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BIG DATA IN MINING OPERATIONS

Master's Thesis

Copenhagen Business School, 2015

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Hand in date: December 18, 2015
Number of pages: 71
Number of characters: 137 727

ABSTRACT

Motivation

Mining is an industry with old traditions and historically high revenues; however, companies had to face several challenges in the previous years which can be rooted to inefficiency in their operational processes. Commodity prices dropped to record lows, but the slow industry could not keep up with the pace of its rapidly changing market, and their expenditures did not decrease the same way either. Easily accessible mines are depleting, and safety concerns are also in the center of attention. Mining companies have to react to these events; they have to alter their businesses to face the new challenges.

Problem Statement

A possible solution for decreasing operational costs is to implement new technologies that can improve their processes and leverage from big data that has been collected by sensors and parsed with advanced analytics techniques. The thesis's research question is *how can mining companies utilize machine-generated big data in their operations?* To find an extensive answer, several topics have to be introduced, such as machine-generated big data, Internet of Things, data analysis techniques and the operational processes of a mining company.

Approach

During the research a delimitation had to be taken: since maintenance costs are the largest contributions of operational expenditures, the paper focuses on this area.

The research builds on interviews conducted with a mining company as a primary data source, complemented with definitions and theories, and it uses numerous sample cases to support the findings.

Results

The results of the interviews are used to create an optimal organization structure that incorporates connected devices and predictive maintenance solutions. The model is validated by examining current market trends and how other companies utilize these technologies.

As mining enterprises have just started to move towards data analytics, they need to implement these solutions in their operations. The thesis provides a model of change management specifically for these cases. It is built on popular frameworks and methods, and it takes existing technologies, risks, and benefits, human behavior into consideration and it gives guidance for practical applications. The model is tested by another change framework that introduced business transformations in the mining industry.

Conclusion

The thesis concludes that companies recognized the need for improving their maintenance-related processes, and to dissolve limitation, further examples are presented to demonstrate other use cases of big data and data analytics in the mining industry.

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ADVANCEMENTS OF MINING INDUSTRY

Since the beginning of our civilization, humans have used stones, metals and other materials that came from under the Earth's surface. These were so important to our race's advancement that scientists use them to categorize the archeological periods (Stone-, Bronze-, Iron Age). These eras lasted for thousands of years respectively, and the transition always happened with the invention of new tools that made our ancestors able to dig deeper and extract new metals and minerals. Technologies evolved in an accelerating speed, which brought two results: we could reach materials that we could never before; we needed more and more of these materials for the new technologies.

Until the XX. Century, mining required hard, physical labor, massive machinery and a stroke of luck, and even the biggest breakthroughs could not shift this pattern. The change came from under the ground: silicon – a semiconductor material discovered 200 years ago – became the foundation of creating integrated circuits, microchips, and all the electronic devices that are now part of our everyday lives. As a consequence, mines got equipped with machines that could more efficiently exploit minerals while reducing safety risks.

But even until this century, little did we know, that there is one further step, that can transform - besides all different industries - mining. And it is the utilization of big data and data *mining*.

MACHINE DATA

It is hard to find anyone who would not has heard of big data: it was one of the most hyped phenomenon of the last couple of years (Rivera & van der Meulen, Gartner's 2013 Hype Cycle for Emerging Technologies Maps Out Evolving

Relationship Between Humans and Machines, 2013) (Rivera & van der Meulen, 2014). Some may argue, that big data is not a new approach, just reframing of existing technologies, but using an enormous amount of data is a clearly visible trend, and many businesses use it to optimize their processes or to implement innovative solutions to gain competitive advantage.

Machine data is a subset of big data, where different sensors and equipment generate a more structured data about their operations, performance or condition. They can be used to various analyses, such as process optimization, improved maintenance or machine-to-machine communication.

THE NEED OF NEW TECHNOLOGIES IN MINING

In the last century, mining industry grew slowly until the 1980s, when commodity prices stagnated. Then came another positive period, when these prices (and the whole industry) grew in an unexpected way, thanks to several factors, such as housing construction boom, increasing demand from China and other developing countries, various economic policies. This boom was called as commodities' "supercycle", but like any other boom, it did not last forever: since 2011, commodity prices started declining. Mining companies had to deal with this new trend; they had to stay profitable even if it was "the end of the Iron Age" (Lee, 2014).

"Mining is an industry with great traditions where change is at times very gradual" (Lee, 2014). It has tried-and-true processes that are used for centuries, and that were good enough before the decline of the recent years. It would be difficult for them to leave these processes behind and adopt new technologies; companies are averse to innovation and change. However, they might need to make a shift for new ways of exploitation, if that would improve their productivity and at the end their bottom line. Therefore, most of the modernization and implementation of new solutions happen at the operational level. While these companies stay reluctant, they cannot turn away from the possibilities coming from big data and machine data, they understand that innovation has to be done to operate in a more efficient way (Lee, 2014).

Mining industry requires innovation to increase their bottom line, to be more effective in the exploitation. In this thesis I try to find ways, how can big data and machine data boost their businesses, what are the possibilities and frontiers. Therefore, I propose the following research question as the main focus of my thesis:

How can mining companies utilize machine-generated big data in their operations?

To answer it, three sub-questions had to be formulated:

What characterizes machine data and how is it different from human generated data?

A deeper insight about mining industry is also needed, to be able to analyze, how machine data can be connected to this field:

How do mining companies generate value in their operational processes?

The two areas have to be connected to locate the areas where the examined companies can benefit from big data. Risks and threats have to be identified as well, to arrive at a balanced overview.

How can operational processes be optimized by machine data and what are the possible complications and disadvantages?

The thesis is structured in a way that while going through its chapters, the reader acquires knowledge about the relevant topics to be able to critically examine the answer proposals for the previous questions.

A deep understanding of machine-generated data, structured/unstructured data, Internet of Things (IoT), process mining is required for the latter examinations.

The first part of the literature review introduces the relevant definitions and technologies that are used in the analysis.

The second part gives a broad overview about the mining industry; how did it develop, how did it transform, what are its characteristics, current challenges, business- and operational processes and how did they get automatized in the last decades.

I demonstrate big data and Internet of Things through predictive maintenance – a use case of these technologies that can enhance mining field operations. I conduct interviews to get deep insights from a mining company, and I use the information to build a model about a company setup with these technologies, highlighting the benefits and possible risks. I also describe a generic process of how to implement predictive maintenance. To support my models, I use case studies from all around the world to evaluate my proposals.

Finally, I take an overview of further possibilities, how the mining industry can benefit from my results and how can it use other big data and IoT solutions.

MOUNTAINS OF DATA

WHAT IS BIG DATA?

Nobody can tell exactly how much data is generated each day, but there are good assumptions: in 2012, 2.5 billion gigabytes of data were generated every single day according to IBM (IBM, 2012), and they predict that this number will increase to 2.3 trillion gigabytes per day by 2020 (IBM, 2013). We live in a world where information overload – a term that originates from Bertram Gross, social scientist – is no longer a futuristic fantasy, but part of our everyday lives. The available data and information are impossible for one person to collect, verify and understand (Hunt, 2014). As a result of the boost of available data, new and original methods have developed to extract useful information from it. In each organization within each industry, a vast amount of data is generated that contains various information from internal and external sources such as data transactions, corporate documents, social media, sensors and other devices. Companies can take advantage of analyzing their data to satisfy customer needs, optimize their operations or obtain new sources of revenue (IBM, 2013).

Big data has many definitions of which the most extensive one was written by Frank J. Ohlhorst: "Big Data defines a situation in which data sets have grown to such enormous sizes that conventional information technologies can no longer effectively handle either the size of the data set or the scale and growth of the data set. In other words, the data set has grown so large that it is difficult to manage and even harder to garner value out of it" (Ohlhorst, 2012). A survey of 154 C-suite global executives showed that the subjects had different ideas about what big data is. Some followed a business approach and looked at it as a new source of opportunities, some defined it from a technological perspective, others looked at legal requirements of storing data or the boom of social data, but they all agreed in one thing: the amount of data to be dealt with is huge (Gandomi & Haider, 2015), and as Ohlhorst defined, too big to be effectively handled. In a world with 4 166 667 Facebook likes or 300 hours of YouTube-video upload per minute (DOMO, 2015), we can agree that this amount of data is impossible to be manually analyzed.

However, there are scholars who do not recognize big data as a novelty. Gupta (2015) argues that enterprises used large data sets already before the Google Flu Trends article has been published in 2008 and started an avalanche of big data related researches and analyzes (Gupta, 2015). Mark Barrencechea states that big data's potential lies in unstructured data, such as conversations, social data, documents, and the utilization of these types of information is the innovation, but he also argues that with time it will be business as usual, just as structured data became the base of the everyday processes (Barrenechrea, 2013).

Characteristics of Big Data

Mayer-Schönberger and Cukier mentioned other characteristics of big data that differentiates it from the previously available approaches. According to their research, the vast amount of data enables extensive analysis of the different features of an examined subject. As different datasets become available, combining them might result in a comprehensive perspective on the same phenomenon. Previously researchers were enforced to use samples for their investigations, with statistical sampling methods to define the individuals that were examined. But now they can analyze the whole population, and they can even access data that they would not have measured in the traditional way (Mayer-Schönberger & Cukier, 2013).

The second attribute is the messiness of the data. The authors state that Big Data encourages the analysts to take the complexity and diversity of the world into consideration when they examine the data sets instead of endeavoring to reach punctual and perfectly accurate results from analyses made in an artificial and controlled environment.

Furthermore, they explain that it is impossible to create a big data setup that is punctual and universal, but this is not its intention. The analysts should accept that big data is messy with varied qualities and complex distribution. However, this imperfection is the property that reflects the real world the most, so it has to be incorporated in the analyses: researchers should not aim for punctual, detailed and exact results, but they have to give generic directions (Mayer-Schönberger & Cukier, 2013). Machine-generated data – as I will describe later – also reflects this messiness, but it is a bit more structured than social data, for example.

The theory of messiness is closely related to the third attribute of big data, namely correlation - the statistical connection between two values. If one of the values change, the chances are high that the other one will change too. Formerly researchers had reservations about analyses built on correlation, and they did not consider them entirely reliable, as they could have inaccurate conclusions: they were either the results of serendipity or external factors have affected them. However, big data can dismiss these worries because implications can be produced from enormous data sets. The authors explain that correlation cannot always unveil the precise causes of a phenomenon, but it can indicate the effects of a happening, which can already be satisfactory (Mayer-Schönberger & Cukier, 2013).

Ohlhorst introduced the concept of 4V's, four dimensions that need to be considered to get value out of big data: volume, velocity, variety and veracity (Ohlhorst, 2012). His model is built on an article written by Gartner analyst, Doug Laney, that forecasted the explosion of data in 2001. Laney mentioned 3 of the 4 V's, data volume, data velocity and data variety (Laney, 2001), that can be seen as the first description of big data.

Volume is the amount of data. It is not a few gigabytes anymore; there are numerous cases where the available data takes up terabytes or even larger scales. To gain insight from this mass of data, special tools are required (Ohlhorst, 2012).

Velocity means that data does not have a stable state, but it is always changing, and new data is generated and transferred in a matter of milliseconds. 6 000 tweets are sent in average in a second (Twitter, Inc., 2015), and around 10 million trades each day on NASDAQ (NASDAQ, 2015). With such fast-paced conditions, real-time information can be retrieved from data, which always reflects the actual trends. However, Ohlhorst suggests that data should be stored, and it should be available from archival sources as well (Ohlhorst, 2012).

Variety means that data comes in many forms. Users can post text content, pictures, videos, share links. But even in more controlled environments, such as a factory, data can be generated by temperature sensors, productivity logs and reports made by technicians. Big data is often unstructured, and it encourages analysts to consider all data sources and types and find correspondence between their values (Ohlhorst, 2012).

Veracity refers to abnormalities, noise and statistical errors in the data. When there are millions of records, it is unavoidable that some of them are not relevant or not correct and would alter the big picture, which could lead to false conclusions. Some examples are inaccurate sensor measurements or the lack of credentials in social media. One of the greatest challenges of big data analysis is to clean the data, remove uncertainty about its veracity (Ohlhorst, 2012).

