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Performance measurement in global production networks to identify knowledge transfer needs using statistical process control

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Abstract

Due to globally distributed value chains, manufacturing companies are increasingly operating in production networks. The management of these often historically grown networks requires the coordination of many tangible and intangible flows, including the transfer of knowledge between sites. In order to remain competitive in a dynamic market environment, the transfer of in-house production knowledge is essential. In practice, the systematic identification of knowledge transfer needs poses a major challenge for industrial managers, one reason being the high complexity of production networks and thus the large number of knowledge transfer possibilities in the network. However, the transfer of knowledge is always time-consuming and costly. An obstacle is to identify if there is a significant need to initiate a knowledge transfer. For this purpose, it should be examined weather the performance within the production network differs significantly or not. This paper presents an approach to measure performance differences in global production networks to identify knowledge transfer needs. Therefore, a hierarchical performance measurement system, consisting of key performance indicators (KPIs) and focusing on four performance dimensions (quality, time, flexibility, and efficiency), is introduced. Depending on the hierarchical level of the production network (workstation, production system or factory segment), a specific set of KPIs is selected and calculated based on production data acquired by different information systems. In a next step, statistically significant deviations are identified using statistical process control (SPC). Control charts are used to examine the stability and thus to identify knowledge transfer needs. The analytical approach is validated with data from a real industrial case study.

Keywords

Knowledge transfer; Production network; Performance measurement; Statistical process control

1. Introduction

The majority of manufacturing companies established production sites all over the world in order to profit from differences in factor costs and gain access to new emerging markets [1]. Current production networks are often historically grown with complex structures [2,3]. As a consequence, these networks are characterised by individualism and isolation of the individual sites, which leads to performance differences within the network [4,5]. Different manufacturing sites are predominantly incapable of learning from each other [6]. However, cross-site learning in production networks enables organisations to minimize the variance in performance by a systematic exchange of best practices in the network [1]. Furthermore, knowledge transfer within an organisation provides opportunities for interunit cooperation, which can also stimulate the creation of new knowledge [7]. Therefore, many authors consider the ability to transfer knowledge across sites and entities to be a critical success factor for global production networks [8,9,1]. At the same time, the practical implementation of knowledge transfer is often a major challenge for decision-makers [10–12].

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In general, knowledge transfer is a process by which one organizational entity (individual, group, department, etc.) passes experience or skills to another [10,13]. This paper focuses on the inter-organisational knowledge transfer in the network of a single company. Particularly in the context of production, this mainly includes knowledge about manufacturing technologies but also operational knowledge, which can be used by the operators as a recipe for actions [9,12].

The question of when to transfer knowledge is a key challenge for decision-makers. This question refers to when knowledge is qualified for being transferred [9]. Due to the high degree of complexity in global production networks, there are almost infinite opportunities for the transfer of production knowledge. Since a knowledge transfer is always associated with time and financial resources of the participants it should only be initiated if the performance levels of the processes differ significantly. However, the process of identifying the need for cross-site knowlegde transfers may require months of information collection and evaluation [14,15].

In order to address this problem, this paper aims to answer the question when to initiate a knowledge transfer. Therefore, an approach is proposed, which systematically identifies the level of need for knowledge transfer using a key performance indicator (KPI) based performance measurement system to identify significant process deviations that trigger knowledge transfer in production networks.

2. State of the Art

The research area of inter-organizsational knowledge transfer contains a wide range of different approaches, which are summarized in the work of MARCHIORI ET AL. [16]. However, only a few scientific works examine the initiation of the knowledge transfer process. CHENG ET AL. investigate the identification of the right time to transfer knowledge and the identification of the right knowledge transfer participants. Therefore, the authors develop a framework to coordinate the implementation of a knowledge transfer. However, this framework serves only as a rough guidance and must be further detailed for practical application. Other authors such as LEYER ET AL., BARÃO ET AL. and MOURTZIS ET AL. use data-based methods to connect knowledge holders in organizational networks to simplify the initiation of knowledge transfer. They focus on identifying relevant knowlegde but they do not evaluate whether the knowledge is suitable for knowledge transfer [17,14,18]. In this context, the challenge is to identify the knowledge of the best practice processes, technologies and procedures in production networks to prevent the transfer of "bad practices" [9,19]. To address this challenge, KPIs can be used to evaluate performance differences between production entities in a production network and identify best practices [20]. To address this in more detail, in the following, approaches for performance measurement in manufacturing are presented as well as approaches for automated analysis of performance differences. Not all of these approaches address the inter-organizational knowledge transfer in production networks dircetly. Nevertheless, important insights can be gained from these approaches to develop a methodology for identifying knowledge transfer needs based on analyzing performance differences.

