Applying Operational Business Intelligence in Production Environments

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Abstract

Operational Business Intelligence (OpBI) discusses a possible support of production-specific decisions by integrating and analyzing production data. The discussion of OpBI focusses thereby rather on common applicability aspects than on certain implementation strategies. This is however less conclusive for a functional reliability of OpBI in production environments and for associated efforts. Therefore, we introduce an OpBI framework to integrate and analyze data of production processes automatically. Following principles of design science research, framework evaluation refers to real-world data from a rod and wire rolling process. In conclusion, our OpBI framework improves information quality perceived by end users analyzing a steel's rolling behavior.
Keywords: Operational Business Intelligence, Smart Factory, Design Science Research

1. Introduction

Manufacturing companies use IT systems to execute, record, model, or control production processes [1]. Common examples are automation systems, tools for product development, or operational execution systems [11]. Moreover, manufacturing managers need intelligent and integrated decision support systems that provide information from different viewpoints of production processes systematically [8]. In order to gain such benefits from using information systems in production, data from different sources (e.g. automation systems) have to be collected, harmonized and integrated [17]. However, dynamic and networked process structures challenge organizations in integrating data from IT systems used in production environments [23]. Integration approaches come along with a huge amount of manual work and lack in standardized and reusable methods [8]. Consequently, analysis of production data is time-consuming and happens in different subsystems, which do not share information for a decision making automatically [17]. In order to address these challenges in integrating and analyzing production data, manufacturing companies have the opportunity to consider IT concepts from an analytical information systems' perspective. Recently, literature studies discuss OpBI as a beneficial strategy to generate decision-relevant information out of production data, which stem from different IT systems [13]. However, this discussion deals rather with a common applicability of OpBI in production environments [19], than with implementations of certain methods and tools for an automated acquisition, consolidation, and analysis of production data. Thus, there is no evidence that OpBI actually works in practice. Efforts, benefits and obstacles of integrating and analyzing production data automatically remain fuzzy in a particular application scenario. The paper's goal is therefore to investigate an actual implementation of OpBI in a certain production environment.

There are currently no studies that deal with automated integration and analysis of production data in a standardized and reusable way. Discussions about Smart Manufacturing [2, 6],

Manufacturing Intelligence [4], or Industry 4.0 [20] demand admittedly a data-driven decision support in production environments, but they do not elaborate on tangible tools and methods in order to prepare and analyze data of production processes adequately. To support such activities, we apply design science research to develop an OpBI framework that joins capabilities like data modelling, data transformation or data manipulation for an integrated analysis and control of production processes. Evaluation happens during a framework application in context of integrating data from a rod and wire rolling process. Analytical tools and methods are used to demonstrate functional reliability of OpBI in an industry-driven use case. Finally, process engineers perform an assessment of the OpBI application in comparison to the traditional approach of analyzing rod and wire rolling data. To the best of our knowledge, this paper is the first contribution that discusses efforts, benefits and obstacles in integrating and analyzing real-world production data by use of established tools and methods from analytical information systems' perspective, yet. We document practical knowledge about an actual implementation of OpBI in a production environment, so that practitioners and researchers gain a standardized guideline to design an automated data-driven management support for production-specific decisions.
The paper is structured as follows: Chapter 2 discusses the status quo of OpBI and its application in production environments. The paper uses phases of design science research presented in Chapter 3. Chapter 4 introduces our framework and Chapter 5 demonstrates its evaluation using an example process of forming industry. A discussion of results follows in Chapter 6. Finally, Chapter 7 concludes the paper's implications and highlights further research perspectives.

2. Status Quo

OpBI supports a decision making of business operation managers [7]. The concept refers to analytical IT system capabilities that collect, integrate, and present business relevant information in a decision-oriented way [9]. This allows an analysis of process performances to identify control actions for a continuous improvement of process design and execution [14]. The dashed line in Figure 1 marks the decision background of OpBI.

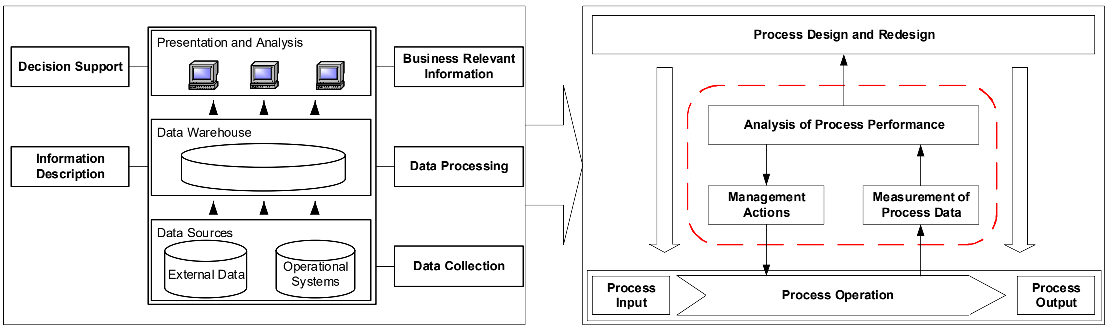

Fig. 1. Decision Background of OpBI according to [14]

An adjacent research area to OpBI are workflow systems enabling automatization and parallelization of process-related operations. These systems define, execute and track business processes [26]. Events like begin of process, moment of finishing, input and output parameters, used resources or interruptions are recorded. However, workflow systems do not support a multidimensional view on these data to evaluate process performance like OpBI, because an analysis of data from workflow systems is limited, yet [16], especially in contexts of sophisticated processes with distributed tasks [3].

