Development of Big Data Analytics in a Multi-site Enterprise on the Example of Supply Chain Management

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Abstract. Currently, advanced data analytics in large multi-site industrial enterprises is a strategic element in making management decisions. Integrated supply chain management (SCM), machinery park management, or data analysis from industrial devices (including using Industrial Internet of Things - IIoT) requires the organization of appropriate analytical platform architecture, the selection of the analytical tools for Big Data, the implementation of advanced algorithms based on machine learning and the development of management dashboards for ongoing tracking the KPI's of assets. This article presents the issues related to the acquisition, analysis, and management of large amounts of data from various enterprise departments. These data come from multiple systems, and they are indifferent data recording standards. They are essential because they form the basis of advanced data analysis in supply chain management in multi-site enterprises. This article discusses the proposal of an analytical platform for SCM and the development of analytical processing for SCM in the multi-site industrial enterprise.

Keywords: Supply Chain Management, Big Data, KPI, industrial enterprise.

1 Introduction

In the case of a multi-site industrial enterprise, the development of analytical systems to support decision-making should be oriented to the specific needs, limitations, and possibilities of individual business areas. The development of analytics is very often not a question of technology but the correct use of large data sets to improve the safety and efficiency of technological processes. Data and analyzes not referring to factors influencing these aspects do not bring added value.

The first decade of the 21st century saw the emergence of software for intelligent data analysis and predictive analysis [Frazzon et al., 2019; Waller and Fawcett, 2013b], which contributed to a better understanding and use of data, thus improving decision making and decision optimization by businesses [Trkman et al., 2015]. In the era of global challenges, enterprises, especially large, multi-site, and production companies, have to take up the challenges they face in connection with the need for advanced data

analysis. Therefore, the definition of strong hypotheses of the potential impact of advanced data analysis analytics on the technological process is crucial, so that already in the early stage of development, it is clearly focused on the increased process context awareness, support for managers in decision making and business benefits. Hence, it is essential, first of all, to identify and select key data sources, to reject irrelevant data, and to plan a data analysis process to acquire necessary information.
One of the key business areas is logistics, responsible for managing the supply chain in all production plants of the company. Supply Chain Management (SCM) is the integration of key business processes from end-user through original suppliers that provides products, services, and information that add value for customers and other stakeholders [Lambert and Cooper, 2000]. The primary purpose of supply chain analysis is to facilitate the understanding of all data produced by various elements of the supply chain [Wong et al., 2011]. These analyses result from the management's needs for making the right decisions [Lai et al., 2018] and make it possible to extract specific hidden patterns from the data as well as acquire valuable insights. The subject of supply chain analysis is continually developing, with new technologies and methods coming into being to increase the effectiveness of forecasts, help detect weak areas, better respond to customer needs, and simulate and implement innovative solutions [Chen et al., 2015; Shafiq and Savino, 2019]. Having complete product information (ready capital-intensive goods, spare parts, consumables, etc.) is a crucial issue of advanced data analysis within an integrated supply chain [Vilminko-Heikkinen and Pekkola, 2017]. The use of advanced data analysis in SCM is a very current issue. Research in this area is discussed in more detail in: [Maheshwari et al., 2020; Tiwari et al., 2018]). In the literature, the problem of analytics development for SCM is cited as marginalized. Much information is provided in a simple form, primarily due to a data sensitivity problem.
Logistics is closely related to most other business areas, especially manufacturing, finance, and purchasing. What is essential here is to ensure the flow of valuable information between all locations. It requires designing an appropriate IT infrastructure in the enterprise, including Big Data tools and analytical systems containing advanced methods and machine learning algorithms. In the papers [Dudycz et al., 2019; Pyda et al., 2019; Pyda et al., 2020], the authors presented the challenges related to the development of IT infrastructure for a multi-site industrial enterprise. A special issue is the limitations of the variety of systems, the diversity of standards for data acquisition and storage, and the quality and availability of them for the appropriate kind of end-users.

