DATA DRIVEN LEAN MINING USING SHORT INTERVAL CONTROL *

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Abstract

Low commodity prices and lack of new high-grade deposits are pushing the mining industry for innovation. Lean mining has been vastly discussed in the past decades as a way to continuously improve mining efficiency. Although very theoretical, lean mining presents a set of new solutions enabled by the digital transformation that the mining industry is going through. This paper proposes a framework for a short interval control system with the purpose to allow timely responses by front line supervisors upon operational deviations. In the first part, the author briefly reviews concepts of short-range planning and lean mining. Then, the materials and methods used for the development of the short interval control system are discussed. Finally, alpha trial results are presented, and next steps discussed.

Keywords: Short Interval Control; Lean Mining; Short-Range Mine Planning; Continuous Improvement.

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1 INTRODUCTION

The mining industry has gone through many transformations during the past decades. The advent of fleet management systems for equipment allocation is a good example of a game-changing transformation [1]. More recently, topics like automation and *big data* are trends among researchers and manufacturers. Meanwhile, mining companies strive to remain competitive during times of scarce high-grade deposits and declining commodity prices [2,3].
Most mining companies have a well-established organizational structure. In terms of mine planning, it is usually divided into two departments: short-range and long-range mine planning. The main difference between the two is the time horizon for which each one is responsible. Long-range planning considers quarterly to yearly planning while dealing with high uncertainty. In contrast, short-term planners must consider time horizons ranging from a shift to one month, ensuring the ore quality and volume required by the longer-term plan [4]. However, due to the complexity of the mining environment, production equipment tends to operate with low efficiency, resulting in throughput below that which is rated by the manufacturer, and deviations from the plan. This fact becomes more challenging to control because of the lack of real-time assessment of operations by planners, where after issued, plans are overseen by front line supervisors (FLS).
A previously proposed way of improving operational efficiency is the application of lean mining techniques. Lean mining is a set of rules and culture building techniques based on what is called lean philosophy. This philosophy was developed by Toyota in the past century, and it was first discussed outside Japan by Womack & Jones in the 90’s [5,6]. In simple terms, this set of rules aims for the elimination of waste in productive chains. Nevertheless, by the fact that the “mine is not a factory”, lean mining has been mostly limited to theoretical considerations and small-scale applications [7,8].
However, the advances in data mining techniques and information technology can be advantageous for new approaches on how to take advantage of lean mining concepts. Data mining can be used to create context, hence information, from operational databases [9]. In the other hand, informational technology, more specifically the Internet of Things (IoT), can be used to connect different devices and timely spread useful information to FLS and planners [10,11]. Therefore, this paper proposes the development of a system that allows for the short interval control (SIC) of a large truck and shovel operation in the United States.

2 BACKGROUND

Short range mine planning involves a range of activities within a limited time horizon. Shift-to-shift or day-to-day planning defines the number of truckloads to be assigned to each block. Therefore, planners assign available assets to each face and define to which process stream the material must be sent. Next, weekly or semi-monthly plans assign each available block to a build (stockpile), ensuring quality requirements of the plant. Finally, the monthly planning decides which blocks should be mined at each week to meet long-term requirements. It is during the monthly planning that drilling and blasting activities are scheduled [4].
The lack of standard planning outlines issued by international organizations such as the International Organization for Standardization (ISO) leaves the planning framework up to every company, which should define the best practices for short-

range mine planning [12]. Generally, planners issue the shift, which after a set of organizational steps, ends up with FLS's, who then assign their crew members to the tasks required to achieve the goals of the shift. FLS's are considered the link between the planners and workforce, having authority to adjust crew assignments when adequate [13]. In parallel, dispatch engineers are responsible for overseeing the fleet operation using FMS. FMS dynamically assign equipment to different faces and crushers to reach the lowest operational cost while respecting plan requirements. Commonly, information about the operation is passed from FLS to dispatchers and planners.

The main limitation of short-range planning is the lack of systems that allow real-time operational analysis and timely communication between planners and FLS. Furthermore, FLS are usually limited to small pieces of information that are released during the shift, making it necessary for supervisors to roam working areas to identify operational flaws. The lack of control of the operation results in unidentified bottlenecks, resulting in operational waste that can only be assessed through end-of-shift reports [13].