Problem Refinement

Production environments open a broad potential application area for OpBI [14]. Manufacturing companies collect a lot of data about products, manufacturing processes or quality issues. Furthermore, automation systems, sensor technologies or computing devices make large amounts of data available. [17] The demand for a pervasive and ubiquitous usage of data in production environments is even increased by future-oriented smart factory initiatives [31]. A tracking of products through plants and working stations represents an exemplary scenario for data usage in a smart factory. In that context, production cockpits [28] are able to visualize throughput times, upcoming bottlenecks, material consumptions, or overall efficiencies.

An important qualification for such capabilities in a smart factory is an accurate, fast and automated integration of underlying production data [31]. OpBI offers standardized tools and methods in this context, which form a basis to take production-specific decisions, e.g. an allocation of new work to idle capacities. It has to be noted that such decisions cannot be easily reversed, if continuous workloads require a steady processing of production orders. Wrong decisions increase risks of defective products and lead to additional efforts for a correct task fulfilment. To avoid such inconvenient situations, the OpBI's activities to consolidate and harmonize production data have to ensure that decision makers are well provided with high-quality information. A seizure of quality in terms accessing and representing information can be guided by the following requirements [21]:

- Concise representation requires compactness and precision of information to avoid overwhelming and unnecessary information.
- Consistent representation requires a coherent and invariant format of information.
- Interpretability requires the usage of appropriate units, definitions or labels.
- Understandability requires unambiguously and comprehensible information.
- Ease of operation requires easy manipulations of information.

A compliance of information quality in context of an automated integration and analysis of production data has not been investigated, yet. Literature studies theorize generally a positive effect of analytical IT approaches like OpBI on aspects of information quality, i.e. decision time and accuracy [15, 29]. However, a usability of OpBI concerning the abovementioned quality criteria has not been confirmed in empirical investigations [15]. The paper investigates therefore the effect of OpBI usage on information quality aspects in production environments.

Related Research

The relevance of integrating and analyzing production data becomes evident by decision support functionalities of industry-driven approaches. For example, Manufacturing Execution Systems (MES) collect, process, and present data in order to coordinate production processes [24]. Furthermore, Advanced Process Control (APC) characterizes an analysis of process data in semiconductor industries. APC solutions encompass modules to conduct operation inspections, error classifications or efficiency calculations. Statistical methods can be used to monitor equipment, or technical processes. [30] The term Manufacturing Intelligence (MI) belongs to the discussion about an extraction of information out of production data for decision support purposes, too [4]. MI focusses on a pervasive usage of data integration techniques to enable a problem-oriented information supply for decision makers [5]. This includes several aspects of analyzing production processes like for example pattern detection, real-time monitoring, or simulations [18]. Considering the need for networked production data within and across manufacturing processes, the catchphrase of Smart Manufacturing asks for an intensification of MI in industrial organizations [6]. This is reasoned by observations, that existing IT solutions in production environments entail only single process improvements with insufficient opportunities for decision support [2].

All of the industry-driven concepts pursue control functions in production environments based on a comprehensive usage of data. However, these concepts do not discuss standardized and reusable approaches for an automated data integration and analysis. A proper handling of production data concerning the aspects of data modelling, model implementations, data transformations or automated report generation is commonly ignored. OpBI is able to fill this gap with tools and methods for an automated data integration and analysis. This finding arises from a literature review across the databases of Business Source Complete, IEEE, AIS, ACM, Emerald, and Science Direct. We used these literature sources to assess research contributions on OpBI in production environments according to MIS journal rankings [22]. In result of the literature review, the application of OpBI is subject of different case studies and conceptual papers. The literature addresses for example the ability of OpBI to improve the analysis and reporting functionalities of MES as part of a company-wide decision architecture [12]. OpBI enables furthermore a consideration of heterogeneous data from technical and economic perspectives [19]. The underlying data integration connects logistical and product-oriented IT systems, so that OpBI is able to support multidimensional views on flexibility requirements of production processes [13]. Looking for actual implementations of OpBI in production environments, the literature contains no knowledge about data integration methods or tools to apply OpBI in practice, yet.

