Data-driven Continuous Improvement Process Framework for Railway Construction Projects

S. van der Veen[a*] P. Dallasega[b] and D. Hall [c]

[a]Rhomberg Sersa Rail Group, Switzerland
[b]Free University of Bozen-Bolzano, Italy
[c]ETH Zurich, Switzerland
E-mail: sascha.vanderveen@rsrg.com, patrick.dallasega@unibz.it, hall@ibi.baug.ethz.ch

Abstract

Delays and cost overruns are frequent in infrastructure construction projects. Traditionally, deviations are often identified late, and it is very difficult to trace back the causes. Decisions are often taken by experience and not with the support of data directly coming from site. Moreover, schedules are often static and thus not able to reflect the real conditions on-site. Emerging technologies like Building Information Modeling (BIM), mobile cloud computing, and advanced sensors can help to overcome the previously mentioned issues. The collection of production data by sensors with the aim to compare production metrics with the schedule in order to introduce a Continuous Improvement Process (CIP).

In the paper, we propose a framework for a digital platform to gather production data in real-time and to identify early on bottlenecks that could potentially lead to delays and deviations. The proposed platform should support in collecting, analyzing, and structuring production data. Furthermore, the platform should give insights and support organizational decision making of a CIP. With a demonstration case we show the three main functionalities of the platform: 1) retrospective analysis, 2) live analysis and 3) predictive analysis. In future research, the platform will be implemented and validated within railway construction projects of the company Rhomberg Sersa Rail Group AG.

Keywords –

Real-time; Lean Construction; Continuous Improvement Process; Infrastructure; Digitalization

1 Introduction

Delays and cost overruns are frequent in infrastructure construction projects. Only around 25% of construction projects worldwide have come within the range of 10% of their original deadlines from 2012 to 2014 (KPMG 2015). Globally, rail construction projects are frequently affected by budget and schedule overruns by an average of 44.7% (McKinsey Global Institute 2015). Whereas other industries almost doubled their productivity over the past decades, the construction industry remained the same (McKinsey Productivity Science Center, 2015). Considering railway construction projects, short durations for maintenance as well as new installments are crucial to avoid a breakdown of the railway network. Otherwise, time overruns are often fined with high penalties.

Traditionally, one of the biggest issues is the usage of static schedules that do not reflect real conditions on-site (Dallasega et al. 2018). As a result, schedules become useless and coordination is based on improvisations. Furthermore, progress tracking is often based on rough estimations and thus schedule deviations are not known in detail. Scheduling is usually done according to the experience of the project or site manager and not based on the monitoring of the construction progress. Thus, it is very difficult to identify bottlenecks, as for example a machine that reduces speed and thus leads to a potential decrease of productivity of the following construction processes.

As a result of the previous mentioned issues, problems are often identified in a late stage making it difficult to implement appropriate improvement actions in time. Furthermore, construction projects are loosely connected and improvements are not systematically stored or transferred to future projects (Tetik et al. 2019). Early identification of bottlenecks and a dynamic definition of improvement actions as well as their impact would decrease variability and thus reduce budget overruns.

In order to minimize delays and defects, other industries such as manufacturing implemented Lean Management Principles that are based on the Toyota Production System. Lean Management focuses on the improvement of the processes by defining and evaluating the Value Stream with a focus on Value-Adding activities and the elimination of waste which is defined as 'any activity that does not add up to the products value' (Womack and Jones 2003). A central element of the Lean Management is Visual Control of process execution and deviations. Appropriate Improvement actions are also visualized and responsibilities are defined that leads to process improvement accountability (Mann 2014).

The Plan-Do-Check-Act (PDCA) approach is a framework to improve processes and track the progress of improvement in manufacturing companies. The approach consists of 4 phases (Chong and Perumal, 2020). The first is defined as the pre-implementation (Plan) where the improvement actions get planned. The second stage is the implementation of the planned actions (Do) in which the Lean tools of improvements get carried out. The third phase is the evaluation (Check) in which the performance of the improvement actions is analyzed. The last phase is the standardization and documentation of the successfully implemented actions (Act) (Chong and Perumal, 2020).

The implementation of Lean Construction is well researched and methodologies such as the Last Planner System (LPS) (Ballard 2000), Takt Planning (Haghsheno et al. 2016), or Location-Based Management System (Kenley and Seppänen 2009) have been applied in practice. However, the identification of waste in construction is usually reactive. Commonly used Key Performance Indicators (KPI), like the Cost Performance Index (CPI) or the Schedule Performance Index (SPI), are unable to provide in-depth analyses about causes of problems and thus they give limited support in suggesting appropriate improvement actions (Dallasega et al. 2020).

