3rd Conference on Production Systems and Logistics

Towards A Data-driven Performance Management In Digital Shop Floor Management

Lukas Longard[1], Sebastian Bardy[1], Joachim Metternich[1]
[1] *TU Darmstadt, Institute of Production Management, Technology and Machine Tools (PTW), Darmstadt, Germany*

Abstract

Key performance indicators (KPIs) are crucial for measuring and managing the performance of industrial processes. They are used to detect deviations in processes, enabling opportunities to improve manufacturing processes within the three dimensions time, quality, and cost.

In this context, the timeliness of information plays a decisive role in the success of measures since delayed information availability can leave decision makers with no time to react. With the introduction of digitization and industry 4.0, increasing amounts of data become available. They can be used to accelerate problem detection and shortening reaction times to define appropriate actions.

This paper presents a data-driven performance management approach integrated in digital shop floor management (dSFM). If a deviation is detected in one process, KPIs of subsequent processes (horizontal level) as well as subordinate levels (vertical level) are checked for correlations and, if present, the associated team is notified by an automatic warning through the dSFM system. Based on the identified correlations, the team discusses the deviations and defines suitable countermeasures. The aim of this approach is to identify deviations more quickly and to quantify their impacts, thus giving shop floor managers the ability to react in time.

Keywords

Shop floor management; Performance management; Key performance indicators; Data Mining; Machine Learning

1. Introduction

Recent advances in digitization offer a high potential for companies operating in the manufacturing domain to reduce reaction time on business-relevant events like unplanned downtimes and quality issues [1]. Providing the right information to the right people at the right time in an efficient manner to empower them to make the right decisions and take the right course of actions is a significant difficulty for many producing organisations [2,3]. If this can be done in a timely fashion, the negative effects of deviations can be reduced and impacts on internal or even worse on external customers can be prevented [1].

The methods of shop floor management (SFM) are widely used in industry to control and improve production processes on a daily basis [4]. One of the most important elements of SFM is performance management. To manage process performance, goals are set by the management and translated into trackable key performance indicators (KPIs) to identify deviations in processes [5]. These are then analysed in shop floor meetings and a problem-solving process is initiated if necessary. Improvements developed in the problem-solving process are stabilized and standardized to reach a continuous improvement of the production processes [6,7]. However, there are several shortcomings of performance management and its application in industry.

Hellebrandt et al. state that performance management is mainly used in middle and top management and KPIs on the shop floor are not connected to these higher levels [8,9]. Furthermore, KPIs on the lowest level are not connected to the individual worker, making it difficult to achieve a sense of responsibility by the employee towards the KPIs [10]. Moreover, due to the large number of KPIs often used, the complex interrelationships can no longer be intuitively understood and anticipated, resulting in a great demand for system-based decision support [11].

Therefore, this paper will present a new data-driven performance management approach in digital SFM (dSFM). The remainder of the paper is structured as follows: Chapter 2 provides the state of the art on SFM, performance management as well as recent advances. Chapter 3 introduces the model of latency to business-relevant events and derives the goals and opportunities of a data-driven performance management approach. Following up, the data-driven approach is described in chapter 4. Finally, the paper closes with a conclusion and outlook for the next steps in the development.

2. State of the art

2.1 Shop floor management and performance management

Hertle et al developed a model to describe the daily routine for a successful SFM (see Figure 1). Based on standardised processes, production goals are set by management. In step one, deviations from the set goals are identified with the help of target-actual comparisons of KPIs, andon or gemba walks. In step two, the deviations are discussed in daily shop floor meetings. The impact of the deviation is evaluated, and short-term countermeasures are initiated. A decision is also made as to whether a systematic problem-solving process (SPSP) should be started. The SPSP is not part of the daily routine and runs separately. A PDCA cycle is used to track the progress of implementation. Step three of the SFM loop comprises the first two phases (Plan & Do) of the PDCA cycle. In the final step, the measures introduced are checked and tested for suitability so that they can be transferred to the standard in the event of a positive vote [5].