3. Research Design

Our research follows principles of design science research (DSR) [10]. We refer to five phases of DSR in order to develop and evaluate an OpBI framework for a production-specific decision support (Cf. Figure 2).

Fig. 2. Phases of DSR according to [27]

The first phase aims to raise awareness for the given problem domain and results in a proposal. This is followed by a suggestion of a tentative design. In context of our research, the first two phases are carried out in the introduction of the paper and in Chapter 2. We discussed a need for an automated data integration to support decisions in production environments and suggest an application of OpBI techniques within this problem area. Subsequently, an OpBI framework will be developed and evaluated in the course of this paper.

4. Development of the OpBI Framework

Figure 3 illustrates the schematic overview of our framework. We build up on framework requirements stemming from a specific process design and operation. First, there is a need for layout data regarding the process equipment (e.g. machines, measuring points and instruments) and in terms of measurement parameters. Second, operational data from different process runs are required. This concerns for example planned input and output data for each process step, machine settings, or measured values. Therefore, it has to be ensured that a measurement of operational data happens actually. Examples for an IT support are sensor systems, process data acquisition tools or control stations.

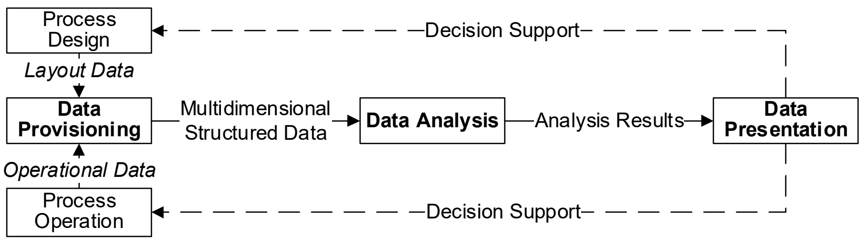

Fig. 3. Design of the OpBI Framework

Both, layout and operational data flow into the data provisioning component of our OpBI framework. The component’s output is a multidimensional structured database that is populated with measured values of process operation. The subsequent data analysis component generates analysis results that will be finally visualized to users in the data presentation component. The dashed line indicates a decision support for process design and operation based on achieved analysis results.

Data Provisioning

The data provisioning component encompasses activities from data modelling right up to data storage (Cf. Figure 4).

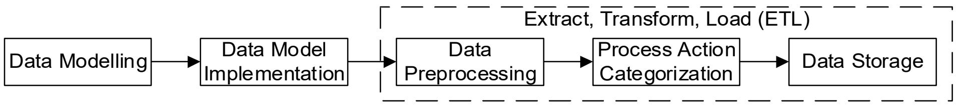

Fig. 4. Activities of data provisioning

At first, a data modelling concerns a semantic conceptualization of a multidimensional database. The content of the data model is thereby derived from process design and operation. This includes process hierarchies with subprocesses, phases, monitoring points, and determinants. Measurement parameters and process runs span further dimensions. In addition to these aspects of a manufacturing process, time-related dimensions (date and time of manufacturing) need to be modelled, too. After creating the data model, it has to be implemented in a database management system. Dimensions are transferred to database tables consisting of keys and content columns. A data type has to be defined for each column. The database tables store either descriptive dimensions or facts. The dimension tables are populated with meta-information from process design. Fact tables are populated subsequently to the data model implementation during an ETL process (Extract, Transform, and Load). Thereby, the measured values collected for example by a process data acquisition system need to be organized according to the implemented data model structure. In order to do so, the measured values from process operation must be harmonized to the data types of the fact tables during a data preprocessing. The data are cleaned up and enriched by additional calculations. The second aspect of the ETL process refers to a categorization of process actions. Logically related activities are filtered based on specified criteria and assigned to a unique identifier. This is especially relevant, if one process station handles different activities or if parallel work occurs. The final step of the ETL process stores the preprocessed and categorized data in the implemented fact tables of a database management system.

Data Analysis and Presentation

The data analysis component executes queries on multidimensional structured process data. This is carried out by a business intelligence or analytics tool in order to generate certain analysis results. An analytical platform provides an interface to different users interested in a basic reporting, an interactive data discovery or a complex ad hoc report generation. The necessary objects to create the reports are also defined in the analytical component. This requires e.g. filter or aggregation functionalities. The analysis results are finally presented and communicated for decision support purposes. Grids and graphs can be used exclusively as well as combined in dashboards or management cockpits. Figure 5 summarizes the activities for data analysis and presentation.

Fig. 5. Activities of data analysis and presentation

5. Framework Evaluation

We use production data from a rod and wire rolling process to evaluate our OpBI framework. The underlying process setting and the evaluation of the framework components is presented in the following. We have used different IT tools and methods for data acquisition, data provisioning and data analysis (Cf. Figure 6).