There are other V's that has been mentioned lately together with big data: validity, volatility, viscosity, virality and value. The first one is an extension of veracity, and it means that the data is correct and accurate for the intended use. Volatility refers to questions like how long should data be stored and how long can it be used in analyses. Viscosity measures the resistance in data flows, that can be caused by friction that occurs when integrating different data sources; virality refers to the speed of information is spread and shared to each unique node (Wang, 2012). Value refers to the outcome, the value that can be extracted from the data sources with big data analysis.

However, these many V's do not help to define big data, rather overcomplicate it. Seth Grimes argues that these "wanna-V backers and the contrarians mistake interpretive, derived qualities for essential attributes" (Grimes, 2013). He describes why the original 3 V's (by Doug Laney, 2001) are sufficient to define big data, and that the other additional properties are "analytics-derived qualities that relate more to data uses than to the data itself" (Grimes, 2013).

In this thesis I use the four dimensions of Ohlhorst, it seems to be the most widely used model defining big data, and it includes veracity in addition to Laney's dimensions, which is necessary to consider when dealing with noisy and highly unstructured data.

Structure in Data

Big data is messy because it is formulated from the real world, and reflects its messiness. However, data can be generated in many forms, some of it in a more structured way, than the others. Data is structured when it "has a predictable and regularly occurring format of data" (Inmon & Linstedt, 2015). It follows a particular schema, and it is typically managed by a database management system (DBMS). Structured data is normally built on a deliberate structure; it is well-defined and predictable. It is stored in relational databases in records, attributes, and indexes. Therefore, it is easier to analyze, run different queries on them, even if they contain millions of individual items (Inmon & Linstedt, 2015). Some examples are customer data (with fields with defined length and type for zip codes, country codes, email addresses, etc.), website visiting statistics and most of the systems that we use today that follow the method of storing individual elements in individual records in a relational database. Structured data is not necessary generated by people, in many cases, it is a result of machine logs, sensor data (which will be described in the following pages).

On the other hand, unstructured data is more natural, typically text-heavy data. It is "unpredictable and has no structure that is recognizable to a computer" (Inmon & Linstedt, 2015). It does not follow a pre-defined data structure or hierarchy that results in slower querying and data analysis. Examples of unstructured data are books, electronic documents, recently social data, or the internet itself with its millions of web pages. However, pictures, audio, and video files represent data that is hard to process and organize, and they also belong to this category. Specialized tools are required to analyze these types of sources, such as natural language processing with artificial intelligence, or special databases, like NoSQL.

Semi-structured data is data that is not organized into structured databases in itself, but it contains some related information that can be processed by computers. These can be the metadata of pictures and documents, or using tags to categorize them (Inmon & Linstedt, 2015).

Machine Data

While big data is usually identified as processing massive unstructured data sources, such as social networks, websites, documents, it does not have to be restricted to human generated information. A significant amount of data is generated by systems and machines. They create structured records, usually in the form of logs or measurements. If the data is collected, it can grow to enormous sizes, and similar techniques can be applied to it as on other big data sets. There is no exact definition for machine data (or machine-generated data), but most authors refer to it simply as data generated by machines during their operations. This kind of data is much less messy, as it does not follow the real world's disorder, but a pre-defined structure. Machine data is generated in every industry from healthcare equipment through handheld devices to industrial machines, and they can be used to find patterns and clusters or to predict trends and unveil previously hidden connections. It has several business use cases, such as debugging, performance analysis, root-cause analysis, predictions, fraud detection, etc. (Surange & Bansal, 2013).

THE INTERNET OF THINGS

In the previous pages about big data, I pointed out that prices of data storage and transfer have dropped; it was never this inexpensive to be connected, and connectivity costs continue declining by 25% annually (CISCO, 2013). It became common that most of the mobile phones, portable devices can connect to the Internet, which was quite a novelty ten years ago. This trend is steadily continuing: a research made by Gartner showed that by 2020, there will be 26 billion devices connected to the Internet or each other (Middleton, Kjeldsen, & Tully, 2013).[1]

Internet of Thing (IoT) – as a concept – has been introduced by Kevin Ashton in 1999, by “uniquely identifiable interoperable connected objects with radio-frequency identification (RFID) technology” (Li, Xu, & Zhao, 2015). However this definition has been extended: Pretz characterized IoT as a things-connected network, in which the objects connect via smart sensors and they can interact without human interaction (Pretz, 2013). Greengard simplifies and generalizes the definition. He states that “the Internet of Things literally means “things” or “objects” that connect to the Internet – and each other.” (Greengard, 2015). These devices must have unique identifiers and Internet Protocol (IP) addresses so they can be identified. Greengard does not limit IoT by the type of connection used, but he also agrees that physical-first objects (ABI Research, 2014) can become part of the Internet of Things by equipping them with active or passive RFID tags[2] (Greengard, 2015).

The Internet of Things (IoT) means that electronic devices are connected to each other or the Internet. But not just the standard machines with a display, but also household appliances, such as washing machines, lights, wearables, and almost anything. Naturally, IoT is not limited to personal usage: in some vehicles there are already hundreds of sensors that track the condition of mechanical parts, there are smart parking solutions, intelligent street lighting, and the different industries also connect the various machines to the network to collect data like vibration, temperature or productivity (machines in factories have already collected many of these data, but the novelty is to connect them to the network so they can “know” about each other, this way enhancing productivity).

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[1] Other researches show an even higher number: a study made by Cisco Systems mentions 50 billion connected “things” (CISCO, 2013).

[2] Active RFID tags need a power source, while passive tags can use the RFID reader’s electric power, so they do not need their own power source. This, their long lifetime (they can function for up to 20 years), and their low cost (a few cents per passive tag) makes them more compelling than the active one, though their functionality is also limited (Greengard, 2015).

If a device or machine has an on/off button, the chances are that it will be part of the Internet of Things.

One particular property of this new phenomenon is that machines no longer need human interaction in many cases: by connecting them to a network, we can enable machine-to-machine communication.

THE INDUSTRIAL INTERNET OF THINGS

While IoT transforms our everyday lives, sensors, and smart connected devices become accessible in the different industries as well. Even moderate estimates show that companies will spend US$500 billion on connected equipment while creating US$15 trillion of value by 2030 (Peter & Annunziata, 2012). And there is a good reason behind this: enterprises can boost their production, deliver better products and decrease costs. Germany's National Academy of Science and Engineering forecasts that operational efficiency can increase 30% by IoT and related processes (Heng, 2014). Some of the key areas, where operations can be made more efficient are better scheduling, inventory management, increased safety, more flexible production and predictive maintenance (Daugherty, Banerjee, Negm, & Alter, 2015). In the Industrial Internet of Things (or Industrial Internet, Industry 4.0 or simply smart manufacturing) there are three typical communication forms: machine to machine (M2M), human to machine (H2M) and machine to smartphone or tablet (M2S). As devices become smarter, they do not need human intervention anymore to work with data that comes from another machine. Furthermore, they can make decisions based on the inputs and previously collected masses of data (Greengard, 2015).

Improving Operations with Predictive Maintenance

Defects can occur in machines during their operation, causing delays, additional cost for the company and other negative effects. It is not surprising that enterprises were continuously investing in new maintenance technologies that were more economical and efficient. Breakdown maintenance (or reactive maintenance) is the traditional reparation technique, focused on fixing failures that have already occurred. Even though this is the least effective method, it is unavoidable in cases when the error could not have been checked. Preventive maintenance uses scheduling to replace parts on a regular basis (for example, after 600 working hours), and proactive maintenance aims to reduce the number of errors by always tracking failures to their root causes and fixing them. However, these methods are expensive and not always efficient. Scheduling can cause replacement of perfectly functioning parts while fixing already broken machines can result in downtimes. Moreover, the operation site has to keep large stocks of replacement parts that use additional areas and other resources (Scheffer & Girdhar, 2004). Advanced sensors can measure vibration, acoustic emission, corrosion or temperature, and companies can collect this data. Algorithms can be used to recognize patterns in the data, and send signals if something might break soon. Predictive maintenance has many benefits, such as an increase in machine productivity, prolonged intervals between scheduled maintenance activities, improved repair times, increased machine lives, better reparation planning, improved product quality and decreased maintenance costs (Daugherty, Banerjee, Negm, & Alter, 2015). These optimizations can result in saving up to 12% over scheduled overhauls while reducing maintenance costs by 30% and eliminating 70% of the breakdowns (Daugherty, Banerjee, Negm, & Alter, 2015). However, Fox and Do's research (2013) shows that companies must be critical in implementing big data solutions in their operations as the hype around the technology might be more significant than the actual benefits, and managers should consider many non-trivial factors before investing in them (Fox & Do, 2013).

New Opportunities

Equipping machinery with sensors is not a novel phenomenon: 30 years old – or even older – machines have had them. But connecting them to a network and utilizing their data to get additional insights is a paradigm shift that does not only improve the existing processes, but it can bring brand new opportunities to the company. A good example is mining companies. Previously, when a drill hit hard rock, they had to analyze the ore to decide how to proceed excavation. Now they can use predictive analyses built on big data acquired from preceding mining operations, and they have results in a fraction of the time that they needed before. Moreover, machines can make decisions themselves without human interaction to streamline processes (Daugherty, Banerjee, Negm, & Alter, 2015). Drone systems are used to analyze and monitor processing landscapes and measure stockpiles (Wilson, 2015), and they are helping exploration of new mining areas while having less environmental impact (Fiscor, 2015). These, and other innovative applications of new and existing technologies can create new business opportunities in all industries, and they can transform how production companies create values.

What Can Go Wrong? – Risks of IIoT

The connected devices, automated processes can enhance production, but they also bring new dangers that companies should consider. There can be interruptions in the operations, network problems, sabotage, cyber attacks and data theft (Daugherty, Banerjee, Negm, & Alter, 2015). As more devices are connected, they become more vulnerable to attack. There have already been several cases, where businesses have been sabotaged by hackers: in 2014, they shut down an oil rig and infected another one with a malware. Internet of Things is a new phenomenon and companies only focus on the benefits while they are not entirely aware of the related risks (Wagstaff, 2014). But besides security issues, there are social aspects as well: IoT transforms professions, and it proposes questions about privacy (e.g., tracking employee fatigue or health-related data) and responsibilities (e.g., who is to blame if an automated machine causes an accident). "At the very least the Internet of Things will deliver new challenges and problems revolving around security, privacy, and how we go about living our digital lives. It will almost certainly create new points of contention and dispute among members of society […]" (Greengard, 2015).

Industrial Internet of Thing is transforming production and operations, but it requires a paradigm shift from companies. Besides optimizing the current processes and discovering new value creation opportunities, they have to expand their risk management practices to be prepared for cyber-security threats.

ANALYZING BIG DATA

Machine Learning and Data Mining

There are different techniques to work with big data. Analysts can run queries on data sets and get exact answers for specific questions, or they can use statistical methods to get the required information. Machine learning is a subfield of computer science, closely related to computational statistics; it applies algorithms on masses of data to learn from them and make decisions and predictions. One of its most acknowledged features is the ability to improve the outcomes with an increase of inputs: instead of following rigid mathematical functions, it builds models, search for similarities, trends. As it was mentioned with big data, machine learning techniques do not unveil the reasons for an event or happening but with the massive amount of data they can build models on correlations that can be used to calculate the results (Alpaydın, 2010).

Data mining is a component of machine learning. It is defined as "the analysis of (often large) data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner" (Hand, Mannila, & Smyth, 2001). These data sets can come from different sources; they can be structured or unstructured. To apply data mining techniques on them, they first have to be transformed to a logical, organized format before they could be used as input for the analyses (Reffat, Gero, & Peng, 2004).

