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Rediscovering Scientific Management – The Evolution from Industrial Engineering to Industrial Data Science

Jochen Deuse[a,b*], Nikolai West[a] & Marius Syberg[a]

[a] Institute of Production Systems, Technical University Dortmund, Leonhard-Euler-Str. 5, Dortmund, 44227 Germany.

[b] Centre for Advanced Manufacturing, University of Technology Sydney, 11 Broadway, Ultimo NSW 2007, Australia.

[a1] *jochen.deuse@uts.edu.au*, [a2] *nikolai.west@ips.tu-dortmund.de*, [a3] *marius.syberg@ips.tu-dortmund.de*

Abstract:

Industrial Engineering, through its role as design, planning and organizational body of the industrial production, has been crucial for the success of manufacturing companies for decades. The potential, expected over the course of Industry 4.0 and through the application of Data Analytic tools and methods, requires a coupling to established methods. This creates the necessity to extend the traditional job description of Industrial Engineering by new tools from the field of Data Analytics, namely Industrial Data Science. Originating from the historic pioneers of Industrial Engineering, it is evident that the basic principles will remain valuable. However, further development in view of the data analytic possibilities is already taking place. This paper reviews the origins of Industrial Engineering with reference to four pioneers, draws a connection to current day usage, and considers possibilities for future applications of Industrial Data Science.

Key words:

Scientific Management, Industrial Engineering, Industrial Data Science, Data Science, Data Analytics, Process Chain.

1. Introduction

Ever since the *First Industrial Revolution* in the 18th century, optimization measures and operational decisions in the manufacturing industry rely on quantitative and fact-based assessments. Fact-based decision-making has always been the cornerstone within the field of engineering, extensively taught by technical education and widely practiced in real-world operations.

Modern advancements due to the still on-going digitalization and globalization of nowadays world of work represent a logical continuation of the observable movements in science and technology. Against the background of this natural and inevitable development, emerging potentials through *Data Science* do not necessarily represent a paradigm shift, but rather a continuation of the development of Industrial Engineering (IE). This development may greatly extend the established tools of today‘s engineers, but still draws on traditional IE principles that have been known for decades if not centuries.

In view of the inflated expectations with regard to Data Science‘s problem solving capabilities and its promises of economic rationalization, this paper draws references to some of the main representatives and pioneers of IE, such as Frank and Lillian

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Gilbreth, John Burbidge, William E. Deming and Eliyahu M. Goldratt.

These five pioneers are among the most prominent contributors to the field of industrial engineering and sparked novel research directions. By examining the respective field of research of these four pioneers of IE, this paper provides a comprehensive review of the historical development of IE to date. Based on the patterns of this historical development, this paper outlines a broad view of contemporary movements, before also considering emerging trents for future research objectives within these four branches of research. Summarizing, the paper embraces these pioneers of IE and it aims to help rediscovering established ideas and principles of Industrial Engineering at times when Data Science is permeating the manufacturing domain.

2. Fundamentals

2.1. Origin of scientific management

The roots of IE stem from Frederick W. Taylor, whose main work *Principles of Scientific Management* was instrumental in shaping the course of industrial manufacturing (Taylor, 1911). By many, Taylor is considered to be one of the most influential scientists of the 19th and 20th century. In addition to his contribution to the invention of high-speed steel, Taylor is best known for working in the area of labor studies. His principles build on the assumption that work needs guidance by precise instructions given by management. This is based on the postulate that there is just one safest and most efficient way to accomplish a given work task. To identify this sequence, Taylor proposed a five-step process:

1. Select 10-15 worker from varied factories/ backgrounds, trained in a targeted activity
2. Observe each elementary movement the tool usage during execution of the activity
3. Measure the execution time of each element and select the fastest method for each
4. Eliminate all incorrect, slow or unnecessary movements from the best practice
5. List the fastest method and the best tools for performing the activity in a table

These five focusing steps help to identify and document optimal movement sequences and suitable tool usage in a standardized manner, using time recordings of any activity. With standard processes, best practice workflows are established; the efforts of the continuous improvement process are secured and made available across plants (Deuse et al., 2020). Along the belief in *One Best Way* to perform a given task, Scientific Management strictly enforces fact-based decision-making based on quantitatively measurable data. Thus, quantifiably optimal solutions take the place of practices previously determined by formerly used rule-of-thumb methods (Merkle, 1980). The onset of a worldwide adoption of Scientific Management Principles defines a starting point for the continuous evolution of Taylor‘s vision. It led to the emergence of IE and it is well established in modern manufacturing.