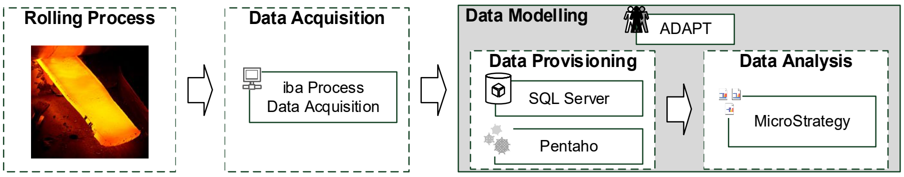

Fig. 6. Evaluation Process

Rolling Process and Data Acquisition

The background of our evaluation is a hot rolling process. In this context, the rolling behavior of different steel grades needs to be analyzed. The process is carried out on a semi-continuous rolling train. This plant produces round wire of eight millimeter diameter out of steel billets with a 45 millimeter edge length. Therefore, materials run through nine stations over a distance of more than 46 meters. The rolling train is divided in a roughing mill and a final rolling pass. Preliminary material is heated to 1,150 degree Celsius before it flows into the roughing mill with two reversing rollers. Different rolling calibers decrement a steel billet's initial dimensions to a diameter of around twelve millimeters. Thereby, the material is handled by two workers using pliers to push the materials in the roughing mill and to pull it out again. After each pass, a button is pressed in order to change the rolling direction. The intermediate products go subsequently through the final rolling pass consisting of four finishing mills, a cooling line, a wire driver, and a looper. The finishing mills are assembled in a so called H-V-H-V arrangement (horizontal, vertical). This allows an alternating height and width reduction of wire. There is a cooling line with three water pipes after the last finishing mill. The wire is cooled down to a temperature of 800 to 900 degrees Celsius, and then looped by a laying unit. A process run consists of eleven roughing mill phases and four finishing mill phases. Before each run, the machines are configured according to technical parameters of a rolling schedule. This includes the determination of the rolling gaps and rolling speed. The process stability is checked in a control station during the process. Mill forces, temperatures, momenta, and electrical parameters are measured by use of a process data acquisition software of iba. This company is specialized on automation systems and has implemented different measuring points (e.g. dynamometer or pyrometer) on the rolling train that are networked to the control station.

Data Provisioning

We carried out activities of data modeling and transformation for the purpose of data provisioning. In context of data modelling, we refer to the method of Application Design for Analytical Processing Technologies (ADAPT). This allows us a modelling of dimensions, hierarchies and analysis cubes by predefined shapes. The semantic data model for the rod and wire rolling process is represented in Figure 7.

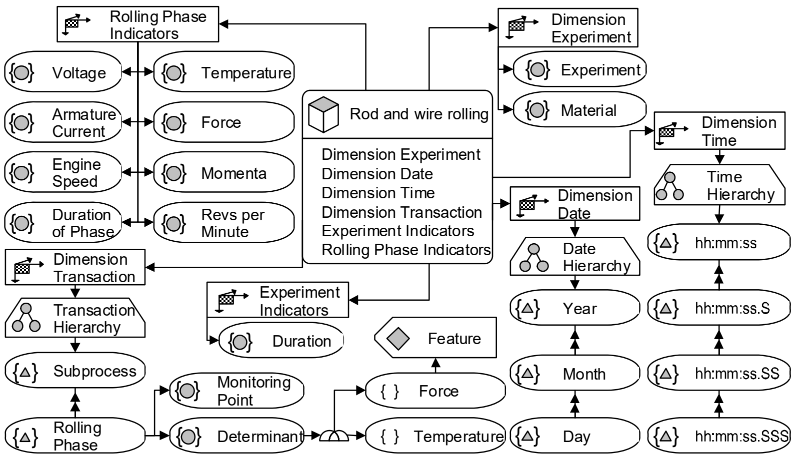

Fig. 7. ADAPT Model of the Rod and Wire Rolling Process

Each rolling pass is related to an experiment, which is conducted on the rolling train. A particular material is thereby formed to predefined dimensions. This is expressed by the experiment's dimension in the ADAPT model. Experiments are conducted on a certain date. The experiment duration is between one and two and a half minutes. The acquisition of measurement data happens in a cycle of two milliseconds. Therefore, the dimensions time and date provide certain hierarchy levels in order to aggregate time and date related information. The transaction dimension represents the process design. The rod and wire rolling process consists of two subprocesses with several rolling phases. Measured forces or temperatures determine the rolling phases. There are overlappings of rolling phases due to the continuity of the finishing train. This happens if more than one monitoring point records measurement data at the same time. For this reason, two indicator dimensions are used in the data model. The rolling phase indicators consider parallel measurement, while the experiment indicator dimension describes the actual experiment duration. We implemented this ADAPT model in a SQL Server database. The *DIM Date* table contains data for the year of 2015. *DIM Transaction* considers 33 rolling phases with three different determinants. There are 14 monitoring points, two subprocesses and 15 features. The table *DIM Experiment* contains 26 experiments and two different steel grades. Time-related data encompass timestamps of a 24 hour day from second level to millisecond level. In order to populate the fact tables of the galaxy schema, we created data transformations in Pentaho Data Integration. The measurement values recorded by the iba process data acquisition system are exported to text files and imported into Pentaho. The data have a string format at the beginning of the ETL process. First, we cut these strings to a desired length and changed the labels of the measurement parameters according to their definition in the fact tables. In a next step we replaced cryptic values and added a column for an experiment ID so that we were able to reference the fact tables with the *DIM Experiment* table in our database. In the further progress, a variety of steps was necessary to calculate a transaction ID for the different rolling phases. We determined these IDs separately for the roughing mill and finishing mill using temperature and force parameters. The initial temperature before the roughing mill amounts approximately 670 degrees Celsius. The force ranges between zero and 15 kilonewton in the initial state of the rolling train. Measurement values meeting the initial conditions are classified to idle state.

