Managing Growing Uncertainties in Long-Term Production Management

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Günther Schuh, Andreas Gützlaff, Niklas Rodemann, Sebastian Pütz, Maria Linnartz, Soo-Yon Kim, Tino X. Schlosser, Steffen Schupp, Morten Endrikat, Martin Welsing, Michael Millan, Verena Nitsch, Stefan Decker, Sandra Geisler, and Volker Stich

Contents

G. Schuh · A. Gützlaff · N. Rodemann · T. X. Schlosser · S. Schupp · M. Welsing (✉)
Laboratory for Machine Tools and Production Engineering (WZL), RWTH Aachen University, Aachen, Germany
e-mail: g.schuh@wzl.rwth-aachen.de; n.rodemann@wzl.rwth-aachen.de; t.schlosser@wzl.rwth-aachen.de; s.schupp@wzl.rwth-aachen.de; m.welsing@wzl.rwth-aachen.de

S. Pütz · V. Nitsch
Institute of Industrial Engineering and Ergonomics (IAW), RWTH Aachen University, Aachen, Germany
e-mail: s.puetz@iaw.rwth-aachen.de; v.nitsch@iaw.rwth-aachen.de

M. Linnartz · V. Stich
Institute for Industrial Management (FIR), RWTH Aachen University, Aachen, Germany
e-mail: Maria.Linnartz@fir.rwth-aachen.de; Volker.Stich@fir.rwth-aachen.de

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Abstract

Long-term production management defines the future production structure and ensures the long-term competitiveness. Companies around the world currently have to deal with the challenge of making decisions in an uncertain and rapidly changing environment. The quality of decision-making suffers from the rapidly changing global market requirements and the uniqueness and infrequency with which decisions are made. Since decisions in long-term production management can rarely be reversed and are associated with high costs, an increase in decision quality is urgently needed. To this end, four different applications are presented in the following, which support the decision process by increasing decision quality and make uncertainty manageable. For each of the applications presented, a separate digital shadow was built with the objective of being able to make better decisions from existing data from production and the environment. In addition, a linking of the applications is being pursued:

The *Best Practice Sharing App* creates transparency about existing production knowledge through the data-based identification of comparable production processes in the production network and helps to share best practices between sites. With the *Supply Chain Cockpit*, resilience can be increased through a data-based design of the procurement strategy that enables to manage disruptions. By adapting the procurement strategy for example by choosing suppliers at different locations the impact of disruptions can be reduced. While the *Supply Chain Cockpit* focuses on the strategy and decisions that affect the external partners (e.g., suppliers), the *Data-Driven Site Selection* concentrates on determining the sites of the company-internal global production network by creating transparency in the decision process of site selections. Different external data from various sources are analyzed and visualized in an appropriate way to support the decision

S.-Y. Kim
Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany
e-mail: soo-yon.kim@rwth-aachen.de

M. Endrikat
Research Unit International Economics, RWTH Aachen University, Aachen, Germany
e-mail: morten.endrikat@rwth-aachen.de

M. Millan
Institute for Technology and Innovation Management (TIM), RWTH Aachen University, Aachen, Germany
e-mail: millan@time.rwth-aachen.de

S. Decker
Information Systems and Databases (DBIS), RWTH Aachen University, Aachen, Germany

Fraunhofer Institute for Applied Information Technology (FIT), St. Augustin, Germany
e-mail: decker@dbis.rwth-aachen.de

S. Geisler
Data Stream Management and Analysis (DSMA), RWTH Aachen University, Aachen, Germany
e-mail: geisler@dbis.rwth-aachen.de

process. Finally, the issue of sustainability is also crucial for successful long-term production management. Thus, the *Sustainable Footprint Design App* presents an approach that takes into account key sustainability indicators for network design.

16.1 Introduction

Production management faces a variety of challenges. Increasing uncertainty combined with growing complexity hinders decision-making and reliable planning. However, shorter product life cycles and disruptive changes require rapid adaptation to change. The benefit of the Internet of Production for production management is to provide data-driven decision support on all levels of managing production in dynamic company environments (Schuh et al. 2019a). Long-term production management sets the future production structure and determines long-term competitiveness. Due to rapidly changing global market requirements and the uniqueness and infrequency of the decisions to be made, it is difficult to achieve a high decision quality (Lanza et al. 2019). However, these decisions in long-term production management are associated with significant costs and can hardly be reversed (Balderjahn 2000). Therefore, the aim of this research work is to improve decision quality despite uncertainty through data-driven decision support. The use of historical data from the company and its environment is combined with appropriate analysis and methods. Decisions in long-term production management are always dependent on the knowledge and experience of the management, so that the interactivity and usability of the data-driven decision supports plays a decisive role in practice (Schuh et al. 2019b).

The data-driven decision support tools are developed for specific tasks and challenges in long-term production management. The *Best Practice Sharing* application aims to facilitate knowledge transfer across sites. In this way, production sites can learn from each other and adapt more agilely to changes. The *Supply Chain Cockpit* can be used to increase resilience through a data-driven design of the procurement strategy to persist in times of disruption. Data from company's internal business application systems like orders and material master data from an ERP system are used to characterize a company's procurement strategy. The approach also explores how improving data quality can drive such data-driven decisions, since the quality of the data included is critical. In the application *Data-driven Site Selection*, the complex process of site selection can be improved in terms of decision quality by using external data such as quantitative and qualitative data from macroeconomics, microeconomics, political economy, foreign trade, and foreign direct investment. A corresponding procedure as well as extensive databases are presented and applied. Further, the growing importance of sustainability is considered in the application *Sustainable Footprint Design*. By means of a software solution, existing cost-based approaches are supplemented by sustainability parameters.