The term IE includes all tasks concerned with ‘the design, improvement and installation of integrated systems of people, materials, information, equipment and energy. It draws upon specialized knowledge and skills in the mathematical, physical and social sciences together with the principles and methods of engineering analysis and design, to specify, predict and evaluate the results to be obtained from such systems’, as defined by the *Institute of Industrial and Systems Engineers* (IISE, 2021).

As such, *Industrial Engineers* lead continuous improvement processes and provide system understanding, method knowledge and problem-solving-competences, along the ever-evolving requirements of various other skills (Richter & Deuse, 2011). In this context, we consider the ability to utilize Industrial Data Science as the latest addition to this catalogue of competences.

2.2. Emergence of Industrial Data Science

The domain of Data Analytics experienced an increase in attention over the past years. Industrial Data Science (IDS) refers to the use of Data Analytics in industrial applications (Mazarov et al., 2019). Early applications of structural data analysis date back almost 70 years before the work of Taylor. A U.S. naval officer and hydrographer, named Matthew F. Maury, recommended supplementing the previously undescribed nautical charts with information, such as longitude, latitude and other notes that seafarers collected on their routes (Maury, 1963). This served to shorten the time at sea, since each seafarer could profit from the experiences of the others. He supplemented the pure information of the route with many additional variables, which all have an influence on the target variable ‘journey time’. He found patterns in this data, derived structures and generated knowledge from it. In doing so, he piloted a process, which we nowadays interpret as the basic problem solving approach of Industrial Data Science (Wierse & Riedel, 2017).

In manufacturing, Taylor was among the first to identify a demand of data for fact-based decision-making within an industrial production environment. Due to scale and complexity of the ever-increasing data acquisition, manual methods for data processing become uneconomical. Hence, manufacturing companies seek the use of IDS for the efficient evaluation and utilization of implicitly available knowledge. As for Knowledge Discovery in Databases, IDS includes all non-trivial measures to identify valid, novel, potentially useful, and ultimately understandable patterns in industrial datasets (Fayyad et al., 1996). It draws on methods from multiple disciplines: Machine Learning, responsible for generation and generalization of knowledge by computers and Statistics, the science of collecting, organizing and deriving conclusions from data, being the most relevant (Awad & Khanna, 2015). This basic idea behind the analysis of data is methodically carried out in the industrial environment today according to the *Cross-Industry Standard Process for Data Mining* (CRISP-DM). With this five-step procedure, todays data scientists perform projects in a structured way from business understanding to deployment (Chapman et al., 2000). We interpret CRISP-DM as a formalization of the basic procedures of Maury and Taylor with a view to today's conditions and challenges.

The application of these methods and procedures in today's industrial environment is both effective and unavoidable. This is explained by the increased complexity in making decisions, as in nowadays systems more variables have to be considered. Simultaneously digitalization has also provided the infrastructure needed to record more data on these variables. The integration of computer technology in the form of Embedded Systems in industrial processes is standard today and enables the recording of a wide variety of data on products and processes. With the help of these Cyber-Physical Systems, all steps from data acquisition with sensors to data storage in databases can be carried out in order to use IDS methods to make intelligent, targeted decisions based on the analysis of every variable required (Lee, 2006).

Some consider the use of IDS tools and methods as part of the Fourth Industrial Revolution, often called Industry 4.0. Other state that it has traits of a more gradual development of quantitative approaches that extend the traditional tools of IE. The emergence of IDS shows distinct characteristics of an evolutionary process and is in line with the development trend of the past century. Following approaches such as Lean Thinking or Agile Manufacturing, IDS represents the latest facet of this traditional evolution of production principles. The advent of the Internet of Things and the availability of Big Data storage systems support the need for data-driven decisions. The approach for data-based decision-making has a predeceasing model in time management and is presented in the following section on the basis of the process chain of data analytics.

2.3. Process chain of Industrial Data Science

IE and IDS involve closely related tasks for a fact-based decision-making processes. With the process chain of time management, all activities for fact-based decision-making are broken down into subtasks and handled consecutively. This has led to the development of the process chain of data analytics, which follows a similar approach. In four stages, tasks of data collection, analysis, use and administration are carried out (Figure 1).