The article presents the main issues related to advanced data analysis as a critical element in supply chain management in a multi-site industrial enterprise. This article is structured as follows. Firstly, the fundamental problems and challenges of Supply Chain Management 4.0 is presented. Next, the proposal of the analytical platform and data model for SCM is described. Finally, the analytics development model for SCM in a multi-site industrial enterprise is presented. The paper ends with a summary.

2 Background of Big Data

The concept of Big Data is related to three primary attributes, i.e., large data volume, number of data diversity (structured and unstructured data), and the amount of data flowing in. For the first time in his work, these attributes were described by Laney in 2001 under the title "3D Data Management: Controlling Data Volume, Velocity, and Variety". With the growing importance and application of technology, subsequent researchers in their work developed BD's concept by defining the following attributes of veracity, value, and variability. [Schroeck et al., 2012] [Demchenko et al., 2013] [Gandomi and Haider, 2014]. In the literature on the subject, you can find further extensions of BD with additional features starting with V. Figure 1 shows the definition of the so-called 9 V's of Big Data.

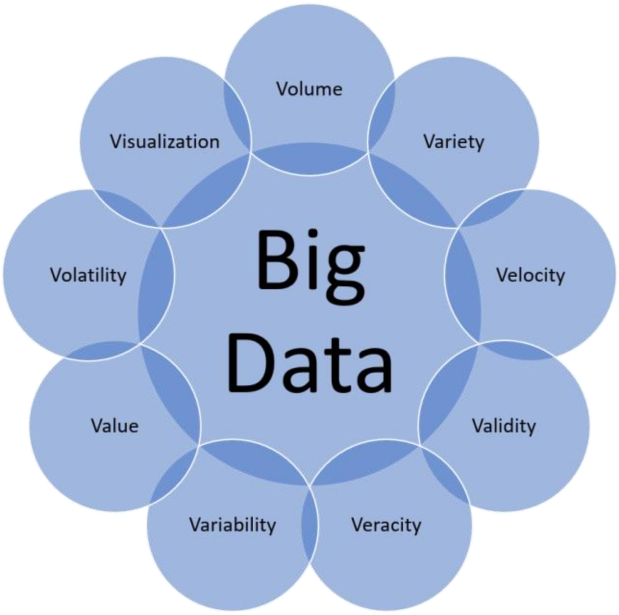

Fig. 1. 9 V's of Big Data

The characteristics of the nine features of BD are as follows::

- Volume – how big is the volume of data?
- Velocity – how often is the data generated?
- Variety - how varied is the data?
- Veracity - how reliable is the data?
- Value - how valuable is the data?
- Variability – how often the structure of data is changing?
- Validity - how accurate is the data?
- Visualization - how challenging the data to visualize is?

- Volatility – how long the data remain valid?

The development and wide availability of technology meant that it was no longer reserved for such big players as Google, Microsoft, or Amazon. Many smaller companies have recognized BD technology's benefits and have embraced many other business areas such as finance and logistics across the entire supply chain.
With the advent of the fourth digital revolution (Industry 4.0), companies began the digital transformation processes, which increased the demand for BD technologies. The increase in the popularity of the Industry Internet of Things in the methods of automation and monitoring of devices also contributed to this.
Koot W. described in his work the use of IoT devices in supply chain management, pointing out that real-time monitoring of the flow of goods contributes to improving logistics operations (tracking, transparency, reliability). [Koot et al., 2020]
The mere acquisition and storage of large amounts of raw data in the BG environment do not yet allow for their analysis. The data must undergo a process of cleaning, validation, often integration, and writing in the form of a business data model. Making the right decisions in complex business processes as part of Supply Chain Management must be based on well-analyzed data. [Speranza, M., 2018].
Combining BD technology and advanced data analysis techniques has led to the emergence of a new definition of the term, i.e., Big Data Analyst (BDA). This concept refers to the process of data analysis in many dimensions and their visualization using dedicated tools operating in a computer cluster environment. BDA was of great interest among managers, in particular managers responsible for the supply chain management.