The practical realization of the described decision support tools takes place through the development of a Production Control Center for long-term production

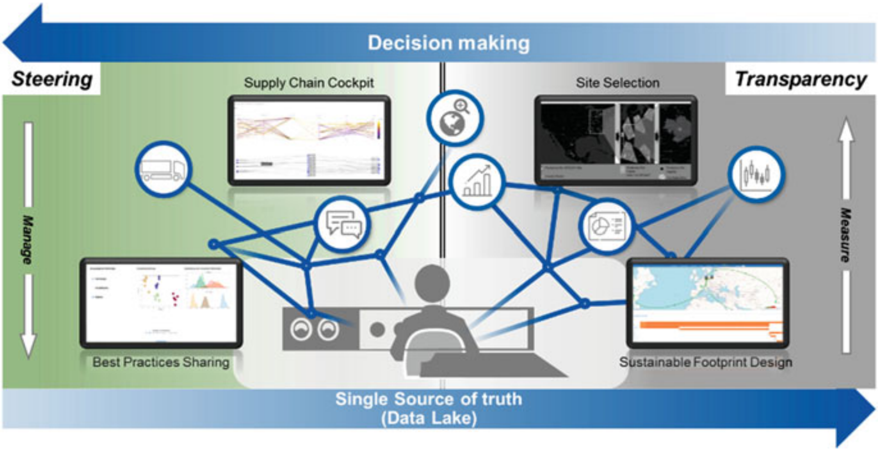

Fig. 16.1 Production Control Center for long-term production management

management. Interlinked applications contribute to increasing decision-making quality under consideration of uncertainty in the production environment. Context-specific data from the IoP data lake is used in the sense of a control loop to generate data-driven transparency via the various applications with regard to emerging adjustment needs and to address these by deriving and implementing suitable measures (Fig. 16.1).

The four applications developed, their specific challenges, the methods used, underlying digitals shadows, and the results obtained through interdisciplinary research are described in detail in the following Sects. 16.2, 16.3, 16.4, and 16.5. Closing, a short summary and outlook is given in Sect. 16.6.

16.2 Best Practice Sharing in Global Production Networks

The sites of manufacturing companies are often globally distributed and form complex and historically grown production networks (Lanza et al. 2019). As a consequence, the sites of these production networks have developed individually and independently of one another and exhibit differences in performance within the network (Reuter et al. 2016). Systematic knowledge transfer between different production sites is not frequently practiced, although globally active companies carry out comparable production processes in different ways at several locations (Schuh et al. 2019a). However, a systematic exchange of best practices in the global production network enables production sites to learn from each other and minimize variance in performance (Friedli et al. 2014). Furthermore, the exchange of knowledge can increase the ability to react to unexpected events by learning from the experiences of others, which makes cross-site knowledge sharing a success factor (Cheng et al. 2008). At the same time, companies face a major challenge when implementing systematic best practice sharing due to the high number and complexity of different production processes in practice (Deflorin et al. 2012).

In the field of knowledge transfer within production networks, there are various approaches that focus on different aspects. Depending on the knowledge type, several approaches suggest distinct transfer mechanisms and develop solutions to increase the absorptive capacity of the recipient (e.g., Nonaka 1991; Ferdows 2006). Often also social aspects of knowledge transfer are considered, but rarely a practical solution to increase transfer acceptance is proposed. In addition, the topic of initiating a knowledge transfer has not yet been adequately addressed, nor have the possibilities of new methods for data analysis and new information technologies for efficient preparation of the knowledge transfer. In general, existing approaches focus only on single criteria to increase the efficiency of the knowledge transfer, but to our knowledge, no approach to date addresses all needs for learning across sites from transfer initiation to transfer mechanism to empowering knowledge assimilation. Thus, there is a need for a holistic approach to enable the implementation of efficient knowledge transfer in production networks (Schuh et al. 2020a). The presented approach tries to close this gap.

16.2.1 Approach for Best Practice Sharing in Global Production Networks

The approach for cross-site best practice sharing is divided into three steps starting with the identification of the requirements for comparing production processes in production networks, followed by determining the utility for cross-site learning and finally performing an efficient and user-friendly transfer of knowledge.