2.1 Performance measurement in manufacturing

KPIs represent an enterprise's relevant success factors [21,22]. KPI systems are multi criteria target systems that can be implemented to measure operational performance of production processes when managing global production networks [23]. For a holistic assessment of competitiveness, several performance dimensions must be taken into account [24,22]. Accordingly, manufacturing companies need to operate on a high level of performance in many dimensions such as time, efficiency, time and flexibility [25]. Another important requirement is the consideration of various KPIs on different hierarchical levels and their links to each other [26,27]. The system levels of production according to WESTKÄMPER ET AL. are structured in semi-autonomous and cooperating production entities on different hierarchical levels like workstation, production system, factory segment or production site [28,29]. Since a transfer of knowledge can take place at different hierarchical levels in the network, a distinction between those levels is necessary when defining KPIs.

The international standard ISO 22400-2 [21], as a further development of the national VDMA 66412-1 standard [30], provides a comprehensive framework for performance measurement in manufacturing consisting of 35 industry neutral KPIs. The majority of the KPIs introduced are ratios, which are beneficial for benchmarking purposes according to many authors [31–33]. However, a classification of the KPIs into hierarchical levels is missing. [21] Based on ISO 22400-2, STRICKER develops a KPI system for the quantitative measurement of robustness in manufacturing systems. In addition to hierarchical levels, the author considers different performance dimensions and the interdependencies between KPIs in order to minimize the set of KPIs, which is used for measurement of robustness. However, since the approach aims at calculating the robustness by means of a highly aggregated measure, there is no focus on performance differences between entities, which can result in a transfer of knowledge. [34] The KPI system developed by HON consists of five performance dimensions (cost, productivity, time, flexibility) and five hierarchical levels within production networks (machine, cell, line, factory, network). Although HON mentions all relevant performance dimensions within a hierarchically structured KPI system, he remains unspecific in the mathematical description of the KPIs and does not provide aggregation relationships for classification into the hierarchical levels. [35] RITTSTIEG proposes a performance measurement system that allows the evaluation of performance differences between production sites. For this purpose, she formulates a set of 15 KPIs, which are reviewed individually regarding their suitability for comparing heterogeneous entities. Since her focus is on identifying cause-and-effect relationships between influencing factors and site performance, a differentiation between the hierarchical levels in the definition of KPIs is missing. [20]

2.2 Analysis of performance differences in manufacturing

Existing approaches in the field of performance measurement mainly focus on the comparison between a KPI and given specification limits. However, many authors emphasize the importance of variance when analysing process behaviour using KPIs [36–38]. Since KPIs are based on the output of operational processes, a simple comparison of individual KPIs is not sufficient to identify statistically significant differences in performance between production entities. To systematically examine KPIs for performance deviations, statistical process control (SPC) and the associated control charts are suitable tools. SPC is an analytical approach developed to continuously monitor and improve the output of processes and systems using statistical methods [39]. Within the context of SPC, the statistical behaviour of processes can be described by means of control charts. A control chart consists of a central line, upper control limit (UCL), lower control limit (LCL) and plotted data points. Both control limits express the natural variation of the process and are statistically calculated. Data points outside the control limits or non-random patterns indicate process instability and require corrective action to eliminate the assignable cause. [40–42]

SPC and control charts are widely used in quality assurance and management [40–42]. Significantly fewer approaches exist for applying SPC to operational performance measures such as KPIs. Nevertheless, several authors confirm the suitability of control charts for monitoring KPIs [36,37,43,38]. WHEELER addresses data analysis by means of SPC in the context of business processes and provides a guideline for the introduction of control charts for the monitoring and optimisation of processes. [38] GERBOTH develops a concept for the use of SPC in administrative business processes without a focus on production-related processes. He discusses the adjustments to be made in the transformation of the control charts for the analysis of KPIs. Moreover, he names feasible types of control charts and validates his approach through real industrial use cases. His systematic approach serves as good orientation for applying SPC to KPIs. [43] As part of the Swedish Innovation program "Produktion2030", ALMSTRÖM ET AL. integrate tools of SPC in their life cycle-oriented performance measurement system as decisions support for manufacturing companies. Control charts, in particular individual moving range control charts (XmR), are used to obtain a better understanding of variation in different KPIs. In addition to the analysis of process stability, the authors suggest the possibility of predictions and obtaining warning signals if a process becomes unstable [36,37].

