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A case study on integrating data analysis and process mining in conventional tunnel construction

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ABSTRACT

Conventional tunnel construction often relies on manual methods of construction process analysis, using tools such as paper-based cycle diagrams or spreadsheets, which lack immediate updates and capabilities, limiting performance evaluation, communication, and decision-making. As a result, moving to a fully digital process incorporating business intelligence capabilities can deliver benefits by improving data-driven decision-making, operational efficiency and resource allocation. This paper presents a case study using construction documentation to evaluate the applicability of data and process analytics in conventional tunnelling. We also present a novel approach to visualising and analysing construction sequence deviations. The study demonstrates how data and process analysis can be utilised to evaluate the activity sequences, the duration of single activities, advance rates, and general project performance. By adhering to established industry standards, this research examines the practical implementation of data analysis methods in operational tunnelling environments, contributing to the development of integrated digital workflows.

1. Introduction

In tunnelling domain, data from geospatial surveys, sensors on tunnel equipment, quality assurance and construction documentation offer opportunities for making underlying processes more efficient and cost-effective (Sun et al., 2018; Feng et al., 2021; Xiao et al., 2022; Park and Kang, 2016). Conventional tunnelling projects present greater challenges for process analysis compared to the industrial sector (Corallo et al., 2020; Dunzer et al., 2021) or building design (Gao et al., 2023; Lagunas and Nik-Bakht, 2024), due to deviations often caused by several factors. A primary cause is geological unpredictability, where unforeseen ground conditions, like complex rock formations or water ingress, lead to deviations from planned excavation methods and timelines (Schneider and Mathoi, 2006; Wild, 2018; Melnyk et al., 2023b). Equipment failures or performance issues can also cause delays, requiring workflow adjustments, while inadequate documentation and delays in updating records complicate progress tracking and timely corrective actions (Kvasina, 2018). As common in the broader construction industry, resource allocation and coordination inefficiencies frequently lead to deviations. Miscommunications or poor documentation data can result in 35 % (Thomas et al., 2018) of work time spent on non-productive activities such as searching for project information, resolving disputes, and addressing mistakes and rework (Wild, 2018). Cost overruns often arise from unforeseen geological conditions, additional resources, plan modifications, and regulatory or safety requirement changes (Schneider and Mathoi, 2006; Stadlmann, 2018).

The inherent complexity of conventional tunnel construction is further complicated by the lack of real-time updates and inefficient tracking of changes due to current analogue documentation practices (Kvasina, 2018; Zach, 2021), making communication and decision-making more challenging. Also, while multiple commercial platforms exist for managing Tunnel Boring Machine (TBM) project data, conventional tunnelling lacks comparable digital solutions, leading to reliance on manual documentation methods like spreadsheets and paper-based reporting that limit data analytics capabilities. Thus, in this domain, performance evaluation still relies on manual reviews of paper-based cycle diagrams (Kvasina, 2018; Huymajer et al., 2024b), which provide limited visualisation and interpretation of aggregated data across multiple tunnelling rounds. Further, construction companies often rely on literature and experience-based approaches for tender bidding rather

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than leveraging aggregated digital data from projects. In this context, the integration of seamless digital documentation and subsequent business intelligence (Zack Jourdan and Marshall, 2008; Negash and Gray, 2008) applications facilitates effective change tracking, enhances operational efficiency, ensures stakeholder transparency, supports data-driven process analysis, and simplifies the identification of deviations from planned processes.

Analysis of advance rates and construction process deviations are key for ensuring timely and cost-efficient tunnel construction that adheres to relevant contractual agreements (Tesch, 2017; Melnyk et al., 2023b). The application of data analysis (Brzychczy et al., 2020; Perez et al., 2018), process discovery and conformance checking (Carmona et al., 2018; Rozinat and van der Aalst, 2008) techniques offers solutions for real-time monitoring and automated tracking of deviations. These methods enable project managers to quickly detect and react to disrupted construction progress, improving adherence to planned processes. Therefore, this study aims to explore data analysis and process mining in conventional tunnelling projects through a case study employing site-sourced data. First, we analyse activity durations and sequence deviations, offering an alternative to traditional daily reviews of paper-based cycle diagrams and providing a more versatile method of visualising, identifying, and addressing construction delays. Second, we employ data analysis to a dataset aggregated from a month of tunnelling project construction to provide a more precise approach for advance rate predictions for the bidding phase. To achieve the study's objectives, we apply the Cross-Industry Standard Process for Data Mining (CRISP-DM) (Chapman et al., 2000) framework to derive specific use cases based on the available data from a case study and develop a prototype for visualising construction process deviations in conventional tunnelling.

The study is structured into five main sections. Section 2 summarises the state-of-the-art process mining approaches in civil engineering and related fields, time and delays, followed by an analysis of divergent process steps specific to a tunnel round. Section 3 describes the data and methodological approach applied for the purpose of this study. Section 4 describes the analysed construction data, which originates from one month of construction of the *Zentrum am Berg*[1] research tunnel (Galler, 2016). The presented case study was conducted to assess the effectiveness of the applied approaches and toolsets for the specific documentation data. Section 4.1 further introduces a prototype to visualise activity sequence deviations and delays in tunnel rounds and assess individual activities at a more granular level, aiding in identifying deviations and inefficiencies within the construction process. Finally, the results of implementing the proposed data analysis, process mining and conformance checking approaches are presented in Section 5, and the limitations of the research are discussed in Section 6. This study suggests that the introduction of digital data management systems is necessary for enhancing real-time monitoring and analysis capabilities in conventional tunnel construction. This shift can improve accuracy and efficiency in data handling, support advanced analysis processes, and facilitate continuous project data collection and review, which can help maintain adherence to contractual performance indicators.

2. Related work

While sharing aspects with other civil engineering disciplines, tunnelling is characterised by unique challenges. These include uncertainties in subsurface conditions like geology and hydrology (ÖGG, 2011), extensive use of temporary support structures (Galler et al., 2009), and adverse conditions such as poor lighting, dust, water ingress, toxic fumes, confined spaces, and loose rock hazards (Girmscheid, 2013). To address these complexities, the tunnelling industry can significantly benefit from digitalisation (Stadlmann, 2018). By adopting established information systems architectures from manufacturing and logistics sectors (Koskela, 1992), tunnelling projects can enhance documentation, control, and data analytics capabilities. Implementing these transformations requires a clear understanding of project objectives, available resources, potential risks, and success criteria from both business and technical perspectives. With this foundation, technologies like cloud-based platforms, mobile applications, and centralised databases have already been effectively deployed to enhance data sharing, collaboration (Costin et al., 2018), and business intelligence (Badakhshan et al., 2022; Zack Jourdan and Marshall, 2008). The sections below analyse conventional tunnel construction documentation data, advance rates relevant for tendering and construction performance evaluation, and applicable data mining techniques. The primary focus is on advance rate forecasts, central to cost estimation and project scheduling in large-scale tunnel projects. This is followed by examining documentation challenges specific to tunnelling and identifying opportunities to enhance information management. The final section discusses the application of process mining in construction, assessing its efficacy in improving data analysis and decision-making processes, all aligned with predetermined business and data mining objectives.

2.1. Documentation in conventional tunnelling

Effective management of tunnelling projects requires complete documentation and constant analysis of construction activities (Kvasina, 2018; Zach, 2021; Melnyk et al., 2023a) including obstructions and unforeseen downtime. According to standards such as the ÖNORM B 2110 (ASI, 2023a), ÖNORM B 2118 (ASI, 2013; Schoiswohl, 2021) or FIDIC Emerald Book (FIDIC, 2019), the contractor is obligated to document all construction progress systematically. Full documentation of all works and conditions is also required by international standards. This documentation, maintained by both the employer and the contractor, includes construction books, reports, meeting records, measurement sheets, plan delivery lists, photo and video documentation, and reports on obstructions and defects (Kvasina, 2018; Winkler, 2020). Tunnel construction sites which adhere to ÖNORM B 2203-1 necessitate comprehensive documentation through daily construction reports, shift reports, excavation reports, and cycle diagrams (Kvasina, 2018; Huymajer et al., 2024a; Winkler et al., 2022). These documents are essential for recording the progress of construction, including any subsurface conditions affecting the construction process. The daily construction report, which marks the beginning of data collection at the site, explicitly details the operations within the tunnel during the current shift, including data on personnel, materials, equipment, and any notable events (Kvasina, 2018).