The first step creates the foundation for learning across sites by enabling the comparability of diverse production processes within a global production network. For this purpose, a solution space is defined to determine which types of production processes can be compared under which conditions. In addition, a target system is defined. In this way, only meaningful knowledge transfers between comparable production processes are allowed and the motivation of knowledge transfers between sender and receiver can be maintained. This requires a description of production processes in order to identify comparable processes across sites. Following Steinwasser, a production process is defined as a composition of product and resource (Steinwasser 1996). Constituent features were developed for both product and resource. For example, a product can be described in terms of its materials, size and weight, or a resource in terms of its degree of automation, machine designation or the necessary employee skills. On the basis of the features and their values, a precise description of the production processes is possible, which is transferred into a data model to enable the data-based mapping of the process description. The sources of the required data are the company-specific information systems such as ERP, MES, PLM, or CRM. Next, a cluster algorithm is used to identify where comparable production processes exist in the production network concerning metric product and resource characteristics (e.g., product weight). If a production process belongs to a cluster is determined by the distance of the characteristics between the individual objects. For clarity, the categories material and technology are plotted on the screenshot of the prototype as an example. The points in the graph each represent a production process. The individual production processes can be entered on the graph with regard to their material and technology. It should be noted that non-numeric features (e.g., material) are converted into binary features. Production processes of a cluster are characterized by the fact that they are close to each other in the considered categories, i.e., the distance between the points in the graph is low. Currently, only two categories can be displayed next to each other in the prototype in order to analyze the differences between the clusters. An extension is being worked on to be able to determine the decisive categories in view of the large number of categories. The two other diagrams in the screenshot allow the user to further analyze the similarities. For example, they show how the various clusters (each color represents a cluster) differ in the categories under consideration. The lower diagram in particular illustrates that there is a clear division of the clusters in terms of technology. However, even here there are overlaps between two clusters that can be caused by a different category.

The decision whether the identified production processes are comparable is made by the user within the qualitative evaluation of the results and a plausibility check. The described approach is already implemented in a prototype including a feedback loop to enable the evaluation of comparability by the user. Furthermore, the prototype has already been evaluated with real data from a coupling manufacturer and it was shown that the approach allows the identification of comparable production processes, but that a weighting of the characteristics has to be done by the user to ensure plausible results (Fig. 16.2).

Fig. 16.2 App prototype for best practice sharing in global production networks

The second step of the approach is to identify the knowledge transfer needs based on the determined cluster of comparable production processes. A cluster of comparable production processes does not necessarily require a need for knowledge transfer, as these processes may already be coordinated with each other. A knowledge transfer always involves effort and should only be carried out when there is a need. Therefore, feedback from production can be used to analyze the performance of production processes. Statistical process control (SPC) is a commonly used method for monitoring processes and to automatically detect process deviations. For the implementation of SPC statistical control charts are used to systematically analyze the output of processes. Upper and lower control limits (UCL, LCL) are determined as a function of the mean value of the outputs within a process cluster (Chatti et al. 2019). For process monitoring in production networks, an adaptive control chart is required because the design parameters vary over time. For example, the width of the control limits must be adapted according to the sensitivity of the processes in a company-specific manner. As an outcome of SPC, process deviations within a cluster of comparable processes can be identified and the upper and lower control limits can be utilized as knowledge transfer trigger points.

If there is a need for learning across sites, the third step should be to make the knowledge transfer as efficient and user-friendly as possible so as not to consume too many resources and not to reduce the motivation of the sender and receiver of the transfer. Therefore, an appropriate knowledge transfer mechanism is required. Here, the right transfer mechanism depends on the type of knowledge and the background of the participants of the transfer (e.g., Chang and Lin 2015; Shen et al. 2015; Asrar-ul-Haq and Anwar 2016). Within the research work an approach to select a communication medium depending on the situation was developed. The approach characterizes a knowledge transfer situation on the basis of three groups: knowledge type (explicit or tacit/implicit knowledge, its complexity, its specificity, and its significance for the receiving unit's performance in cost, quality, and adherence to schedules), communication situation (number of hierarchical levels involved, number of knowledge recipients, degree of familiarity between the participants, prior knowledge levels of the recipients and the participants' language skills), and the urgency of the transfer (Schuh et al. 2020b). Once a knowledge transfer situation has been characterized, the relevant characteristics can be weighted using a metric and a requirement level can be calculated. Depending on the requirement level, the appropriate communication medium can subsequently be selected. For global production networks, the following media are suggested as possible means of communication: face-to-face, video/telephone conference, video/telephone call, short message, email, and the companies' intranet database. The selection of the right medium depends on the need to be able to receive feedback and whether sending non-verbal signals is beneficial. In addition, the usage effort in the context of daily application is important and influences the selection of the medium for a knowledge transfer situation.

16.2.2 Outlook of Best Practice Sharing in Global Production Networks

While the current development of the Best Practice Sharing application focuses on inducing knowledge transfer to optimize the productivity of production processes, overall productivity is not the only criterion in production system design that can be addressed using the outlined approach. Following the agenda of the International Ergonomics Association, work system design should always jointly consider the two objectives of system performance (i.e., system productivity) and human well-being (IEA Council 2020). Not only are both goals of significant value in their own right, but they also tend to complement each other, leading to an alignment of business and social goals (Neumann and Dul 2010). Expanding the framework of the Best Practice Sharing application to include an anthropocentric perspective aimed at improving human working conditions thus offers the opportunity of a more holistic approach to process optimization. First, the aspects that are considered for identifying similar processes can be extended by adding task characteristics of the involved production workers. Second, the evaluation system that is used to compare similar processes and to identify knowledge transfer opportunities can be expanded to include metrics and assessment methods that quantify the impact of the production system design on workers. Here, a special focus can be placed on the imposed physical and cognitive workload. While the outlined advancement of the Best Practice Sharing application is the subject of current research efforts, the first results are presented and discussed in the publication ▶ Chap. 22, "Human-Centered Work Design for the Internet of Production"

