc), some machines or systems could be still disconnected, non-monitored, or only allowing manual interaction. And finally, productivity, efficiency data, and other KPIs, are known a-posteriori, and not in real–time. The new Industry 4.0 approach is, thus, a change of paradigm, as can be seen in Table 2.

Table 2. Comparison of traditional automation–based industry vs. Industry 4.0 approaches.

Traditional industry	Industry 4.0
Mass production	Unit production
Rigid processes	Flexible processes
Client purchases what is manufactured	Customized products
No direct connection with the customer	Client is connected; known needs
Push: manufacturing from sales estimations	Pull: real demand is known

As a consequence, it is not obvious nowadays how to relate process data with specific manufactured units. It is quite easy to know the temperature of a cabin, but the OT layer is not always aware of the specific reference which is circulating in it. It is necessary to share data of different sources, structurate them, and merge them so that it is possible to associate and couple every involved data in the manufacturing of an unit. Analogously, it is not obvious how to calculate the carbon footprint of every subcomponent, a very useful data to fulfill circular economy policies. How to know the exact energy cost of every specific manufactured part? Again, it is based in data sharing, structuration and association, but, since it has not traditionally been a priority, these data are not universally available.

2.3. Vision

The main purpose of a data analytics system is supporting decision making to improve productivity, quality and efficiency. This creates a necessity for functionalities such as data gathering from different sources, data visualization, data storage, alerts, statistical control, data correlations, and intelligent behaviours such as quality prediction, predictive maintenance, and optimization of parameters.

One step to achieve this is the construction of the part instance (car instance in our case), which means a vector with all the specific manufacturing characteristics of every produced unit [24]. This means to gather voltage values from welding devices during assembly of subcomponents into the car body, for instance, or a specific temperature of a cabin in the moment that a specific car is being painted. This large list can be used afterwards in complex analyses to search process improvements and unknown data correlations.

There are vast amounts of data in a manufacturing process: the objective is gathering usually volatile unused data and transforming them into information. We are talking not necessarily of Big Data, but Smart Data [25]. The main challenge, especially in a large manufacturing company, is that manufacturing processes are handled with independent confined systems that have evolved with different goals, technologies and purposes. Due to this, there is a remarkable risk of automating chaos. That is why every digitalization project should be used to audit the process and assess if the approach is correct.

Other aspects to take into account are:

- A data analytics system needs to be, in long term, profitable. This cannot be forgotten during the –usually long– integration process.
- The integration of the data analytics system in a brownfield scenario should be iterative and incremental, based on pilots on measurable limited zones.
- A 4.0 project is not a product to purchase. It requires deep changes, own time, external help, new skills, and investments.
- The capacity of absorbing innovations while producing, is limited. This should guide the integration schedule.

3. Methodology

Once the typical manufacturing background is commented, this section presents the next steps of the integration process.

Firstly, it is recommendable to start by the definition of a limited section of the manufacturing process to implement the first group of pilots, as first chapter in a long-term roadmap. It is relevant that this choice is oriented towards the economical impact and the possibility of achieving short-term victories to engage all the layers in the organisation. Afterwards, the identification of data sources, the selection of tools and architecture, and the definition of the analytics protocol, are presented.

3.1. Data sources

From a high–level perspective, a data analytics solution means a new parallel database which gathers data from diverse data sources and allows a proper exploitation of these data through an incremental use of complexity, from simple charts to complex algorithms.

When we refer to data sources, it is important to highlight that any manufacturing factory generates and provides a large variety of types of data. One classification refers to process, product and environment data [26]. Focusing on process data, these are usually volatile (they are used in OT but not always stored), and are restricted in the OT layers.

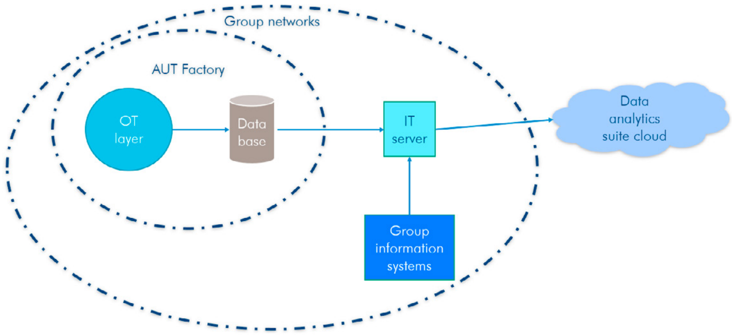

Fig. 1. General–purpose architecture for a data analytics solution.