Lean mining offers several solutions to reduce or eliminate operational waste. From the several types of waste, waiting time, repairing, re-handling, and inventory management are the most impactful for truck and shovel operations [14]. The most common method to identify processes that generate waste is called value stream analysis (VSA). VSA is performed by mapping the productive process and verifying at each step if value is created. The product of a VSA is the list of steps that add value and those that are considered waste. Steps that generate waste and are not necessary to reach the final product must be immediately eliminated, and those necessary must be improved or replaced. In lean, continuous improvement initiatives for the elimination of waste are called *kaizen.*

Loow [8], in his lean mining review, emphasizes that *kaizen* initiatives must be worker driven and team based. Consequently, operators, FLS, and engineers must work together to identify and develop plans to improve overall operational value. Plan-Do-Check-Act and root cause analysis (RCA) are examples of *kaizen* initiatives used in the mining industry. The continuous improvement of tasks leads to a state of stability that pushes for the standardization of work. In many industries, best practices are translated to standard operation procedures (SOP) that are passed along in the format of manuals and training for workers [7].

Furthermore, in mines that have already gone through the digital transformation stage, data can be utilized as an important tool to facilitate *kaizen* initiatives in shorter intervals [15]. To do so, data mining and IoT techniques can be applied to transform data in information and communicate findings with the interested parties [16]. Vorne Industries Inc. [17] briefly proposes a SIC framework where decision-makers must regularly assess shift operational data and look for improvement opportunities (Figure 1). In the mining context, this concept can alert FLS's and planners when there are throughput deviation, allowing timely actions to fix problems [12,18]. In addition, logged actions can be used to further explore problems and continuously improve operational practices.

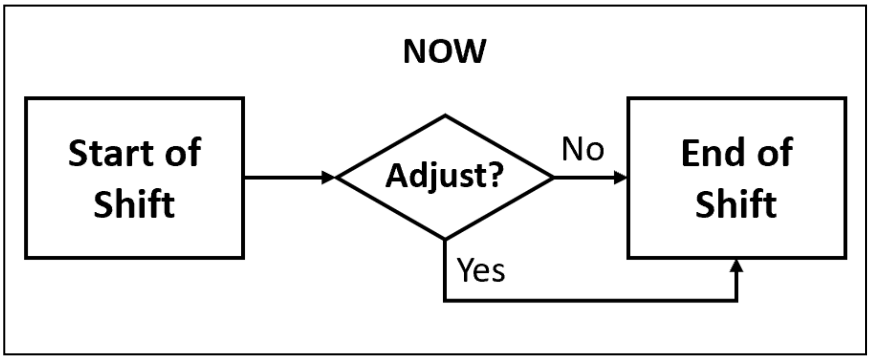

Figure 1. SIC concept. Adapted from Vorne Industries Inc. [17].

As shown in Figure 1, the driver behind the effectiveness of SIC is the reduction in the amount of time that occurs between meetings where important production decisions are made. Prior to adopting SIC, FLS's might assign tasks at the beginning of a shift, and risk not knowing about the status of those tasks until the shift was over [12]. Having less time between decisions reduces waste by ensuring that tasks which deviate from plan are corrected sooner.

3 MATERIALS AND METHODS

The operation studied consists of a large truck and shovel operation. The main shovels have 83 ton buckets while the trucks have four different sizes (240, 320, 360 and 400 tons).
During the case study, room for improvement on the control and information from planners and FLS regarding the state of production in the mine was observed. In general, production plans are issued by planners, and it is the duty of FLS to ensure that the assets available will deliver the expected throughput. Generally, the control of the production is performed through end-of-shift reports analysis and/or by alerts when equipment is down. However, general deviations are hard to track, especially those caused by human behavior.
For the scope of this paper, a SIC framework applied in the studied truck and shovel operation is discussed. The motivation for the development of this system is the need for the timely control of operational deviations by front line supervisors (FLS). The shorter time interval between events and actions should allow for the continuous improvement of operational practices. Furthermore, the system can bridge FLS decisions with engineering plans.
The development of the system can be divided into the following steps:

1. Value Stream Analysis
2. Data analysis
3. System development, and
4. System alpha trial.

3.1 Value Stream Analysis

A VSA was performed to allow the identification of FLS tasks that do not add value to the production chain. One of the advantages of such analysis is the possibility of applying it in both macro (whole operation) and micro (one equipment) scale. Figure 2 displays a flowchart of the shift activities performed by FLS and equipment operators.