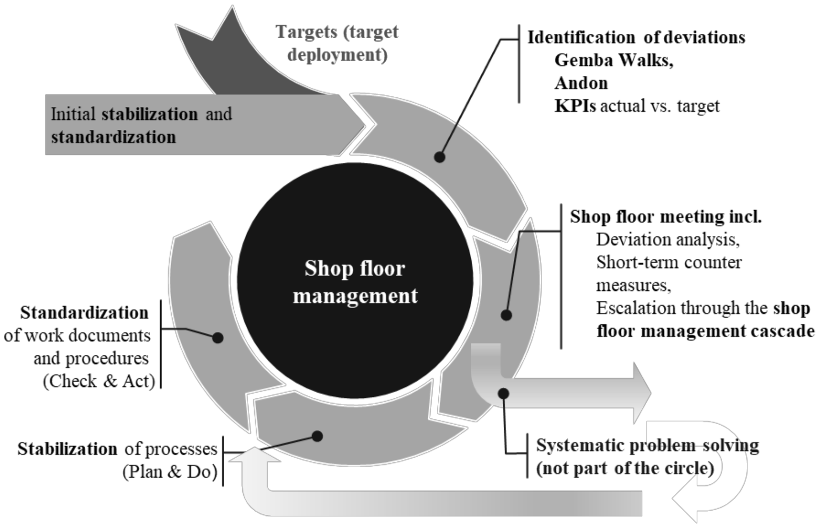

Figure 1: Shop floor management model [5]

To implement KPIs there are two main prerequisites. Firstly, management must define targets for the production processes and, secondly, ensure multidimensional measurement of production performance (performance measurement) in order to be able to visualize the degree of target achievement [3,12]. If every target is linked to an improvement activity which supports the achievement of the long-term vision of the company, the approach is called Hoshin Kanri [13]. In this context a performance pyramid is often used for visualization (see Figure 2). Based on the corporate vision, strategic goals are derived for the three performance levels of strategical management, tactical management, and operational level in the sense of a top-down approach. The achievement of the goals in the respective levels is determined by KPIs. The indicators are aggregated in a bottom-up approach so that causal relationships exist between the indicators of the different levels. [12,13]

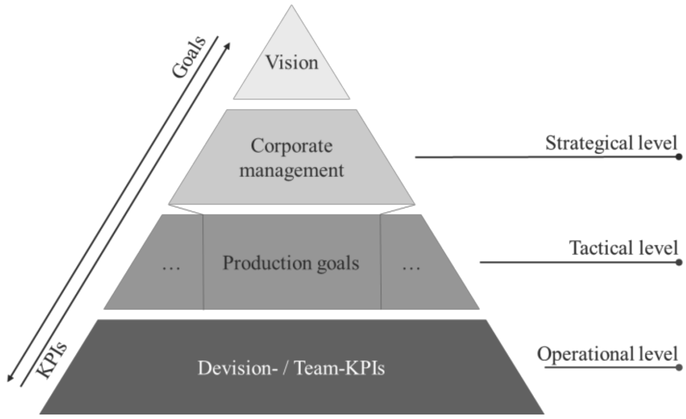

Figure 2: Performance pyramid for production, adapted from [14]

2.2 Recent advances in shop floor management, performance management and problem solving

With the introduction of digitization and industry 4.0, increasing amounts of data become available for processing and use in smart manufacturing systems [15]. Meissner et. al developed a target state for dSFM. They suggest using KPI data to forecast KPIs and predict trend impacts of upstream or downstream processes.. Then the information is visualized and managers of the process as well as downstream processes are warned. [16] By integrating machine and manufacturing data into the performance pyramid, KPI calculation can be automated [17] and generated real-time data enable further insights [18].

The new possibilities in dSFM are not only viable for performance management but also translate to problem management. In classic problem management, the deviations in KPIs are presented to the employees/managers where they must make the decision how to handle the deviation. This can be categorized into three different levels of reaction: If the deviation is not impactful or even a false alarm it can be ignored. If the deviation has an impact on production performance and the root cause is clear immediate action should be taken to prevent further losses. Finally, if the deviation has an significant impact on target fulfilment and cause is unknown a systematic problem-solving process (SPSP) is used to find the right countermeasure. [19]