The tunnel construction industry has embraced digital platforms for enhanced project management and documentation (Piskernik and Winkler, 2017; Zhou et al., 2018), primarily through Building Information Modelling (BIM) (Sharafat et al., 2021; Erharter et al., 2023; Mayer et al., 2016; Hegemann et al., 2020; Song et al., 2019) and Geographic Information System (GIS) applications (Li et al., 2016; Rabensteiner et al., 2022; Khan et al., 2023). In conventional tunnelling, BIM primarily supports unstructured data management (Baraibar et al., 2022) and post-excavation modelling (Mitelman and Gurevich, 2021; Wenighofer et al., 2020). Also, while digital twin technology offers a promising advancement over BIM, existing research is mainly limited to a BIM data mining framework for project management in high-rise construction (Pan and Zhang, 2021b), theoretical frameworks for tunnelling (Li et al., 2024), or digital twin-based decision analysis focused on tunnel operation and maintenance (Yu et al., 2021). Recent research (Mitelman and Gurevich, 2021; Winkler et al., 2022; Huymajer et al., 2024a; Sharafat et al., 2021) underscores that while BIM provides robust documentation capabilities, persistent gaps in real-time data capture and standardisation across project phases hinder full-scale adoption. While BIM approaches in tunnelling have traditionally focused on

[1] https://www.zab.at/

representing permanent structural elements, construction operations generate large amounts of process-related data, such as shift activities, material usage and temporary support measures that need to be documented separately. According to the analysis by Huymajer et al. (2024a), the implementation of construction process-related information, such as work shifts, material usage, temporary support structures and equipment usage, remains inadequate in current BIM approaches. In addition, temporary support measures, activity sequences and durations as well as resources, such as explosives, are often not modelled or documented using BIM, resulting in incomplete as-built documentation that does not capture the full extent of tunnelling operations and therefore hinders subsequent data analysis. Therefore, robust digital documentation is required to enable data analysis in conventional tunnelling, bridging the gap between theoretical frameworks and practical applications.

In mechanised tunnelling, multiple commercial products exist for TBM data management, shift and construction site reporting, and analytics. For instance, platforms like Tunnel Insight,[2] TunnelLink,[3] and the MissionOS[4] have been extensively employed for managing data on some of the world's largest urban tunnel projects. However, most of these platforms are designed only for TBM projects and do not account for the multitude of tools, various construction methods, teams and tasks, and dynamic, permanently changing approaches in conventional tunnelling in response to local geological conditions. Therefore, many conventional tunnelling projects rely on paper-based documentation, such as Microsoft Excel (Kvasina, 2018; Melnyk et al., 2023a) or Microsoft SharePoint (Rist, 2023) for daily shift reports, data and project management, which limits subsequent analytics applications. Due to the absence of off-the-shelf solutions, some companies develop internal proprietary project management platforms, such as IRIS (STRABAG SE, 2020; ITC Engineering, 2014) or Hydra (ITC Engineering GmbH & Co. KG, 2023) for TBM projects, or use general commercial platforms like Thinkproject (Thinkproject, 2024), which offer limited support for conventional tunnel projects. This approach raises development costs for such internal solutions and does not allow for industry-wide adoption. Tunnelsoft's TPC,[5] a commercial software platform initially developed for TBM projects, has been extended to support conventional tunnelling applications. However, the extent of features relevant for complete reporting, interoperability, and subsequent process analytics, especially covering different standards applied for documentation and invoicing such as the ÖNORM B 2203-1 (ASI, 2023b) used in multiple large-scale projects (BBT SE, 2013; Geoconsult India Pvt Ltd, 2015), is unclear. While the software enables shift-related analysis of project progress and pie-chart analysis of working time information gathered in shift reports, an open-source solution proposed in this study can provide more versatility regarding specific documentation types and the ability for construction companies to expand the platform's functionality as project demands evolve. In this context, an open-source documentation platform specifically designed for conventional tunnelling projects, such as TIMS (Huymajer et al., 2022), offers a promising solution for documentation and provides potential for extension to facilitate subsequent data analysis.

The extensive documentation required in conventional tunnel construction, when managed using traditional paper-based methods, complicates the processes of evaluation and traceability (Schiefer, 2018; Kvasina, 2018). Thus, digital documentation software integrated with an Enterprise Resource Planning (ERP) (Kouhestani and Nik-Bakht, 2018; Melnyk et al., 2023a, 2024) system can streamline documentation and process analysis during construction. ERP software facilitates digital work preparation, operational planning, monitoring, documentation and real-time process analysis. Model-driven engineering (MDE) (Kent, 2002) helps develop data models for TIMS, with data serialised according to Extensible Markup Language (XML)[6] Architecture, Engineering and Construction (AEC) standards (Kouhestani and Nik-Bakht, 2018; ASI, 2021). For instance, the data model of TIMS is designed by extending the Tryton ERP[7] framework to include construction and tunnelling-specific concepts. Paper-based data collection in tunnelling is fraught with repetitive data entries, inconsistencies, and errors (Kvasina, 2018; Schiefer, 2018; Winkler, 2020). Thus, a digital documentation tool is crucial for accurate, centralised on-site data recording, aiding in business intelligence applications (Zach, 2021; Huymajer et al., 2022). When formatted as machine-readable documents (Huymajer et al., 2022; Melnyk et al., 2023a), these reports can be leveraged for data analytics applications like process mining thus enabling more accurate performance forecasts, cost estimation (Mitelman and Elmo, 2018), and enhanced project scheduling.

2.2. *Advance rates in tunnelling*

The conventional tunnelling approach considers the geomechanical behaviour of the rock mass, using timely and optimised support measures based on measurement and monitoring (Galler, 2014; Girmscheid, 2002; Schubert and Lauffer, 2012). This excavation and support process is conducted in cycles, known as tunnel rounds, with the length varying based on the geology (Galler, 2014). The adaptability of support measures such as shotcrete, anchors, and lattice girders to rock conditions makes conventional tunnelling methods favourable in areas with uncertain geological conditions (ÖGG, 2011; Schiefer, 2018). However, this flexibility poses challenges in tendering (Speckmoser, 2021), cost estimation (Stadlmann, 2018), documentation (Kvasina, 2018), and subsequent data analysis. Performance forecasts are a crucial basis for cost estimation and project scheduling in large-scale construction projects (Schneider et al., 2010; Falanesca et al., 2023). In tunnel construction, the key performance indicator is the excavation performance, referred to as the advance rates, which are measured in meters per day (ASI, 2023b). Following Hofstadler (2022), Winkler (2020), the advance rates are categorised as follows:

- **Predicted:** Based on calculations from the contractor and established through contractual agreements with the client.
- **Actual:** Determined by the number of tunnel meters excavated daily during construction.
- **Average:** Calculated as an average value, taking into account either significant segments or the entirety of the excavation.

In many commonly used contractual frameworks (Tesch, 2017) for conventional tunnelling projects, necessary measures for managing on-site geology are categorised into tunnelling classes based on various factors, with contractors specifying advance rates during the bidding process. This approach allows for predicting expected ground behaviour, and tunnelling classes are set accordingly for invoicing purposes (Winkler et al., 2022), following ÖNORM B 2203-1 (ASI, 2023b) standard. In the construction phase, rock types are identified, and a short-term forecast of rock conditions is made to guide excavation and support measures and predict system behaviour (Galler, 2014; Maidl et al., 2013).

ÖNORM 2203-1 bases its framework on a flexible construction schedule model for tunnelling progress, allowing fixed times only for the initial construction phases and the transition from tunnelling to project completion, where geological conditions permit (ASI, 2023b; Ortner, 2013). This framework allows for flexibility in construction times based on actual tunnelling classes encountered, with specific contract terms considering tunnelling interruptions and other operational pauses (Galler, 2010). Further, according to ÖNORM B 2110

2 https://gamuda-get.com/tunnel-insight

3 https://www.binni.co/tbm

4 https://www.maxwellgeosystems.com/applications/tunnels-data-management-system

5 https://www.tunnelsoft.de/tpc/allgemeine-features.html

6 https://www.w3.org/TR/xml

7 https://www.tryton.org

standard (ASI, 2023a), the scope of work (construction requirement) is defined as all contractor services determined by the contract, including specifications, plans, and legal conditions, under the objectively expected circumstances of service provision. This expected construction time considers the predicted distribution of tunnelling classes (Österreichische Gesellschaft für Geomechanik, 2021) and the tunnelling speeds stated by the contractor. The planned construction time thus aligns with the predicted distribution of tunnelling classes and the tunnelling speeds indicated by the bidder. The actual construction time reflects the real progress made, while the revised construction time, known post-adjustments for changes in scope (such as quantity changes and modified or additional services), becomes a binding contractual schedule (Ortner, 2013). Contract penalties, stipulated in contracts during the tender phase, mandate compensation for non-achievement of defined performance targets by specified deadlines (Kropik, 2023), streamlining claims for damages without detailed damage calculations, and pressuring the contractor to meet contract obligations.

During the design and tendering phase, the total time required to complete a section of tunnel, known as the advance rate (Roberts, 1992; Falanesca et al., 2023), is estimated from the corresponding construction activities. An example of such an estimate is shown in Table 1, where the activities planned for a particular tunnelling class are detailed. Most values derived from the literature were retained, but some calculations in this table have been slightly adjusted or anonymised to comply with the construction companies' data distribution policies and prevent re-identification. The typical sequence of activities for tunnel construction (Galler et al., 2009; Girmscheid, 2013) includes drilling, loading, mucking, and operating excavators. Optionally, shotcrete may be applied to the tunnel face to ensure structural stability. Additional measures, such as installing spiles ahead of excavation in unstable ground conditions, help support cavity walls (Galler, 2014). The installation of anchors follows this, as well as reinforced meshes, lattice girders (in the case-study documentation generalised as "support arches"), and shotcrete to reinforce the tunnel crown (Maidl et al., 2013). Further, each activity is divided into sub-activities necessary to complete the task, and the duration of each sub-activity is calculated to determine the duration per round (Schönwälder, 2010; Girmscheid, 2013). These durations, expressed in minutes per round, are then compiled for multiple tunnelling classes into a round cycle with the estimated construction speed provided in rounds or meters completed per workday (Schönwälder, 2010; ASI, 2023b).