To identify the further rolling phases of the roughing mill, we differentiated temperature and force operations. There is a pyrometer before and after the roughing mill. The temperature jumps up, if the material is right in front of the roller. This identifies the first rolling phase. Then, a measurement of forces happens during the first pass and determines the second phase. If the material is completely gone through the rollers, only the values at the output pyrometer differ from the initial state. This identifies the third rolling phase. However, these conditions are valid for different rolling phases, because several passes happen on the roughing mill. Therefore, we added a sequence and calculated the transaction ID based on changing operations. This represents the calculation of the transaction ID for the roughing mill. In case of the final rolling pass, the identification was easier due to the continuity of this rolling train part. We filtered the phases according to the different monitoring points. So, ten rolling phases were derived, which overlap each other. We built also a dataset without overlappings in order to trace the complete final rolling pass. Next to transaction ID and experiment ID, a date column was determined, too. We used a calculation to remove the time part from imported timestamps. Furthermore, measurement interval are calculated. This allows to determine the durations of each rolling phase and experiments. In result, our ETL implementation encompasses five transformation processes using the table output function of Pentaho. We run four ETL processes to transfer the transformed measurement data to 13 temporary fact tables and integrated them later to one phase-related fact table in the SQL server database. The experiment-related fact table was populated by a separate transformation.

Data Analysis

The data analysis was performed on the analytical platform of MicroStrategy. We created several reports that are presented via a web interface for example in report documents or analysis dashboards in context of basic reporting. In addition, the development environment provides extensive possibilities to investigate the data according to various aspects. MicroStrategy uses a meta-data database and our implemented rolling database connected via ODBC to the analytical platform. In order to generate reports, we built first attributes and metrics within the tool environment. Attributes and metrics are placed on grid or graph templates and enable also the creation of additional report objects, e.g. filter or consolidations. The report objects definition is stored in the meta-data database. If a process is run, an analytical engine generates SQL statements in order to query the rolling database. Figure 8 illustrates an example report.

Subprocess	Rolling Phase	Experiment	Experiment 15		Experiment 26	
		Material	100Cr6		C45	
		Feature	Duration of Phase	Ratio Duration Phase to Experiment	Duration of Phase	Ratio Duration Phase to Experiment
Roughing mill	DF1	K02/001 Sw. oval	622	0.41%	614	0.53%
	DF2	K05/001 rotund 36 mm	704	0.47%	694	0.60%
	DF3	K02/001 Sw. oval	484	0.32%	480	0.42%
	DF4	K05/002 rotund 27 mm	634	0.42%	626	0.54%
	DF5	K03/001 oval	816	0.54%	826	0.72%
	DF6	K05/003 rotund 20 mm	1,056	0.70%	1,072	0.93%
	DF7	K03/001 oval	1,408	0.94%	1,412	1.23%
	DF8	K05/004 rotund 15 mm	1,876	1.25%	1,860	1.62%
	DF9	K03/002 oval	2,274	1.51%	2,258	1.96%
	DF10	K05/002 rotund 12 mm	2,780	1.85%	2,764	2.40%
	Total		12,654	8.42%	12,606	10.95%
Final rolling pass	F1	K3/50 B	406	0.27%	392	0.34%
	F2	K9/24 A	404	0.27%	382	0.33%
	F3	K3/21 A	402	0.27%	374	0.32%
	F4	K9/23 B	388	0.26%	364	0.32%
	Total		1,600	1.06%	1,512	1.31%

Fig. 8. Example report – relation of phase durations to experiment duration

6. Discussion

The OpBI framework introduced in Chapter 4 has been evaluated in context of a rod and wire rolling process. We demonstrated that the integration of rolling data is feasible from a technical point of view and leads to consistent results from a functional perspective. Our framework has been discussed with engineers responsible for the rod and wire rolling process in order to make a comparison to the traditional analysis approach. Therefore, we use information quality requirements presented in the problem refinement of the paper.