3 Supply Chain Management 4.0 - basic problems and challenges

In [Schoenherr and Speier-Pero, 2015] results of an online survey regarding the barriers to the SCM predictive analytics have been presented and supported by statistical analysis. Results show that the most critical obstacles in the implementation of SCM tools are:

- Employees are inexperienced (need to train);
- Time constraints;
- Lack of integration with current systems;
- Cost of currently available solutions;
- Change management issues (resistance to
- change);
- Lack of appropriate solutions for SCM;
- Overwhelming, challenging to manage.

The statistical analysis conducted in the article shows that these barriers are essential in all three groups of users: those who currently do not use analytics but plan to do so in the future already use analytics to some extent and use analytics tools to a great time. Survey results analysis also showed that SCM predictive analytics benefits were mostly seen in the more information-based decision-making process, improved supply chain efficiency and visibility, and lower overall cost of a supply chain.

Lambert and Cooper [2000] pointed out that the crucial role in the context of a successful SCM implementation is played by key people in the organization (with the division of responsibility for basic processes and auxiliary processes), the network of related processes, and the degree of their integration. According to the authors, the ineffectiveness of the supply chain is primarily influenced by the lack of coherence of activities between individual departments of the organization.

Thompson and Drucker argue that one of the most critical issues is seeking or anticipating company changes, accepting them, and responding to them to explore the possibilities of mitigating the effects of uncertainty [Thompson 1967, Drucker 1968].

According to [Azvine et al. 2007], the prosperity and further activities of an organization depend on how well it understands and interacts with the changing environment. The agile training of the enterprise allows to predict and estimate the nature and size of the change and to react to it accordingly.

Researchers and practitioners indicate that performance in conjunction with global goals throughout the supply chain depends to no small extent on close cooperation and coordination between actors in the supply chain, which in turn facilitates important decisions and formulating effective supply chain strategies [Dong et al., 2009; Cheng et al., 2010; Power, 2005; Van and Vander, 2005; Stevenson, 2009] concludes that SCM is strategic coordination between members of the supply chain to integrate supply and demand management which translates into the essence of combining internal and external systems.

Determining business requirements and customer expectations in the context of obtaining, integrating, and analyzing data and making joint and coherent decisions within the supply chain are the main challenges in the context of applying analytics for the supply chain [Sahay and Ranjan, 2008].

Successful implementation of an analytical platform for processing large amounts of data for supply chain management largely depends on the support of the management board as part of the company's strategic tasks and appropriate management competencies [Dong et al., 2009].

The implementation of individual business processes as part of an integrated supply chain 4.0 depends on three key elements that an enterprise must have (Fig. 2):

- Identified and well-described processes taking place inside the enterprise along with the identification of the needs for the implementation of new processes;
- Qualified employees who have knowledge of the ongoing business processes and have the skills to use dedicated software. Management staff with the skills to identify gaps in business processes and design new ones, responding to new business needs (ideas);
- IT tools for managing the entire supply chain, appropriately selected at the stage of analysis and feasibility study of given business processes.

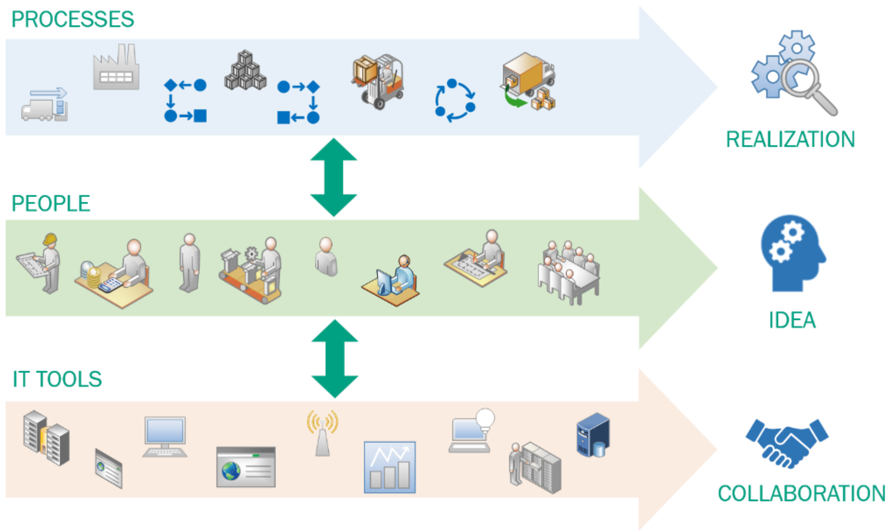

Fig. 2. Processes, People, IT Tools. Source: Own work.