The calculation of excavation cycles for all advance rates is conducted during the project's bidding phase, determining the required net times for all tasks directly associated with the construction team (Zare and Bruland, 2006). These times depend on various conditions, such as the number and type of support measures and the excavation method (ASI, 2023b). After determining the net cycle time, additional times are added during which the construction team cannot work at the tunnel face (downtime due to ventilation breaks, geological surveys, or obstructions). The gross cycle time and the length of the excavation thus determine the cycles per day (Schönwälder, 2010). The results are presented in minutes per linear metre to improve the comparability of the tunnelling classes by dividing the cycle times by the respective round lengths. This overview shows the proportion and magnitude of the times between the different classes. Based on the calculated advance rates, an accurate prediction of the tunnelling speed is important in the early stages of the project, especially for large tunnelling projects. Precise planning of the construction process is becoming increasingly important for the client, requiring even more accurate prediction of the construction speed. For construction companies, advance rates are a crucial input for bid calculations, cost estimate and estimating schedule risk (Schoiswohl, 2021; Melnyk et al., 2023b). As stated in previous studies (Schiefer, 2018; Winkler et al., 2022; Huymajer et al., 2022; Melnyk et al., 2023a) a robust documentation and data evaluation tool is essential to enhance the accuracy of advance rate estimates during planning and refine projected timelines during construction. Considering the central role of advance rate analysis in tunnel construction, employing statistical analysis tools in conjunction with process mining could be highly beneficial for contractors and site supervisors. Visualisation methods such as the distribution of round durations, analysis of different tunnel construction activity durations, and relative transition matrices of activities provide an overview of the construction process, including parallel activities and interruptions. These visualisation techniques offer more accurate insights into the actual processes on-site than traditional paper-based reports.

2.3. Data analysis and process mining in construction

Recent studies in construction process analytics encompass a variety of approaches and applications. The studies by Palaneeswaran and Kumaraswamy (2003), Dong et al. (2023) explore high-velocity knowledge mining frameworks and graph databases for process simulation, leveraging advanced technologies such as BIM, surveillance videos, and IoT networks to enhance digital integration in construction management. Additionally, Le et al. (2021), Roslon et al. (2018) explore data-driven process models and the broader implications of data mining in construction. Their research highlights the importance of data-driven construction management and process mining for knowledge maintenance and improvement. Lastly, the analysis and management of construction processes have been enhanced through various studies. Mo et al. (2017), van der Aalst (2011) have significantly contributed to this area. Their research on predicting work plans for facility management using text mining and applying process mining techniques in analysing construction invoice processing demonstrate these advanced methods' practical implications in real-world scenarios. Some applications of data and process analysis have also been explored in the field of subsurface engineering.

Multiple studies applied data analysis to tunnelling operations, covering topics such as performance analysis in pipe jacking (Lehmann et al., 2022; Zhang et al., 2018a), machine learning based on video feeds (Wu et al., 2020) or displacement data (Marcher et al., 2020; Akutagawa et al., 2014), and monitoring rock deformation data. However, most studies focus on data analysis for TBM tunnel construction to enhance machinery utilisation (Leng et al., 2020; Xiao et al., 2022; Feng et al., 2021; Brzychczy et al., 2020) or explore performance prediction (Zhu et al., 2020) and risk transfer and safety adherence processes (Wu et al., 2023; Cheng et al., 2020) in shield construction. Some of these studies employ a mix of text mining, machine learning, and complex network analysis (Fabozzi et al., 2021; Ninić et al., 2024). Research efforts have also integrated cost and schedule control (Cho et al., 2014) using construction equipment data and performance-based evaluations for NATM tunnels (Moon et al., 2020). Although data analysis has advanced in mechanised tunnelling, large infrastructure projects, particularly conventional tunnelling, continue to generate large amounts of unanalysed data, and research on process and construction data analysis remains limited (Wang and Zhang, 2021; Xie et al., 2022; Sharafat et al., 2021).

Process mining can be categorised into three types: process discovery, conformance checking and process enhancement (van der Aalst et al., 2012). Process mining can be viewed from four perspectives: control flow, organisational, case, and time (Urrea et al., 2021). Each offers different insights, like the sequence of activities, actor relationships, case properties, and event frequencies and durations (van der Aalst, 2011). A process mining project typically involves data preparation, modelling, and analysis. Data preparation is crucial due to the complexity of enterprise information systems and consists of identifying relevant data sources, handling syntactic and semantic errors, and converting data into event logs in formats like XES.[8] or MXML (Verbeek et al., 2011) This phase often includes data filtering to manage the

[8] https://xes-standard.org

Table 1
Estimate of tunnel advance rates based on construction activities, based on Girmscheid (2013), Schönwälder (2010).

Tunnelling Class 7/10,30						
Activity	**Subactivity duration**	**Description and calculation**	**Value**	**Unit**	**Duration per round**	
Excavator drive	Excavated volume (loose):	Excavation cross-section x cut-off length x additional excavation in % x loosening factor	74,49	m³/round		
	Loading cycles per hour:	60min : loading cycle time	66,67	cycles/h		
	Loading performance:	Excavator bucket content x loading cycles/hour x bucket fill factor	31,67	m³/h		
	Loosening + mucking per round:	Loose excavation volume : loading capacity/hour x 60min			**141,1**	**min/round**
Shotcrete (tunnel face)	m³ of shotcrete per linear meter (actual):	m³ of shotcrete per linear meter (theoretical) x rebound factor at face	2,09	m³/lm		
	Shotcrete duration:	m³ of shotcrete per linear meter (actual) : (shotcrete performance per machine) x 60min	12,52	min/lm		
	Time required for shotcrete per round:	Shotcrete duration x round length			**12,5**	**min/round**
Spiles	Length of spiles per round:	Number of spiles x length of spile	80,00	m		
	Gross drilling performance:	Net drilling performance x drill depth : (drill depth + repositioning x net drilling performance)	2,21	m/min		
	Spile installation per round:	(Length of spiles per round : gross drilling performance + length of spiles per round x installation time of spile) : 2 drilling arms			**58,1**	**min/round**
Anchors	Anchor drilling meters per round:	Number of anchors per round x anchor length	24,00	m/round		
	Gross drilling performance:	Net drilling performance x drill depth : (drill depth + repositioning x net drilling performance)	1,60	m/min		
	Anchoring per round:	(Anchor drilling meters per round : gross drilling performance + anchor drilling meters per round x Installation time of anchor) : 2 drill arms			**17,1**	**min/round**
Reinforcement mesh	Area per round:	Double-layer + face (0%)	37,37	m²/round		
	Reinforcement mesh per round:	Reinforcement mesh area per round x labour input for installation			**26,2**	**min/round**
Arch and load distributor	Number of tunnel arches per round:		1,00	unit/round		
	Arch installation per round:	Invoicing line x number per round x labour input for installation			**29,2**	**min/round**
Shotcrete for crown	m³ of shotcrete per linear meter (actual):	m³ of shotcrete per linear meter (theoretical) x rebound factor for vault	7,79	m³/lm		
	Shotcrete duration:	m³ of shotcrete per linear meter (actual) : (shotcrete performance per machine) x 60min	46,71	min/lm		
	Time required for shotcrete per round:	Shotcrete duration x rounding length			**46,7**	**min/round**
Round cycle (excerpt)						
TC 7/10,30	**Net round duration:**				**330,9**	**min/round**
	Delays per round:	Round duration x extension of the round cycle (5%)			22,1	min/round
	Gross duration:	Round duration + preparation + rounding and ventilation + geological survey + delays			**353,0**	**min/round**
	Rounds per day:	24h : (total gross duration : 60min)			4,08	round/workday
	Projected daily output:	Rounds per day x round length			**4,08**	**m/workday**

scope of the model (van der Aalst, 2011). Lastly, process models can be categorised as "Lasagna processes" (well-structured, simple processes) and "Spaghetti processes" (less structured, complex processes). While the former benefits more from advanced analyses like conformance checking (van der Aalst, 2011; Carmona et al., 2018), the latter offers greater value from classical process mining.

Conformance checking, a key aspect of process mining, involves comparing a process model with an event log to verify if the actual execution aligns with the modelled expectations (Carmona et al., 2018; Ailenei et al., 2012). This visual approach allows project managers to overlay event logs (De Weerdt et al., 2012) onto the process model, highlighting deviations, thus making it easier for project managers to identify issues (Rozinat and van der Aalst, 2008; Rashid and Louis, 2020; Pan and Zhang, 2021a; Berti and van der Aalst, 2021). Conformance checking is particularly useful in business alignment and auditing for comparing the performance of various process discovery algorithms and improving models that do not reflect reality. The key metrics derived from conformance checking are *Global Conformity Metric*, which looks at overall conformity between the process model and event log, and *Local Diagnosis*, which marks discrepancies in specific parts of the event log and process model (Kouhestani and Nik-Bakht, 2020; Zhang et al., 2018b). In tunnel construction, where precise coordination of tasks such as drilling, blasting, and lining works is crucial, conformance checking can help visualise and identify inefficiencies and deviations from the model. By analysing the event logs from tunnelling activities, this technique can detect deviations such as geologically caused delays, unexpected activity sequences, or unapproved methods, ensuring that the construction process aligns with the planned workflow. For instance, if the process model requires specific safety checks or sequential operations not reflected in the event logs, these deviations can be quickly identified and addressed, enhancing operational efficiency. For these reasons, we employ conformance checking to analyse the alignment between planned and executed construction sequences.