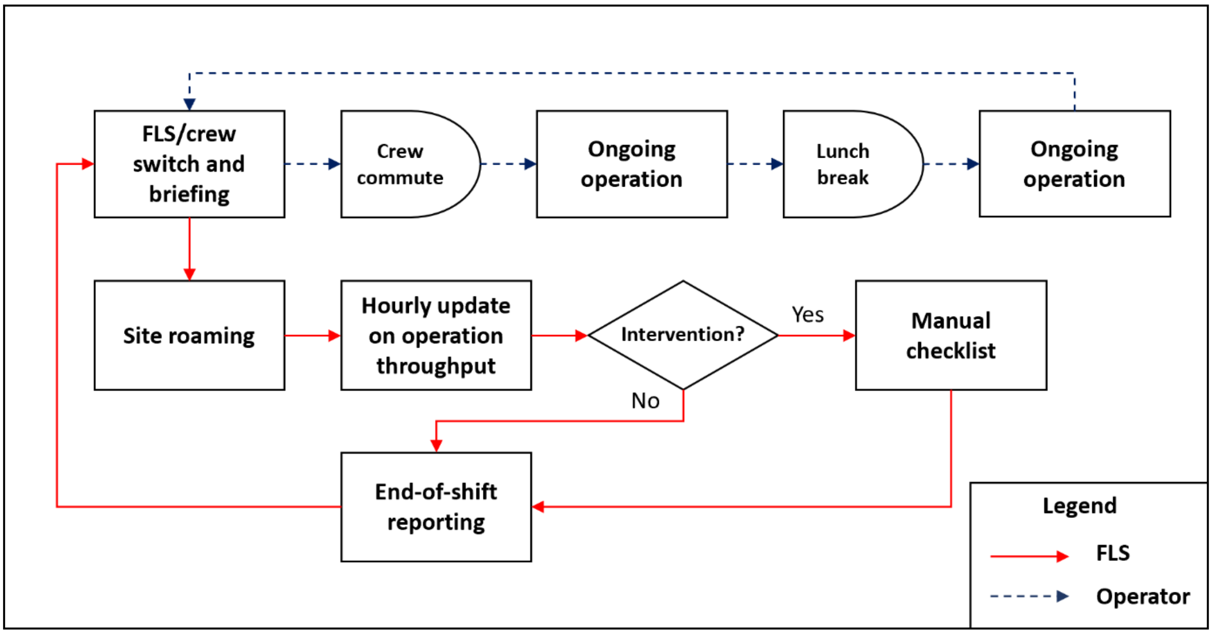

Figure 2. FLS and operators shift flowchart.

During the observation of the operators' activities, it was noticed that there is a period in which the operation does not reach its full potential, also known as start-up time. This period of lower productivity is a product of the shovel-truck synergy adjustments, where queue times tend to decrease with time until reaching the planned flow. This phenomenon tends to occur twice during the shift: during the first hour of operation (due to crew commute) and around lunch break.

In terms of FLS activities, the primary waste source is observed in the lack of timely information access, since it is only possible to check production throughput every hour, and this information is only accessible in the FLS office. Visual supervision is mostly performed at the beginning of the shift through site roaming or when the FLS is notified by radio that there is a problem somewhere in the mine. Finally, checklists and end-of-shift reports are filled manually, which also contributes to the time wasted during the shift.

Therefore, from the value stream analysis, it was determined that there is a need the creation of a system to make operational deviation alerts timelier and automate end-of-shift reports and checklists.

3.2 Data Analysis

Large companies have well-stablished data infrastructure, obtaining and storing data from sensors, equipment health systems, and FMS, totaling an average of five terabytes of data stored daily [19]. Data analysis consists of data characterization, cleaning, processing, and visualization steps.

Data characterization is an essential step in the system development. During this step, the data is contextualized, where it then becomes information. Cleaning and processing the data is helpful to reduce the amount of information displayed as well as drop uncontextualized outliers.

Firstly, Microsoft SQL Server Management Studio was used to query the on-premise database and obtain cycle data generated by the FMS between January 1st, 2019 to March 18th, 2019, totaling 272,000 rows of data. Next, the data was transformed using the Python library *pandas* on a Jupyter Notebook. The data was cleaned by filtering it to only display production shovels and by dropping all unnecessary columns. Furthermore, rows with uncontextualized outliers and null values were also dropped. Finally, shift cumulative were calculated (Table 1).