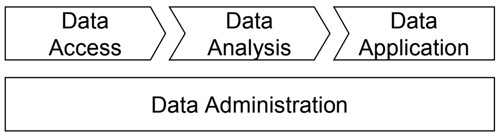

Figure 1. Process Chain of Industrial Data Science.

Since all fact-based decisions require a data basis for quantification, the first step in the process chain is to access all data sources that are necessary and related to the current task or project. This often includes the identification of relevant sources for a given analysis task, recoding missing data with suitable collection methods, and providing the data to an analysing system. The step is closely related to the initial phases of the well-established CRISP-DM and required not only a good data understanding but also a solid business understanding. After ensuring a reliable end-to-end access to relevant data, the next step of the process chain is to analyse the provided data. For this, a suitable method for the analysis task must be selected from the wide range of available options. A number of pre-processing steps and transformations for subsequent usage may accompany the application of the analysis. While the first two steps are arguably necessary, a monetary gain will only arise through the operational use of the information generated during the analysis. Hence, the third step is to apply the results of the analysis to the industrial use case, creating economic value. This includes both the application of selective analyses for specifically targeted questions as well as the implementation of continuous monitoring systems. Finally, to administrate these tasks a wealth of supporting duties needs to be fulfilled. Among others, this includes assigning a long-term data stewardship, allocating a clear data governance, ensuring an end-to-end data security or securing an ethical data usage.

3. Pioneer Case Studies

3.1. Time and Motion Study – Frank and Lillian Gilbreth

Past. Temporal measurements of industrial process increments form the basis for operational planning and decision-making processes. For IE, time data is essential for the analysis, design, modelling and simulation of production systems as well as for the design of workplaces and the control of manufacturing and assembly systems. Time and Motion Study enables an Industrial Engineer to control and plan from a quantitative basis, according to Taylor's basic idea. Frank and Lillian Gilbreth, whom we consider pioneers of Time and Motion Study, recognized at the beginning of the 20th century that the conversion of movements into time data is essential for work analyses (Gilbreth, 1912). The Gilbreth Clock allowed a detailed analysis with regard to a tasks duration and usefulness, so that value-adding and non-value-adding elements become distinctive. The stopwatch was the device for manual data recording.Gilbreth determined that the time to carry out an activity for a singular sequence with equal practice, equal aptitude and equal effort of the workers within realistic limits depends solely on the method used. Asa B. Segur assigned standardized time values to the standard elements in industrial processes devised by Gilbreth by studying numerous workers of different skill levels (Maynard & Zandin, 2001). This enabled analyzing work processes using a standardized scheme. Thus, Motion Time Analysis is considered the first predetermined motion time system.

Present. Still, time recordings hold a fundamentally vital role for process management. Predetermined motion time systems are still widespread today. Numerous companies leverage the MTM method, developed between 1940 and 1950, to analyze manual work processes today. In German-speaking countries, over 250 companies belong to the MTM Association, thus representing over 2 million employees (MTM ASSOCIATION e. V., 2021). This underlines the relevance of precise data recording and attention to detail. Today, time data from production forms the core of strategic and operational process planning. The analysis of work processes via video recordings and motion capturing approaches makes the use of systems of predetermined times even more direct and universal (Bortolini et al., 2020).

Future. IDS research deals with automatic data access through image recognition via machine learning or the use of sensor technology. The ease of access to the technology underlying vision-based and sensor-based analysis serves as enabler for further development. It is equally conceivable to apply Gilbreth's visionary ideas to the use of robots and to the optimization of industrial human-machine interaction (Wang et al., 2011). Motion data in the form of human silhouettes or human skeletons elaborates human movement. Additionally, the movement of robots can be captured by the control system. The combination of such data as well as an enrichment by other data sources and the necessary forces for the different tasks forms the basis for the analysis and optimization of the technology-determined workstations (Figure 2).

The usage of machine learning is a possible potential to be explored for automatically analyzing recorded motions. It allows suggestions of process improvements based on MTM studies using motion capturing data (Deuse et al., 2019). The integration of MTM approaches with Virtual Reality (VR) provides the advantage of preventing suboptimal workplace designs during the planning phase without the need for physical mock-ups (cardboard engineering) for data collecting (Gorobets et al., 2021).