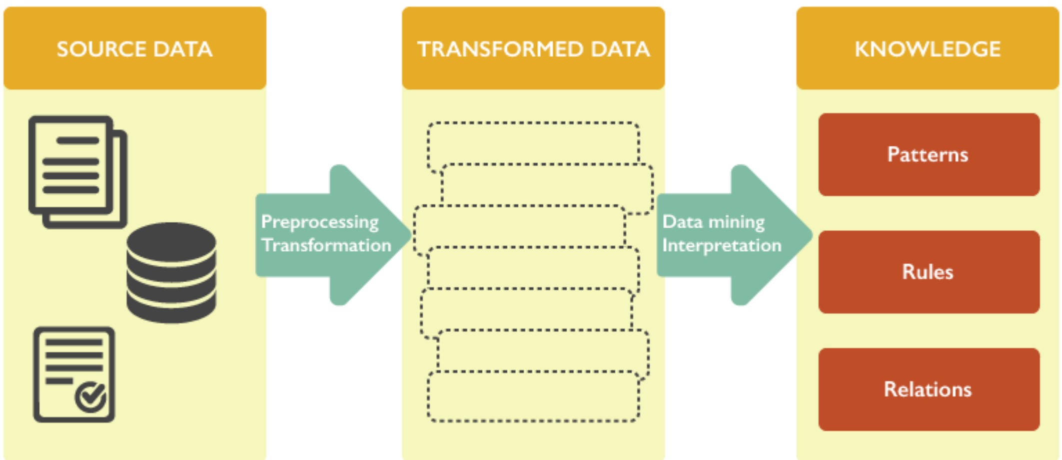

Figure 1 - Pre-processing and transformation of data into a format suitable for data mining (Reffat, et al., 2004)

There are several analysis techniques in data mining, based on the purpose of the research. They can be classified into two broad categories: supervised learning or unsupervised learning. The first one assumes labeled data, which means that each instance is labeled by a response variable, while in unsupervised learning, variables are not divided into response and predictor variables (van der Aalst, 2011). Some authors mention semi-supervised learning as well, but I only focus on the two original groups in the research.

Classification and Regression

Classification techniques are used to categorize instances based on a defined predictor variable. The resulting groups can take on discrete values. The simplest examples are binary values (tests that can have one of two possible values, for example, yes or no). However, multiclass targets can be defined as well (e.g., low, normal, high or unknown viscosity of engine oil). Classifications do not imply the order of the instances and they use algorithms to find relationships between the predictor and target values (van der Aalst, 2011).

Regression techniques, on the other hand, expect numerical response variables. The aim of these techniques is to fit the data somewhere on a range. For example, a function could suggest that the wearing of ball studs (in percentage) is calculated by the days since their installment divided by 800 (e.g. a 600 days old ball stud is assumed to be 75% worn out). Regression tries to find the function that can predict the response variables with the highest precision based on the predictor values (van der Aalst, 2011).

Decision Trees

Decision trees are used to make models to predict specific values based on different input variables. The model goes through numerous attribute value tests with two or more possible outcomes.

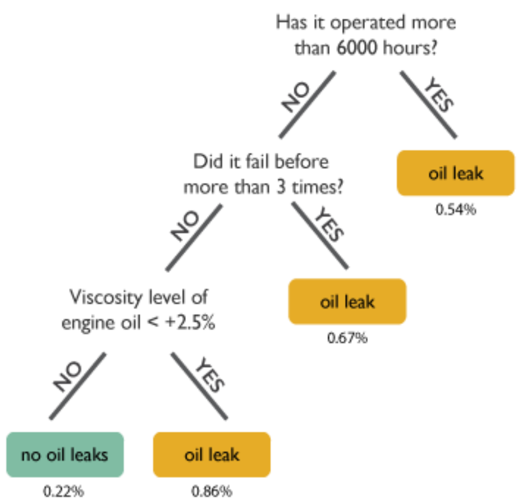

Figure 2 - Decision tree about engine oil leaks

Figure 2 shows a sample decision tree about engine oil leaks. The root node arrives to the first test and forwards the inspected item to one of the branches. Values must belong to either one of them unambiguously. After the test, the new node can have further tests until the recursive process reaches an end point, where the model can provide reasonable estimates of the examined target value. The nodes that do not have further tests are called leaves, and the probability can be calculated for them (in this case the chances of oil leaking in the engine, in percentage) (van der Aalst, 2011).

Clustering

Clustering is the unsupervised technique of grouping objects together that belong to the same class (cluster). It uses unlabeled data and a function to determine the classes and the instances belonging to them. They can be analyzed by two or more attributes (dimensions). The most common algorithm is k-Means clustering, which distributes the instances into a pre-defined number of groups based on their Euclidean distances). It is the base of many other methods, such as pattern recognition, text mining, various analyses, face recognition, diagnostics. It is a scalable technique, and with the increase of the examined data set, the clusters become more reliable (van der Aalst, 2011).

Pattern Recognition

Human beings can easily recognize things or objects based on past learning experiences. Pattern recognition aims to achieve similar results by computation method. It uses different techniques and algorithms to find the most likely matching of the inputs, considering their statistical variation. Pattern recognition methods can be applied on supervised and unsupervised data sets. In supervised learning, the model is built on a set of training data with appropriately labeled instances and the resulted output. A learning procedure then generates a set of rules that can be generalized and applied to new data sets. The process is efficient if the outcome of the new data is correctly determined. In unsupervised learning, training data is not labeled, so different techniques can be used to identify patterns in the data that can predict the correct output value for new data instances. Pattern recognition is used in multiple areas, of which the most relevant ones are speech recognition, optical character recognition, face recognition, landscape analysis in geology and other monitoring functions (Bishop, 2006).

Anomaly Detection

In data mining, anomaly is a pattern that does not conform to an expected behavior, and anomaly detection is a method that aims to identify these peculiarities. There are many use cases where its techniques are used, such as bank fraud detection, cyber intrusions or predictive maintenance. Most algorithms start by defining the normal values, but the boundary between normal and deviant behavior is usually not exact. Anomaly detection uses different functions to examine which instances represent extreme values and fall out of the boundaries, but there are some challenges: data might contain noise, and it might evolve with time resulting different normal behavior groups. Supervised and unsupervised techniques can both be used, based on the fact that if the data set is labeled or not (Chandola, Banerjee, & Kumar, 2009).

All the previous techniques and methods are based on the concept that larger data sets can result in better generic models and reduce uncertainty in predicting the outcome. Moreover, data sets are constantly evolving, and data mining analytics has to always reflect the current inputs. However, the high number of instances also require tremendous computing capacity that only computers can provide.

AN OLD INDUSTRY WITH NEW CHALLENGES

A QUICK OVERVIEW

Mineral exploitation was always crucial to mankind, it drove new technologies, contributed to the development of societies. However, in the last century, there were several periods where many believed that mining was an industry with not much potential left in it. New booms have always proved these views wrong, as shares and commodity prices increased and reached record heights. The latest one of them happened at the dawn of the 21st century when housing constructions, commodity speculations, economic rise of developing countries made commodity prices rocket (Lee & Prowse, 2014). Andrew Mackenzie, CEO of the world's largest mining company, BHP Billiton, said: *"Mining was a low-growth business for much of the 20th century, so we were caught off-guard by the pace of China's early 21st-century urbanization and industrialization"* (MacKenzie, 2013). However, this last boom had not lasted forever either, as there was a halt in commodity prices, followed by a tremendous fall. China's economic growth's pace has slowed down, housing expenditures have been moderate, that resulted in a steady decline (Lee & Prowse, 2014). A remarkable example is iron ore, that was worth US$187.18 (per 1 metric dry ton) in 2011, but by August 2015 its price dropped to only US$55.38 (TradingView, 2015).

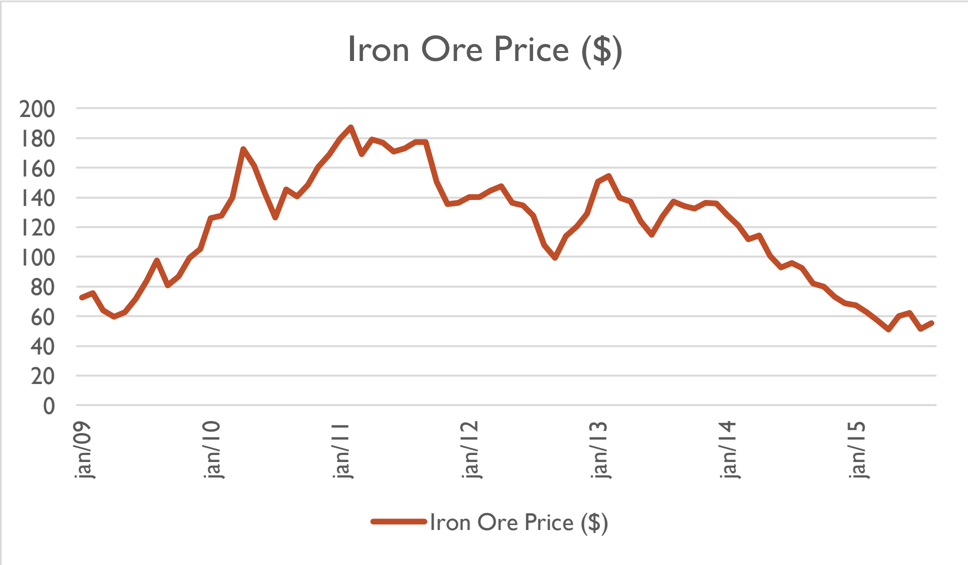

Figure 3 - Iron ore commodity prices between 2011 and 2015 (source: TradingView)

It is not a surprise, that to compensate the negative market trends, mining companies had to act quickly to stay profitable. Since they cannot have a direct impact on the commodity prices, they have to optimize their activities to decrease cost – so they can counterbalance their loss. One of the areas where mining companies – such as BHP Billiton – tries to save money is operations. *"Demand was met in part by higher cost – much higher cost – operations. (...) Finding five dollars of savings per metric ton did not seem as pressing when prices were skyrocketing. But it really matters now"* (MacKenzie, 2013). However, even after years of stagnation and fall in revenue, mining companies still generate a remarkable revenue: in 2014, the top 40 mining companies' aggregated revenue was 453 billion US dollars (PwC, 2015).

GLOBALIZED MINING INDUSTRY

There is virtually no country in the world, which would not be involved in mining, even if it is no more than sand or gravel pits. In most industries, production tries to take place close to consumers to minimize transportation costs. However, mines have fixed locations (where mineral reserves can be found), and many factors have an impact on where can companies start digging in the ground, such as environmental issues, land ownerships. Therefore, the exploitation usually takes place on an entirely different continent than where the mining company is incorporated and where the commodities are used. Mining firms' headquarters are located in a handful of – mostly English speaking – countries. The reasons are primarily historical: The United Kingdom has traded with minerals for centuries, experts know about the industry, their legal system and regulations are well-established and extensive in this field. Many of these corporations are controlled from UK – even ones from countries that have never been part of the Commonwealth realm, such as Kazakhstan. It is attractive for mining enterprises to be listed in these markets, because "UK market has both the expertise and capacity to raise substantial amounts of capital for these, particularly the mining companies, and also has the required sophisticated investor base to subscribe for equity stakes and offer a liquid secondary trading environment" (Coulson, 2011).

But besides England, there are other countries where mining industry gives a relevant part of the GPD. Some of the largest mining countries are:

Country	Mineral rents (% of GDP)	GDP (bn USD)	Mineral rents (bn USD)
Australia	5.4	1 560	84.24
Brazil	2.3	2 392	55.01
Canada	0.7	1 838	12.86
Chile	14.6	276	40.269
China	1.8	9 490	170.82
Russia	1.2	2 079	24.95
South Africa	3.7	366	12.432
United States	1.2	16 768	201.22

Table 1 - Total natural resources rents (% of GDP) 2013 data, (The World Bank, 2014a), GDP 2013 data, on current US$ (The World Bank, 2014b)

China's robust growth and insatiable demand affected the whole mining industry. The increasing demand for raw materials drove commodity prices to record heights, and the country is also rich in resources. This would make mining in China an appealing investment opportunity, but there is a strict and closed political system, and foreign investors cannot rely on the same protection as in western markets. Moreover, there are legal limitations on foreign capital involvement in the mineral resources (Coulson, 2011).

It would be out of the scope of this thesis to introduce the mining sector in all of these countries – with their current problems and challenges – but it is important to understand, that even though some exploitation happens in almost every country, there are some, where it is more relevant. In this document, we do not limit the analysis to any particular geographical location, as the operation of mines is similar, no matter where they are located.

MINERALS

As Encyclopædia Britannica defines, mineral is a "naturally occurring homogeneous solid with a definite chemical composition and a highly ordered atomic arrangement; it is usually formed by inorganic processes." (Encyclopædia Britannica). Minerals are formed through natural processes, usually through millions of years and they provide the material used to make most of the things of industrial- based society. (Encyclopædia Britannica)

Minerals are inorganic substances that occur naturally. Earth's crust - except organic materials – is made up of minerals. These are finite, non-renewable natural resources; some of them are close to the surface, but some of them are located deep under the ground. There are several thousand known mineral species, of which the industry utilizes about 80. Because of their limited availability and complicated excavation, minerals are valuable resources and their exploitation has to be guided by long-term goals (Qazi & Qazi, 2010) (Encyclopædia Britannica).

