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Strategies for Effective Product Roadmap Development and Execution in Data Analytics Platforms

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Abstract

Manufacturing is only one of several industries going through a digital transformation in this era of digital disruption. Manufacturing businesses are racing to adopt IoT-based solutions in order to innovate, increase productivity, lower costs, and gain greater market share because of the enormous transformational potential offered by Internet-of-Things (IoT) & Big Data. It is being used by industrial companies all over the world to increase flexibility while achieving cost savings, reduced inefficiencies, and better performance. It is no longer a trend for the future. But putting Industry 4.0 technology support into practice is a tough endeavour that gets increasingly harder in the absence of a common method. These are produced during the course of business operations and are kept in databases, email communication, transaction logs, free form texts on (business) social media, and other places. Businesses want to integrate data analytics methods into their decision-making processes by utilisation of these data. The field of Big Data analyses has seen tremendous progress in the IT sector in recent years. It appears that in order to deal with the extremely dynamic situations of today, new methods for product route mapping are required. This article provides an overview of the literature in science on product road mapping in order to shed light on the current state of the art & pinpoint research gaps. In order to demonstrate the influence of Industry 4.0 technological innovations on the manufacturing sector, this study provides an organised and content-focused evaluation of the literature. This paper offers recommendations for converting a legacy manufacturing facility into an Industry 4.0-compliant smart plant. Research gaps encompass topics including how to include objectives or results in product roadmaps, how to match a roadmap with the item's vision, and how to include activities related to product discovery in product roadmaps.

Keywords: Internet-of-Things (IoT), Business Process, Manufacturing Industry, Industry 4.0, Roadmaps, Big Data Analytics, IT Industry, Transformational Potential, Highly Dynamic, Business Process, Intensive Operations.

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I. INTRODUCTION

One important component of a company that lays out the goals and trajectory of its product line is a product roadmap. It outlines the steps necessary to achieve a set of company goals and how an item or product range will do so. Despite the fact that road mapping is seen as being extremely significant, many businesses are presently having trouble with their transportation mapping strategy [1, 2]. Product roadmaps typically cover relatively lengthy time horizon and include concrete goods or features along with concrete release dates, according to a recent study on the current state of the practice [2].

One way to describe them is as feature-based roadmaps. Such feature-based roadmaps appear to have outlived their usefulness in light of changing market conditions, particularly when it comes to the development of IT services and software [2, 3]. Features or products on feature-based approaches product roadmaps frequently do not function, that is, they are not contributing to the anticipated goals or outcomes, which is one of the main issues with these roadmaps [3, 4]. One explanation is that management, investors, or additional stakeholders (such customers or sales) come up with ideas for new goods, services, or features with an expectation that they would be quickly put into action. Another reason is that financial considerations are frequently the primary factor used to prioritise the features, goods, or services that need to be produced [4].

In both situations, features have not been verified in light of consumer value or other factors before to implementation, and client requirements are not given enough thought. Customers frequently decide not to purchase or utilised the product as a result of their lack of enthusiasm for the concepts put into practice. Moreover, product roadmaps need to be updated frequently due to unstable settings. Modifications to feature-based roadmaps that are deemed necessary frequently result in significant additional costs and even cause new product launches to be delayed [5]. Furthermore, it's common for people to lose faith in products or delivery management processes as a result of continuously shifting roadmaps. The failure to match a roadmap and the business's objectives or the product's vision is another issue that frequently arises in practice. Strategic objectives are frequently ambiguous or dynamic. This typically results in developers being less able or willing to align ourselves with strategic aims. Whenever a roadmap has a large number of concepts, [5] regardless of the number of disclaimers included, employees throughout an organisation frequently view the plan of action as a promise to produce every item on the list. Teams frequently provide the specified features or products month after month without stopping to think about if the results help achieve objectives like customer or corporate goals [6].