Due to the extensive range of functionalities offered by the software available on the market, a direct comparison of individual tools on a general level is not an easy task. According to the Business Application Research Centre (BARC) surveys, there are significant discrepancies among software properties cited as most important by industry leaders and smaller companies. However, it is understandable - leaders are large companies looking for comprehensive solutions that cover problems often unknown to smaller companies. For this reason, larger companies value software flexibility more. The vast majority of companies participating in the surveys use this software to prepare internal reports and corporate reports. Another popular application of the software is the preparation of simple analyzes and ad-hoc inquiries - 70% and 78% of companies, respectively, declare using tools in this area. Less than 70% of users also use these tools to create interactive data dashboards and scorecards. The software is much less prevalent in strictly financial applications - about 1/3 of the respondents declare using it for planning and budgeting, and financial consolidation.

A widespread mistake made by organizations is trying to solve a given business problem by purchasing IT systems first and then trying to adapt them to the existing and future business processes. Such an approach very often ends with the failure of the entire project - lack of experience in handling a given software, high costs of external companies adjusting the system to support existing and new processes, or even poorly selected software that does not meet expectations.

Fulfilling the requirements in each of these three areas seems quite trivial, but in practice, it isn't easy to implement. The scope of processes often requires the introduction of appropriate organizational changes and changes in handling business processes. The area related to employees requires a proper selection of staff to carry out specific tasks, introduce dedicated training or start the process of retraining employees. The area of selecting the appropriate IT tools in large multi-plant industrial enterprises may turn out to be the most difficult. Identifying systems and data needed to support a given business process, building data flow and their integration, or building dedicated data models without experienced employees may turn out to be very difficult to implement. The success of this task may largely depend on the maturity of a given enterprise and on whether and to what extent it uses methodologies such as TOGAF in the field of managing IT architecture of the enterprise or DAMA-DMBOK Guide [Dama International, https://dama.org /] – a guide containing a collection of processes in individual thematic areas (specializations) related to data management in the form of good practices.

Successful implementations of those tools may yet yield significant advantages. Below, some of the examples of implementing the SCM tools in the industry have been described.

- Schneider Electric is a company that specializes in providing digital energy management and automation solutions that uses Supply Chain Guru software, a product of Llamasoft, for demand forecasting. According to Schneider Electric, implementing the solution allowed for savings in the amount of 9.32 mln USD per year by changing the supply chain's flow.
- Siemens Building Technology is a technology partner for energy-efficient and environmentally sustainable buildings and infrastructure, using the Supply Chain Guru software. The company values the solution that is described as an integrated optimization and simulation platform with a growing community of users.
- Dematic's Warehouse Execution System (WES) is a platform that can manage all aspects of warehouse operations from receipt to shipment. The software was used by one of the American retail clothing companies. The company's goal was to create a distribution center for quick stock replenishment at 3,900 retail stores. The company said the system was able to store up to 600,000 replenishment items per day in stores, which was in line with the item's demand.

4 The proposal of Analytical Platform for SCM

Effective supply chain management without a dedicated analytical platform is impossible in current times. Mangers should have quick access to essential data of the company's processes as well as tools and analyzes that will allow them to predict future events.

With the increase in the number of business processes inside and outside the organization that must be subjected to, the employee has the amount and size of data. Data must be obtained, cleaned, and integrated. They are finding a single source for the production of analytical and predictive models, reports, and KPIs [Govindan et al., 2018]. The implementation of the tasks mentioned above is introduced with the design of the infrastructure, the implementation of IT infrastructure, and the introduction of organizational changes.

Literature studies show that many industrial enterprises have problems adapting their IT infrastructure and implementing appropriate tools for advanced data analysis [Dudycz et al., 2019].