In my thesis, I do not focus on *a* particular mineral, because the technologies used for their exploitation are very similar, and different materials can often be excavated from the same deposits (Coulson, 2011). A good example is zinc, silver and lead, which usually exist in a polymetallic environment (Coulson, 2011). However, I exclude oil and gas, as their extraction requires specific drilling technologies, and different market impacts affect their demand; therefore, they are out of the scope of this study, and it focuses on solid minerals and metals.

Classification of minerals can be done based on their chemical composition and physical properties (Klein), but from the mining perspective they are categorized by a combination of these attributes and their utilization:

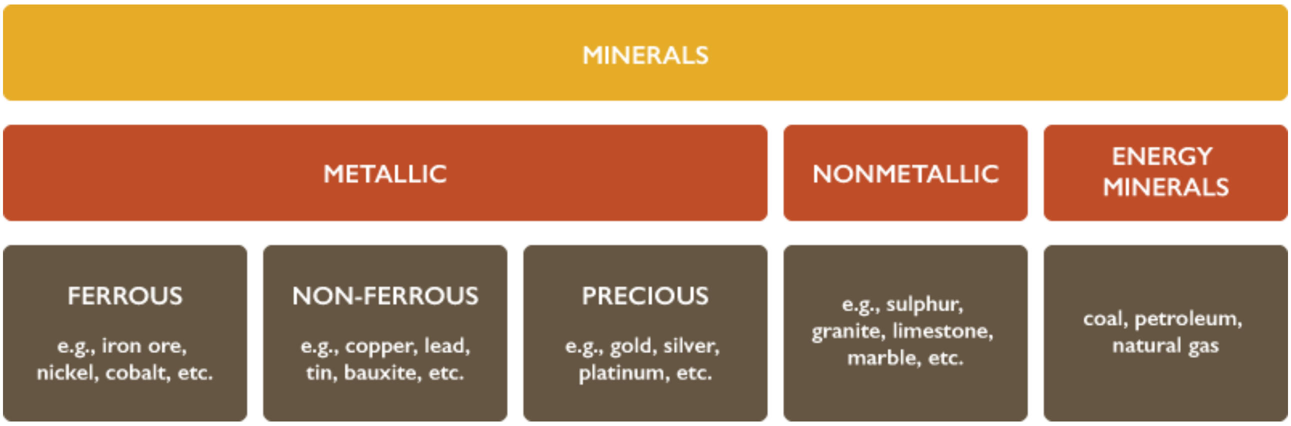

Figure 4 - Classification of Minerals (Qazi & Qazi, 2010)

Some of the metals are not mined in their final forms (e.g., aluminium is produced from bauxite, steel is smelted from iron ore and carbon). As the classification shows, metals can be divided into three groups. Ferrous metals are minerals that contain iron in appreciable amounts. Non-ferrous metals are generally more expensive because they have desirable properties (e.g., low weight, high conductivity, non-magnetic property, etc.) (Qazi & Qazi, 2010).

Coulson categorized metals based on their market role:

- Major industrial metals (e.g., copper, zinc, lead, tin, nickel, bauxite, etc.)
- Minor / specialist metals (e.g., tantalum, cobalt, tungsten, etc.)
- Industrial minerals, precious metals minus gold (e.g., silver, platinum, etc.)
- Gold (Coulson, 2011).

These categories are unsettled because a shift in technologies and economic impacts can make change the demand for minerals. For example, copper used to be the main material for domestic water piping, but plastic pipes replace it. However, copper is still an essential material in electronics, as it is an efficient conductor of electric current. Another example is lead, which was also used in domestic piping, but now we know that it is highly poisonous, so other materials replaced it. Lead is still widely used in other areas, such as in batteries, bullets or radiation shields.

But there are examples of materials that gained attention lately, too. Tantalum, a metal that was of no interest until the last decade is now widely used in mobile telephones, DVD players and many electronic devices in their capacitors. The technological boom increased its demand drastically, pushing its price to record heights (Coulson, 2011).

It is important to have a comprehensive knowledge about the most important minerals, but this thesis does not aim to discuss each one of them in details.

THE MINING PROCESS

Exploitation of minerals is a very complex task, that starts with locating natural reserves, extracting and processing the materials and even closing and reclaiming the mine. The process is similar in the case of most minerals, but the excavation methods can be different:

- *Surface mining* is used when the mineral is relatively close to the surface of the ground. The rocks and soil are removed by earthmovers and other heavy equipment, so the machines – such as dragline excavators or bucket-wheel excavators – can get access to the mineral deposits. Surface mining can be divided into further sub-groups, such as strip mining, open-pit mining, mountaintop removal, dredging. The operations' cycle consists of the following steps: vegetation cleaning, soil removal, drilling and blasting, removal of the mineral commodity, and lately there is a huge claim about rehabilitation after the exploitation is finished and mineral resources are exhausted (Hustrulid & Bullock, 2001).
    - *Strip mining* is the removal of overburden (soil and rock) followed by the excavation of the minerals under. This is the most common surface mining, and it can be divided into contour mining (when a slope/side of the hill is being removed) or area mining (when the mineral deposits are located close the relatively flat-lying surface) (Hustrulid & Bullock, 2001).
    - *Open-pit mining* is similar to the previous one, but in this case, the minerals are excavated from a pit following a circular path. The excavation creates stepped sides of the whole that result in the continuous increase of the mine's size (Hustrulid & Bullock, 2001).
    - *Mountaintop removal* involves the mining of the summit. In most of the cases, explosives are used to loosen up the overburden, and the excess rocks and soil

are left in the nearby valleys. After this, the unveiled minerals are excavated like in the other surface mining methods (Hustrulid & Bullock, 2001).

- *Dredging* is the excavating process carried out underwater, in shallow seas or freshwater. The materials are removed from the bottom of the water, and they are then processed to find minerals in them. Dredging has played a significant role in gold mining (Hustrulid & Bullock, 2001).

- *Underground mining* takes place when the mineral deposits are located too deep under the ground to be extracted with surface mining. Nowadays these mines usually utilize continuous mining – a technology that eliminates most of the human labor from the working face, automatizing most of the tasks. Underground mining can be divided to hard rock and soft rock mining, and based on the entries of the mines, they can be shaft mines, slope mines or drift mines (Hustrulid & Bullock, 2001).
- *Shaft mining* is a type of underground mining when the working areas are reached through a vertical hole called a "mineshaft". Workers, tools and the minerals exploited are all transported through this shaft, by elevators (Hustrulid & Bullock, 2001). Because shaft mining requires advanced technologies, these mines are mostly concentrated in Canada and South Africa (Coulson, 2011).
- In *slope mines,* mineral reserves are accessed through an inclining tunnel. Miners and extracted materials are raised and lowered with mine hoists or locomotives and trucks
- *Drift mines* go straight into the mountain on a near-horizontal passageway. They are used when resources are located near the sides of the hill (Hustrulid & Bullock, 2001).

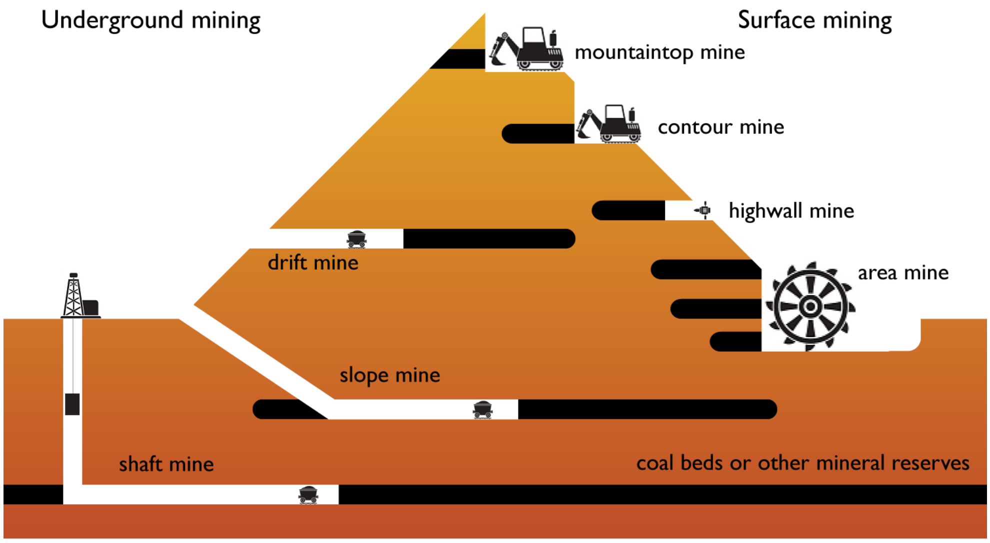

Figure 5 – Methods of underground and surface mining (Greb, 2012)

FROM EXPLORATION TO RECLAMATION

It became harder to find new areas where potential mines could be established: many of the deposits have been already extracted, there are environmental concerns, ownership issues, strict legal requirements. However, there are still untouched fields where companies can begin their operations. Table 2 shows the lifecycle of mines from exploration through daily operations and actual mineral extraction to the reclamation of the area. Note that mining companies also do other activities, such as trading resources, but this table only focuses on their exploitation activities.

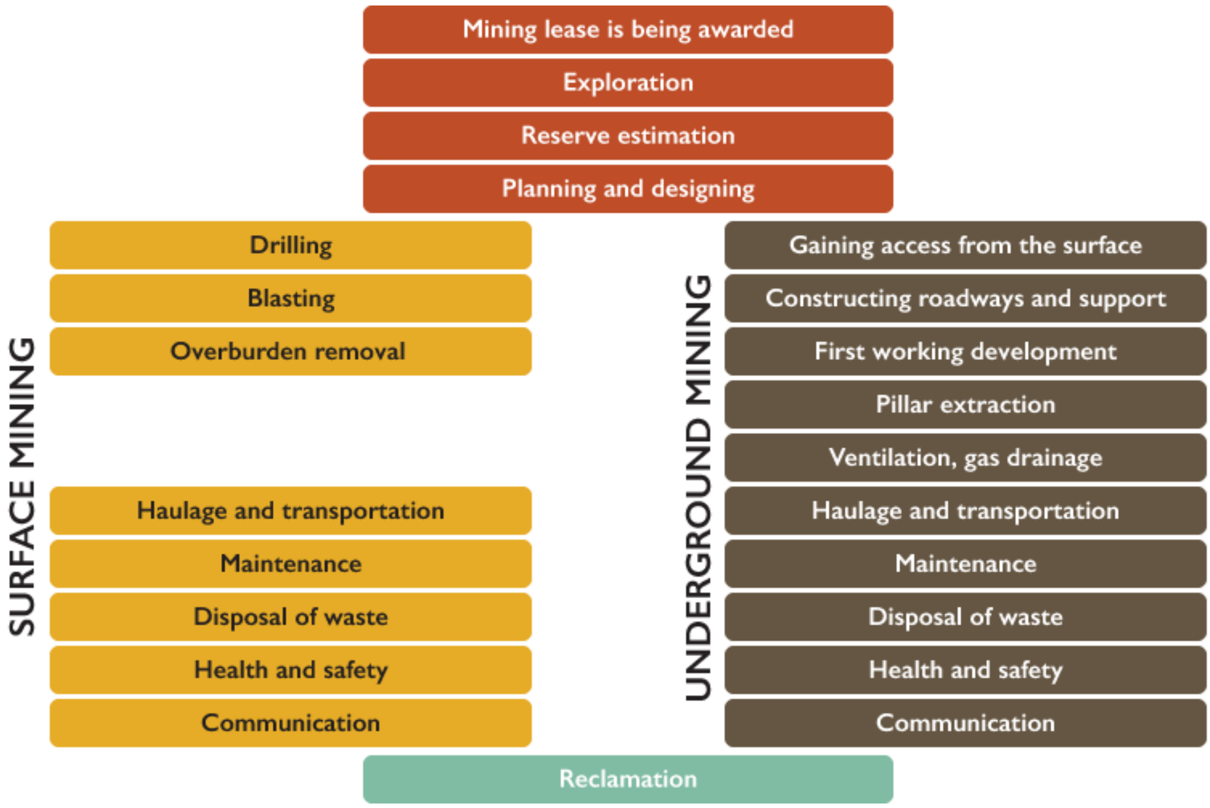

Table 2 - Mining process (based on Kennedy, 1990; Hustrulid & Bullock, 2001, own research)

CHALLENGES IN THE INDUSTRY

General Overview of Challenges

Mining companies had some difficult years behind them. Up until 2010, commodity prices were reaching record heights due to increase in housing constructions, pro-growth policies, speculations, and emerging markets, especially China. But in 2011, this 'supercycle' reached its peak and ever since prices have moved downward. With China's slowing economy the demand for metals and minerals have decreased while supply stagnated (Lee & Prowse, 2014). As expected, these events resulted in a decline in revenues in the past years; but mining companies could not lower their expenditures with the same pace that caused catastrophic profit margins: while the net profit margin was 25% for the top 40 mining companies in 2010, it dropped to 2% in 2013, and the industry seems to be slow to regenerate (PwC, 2015).