16.3 Supply Chain Cockpit – Improving Data-Driven Decisions in the Context of Procurement

Companies are part of complex supply chains and operate in an increasingly volatile environment (Kamalahmadi and Parast 2016). This affects procurement which focuses on the supply of external materials and parts required for the internal processes (Pereira et al. 2014). Current developments show that the complexity of companies' procurement processes is increasing, which contributes to a higher vulnerability to supply chain disruptions (Piya et al. 2020). A means to prepare for disruption is strengthening the company's resilience. Supply chain resilience involves reducing the likelihood of facing sudden disruptions, resisting the spread of disruptions by maintaining control over structures and functions, and recovering and responding through reactive plans to overcome the disruption and restore the supply chain to a robust operating state (Kamalahmadi and Parast 2016). Resilience is significantly influenced by long-term decisions which makes the design of the procurement strategy particularly important (Pereira et al. 2020). To take into account various factors that influence the procurement strategy and ensure objective decisions, data-based approaches for decision support are required. Especially for long-term decisions, the quality of data plays a major role: insufficient data quality hinders the exploitation of data-based decision support. Therefore, this approach aims at analyzing how the data-based design of the procurement strategy can increase resilience and also investigates how improving data quality can enable such data-based decisions.

16.3.1 Data-Based Design of the Procurement Strategy

Through the design of the procurement strategy, a company specifies the fundamental design of the supply processes. It determines for example from how many suppliers what type of objects are purchased (Lasch 2019). Since each manufactured product requires different articles and raw materials, and the various articles have different characteristics, the procurement strategies must be adapted accordingly (Schiele 2019). The main objective of this research is to identify "how the procurement strategy can be evaluated and designed based on internal and external data to ensure high logistics performance in an uncertain environment" (Linnartz et al. 2021). By taking into account different data sources and considering the criticality of purchased articles the complexity can be handled. This allows a systematic design of the procurement strategy that focuses on the articles with a major impact on resilience.

Existing approaches for procurement strategy design rarely use business data to assess the procurement strategy or supply risks but instead focus on qualitative assessments. In order to increase resilience in procurement, recommendations for designing the procurement strategy and an evaluation of purchased items concerning the supply risks are required. Data-based approaches are currently uncommon in the context of criticality assessment of these items, as they require an overview of various risks and criticality factors. Nevertheless, it becomes apparent that a data-based approach is necessary for such an assessment to ensure objectivity (Linnartz et al. 2021).

The proposed approach is based on a combination of action research and the CRISP-DM (Cross Industry Standard Process for Data Mining) framework for data mining projects. It builds on three action research cycles, which are detailed according to the different phases of CRISP-DM. Within the first cycle, an application is developed that supports the characterization of purchased articles with regard to supply risks. In the second cycle a calculation logic to identify success-critical purchased articles is designed, while the third cycle focuses on adapting the application to ensure general applicability (Linnartz et al. 2021).

The current results focus on the first action research cycle and contribute to increased transparency of the procurement situation. For a structured evaluation of purchased articles and supply risks, a systematic literature review was conducted. It aimed at identifying and structuring relevant supply risks that need to be considered when designing the procurement strategy. The identified supply risks were divided into five categories, including factors such as transport complexity or natural hazards. Additionally, factors to characterize purchased articles were systematically identified building on existing raw material criticality assessments. The framework for purchased article characteristics contains both supplier-related factors, like their location or delivery reliability, and non-supplier-related factors, for instance, economic aspects (price volatility, purchasing volume, etc.) or product characteristics (specialization, substitutability, etc.). It serves as the basis for implementing an app prototype that supports companies in analyzing their purchased articles.

The app prototype integrates data from the company's business information systems and classifies purchased articles based on different characteristics. The characteristics are described through indicators. In the upper part, each column represents one indicator and its expression using a vertical scale. As an example, the app contains the indicator "number of potential supplier" which is derived from past orders, material master data, and supplier master data from an ERP system. Another example is the indicator "transport distance" which is calculated using the location of a supplier. Each horizontal line represents one purchased article and its values regarding the indicators. It thus gives an overview over the specific combination of a purchased article's characteristics. Different colors enable to highlight one characteristic and further contribute to an increased transparency of the procurement situation. The app prototype further allows for multidimensional filtering. Further below, product and supplier data are linked to show how final products (left), purchased articles (middle), and suppliers (right) are connected to each other. The lines in the left part of the sankey diagram demonstrate which purchased articles are part of which final products. The lines in the right part demonstrate which supplier delivers which purchased article (Fig. 16.3).

The developed frameworks for structuring supply risks and characterizing purchased articles are the foundation for analyzing the interdependencies between article characteristics and supply risks. Further research focuses on developing a calculation logic to identify critical articles which will be integrated into the app prototype.