The target architecture of the analytical platform may take various forms depending on the given enterprise. It depends on the existing IT solutions, purchased cloud services, and target expectations. There are many commercial cloud solutions on the market, such as Microsoft Azure, IBM Cloud, Amazon Web Services (AWS) - Cloud Computing Services, Oracle Cloud, Google Cloud Platform, or Open Source solutions. The target platform may be entirely based on on-premises solutions or, to some extent, be a hybrid in combination with cloud solutions from one or more vendors. As mentioned in the previous point, it is essential to identify business needs and the described processes of their implementation and map these needs to specific IT tools. At this point, we will discuss the general architecture of the analytical platform presented in Fig. 3. This model has many advantages, such as the possibility of using open-source software, which may prove very important in small companies developing their activities or larger ones who want to see the rightness of implementing a specific solution. It also has no barriers to scalability and further expansion using tools from different vendors. Its heart is a data warehouse, which can also be open-source software.

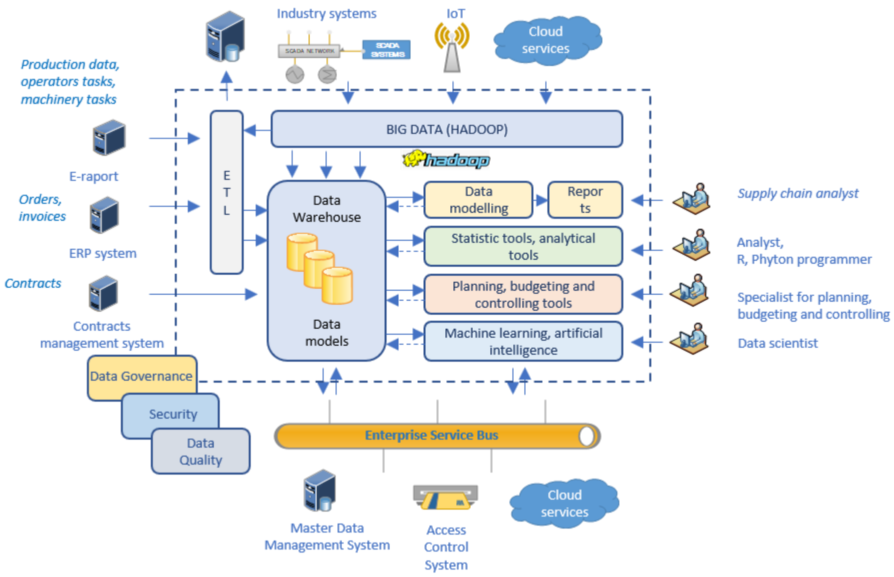

Fig. 3. An example of an analytical platform. Source: [Pyda et al., 2020]

The analytical platform is a combination of ICT infrastructure with a set of IT systems and tools that enable the acquisition, storage, processing, management, presentation, and sharing of data. The platform should be designed so that it is scalable, easy to expand, maintain and configure. It should provide the possibility of modular construction from components that will not lead to dependence on a single supplier (so-called Vendor lock-in). This issue was widely described in [Woo et al., 2018].

An analytical platform is a set of interconnected IT systems and tools between which data is transferred. We can distinguish three groups of tools that can create a platform (Fig. 4).