A significant change in the state of technology is a hallmark of industrial revolutions. There have been four periods of industrial revolution in the history of mankind [5, 6]. Mechanisation was the first revolution, the invention of electricity was the second, and electronics, telecommunications, and computers were the main products of the third revolution. There were three periods of industrial development in a span of nearly two centuries. The German term "Industry 4.0" from 2011 is the source of the term "the fourth industrial revolution," or Industry 4.0 [6, 7]. The phrase "Industry 4.0" is relatively new, but the technologies that make it possible—illustrated in Figure 1—have been available for several decades and have greatly benefited a number of businesses. Cyber physical systems that

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enable the real-time fusion of the virtual and physical worlds are what define Industry 4.0. The entire manufacturing value chain can gain a lot from the adoption of technologies associated with Industry 4.0 [8].

These advantages include, but not limited to, higher levels of efficiency and productivity, more knowledge exchange and collaboration, flexibility and agility, simpler regulatory compliance, better customer experiences, lower costs, and more revenues [8, 9]. Industry 4.0 is attracting interest from academic institutions, research centres, corporations, and even governmental bodies due to these advantages. Initiatives that allow them to promote modern manufacturing facilities are funded by all manufacturing-savvy nations [9].

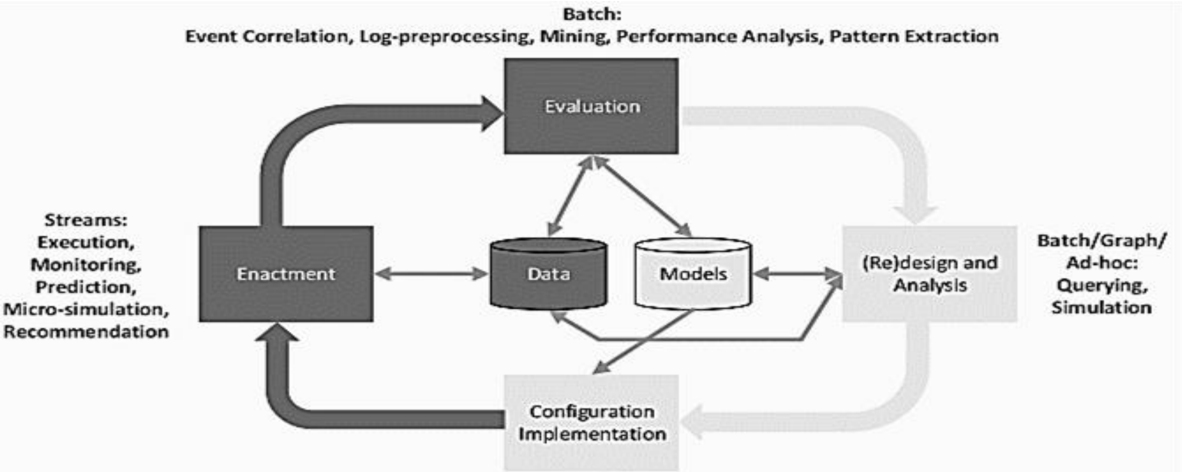

Fig. 1 Lifecycle of a business process based on. [9, 10]

Large amounts of data stored in a system of files that are distributed are commonly referred to as " Big Data," or Big Data processing has connections to the Map Reduce computation paradigm. Big Data systems can be broadly divided into two categories: live (stream) processing and offline (batch) processing. For the former, different computational frameworks than MapReduce might be used depending on the type of data. For example, in terms of speed and ease of result production, the Bulk Synchronous Parallelism (BSP) computing paradigm is recommended to process huge graphs such as social networks [10]. In the latter case, MapReduce is unable to manage the time overhead constraints to react to new data as it comes in. As a result, alternative computing models that divide processing among several operators and handle data instantly must be employed [10, 11]. The latest generation of technologies for Big Data, such as Spark, F-link, Storm, and Impala, is being adopted.

These systems offer technological alternatives that maintain the capacity to make decisions after processing and examining all available data. The advantages of Big Data processing have not yet been completely reflected in BPM-related practice and research. This article's main goal is to draw attention to the current disconnect between BPM and technological advances in Big Data and offer a number of suggestions for closing it. We demonstrate how processing of Big Data can be integrated into the various stages of a business partner's lifecycle in order to more clearly express the possible advantages [11, 12].