3.2. Group Technology – John Burbidge

Past. For IE, Group Technology is essential for production optimization. The term describes the approach of grouping objects and resources according to their similarity. Organizing processes and structures is often more efficient and effec-tive based on such groupings. Sergei P. Mitrofanov was

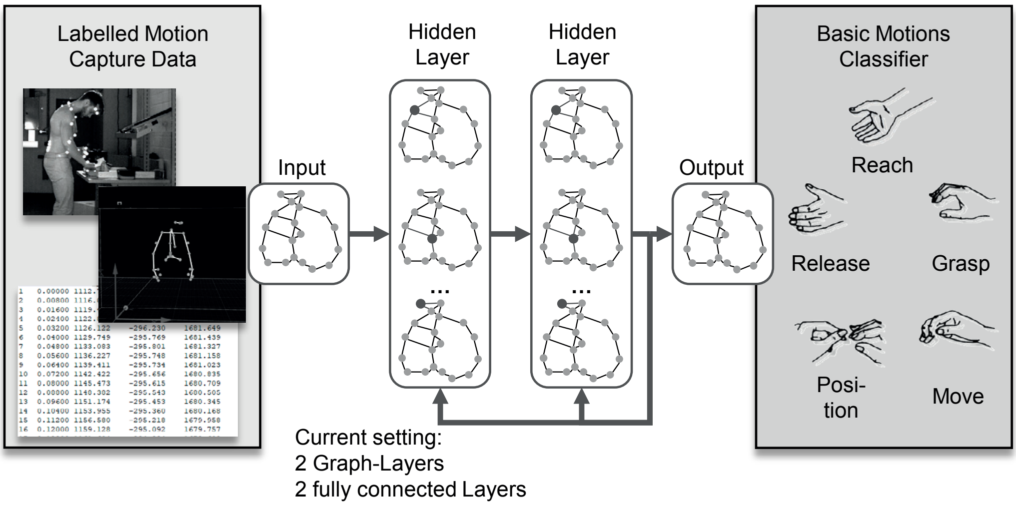

Figure 2. Convolutional Neuronal Networks (CNN) with 2 Graph Layers, 2 fully connected layers as one Machine Learning Method to Enhance MTM (Own figure, MTM Summit 2021).

the first to research the idea of classifying process methods based on the shape of the resulting products using the research results of A. P. Sokolowski (Sokolowski, 1938; Mitrofanov, 1946). He established a classification system that structured work pieces according to function, shape and technological features based on his finding to work on similar parts of a group with the same equipment of a lathe (Burbidge, 1991). John Burbidge, whom we consider as pioneer of Group Technology, based his research on Mitrofanov and Sokolowski and successfully applied the grouping on a larger scale (Burbidge, 1975). Thereby, he validated the prior research and coined the terms 'group' as a set of machines, and 'family' as a set of parts. Burbidge introduced a production analysis method with the Production Flow Analysis. According to his research, products passing through the same machines should also be manufactured in one machine group (Burbidge, 1963).

Present. Searching and finding similarities in industrial processes is essential for economically successful enterprises and possible with four different procedures: Classification systems, production-analytical methods, cluster-analytical methods and artificial intelligence methods. Classification is the key method used by Sokolowski and Mitrofanov. Production-analytical methods use the frequency of the production sequences or work piece-resource-matrices for part family formation. Cluster analytical methods use methods of multivariate statistics, such as regression, to analyze different characteristic values for similarities and identify homogeneous groups between which there is a possibility of dissimilarity. Last, it is possible to use knowledge-based approaches and artificial neural networks, both methods of artificial intelligence for part family formation (Eversheim & Deuse, 1997; Kusiak & Dagli, 1994). Those approaches help with different challenges, such as building structures in low volume and high mix productions. Levelling taking into account product families helps serving transparency, calming of variability and leads to output improvement (Bohnen et al., 2013). Research in practical pattern recognition by using sensors and software for analyzing images, characters and text show high potential (Feng & Hua, 2020). For subsequent analyses, it is necessary to record different data which is then analyzed for similarities. Visualization using flowcharts allows easy access the subject matter.