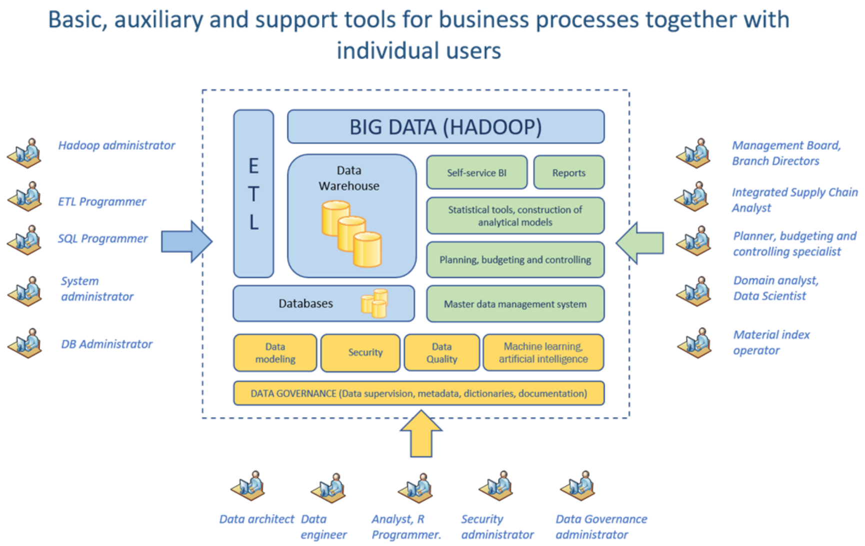

Fig. 4. Three main groups of analytical platform tools. Source: Own work.

The first includes essential software for storing, processing, and acquiring data:

- Data warehouse - a vital element of the platform, where temporary data obtained from sources, business data, and thematic warehouses (Data marts) are stored;
- Databases - used for auxiliary purposes;
- Big Data platform for storing and processing non-standardized data based on computer clusters (e.g., Apache Hadoop);
- ETL (Extract Transform Load) tools for creating data acquisition, transformation, and loading processes.

The second group includes supporting tools:

- Data management tools;
- Data quality and consistency tools;
- Tools for data model development, documentation, and data dictionary development, often referred to as metadata management tools;
- Tools ensuring data security (authorization systems, logging, and auditing);
- Tools for the operational management of master data as the only source of master data concerning, among other things, consolidation of the customer and product data using multiple domain systems;
- Tools are supporting the use of algorithms and methods of machine learning and artificial intelligence.

The third group includes tools supporting business processes:

- Tools for creating logical data models by users, the so-called Self-service BI;
- Data reporting and presentation tools;
- Statistical tools, development of analytical or predictive models;
- Planning, budgeting, and controlling tools;
- Other dedicated tools tailored to the specific needs of the company.

Depending on the specific business requirements, the platform may consist of any combination of the components mentioned above. In the development phase, usually includes tools belonging to the first group. With the growth and complexity of data processing, tools from the second group can be incorporated. Additional applications from the third group can be added to meet new business needs.

As already mentioned in chapter two, when creating an analytical platform supporting decision-making in an enterprise, access to qualified employees fulfilling appropriate business roles and using particular tools should be provided.

Getting started with the analytical platform begins with identifying the source data that must go through a long process, including the stage of acquisition, cleaning, transformation, integration, and finally, data storage in the data warehouse. Fig. 4 shows a model of data integration from various source systems. In many cases, the primary sources of data are ERP systems and domain systems, e.g., contract management systems, project management systems, etc. In obtaining data from industrial devices and systems, we deal with various types of files (CSV, XML, TXT), especially in the case of old systems as the only way to export data. The new ones provide a dedicated API (Application Programming Interface) through which, for example, we can obtain data via a data bus.

The analytical platform can also be powered by a corporate service bus that gets data from both its internal and third-party systems (websites and cloud services). When dealing with huge volumes of data, especially unstructured data, the data source is often a Big Data system. Data stored in business data models, the so-called Data marts, aggregated data, or calculated key performance indicators can be used by external applications dedicated to handling specific business processes (statistical tools, tools for building analytical models, planning and budgeting tools, machine learning, artificial intelligence, etc.). Working with these applications can be a source of data for the platform, adding value as an enrichment of the data business model. Details on the data model are presented in the next chapter.

5 The data model for SCM

The data model is the basis of the analytical platform. It is created by analysts and programmers using the first group's tools mentioned in the previous chapter. The life of the data model begins with the implementation of the first business process on the platform. It starts by creating physical data structures in the warehouse in the form of tables linked by relationships. Relationships usually reflect the realities of a given business area. In addition to tables with data from domain systems, dictionary tables, auxiliary tables for data processing, or tables storing aggregated data are also created. The

logical data set is classified under a thematic data warehouse. When handling another business process, we save the corresponding data in the existing thematic warehouse or create a new one if the given process fits in a different thematic area. And so, for example, data related to the service of business processes in the area of project management will be saved in the thematic data warehouse under the name "Project Management," and data from the scope of purchases in the thematic data warehouse under the name "Purchasing Proceedings." An exemplary data model is presented in Fig. 5. As the supported business processes increase, our data model is extended with new thematic warehouses or the existing ones.
Additionally, thematic data warehouses may contain tables with economic and financial indicators, calculated based on implemented algorithms. They can also be fed with the results of calculations made with external tools. Depending on the needs, the data model can be extended with data from another business area or connected by a relationship with another business model. Ultimately, enterprises strive to build such a model to cover the entire supply chain and its subprocesses.