However, classic detection mechanisms like KPIs are often only able to detect the symptoms of underlying problems. Remedying those symptoms is not sufficient to resolve the underlying problem and to find a sustainable solution [20]. Without a systematic approach to problem-solving, employees are tempted to hastily identify causes and introduce immediate measures. These are usually based on experience and feelings, but not on a sound analysis of the root cause of the problem at hand. German studies have shown that up to 60% of emerging problems are recurring [21], which indicates that it is rare that lessons are learned from past mistakes and the root cause of problems is sustainably eliminated [22]. Meissner et al. put in perspective that digitalization can enrich the information available for root-cause analysis. Furthermore, through algorithms root-causes as well as solutions for the problems can be proposed by the system to the employee. [23] To comprehend these complex relationships, data mining (DM) can be used as an analysis support [24]. In their literature review, Longard et. al show the potentials of using DM in SPSP. As problem solving requires a lot of experience and creativity, humans are superior to machines and computers in this field. Data can especially support hypothesis formulation and problem delimitation as well as analysis. In particular, correlation analyses between miscellaneous process parameters can provide valuable insights to support the interpretation of the results and prepare the creative work in finding solutions. [25]

3. Goals of a data-driven performance management

Hackarthon developed a model for business intelligence that considers the different time elements between the occurrence of a business-relevant event and the initiation of remedial action (reaction time) that can be transferred to the domain of SFM. According to the model, the reaction time can be decomposed into data, analysis, and decision latency [26]. The longer the process takes from the occurrence of a business-relevant event, through detection and analysis, to the initiation and implementation of countermeasures, the more business value is lost (see Figure 3 - left).

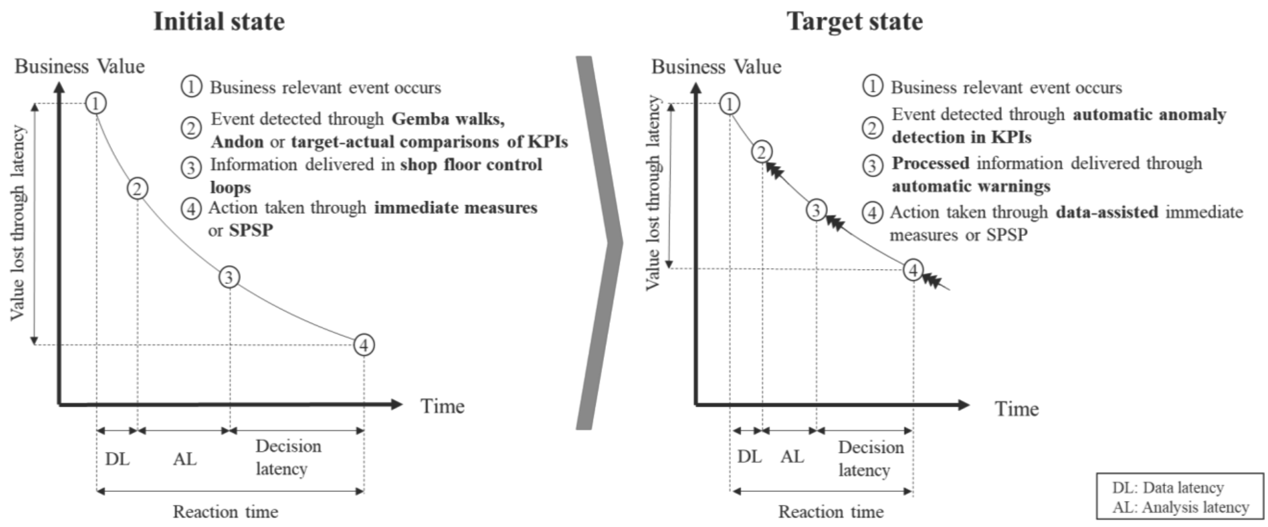

Figure 3: Deviation management in SFM – initial state versus target state, adapted from [1,26]

The data or detection latency describes the delay between the occurrence of a fault and its capturing. In the classical sense, this is recognized in SFM by means of Gemba walks, the target-actual comparison of KPI or Andon signals triggered by employees as well as machines [5]. These simple methods are able to identify many process or product deviations in order to restore the desired condition. Nevertheless, valuable time is lost since these measures only have a delayed effect on the actual cause and are therefore considered reactive measures. Even though the automated calculation of KPIs is an important step towards reducing detection latency, the gap between the occurrence and detection of a business-relevant event can only be closed by connecting sensors that measure as close as possible to the actual root cause. The described relationships are shown in Figure 3. The use of automatically calculated KPIs and sensor data can lead to a reduction in the detection latency (shift upwards along the curve).