There are other challenges that mining companies have to face. Vic Pakalnis, president of MIRARCO Mining Innovation, says that "our ores, near-surface ores, are getting to be depleted, so we need to go further down" (Lee & Prowse, 2014). The more minerals are exploited, it becomes more challenging and expensive to locate and mine new deposits. This phenomenon results in more remote destinations, deeper quarries (75% of newly discovered base metal reserves are hidden under 300m); and, moreover lower-grade ores (there are gold projects that result less than 1 gram of gold per tonne). While the capacity to build a tonne of iron ore was 96 US$/mt in 2007, this number increased to 150 US$/mt by 2012; but other metals and minerals show the same rise (Deloitte, 2014). Mining companies have to balance expenditures and efficiency to be able to extract metals and minerals at a lower cost than their competitors (Lee & Prowse, 2014).

The mining operations take place in distant locations, and they are hard to access, and furthermore mining companies have to deal with other difficulties: in many cases, the fields are situated in natural areas, so corporations have to meet rigorous requirements. Environment-friendly operations are not sufficient; they have to plan ahead the rehabilitation of the area. In the past, they just transferred the machines after exploitation with all the waste and overburden remaining in the valleys. New vegetation could not develop on the empty rocky landscapes; however, today strict and comprehensive legislation regulates reclamation after mining operations all around the world (Macdonald, et al., 2015).

Just as any industry, mining has also been revolutionized by information and communication technology (ICT). Companies recognized the benefits of modernization, implementing new solutions in both operations and management. The total ICT spending of the sector was US$16.3 billion in 2010; and it is expected to reach US$26 billion by 2018 (Lee & Prowse, 2014). Internet of Things with connected machines and utilization of big data is appealing to all mining companies. However, the current trends of low commodity prices and the consequentially minuscule net margins slow down the process of introducing new technologies. Mining enterprises have to minimize their expenditures to ensure their liquidity and to be able to continue their going concern. As a result, they are not focused on R&D activities, but they are examining ICT solutions that can help saving costs and help their businesses to recover (Lee & Prowse, 2014).

And there is place for optimization: the industry wastes a lot of energy, even though it is responsible for 40-60% of a mine's operating costs; surveys showed that trucks can stay idle for 50% of the time (Deloitte, 2014). It is not necessary to implement new technologies, sometimes companies should take a deeper look at their operations' data and improve their processes.

Remote mining exploitation also results in demand for higher safety measures. Mining is still a dangerous industry with more than 2000 fatalities in China in 2011 (Deloitte, 2014). But tragedies occur even in countries with more rigorous restrictions and requirements about human safety: 45 workers lost their lives in 2014 the US (U.S. Department of Labor, 2015). Many of the injuries have measurable and preventable causes; so mining companies should focus on collecting and interpreting safety data, model high-risk events, re-examine workplace practices and create risk assessment strategies to decrease – and preferably entirely eliminate – fatalities (Deloitte, 2014).

Besides issues about minerals and operations, mining companies have to face different challenges about legislation, dependency on unpredictable government actions, aging and retiring top management (Deloitte, 2014).

The Structure of Operational Costs

A mining site's cost structure consists of three main parts: maintenance, labor and consumables.

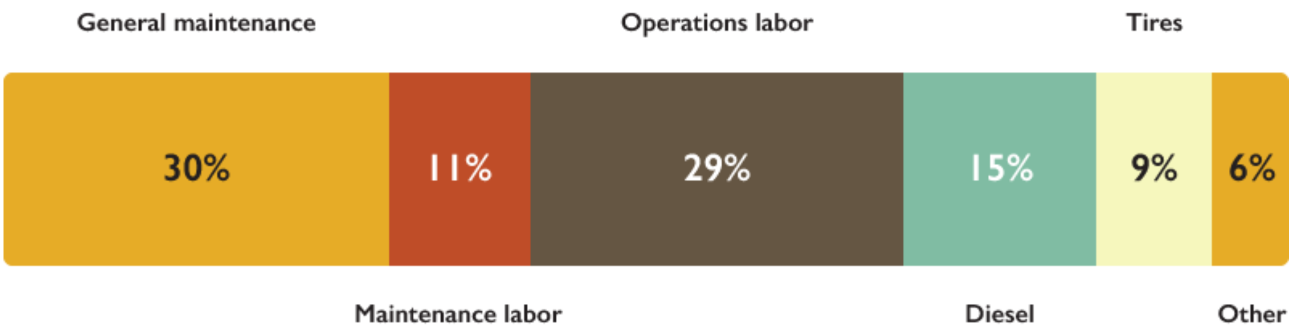

Figure 6 - Breakdown of direct mining costs in large open pit mines in the USA (Campell & Reyes-Picknell, 2006)

Figure 6 shows that maintenance related costs account for about one-third of total operational costs (Campbell & Reyes-Picknell, 2006), which makes maintenance the largest controllable cost. It includes items such as replacement parts, human resources, supplies and other items (Lewis & Steinberg, 2001). Though it demonstrates the expenditures of North American open pit mines, other locations and mine types show similar proportions[3]. Mining companies can focus on improving maintenance processes with advanced technologies (such as big data and connected machines), as this area is the largest contributor for their operational expenditures.

To summarize the previous pages, the main challenge for mining companies is, how can they reduce their costs to counterbalance the drop in their revenues, even if new mineral deposits are located in remote areas and usually deep under the ground. These conditions are limiting the enterprises', but they might also result in new, innovative solutions. Glenn Ives, North American Mining Leader and Chair for Deloitte Canada says: "There's no doubt the mining industry is experiencing tremendous pressure on costs. But cost constraints often lead to innovation. Mining has grown bigger over the past 200 years – bigger plants, bigger trucks, bigger blasts. But the industry itself hasn't evolved much. Now is the time to make fundamental and dramatic changes." (Deloitte, 2014).

[3] During my research interviews I received the information that mines in Australia has similar cost structures, no matter if they are underground or surface mines

RESEARCH METHODS

As it was explained in the previous chapter, mining companies are moving towards big data and the Internet of Things, but they do not harness all of its benefits yet. Their main challenge is lowering their expenditures to balance their decreasing revenues. Therefore these are not the best times for expensive R&D activities. However, since mining machines are already equipped with various sensors, connecting them and processing their data to gain new insights is not as costly as developing brand new tools, while the benefits can be just as valuable – if not even more. In the rest of this paper, I will try to demonstrate what opportunities do they have to optimize their operational processes.

Mining operations is a complex process with numerous procedures and sub-tasks. Most of the steps can be enhanced with big data and IoT, but the size limits of this document do not allow me to examine all of them. Consequently, I focus on one particular area – predictive maintenance.

The thesis aims to answer, how can mining companies utilize machine-generated big data in their operations? However, concentrating on *a* specific field does not make the research insufficient, because improving even only one part of the whole process results in an overall enhancement (Ghalayini & Noble, 1996). Moreover, maintenance costs are the largest expenditures in the daily operations of mines, so the company could certainly benefit from enhancing its processes. In the following chapter, it will become apparent that there is room for improvement in this area, which can extensively boost the everyday operations. However, at the end of the research, I introduce examples of other fields too, to demonstrate other use cases of IoT and big data in mining operations.

I approach the optimization from a business perspective. Therefore, the research I am conducting is a management research (Saunders, Lewis, & Thornhill, 2009). Because of that, it has to fulfill four criteria: knowledge should be developed by other disciplines; it should provide commercial advantages (or personal for the managers who contribute); it should address well-educated readers (managers); and it should have some practical consequences, such as actionable statements (Easyerby-Smith et al., 2008). While following these principles, I complete an exploratory research (Saunders, Lewis, & Thornhill, 2009). I obtain my primary data by interviewing relevant subjects from a mining company in Western Australia. Yin concluded that multiple case studies may be preferable to a single case study (Yin, 2003), so in the second part of the research I support my findings with various cases as secondary data sources, that examined the same areas. These are all qualitative sources of data, but as part of my research, I also try to demonstrate the initial investments, immediate and long-term returns of implementing predictive maintenance solutions in a mining company, that I base it on various quantitative sources. Tashakori and Teddlie (2003) argue that this mixed approach is useful if it can help answering the research question or if they can help evaluating if the findings can be trusted.

Consequently, I attempt to cover two segments:

I try to define the characteristics of well-performing predictive maintenance technologies with the required organizational structure, roles and positions, new tasks. I touch upon the unique attributes of underground and surface mining and demonstrate the technologies used in them. I investigate what kind of data is relevant, how is it collected, transferred, analyzed, and processed, and I try to remark if data quality and quantity produce more accurate results.

After that, I construct a model about how can companies implement predictive maintenance in their operations. The purpose of this model is to provide a generic approach that can be applied in different situations and move the companies towards a desirable outcome with successfully integrated predictive maintenance processes.

As the first part of my research, I introduce a mining operation in Western Australia. The company, Downer Group, was established in 1933 in New Zealand and ever since it focuses on providing engineering and construction services to public and private infrastructure sector. With its 20 000 employees, it operates primarily in Australia and New Zealand but it is also involved in projects across the Asia-Pacific Region, South America, and Southern Africa. As an Australian Stock Exchange Top-100 company it provides services to cover its customers' entire physical asset life-cycle from designing, creation, operation, maintenance and final decommissioning. During my research I focus on one of their operations in Western Australia, relatively close to Perth, as they have implemented predictive maintenance technologies supported by analysis of big data there, and I could gather information about the whole process from identifying the need for improved maintenance processes through planning and execution to benefiting from it on a daily basis.

To define the characteristics of well-performing predictive maintenance solutions within a mining organization I have to investigate, for what extent do they utilize IoT in their machinery, and what sensor data do they collect. As companies focus on cost reduction and they have limited resources, I look at what upgrades are needed on existing machines to provide the required data. I examine how these systems are connected and how do they transfer the data to the place where it is processed. As mining industry just started to utilize big data, I assume that their organization did not have specific analysts. I investigate what organizational changes, new positions had to be introduced to be able to efficiently analyze data and if is done within the company or through external partners. I compare previous malfunctioning and reparation efficiency to predictive maintenance. I try to find further correspondences with work safety, energy efficiency or other areas; and finally, I investigate if the precision and reliability of predictions increase with the amount of data and if so, I review if they utilize data from numerous mines to get better results. I achieve it by contacting relevant employees of the company, who are involved in different phases of the mining production. I complete semi-structured, qualitative research interviews (King, 2004) because the examined area is complex with a large number of topics involved and the questions vary based on the subject (Easterby-Smith, Thorpe, Jackson, & Lowe, 2008). I enquire a plant asset coordinator about the technological details of sensors, data connectivity and practical implementation of predictive maintenance solutions with big data. I continue the research with information from data analysts at the company and I ask about the ways they can gain insight of the mass of data. At the end, I try to get an overview of the business scope and potential benefits. I deliberately relate my questions and discussions to existing theoretical propositions, to strengthen the generalizability of this qualitative research (Yin, 2003).

After the extensive analysis of the company I am highlighting the critical factors of successfully utilizing big data, IoT, predictive maintenance technologies to enhance production, decrease delay time and boost business, in general, while I consider the current challenges of the industry with its low profitability and high expenditures.

Finally, I am constructing a generic model that mining companies can use to incorporate these methods into their business and benefit from them, saving time and money. I do not only focus on the technological perspective, but I consider the whole integration process as a corporate change, and I build my model on theories of change management. Although the framework concentrates on implementing predictive maintenance, with slight alterations it can be extended to include other big data and IoT solutions as well.