3. Methodology

This study aims to address issues with current advance rate predictions and construction performance evaluation using data from a case study. It involves the collection and analysis of data from the *Zentrum am Berg* (Galler, 2016) research tunnel, focusing on excavation and shift reports. For this, we utilise the widely adopted CRISP-DM (Chapman et al., 2000), an open framework that defines common methodologies for data science projects. Applying this model to the specific use cases of the conventional tunnelling industry enables an actionable approach to prototype development based on available construction data. This analytics model consists of six phases: Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, and Deployment. The study is structured accordingly to accommodate these phases. As shown in Fig. 1, the sequence of the phases is indicated by arrows in the process diagram, highlighting the frequent dependencies between phases.

The objectives in the *Business Understanding* phase, addressed in Section 2, include leveraging digital documentation and business intelligence techniques to enhance operational efficiency, enable digital monitoring, and improve resource management by identifying deviations from planned processes. To determine the stakeholder and project requirements, we discuss the challenges in construction documentation, the importance of advance rate evaluation, and available data analysis methods in conventional tunnelling. The purpose of data mining, following this review, is to assess the effectiveness of process mining and data analysis techniques using construction data from a tunnelling project to improve and speed up decision-making processes. The project plan described below outlines the tools and libraries for data retrieval, followed by statistical and process-oriented analysis.

During the *Data Understanding* phase, outlined in Section 4, initial data collection focuses on gathering construction data from one month of the *Zentrum am Berg* tunnel (Galler, 2016). The data collection involved capturing and recording relevant information from a real-life conventional tunnelling project. The data sources include 87 tunnel rounds corresponding to an advance of 87.6 m, activities, and support measures. The primary data source was the excavation report or shift report, which documents the activities, personnel, equipment, materials used, and incidents during each shift. Workers manually collected the data and then converted it into a table format, each cell representing a 15 min interval. Additionally, the tunnel cycle diagram (Winkler et al., 2022) within the tunnelling report provided a chronological

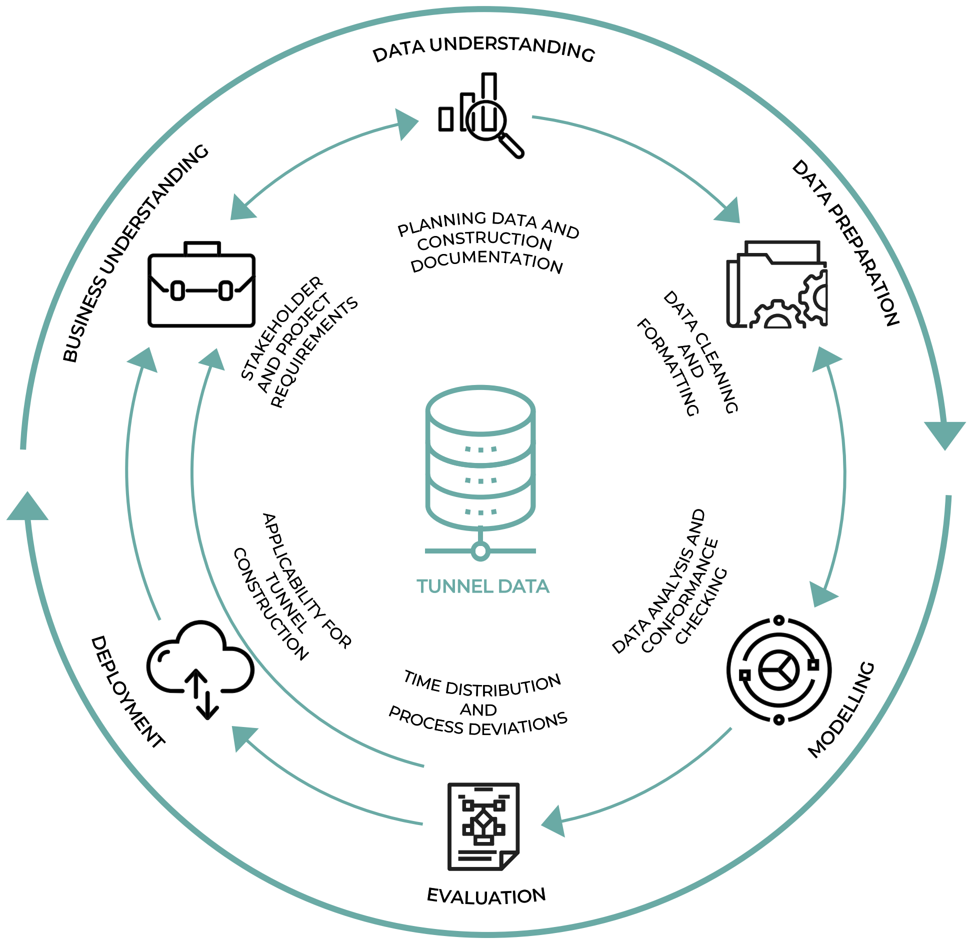


Fig. 1. CRISP-DM approach for tunnel construction data analysis.

overview of activities over 24 h, including details on the installed support measures. Data were digitised by entering them into the Tunnelling Information Management System (TIMS) (Huymajer et al., 2022). Data quality was verified by comparing digitised data against the original paper documents and validating the integrity of the data.

During *Data Preparation*, data are fetched from TIMS using a Representational State Transfer Application Programming Interface (REST API) (Fielding and Taylor, 2000) and cached for analysis. The data consists of tunnel rounds and associated activities. Data serialised as JavaScript Object Notation (JSON) are converted to a tabular format, and the time columns are converted from string representations to native types of the Python programming language. Moreover, durations are calculated based on tasks' start and end times and checked for negative values. Data are then cleaned to correct any inconsistencies, such as erroneous timestamps or missing values, ensuring it is ready for subsequent analysis. The table is finally converted into an event log required for process mining.

The *Modelling* phase for data evaluation, described in Section 4.1, was conducted using two approaches to assess construction activity sequences and determine the durations required for individual activities. Two approaches are selected to analyse activity sequences and durations in the modelling phase. The first technique employs the Process Mining for Python (PM4Py)[9] package version 2.7.12.4, which supports various process mining algorithms and methods, offering flexibility in analysing and enhancing business processes (Berti et al., 2019). The second technique utilised statistical analysis to develop further understanding of the available information. The validity of the process models and Business Process Model and Notation (BPMN)[10] diagrams was assessed against expected sequences, with validation supported by domain knowledge and general data validation performed as outlined by Koorn et al. (2021).

Finally, the *Evaluation* phase in Section 5 involves assessing whether the identified deviations and round duration analysis meet the business objectives of improving operational efficiency through real-time monitoring. Based on this review, the findings are discussed in relation to data and documentation quality, process analysis, and the potential applications of the methodology in tunnel construction. In the *Deployment* phase in Section 6, suggestions for future work are presented to implement the conformance check insights into the construction project's documentation and decision-making processes. Based on the findings, we present recommendations to enhance model functionality, including adding features like time prediction and improving data aggregation for better stakeholder communication. To address the current limitations, we suggest extending the analysis period, incorporating additional data sources, and refining documentation categories to improve the model's accuracy and applicability.

4. Case study

The case study was conducted in the *ZaB* research tunnel, an underground facility primarily focused on research, development, education, and training (Galler, 2016). This facility consists of approximately 3 km

[9] https://pm4py.fit.fraunhofer.de

[10] http://www.omg.org/spec/BPMN

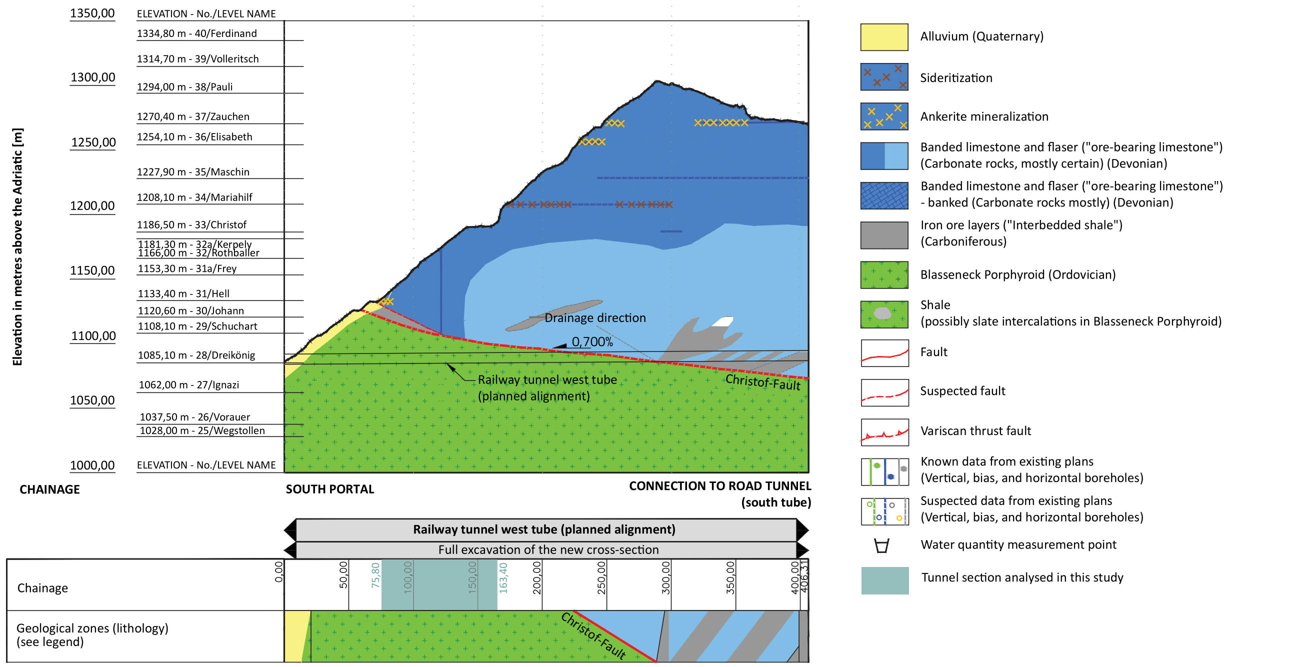


Fig. 2. Geological longitudinal cross-section of the railway tunnel west tube.