Reducing detection latency to a minimum only has a positive effect if the decision-makers receive the relevant information in time [27]. Zur Mühlen et al. define the analysis latency as "[…] the delay between the storage of event information in a repository and the subsequent transformation of this event information into an analysable format, such as a notification, report, or indicator value." [1]. This is where traditional SFM systems with their fixed communication cycles [7] and rudimental information (e.g. visualization of KPIs) [8] reach their limits and therefore have to be adjusted. It is particularly important to quantify impacts of deviations on subsequent processes as well as subordinate levels. Moreover, to exploit the full potential of the data, decision-makers must receive information on relevant events as quickly as possible and in a form that is easy to understand. Especially, when dealing with sensor data, without contextual information, it is almost impossible to evaluate a situation and draw the right conclusions [28]. In addition, the right amount of information has to be determined to not cause an information overload [3].

After detecting (e.g. through anomaly detection on sensor data) and transforming the information into an analysable format, adequate remedial actions have to be initiated. Decisions must be made quickly, and the decision latency must be kept as low as possible to minimize the impact on business value (see Figure 3). In contrast, the root cause of a problem and not just its symptoms should be addressed through SPSP to benefit in the long run. The use of immediate measures should therefore only be used for damage limitation and should not replace a SPSP. Both the selection of an immediate measure and the root cause analysis with the underlying cause-effect relationships require in-depth knowledge.

In summary, to reduce the reaction time to business-critical events and minimize resulting value losses, a data-driven performance management approach in dSFM must address the following shortcomings of current approaches:

- **Goal 1**: To be able to recognize deviations earlier, information must be available as quickly as possible. Data (especially from sensors) should be used to shorten the gap between occurrence and detection of business-relevant events.
- **Goal 2**: Decision-makers should receive information on relevant events as quickly as possible in the right amount and quality.
- **Goal 3**: To enable prioritization, the impact of deviations on subsequent processes or higher levels should be quantified.
- **Goal 4**: Data should assist problem solvers in finding the root causes faster, thus shortening the decision latency.

4. A data-driven performance management approach

The developed approach aims to quantify the potential impact of business-critical deviations at the horizontal and vertical level, alert the associated operations managers, and give them time and information to define appropriate countermeasures. Here, the horizontal level refers to the value stream and attempts to quantify the effects of deviations on subsequent process steps. This is to enable the subsequent processes to react to the impending effects and to take appropriate measures. If a deviation is detected in one process, KPIs of subsequent processes are checked for (time-lagged) correlations and, if present, the associated team is notified by an automatic warning through the dSFM system. Based on the warnings, the team discusses the deviations and defines suitable countermeasures (see Figure 4 - left). In contrast, the vertical level describes the effects of a deviation in a process along the company hierarchy. If again a deviation is detected in one process, KPIs of higher-levels are checked for correlations and, if present, the ones responsible are notified (see Figure 4 - right). The objective is to quantify the impact of sub-areas at aggregate levels to inform higher-level managers when production goals are in jeopardy. This is intended to simplify the escalation process and give quantitative reference.