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Prior to delving deeper into the specifics, let's clarify what an intelligent manufacturing facility is: This highly efficient connected manufacturing facility has the capacity to launch new products in response to market conditions, is scalable to accommodate variations in demand for current products, can produce finished goods at the lowest possible cost, and is equipped with intelligent machinery, robots, and sensors that seamlessly communicate with the information system architecture enabling a high degree of automation in the processing of transactions [12, 13]. Real-time analytics further enhances operational efficiency by reducing downtime. All of the major stakeholders in an ecosystem, such as suppliers, operation, Information Technology (IT), planning, sales & marketing, & customers, work closely together in a smart factory [13]. It establishes a single platform on which teams from many business departments—including purchasing, planning, production, sales & distribution, finance, and accounting—cooperate to achieve overall company goals. [14].

II. SMART FACTORY KEY BUILDING SECTIONS

By definition, the term "Smart Factory" refers to any included system. But building a smart manufacturing involves a great deal of complexity. It combines cloud computing, automation, Internet of Things, and linked systems. The implementation process typically takes several years and phases [14]. Three essential components comprise a smart factory:

A. ‘‘SMART’’ EQUIPMENT

One of the main elements of a smart manufacturing facility is equipment. While in operation, equipment produces large amounts of data. Typically, this data is unstructured and underutilised. Unstructured data can now be easily examined thanks to Big Data and the Internet of Things. Shop floor activities can be better understood with the help of such analysis [15, 16]. One of the most important prerequisites, nevertheless, is that the apparatus be prepared to collect the data and transfer it to a platform for analysis. Sensors and industry-standard protocols including TCP/IP, OPC (Open Platform Communication), GEM (Generic Equipment Model), and SECS (SEMI Equipment Communication Standard)/GEM (SEMI Equipment Communication, Standard) must be supported by the equipment [17].

B. ECOLOGICAL SYSTEMS SEAMLESSLY INTEGRATED

An ecosystem of interconnected devices, machinery, and applications via common protocols is required within a factory. Enterprise resource planning (ERP), Manufacturing Execution System (MES), and Product Lifecycle Management (PLM) tools are examples of critical apps that need to be in place and integrated with one another [17]. To control process processes, equipment PLC (programmed logical control) should be connected with MES. On the shop floor, devices like handheld scanners, cell phones, tablets, etc., should be able to interface with the aforementioned apps [17, 18]. By doing this, a closed loop collecting data and control mechanism is ensured.

C. ADVANCED ANALYTICS

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The Internet of Things (IoT) and other advanced analytics systems can collect data through connections from a variety of sources, including files, apps, sensors that are and devices. This allows for complicated analysis, include what-if analysis [18].

III. TECHNOLOGICAL DESIGNS ENABLED BY INDUSTRIAL 4.0

3.1 Manufacturing via Additive

This is a catch-all word for a number of techniques that can be used to create 3D objects by building layers on higher than one another. Since the 1980s, when the first Additive Manufacture (AM) technique was developed, the number, functionality, and applications of these technologies within the manufacturing industry have grown [18]. AM is classified into seven different categories: directed energy deposition, sheets lamination, extrusion of materials, binder jetting, powder bed fusion, and vat photo polymerisation. With limited production runs and quick turnaround times, AM (additive manufacturing) can create products with premium materials, complex geometries, and lower manufacturing costs [17].