Table 1. Cleaned dataset.

Timestamp	Shift #	Truck #	Truck Equipment Size	Truck Fleet	Shovel #	Shovel Equipment Size	Shovel Fleet	Calc Cycle Time (Sec)	Shift Hour	Cumulative (tons)
1/2/2019 11:47	1	13	400	2	11	83	X	995	6	37,520.00
1/2/2019 11:48	1	28	400	2	10	83	X	867	6	43,440.00
1/2/2019 11:49	1	12	400	2	9	83	X	719	6	27,200.00
1/2/2019 11:49	1	17	400	3	11	83	X	1061	6	37,920.00
1/2/2019 11:51	1	1	400	4	9	83	X	935	6	27,600.00

In order to obtain insights from the table, the data was grouped in 10 minutes intervals. Production rate was calculated by taking the cumulative production of the interval and multiplying it by 6. Figure 3 displays a dual axis production chart from one of the shovels during one day shift in the month of March. It is important to mention that the day shift goes from 6:30 a.m. to 6:30 p.m.

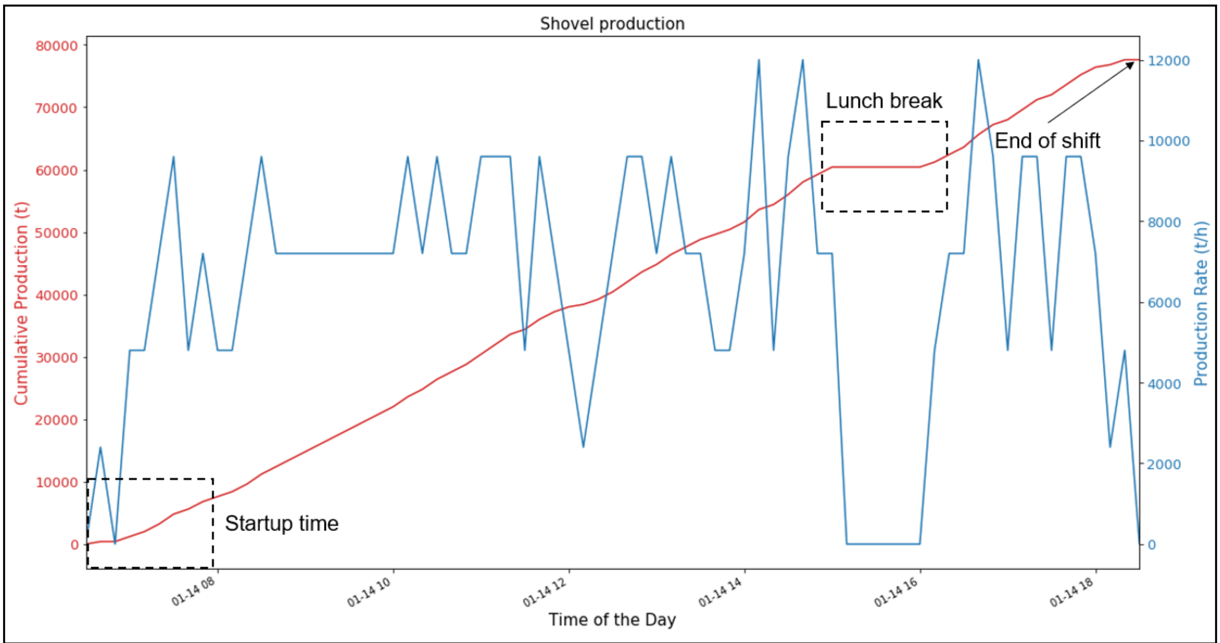

Figure 3. Shovel production during one day shift of March, 2019.

It can be observed in the figure above that during the first hour the cumulative production has an exponential behavior, explained by the previously discussed start-up time. Once truck and shovel synergy is reached, the cumulative line adopts a constant slope. The same behavior happens after the lunch break, but it soon starts to flatten out since the shift is reaching its end. These considerations can be supported when visualizing the production rate plot, which shows that the highest variance in rate occurs during the startup time.