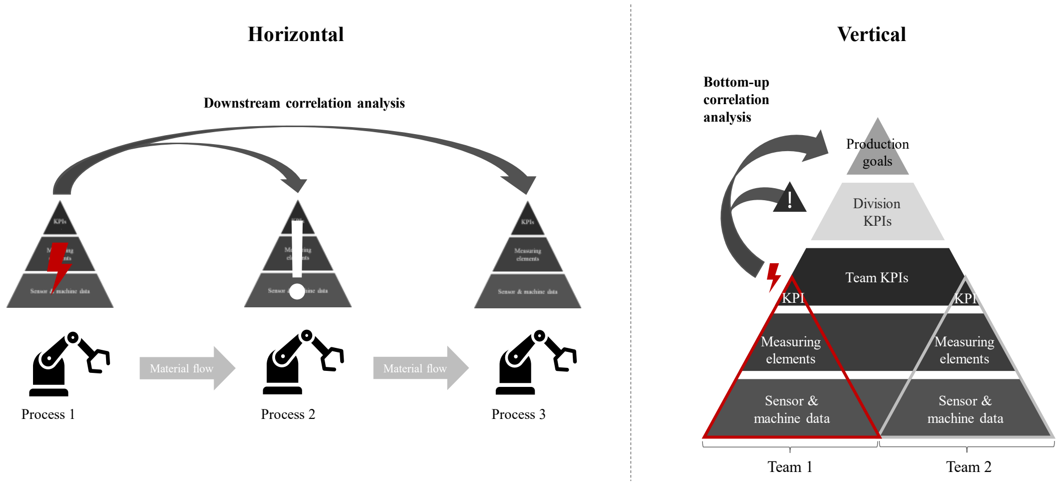

Figure 4: A data-driven performance management approach

In comparison to traditional performance management approaches, which focus primarily on the vertical consistency of business goals using KPIs, this new approach is intended to form a KPI network that also considers horizontal dependencies to promote value-stream-wide collaboration. The fact that these KPIs represent all 3 dimensions - time, quality and costs - means that a targeted focus for improvement can be established. To implement this data-driven performance management approach, the three latencies (data, analysis & decision) are addressed in a targeted manner through the three phases of deviation detection, impact quantification as well as warning & impact assessment (see Figure 5). These will be discussed in the following.

4.1 Deviation detection

The starting point of the SFM control loop is the detection of deviations [16,23]. As described in Chapter 3, current approaches are not able to fulfil the requirement of using data to bridge the gap between the occurrence and detection of business-relevant events (Goal 1 + 4). For this reason, a three-level approach was defined that starts at a high level with anomalies in KPIs and gradually gets finer by incorporating their measurement elements up to machine/sensor level data (see Figure 5 – Deviation detection). From a technical point of view, the detection of deviations requires different methods and algorithms for each level. On the KPI-level a simple target-actual comparison realized by a corridor with upper and lower limit is sufficient to capture most of the relevant deviations. Since KPIs are often calculated from a large number of so-called measurement elements (e.g. good quantity, part quantity, actual unit processing times), a deviation detection only at KPI level would lead to a certain lack of clarity and make root cause analyses more difficult. Therefore, the next step is to look at this level. The time series of the measurement elements have similar properties to the KPIs with the difference that higher measurement frequencies are often available. This is due to the fact that KPIs are often formed only once per shift or day, but the underlying measurement elements are recorded more frequently and are thus available for analysis. In contrast to detecting KPI deviations, applying target-actual comparisons on the measuring elements is not applicable, since there are usually no specified targets for those. One way to solve this problem is to define dynamic target values (e.g. dependence on time and product). In addition, statistical process control and trend analysis, could provide valuable results.