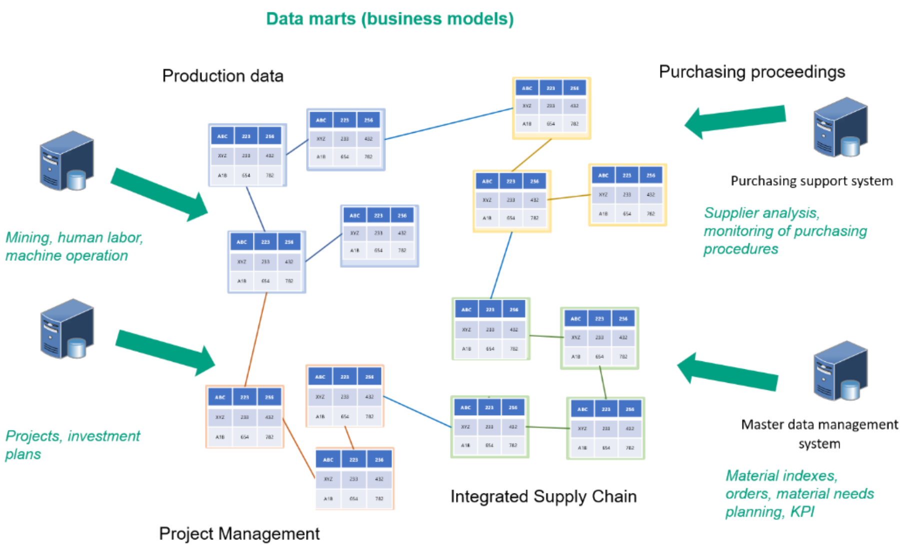

Fig.5. An example of the data model. Source: Own work.

With a comprehensive set of consistent data located in one place, an integrated supply chain analyst can create any combination of relationships and data processing (the so-called logical data model), providing information for a specific business area.
The main expectation of the platform is to ensure quick and easy access to up-to-date, consistent, standardized, and reliable data for re-processing or presentation using reports or dashboards.
The next chapter presents the use cases of various tools based on specific data models.

6 The analytics development model for SCM in a multi-site industrial enterprise

The development of analytics to support the management of the supply chain requires clarifying the current needs of potential users. From the point of view of large multi-site industrial enterprise, we can distinguish:

- development of a tool for planning material needs and services (application, control tools),
- development of tools to support the planning of selected materials based on automatic procedures based on production indicators and usage standards,
- development of the SCM platform in the field of aggregate management of orders, their implementation and rationalization of warehouse management,
- creation of a platform for the exchange of information on material inventories (their age, determination of the degree of usefulness, the possibility of further distribution),
- development of controlling tools for managing costs by type in real-time (budget of the company, departments, cost execution, trend research),
- others.

The following sections present the fundamental issues related to the development of analytics for SCM on the example of multi-site industrial enterprise.

6.1 Development of pre-processing data tools

As presented earlier, the main problem of the development of analytics in a multi-site industrial enterprise is the issue of various standards in data acquisition and storage. There are inconsistent names of materials between plants, especially in the field of consumables. Records of repairs, replacement of sub-assemblies, or wear of consumable parts are very often kept in flat files or systems in the form of unstructured data. Jargon, mental shortcuts, and spelling mistakes are common. One entry may refer to several components, which significantly complicates cost settlement, including the calculation of the unit cost of manufacturing a unit of the output product. The total cost for all entry activities is given, including materials, own labor, and the cost of service companies. All this limits the development of analytics, analytical teaching models, and automation of calculations. First of all, the material indexes should be unified to create a one nomenclature standard applicable in all plants. The next step is to provide tools that ensure access to crucial information on the current and historical usage of materials and refer this information to asset and infrastructure monitoring systems. The critical challenge is the development of validation tools for the correct synchronization of various data sources. One of them is the development and adjusting of Text Mining tools to the enterprise ecosystem to standardize the forms of entries, distinguish them on individual entries according to the categorization of maintenance and repair activities, and estimate the cost of materials.