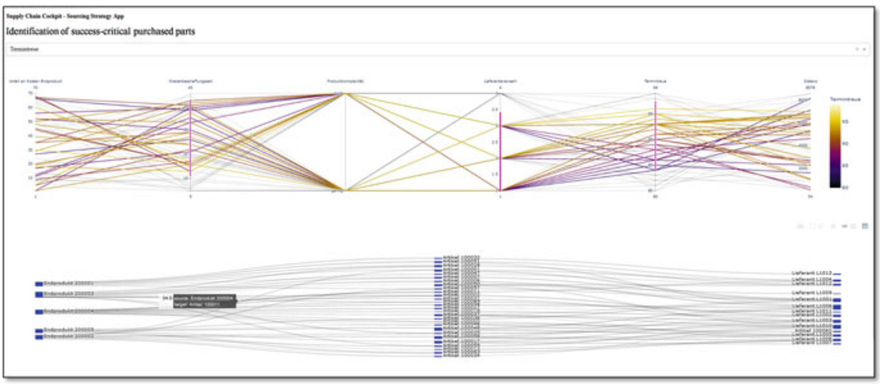

Fig. 16.3 App prototype for increasing transparency of current procurement situation

16.3.2 Master Data Quality Improvement

In the context of the *Supply Chain Cockpit*, the topic of master data quality is also being developed in an interdisciplinary research project. A crucial aspect for a data-driven procurement strategy design is the quality of the incorporated data. However, this aspect can also be applied to all other decision supports presented. Unreliable data can bear high costs for businesses and may lead to poor strategic decisions (Haug et al. 2011). Data about the most essential entities within a business, such as suppliers, employees, or materials, is called *master data*. Master data presents the fundament for many business decisions: For example, replenishment times of purchased articles are used in production planning and sourcing. While the need for high-quality master data is clear, several challenges arise regarding its realization. For one, the lack of responsibilities for maintenance of master data presents a main quality barrier (Haug and Albjørn 2011). Furthermore, a lack of both, intra- and cross-company data standards, may limit master data's fitness for shared use (Otto and Österle 2016). This occurs for example, when supplier and purchaser intend to refer to the same product, but run into issues as they each maintain their own product master data. Our work aims at developing a data ecosystem model for the procurement context which captures how master data is produced, maintained, and used. This model will serve as the fundament for an application that identifies and prioritizes data quality requirements in master data and gives actionable recommendations for quality improvements.

Data quality can be described in the form of various dimensions, such as accuracy, completeness, or timeliness. There exist approaches to identify relevant dimensions per master data class (Falge et al. 2012) and to develop master data management frameworks incorporating data quality (Otto and Österle 2016). The approaches rarely focus on illustrating the environment and contexts in which data is produced, exchanged, and used. An emerging concept for modeling such an environment is data ecosystems (Geisler et al. 2021; Oliveira and Lóscio 2018). Data ecosystem models incorporate components such as the resources of interest, the involved actors, and their relationships to each other, but also the key elements regarding the functionality of the ecosystem, such as data operators, security, and services. While there exist several reference models for general business collaborations (Otto et al. 2019), there is a need to adapt these models to the context of supply chain management and procurement.

We propose a design science research approach (Hevner et al. 2004) for developing an adapted data ecosystem model. A literature review on the "flows" of master data will be conducted, i.e., the processes in which master data is generated and maintained as well as an analysis on which master data is used in which procurement decision. Incorporating this knowledge, a first model, adapted from existing reference models, will be built. The model will be applied and evaluated on use cases and consistently refined.

As a first result, existing data ecosystem models have been analyzed and a framework for an adapted model has been developed. The framework comprises five levels. The first level specifies the business processes and involved actors. In the second level, the relevant master data is elaborated and connected to the processes from the first level. This mapping of data onto processes is used in the third level to derive data quality metrics appropriate to the context in which the data is used. On the base of those metrics, the quality of data is evaluated. In the fourth level, required functionalities are formulated, e.g., regarding security. Finally, governance aspects such as policies are contained in the fifth level. By structuring the framework into these levels, a detailed analysis of the aspects that have to be taken into account when improving the data quality is enabled.

The developed model is intended to reveal requirements for master data quality management in the procurement context as well as to highlight how data quality aspects can reduce risks and leverage opportunities in the functionality of such an environment.

16.4 Data-Driven Site Selection

Supply bottlenecks, increasing regulations and growing market uncertainties pose major challenges for global production networks and force companies to constantly adapt to new conditions (Lanza et al. 2019). In this context, the search, evaluation, and selection of potential new locations is an important factor in ensuring the future competitiveness of manufacturing companies.

According to the approaches in the literature, location factor systems are usually classified according to global, regional, and local aspects (Burggräf and Schuh 2021), but there is no consensus-based location factor system, since location factors cannot be clearly delimited and overlapping aspects exist (Haas 2015). In general, location factors can be divided into quantitative and qualitative aspects (Hansmann 1974), whereby internal and external factors (Hummel 1997) and network aspects also play a role (Kinkel 2009). Furthermore, country- and sector-specific differentiations are possible (Hummel 1997). A distinction between hard and soft location factors is also required. Hard location factors are characterized by quantitative data (e.g., wage costs, taxes) and soft factors by qualitative data (e.g., political stability, culture) (Kinkel 2009), whereby all factors must ultimately be aligned in the location evaluation. The evaluation of location alternatives is carried out using established methods such as utility value analysis (Zangemeister 1976), checklists, or country rankings (Kinkel 2009). Since these established methods require the evaluation of both qualitative and quantitative data, a large number of subjective decisions are made, especially with regard to qualitative data (Blohm and Lüder 1995). However, these evaluation methods do not fully reflect the complexity of the current environment and thus do not adequately meet today’s requirements (Burggräf and Schuh 2021). Since the development of new locations is associated with high, often irreversible costs, an approach is required that takes into account quantitative, objectively assessable information in particular (Verhaelen et al. 2021). Therefore, this subchapter presents an approach for systematic and data-driven decision support in the site selection. This makes it possible to map all factors by means of exclusively quantitative data. This can increase the quality of decisions as well as the transparency in the decision-making process in order to improve site selection on a global and regional levels.