Commonly used software tools, like Vico Office Software (https://vicooffice.dk/en/), visualize construction schedules with a flowline based on quantities and production rates derived from BIM models. However, these types of software give a limited support in proposing appropriate improvement actions in case of schedule deviations. A platform that collects production data in real-time and compares it with the planned ones, incorporating a continuous improvement process (CIP) would enable higher productivity rates. So far most of the works in this area are very conceptual and lack empirical validation (Tetik et al. 2019).

Considering the manufacturing industry, the usage of real-time data to optimize production processes is one of the main pillars of Industry 4.0 (Schuh et al. 2012). Although, the utilization of real-time data coming directly from site to support scheduling and monitoring processes is currently not widely researched and practiced in construction. Therefore, we propose a framework for a digital platform that allows the comparison of planned and as-built data enabling a CIP to support early identification of problems in construction. The proposed framework for the digital platform is structured in three main functionalities:

1) retrospective analysis, 2) live analysis, and 3) predictive analysis.

The previously listed functionalities are motivated by using three demonstration cases that were derived from a project of the company Rhomberg Sersa Rail Group in Switzerland.

2 Literature Review

Traditionally, live data is barely collected in the construction industry and, therefore, platforms to document progress or production data in real-time are not widely distributed. According to Zhao et al. (2019), the traditional process of data collection has remained manual in the construction industry. In their research they propose a platform model that combines Bluetooth Low Energy technology and 3G/4G network as connection methods that explore the movements and time information of workers on site which is used to manage resource flows using lean principles (Zhao et al. 2019).

Similarly, Tetik et al. (2019) proposed a framework to improve construction performance through closing the loop from construction to design. They propose to centralize the As-Built BIM model and gather production data for reuse in future projects. The aim is to use the platform as a knowledge database. However, live data analysis is not part of the research.

Another digital platform is proposed by Rossi et al. (2019) that focuses on the productivity measurement of machines to identify their value-adding activities. Although, they do not consider interdependencies of different machines which is an important aspect to consider in infrastructure projects. In this way, bottlenecks can be identified but appropriate improvement actions cannot be derived.

According to Akhavian and Behzadan (2015) direct observations such as surveys in the field to obtain large volumes of high-quality data is inefficient since manual gathering is time consuming and inaccurate. Automated data collection using sensors, vision-based systems and laser scanners gained importance in quantitative analysis of construction activities. The authors propose a framework to analyze the production data on different granularities to gain accuracy in the data collection and establish a Level of Detail (LoD) for processing production data. (Akhavian and Behzadan 2015).

Song and Eldin (2012) propose a framework for real-time tracking that contains process knowledgebase, adaptive modeling and simulation services. The system constantly tracks operation activities and data is used for accurate lookahead scheduling However, a structured way to identify root causes is not considered in the approach.

Another framework for data gathering and processing was proposed by Vasnev et al. (2014), which should support decision making based on production data in three different levels: operational, tactical and strategic. The aim of the framework is to run post-construction analyses of the production process (Vasnev et al. 2014).

The literature review shows that a platform that processes production data is researched in the field. Several functionalities of a platform are proposed with a different focus. The reviewed research mostly focuses on the data gathering and the evaluation of productivity rates respectively value adding activities. Nevertheless, to the best of our knowledge, a platform that focuses on Continuous Improvement actions based on production data can be considered as novel in the field.

3 Concept

This paper proposes the framework for a CIP platform to collect, analyze and adapt the production planning of railway construction projects. The platform will collect as-built production data. It will analyze how causes of problems (losses) can be identified retrospectively (Demonstration case - Scenario 1) to provide better planning data for future infrastructure projects. Next, it will identify problems in real-time to implement appropriate improvement actions (Demonstration case - Scenario 2). Moreover, it will identify potential future problems before their occurrence to proactively avoid budget and schedule overruns (Demonstration case - Scenario 3). The developed framework will be implemented and validated in selected project scenarios of the company Rhomberg Sersa Rail Group.

The proposed framework of the platform should support the collection, analysis and structuring of production data in real-time. A centralized platform will enable on site as well as remote access to the data. Gathering the data in an overall database promotes a holistic view on construction performance. It will run a live comparison with the planned schedule data in order to identify bottlenecks that led to potential deviations. The system that performs the analysis will be defined within the future implementation. As shown in Figure 1, the platform is the link between Planning and Production that processes both sides and can enhance data driven decision making.