Lastly, using the seaborn python package, a box plot chart was plotted to verify the variance in the production for each hour (Figure 4). The data plotted correspond to all production shovels cumulative tonnage during the day shift for the whole data interval. It can be observed that there is a high variation in the cumulative production by the number of outliers above the maximum value of the fourth percentile and the minimum value of the first percentile.

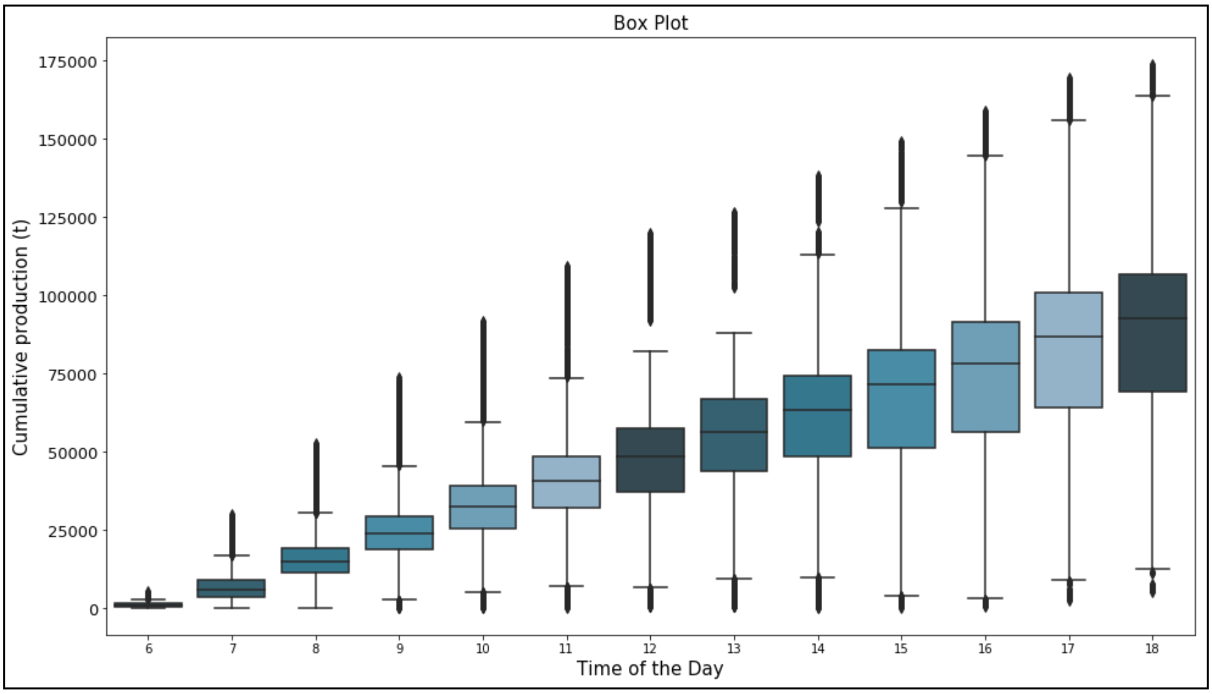

Figure 4. Box plot showing the cumulative production variation during the queried interval.

The data analysis stage supports the assumption of high production variation and justifies the need for a system that allows the continuous improvement of site practices.

3.3 System Development

During the development of the system, best practices for FLS intervention were discussed. Consequently, rules are necessary in order to filter which tasks should by assigned to FLS. The main idea under the system is that a certain deviation threshold must be respected. The threshold selected is that the hourly production of the shovel must be kept at a certain level in order to guarantee the required end of shift production. When the threshold is not met, the FLS must be alerted and decide to intervene or not. The intervention can be performed on both shovels or trucks through standard checklists.
The rule created is that at every 15 minutes interval, queries are performed in the on-premise database, collecting shovel and truck data. The key performance indicators (KPI's) used for the threshold analysis are the production rate of the shovel and the average cycle time of each truck. The analysis uses the KPI's calculated within the interval, where equipment that does not respect the rules are reported to the crew FLS. The communication between the built-in algorithm and FLS is done by using a mobile phone application, which receives a push notification (Figure 5). In order to ensure higher safety, the same notification is also displayed in a wearable device (smartwatch). In the app, the FLS has access to each shovel production, level of deviation from the assigned plan and a list of the trucks assigned to that shovel that have the worst cycle times.