2.3 Research need

The examined approaches show that there is already some research done regarding performance measurement in productions networks using KPIs. However, none of these approaches aims at initiating knowledge transfer within the network. Furthermore, a concept for selecting and calculating the KPIs from measured elements extracted from heterogeneous IT systems is required. In the field of research regarding SPC, few studies suggest the use of SPC for operational KPIs. None of the approaches provides a method for benchmarking the performance of multiple processes using control charts. Consequently, performance measurement approaches should be combined with control charts to create a holistic methodology which enables identifying and quantifying significant knowledge transfer needs in global production networks.

3. Approach

Derived from the requirements for the KPI based identification of knowledge transfer needs and the examination of existing approaches in this field, a new approach is presented in Figure 1. The approach is divided into three steps beginning with a KPI matrix, followed by the KPI selection and calculation from different databases and SPC to identify knowledge transfer needs.

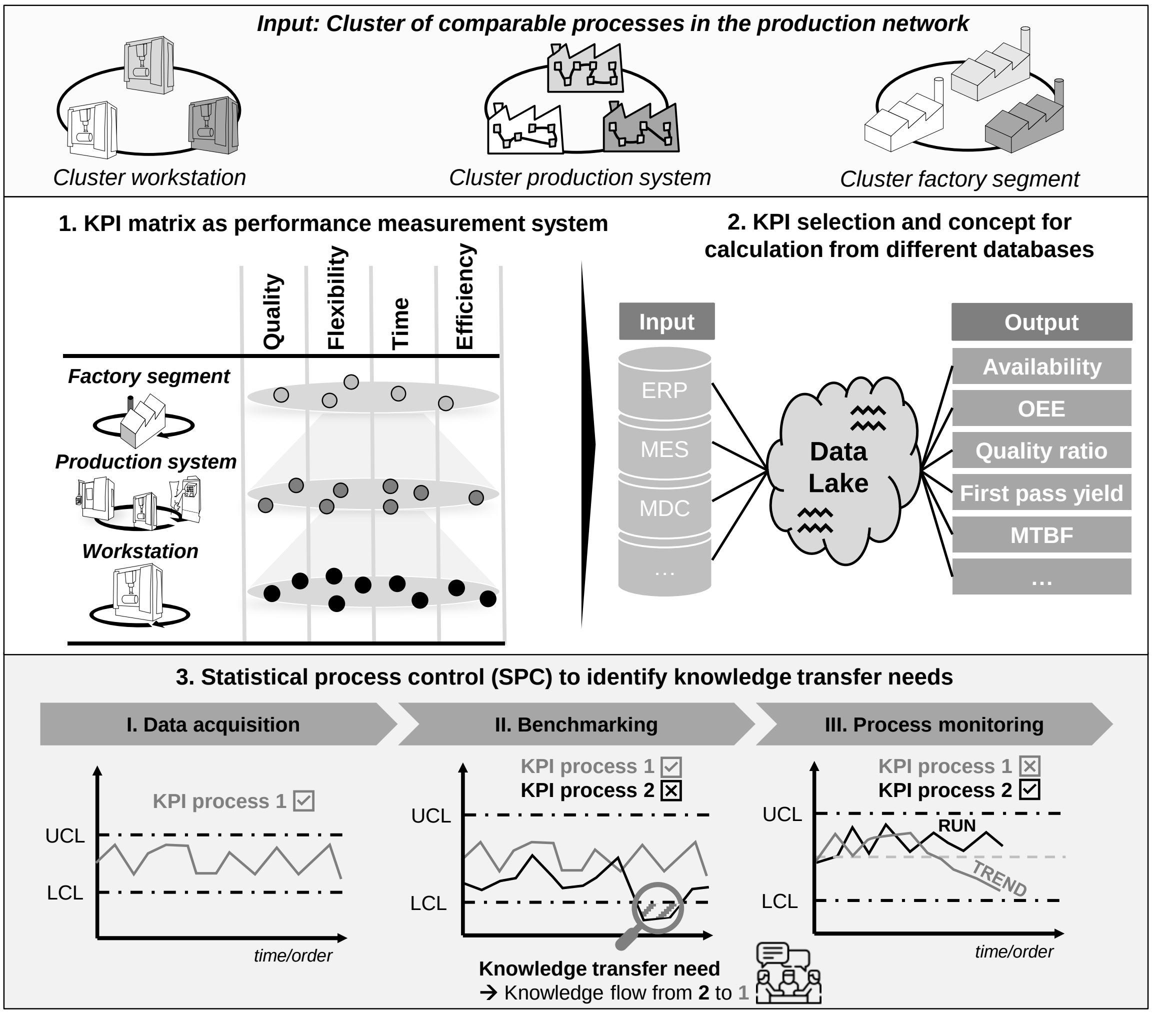
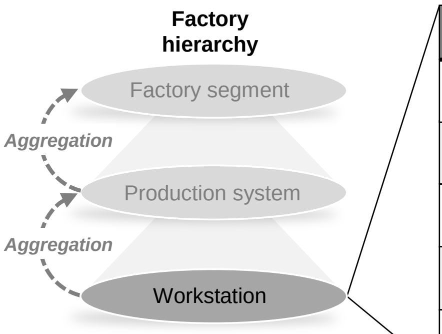