6.2 Development of data mining tools

At this stage, it is possible to conduct an exploratory analysis of historical data. In this regard, long-term data analysis tools should be provided to recognize how the usage of materials and stocks has changed between plants over time. Successful tracking of the variability of use, wear, and distribution of material costs in individual plants requires the development of statistical analysis methods and machine learning for pattern recognition. It is particularly important that the tool identifies seasonality and trends in data and unique regularities occurring in individual departments/plants with the possibility of flexibly setting contexts and conditions. The development of unconventional behavior detection procedures is also crucial. Thanks to this, it will be possible to answer the basic questions from the point of view of decision making and planning:

- what components and materials and on what scale are used in individual plants?
- how much did individual plants pay for the same part and from what supplier?
- where are the unique materials consumed most often, and what are the contexts?
- which warehouses/material stocks are properly managed?

6.3 Application of a predictive maintenance policy in the enterprise

Another important aspect is the access to information and the current technical condition of the machine park with the estimation of a residual lifetime for individual machines and their critical components. There is a global tendency to develop dedicated Industrial Internet of Things (IIoT) platforms with the use of low-cost sensors for monitoring the operational parameters of assets. In most cases, calculations are performed in real-time in the computing cloud. In terms of analytics, it is necessary to develop methods of fault detection in the early stages of development and KPIs. In the literature, the topic of predictive maintenance, especially technical diagnostics, is very well developed. The effectiveness of damage detection and prediction is an individual matter and depends on the type of machine component and its symptoms of incorrect operation. Therefore, it is also essential to develop reliability models, which is possible in the case of a well-prepared database of machine failures and repairs. In this respect, the multidimensional failure rate analysis and the identification of association rules are also critical. It is essential to follow the history of repairs against the background of the measured diagnostic symptoms to assess the effectiveness of the service staff's performed repair work. The above tools are necessary to estimate the future demand for individual material indexes in individual plants.

6.4 Benchmarking and simulation tools

Another area of analytics development is tools supporting managers in making decisions in various fields of activity. An example of proper functionality is the comparison engine in terms of reliability and costs of original parts and replacements or their respective suppliers. It is essential to access the current and historical market prices and materials offered in one place. The analytical system must be capable of multi-criteria evaluation of material suppliers so that the manager has access to supplier ranking tools when planning purchases. Besides, the critical direction is simulation tools for analyzing future orders about the state of demand and stock levels under various scenarios.

7 Summary

The article discusses the importance of advanced data analysis in SCM. The analytical platform proposal for SCM in a large enterprise was described. It consists of three groups. The first includes essential software for storing, processing, and acquiring data. The second group comprises supporting tools. At the same time, the third group contains tools supporting business processes. The proposed enterprise analytical platform model for SCM is characterized by flexibility, allowing it to connect to compatible commercial and open source systems. The data model for SCM has also been proposed. This data model is the basis of the analytical platform. The areas important for the development of advanced data analysis for SCM in a multi-branch industrial enterprise were also discussed. They are the development of pre-processing data tools, development of data mining tools, application of predictions to diagnostics of device maintenance, benchmarking, and simulation tools.
Further works will concern the construction of a model of production data to be ultimately associated with the integrated supply chain model. It is assumed that this will allow the identification and analysis of the correlation between production plans and orders for materials and services. Research into advanced data analysis in multi-site industrial enterprises will also be continued. This research will also include the development of assumptions for constructing a data and service management center, including trends resulting from the concept of Industry 4.0 and Reference Architecture (RAMI). This should include not only a look from the IT angle but - first and foremost - from the perspective of business processes. Each analytical solution must be primarily focused on business benefits, based on hypotheses concerning the potential impact on the operations and business areas.

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