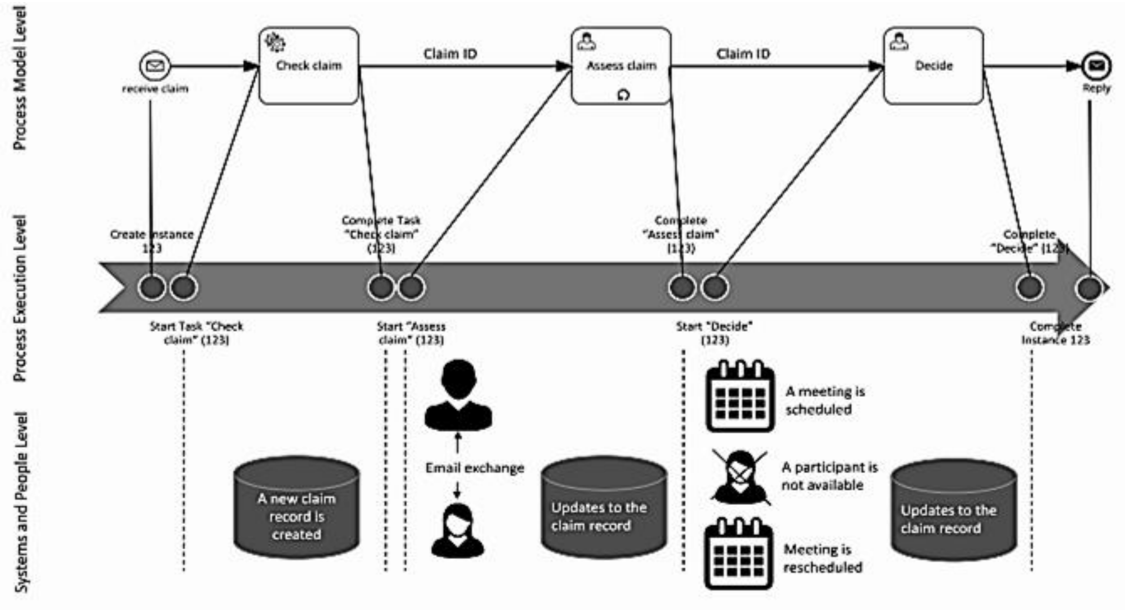

Fig. 2 An Example of a Process Footprint. [16, 17]

As illustrated in Figure 2, the optimal environment for implementing a BP is to have a specialist execution engine that ensures that a process instance adheres rigidly to a pre-defined BP model. However, the enactment phases become uncontrolled in many real-world settings where there's no such execution engine. The unstructured approach of implementing BP is prevalent for a variety of reasons. For instance, a lack of process understanding affects a lot of businesses. The administration in these kinds of organisations from top management all the way down towards the operation level, does not understand what a process is [14, 17]. Every role lacks an end-to-end view and can only see their actions

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from a local perspective. Furthermore, in some businesses, the organization's maturity has not yet reached the point where all or the majority of the procedures are well-established and configured.