Future. As manufacturing processes and products become more complex, simplification becomes more difficult. The search for similarities based on shape or machine group is also no longer efficient in variable production environments due to the high complexity of products and increased amount of different manufactured variants. For the homogenization of the product routes of a production the use of statistical methods like Modified Jaccard Index is feasible (Maschek et al., 2014). Other methods for identifying process-routes weaknesses and subsequent their improvement, such as Value Stream Mapping as a tool from the field of lean management are also evolving with the tools currently available to map, predict and control dynamic effects on value streams. Emerging technologies provide completely integrated production environments with real-time data gathering and transmission (Valamede & Akkari, 2020). The cloud connects all resources on the manufacturing floor to supervisory and control terminals and and combines data from different sources. This is combined with ontology-driven modeling-based graphical database technology or a multi-agent system based on Cyber-Physical Systems to visualize the productivity of customer-driven dynamic manufacturing processes. (Huang et al., 2019)

Another approach to simplify complex process systems is Process Mining. Based on business process management, Van der Aalst developed a method for analyzing the data of event logs of processes that uses the process knowledge implicit in these events to graphically represent process sequences and information of process steps on the basis of paths, thus making potentials visible (van der Aalst et al., 2012). Process mining techniques can help increasing the management productivity by modelling production planning processes in a manufacturing company (ER et al., 2018). With this information it is possible to identify the commonly unrecorded operations implemented to adapt the production plan to any changes in demand. This improves the ability to optimize its production process by balancing production efficiency and flexibility (Corallo et al., 2020). In combination with different IT systems of a company, process mining enables the visualization and optimization of both value-added production processes and their management and planning processes (Knoll et al., 2019).

Considering Burbidge‘s ideas, we see the consistent use of all data as a logical step to streamline processes by searching for similarities and forming groups, especially in highly complex systems. For IDS, using Process Mining in industrial systems is the logical next step in the development of Group Technology.

3.3. Quality Management – William E. Deming

Past. Quality Management (QM) holds an integral part of continuous improvement in IE, since it serves as a prominent starting point for process improvement and often acts as significant driver of costs. Early on, Taylor acknowledged QM as a crucial factor for the maximization of productivity in industrial processes. In the 1920s, Walter A. Shewhart recognized that preventing quality related issues is significantly more economical than sorting out defective parts or repairing them, as Taylor had suggested. His invention of Quality Control Charts serves as a static method for process control that allows for scientifically based and economically founded decisions based on recorded process metrics. For this purpose, it was necessary to develop target metrics and a tolerance range for all processes recorded on the control chart. The observed deviation between actual system performance and target metrics allowed for unprecedented levels of process monitoring and control (Shewhart, 1931). We consider William E. Deming, a student of Shewhart, as pioneer in the field of QM, for he specified and propagated the early ideas. While initially unnoticed in the Western world, Japanese companies adopted Deming’s methods in the 1950s and established his status as a visionary in QM. Particularly successful was the application of Statistical Process Control, which aimed for efficient process operation by producing more specification-confirmative products while causing less rework or scrap. Consideration of the temporal course of statistical values, such as current the range between actual and target metric, paired with the visualization on control charts allowed for detection of negative deviation as well as short-term adjustments during production (Deming, 1950).

Present. Several of Deming’s approaches can be found in widely used standards, such as the prominent PDCA-Cycle that is included in the ISO 9001. The principles of Statistical Process Control lead to the emergence of the ideal of Zero-Defect Manufacturing (ZDM) that modern manufacturing companies still seek to achieve. ZDM aims to reduce defects through prevention and targets the development of workers desire to perform a job correctly at all times (Wang, 2013). To quantifiably record the occurrence of any defects, manufacturing companies utilize different strategies or platforms to bundle the wide range of potential sources for quality data. Such collections allow using newer approaches, such as Machine Learning, to detect different types of defects on a large scale (Schulte et al., 2020). A mayor task is building autonomous QM systems that achieve trustworthy results within an Industry 4.0 setting, while remaining economically viable.

Future. Quality control is usually reactionary and can only detect defects, not proactively prevent them. As an ongoing research subject, modern QM is primarily concerned with predicting future quality. The increased data availability allows drawing conclusions about the quality of products that are still in production, only using the recorded process data. Utilizing supervised and unsupervised Machine Learning models, allows for advanced quality-based process control (Lieber et al., 2013). Additionally, it enables the prediction of quality-related features and identification of ideal process parameters (Schmitt et al., 2019) (Figure 3).