In a nutshell, using our OpBI framework improves analysis capabilities of users conducting experiments on the rolling train in favor of a profound analysis of a steel's rolling behavior. This encompasses for example faster analyses in an automated way or the possibility to calculate indicators on a different level of detail. The traditional approach was related to spreadsheet software (e.g. MS Excel) and an analysis add-on of the process data acquisition software. In particular, the engineers pointed out that analysis results were generated in a time-consuming, manual, and error-prone process. A detailed comparison of the framework approach and the traditional approach follows in Table 1.

Table 29. Comparison of the proposed solution to the existing approach.

	Traditional Approach	OpBI Framework
Concise Representation & Consistent Representation	• Two-dimensional presentation of measurement parameters • Experiment-related presentation • Manual and unstandardized reports • Presentation by simple graphs or spreadsheet programs	• Multidimensional presentation of descriptive information and measurement parameters • Use of hierarchies • Process-related presentation • Automated and standardized reports • Various presentation options

	Traditional Approach	OpBI Framework
Interpretability & Understandability	• Difficulties to consider external or additional parameters • Static analysis perspectives	• Different levels of detail • Opportunity of add data perspectives • Flexible analysis perspectives
Ease of Operation	• Limited data manipulation options • Time-consuming aggregations and calculations	• Flexible options for data manipulation (drilling, pivoting, filtering, sorting) • Simple aggregations and calculations

Table 1 indicates a positive effect of OpBI on information quality compared to the traditional approach of analyzing the rod and wire rolling process. The engineers mentioned in terms of consistent representation:

> *The OpBI system presents the rolling process consistently from functional and technical viewpoints.*

Concerning consistent representation, the importance to explain and predict measurement values like temperatures or forces has been pointed out. An engineer said in that context:

> *We have often complex issues in which we need to describe the effect of various influencing factors on a specific measurement parameter. Thereby, the OpBI system allows us to keep track of interactions between materials and rolling measures in different functional areas of the rolling train.*

The opinion in terms of interpretability and understandability was two-minded. Major improvements are expected in context of analyzing experiments conducted on the rolling train. The improved representation has been associated with a better interpretation and understanding of analysis issues. However, the engineers emphasize the importance and the need of expert knowledge, so that they see only an indirect effect of the OpBI system in this context. Moreover, the relevance of our framework approach for interpretations of workers operating a machine has been discussed. A technical assistant mentioned:

> *Each run on the rolling train lasts less than two minutes. So, there is no time for interpretations during an experiment.*

In this context, the OpBI system cannot bring an advantage compared to the previous approach. Changes on working behavior will still concern subsequent experiments. In order to identify such changes, the ease of operation of the OpBI system was commended by the engineers:

> *Using the traditional approach provides us values always on the minimum level of detail. So it is difficult to determine average values for process phases at the flick of a switch without the OpBI system.*

The discussion with the engineers reveals direct and indirect relationships between the criteria of information quality introduced in Chapter 2 (See Problem Refinement) and the usability of OpBI. This circumstance is illustrated in Figure 9. OpBI improves directly a concise and consistent representation of information generated from production data. A direct effect also exists in context of manipulating the data during analysis activities (ease of operation). Understandability and interpretability are indirectly improved by a better representation and ease of operation. However, both quality criteria depend also from analytical skills and experiences of end users. Following literature about information success e.g. [25], we are able to confirm a relationship between information quality and the usability of OpBI in production environments.