I try to prove that any mining company can benefit from implementing big data solutions. However, Marshall and Rossmann (1999) argues that interviews reflect the reality from when they were conducted, and the situation may be subject to change. Therefore, I use existing case studies from other mining operations as secondary data sources. This enables me to compare my findings with other cases from different locations, sizes, situations and times. This comparison provides proper evidence to support the results of my research.

RESEARCH RESULTS

My research is primarily based on interviews about maintenance solutions at the Australian mining operations of Downer Group. They work in mining fields across the whole country, including both underground and surface mines. I examined their asset management and maintenance in Western Australia where the company operates in 6 sites, controlled from Perth, WA, where they carry on coal and metalliferous mining in surface mines.

Since these locations are distant from densely populated areas, FIFO (Fly-in fly-out) method is used to temporarily fly workers to the remote sites to do their jobs, and then fly them back home.

Clinton Cheney, Mining Plant Asset Coordinator of the company, described how essential maintenance is for the enterprise. They have approximately 380 heavy equipment in Western Australia, such as dump trucks, excavators, loaders, graders, wheel dozers, etc., and 1800-2000 smaller ones, such as generators, air compressors, service trucks or other vehicles. These machines are used in harsh conditions, and a failure can halt exploitation, costing hundreds of thousands of dollars to the company. Cheney explained that some of their dump trucks use MTU engines, and it costs 500 000 AUD to the company if they fail, but only 25 000 AUD if the error is caught before the failure.

They use different kinds of maintenance techniques. Breakdown maintenance is used in failures that were not prevented. This is the most expensive for the company, because in this case the breakdown had already happened, so it is not enough to replace or repair parts of the machine. Some manufacturers would buy back their used engines for about 2/3 of their original price if they are not broken, which is also a significant saving for the company (one of these engines cost approximately 3-400 000 AUD). Therefore, it is essential to minimize failures by other, more efficient maintenance techniques.

Downer Group uses preventive maintenance in most cases, but instead, of physical inspections they tend to rely on more and more data coming from the machines. In some metal parts, such as ball stud components, ultrasonic tests happen on a pre-defined schedule (every 2000, 3000 or 6000 hours, based on the age and condition of the equipment); or some engines' oil consistency have to be checked every 250 hours, and after 2000 hours all liquids have to be dropped and replaced. These preventive maintenance solutions are useful in many cases, but they can result in the replacement of otherwise well-functioning parts. Therefore, the engineering team (located in Brisbane) continuously evaluates data, and they try to increase the scheduled times between maintenance - first on a small set of machines - to see if the inspections could be carried out less frequently.

In the last years, the company consciously moved towards predictive maintenance technologies to further decrease their expenditures in operational costs. With the increasing amount of available historical data, analysts can provide more exact descriptions of a machine's state and the possible failures, so that mechanics can focus on the perilous areas. An example is oil sample analysis: based on the components' oil concentration, the oil lab can predict which bearing might fail in the future; or they figured out that elevated viscosity is caused by diluted oil, that is in correspondence with leaking injectors. But besides manual sample taking, there are various machines that are connected and provide real-time data from a number of sensors, which can be stored and analyzed to get immediate alerts if some of the parts might wear out.

In Eastern Australia data sampling is more rigorously regulated by the authorities, because there are more underground mines that involve more safety concerns; moreover, there are legal instructions about how often do they have to replace particular parts, no matter how good their conditions are: ball studs have to be replaced every 6 months, disregarding their physical state.

But safety concerns appear within the company as well: some of the failures could harm workers, so it is crucial to prevent them. For example, steering pumps are changed predictively, because if they break, the trucks lose steering, which could end up in accidents. The company shares failure data with the machines' manufacturer as well (in most cases Caterpillar) who can analyze the problem and if needed, alert all mines around the world, where these tools are used, to prepare them for a possible error.

The number of failures has drastically changed in areas where they introduced predictive maintenance: five years ago planned or predictive maintenance only covered 70% of the issues, which meant that 30% of the problems were solved in a reactive way, costing enormous amounts of money for the company. They had to keep a much larger inventory of spare parts on the sites, stock levels were higher, and the bottom line was far more expensive. Cheney explained that there is still a site where most maintenance activities are reactive, and the difference is clearly visible compared to the other mines.

As a result of implementing several predictive maintenance technologies and collecting data in the last years, the accuracy of these forecasts have drastically increased: the more historical data they have, the better predictions can they provide. And that is a requirement to save more on the equipment with time, as they have to include maintenance and failure in cost calculations. Even machines that are maintained on a scheduled basis can benefit from historical data because engineers can push the frequencies of inspections to find a perfect timing, as previously described.

However, these solutions require additional technologies and processes within the mining site and across the company. Firstly, machines have to be connected to be able to transfer data. There are different methods for different instruments: Wi-Fi breadcrumb is used on dump trucks, which means that all of them are equipped with special wireless nodes. Data is always transferred to the closest node, creating a chain of connections until it reaches a data entry point. This technology enables trucks to be mobile but still provide real-time information. A similar method is used in underground mines: the backbone of the system is a wired-WLAN network, and mobile nodes are used to reach working areas and provide continuous connectivity.

Some other heavy machines collect data and only transfer them once a day. They use a satellite system for communication (provided by mining technology company, Komatsu) that circulates above Australia: it is above the Eastern side of the country during the daytime, and it collects data from Western Australia during the night.

The company generates around 150 MB data a week only in its six mining operations in Western Australia. This includes machine logs, sample data (500 oil samples a week), maintenance and error reports (90 machines are serviced a week) and all documents as the company tries to store everything digitally to have all information available through their Integrated Management System. They store everything infinitely in the cloud, as storage costs are very low compared to the additional benefits they can get if they need old data. For example, they might suspend using a particular brand or type of machine, but if that is the only available, they might have to return to it, so historical data of the brand and the maintenance history of the machine should still be available.

They store most documents in a general Integrated Management System, including policies, procedures, safety information, service sheets and Project Management Plans. This system is accessible from all mines across the country and used to distribute information about machines and processes. However, it does not give an answer to one of the main challenges in mines: how to integrate data from different devices and utilize them to get better insights. Currently, there are some attempts to analyze various factors together, for example, load, fuel burn, operating temperatures and oil samples are compared together to predict engine conditions, but most other components have only one factor to evaluate them. I learned, that it is a real need to be able to analyze multiple factors together, and General Electrics is already working on a platform called Predix, that operates as a mobile operating system (similar to Android) and provides an interface to develop specific applications to control the industrial internet of things and generate predictions on consolidated data coming from different sources.

The analysis of maintenance-related data happens on different levels: engine fault codes, exhaust temperature sensor measurements are processed on the mining site. There are IT systems that can flag possible errors if they find patterns in the input data, or if some of the metrics reach a specified threshold. Many of the analyses happen in the center at Perth, where there are component specialist employees who work with different data types, such as oil samples. The engineering team always looks at previous failures and based on the preceding measures they try to examine what could have caused the problem so that the maintenance procedures could be fine-tuned. And the equipment manufacturer also participates in the analysis: Caterpillar, for example, receives all oil samples in bundles, so they can study them together with samples coming from other mines across the country (or even other countries). In exchange, they can provide better insights (for example, they can notice that there is high viscosity, that can be a result of wet breaks) and they can alert all of their partners if they find a potential error that affects many machines.

As it was mentioned before, most of the data is analyzed by industry experts in a special department, far from the mining sites. During the interviews I was investigating, what techniques do they use to extract valuable information from the input data. The process of data mining follows the theoretical frameworks: firstly, analysts have to clear and organize the inputs. Even though they are collected from machines, they are not only well-structured log data, but sometimes reports, or other documents. Oil samples are more specific because they have to be analyzed first in a distinct laboratory. Analysts also work with information returned from manufacturers. There are well-defined processes how data should be organized, that has to be reviewed whenever a new technology is implemented, new types of machines are installed, or new methods are established.

From the time when the data is structured, analysts use dedicated computer software to calculate different predictions. When they work with maintenance, they use all of the previously introduced techniques, such as classification, regression, clustering (though most data is labeled already). Since they know the machines' history from previous report, the models are usually supervised ones, as they could use well-labeled training data to construct their models. However, pattern recognition and anomaly detection models are both built probabilities and unsupervised techniques for some extent.

Once a model is built and live, it automatically adjusts itself based on new information and knowledge. Most models have alerting mechanisms, which means that they flag possible future failures or extreme values.

At the end of the analysis process the experts upload their results to the company's IT system with comments, notes and recommendations about the findings, so the workers can pay attention to the examined machines. Field workers receive the information immediately on their handheld devices and computers so that they can take the necessary actions.

Investing into better prediction technologies is essential for the companies, as failures can cost millions of dollars. In a recent case, one of the drills wore out, and one of its teeth fell off. It would have been already an issue in itself, but it fell into a crusher, destroying that as well. Continuous inspection of ground engaging tools is mandatory to minimize this kind of events because they are used in harsh conditions.

The company endlessly tries to implement new methods that improve their assets and their maintenance: for example, hydraulic wheel dozer swing drives (they are responsible for turning the upper part of the machine, there are four of them per machine, worth around 60 000 AUD each) did not have any monitoring in the past, and their failure contaminated and damaged the other three. By installing alarms that detect errors and shut down the equipment, the company could prevent further harm. In Western Australian sites, four engines get replaced on average on a monthly basis. If the engines are still operating, the manufacturer buys them back for around 2/3 of the original price, that can also result in enormous savings. However, there are many parts that are not that business crucial and their breakdown do not cost additional expenditures to the company and do not have safety risks, so they use them until failure. As it was mentioned before, underground mines are regulated by the authorities, so in many cases, the company do not have options about when to replace the parts.

Finally, I examined how change is implemented at the company and who initiates it. I found that new development concepts can originate from all levels within the organization: sometimes manufacturers introduce their new products or measures, and the management finds them appealing. In this case, the engineering team evaluates them, and if they found the change worthwhile, they can incorporate it to the maintenance processes (with the leaders' approval). However, in many cases, site workers or data analysts have a better overview of the everyday processes, and they have hands-on experience about them, so they can propose changes (these are usually not concerned about investing in new machines but changing methods). In this case, they use templates to describe the change with its presumed benefits or even ideas about the implementation. After two levels of validation, the document arrives at the engineering team, which then considers all technological aspects and from that point, they treat the case exactly as if it came from a manufacturer. The changes are then implemented first in a selection of machines or areas through pilot projects, and if they succeed, they are rolled out across the whole organization. All relevant processes and documents are available through the company's Integrated Management System; but to stay flexible and answer unique needs, each site can have their specific service sheet with custom metrics, and there can be slight differences in their operations. For example, one of the mining fields has harder ground that results in faster wearing of the ground engaging tools. Therefore, maintenance samples have to be taken more frequently than in standard conditions.

As my research showed, the mining company is eager to improve its maintenance processes improve the lifecycle of its valuable assets and even though there are rigid rules and well-defined processes, change is always embraced. Predictive maintenance methods are already part of their everyday business all across their mining sites, and with the increase of data and better analytic solutions, they could drastically reduce reactive maintenance and the stock levels of spare parts.

A GENERIC STRUCTURE FOR EFFICIENT MAINTENANCE IN MINING

Based on the interviews I conducted I introduce a structure for mining company operations that can effectively utilize predictive maintenance while it takes practical problems and possibilities into consideration. The setup is supported by the previously presented definitions and theories.

INTRODUCING A GENERAL STRUCTURE

Figure 7 (next page) shows an overview of the mining company. It is divided into numerous parts, such as the mining site, a data analysis center, engineering team, management team. Each company can have multiple operating sites, analyst and engineer teams and they might choose to include external partners for some of the tasks. All of these divisions can be geographically distant from each other as the data is stored in the cloud so that they can have access to it.

Most of the work happens in the mining fields. Heavy machines are used to exploit minerals from the ground, process and transport them, and the processes are supported by light equipment. Most of them are enabled with sensors, that do not only measure their performance, but also their condition. In some cases, multiple sensors are installed on the machines, especially on ground engaging tools, that are more business critical and more expensive. Machines usually measure their parts' temperature, vibration, pressure, mechanic or electronic functioning.