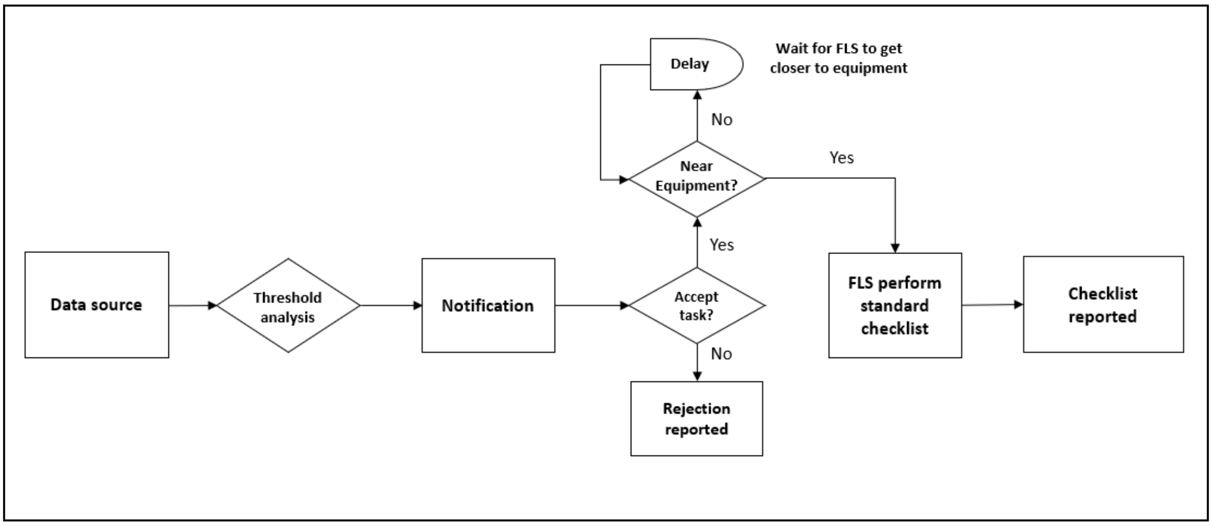

Figure 5. Proposed system flowchart.

It was decided that the development of the system would utilize the Office 365 environment [20]. This choice is supported by the fact that the company already uses the environment, and it allows a less complicated development. The tools selected as part of the system are Microsoft PowerApps, which is a platform for app development; Microsoft Flow to create the scripts that alert FLS; Power BI as a visualization and end-of-shift reporting tool, and; Azure SQL database, that is a cloud-based relational database to be used to store the checklists and events recorded during the shift.

The development with PowerApps first requires the design of the user interface (Figure 6). Next, connections are created with the data sources, which in this case are the on-premise database, and the cloud-based database, where the recorded data will be stored. The checklists performed by FLS are stored as forms where each question is a column in the table. Furthermore, metadata is stored to help the assessment of the system performance. GPS data is stored when FLS accepts a task, and when performs the checklists. Also, the app captures the amount of time taken to fill the checklist. All checklists were designed in partnership with engineers and FLS. Power BI is used to access the databases and collect information about daily production from shovels and trucks, and information regarding the interventions performed by FLS.