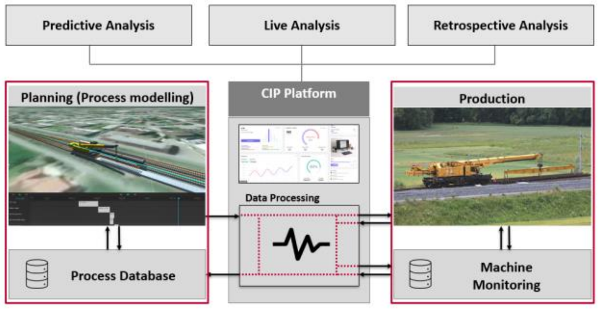

Figure 1: Concept diagram

In order to run a comparison of the planning- and production data, the dataset has to be aligned and defined by the same measurement unit e.g production speed. The data analysis comparison is performed by overlaying the data in a backend system respectively database that runs a permanent data evaluation. The analysis can be performed in various ways respectively with different scopes. Our concept proposes three main functionalities for the evaluation of the production data: retrospective analysis, live analysis, and predictive analysis.

1 Retrospective Analysis

The retrospective analysis identifies production bottlenecks after the construction process was carried out. If the analysis is executed in short cycles, appropriate improvements can be made for following processes within the actual or future projects. For example, if the daily target of a construction site is not reached, the proposed platform will support the identification of the root cause by pointing out the bottleneck. Improvement actions in order to adhere to the schedule in the following days or to avoid the problem to cause deviations again are suggested.

2 Live Analysis

The live analysis compares the production data in real time and indicates deviations from the planned schedule. Then, adjustments can be evaluated and implemented in real time. For example, the productivity rate that is necessary in order to adhere to the schedule can be displayed in the cockpit of the machine. The data provides live performance measures and the status of the production. It requires a setup with high bandwidth on site in order to process the data between the machines and the platform. The live comparison of the production data to the planned production schedule leads to the possibility to take live improvement actions such as increasing productivity rates. Even if an unpredictable deviation occurs, the data processing conducted live in the background can propose the right production speed to recover delays and assure schedule adherence.

3 Predictive Analysis

Based on data of previous projects, problems can be identified before they occur. The provision of production data respectively the production problems in the design and work preparation leads to a more stable schedule and a decrease of variation. The more high-quality data is provided the more stable the prediction will get. Technologies such as Artificial Intelligence (AI) can support the analysis of large data sets. Machine Learning can support a predictive analysis of a likelihood of a certain problem if the input data is structured accurate. (Taofeek et. al, 2020)

For each process or machine a threshold productivity value has to be defined that can be supported by Machine Learning. If the value is out of the defined threshold, then the platform will give a notification for that point in the schedule. The notifications can then be set in focus and the reason for deviation identified and categorized. The proposed classification functionality will get integrated and the reasons that commonly lead to deviations predefined. If a certain deviation occurs the platform supports in the identification of causes and improvement actions. As a structure to support the root cause analysis the Lean tool `five whys` will be used. According to David Mann the 5 whys is a basic method of root cause analysis. Every Why is intended to go deeper into the cause of a situation (Mann, 2014). The predefined tree diagram extends over the time and the user has the ability to complement the categories in order to cover every reason for deviation and preparation for further deviations. The classification according to the tree diagram respectively 5 Why can enhance project specific as well as organizational decisions.

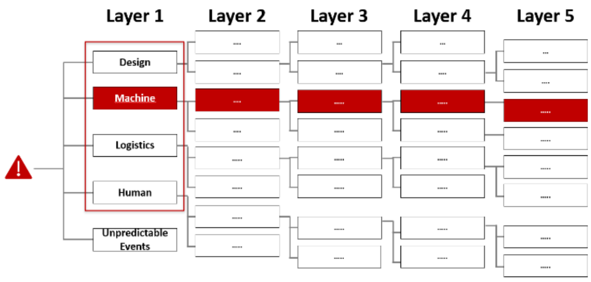

Figure 2: Problem Classification - Tree diagram

The tree-diagram (Figure 2) captures the layers of the 5 Whys' and supports in defining the root cause by proposing previous documented reasons for deviation.
If e.g., the overall evaluation points out that a high percentage of problems lead back to production machines, improvement actions can be focused to maintenance tasks. We propose each level of the tree diagram has a named definition and will be accessible by the people who can use the information for their decision making. However, the adoption of the tool is an important aspect of success. In order to analyze the root causes the categorization is essential. The layers will be defined by analyzing reasons for deviations of past projects by evaluating existing data and experience from people working on site. The definition of the layers will be defined according to the results of the analysis.