Figure 1: Approach for Performance measurement to identify knowledge transfer needs using SPC

The input for the presented approach is provided by clusters of comparable processes in a production network. The processes within a cluster are suitable for potential knowledge transfer due to their similarity of characteristics. Clusters of comparable processes can be formed on three hierarchical levels (workstation, production system or factory segment). The data-based methodology for identifying these clusters has been developed through previous research and is considered a prerequisite for this paper. [44]

In a first step of the presented approach, the processes within a cluster are evaluated by a KPI matrix with regard to their operational performance (cf. Figure 1). In order to ensure a multidimensional measurement of performance, four different performance dimensions are considered (quality, flexibility, time, and efficiency). In addition to the dimensions, the factory hierarchy structures the framework vertically in workstation, production system and factory segment. Within the scope of a literature research, 39 generally valid and manufacturing related KPIs are identified and classified into the matrix. The majority of the selected KPIs originate from ISO 22400-2 [21] and are determined as ratios. Figure 2 depicts an extract from the matrix including calculation formulas on workstation level, unit of measurement, and improvement direction for selected KPIs.



KPI	Formula	Unit	Improvement direction	Performance dimension
Overall equipment efficiency (OEE)	$A \times QR \times E$	%	max	Efficiency
Effectiveness (E)	$\frac{PRI \times PQ}{APT}$	%	max	Efficiency
Quality ratio (QR)	$\frac{GQ}{PQ}$	%	max	Quality
Availability (A)	$\frac{APT}{PBT}$	%	max	Time
Setup ratio (SR)	$\frac{AUST}{AUPT}$	%	min	Flexibility

Elements used in KPI description:

$AUPT$: Actual unit processing time; $AUST$: Actual unit setup time; APT: Actual production time; GQ: Good quantity; PBT: Planned busy time; PQ: Produced quantity; PRI: Planned run time per item

Figure 2: Extract from KPI matrix showing KPIs on workstation level

The input for the description of the KPIs is provided by time, logistical, and quality elements which are directly measured on the shop floor. Since knowledge transfer between entities can occur on workstation, production system, and factory segment level, appropriate KPIs must be assigned to these levels. In principle, many of the identified KPIs can be used on multiple hierarchical levels. However, this requires an adjustment of the calculation formula. Hence, lower level KPIs (e.g. quality rate of a workstation) are aggregated across all subsystems (e.g. interlinked workstations of a production system) to the KPI of the higher level (e.g. quality rate of the production system). For example, the quality rate on production system level can be calculated as the sum of all good quantities in the production system divided by the sum of all produced quantities in the production system. Subsequently, the vertical and horizontal interdependencies between the KPIs can be identified by analysing and visualising the mathematical links.

In a subsequent second step, different KPIs, depending on the cluster to be examined, are selected from the matrix for benchmarking of the processes. In case of clusters on workstation level, it is logical to consider only those KPIs on workstation level. However, for clusters on production system and factory segment level, not only the KPIs of the respective level but also all lower KPIs linked via interdependencies must be included in the analysis. This is due to the avoidance of substitution effects which occur when several strongly deviating lower level KPIs compensate each other when looking only at the aggregated KPI. The calculation of the KPIs requires access to a large amount of heterogeneous production data which is typically stored in different information systems such as ERP (enterprise resource planning), MES (manufacturing execution system) or MDC system (machine data collection). However, such mixed information system landscape restricts transparency regarding performance on cross-site level [45].