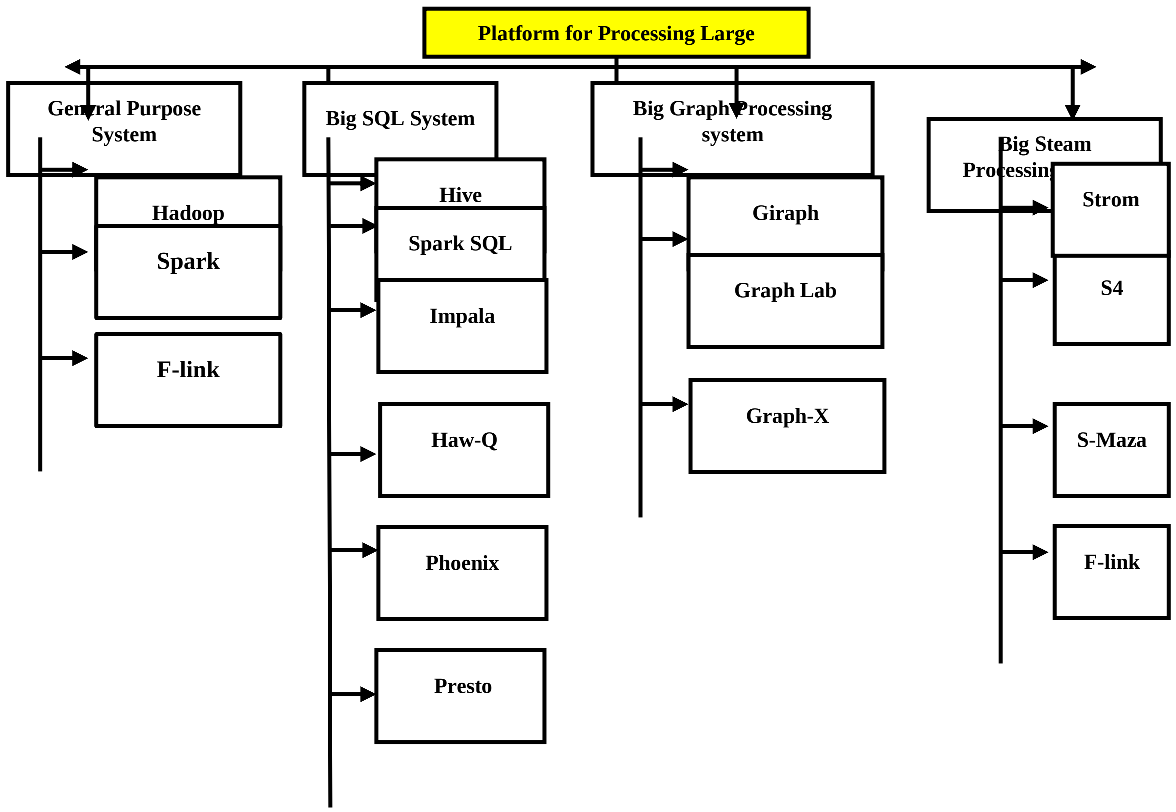

Fig. 3 Big Data processing systems are usually classified. [18]

IV. WHERE CAN BIG DATA TECHNOLOGIES AND PROCESS ADMINISTRATION COLLABORATE?

We go into further detail about how BPM might profit from Big Data strategies in the next section. We segment this conversation according to the various stages of the process lifecycle shown in Figure 3 and the process analysis procedures covered in Sections [17, 18].

A. DESIGN OF PROCESS-(RE)

Process information as well as insights from other analytics can be used to enhance process models during the process (re-)design phase. Improvements can be made to the procedure model structure, such as by rearranging or adding tasks, or by simulating the process using more precise metrics for performance variables like duration of tasks. Validation experiments can also be conducted using data

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from real execution insights. The majority of these enhancements are based on analytics findings from the assessment stage [17]. On the other hand, some analytics methods are used on process artefacts during the design stage. These analytics are associated with approaches for process querying.

For many years, the principal scientific conferences of the Business Process Management (BPM) research group has featured business process mining techniques as one of its core subjects on the annual program. Moreover, BP engineers have access to a range of process mining packages and tools, including as ProM, Disco, Celonis, or minit. As an illustration, ProM is a well-known corporate process mining framework. Its development began in 2003, and as of right now, it contains over 1500 plugins that use different process mining approaches [18, 19]. But most of these methods rely on traditional models of computation and don't make use of new distributed and scaled methods [19]. Partitions the event log across the computing cluster's nodes such that each node is in charge of processing a certain portion of the event data is a necessary step in distributed process mining solutions. Partitions the event log can be done in two basic ways, in theory:

1) ***Case-based partitioning,*** *also known as vertical partitioning, divides events into cases so that every instance is associated with a single node.*
2) ***Activity-based partitioning,*** *also known as horizontal partitioning, divides instances into shorter traces that focus on subsets of activities by allocating events according to the activities they relate to. As a result, every compute node takes part in processing every case [19].*

Approaches that utilise modern batch processing platforms, like Spark, have been introduced recently. An effective method for correlating events. There are two distinct sources of efficiency. First off, compared to Hadoop, using Spark ensures superior runtime performance. Second, the method is based on the idea of filter and verification, in which correlations that are not noteworthy are found early enough and eliminated [19, 20]. The important thing to remember is the reality that the algorithm's structure minimises the cost of data transfer over the network simply by being aware of it. We propose another recent method that takes explicit log splitting into account. Online conformance verification of events as they happen is addressed by the method [19]. The method can support both batch and stream conformity verification because it is based on Apache Spark. In summary, given the broad range of applications for both BPM and large-scale data mining systems, it is critical to choose the right Big Data system to leverage in order to tackle and provide a scalable method for implementing a particular process's heavy on data operations [20]. However, the following general recommendations can be advised in this particular context:

- The Hadoop architecture has been the mainstay of the majority of strategies that have been put forth for using processing of Big Data engine in the context of company processes analytics [20, 21]. But as was already mentioned, one of Hadoop's primary drawbacks is how inefficient it is in carrying out repetitive tasks. Due to the iterative nature of process discovery, event connection, and the enhancement techniques, it would therefore be more appropriate to rely on additionally primary memory-based Big Data analysis engines that naturally support iterative processing, like Spark along with its machine learning extension, MLlib. 10 Apache Mahout, 11 SystemML12, and

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bigml13 are other examples of recently developed systems that can be used effectively in this context and have been designed to provide adaptable machine learning alternatives on top of various Big Data processing engines [23, 24].

- Because business process models are inherently graph-based, large-scale graph processing systems (like Giraph, GraphLab, and GraphX) are valuable tools that can be used to implement scalable graph bitcoin mining and graph analytics methods for identifying business process models from event logs [24]. Large graphs that represent organisational social networks, such as those that link departments, groups, jobs, and other organisational units with the organization's resources, can also be effectively analysed by these systems. Based on the established knowledge that event logs include the reference section to the human resource that completed a particular task within a case [25], the interconnectivity between those assets and activities can be visualised as graphs, with resources or activities represented as vertices, and relationships between resources represented by edges. For example, relationships between resources that involve co-working may be represented by edges that connect a resource's vertex to an activity's vertex. These edges may have characteristics that indicate how frequently they collaborate. With such a graph, a number of intriguing analytics use cases have surfaced. Identifying (sub)teams among process participants, for example, can help to improve the evaluation of performance based on the logs and may also help to explain why some individual resources perform different even when performing the same task [28].
- The primary goal of compliance monitoring techniques is to find any deviations that may have occurred during the execution of the process instance by searching for the incident logs, which are typically structured [28, 29]. As a result, in this situation, taking advantage of large-scale structural information processing engines (such Hive, Impala, & Spark SQL) is a suitable strategy for successfully meeting this challenge [29, 30].
- Some techniques, such as proactive business process keeping track of and runtime compliance monitoring, are online and real-time, whereas process model discovering things event correlation, and techniques for augmentation are offline and can be carried out by sequential processing engines (e.g., Hadoop and Spark). Large-scale stream processing engines (like Flink and Storm) would therefore be able to handle these techniques adequately in order to create scalable and effective solutions that can address these issues. These technologies would specifically enable the generation of an event streams during the execution of a business activity and process it online [29].
- A portion of data from processes that is naturally structured, such as event logs, is the focus of the majority of process analytics techniques. The concept of Process Footprint, as expounded in Section II, remains outside the purview of extant analytics methodologies [30]. However, the technological capacities of current Big Data systems

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for processing enable the creation of algorithms that gather such footprints data from their various sources then further processing it for additional insights.

V. CONCLUSION

Throughout the process lifecycle, we highlighted a number of data-intensive business process operations in this post. We also talked about Big Data systems-based remedies for some of those analytical tasks. We recognise that solutions based on Big Data technologies have just lately begun to surface. We talked about more advancements for these strategies. Numerous use cases listed below are Big Data challenges for which there are currently no scalable solutions. The concept of Process Footprint has been introduced, and we have talked about how Big Data systems may help in gathering that footprint and provide the infrastructure needed to analyse the data gathered, potentially yielding insights that surpass the capabilities of current cutting-edge process analytics methods. This creates additional difficulties for process analysis and establishes a crucial line of inquiry.

The industry that produces goods has seen a change thanks to Industry 4.0. But there are still significant obstacles standing in the way of both its adoption and its application. The paper makes two practical contributions. IoT has great potential for the manufacturing sector, but it's not a magic bullet. It requires a large financial and human resource commitment. Repayment frequently does not follow the instructions given by Corporate Finance.

In conclusion, we drew out a roadmap and offered some suggestions for advancing the state-of-the-art in the field of business process analytics by using Big Data technology. We hope that reading this will motivate the reader to advance company operations analytics.

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