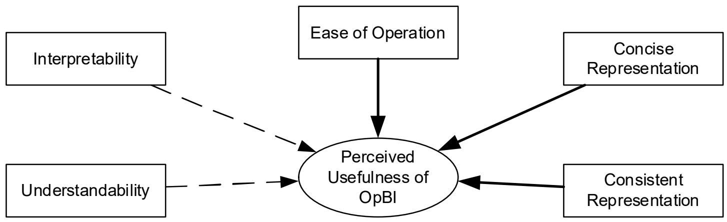

Fig. 9. Relationship between Information Quality Criteria and OpBI

The illustrated usability and the gained benefits from OpBI depend on main efforts in context of data modelling, database implementation, transformation processes, and report generation. However, these activities have to be performed only once and can be adapted in case of changed situations. Created report objects are reusable for new report definitions. It has to be noted that the implemented data model is only valid for a specific process configuration. Adaptations are required in case of e.g. new monitoring points or process stations. Implementations of new database models and transformation processes will be necessary, if the rolling train is retooled to another configuration (e.g. hot-rolled strip).
Next to the comprehensive analysis opportunities, the framework is beneficial to identify and carry out control actions. This concerns material characteristics in dependence on measured values. It is for example possible to determine hold times in order to reach a specific temperature. An interesting decision area is the roughing mill in context of the rod and wire rolling process. Due to the interaction of humans and machine, there are various potential relationships as for example the reversing time on a material's temperature profile. Furthermore, decisions can be made about the usefulness of monitoring points and measurement parameters in a given process configuration. The framework and its analytical tools builds upon a process data acquisition software. Such tracking systems to control process stability are not replaced. However, the analysis opportunities of our proposed OpBI solution allow process engineers to link measurement values with input parameters of machine controls dynamically. This makes a parameter setting in a given context more precise than a merely experience-based approach.
The application of OpBI in the given context requires tools that integrate and analyze production data. In order to evaluate our framework components, we used specific data integration and analysis tools. The framework application is however independent from the presented tool selection and can be done by comparable BI-related tools, too. Nevertheless, a new acquisition of software solutions or an extension of already existing analytical environments is required. This forces system developers to examine design and execution data in order to gain a comprehensive understanding of the underlying process. The consistency of the analysis results should be scrutinized by experts during each OpBI project. This ensures a coherent and accurate information base to analyze a material's behavior on the rolling train and to derive actions for decision support. Gained experiences need to be documented for future projects.

7. Conclusion

OpBI is able to automate the integration and analysis of production data in favor of a multidimensional decision support, if specific efforts in context of data provisioning and data analysis are managed. The paper's contribution takes the implementation of OpBI functionalities into account in order to improve the analysis capabilities of decision makers in production environments. In this context, we designed and evaluated a framework that guides actual applications of OpBI to integrate production data automatically. Central components of our proposed solution are a modelling of multidimensional data structures as well as a deployment of corresponding data transformation processes. These data processing activities enable an annotation of stationary recorded and machine-located measurement values with descriptive information of a certain process design. The multidimensional structured production data form a basis for subsequent analyses and a production-specific decision making.

The paper demonstrates an OpBI-driven framework that allows a flexible design of analysis dimensions to assess process-related measurement values in the overall context of a production process. Considering opportunities for decision support in production environments, a feasibility of OpBI becomes evident. The paper demonstrates a new application field to research and study OpBI. This enhances recent discussions about topics like Smart Manufacturing or Industry 4.0 with novel methods and tools coming from an analytical information systems perspective. The proposed framework and its evaluation in a real-world context introduce new knowledge and experiences regarding OpBI implementations in production environments. Practitioners and researchers gain insights about data integration approaches, so that they are able to extract valuable information from production data recorded for example by process automation systems. Thereby, the present investigation addresses cost in terms of data management or software tools in context of an OpBI-driven integration and analysis of production data.
The framework evaluation with data from a rod and wire rolling process provides a valid proof of concept. This is however only one example and embodies a gambit for repeated applications of OpBI in order to automate the integration and analysis of data from production processes. Thus, further evaluations should be part of subsequent research activities, so that the paper's findings can be consolidated in favor of scalability. Thereby, comparisons of different application scenarios will lead to a generalizability of the OpBI-driven approach and to conceptual improvements. Moreover, upcoming technologies in smart factories will lead to new sources of generating production data. Their usage for decision making opens a broad field of research for an automated data integration and analysis. The feasibility of existing tools and methods from OpBI perspective has to be permanently evaluated against their usability in future smart factories. This provides a promising field for further research in order to study and to apply adaptations and advancements of the presented data integration approach.

References

1. Bharadwaj, S., Bharadwaj, A., Bendoly, E.: The Performance Effects of Complementarities Between Information Systems, Marketing, Manufacturing, and Supply Chain Processes. Inf. Syst. Res. 18 (4), 437-453 (2007)
2. Brodsky, A., Krishnamoorthy, M., Menascé, D.A., Shao, G., Rachuri, S.: Toward Smart Manufacturing Using Decision Analytics. In: International Conference on Big Data, pp. 967-977. IEEE, Washington DC (2014)
3. Cheung, M., Hidders, J.: Round-trip iterative business process modelling between BPA and BPMS tools. Bus. Process Manag. J. 17 (3), 461-494 (2011)
4. Chien, C.F., Chen, Y.J., Hsu, C.Y.: A novel approach to hedge and compensate the critical dimension variation of the developed-and-etched circuit patterns for yield enhancement in semiconductor manufacturing. Comput. Oper. Res. 53, 309-318 (2015)
5. Cooley, J., Petrusich, J.: Delivering optimal real-time manufacturing intelligence. In: Proceedings of PICMET '13: Technology Management for Emerging Technologies, pp. 1658-1668. IEEE, San Jose (2013)
6. Davis, J., Edgar, T., Porter, J., Bernaden, J., Sarlie, M.: Smart manufacturing, manufacturing intelligence and demand-dynamic performance. Comput. Chem. Eng. 47, 145-156 (2012)
7. Davis, J., Imhoff, C., White, C.: Operational Business Intelligence: The State of the Art. Beye NETWORK Research, Boulder (2009)
8. Delen, D., Pratt, D.B.: An integrated and intelligent DSS for manufacturing systems. Expert Syst. Appl. 30 (2), 325-336 (2006)
9. Eckerson W.W.: Best Practices in Operational BI: Converging Analytical and Operational Processes. TDWI Best Practices Report, Renton (2007)
10. Gregor, S., Hevner, A.R.: Positioning and Presenting Design Science Research for Maximum Impact. MISQ 37 (2), 337-355 (2013)