Random forest integrated inside the Bayesian optimization approach are one option to enable organizations to manage large-scale product quality prediction in process industrial cyber–physical systems (Wang et al., 2020). In another example, measurements such as tightening data of screw driving processes help to predict the final condition of engines without requiring end-of-line testing (West et al., 2021). Identifying process anomalies and predicting likely assembly defects with IDS enables early initiation of corrections, such as a partial deconstruction.

3.4. Production Control – Eliyahu M. Goldratt

Past. With the Theory of Constraints (ToC), Eliyau M. Goldratt introduced a novel approach to Production Control in 1984. According to ToC, the output of every production system is inevitably constrained by one single limiting factor. Similar to the weakest link in a chain, such a factor poses a bottleneck for the entire system. All improvement activities must target that bottleneck, since optimizations of non-bottleneck stations do not improve the performance of the system but cause increased Work in Process (Goldratt & Cox, 1984). With regard to Production Control, this meant that the control system must also primarily account for the bottleneck. To implement bottleneck-oriented Production Control, Goldratt proposed the Drum-Buffer-Rope (DBR) method. In the ToC, DBR is a method for process scheduling that increases production flow by leveraging the system's bottleneck (Goldratt & Fox, 1986). Through DBR, only a bottleneck needs scheduling, which is easier than scheduling every job at every station. In addition, the bottleneck's capacity provides a simple way to plan due dates, since it matches the system's overall output. Through the development of ToC and its application using DBR, Goldratt made an innovative contribution that shaped the further course of IE.

Present. While ToC and DBR were primarily aiming to manage static bottlenecks, modern production systems often encounter shifting bottlenecks. Due to variability-related factors, such bottlenecks move between workstations over time. Adaptations of the ToC, led to new methods for real-time bottleneck identification. Such methods require continuous monitoring of the production system, which only became possible in the last decade due to the increasing digitalization. Whereas Goldratt, for example, suggested interviewing employees to identify bottlenecks, these methods utilized quantified metrics. A prominent example is the Active Period Method (APM) that identifies a bottleneck as the station working the longest without interruption. APM assumes that stations in interconnected production systems starve or block each other. An active machine running for extended periods is more likely to block or starve other machines. Hence, the machine with the longest uninterrupted active period has the largest effect on the overall output and acts as the current bottleneck (Roser et al., 2002). Near real-time knowledge of bottleneck locations, as well as

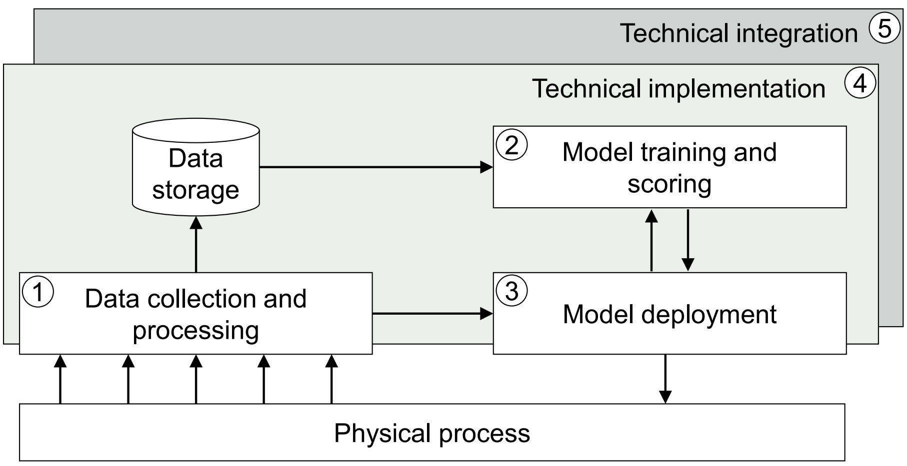

Figure 3. Framework for predictive model-based quality inspection (Schmitt et al., 2020).

knowledge of the relative frequency of occurrence, enables a targeted Production Control and real-time fault repair prioritization (Wedel et al., 2015). However, identification methods do not manage to avoid productivity losses at shifting bottlenecks, but only help to mitigate the effects.