In order to integrate the different systems and calculate KPIs based on the data contained, a data lake can be implemented and used as a "Single Source of Truth" for measuring performance. In a data lake, all types of raw data from various information systems are stored unchanged and made available for further analysis, such as KPI calculation [46]. A data lake is characterised by simple scalability and high flexibility compared to other approaches like data warehouse [47]. Due to these benefits, a data lake is suitable for mapping a heterogeneous data environment like that of manufacturing companies and providing raw data for the calculation of KPIs.

The third step of the developed approach focuses on the systematic identification of knowledge transfer needs based on the calculated KPI time series of processes within a cluster (cf. Figure 1). Therefore, statistical process control (SPC) and Shewhart control charts are used to identify significant performance differences within a cluster. This step can in turn be divided into three phases, which must be executed chronologically.

In phase I, a separate control chart is created for each process within a cluster and examined with regard to its stability. The separate analysis is necessary to first identify instabilities of a single process before investigating performance differences between multiple processes in phase II. Therefore, a time series of at least 25 KPI values is recorded during data acquisition. The minimum of 25 observations is required to ensure reliable estimates of the process variability and consequently the control limits [48]. The control limits are placed at a distance of 3σ on each side of the center line, where σ is the estimated standard deviation of the KPI time series. Since it is not possible to form subgroups for sampling, the SPC is assessed using individual moving range control charts (XmR) [41]. The control chart indicates an out-of-control condition and hence process instability if one or more points fall beyond the critical control limit. For KPIs that has to be maximised (e.g. OEE), the critical control limit is defined as lower control limit (LCL). The upper control limit (UCL) is used as critical control limit if smaller KPI values are better, such as Setup ratio. For points outside the critical control limit, investigation and corrective action is required to find and eliminate the assignable cause for this process behaviour.

If all individual processes of the cluster are stable, benchmarking within the cluster is performed in phase II. For this purpose, the comparable processes are analyzed in one joint control chart for significant differences in performance. Upper and lower control limits are determined by the KPI time series of all processes. If one of the points exceeds the defined control limits, there is a significant difference in performance and consequently a need for knowledge transfer between the entities of the cluster. Accordingly, the upper and lower control limits are considered to be trigger points for a knowledge transfer initiation. The direction of the knowledge transfer can be derived from the control chart and depends on the improvement direction of the KPI. Moreover, the urgency with which the transfer is to be initiated is quantified using the joint control chart. The urgency is needed to adapt the transfer of knowledge to specific transfer situations and influences the selection of the communication medium [49].

While phase I and II are based on retrospective data analysis, phase III monitors the processes in real time. For this purpose, the control charts from phase II are continued by comparing the KPI values with the control limits. In addition to the control limits, further criteria for stability analysis like run and trend are applied to recognize unusual process patterns and identify deviations at an early stage. The run-criterion tests whether seven or more consecutive KPI values are on one side of the center line. A trend is a steadily increasing or decreasing sequence of at least seven consecutive KPI values. [42] For practical applicability of the process monitoring it is crucial to adapt the sensitivity of the control chart depending on the KPI considered and the specific use case. Therefore, the use of moving average control charts is recommended in phase III. For this type of control chart, p consecutive KPI values are aggregated to a moving average. The moving averages are added to the control chart and examined for stability using the defined criteria. The larger the quantity p, the smoother the time series and the lower the sensitivity of the control chart to individual outliers. [40,50]

4. Case sutdy

The presented approach was applied using production data from a global manufacturer. The goal of the industrial case study was to identify performance differences in the production network and thus knowledge transfer needs between entities. The initial data set consists of measured elements such as produced quantity (PM) and actual production time (APT) that had been recorded for about 4000 operations at 40 workstations over a period of two years. By applying a cluster and similarity analysis according to the methodology developed by SCHUH ET AL. [44], multiple clusters of comparable workstations are identified. From these, an exemplary cluster consisting of two workstations is selected to illustrate the methodology (c.f. Figure 3). Following the presented approach, KPIs are calculated for the comparable entities. As the cluster is arranged at workstation level, only workstation level KPIs are selected for further analysis. In the following, the validation will be explained with the example of the throughput rate. After both workstations proved to be stable in phase I, the two processes are examined in phase II and phase III for significant performance differences using joint control charts, which are shown in Figure 3 on the right side.