16.4.1 Data-Driven Site Selection Framework

In the following, a four-step approach is presented, which objectifies the site selection process individually for each company (Schuh et al. 2022).

16.4.1.1 Step 1: Analysis of the Industry Sector, Its Dynamics, and Competitors

The first step is to analyze the business environment in order to identify possible trends and changes. Detailed sector analyses already provide a high added value, as they deepen the understanding of the strategies of competitors, the needs of the markets, and possible future developments. Existing clusters of competitors provide valuable information about potential regions for new locations, as they, in combination with region-specific economic and political indicators, allow conclusions to be drawn about the background of past location decisions. The identified agglomeration effects have a significant influence on location decisions not only against the background of possible knowledge transfers, but also with regard to available resources (Krenz 2019). The evaluation of geocoded information on foreign direct investment in production locations is suitable for determining existing clusters. Such representations also allow for the calculation of distances and travel times as well as the combination of such data with other data sets on topography, geography, and infrastructure. Panel (a) of the GIS-supported competitor and supplier analysis shows the investment projects in production sites of foreign automobile manufacturers in North America in the period 2010 to 2019 and the identification of clusters using an appropriate density-based spatial cluster algorithm in panel (b). Furthermore, in panel (c) comparable investment projects of the automotive supplier industry are localized in the same period. The agglomeration of supplier locations within a radius of 3 h travel time around the OEM locations is clearly visible for the exemplary extract (Fig. 16.4).

16.4.1.2 Step 2: Analysis of Regional and Supra-regional Location Determinants

To further narrow down the location alternatives, potential regions are evaluated in the second step top-down with regard to relevant criteria (Wiendahl et al. 2014). The analysis is also possible without a prior industry sector and competitor analysis, but it offers the possibility of implicitly comparing one's own location assessments with those of the competition. Relevant variables should include as many dimensions as

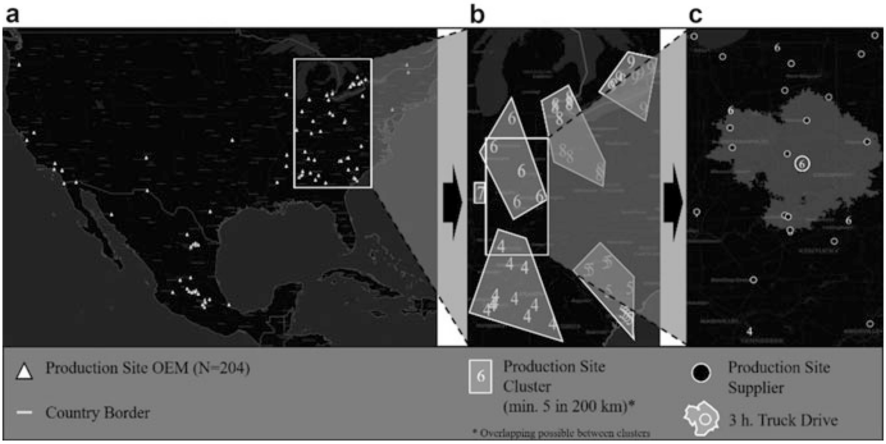

Fig. 16.4 GIS-supported competitor and supplier analysis

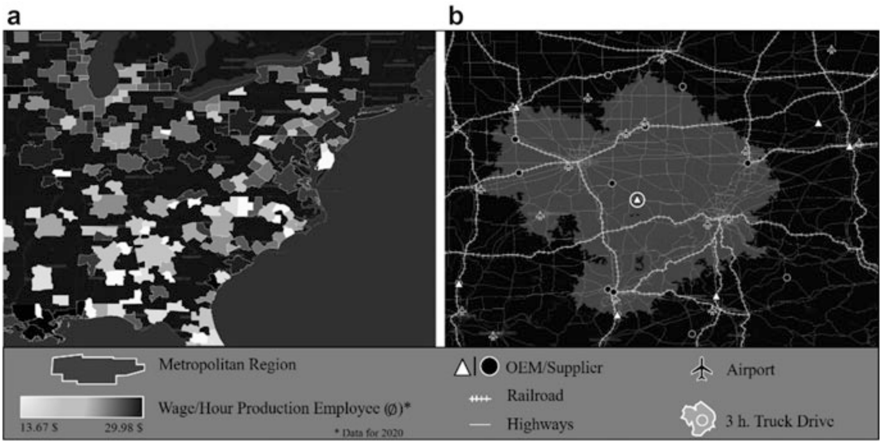

Fig. 16.5 Sample visualization of regional labor market and infrastructure parameters based on data from the U.S. Bureau of Labor Statistics and FDI Markets

possible, whereby the exact information required is ultimately case-specific and can include economic, political-economic, foreign-economic, infra-structural as well as geographical and topographical variables. In the sample visualization of regional labor market and infrastructure parameters based on data from the U.S. Bureau of Labor Statistics and FDI Markets, it is shown how the analysis is initially narrowed down from a global level to a national level (panel (a) for the eastern United States) and further to a local level (panel (b) for the Indianapolis/Cincinnati metropolitan area). It shows that significant differences (e.g., in wage levels or the availability of skilled labor) can also differ both nationally and regionally (Fig. 16.5).