Thus, a first step is collecting these potentially interesting OT data so they are periodically and automatically stored in a database. Gathering data is a tough process and requires a deep level of consultancy and wide vision.

Although the lack of representative available non–biased data is very common in industry, in the case of large manufacturing companies, the problem is exactly the opposite: the existence of dozens of information systems, using different databases, usually not interconnected, and slightly overlapped [27]. These systems provide very relevant data, normally of good quality, in contrast with raw PLC data. That is why working with these existing systems should be a priority, in terms of standardization of access and efficiency. Unfortunately, they do not include all potentially interesting data (especially process data), and gathering from PLCs is inevitable.

A very special subgroup of these existing systems are those ones related with quality control, including geometrical, aspect or dimensional resulting data. These systems provide output data which is useful in quality prediction, by searching correlations with process and environment data, being basic in the analytics phase.

3.2. Tools and architecture

A series of tools and technologies are necessary in order to fulfill the overall data analytics functionalities. These tools can be all part of a data analytics suite, or a combination of two or more information systems.

1. Data gathering and monitoring. Some application has to connect to heterogeneous sources of data, including PLCs, databases, files, machinery, other systems, and almost any protocol. This tool needs to be flexible, scalable and robust. The gathered data are usually combined in a local OT data warehouse.
2. Storage. Some tool or group of tools is necessary for data structuration–preprocessing and data warehouse. The instance of a manufactured part is born in this step. A cloud no–SQL approach is the tendency nowadays regarding storage.
3. Visualization and alarms. Another tool should help to define and exploit all sorts of charts and diagrams which allow a proper data visualization adapted to different profiles. This includes the creation of alarms (static threshold values on variables which trigger some message to a stakeholder) and reports (configurable or adaptable dashboards with export capabilities).
4. Analysis. Once the previous steps are covered, some tool should handle the configuration and execution of intelligent algorithms for prediction (quality, reliability), simulation of what-if situations, rapid crisis solving, among other modules. These algorithms can be real–time (continuously being applied on the gathered data), or be used on–demand on ad–hoc analyses.

A general–purpose architecture is shown in Fig. 1. In our case, one tool is devoted to data gathering, meanwhile a data analytics suite deals with storage, visualization and analysis. It is important to mark the difference of OT and IT data, as well as the inclusion of other information systems with already available information.

3.3. Analytics protocol

Once an architecture and a set of tools are defined, the idea is to apply a common protocol to start pilots of diverse use cases.

For each of these subprojects, an incremental workflow is executed, from less to more complexity:

- Problem description. Understanding the use case, the problem itself, collecting requirements and experience from the process experts.
- Identification of data sources, data structuration and manual experimentation. Before any real-time monitoring, a manual analysis is performed in order to check the feasibility of the problem and extract a first set of results.
- Monitoring variables in real-time to a common database. This allows to collect large amounts of data to perform more representative analyses.
- Creation of dashboards and basic statistical control. This means that any stakeholder can visualize the data and start to operate with them to monitor nominal values and set alerts.
- Advanced analytics, using diverse intelligent tools to check correlation of variables, and create and execute prediction models.

4. Economical Impact

A proper and thorough calculation of the savings directly provoked by the usage of the data analytics system is a very important task, since it provides the ability to measure and trace its impact in economical terms. This can be used as a guide to continue the implementation throughout the factory. We identify several different types of impact:

- Quality impact: first we need to define the improved non–quality ratio, as the difference between the percentage of non–quality units before and after the usage of the data analytics system. Secondly, every non–quality situation triggers a reworking process, which requires a specific reworking time, with its associated cost per unit. We also define the potential incidence period as the time that the non-quality situation could have happened in case the data analytics system did not exist. After these definitions, the quality impact can be defined as the saved reworking time, during the potential incidence period, over the improved non–quality ratio.
- Energy impact: analogous to the previous one, but referring to energy saved thanks to data analyses.
- Production improvements: also analogous, but in this case related with increase on the production capacity (additional units manufactured).
- Raw material or, in general, material savings: in the same line, any reduction on necessary components to manufacture.
- Reliability impact: in a similar way to quality: there is an improved reliability ratio, as the difference between the incidence of a reliability problem before and after the usage of the data analytics system. Secondly, every reliability problem can potentially damage the production, with its associated cost per unit, as well as spare parts. And there is also the potential incidence period, as defined before. The reliability impact can be defined as the saved costs during the potential incidence period, over the improved reliability ratio.
- Destructive testings avoided: any exploratory destructive test which can be prevented due to any information provided by the data analytics system.
- Other savings.