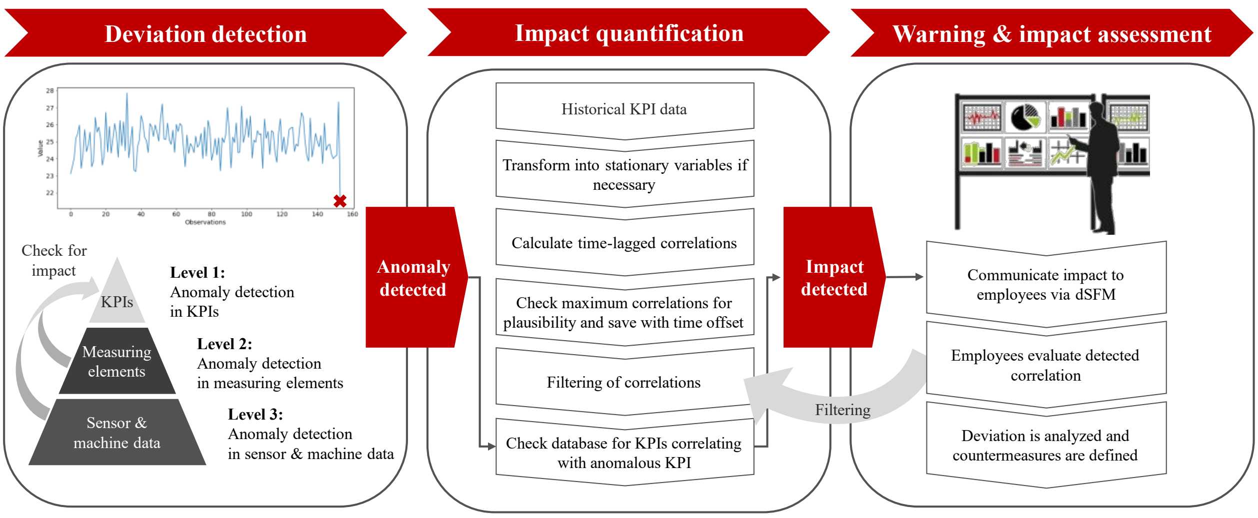

Figure 5: Model pipeline of data-driven performance management approach in dSFM

With the integration of the sensor and machine data, the goal is to measure as close as possible to the root cause of a problem or deviation. The integration of new measuring points provides the possibility to get even closer to the process, which is not yet done today. To find anomalies in the high-frequency data of sensors or machines, it is recommended to use more sophisticated methods and algorithms. The rapid developments in this direction in recent years have produced many such methods and algorithms. These include machine learning (ML) and artificial intelligence (AI) approaches like support vector machines [29] and neural networks [30] but also statistical approaches like ARMA or ARIMA [31] to name a few.

4.2 Impact quantification

The knowledge of the quantitative impact of deviations can only be generated from long-term data. This data must be pre-processed and transformed into stationary variables, to reduce the probability of encountering spurious correlations. In the next step, the relationships between the different KPIs are quantified via (time-lagged) correlation analyses. The focus on time-lagged KPIs is due to the fact that it is precisely those impacts that are interesting from a management perspective, which have a time-lagged reaction and can thus be counteracted by an action (Goal 2 + 3). In addition, the direction of the correlation must be determined to be able to make a statement about positive or negative impact of the leading KPI on the lagging KPI. Thereby, the model must also reflect domain knowledge, since different KPIs have different optimization goals (e.g., maximizing OEE as opposed to minimizing scrap rates). In order to be able to capture the multitude of different correlations (e.g. linear, quadratic) between KPIs, more advanced methods must be used in addition to the standard correlation methods Pearson, Spearman, Kendall (only able to capture linear correlations). In the recent past, the Maximum Information Coefficient has stood out and will be taken into account in future studies [32]. After the maximum lagged correlation has been determined for each pair of KPIs, the determined offset must be checked for plausibility. For example, from a practical point of view, it may not make sense if the detected offset is larger than the lead time between the processes belonging to the KPIs. Afterwards, all detected correlations and their corresponding offsets are saved in a database.

The final step of the impact quantification phase is to match detected anomalies with the detected correlations. If an anomaly is detected in a KPI, the database is searched and correlations belonging to the KPI are returned. If an anomaly is detected at the measuring element or sensor level, it is first checked (e.g. by correlation or regression analyses) whether this has an impact on the KPIs of the associated process (see Figure 5 – Deviation detection). If this can be confirmed, the procedure is the same as described above.

4.3 Warning and impact assessment

The next step is to notify those managers whose KPIs correlate with the anomalous KPI. To keep the latency as low as possible, it is advisable to send the warnings via mobile devices, emails or push messages in the dSFM. The criticality of the deviation should be used when choosing the communication medium. This can be determined by an interaction of the correlation coefficient, the temporal offset, possible effects on higher levels, and employee-defined intervention limits and assessments of past cases. To make the information processable for the employees, it must be prepared in a suitable form (Goal 2). This can be achieved both by the form of visualization and by context provided for the information [33]. This includes information on when the impact is likely to occur, which of the team´s own KPIs are affected, and which KPI (which team) is the cause of the deviation. In addition, context is also given to similar warnings that have occurred in the past. After that, the employees evaluate the warning based on the available information. In doing so, they are given the opportunity to evaluate the correlations recognized by the algorithm, for example, to hide spurious correlations for future warnings. In this way, the underlying model is continuously improved by the employee (active learning). Finally, a decision is made as to whether an action or SPSP should be initiated or whether the information should merely be noted and communicated to employees in the dSFM.

5. Conclusion and outlook

In this publication, a data-driven performance management approach for dSFM is presented, focusing on the three steps deviation detection, impact quantification and warning & impact assessment. The goal of the approach is to significantly reduce the time between the occurrence of a business-relevant event and the initiation of remedial action to prevent the loss of business value. To achieve this, the concept of three latencies, data latency, analysis latency and decision latency was introduced and countermeasures for reduction were developed. At the core of the approach is anomaly detection at the KPI, measurement element, and sensor/machine level using ML and AI algorithms and quantifying the impact of these anomalies on downstream processes as well as higher hierarchical levels through correlation analyses.