Future. In modern manufacturing systems, identifying bottlenecks will continue to be the focus of research due to the prevailing dynamics of increasingly complex systems. To minimize bottleneck-related losses of potential outputs, anticipatory knowledge about future system behavior is required. This thought led to the idea of bottleneck prediction, as a current subject of research. Predicting a bottleneck shifting before it occurs, allows a production control system to counteract this change and prevent a shift. While established approaches for bottleneck detection require a measurable effect, their nature is similar to fire-fighting strategies known in maintenance. Only by anticipating an emerging bottleneck, the effect can be controlled without effecting the overall output. In addition, the recent idea of bottleneck prescription proposes a novel type of system that fully subjects a system‘s control mechanism to the predictions of future bottleneck occurrences (West et al., 2022). Since a bottleneck’s existence is inevitable, this approach will not eliminate a bottleneck, but it can avoid or reduce the adverse influence of shifting bottlenecks. Predicting bottlenecks requires a real-time, databased bottleneck identification capability (Deuse et al., 2016; Roser et al., 2017). While theoretical approaches to bottleneck prediction are emerging in the scientific literature, practical implementation represents a future need for action in IDS (Figure 4).

4. Discussion

The development of the individual fields of industrial engineering shows the strong connection to data analysis from the beginning. The pioneers mentioned, Gilbreth, Burbidge, Deming and Goldratt, proved the dependence of optimisation and improvement on data analysis. The present solutions prove the relevance of this approach equally. Industrial Data Science is therefore the logical evolutional step of working with data in Industrial Engineering. Many manufacturing companies face much more complex and complicated problems in parallel. For these companies, we consider Industrial Data Science as a novel tool that enables them to utilize the original ideas of the four pioneers in a more efficient, large-scale and goal-oriented fashion.

The different fields of IE need to be differentiated in this context. Every company uses the ideas of Gilbreth, Burbidge and Deming, in many productions they are even the basis of optimisations and the continuous improvement process in different sectors. The methods of Industrial Data Science *extend* the previous procedures making them reach the next stage of their development. Image recognition enables fast, accurate time recordings, machine learning enables the automatic creation of work plans of products of the same group and product and process quality can be dynamically detected, predicted and thus predictively improved in real time.

Industrial Data Science is influencing the field of Bottleneck Analysis, pioneered by Goldratt, in a different way. Although Goldratt‘s ideas have a fundamental character for all production systems,

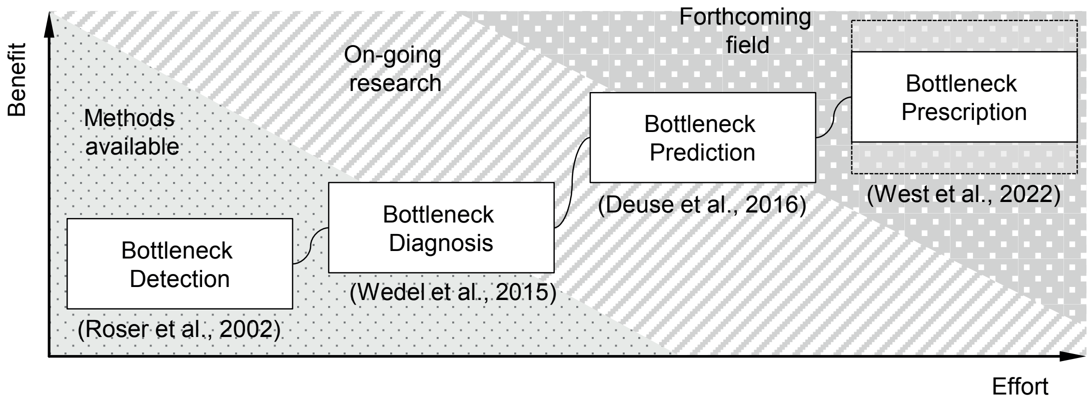

Figure 4. Methodology for Bottleneck Analysis with corresponding research based on West et al. (2022).

the detection of a bottleneck is not possible for every company with the developed methods. This is a result of the dynamic behavior of the different variables affecting the processes and consequently the occurrence of shifting Bottlenecks. In addition, different methods for bottleneck detection do not always have the same result. This complicates the interpretation of the analyses and their target-oriented use. The application of Industrial Data Science is an *Enabler* in this field, as it allows industrial users to generate more knowledge about their processes and to analyse a larger amount of data more precisely. This opens up the field of bottleneck analysis to a variety of other companies.