of tunnels, traversing beneath Erzberg's highest point, Erzbergspitz, and areas with minimal overlying material, allowing for the evaluation of diverse tunnel conditions. The research complex features four tunnels exceeding 4 km. The *ZaB* facility includes two parallel road tunnels and two parallel railway tunnels, all interconnected by cross-cuts. The road tunnels meet contemporary construction and equipment standards and provide around 800 m of tunnel space for research and education (Galler, 2016). Similarly, the railway tunnels adhere to existing standards. Additionally, the adit system comprises remnants of past mining operations at Erzberg, extending over 2 km and exhibiting a variety of structural configurations. The case study specifically evaluated a tunnel segment starting at 75.8 m and ending at 163.4 m in the cross passage of the *Railway Tunnel West* constructed over one month, resulting in a total length of 87.6 m. The analysed tunnel section is located in an area with diverse general geology, highlighted in turquoise colour, as shown in the geological cross-section from the tender in Fig. 2. The tunnels traverse a mix of rock types, reflecting the complex geological setting of the Erzberg region (Hiessleitner, 1929; Melcher et al., 2022). The area is specifically characterised by sedimentary and metamorphic rock types, with varying degrees of competence and jointing (Schulz et al., 1997). A potential fault zone intersects portions of the tunnel system, posing challenges related to structural stability and geotechnical risks. Fault zones often exhibit weaker material properties, increased fracture density, and heightened susceptibility to deformation under stress, which are critical considerations in tunnelling operations (Zhang et al., 2024).

The analysed construction data for the selected tunnel section are primarily organised into two categories: "Rounds" and "Activities". The initial phase of the research methodology encompasses a data understanding process, including the acquisition, description, and exploratory analysis of these datasets. Of particular significance is the "Activities" matrix, shown in Table 2, which offers insights into round execution. The extracted activities include the ID and round number, the timestamp, its duration, and the type of activity, such as loading, mucking, and spraying of shotcrete among others. A systematic data understanding process is followed by the data preparation phase, which involves data cleaning, formatting, and quality assessment to ensure data integrity. The preparation process further includes the selection of relevant data attributes, deriving new variables where appropriate, and integrating data from multiple sources to create a cohesive dataset suitable for analysis.

Subsequent steps included data visualisation, as shown in Fig. 3, to facilitate understanding of the activity distribution. The diagram illustrates the frequency of different types of activities, with a particular emphasis on those lasting 15 min – a standard temporal resolution in tunnelling documentation. This implies that each recorded activity has a minimum span of 15 min. As Fig. 3 demonstrates, activities such as *Mucking*, *Loosening*, and shotcrete *Spraying* on tunnel face as a rockfall prevention mechanism (Kikkawa et al., 2021) are particularly prevalent, a distribution that appears plausible given the processes involved. The *Miscellaneous* activity category in the presented dataset combines various tasks not regularly encountered in the excavation process. This category includes everyday tasks like cleaning equipment or site visits and more specialised actions such as unplanned safety checks, water pumping, or geological surveys under unexpected tunnelling conditions. The category *Drilling* summarises the drilling, loading, and blasting sequence of excavation and is only present in specific tunnelling classes where these activities are necessary due to mixed geological conditions (Maidl et al., 2013). Since the tender documents specified that the primary advance approach for the tunnelling class 7/10,30 is excavator-driven, drilling and blasting were occasionally employed in specific sections seen in Fig. 3. However, to comply with the tender-specific tunnelling class definition, it was not included in the subsequent advance rate analysis presented in Table 5.

4.1. Data analysis and conformance checking

In process mining, *Celonis* (van der Aalst, 2016; Rehse et al., 2018), *ProM* (van der Aalst et al., 2009; Claes and Poels, 2013; Verbeek et al., 2011) and *PM4Py* (Berti et al., 2023) represent commonly used solutions. *Celonis*, a commercial product, is recognised for its user-friendly interface and integration with business intelligence, facilitating process efficiency improvements and insight generation for organisations. It offers an intuitive platform well-suited for businesses integrating process mining into their digital strategies, although it may not feature the depth of algorithms found in more specialised tools. *ProM* (van der Aalst et al., 2009) is an open-source tool that has often been utilised in the academic and research community (Claes and Poels,

Table 2
Excerpt of activities.

id	round	shift	end_time	start_time	type	comment	measures	typeName	typeId	duration	duration_seconds
402	36	4	2018-05-02 06:30:00	2018-05-02 05:30:00	8	None	[]	Loosening	8	0 days 01:00:00	3600.0
403	36	4	2018-05-02 06:00:00	2018-05-02 05:45:00	6	None	[]	Mucking	6	0 days 00:15:00	900.0
404	36	4	2018-05-02 06:30:00	2018-05-02 06:15:00	6	None	[]	Mucking	6	0 days 00:15:00	900.0
405	36	4	2018-05-02 06:45:00	2018-05-02 06:30:00	11	None	[]	Spraying	11	0 days 00:15:00	900.0
406	36	4	2018-05-02 07:15:00	2018-05-02 06:45:00	8	None	[267, 268, 269, 270, 271, 272, 273, 274, 275]	Loosening	8	0 days 00:30:00	1800.0

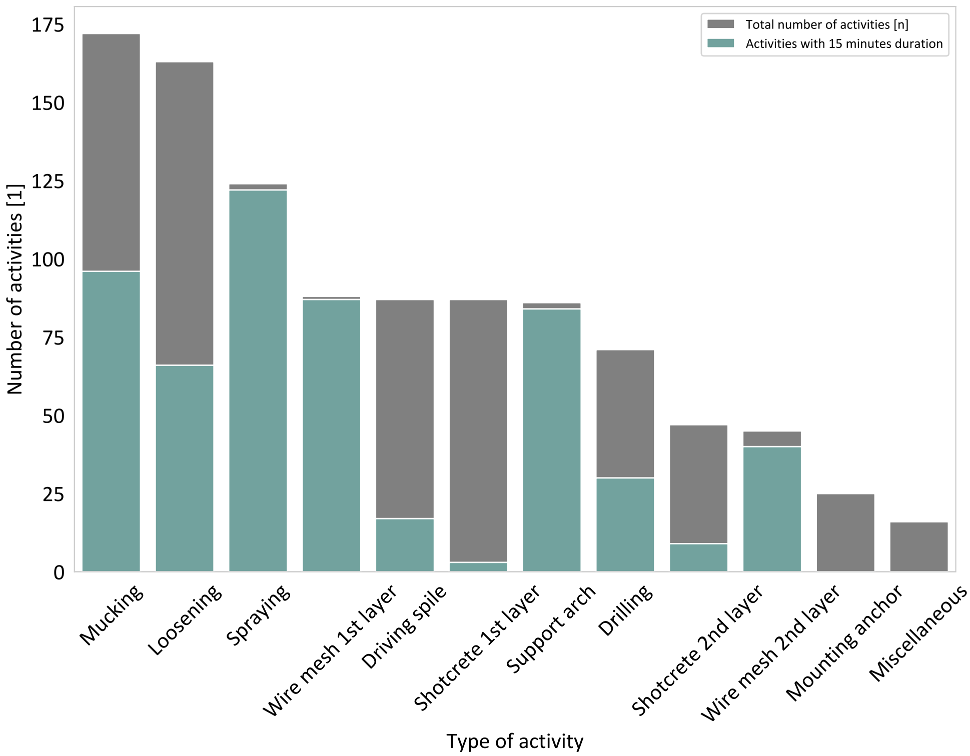


Fig. 3. Counts per activity type from the dataset in the case study.