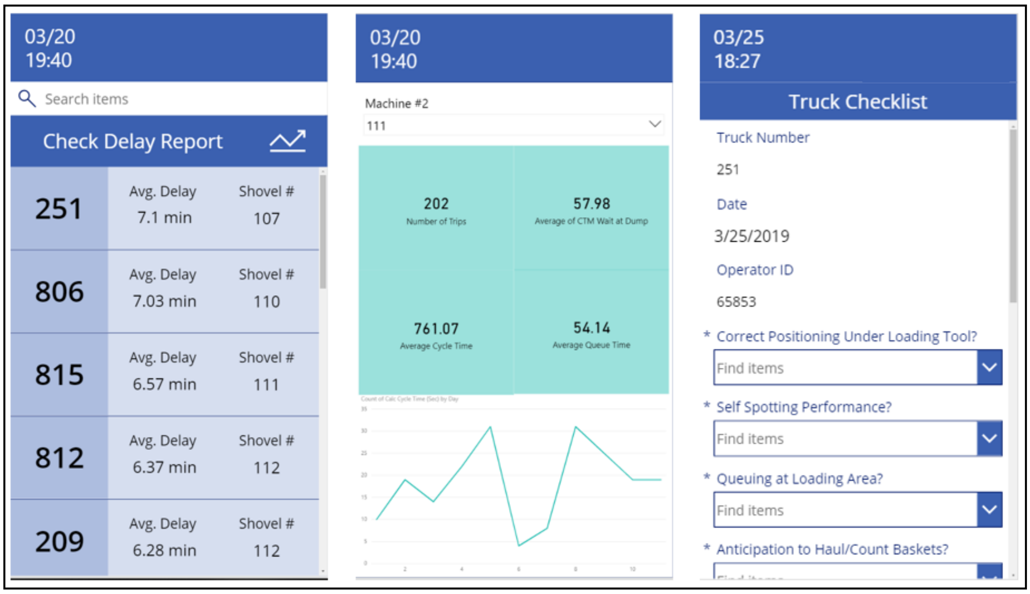

Figure 6. App interface, displaying task lists, Power BI operational report, and truck checklist.

All system interactions are possible using scripts to automate queries in the database and the use of Microsoft Flow scripts to send push notifications to the app. System security is assured by the fact it is hosted within the Office 365 environment, which allows restricted access.

3.4 System Alpha Trial

An alpha trial test has been performed to ensure the functionality of the alerting system. During the trial, several task items were added to the Azure SQL database. Once each item was added, the Microsoft Flow script was triggered, and a push notification was sent to the phone and wearable.
It was observed that the communication between database and app is timely, as well as the submission of checklists. In order to avoid the situation when there is poor internet network coverage, an SMS text is also sent, allowing the FLS to fill the checklists forms and saving it in the phone memory. Once back within internet range, the forms can be set to automatically be uploaded to the database.
As can be seen in Table 2, the application collects the time and GPS data when the FLS decides to accept or reject the task, and when an intervention is performed. Also, the checklist filling process is timed. Lastly, if the FLS rejects a task, a reason for it must be given and additional comments are recorded.

Table 2. Data gathered during the alpha trial.

Status	Time of Decision	Time of Action	Reason	Rejection Comm	Lat_Decision	Long_Decision	Lat_Action	Long_Action	Filling_time
Completed	4/8/2019 9:43	4/8/2019 9:45			40.76661365	-111.847951	40.7666045	-111.84795	0:48
Completed	4/6/2019 22:58	4/6/2019 23:00			40.76595189	-111.8578133	40.7659519	-111.85781	0:42
Completed	4/6/2019 22:58	4/6/2019 22:59			40.76595189	-111.8578133	40.7659519	-111.85781	0:52
Completed	4/6/2019 22:59	4/6/2019 23:01			40.76595189	-111.8578133	40.7659519	-111.85781	0:44
Rejected	4/6/2019 22:58		No Time to Act		40.76595189	-111.8578133			
Rejected	4/6/2019 23:01		Intervention Already	Test	40.76595189	-111.8578133			
Completed	4/8/2019 11:58	4/8/2019 11:58		NA	40.76632963	-111.8477935	40.7663102	-111.8478	0:44
Completed	4/11/2019 8:41	4/11/2019 8:48		NA	40.76642081	-111.8478284	40.766579	-111.84782	1:05
Rejected	4/11/2019 8:41		No Time to Act	NA	40.76640102	-111.8478237			

4 NEXT STEPS

Since the app and connections with the databases are functional, the next step is to develop an algorithm to automated queries on the database and perform the threshold analysis. Once finished, a beta version of the system should be deployed in the mentioned operation. During the beta test, a positive culture towards the system must be built, and user feedback should be used to continuously improve the functionalities of the system. At the end of the beta stage, a final product is expected to be launched and spread to other operations.

5 CONCLUSIONS

Lean mining is a philosophy that has been underutilized due to the complexity of mining operations. Nevertheless, advents like IoT and data mining open new opportunities for the development of data-driven lean mining techniques. SIC is a lean-based system that allows timely responses to deviations in shift plans. The proposed SIC framework has the potential to improve response from FLS to problems in the operations. Furthermore, it should enable an easier stream of information between FLS and short-range planners. Positive results from the alpha trial moves the system development to the next state, which consist in the automation of alerting and beta deployment in the operation. Finally, once feedback and adjustments are performed, the system can be deployed in larger scale, allowing the facilitation of continuous improvement initiatives.

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