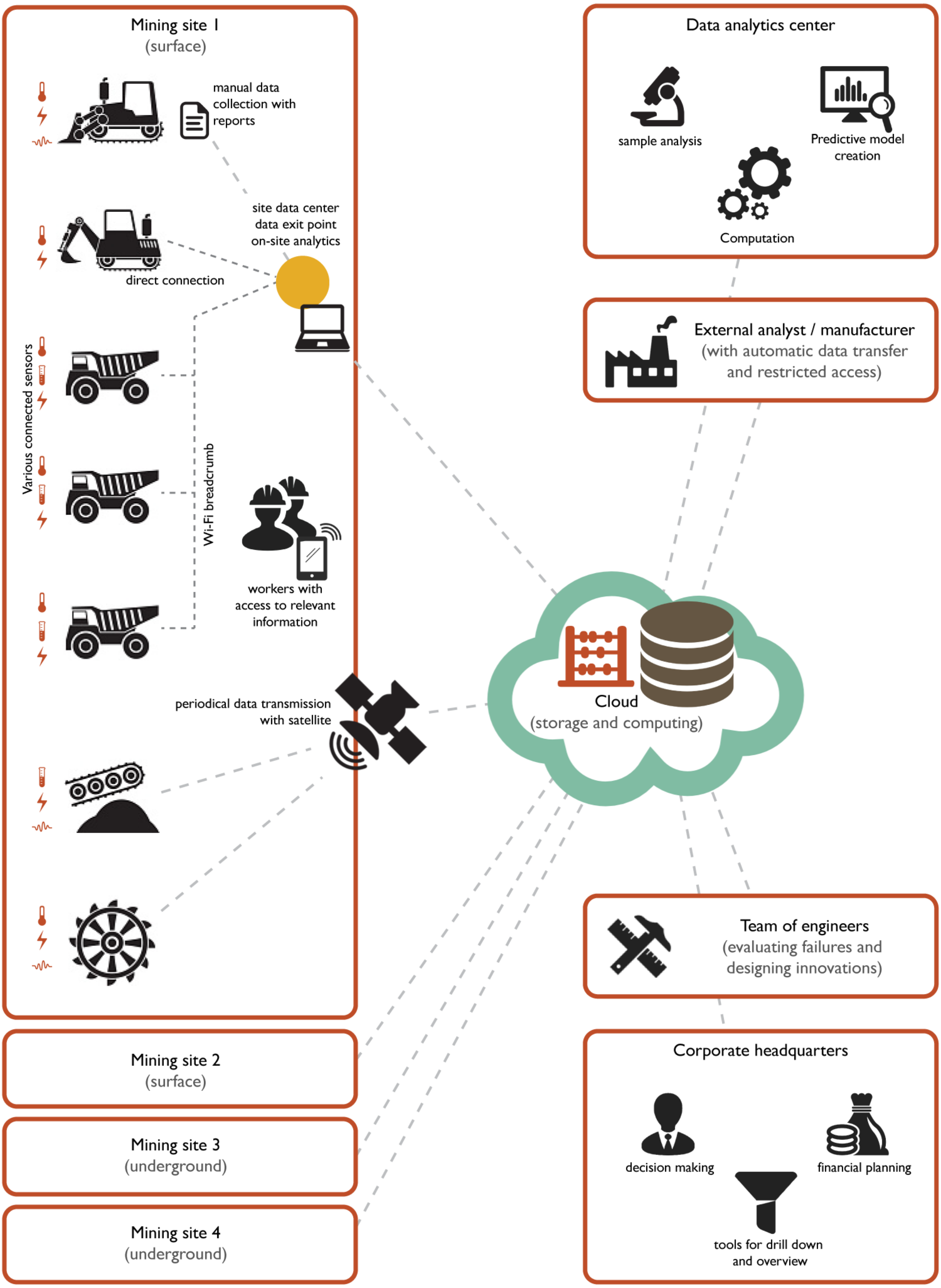

Figure 7 - Mining company structure with connected devices and data mining techniques

Since mining sites are usually located far from urban areas, wireless data coverage is not present. However, as the research showed, data is a key factor in optimizing maintenance processes. Mining companies has different options to extract information from the machines' sensors:

- If the device is not connected to a network, data has to be manually obtained from it, that requires a site worker. Sample data (e.g., oil samples) is usually taken in a similar way.
- Moving equipment (such as dump trucks) needs live connectivity to provide real-time data. However they have to cover a large area. Wi-Fi breadcrumb technologies are used with them, where the machines are equipped with wireless transmitter-receivers, and they send information to the data exit point through each other.
- Underground mines use similar techniques, but the Wi-Fi network is constructed of mobile nodes that can be quickly set up in the tunnels, and they forward data.
- Other machines collect data, but it is not critical to have real-time monitoring of them. These devices periodically send their content to a satellite, which forwards them to an analysis center.
- Some machines are directly connected to a wired network.

When possible, machine-to-machine communication should be enabled, even between machine parts to prevent errors and failures (e.g., automatically shut down systems if sensors measure extreme values that could be signals of breakage and alert the personnel). Connected devices can generate further real-time insights for maintenance. The setup can reduce the size of on-site inventory of replacement parts, and asset-management can be more agile.

Data analysis should happen on multiple levels, but more automatized: real-time information should be analyzed on-site (but if data is already stored in the cloud, computing can happen anywhere if the models are well defined). There are cases when physical measurements have to take place, and the analysis requires advanced laboratories. In these situations, it is better to send the samples to a central department to reduce costs. However, the outcome of these tests should be immediately available for the workers who are responsible for the machines so that they can take the necessary actions. Some of the analyses can be outsourced, if that brings additional economic benefits for the company, but only to that extent that the results are still available in a short time. If the enterprise has engineer teams, they should also have access to all data, and be notified about uncommon events. Cloud storage can ensure instant access for the relevant people, and it can help in examining historical data and trends. Moreover, it can help managers to improve their planning, not only on a site level but also across the whole organization.

Suppliers and manufacturers are already involved in data analyses; however, the communication usually requires human interactions. Cloud-based solutions can have APIs that enable the partners to access the needed data and also to return their findings. This, and data analysis outsourcing can increase efficiency as processes are more automated and faster, but it also requires a well-established access management so that the information system can grant access to the relevant data for each user.

Workers should be equipped with handheld devices that have access to maintenance data, and they should be able to see reparation history, use drill-down techniques, read analyst notes and recommendations of the machines. Besides providing these data, handheld devices can contain manuals and instructions for the equipment, and they can be used as a notification center for various warnings and alerts. Real-time monitoring applications can also support maintenance, and advanced analytical tools can use the devices computing capacities to do smaller predictions – even on data derived from multiple sources.

This level of integration has numerous benefits – not only does it improve maintenance efficiency – but if combined with data from other parts of the company (for example, real-time exploitation data, information about stock levels of different minerals), it can provide a more extensive overview for management, so leaders can base their decisions on facts instead of "best guesses".

Implementing the described structure in a mining company means immediate investments and mining companies are already challenged with cost reduction. However, many of them already has technologies, so they should only build the connected infrastructure and processes around them, that can result in rapid returns. The following main chapter demonstrates how can an implementation process be executed to move forward towards IoT technologies and predictive maintenance, data mining.

REAL LIFE APPLICATIONS

The previously introduced structure defines how mining companies can efficiently integrate predictive maintenance in their operations. To test its validity, I looked for examples in secondary data sources.

"Operators are increasing their focus on productivity and improving the efficiency of the capacity that they do have.", says Derick Moolman, commercial product leader, mining, GE Intelligent Platforms (Earls, 2013). Market trends support this statement as they show that mines are trying to move towards new technologies, such as predictive maintenance, and manufacturers try to align their products to fulfill the new requirements. This has generated a new business for technological companies as well. Martin Politick, director of research and development at Wenco International described: "Predictive maintenance is now an 'expected' feature of a fleet management system (FMS), miners (and their purchasers) have it on their checklist of features they 'must' have." (Earls, 2013).

Both heavy and light equipment can be enabled with different sensors that measure their performance, or their condition. The most commonly used attribute that they measure is vibration, but sound, temperature, and other specific properties can be examined as well. IMI Sensors, a manufacturer of mining equipment pioneers in implementing sensors that can be used for predictive maintenance. James C. Robinson, a consultant at the company states, that “many vibration problems common in industrial machinery can be detected and their severity can be approximated” that can help to prevent failures of the machines (Robinson, 2014).

Machines have to transfer the collected to systems that can process and analyze them. GE, for example, uses cloud solutions for the analytics. They provide storage and computing tools as well, to notify site workers about potential failures – days, weeks or even months before they would occur. However, not all manufacturers support real-time data transfer. However, building communication networks is expensive and sometimes not economical: “We can't just stream all the real-time data back to the office; this would have significant detrimental effects on the radio network.”, says Politick from Wenco. Therefore, the company enables their solutions with Wi-Fi and physical ports so that log data can be fetched by workers. (Earls, 2013). Traditionally, communication happened through radio frequency. However, the need for transferring large amounts of data had revolutionized old technologies. Motorola, a leader in industrial wireless networks, developed new products and systems that replace radio communication with Wi-Fi and mobility enabled access technologies, even in harsh environments (Mining-technology, 2015).

As described above, data analytics can happen on various levels: sometimes small calculations can be done by utilizing the computing power of handheld devices or computers built in the machines. However, better results can be obtained from gathering larger amounts of data, and combining them to generate better predictions. Many of the existing manufacturers begin to provide analytics tools that can enhance the process. Komatsu Ltd, a global manufacturer of mining equipment, announced partnerships with General Electric to extend their services. Sean Taylor, Komatsu Australia's Managing Director, said, "Now we want to start offering data analysis services to mining and resources companies in the near future, including iron ore and coal mines in Australia and New Zealand as well as other mining regions." (Komatsu, 2015). But manufacturers, who already analyzed data generated by their machines also emphasize their analytics solutions: at the same time of the announcement of the previous collaboration, Caterpillar, a market leader in mining machine production also established a new analytics and innovation division, signaling that they see potential business opportunities in this field (Caterpillar, 2015).

The previous examples demonstrate that mining companies and their partners constantly search for new possibilities, how technologies can be applied to enhance their asset management, with predictive maintenance as the leading area. The organization has to adapt for the new environment; changes have to be made to prepare both machines and human resources for the new tasks and challenges. In the next chapter, I elaborate on how can they implement profitable changes in an efficient and smooth way.

A MODEL OF IMPLEMENTING PREDICTIVE MAINTENANCE IN MINING COMPANIES

There are numerous different approaches of describing changes in corporations or other organizations, of which Lewin's three-step model is the most widely used by scholars, as it is easily applicable in different situations and it covers the whole change process. Although implementing IoT solutions in mining companies might seem like a technological issue, it requires new business processes, new roles and a shift in mindset. Therefore, Lewin's model (1947) can be used to analyze them, as it presents a structured way of planning, designing and implementing changes in an organization.

The model divides the change mechanism to three distinct parts: *unfreeze-move-freeze*. Maon, et al. (2009) introduced an additional step that precedes Lewin's procedure, called *sensitize*. It states that change starts with raising awareness of different internal and external drivers.

When the organization notices these factors, it moves to the *unfreeze* step. It needs to clarify the direction in which it wants to move forward. Existing processes, behaviors, values and beliefs have to be unlearnt in order to prepare for the new ones that would replace them. In this step the company has to plan the change itself, as well.

During the *move* step, the organization implements the defined adjustments in all the levels: not only introducing new technologies but also aligning business processes with them while involving employees so they can understand why and how the change is happening. This step ends with an evaluation, and the process might move back to unfreeze as long as the outcomes do not meet the previously determined goals. This iterative approach ensures that the new behaviors, methods, technologies are institutionalized only when they can deliver the expected results. This standardization happens in the *freeze* stage with integrating and strengthening the new procedures and adopting the change across all levels of the company.

However, it is a continuous process, and with time, the organization might have to start over with the unfreeze step (Maon, Lindgreen, & Swaen, 2008).