11. Groover, M.P.: Automation, Production Systems, and Computer-Integrated Manufacturing. Prentice Hall Press, Upper Saddle River (2008)
12. Hänel, T., Felden, C.: Limits or Integration? Manufacturing Execution Systems and Operational Business Intelligence. In Proceedings of the 17th Amercias Conference on Informations Systems (AMCIS). AIS, Detroit (2011)
13. Hänel, T., Felden, C.: Operational Business Intelligence Meets Manufacturing. In: Proceedings of the 19th Americas Conference on Information Systems (AMCIS). AIS, Chicago (2013)
14. Hänel, T., Felden, C.: Towards a Stability of Process-Oriented Decision Support Concepts Using the Example of Operational Business Intelligence. In: Proceedings of the Pre-ICIS BI Congress 3: Driving Innovation through Big Data Analytics. AIS, Orlando (2012)
15. Hänel, T., Schulz, M.: Is There Still a Need for Multidimensional Data Models? In: Proceedings of the 22nd European Conference on Information Systems (ECIS). AIS, Tel Aviv (2014)
16. Kang, B., Kim, D., Kang, S.H.: Periodic performance prediction for realtime business process monitoring. Ind. Manag. Data Syst. 112 (1-2), 4-23 (2012)
17. Kassner, L.B., Mitschang B.: MaXCept – Decision Support in Exception Handling through Unstructured Data Integration in the Production Context. An Integral Part of the Smart Factory. In: Proceedings of the 48th Hawaii International Conference on System Sciences (HICCS), pp. 1007-1016. IEEE, Kauai (2015)
18. Kuo, C.J., Chien, C.F., Chen, J.D.: Manufacturing Intelligence to Exploit the Value of Production and Tool Data to Reduce Cycle Time. IEEE Transactions on Automation Science and Engineering 8 (1), 103-111 (2011)
19. Lasi, H.: Industrial intelligence - a BI based approach to enhance manufacturing engineering in industrial companies. In: Proceedings of the 8th CIRP conference on intelligent computation in manufacturing engineering, pp. 384-389. Elesevier, Gulf of Naples (2012)
20. Lee, J., Bagheri, B., Kao, H.A.: A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. Manuf. Lett. 3, 18-23 (2015)
21. Lee, Y.W., Strong, D.M., Kahn, B.K., Wang, R.Y.: AIMQ: A Methodology for Information Quality Assessment. Inform. Manag. 40 (2), 133-146 (2002)
22. MIS Rankings (2016), http://aisnet.org/?JournalRankings. Accessed June 26, 2016
23. Nahavandi, S., Creighton, D., Le, V.T., Johnstone, M., Zhang, J.: Future Integrated Factories: A System of Systems Engineering Perspective. In: Fathi, M. (ed.) Integrated Systems: Innovations and Applications, pp. 147-161. Springer, Cham (2015)
24. Saenz de Ugarte, B., Artiba, A., Pellerin, R.: Manufacturing execution system - a literature review. Prod. Plan. Control 20 (6), 525-539 (2009)
25. Seddon, P.B.: A Respecification and Extension of the DeLone and McLean Model of IS Success. Inf. Syst. Res. 8 (3), 240-253 (1997)
26. van der Aalst, W.M.P., van Hee K.M.: Workflow Management: Models, Methods, and Systems, MIT Press, Cambridge (2002)
27. Vaishnavi, V., Kuechler, W.: Design Science Research in Information Systems (2015), http://www.desrist.org/design-research-in-information-systems. Accessed June 26, 2016
28. Vasyutynskyy, V., Hengstler, C., McCarthy, J., Brennan, K.G., Nadoveza, D., Dennert, A.: Layered architecture for production and logistics cockpits. In: Proceedings of the 17th International Conference on Emerging Technologies & Factory Automation (ETFA), pp. 1-9. IEEE, Krakow (2012)
29. Vujošević, D., Kovačević, I., Suknović, M., Lalić, N.: A Comparison of the Usability of Performing Ad hoc Querying on Dimensionally Modeled Data Versus Operationally Modeled Data. Decis. Support Syst. 54 (1), 185-197 (2012)
30. Yugma, C., Blue, J., Dauzere-Peres, S., Vialletelle, P.: Integration of Scheduling and Advanced Process Control in Semiconductor Manufacturing: Review and Outlook. In:

Proceedings of the International Conference on Automation Science and Engineering (CASE), pp. 93-98. IEEE, Taipei (2014)

31. Zuehlke, D.: Smart Factory - Towards a factory-of things. Ann. Rev. Control 34 (1), 129-138 (2010)