2013; Verbeek et al., 2011; de Medeiros et al., 2008). It supports a range of process mining tasks like process discovery and conformance checking. Still, it requires a more profound technical expertise, which may not be readily available in all organisations. While it is robust in its technical capabilities, *ProM*'s user interface and lack of commercial support can be limiting factors for broader adoption. For this work, the *PM4Py* package supports many process mining algorithms and techniques, providing versatility in analysing and improving business processes (Berti et al., 2019). This Python-based package integrates seamlessly with existing Python data processing and analysis workflows, which is particularly advantageous for organisations already using Python for data science tasks (Berti et al., 2022). The *PM4Py* library provides several algorithms for conformance checking, such as token-based replay and alignments, which can be used to assess how well log traces conform to a process model. Token-based Replay (Berti and van der Aalst, 2021) checks conformance by replaying the log on the process model and counting missing and remaining tokens to quantify deviations.

For tunnel round analysis described in Section 4.2, we developed a script that performs several functions: loading data, extracting activities for the specified round, creating an event log, analysing deviations, generating and customising a BPMN diagram, and highlighting any deviations. A BPMN diagram is widely used to display processes in the construction industry. This diagram includes flow objects such as events, which mark a process' start, intermediate steps, and end; activities tasks performed as single units or detailed sub-processes; and gateways, which control the process flow through decisions or parallel paths. Connecting objects like sequence flows indicate the order of activities. The script starts by importing necessary libraries for data handling, process mining and visualisation. Using a defined function, it then filters activities based on a specific round number. To create an event log, the script initialises an empty event log, iterates over the activities for the round, creates events with the activity type and start time, appends these events to the trace, and adds the trace to the event log. The script analyses deviations in the activities by identifying the most common sequence of activities in the event log, and comparing the activities in the specific round to this common variant to find deviations. Alternatively, a conformance check can be conducted using a predetermined round sequence. In this case study, we used tunnelling class 7/10,30, as it was the most frequently occurring class during this month of construction. Finally, a function is defined to discover and generate a diagram of the process from the event log and convert it to a BPMN model.

The Section 4.3 further presents an approach to analysing round and activity durations in conventional tunnelling, employing two complementary methods. The first method, summing the durations of individual activities within a round seen in Fig. 6, provides cumulative working time but does not account for potential parallel activities or interruptions. In contrast, the second method uses a dedicated round table, incorporating each round's start and end times to overview the entire duration, including all parallel activities and interruptions. These methods are concurrently applied to provide insights into working

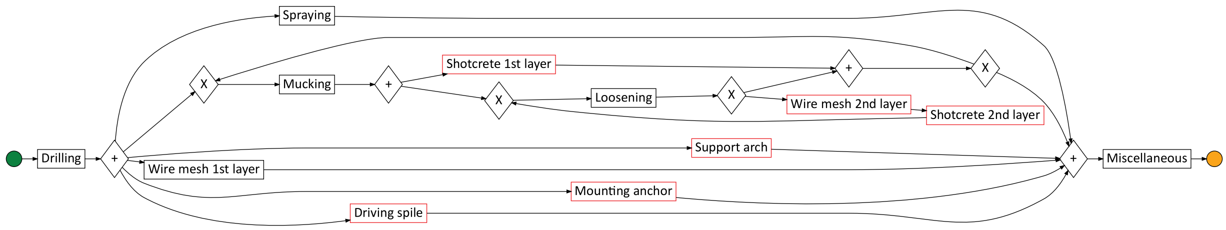


Fig. 4. BPMN diagram of round 83 with differences highlighted. Red activities indicate that subsequent steps deviate from the standard sequence.

Table 3
Table generated alongside the diagram to specify the order deviation of tunnel activities.

	Time and Date	Activity Type	Order Deviation	Expected Next Activity
0	2018-05-09 05:15:00	Drilling		Mucking
1	2018-05-09 05:45:00	Mucking		Loosening
2	2018-05-09 06:00:00	Loosening		Spraying
3	2018-05-09 06:30:00	Spraying		Wire mesh 1st layer
4	2018-05-09 06:45:00	Wire mesh 1st layer		Support arch
5	2018-05-09 07:00:00	Support arch	deviation	Shotcrete 1st layer
6	2018-05-09 07:15:00	Wire mesh 2nd layer	deviation	Shotcrete 2nd layer
7	2018-05-09 07:30:00	Shotcrete 1st layer	deviation	Wire mesh 2nd layer
8	2018-05-09 08:00:00	Shotcrete 2nd layer	deviation	Driving spile
9	2018-05-09 08:00:00	Loosening	deviation	Spraying
10	2018-05-09 08:30:00	Driving spile	deviation	Drilling
11	2018-05-09 08:45:00	Mounting anchor		None
12	2018-05-09 09:30:00	Wire mesh 2nd layer		Shotcrete 2nd layer
13	2018-05-09 09:45:00	Shotcrete 2nd layer	deviation	Driving spile
14	2018-05-09 09:45:00	Loosening	deviation	Spraying
15	2018-05-09 10:30:00	Mucking		Loosening
16	2018-05-09 10:30:00	Loosening	deviation	Spraying
17	2018-05-09 17:00:00	Shotcrete 1st layer	deviation	Wire mesh 2nd layer
18	2018-05-15 04:00:00	Miscellaneous		None

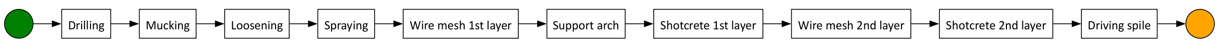
times and total durations, including breaks and parallel activities. This approach enables the detection of abnormalities, deviations from standard durations, unexpected downtimes, and documentation errors, contributing to the iterative process of model refinement and validation within the CRISP-DM framework.

4.2. Resulting process maps

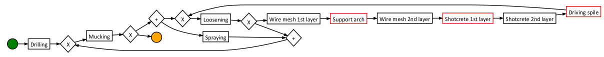
This section analyses the tunnel construction processes based on digitised construction data. The proposed script implements conformance checking primarily by identifying the most common variant (standard sequence) activities within the event log. The techniques involved include trace alignment and variant analysis. Specifically, the script identifies the most common sequence of activities within the entire dataset, which serves as the reference model or expected process behaviour. For a specific round, the script compares (trace alignment) between the actual sequence of activities and reference deviations, which are noted when the next activity does not match the expected next activity. These deviations are then highlighted in a BPMN diagram (Fig. 4) generated using the inductive miner (Leemans et al., 2013) and documented in a comparison table (Table 3). This implementation of process discovery and conformance checking allows users to visually and tabularly identify where and how the actual process deviates from the expected process, enabling process improvement by highlighting specific activities and transitions that require attention.

For this case study, we evaluated the deviation analysis functionality of the developed script using data from tunnel round number 83, which includes multiple repeated activities and an initial drill and blast step. The planned round duration for tunnelling class 7/10,30 shown in Table 1 was projected to take a total of 489.1 min, or approximately 8 h and 9 min. As can be seen in Table 3, the actual process began at 05:15 and ended at 17:00, spanning a total duration of 705 min, or 11 h and 45 min. The process map seen in Fig. 4 highlights several deviations from the expected sequence, particularly in the installation of support structures such as wire mesh and shotcrete layers. These deviations can arise from a number of causes. As described in the introduction, unexpected geological conditions such as harder-than-anticipated rock or sudden water ingress can disrupt planned drilling and mucking sequences, requiring immediate adjustments that lead to deviations in subsequent activities. Specifically, in round 83, deviations were observed in tasks such as the support arch and shotcrete layers, where steps were repeated, likely due to structural issues or misalignment that needed correction. Additional steps such as loading and charging, blasting, and ventilation breaks are required to complete the round (Maidl et al., 2013) if harder rock formations are encountered. These steps could lead to extended durations, however, this is not supported by the provided documentation. The analysis reveals that the tunnel round sequences often deviate from the standard excavation process described by Galler et al. (2009), Girmscheid (2013) and do not always follow a uniform pattern. Nonetheless, the tunnel rounds start and finish with the typical sequences in tunnel construction, starting with the drilling activity and ending with removing the resulting muck (Girmscheid, 2002). This aligns with the concept discussed in the literature that, due to the adaptability required for conventional tunnelling, the construction process may need to deviate to accommodate changing geological conditions.

Additional factors can also contribute to process deviations. Firstly, equipment failures and availability issues can contribute to delays. If key machinery, such as drilling rigs or shotcrete machines, were unavailable or malfunctioned during round 83, progress would be halted, leading to downtimes and rescheduled activities as a consequence. Another potential cause could be that the team excavated a length corresponding to multiple rounds and subsequently installed the support measures for those rounds at once. This approach would



(a) Expected activity sequence



(b) Round 42

(c) Round 119

Fig. 5. (a) Expected activity sequence.

not adhere to standard protocol and would require site supervision intervention to ensure compliance with safety and construction standards. One more major factor contributing to this deviation could be reduced team strength. In a comparative case study by Wild (2018), reducing team strength by 40 % resulted in substantial increases in required person-hours and overall cycle duration. Such reductions in the workforce could further contribute to activities taking longer to complete or the order of tasks being disrupted. Finally, the construction company uses the *Miscellaneous* activity at the end of the process chain to include cleaning or presetting construction equipment, repairs, safety measures, or visits by external groups. However, the ambiguity of this term and the lack of granularity make it challenging to determine the exact process steps without supplementary documentation. Given the difficulty of interpretation, avoiding this category in timekeeping documentation is advised by separating the miscellaneous tasks into subgroups to facilitate more straightforward data interpretation in the future. Analysing individual processes can help identify documentation errors that could negatively impact the invoicing process. Thus, standardised documentation techniques are necessary to enhance the quality of data analysis.