These two functions, *Enable* and *Extend*, can be transferred to other fields of IE. Kingman and Little, for example, are Pioneers in the field of Operations Research (Kingman, 1961). They have mathematically proven correlations between queue length, arrival time and utilisation of a system (Little, 1961). This dependencies are used to Material Flow and Buffer research questions in production environments in the literature (Lödding, 2013). This works under certain boundary conditions. In this field, Industry 4.0 and Machine Learning approaches can be both *Enabler* and *Extender* by enhancing the current limits of application of their ideas by capturing further influencing parameters, making them measurable and providing tools to recognise even more complex patterns (Gallina et al., 2021).

What applies to this practical field of IE can be transferred to the organisational field. Projects have existed for thousands of years, but it was not until the 1940s that US military industry-academic-research project management was formalized in institutional processes (Johnson, 2013). Getting combined with Systems Engineering and Operations Research later, it became an essential aspect of the Industrial Engineer‘s tasks (Johnson, 1997). As of today, the IIoT and different AI approaches connect project management directly to events the shopfloor.

With Lean principles as a pillar of IE and self-optimisation equally as a pillar of Lean principles, the question of effort and benefit in IE has always arisen. With the value-creating processes at the centre of its own basic idea, Industrial Engineering, as a staff unit only indirectly involved in value creation, constantly questions itself. Sustainable economic successes by finding the right balance between good work preparation and targeted continuous improvement have proven the role of IE in the past (Deuse et al., 2006). The expansion through and development towards Industrial Data Science poses the question of effort and benefit again. The initial effort to enable its production to use modern approaches to data analysis seems large. In addition to increasing the knowledge of the workforce involved, physical resources must be digitised or replaced, hardware must be purchased and installed, and software licences must be acquired. In addition to increasing the knowledge of the workforce involved, a company must digitise or replace physical resources, purchase and install hardware and acquire software licences. In addition, sensors support the former manual data acquisition, artificial intelligence helps with decisions or even relieves the industrial engineer.

The rapid development of recent years refutes those arguments in different ways. First, the initial costs on the hardware side are declining due to the high demand and the resulting sharp increase in availability. Open source solutions also make simplify starting with interface management and IIoT in order to be able to analyse data using different methods (Strauß et al., 2018). At the same time, the range of educational opportunities in the industrial sector has grown considerably, so employees can easily be empowered. Second and most relevant, digitalization and the application of IDS has a direct impact on a company‘s financial performance (Eller et al., 2020). The development of the individual areas of IE and the markets as such shows that a company without targeted digitization and the application of data science will not be marketable in the future. Strategic and operational implementation is essential for success (Dold & Speck, 2021). IDS helps the Industrial Engineer in multiple ways and sometimes replaces some decisions, but brings new challenges to the job profile. Domain knowledge is still indispensable for industrial issues, the industrial engineer must select and connect the right data sources as well as manage the targeted application of Hardware, AI approaches and employee‘s data-science-education. The benefits overcome the effort of implementing IDS mid- and long-term by a multiple.

5. Conclusion

The case studies of the pioneers of IE have shown the development of Scientific Management in four different domains as a rather evolutionary process. The contemporary trend towards a more widespread application of Industrial Data Science is an inevitable result of a decade-spanning development process. Leveraging the growing data sources is merely the next logical step in an environment that relies on fact-based and quantified decision-making. Thus, the application of Data Science in Industrial Engineering under the umbrella of Industrial Data Science will continue to grow in importance in the coming decades.

At their core, manufacturing companies will continue to use the original concepts of the discussed pioneers, but increase the effectiveness through the addition of digital and data-driven methods and tools, even in other fields of Industrial Engineering. Accessing, analyzing, applying and administrating data is going to be vital for future applications of Industrial Data Science.

The pioneers presented in the paper, as well as their associated research areas, were selected primarily due to their high relevance to IE. Nevertheless, these representatives have to be called a selection of pioneers. In the continuing development of Scientific Management since Taylor, many scientists have distinguished themselves. As research limitations, we would therefore emphasize the small number of pioneers studied and the selection of application examples.

For future competitiveness, an Industrial Engineer‘s collection of applicable methods and tools has to be expanded to accommodate for the capabilities of IDS. At the same time, companies must create the technical and educational basis for applying IDS in order to be able to assert themselves in the market. In addition, the multitude of requirements for an integrated and networked application of industrial data analysis in dynamic value creation networks will shape the further course of IDS research.

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