There is also a big group of activities, which help to support decision taking, with no direct measure, but that we believe it has a huge economical impact. The time spent interacting with the data analytics system, either on visualization or advanced analyses, and especially solving unusual parameters behaviour, can save time of process and quality technicians. We believe that supporting decision taking has a multiplier effect. In our case we have measured this multiplication factor as: every hour spent interacting with the data analytics system saves three hours of expert time.

Last but not least, another discussion can be made regarding qualitative and indirect savings, that can be framed in cultural changes, and unblocking of opportunities.

To sum up, savings calculation is a hard and sometimes subjective task, that deserves focus of the organisation, in order to measure these impacts with as much accuracy as possible, as a mean to allow a more formal monitoring of the incremental implementation of the data analytics system.

5. Learned lessons

The methodology and approach presented in this paper have been applied in the Stellantis factory of Vigo, Spain, since 2017. It started in the Paint Shop, but it has been progressively extended to the rest of the areas of the factory, such as the Stamping Line, the Welding Line, the Assembly Line, and Logistics. After a first validation and learning experience, the roadmap includes now the extension to other factories in the group.

More than 5.000 variables are currently being monitored in real time and transferred to a cloud platform, so these data are available online to perform different data analyses. There are more of three years of monitored data, which are continuously improved, by adding more variables. These are mainly process data (such as parameters of machinery while painting and drying), environment data (temperatures of cabins while the vehicle is being processed) and output data (final quality control).

The daily usage of this approach has given a new set of possibilities to the decision making in the management of the factory, focused on providing savings in terms of quality, production and efficiency. This includes production time saving, energy consumption or defects outbreak. Additionally, the average analysis time in unusual quality situations, has been radically decreased. What took hours in the past, it is now approached in a matter of minutes, providing valid hints to the technicians to solve a specific problem. In addition, after each experience, new alerts are implemented in order to prevent a new occurrence of the issue.

Following, in order to illustrate the collected knowledge during this process, a list with the most relevant key learned lessons is presented:

- Field and process experts are essential for the success of the integration of a data analytics system in manufacturing. They can provide key know-how to select the good data sources, the good parameters, which is basic in such complex processes.
- Data analyses are not the same than consuming datasets. A physical presence in the factory of every involved personnel in the project is recommendable, since this helps to understand the process, the relationships between data, etc. And especially to exchange experiences with the process experts. This is especially useful for data validation.
- Data structuration is usually the most time-consuming activity. This includes preprocessing, filtering, validation, and any other task to ensure that the data are ready to be included in an analysis.
- Representative and non–biased data of sufficient quality are scarce. Time needs to be invested in a proper and thorough selection of data sources.
- Short-term victories and quick-win results are crucial when implementing and using data analytics, and economical impact is essential to guide the process. Long opaque projects, with unknown impact, are not recommendable.
- Most of the times, the simpler, the better. The manufacturing process is usually modifiable, so hints to the experts, or explainable correlations [28], are normally more interesting than in–line machine learning prediction models [29].

6. Conclusions

In this paper, the background and justification to industrialize a data analytics system in manufacturing is presented, and also illustrated with a methodology and learned lessons extracted from an automotive use case. The integration of such kind of systems is always a challenge due to many circumstances, so that this paper aims to act as a cheatsheet to inspire and guide this process.

Starting with limited pilots, and studying the economical impact of the usage of the data analytics solution, should be permanently in mind, especially in the initial stages of the integration process.

Finally, and although short term victories are also necessary, it is important to understand that a digital analysis approach is a long term race, with cultural implications in the company. This means that the main result of integrating a data analytics system is not the execution of a series of tools, or the specific outcomes of the analyses, but the emergence of a new culture to be spread throughout the organisation, to be preserved and extended in the present and next generations.

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