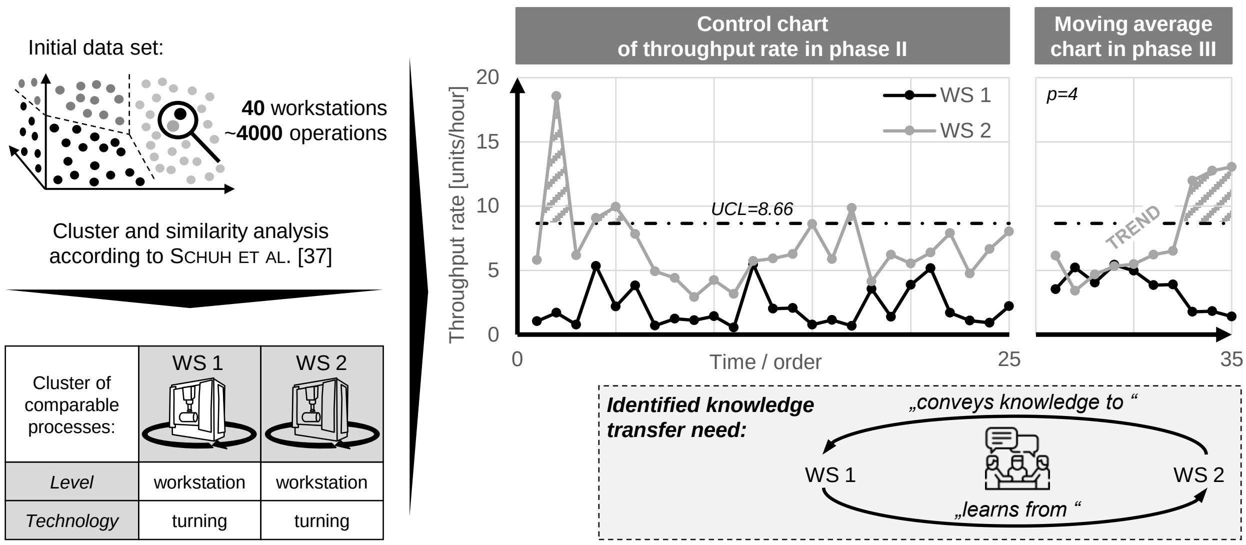


Figure 3: Case study based on real production feedback data from a global manufacturer

The throughput rate of workstation 2 exceeds the upper control limit (UCL) four times, indicating a difference in performance between the processes of the two workstations. Since throughput rate is a KPI that has to be maximized, workstation 2 shows significantly higher performance in terms of throughput. Based on this difference in performance, a need for knowledge transfer between the entities is derived. Process monitoring in phase III detects a positive trend for workstation 2 (increasing sequence of 9 KPI values). Thus, workstation 2 also performs significantly better in phase III. By using moving averages (p=4), the KPI series are smoothed out allowing long-term shifts and trends in performance levels to be identified more easily. As a result of the SPC analysis, the involved entities should address the identified performance shortfall of workstation 1 via a knowledge transfer.

5. Conclusion and future research

In this paper, a performance measurement-based approach for systematic identification of knowledge transfer needs in production networks is presented. Due to the complexity of historically grown production networks and many knowledge transfer opportunities between entities in such networks, the identification of knowledge transfer needs is a major challenge for industrial managers in practice. To address this, a data-based and automated approach is chosen. In the first step, a universal KPI system for measuring the performance of production processes is developed. The KPI system structures operational KPIs based on three hierarchical levels (workstation, production system, and factory segment) and four performance dimensions (quality, flexibility, time, and efficiency). The second step describes the situation-specific selection of the KPIs and the subsequent calculation using various information systems. In a third step, SPC and control charts are used to identify significant performance differences and thus knowledge transfer needs between entities. For this purpose, control limits in the control chart serve as trigger points for knowledge transfer initiation.

Future research is required in the holistic validation of knowledge transfers in global production networks. Therefore, knowledge transfers should be implemented in the context of scientifically supported industry studies after being identified based on production feedback data using the developed methodology. Subsequently, performance measurement and statistical process control can be performed again to determine how effectively performance differences in the network are compensated by systematically identified knowledge transfers.

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Biography

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