After the data-driven performance management approach in dSFM has been developed in this paper, a practical evaluation of the individual phases will be carried out in the future. To achieve this, a dSFM system available on the market will be further developed around the data-driven performance management approach and put into real use at a company from the process industry. In particular, it will be investigated which different correlation methods are suitable for quantifying the effects and how these correlations can be prefiltered automatically (e.g., from spurious correlations). To not only uncover that a relationship exists (correlation), but also to quantify the magnitude of that relationship, regression models for KPIs will be built in the future. Furthermore, from a research point of view, it will be interesting to see whether the described approach can increase production performance and what factor the integration of sensor and machine data plays.

Acknowledgements

This project (HA project no. 1012/21-14) is financed with funds of LOEWE – Landes-Offensive zur Entwicklung Wissenschaftlich-ökonomischer Exzellenz, Förderlinie 3: KMU-Verbundvorhaben (State Offensive for the Development of Scientific and Economic Excellence).

References

[1] zur Mühlen, M., Shapiro, R., 2010. Business Process Analytics, in: vom Brocke, J., Rosemann, M. (Eds.), Handbook on Business Process Management 2. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 137–157.

[2] Harris, C., 2012. Lean Connections: Making Information Flow Efficiently and Effectively. Taylor and Francis, Hoboken, 166 pp.

[3] Eaidgah, Y., Maki, A.A., Kurczewski, K., Abdekhodaee, A., 2016. Visual management, performance management and continuous improvement. International Journal of Lean Six Sigma 7 (2), 187–210.

[4] Pötters, P., Schindler, P., Leyendecker, B., 2018. Status quo Shopfloor Management. Zeitschrift für wirtschaftlichen Fabrikbetrieb 113 (7-8), 522–525.

[5] Hertle, C., Tisch, M., Metternich, J., Abele, E., 2017. Das Darmstädter Shopfloor Management-Modell. Zeitschrift für wirtschaftlichen Fabrikbetrieb 112 (3), 118–121.

[6] Peters, R., 2009. Shopfloor Management: Führen am Ort der Wertschöpfung. LOG_X, Stuttgart, 141 pp.

[7] Suzaki, K., 2014. New shop floor management: Empowering people for continuous improvement. Free Press.

[8] Hellebrandt, T., Ruessmann, M., Heine, I., Schmitt, R.H., 2019. Conceptual Approach to Integrated Human-Centered Performance Management on the Shop Floor, in: Kantola, J.I., Nazir, S., Barath, T. (Eds.), Advances in Human Factors, Business Management and Society, vol. 783. Springer International Publishing, Cham, pp. 309–321.

[9] Kantola, J.I., Nazir, S., Barath, T., 2019. Advances in Human Factors, Business Management and Society. Springer International Publishing, Cham, 710 pp.

[10] Ohlig, J., Hellebrandt, T., Poetters, P., Heine, I., Schmitt, R.H., Leyendecker, B., 2021. Human-centered performance management in manual assembly. Procedia CIRP 97, 418–422.

[11] Burdensky, D.M.A., Kneissl, B., Alt, R., 2018. Deskriptive Analyse von Kennzahlenrelationen: BMW Group, Leipzig München, Deutschland. Multikonferenz Wirtschaftsinformatik, 59–70.

[12] Kleindienst, B., 2017. Performance Measurement und Management: Gestaltung und Einführung von Kennzahlen- und Steuerungssystemen, 1. Auflage 2017 ed. Springer Fachmedien Wiesbaden, Wiesbaden, Online-Ressourcen.

[13] Diez, J.V., Ordieres-Mere, J., Nuber, G., 2015. The HOSHIN KANRI TREE. Cross-plant Lean Shopfloor Management. Procedia CIRP 32, 150–155.