16.4.1.3 Step 3: Comparison of Potential Locations Using a Target Function Method

The third step is to quantitatively evaluate and compare the potential locations. In order to integrate the large number of variables, which can be grouped into different dimensions in terms of content, into a common framework, an analysis using a target function method is suitable. The variables are standardized and combined into appropriate groups of assessment dimensions. These evaluation dimensions are then weighted. The weighing has to be defined individually for each company and even for each project. A pairwise comparison is recommended, in which the different dimensions are prioritized against each other and the weights of the assessment dimensions can be derived from this. In the methodology described, the weighting of the evaluation dimensions is the only decision to be made subjectively by the management. All other steps in the site selection process are based on quantitative data. The methodology now allows the calculation of marginal rates of substitution, a common concept in economic utility theory. This makes it possible to quantitatively assess cross-border decisions on a national, regional, and international level.

16.4.1.4 Step 4: Sensitivity and Scenario Analysis for the Ranking of Alternatives

In the last step, the ranking of the alternatives must be checked with regard to their resilience. Compared to other approaches, this minimizes the risk that the derived recommendations for action are influenced by measurement errors in the raw data or misspecification of the target function due to subjective misjudgments. Possibilities for sensitivity analyses are, for example, the (slight) variation of the weights or the variation of the indicators used. In addition to the sensitivity analysis, a scenario analysis is carried out based on the target function method. On the one hand, scenarios can concern company-specific factors, such as different forecasts regarding future growth strategies. On the other hand, scenarios can also be differentiated with regard to location factors, especially if not only present and past values are taken into account for certain valuation dimensions, but also projections about their future development. Based on the ranking with regard to the objective function and the resilience of the alternatives, the suitable location alternative can now be derived.

16.4.2 Conclusion and Outlook of Data-Driven Site Selection

This subchapter presents a systematization of site selection by means of a data-driven approach that creates the preconditions for more objective decisions compared to existing approaches. The step-by-step approach and the economic data on which the selection process is based combined with geo-information, allow better location decisions. This approach offers the user an improved understanding of the information through the data-driven approach and the underlying empiricism paired with the geo-designed visualization and provides decision support. Compared to other established approaches, the described methodology provides an increased degree of transparency and objectives in the decision process. All decision-making steps are mapped as quantitative data with regard to both soft and hard factors and are therefore transparent, measurable, and comparable. In the next steps, the approach will be expanded to include further functions. For example, an assessment of the dynamics of industries and the development of industrial clusters will be used to derive patterns. The resulting insights about future emerging regions should help companies to realize first-mover advantages by being able to develop regions at an early stage.

16.5 Sustainable Footprint Design App

The location of an industrial activity is a major influence to determine whether it is sustainable or not (Sihag et al. 2019). Depending on the environmental and societal conditions around a factory, renewable resources can be provided in different quantities (May et al. 2020). Therefore, the relocation of production processes can enhance the sustainability of a company without any changes to the processes or products. For example, water-intense production processes should be moved from regions with water scarcity to regions with sufficient precipitation to enhance the ecological footprint. To benefit from this potential, companies need to evaluate their production footprint not only with respect to their economic advantage, but should also consider the social and ecological consequences of their global production network. However, it is widely acknowledged that global production networks of manufacturing companies are one of the most complex and dynamic man-made systems (Váncza 2016). Hence, the required level of transparency is only possible with database solutions. The Sustainable Footprint Design App is a web-based application with the ability to provide decision-makers in industrial cooperation with all crucial information to evaluate the site-dependent sustainability criteria of their production network.

Several authors have identified both, the need for and the challenge of a transparent evaluation of global production networks. This section provides a brief overview of existing approaches and compares them with the unique vantages of the Sustainable Footprint Design App. Mourtzis et al. present a toolbox for the design, planning, and operation of manufacturing networks. This software required data about the plant capabilities, locations as well as the bill of materials and processes to evaluate a production network with respect to cost, lead time, quality, CO_2 emissions, and energy consumption. Other relevant sustainability criteria like water, waste, or biodiversity are not part of the evaluation scope (Mourtzis et al. 2015). The approach of Govindan et al. supports the design of a sustainable supply chain network with the use of hybrid swarm intelligence metaheuristics. Although this considers a broad variety of sustainability-related criteria, the optimization model is too complex for adaption in the industrial practice, due to its extended data requirements (Govindan et al. 2019). The web-based platform for eco-sustainable supply chain management from Papetti et al. trace supplier and their processes. Additionally, this information can be used to perform a life cycle assessment of these processes within the tool. With these features, the tool provides both transparency and a comprehensive ecological evaluation. However, the focus is on suppliers and not on intra-organizational processes (Papetti et al. 2019). The MS Excel-based toolbox of Blume is designed to evaluate the resource efficiency in manufacturing value chains. This approach includes economic and ecological criteria, but does not focus on the characteristics of production networks. It can be seen that no approach takes ecological factors into account to a sufficient extent in the design of global production networks. The following section presents an approach to this problem.