Subsequent validation of the expected tunnel process model used for process deviation analysis is conducted by applying quality metrics for conformance checking, with *fitness*, *precision*, and *generalisation* metrics commonly used to assess the process trees (Buijs et al., 2012; Munoz-Gama, 2016). Fitness determines the extent to which a process model can match the activities in an event log, considering activity correspondence without strict sequence constraints (Syring et al., 2019). Precision quantifies a model's ability to capture observed behaviour without allowing unobserved behaviour (Munoz-Gama, 2016), and generalisation assesses the ability to account for potential process variations not directly captured in the original event log. Table 4 shows the alignment of an expected process model with five tunnel rounds selected from the dataset. The *fitness* values range from 0.70 to 1.00 across the selected rounds, with the highest fitness observed in round 119 (1.00), indicating that round 119 can be replayed from the expected process model. However, the fitness values in other rounds (e.g., round 39 with 0.71) are lower, suggesting that these rounds deviate more from the expected process, possibly due to missing activities from schedule changes or additional activities required in construction not accounted for in the expected model. This relationship is further demonstrated by comparing the generated BPMN diagrams in Fig. 5. The top figure depicts the expected tunnelling class 7/10,30 activity sequence, while the bottom left figure represents round 42, and the bottom right illustrates round 119. Round 42 has a lower fitness value of 0.75, whereas round 119, which aligns perfectly with the expected process, achieves both fitness and precision values of 1.00. High *precision* implies that the model is not over-generalised, but only allows for processes encountered in the logs. Round 119, with a precision value of 1.00, means that the expected process model does not allow any deviation to the sequence of events of that round. Correspondingly, a low generalisation value presents the inverse relationship. The deviation in generalisation values can be attributed to several factors, such as the model not accounting for the variety of ways activities might be executed or the variations in the timing or sequence of steps, leading to lower generalisation values. Nevertheless,

Table 4
Conformance analysis for different rounds against the found process model.

Round	Fitness	Precision	Generalisation
39	0.71	0.8	0.14
42	0.75	0.86	0.11
83	0.72	0.86	0.17
101	0.89	0.78	0.00
119	1.00	1.00	0.00

these findings highlight the need to develop a more generalised tunnel construction model that is consistent with the expected behaviours outlined in the literature (Galler et al., 2009; Girmscheid, 2013) and the variability observed in real-world scenarios, ensuring its adaptability to specific project specifications and validity through cross-referencing with the expected model. The use of replay-based and alignment-based conformance checking approaches could also provide additional insights into discrepancies between real-world tunnel construction processes and expected models, balancing computational efficiency with precision analysis. To enhance the applicability and validation of a generalised tunnel construction model, leveraging both replay-based (Buijs et al., 2012) and alignment-based (Casas-Ramos et al., 2024) conformance checking approaches can provide complementary insights, with replay-based methods detecting local deviations and alignment-based techniques offering a comprehensive, global analysis of discrepancies between actual and expected processes.

A transition matrix, which contains the probabilities of transitioning from one activity (or state) to another within a system, can be seen in Fig. 6, providing additional insight into these sequences. Further analysis provided the median waiting time before and after specific activities. The median waiting time after all activities was 0 min, indicating that, on average, no activity required unusually long preparation time. Conversely, the median waiting time before some activities, particularly "Loosening" and "Mucking", is 15 min, suggesting that these steps require preparation. The statistical analysis also included an examination of starting and finishing activities in cyclical processes. The data analysis confirmed that the first and last activities are often identical in such processes. The analysis shows that in 55 % of cases, the loosening of soil and rock masses serves as the starting activity, aligning with the conventional tunnelling model described in literature (Galler, 2014). Other activities, such as drilling and mucking, displayed no unusual patterns. Similarly, the concluding activities were analysed. In 60 % of cases, debris removal is the last activity, consistent with expectations and model assumptions. Other identified concluding activities showed no anomalies.

4.3. Tunnel round duration

Two methods are available for investigating round durations in tunnel construction. The first method, summing the durations of individual activities within a round seen in Fig. 7, provides cumulative working time but does not account for potential parallel activities or interruptions. For each activity, a box plot summarises the distribution, with the box (in turquoise) representing the Interquartile Range (IQR), which contains the middle 50 % of the data. The magenta vertical line within

Fig. 6. Transition matrix of activities. The probabilities have been multiplied by 100 for readability.

the box marks the median duration of the dataset. The horizontal lines extending from the box, or whiskers, show the durations range within 1.5 times the IQR from the box edges, excluding outliers. The circles ◯ represent individual data points representing outliers, indicating unusually short or long durations compared to most data for a specific activity. The activities are labelled along the y-axis, including drilling, mucking, and spraying, while the x-axis represents the duration in hours and minutes.

In contrast, the second method uses a dedicated round table, with the start and end times of each round, to provide an overview of the total duration, including all parallel activities and interruptions. The round-table approach is more suitable for visualising tunnelling rounds and provides a more accurate insight into the actual process than the standard paper-based reports. Both methods could be used simultaneously to highlight both working times and total duration with breaks and parallel activities. In the boxplot visualisation of the durations of different tunnel construction activities, the *Miscellaneous* type is particularly noticeable. The diverse nature of tasks within this category suggests a significant variation in activity durations, as confirmed by sub-classes shown in Fig. 7. Comparing the time distribution of specific activities to those with a predetermined 15-minute duration can assist in evaluating the discrepancies between predicted and actual advance rates for specific tunnelling classes.

Examining the typical number of activities within a single tunnelling round indicates that variations in the process flow are relatively frequent in conventional tunnel construction, even with standardised procedures. Such deviations highlight the dynamic nature of tunnel construction, where standardised processes often need to adapt to varying on-site conditions and challenges. The resulting process data show that the median duration of aggregated activities is 4 h and 30 min. However, further analysis of round data reveals a median round duration of 3 h and 52 min, attributed to parallel activities within some rounds where individual activity durations do not add up cumulatively. From a process-oriented perspective, the analysis also explores which This difference is activities follow others and whether specific patterns emerge in activity sequences.

Table 5, which compares tunnel advance rates with literature-based predictions, shows a significant discrepancy, with actual construction times on average 20 % faster than estimated. As mentioned, the project documents specified that the sections with Tunnelling Class 7/10.30 would be driven using an excavator. However, in certain sections of the analysed tunnels, the construction documents assign occasional drilling and blasting to the same tunnelling class, leading to discrepancies between the tender and the construction documentation dataset. Therefore, the advance rate analysis does not include these drilling and blasting sections in order to comply with the project-specific definition of the tunnelling class. As can be seen in Table 5, the difference in activity duration is most pronounced in the excavation, loosening and mucking activities, where actual durations were significantly shorter than predicted. This suggests that different excavation equipment, possibly including a backhoe with a larger bucket volume, are thereby improving excavation performance. Another notable discrepancy is observed in anchor installation speeds, which may be attributed to factors such as the type of drill hammer used, the number of drill arms, and the actual geomechanical properties of the rock encountered during construction (Thuro, 1996), which differed from those predicted. Additionally, installing tunnel lattice girders (documented as support arches) required less time than estimated, while shotcrete application took slightly longer, potentially due to operational or equipment-specific reasons. These findings highlight that singular activities often show more significant variation from tender estimates, demonstrating the value of using actual construction data

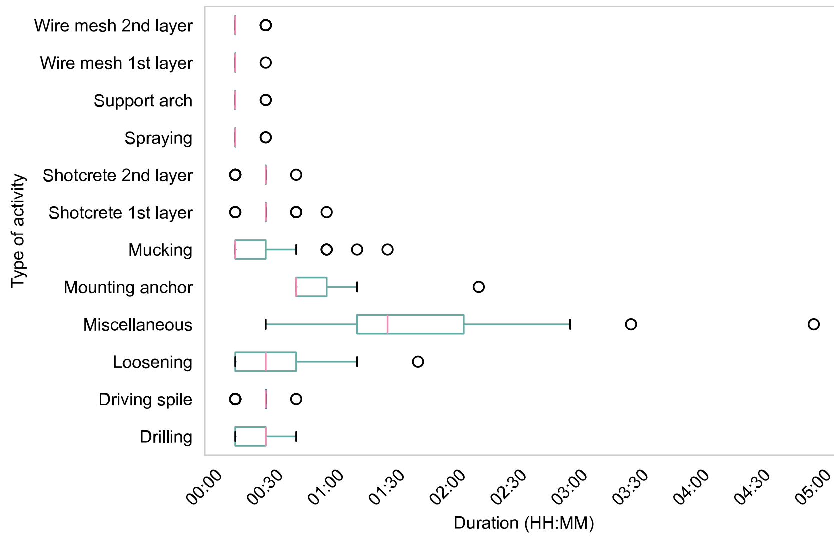


Fig. 7. Duration of different tunnel construction activities.

Table 5
Literature-based and actual tunnel advance rates based on construction activity data.