4 Demonstration Case

The scenario of the demonstration case was derived from a previous project of Rhomberg Sersa Rail Group. The planned data was gathered according to a project schedule. Nevertheless, the As-Is production data was derived from feedback of the site manager based on his knowledge. The production data wasn't gathered while operations because such a system isn't in place on the construction sites of the Rhomberg Sersa Railgroup. To describe the functionalities of the platform, two processes are focused. The goal of the chosen schedule cutout is to build the ballast track bed and the laying of rails. Both processes are conducted by machines (M1: Ballast Track machine, M2: Track crane).

Productivity rates of both machines are the same that leads to a harmonized production speed. The construction of 200 m starts at 06:00 am and the completion is planned at 12:30 pm (Figure 3). The As-Is completion occurred at 13:30 pm. Thus, the schedule was exceeded by one hour. A reflection of the delay was conducted but a valid identification of the root cause was not possible due to missing data. The usage of the proposed platform will enable different ways of analyzing the data and furthermore conduct appropriate improvement actions. The Rhomberg Sersa Railgroup is currently developing a software used to model the construction processes within a BIM environment. A novelty of that software is that the machines are integrated into the 4D planning environment and their motion respectively process execution is simulated. The aim of that software is to run process simulations in order to check the feasibility based on 4D clash detection and decrease variability. Standardized construction process modules can be used in order to improve the planning process. However, the integration of feedback from site in real-time is not yet considered in the software. Furthermore, the Rhomberg Sersa Railgroup recently launched a machine monitoring tool that structures complex machine data and makes it accessible. In the following chapters we describe the functionalities of the platform according to a demonstration case.

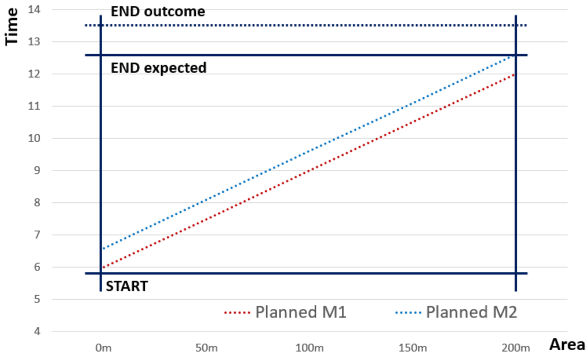

Figure 3: Demonstration Case: Schedule (Planned)

4.1 Scenario 1: Retrospective Analysis

The retrospective analysis of the production data leads to a bottleneck identification after the construction process was carried out. If the analysis is executed in short cycles appropriate improvements can be made for following processes within the actual or future projects. The analysis of the As-Is data in this scenario points out that M1 had a loss of productivity in the area between 75m and 100m. The loss occurred between 08:15 and 10:00 am. M2 had to adjust the speed due to the loss of M1 (Figure 4). According to the data M1 is the bottleneck and the reason for the delay. The red marked area highlights the area the deviation occurred. The As-Is graph of both machines points out that the adjustment of M2 was reactive and a collision was prevented on short notice on site. The analysis gives an indication about the time and the area. The identification of the root cause of the problem can be narrowed down with this information and further investigations can be done. The identified problem point will then be classified supported by the proposed root cause analysis tool respectively with the tree diagram.

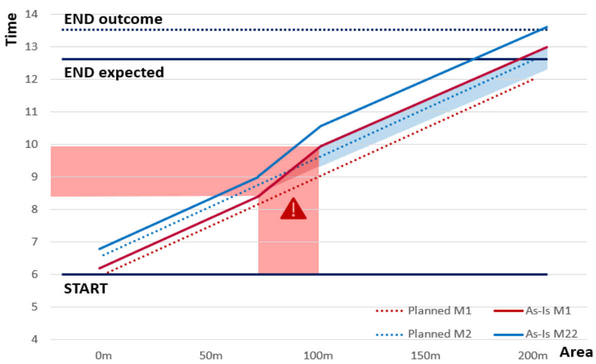

Figure 4: Way-time diagram - Retrospective Analysis

4.2 Scenario 2: Live Analysis

As described in the concept the machines are connected through the platform and the productivity can be compared to the planned in a continuous way during production. At 08:00AM when M1 slows down the information goes directly to M2, which can adjust its speed (Figure 5). At the moment when the productivity reaches the average, the platform can propose the right speed in order to adhere to the schedule. The information can be integrated into the system and the machine can be operated according to the information calculated in the platform. The live analysis enables not just live evaluation but also a live conduction of improvement actions such as the adjustment of the productivity rate in order to reach the planned schedule.