16.5.1 Approach for Sustainable Footprint Design

The Sustainable Footprint Design App allows the calculation of all ecological key performance indicators (KPIs), which can be influenced with the design of the production network. This is the case, if a site-dependent factor is combined with the characteristics of a production process. For example, a machine might need a lot of thermal energy for a production process and the possible production locations can provide either geothermal heat or fossil fuel-based heat. In that case, the difference of CO_2-Emissions can be influenced by the network design and is included in the set of ecological KPIs.

The Screenshot of the Sustainable Footprint Design App with Emission-KPIs shows how the CO_2-Emission are visualized in the app, which is based on the existing software *OptiWo* (Schuh et al. 2019b). The upper part contains a map with the locations and transport connections of the production network. The size of the arrows and bubbles presents the absolute amount of emissions, while the color represents their intensity (e.g., emissions per part). Other KPIs, which are included in the tool, are the amount of energy required by each machine, facility, and transport vehicle. For every energy consumed the corresponding emissions are calculated. In addition, the required water and effluents at each location are combined with the local water stress to evaluate the water footprint. Further, the amount recycled feedstock and waste material are estimated with respect to the local recycling infrastructure. On top of this, the land use of each location is set into context with the local biodiversity (Fig. 16.6).

Besides the described ecological KPIs there is also the option to evaluate additional ecological, social, and governmental KPIs on a holistic country level for a further benchmark of the existing production network. For an assessment of countries' ecological performance we selected 41 KPIs focusing on emission, pollution, energy, agriculture, biodiversity, resource productivity, waste, and water. Eight social KPIs cover equality and diversity, workforce, and hygiene performance of the respective country. For an evaluation of the governmental risks and opportunities of the country, six KPIs were included in the tool. In total 55 KPIs were included from

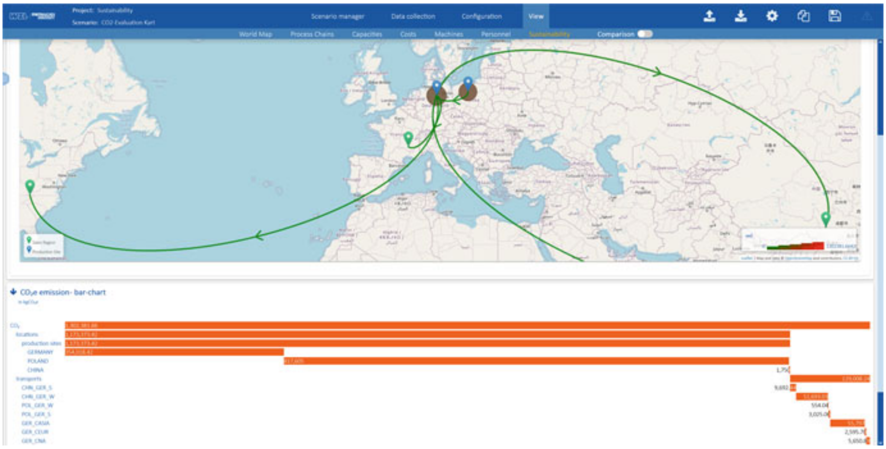

Fig. 16.6 Screenshot of the Sustainable Footprint Design App with Emission-KPIs

160 countries and with a timespan of more than 15 years ensuring an historical assessment and performance tracking. The set of KPIs is based on the following sources: United Nations Statistics Division, 2020 Environmental Performance Index Report (EPI) and the World Bank and Global competitiveness reports from 2006 to 2019. Data, which is company specific and cannot be found in public database needs to be imported by the planner from local IT-systems, such as ERP, MES, PLM, or FMS. For an assessment, the percentile rank scoring methodology is applied to calculate an overall score for each KPI per country. The calculation is based on the following aspects: countries with worse score, countries with same values, and countries with a value at all. Besides the overall score from zero to one per KPI, a best-in-category value and the respective country name are displayed. An aggregated environmental, social, and governmental score per country is also available.

The tool creates transparency for companies due to an aggregated and bundled overview of important sustainable KPIs. With this they can quickly select relevant KPIs, e.g., hiring and firing practices or the estimate for control of corruption and assess countries, which they are operating their production in, with best-in-class countries.

16.5.2 Conclusion and Outlook of Sustainable Footprint Design App

The app demonstrates how the production footprint design can enhance the sustainability of a manufacturing company. To benefit from all possibilities, a close integration with existing IT-systems like the ERP or MES is required. The design and implementation of such APIs remain a future research topic. Another challenge is the need to transfer the insights gained from the transparency of the app into strategic guidelines and operational measures to change the production network. Further, the relocation of production processes to enhance sustainability should always be a midterm solution for process technologies, which cannot be adapted easily. For a truly sustainable manufacturing company, all processes must be redesigned to reduce their negative impact on nature and society.

16.6 Conclusion

In this paper, the work of the IoP's long-term production management research group was presented. This includes four individual and partially interlinked applications that address a variety of issues in long-term production management. They pursue the common goal of data-driven decision support in the Production Control Center in order to increase the decision quality concerning uncertainty in the dynamic and changing environment. The applications presented currently differ partially in their implementation status and are continuously being developed further. This includes in particular the continued interlinking of the work within the research group as well as in the entire IoP. In the medium term, all developed prototypes are to be integrated into the IoP Kubernetes cluster, and in the long term, the real-time capability is to be increased for use in real production environments.

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