Tunnelling Class 7/10,30		Activity durations		
Activity (literature-based)	**Activity (construction data)**	**Predicted**	**Actual (mean)**	**Unit**
Excavation	Loosening + mucking	141,1	53,4	min/round
Shotcrete (tunnel face)	Shotcrete (tunnel face)	12,5	15,2	min/round
Spiles	Spile drilling and installation	58,1	53,6	min/round
Anchors	Anchor drilling and mounting	17,1	55,2	min/round
Reinforcement mesh	Mesh 1st and 2nd layer	26,2	31,8	min/round
Arch and load distributor	Arch installation (per round)	29,2	15,3	min/round
Shotcrete (tunnel crown)	Crown shotcrete per round:	46,7	58,0	min/round
Round cycle				
TC 7/10,30	Net round duration:	330,9	-	min/round
	Gross duration (incl. delays):	353,0	282,7	min/round
	Advance rate:	4,08	5,09	m/workday

over literature values for more accurate project predictions. Given the dynamic nature of tunnelling, where machinery, team performance, and construction methods can vary, adjusting tender data based on actual performance can provide a more precise assessment of project outcomes.

5. Results

Though resource-intensive, documentation and reporting in tunnelling projects are necessary due to contractual obligations (ASI, 2023b; Melnyk et al., 2023b) and the strategic interests of construction companies. Conventional tunnelling documentation predominantly relies on analogue methodologies, with progress analyses constrained to daily cycle diagram evaluations and manual data transcription into spreadsheet software (Huymajer et al., 2024a). Unlike mechanised tunnel construction projects characterised by continuous and parallel activities, conventional tunnelling encompasses more sequential processes, resulting in distinctly varied documentation approaches. Transitioning from paper-based documentation and manual cycle diagram analysis to digital documentation and data analytics offers enhanced capabilities for project management and performance predictions. These capabilities allow construction companies to aggregate, visualise, and utilise construction data through suggested systematic data analysis to support project bidding and strategic planning.

The *Evaluation* phase, the study focuses on determining whether the constructed models align with the business objectives and meet the expected criteria. The results showed that while the overall tunnelling process adheres to standard procedures, significant deviations occurred in tasks like installing support measures due to unexpected geological conditions. These insights are validated through the generated BPMN diagrams and deviation tables, which visually and tabularly document where the actual process diverged from the planned sequence. This evaluation provides evidence that the script effectively identifies process deviations, enabling targeted improvements in tunnel construction sequence evaluation. The case study shows that in tunnel construction, where precise coordination of tasks such as drilling, blasting, and lining is crucial, process discovery and conformance checking can identify inefficiencies and visualise issues during construction. This approach allows project managers to overlay event logs onto the process model, highlighting deviations and ensuring the construction activities adhere to the planned sequences. It can also help identify issues such as delays or unapproved methods, ensuring the construction process aligns with the planned and contractually agreed upon workflow. It is beneficial for cost management, allowing for the analysis of processes concerning geological conditions and enhancing stakeholder engagement through data aggregation, visualisation, and identifying discrepancies. Finally, the suggested tools equip construction companies with additional data analysis techniques, promoting transparency and a better overview through centralised digital documentation.

6. Discussion

The application of tools for data analysis of activity durations over a month provides additional insights relevant to construction supervision. The case study demonstrates that the distribution of round durations and box plots of the duration of different tunnel construction activities provide a practical approach to visualising tunnel construction rounds. This method provides additional insight into processes compared to traditional paper-based reports. The real-time data can help predict downtimes and detect abnormalities, deviations from standard durations, unexpected downtimes, or errors in documentation, which may occur due to equipment malfunctions, maintenance requirements, or unexpected geological conditions. The comparison of tunnel advance rates with tender predictions shows actual construction times were on average 20 % faster, especially in excavation and mucking activities. This highlights the importance of using actual construction data in addition to literature estimates for more accurate project predictions, as variations in equipment, geology, and methods can significantly impact performance. Given enough data, predictive analytics can help schedule maintenance proactively and optimise logistics to minimise downtime. Though the study is focused on presenting the applicability of data analysis and conformance checking in conventional tunnelling through a case study, the approach is generalisable. As highlighted by Girmscheid (2013), Galler (2014), every conventional tunnel project inherently follows similar fundamental steps, enabling the proposed methodology to be applied across diverse project contexts, activities and sequences. The inherent procedural similarities across tunnelling projects provide a robust framework for transferring analytical methodologies while accounting for the complexity and site-specific variations.

In the *Deployment* phase, the emphasis shifts to operationalising these findings to ensure the insights are actionable within the business context. This study summarises outcomes based on specific case-study data, which may not be universally applicable across the construction industry. Therefore, the proposed approach should be adapted to incorporate identified deviations based on the unique projects of construction companies and potential factors such as equipment failures or reduced team capacity. Construction companies can maintain and improve the production model by incorporating project-specific documentation data insights into daily operations, leading to continuous advancements in tunnel construction methods. The developed scripts are co-deployed alongside the TIMS (Huymajer et al., 2022) open-source software and distributed to construction companies to incorporate monitoring and maintenance strategies, further advancing its development.

This application of construction data in conventional tunnelling, highlights the need for standardisation of digital documentation techniques to improve data quality. The research was limited in scope as it analysed construction data from only one tunnelling project and one month. For a more comprehensive understanding of process and progress deviations in tunnelling projects, the use of larger datasets from multiple sites, ideally spanning at least one year, would be beneficial. In addition, the documentation category *Miscellaneous*, which is commonly used to consolidate various non-standard activities due to limited paper-based documentation facilities, could be refined. Breaking these activities down into more precise sub-categories, such as unplanned safety checks, water pumping or geological surveys under unexpected conditions, would lead to more accurate process maps and activity analysis. Finally, this study used the *PM4Py* package which, despite its flexibility, requires a solid understanding of Python to generate and manipulate data, visualisations and graphs. This requirement may limit its wider adoption by construction companies. Developing a user-friendly interface and testing the prototype on an active construction site could provide valuable feedback and identify additional use cases for the construction community.

The case study points to additional functionality relevant for future studies, including developing time prediction capabilities for each process, and enhancing scheduling accuracy and resource allocation. Aggregated information from daily construction reports can be extracted to provide a high-level overview for project stakeholders, such as clients, who may not require detailed reports and analysis by site supervisors. Future studies could enhance functionality and analysis by incorporating additional data sources, such as log files from construction logistics and information on machinery and personnel. Process mining mostly analyses completed processes, but emerging operational support capabilities (Ceravolo et al., 2022), including real-time detection, prediction, and recommendation, should be considered for future studies on their application in conventional tunnel construction. Visual representations of activity deviations over a month from the expected process can also be introduced, and the frequency and nature of these deviations can be categorised and displayed across tunnel round steps. Further investigation is needed to establish robust methods for categorising and visualising deviations from expected processes, particularly in understanding the root causes of frequent deviations at specific steps. A more user-friendly system should encompass an overarching process visualisation and analysis for an integrated data-driven construction and logistics process analysis and visualisation.

7. Conclusion

As the tunnel construction industry faces increasing pressures to complete projects on time and within budget, the push towards digitalisation in tunnel construction becomes highly beneficial. This study presents a data-driven analysis approach for conventional tunnel construction, using real construction data and integrating with TIMS for enhanced project management. It explores the applicability of this technology to improve the understanding, prediction and optimisation of construction operations. The conducted case study design utilises construction data recorded over one month to evaluate the efficacy of digital documentation, data analysis and process mining techniques. The primary data sources were excavation or shift reports, which recorded detailed information on activities, personnel, equipment, materials, and any incidents for each shift. Further, the analysis of tunnel construction processes that use digitised data and conformance-checking techniques identifies deviations from expected sequences, providing insights into issues like unexpected geological conditions or equipment failures. In the presented case study, spanning one month, a comparison of tunnel advance rates with tender predictions reveals a notable discrepancy, with actual construction progress being on average 20 % faster than the literature-based estimates. The discrepancy underscores the importance of using actual construction data for more accurate project performance predictions, given the variability in machinery, team performance, and construction methods. The described approach helps optimise project timelines, manage unforeseen downtimes and deviant activity sequences, and ultimately enhance communication and reduce costs in tunnel construction projects.

The use of statistical methods and process mining in conventional tunnelling has demonstrated several benefits. It facilitates rapid data visualisation, which improves resource allocation and enables effective monitoring and control of advance rates, activities and tunnel round durations by clearly illustrating various tasks based on live construction data. It also improves communication and coordination by providing insight into construction processes, identifying and comparing downtime with productive time, and highlighting deviations from expected durations, allowing appropriate analysis and adjustment of tender calculations. It facilitates accurate monitoring and adjustment of construction schedules based on actual data collected during the project. Visualisation of individual activities and their interrelationships can also help identify documentation errors. This method can potentially improve the flexibility and accuracy of the construction schedule by aligning it with real-world conditions and expected ground behaviour, which is critical for dealing with unforeseen subsurface conditions. Future studies could benefit from incorporating a broader data set over longer periods and from different sources, such as construction logistics log files and details of machinery and personnel. With standardised digital documentation and a more granular approach to activities, reporting can improve the accuracy of process discovery.

CRediT authorship contribution statement

Oleksandr Melnyk: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Marco Huymajer:** Writing – review & editing, Formal analysis, Data curation. **Christian Huemer:** Writing – review & editing, Resources, Funding acquisition. **Lucas Rosenberger:** Software. **Alexandra Mazak-Huemer:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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