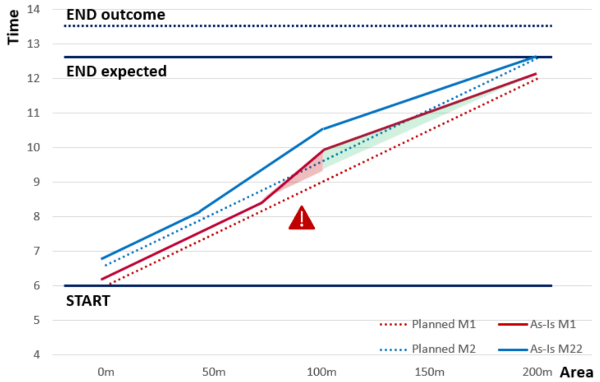

Figure 5: Way-time diagram - Live Analysis

4.3 Scenario 3: Predictive Analysis

In this scenario a potential problem will be highlighted in advance (Figure 6). The construction team is able to perform measures in order to prevent the occurrence of the problem. The platform detects a potential risk based on the data of previous projects. The graphs show that the As-Is production was as planned. The machines were able to perform the planned productivity starting 06:00AM to 12:30PM. Furthermore, proposals for the mitigation of the risk are linked based on the previous improvement actions. As shown in Figure 6 the productivity remains as planned. Both machines can work as planned and the risk for delay can be eliminated. The outcome assures schedule adherence.

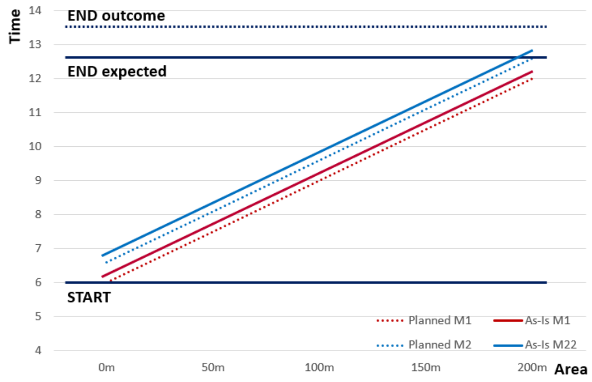

Figure 6: Way-time diagram - Predictive Analysis

5 Discussion

The proposed framework has its focus on railway construction projects. Nevertheless, the functionalities can be transferred to other machine-driven infrastructure projects such as road construction. Due to the lack of possibilities of data collection supported with sensors the use in building construction projects it is not in scope but can be further evaluated in the future research.

6 Conclusion & Outlook

A platform for the analysis of production data in real-time by comparing it with the planned schedule and providing a structure to categorize reasons for deviations would decrease variability in the construction industry. As described in the literature review several concepts for live data collection and analysis were proposed. However, to the best of our knowledge, a platform that focuses on Continuous Improvement actions based on production data could be considered as novel in the field. The proposed functionalities of retrospective, live, predictive analyses offer different ways to analyze and improve the production. The retrospective analysis enables a data driven review and supports identifying bottlenecks retrospectively. The live analysis enables live improvement actions such as increasing or decreasing productivity rates. The live processing of the data enables a data driven proposal of adaptions. When combined with machine learning, the collection of this high-quality production data can enable predictive analyses. The knowledge of previous construction projects can so be used to improve the planning process by considering potential risks that usually appear during construction.

The detection of problem points with the classification functionality enables a focused CIP. The overall evaluation of the problems from production will enable a data-based decision making on different organizational levels. However, the implementation has to be accompanied with a comprehensive roll-out plan in order to increase acceptance. The unveiling and visualization of problems can lead to resistance from the workforce.

The framework will be developed and practically evaluated in future projects of the company Rhomberg Sersa Rail. Further research activities should be the creation of a database for the comparison of the planned and the production datasets. The gathering of production data of manual tasks is very difficult and therefore it should be analyzed how this could be supported with emerging technologies (e.g., reality capture, motion capture and others).

The functionality of the deviation recognition should be implemented based on the dataset to allow a Continuous Improvement Process or Root Cause Analysis of identified problems. The tree diagram as shown in Figure 2 should be systematically developed and extended with specific construction site experience.

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