[14] Lynch, R.L., Cross, K.F., 2003. Measure up!: How to Measure Corporate Performance, 2. ed., reprinted, transferred to digital print ed. Blackwell Business, Malden, Mass., 250 pp.
[15] Jourdan, N., Longard, L., Biegel, T., Metternich, J., 2021. Machine Learning For Intelligent Maintenance And Quality Control: A Review Of Existing Datasets And Corresponding Use Cases. Proceedings of the Conference on Production Systems and Logistics: CPSL 2021, 499–513.
[16] Meißner, A., Grunert, F., Metternich, J., 2020. Digital shop floor management: A target state. Procedia CIRP 93, 311–315.
[17] Longard, L., Meissner, A., Müller, M., Metternich, J., 2020. Digitales Shopfloor Management - Wohin geht die Reise? Zeitschrift für wirtschaftlichen Fabrikbetrieb 115 (9), 645–649.
[18] Wuest, T., Weimer, D., Irgens, C., Thoben, K.-D., 2016. Machine learning in manufacturing: advantages, challenges, and applications. Production & Manufacturing Research 4 (1), 23–45.
[19] Meister, M., Böing², T., Batz, S., Metternich, J., 2018. Problem-solving process design in production: Current progress and action required. Procedia CIRP 78, 376–381.
[20] Liker, J.K., Meier, D., 2006. The Toyota way fieldbook: A practical guide for implementing Toyota's 4Ps. McGraw-Hill, New York, 475 pp.
[21] Klamma, R., 2000. Vernetztes Verbesserungsmanagement mit einem Unternehmensgedächtnis-Repository. Technische Hochschule Aachen, Dissertation, 281 pp.
[22] Jung, B., Schweißer, S., Wappis, J., 2017. 8D - Systematisch Probleme lösen. Carl Hanser Verlag GmbH & Co. KG, München, 123 pp.
[23] Meissner, A., Müller, M., Hermann, A., Metternich, J., 2018. Digitalization as a catalyst for lean production: A learning factory approach for digital shop floor management. Procedia Manufacturing 23, 81–86.
[24] Bramer, M., 2020. Principles of Data Mining, 4th ed. 2020 ed. Springer London; Imprint Springer, London, 571 pp.
[25] Longard, L., Schiborr, L., Metternich, J., 2022. Potentials and obstacles of the use of data mining in problem-solving processes. Manuscript submitted for publication.
[26] Hackathorn, R., 2002. Minimizing Action Distance. DM Review, 1–5.
[27] Lanza, G., Hofmann, C., Stricker, N., Biehl, E., Braun, Y., 2018. Auf dem Weg zum digitalen Shopfloor Management: Eine Studie zum Stand der Echtzeitentscheidungsfähigkeit und des Industrie 4.0-Reifegrads.
[28] Ohlig, J., Hellebrandt, T., Metzmacher, A.I., Pötters, P., Heine, I., Schmitt, R.H., Leyendecker, B., 2020. Performance management on the shop floor – an investigation of KPI perception among managers and employees. International Journal of Quality and Service Sciences 12 (4), 461–473.
[29] Aggarwal, C.C., 2017. Outlier Analysis, 2nd ed. 2017 ed. Springer, Cham, 466 pp.
[30] Bishop, C.M., 2006. Pattern recognition and machine learning. Springer Science+Business Media LLC, New York, NY, 758 pp.
[31] Chang, I., Tiao, G.C., Chen, C., 1988. Estimation of Time Series Parameters in the Presence of Outliers. Technometrics 30 (2), 193–204.
[32] Reshef, D.N., Reshef, Y.A., Finucane, H.K., Grossman, S.R., McVean, G., Turnbaugh, P.J., Lander, E.S., Mitzenmacher, M., Sabeti, P.C., 2011. Detecting novel associations in large data sets. Science (New York, N.Y.) 334 (6062), 1518–1524.
[33] Peral, J., Maté, A., Marco, M., 2017. Application of Data Mining techniques to identify relevant Key Performance Indicators. Computer Standards & Interfaces 50, 55–64.

Biography

Lukas Longard, M. Sc. (*1992) is chief engineer and PhD student at the Institute of Production Management, Technology and Machine Tools (PTW) at Darmstadt University of Technology since 2019. His research interests include the further development and introduction of machine learning to digital shop floor management and performance management systems.

Sebastian Bardy, M. Sc. (*1991) is PhD student at the Institute of Production Management, Technology and Machine Tools (PTW) at Darmstadt University of Technology since 2019. His research interests include the further development and introduction of resource-efficiency in digital shop floor management.

Prof. Dr.-Ing. Joachim Metternich (*1968) has been the head of the Institute for Production Management, Technology and Machine Tools (PTW) at Darmstadt University of Technology since 2012. He is spokesman of the medium-sized businesses digital competence centre Darmstadt, he has been president of the International Association of Learning Factories (IALF) from 2015 to 2021 and he is a member of the scientific society for production technology (WGP).