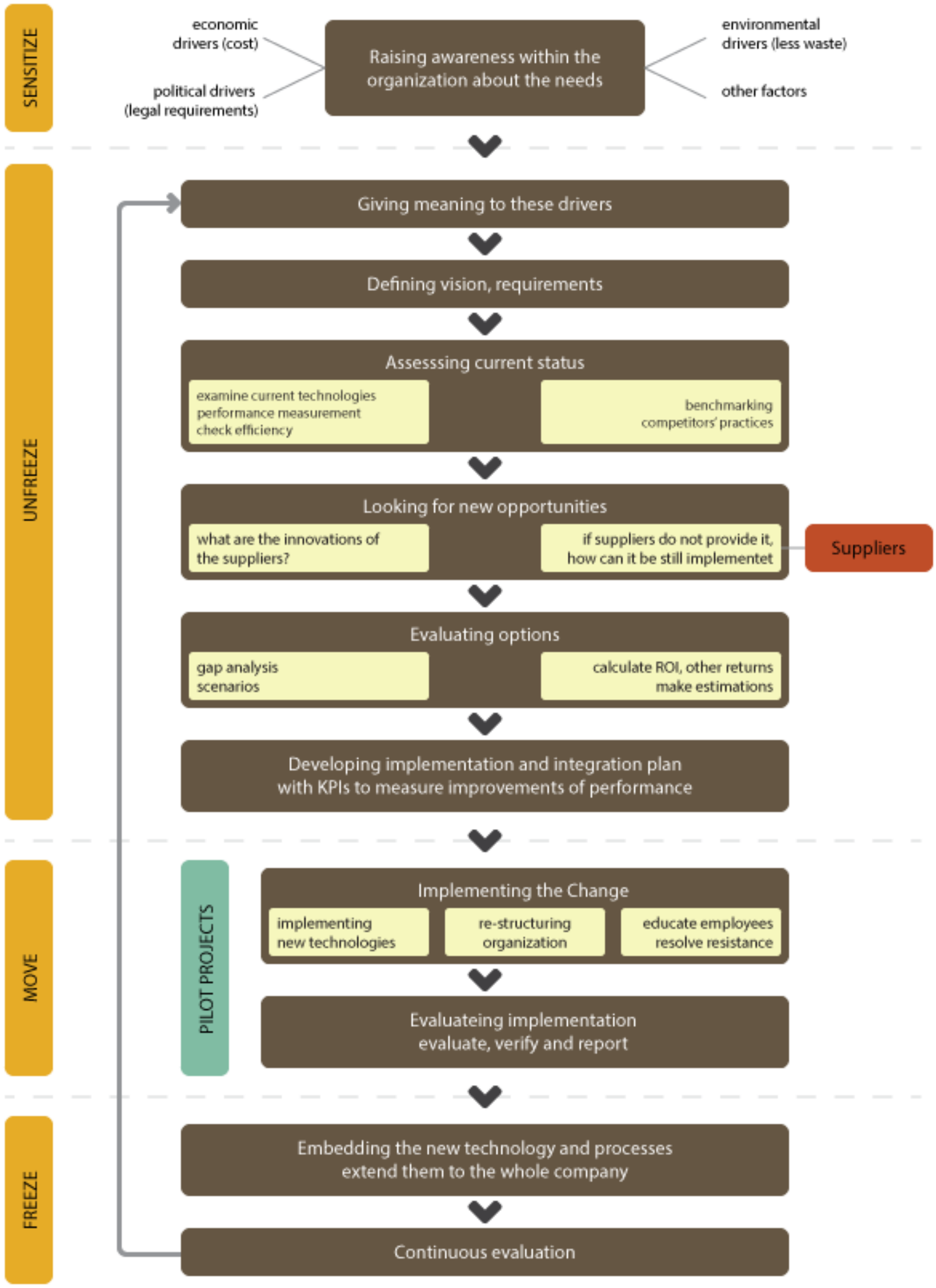

Figure 8 - Implementing predictive maintenance in mining operations (own work based on Lewin, 1947 and Maon, et al. 2009)

SENSITIZE

The first step of the change model was not part of Lewin's original work, however, many scholars found that it is appropriate to include the motivations and drivers for the change to understand the whole process. In this stage, companies start to realize the need for a change. The signs might originate from internal and external sources, and they usually affect different levels of the organization. Most of the cases there are numerous reasons that drive the change. If we refer back to the challenges of the mining industry, we can see a definite pattern in the possible drivers. The slowing economy resulted in a major decrease in demands for metals and minerals, and consequently, commodity prices are record low. However, since near-surface ores are getting depleted, companies have to extract them from more distant locations that are harder to access, while considering environmental impacts. These factors have contributed to a negative trend in not just the revenues of mining companies, but also, more importantly, their profits. These organizations could not decrease their expenditures with the same pace as their incomes dropped and that resulted in alarming financial reports year-by-year. These signs were unambiguous; companies had to stop overspending and alter their operations to give an answer for these factors. But besides the economic drivers, there were other aspects that called for change, such as safety concerns, sometimes even regulated by law, environment protection issues or recognizing innovation and noticing the advancements of competition. As the model shows, a number of these drivers can lead to raising awareness of the need for the change.

INTERPRETING THE DRIVERS

The first real step of change is recognizing the previous factors and giving them meaning in the context of the company's operations. As this stage is already in the unfreeze part of the model, it requires conscious actions from the managers. Their perception of their business and the surrounding world alters because of the different factors, and this modification triggers them to examine the situation and introduces changes if needed. The shift of their awareness can be categorized as either reactive or proactive. In the first some the organization takes on an undesirable state, so managers need to move it away from this condition. As it is a response to external factors, people tend to have more negative feelings about it, and the required changes might meet more resistance from the employees. In the proactive one the desire for change rises from within the company, by deliberating on ideas and experiences coming from individuals or groups inside the organization. Therefore, it is a more positive, opportunistic stance, in which the participants feel that the change is their own (Paton & McCalman, 2008). In mining enterprises both drivers appear: the challenges with shrinking profit margins, the environmental issues, new legal restrictions are coming from outside the organization, and it is inevitable to address these challenges. Additionally, technological advancements, new knowledge derived from data can drive change from within the company. Accordingly, managers have to interpret the signs that surround them and recognize the need for change. In the following steps, I present ways of making decisions and how to implement them successfully in mining organizations.

DEFINING VISION AND REQUIREMENTS

As part of planning, the company must clearly define what it wants to achieve with the change. This decision should be based on the drivers that managers interpreted in the preceding step, and it should give a response to the issues that has been identified. In the case of mining operations, the vision can be:

- Decreasing ongoing operational costs,
- Improving productivity by minimizing halt times in mineral extraction,
- Optimizing the inventory of assets,
- Increasing safety measures,
- Lowering environmental impact.

Usually, companies aim to achieve a combination of these goals, as they do not exclude, but rather compliment each other. A company might want to decrease delays that occur by failure of machine parts, but it might also want to keep the inventory on a minimal level. And besides these, as the example of the change of oil consistency in vehicle breaks showed, they might also target to increase worker safety at the same time.

The company might specify more detailed requirements for the change, but they always have to be aligned with the high-level objectives.

The vision gives an unambiguous goal for the company; and after formulating it, decision makers can start evaluating the different options to select one that will lead to this objective.

ASSESSING CURRENT STATUS

The company has to evaluate its current technologies and processes before moving to predictive maintenance. The outcome of this analysis is used as a basis for further improvements, and it defines the degree of change needed. A highly modernized mining field might already be equipped with sensors, so maybe it is enough just to collect their data and process them to provide information about the state of the machines and when do their parts have to be replaced; while in other cases old technologies might have to be upgraded to be able to collect data. It is advised to measure the current performance, too, to have a basis for future comparisons. In the case of predictive maintenance, the measured indicators can be the number or faults per time period, the cost of an error (including the price the of replacement part, extra costs because of the failure, delay time, restoration). The company should not only focus on its own technologies; it can look at other players' solutions. Benchmarking and following the latest trends might bring new ideas and opportunities that can be applied in the organization's own operations. For example, a mining company can see that its competitors use sensor data not just to predict failures, but also to optimize energy consumption with scheduling tasks based on big data.

But the mining firm must also consider the less technical scopes that might be altered during the change, such as the current organizational structure, roles and positions, tasks, responsibilities etc.

When assessing existing technologies and the current status, the company might consider the amount of minerals left in the deposits of the mining field. As figure 9 shows, these are two variables have to be taken into account. The *1. mine* plots a mining operation where machines are relatively new with the latest technologies, and the area still contains plenty of resources. On the contrary, there are not many opportunities left in the *2. mine*, and the equipment is also old and obsolete.

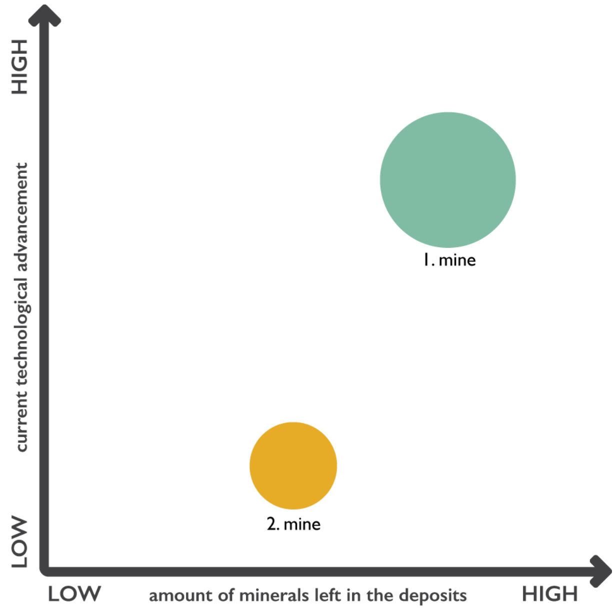

Figure 9 - Decision model of implementing predictive maintenance solutions (own work)

As I found during my research, companies evaluate each investment by estimating how much more resource is left in the deposit. When it is relatively new, intact exploitation area, this number is usually high, so implementing modern (and sometimes expensive) systems might still be a better option because they might bring more benefits in the long run. On the other hand, nearly depleted mines with existing machines do not require high technologies, so the company should not invest there anymore, or it should even consider relocating its assets to more prosperous areas. This evaluation can be used on both new mining fields and existing ones. However, in most cases new ones are already equipped with the latest technologies from the beginning. Therefore, the figure is more relevant in on-going exploitations.

After assessing the current status, the company can have a better understanding of the existing situation, and it can specify the gap between the actual and the ideal state.

LOOKING FOR NEW OPPORTUNITIES

Mining companies use tools and machines that are produced by external vendors. To improve the overall exploitation process, managers need to take a look around the world and see, what are the possibilities, the latest technological trends. They need to be aware of all the possibilities to make well-considered decisions about implementing predictive maintenance solutions – or any other innovations in their equipment.

The first part of it is to look at the company's operations. Usually, a mining enterprise operates numerous exploitations in different locations, with slightly different technologies. Therefore, they can share knowledge within the organization by determining which technologies perform better than the others.

Managers can benchmark the competitors' processes and machines, too. This way they might find actual results and benefits compared to information received from the suppliers about the equipment's' performance. It is advised to examine mines with similar attributes that the company's mines have. Benchmarking is also useful to see, what kind of new processes, organizational changes are needed to implement a given technology.

Besides collecting information from the company's existing suppliers, it is advised to look at what other vendors could provide as they might have better and more advanced solutions. As an example, I learned during my research interviews that Downer Group exclusively used mining equipment produced by world leader Caterpillar. However, they were constantly looking for innovations made by Joy Global, another machine producer company, and they were trying to analyze their solutions and they were considering if they could use some of them in their operations.

Mining companies work very closely with their machine suppliers. Since there are not so many of them in the world, they obtain an enormous bargaining power over them, and they can push the suppliers to develop equipment for their particular needs, especially if the advancement can be incorporated into the product and offered as a feature of the machine. This close collaboration appears on many different levels, for example, Caterpillar collects error logs from its customers and if it finds a pattern in malfunctioning parts, it notifies all of its partner mines to pay additional attention to the particular object. However, the cost cuts in mining industry in recent years has set back the suppliers as well. Therefore, they can not spend that much on R + D. And while it is beneficial for mines to have more advanced machines that require less maintenance, it hurts the suppliers' own businesses, as they are usually the ones who provide replacement parts as well (Brewer, 2015).

EVALUATING THE DIFFERENT OPTIONS

When managers have an extensive list of possibilities to improve operations, they are aware of the current situation and desired status, they must evaluate their options. There are plenty of tools and techniques to decide which investment would be the most fruitful for the company. But as I learned during my research, different forms of gap analysis are widely used to prepare the decisions, followed by various project return calculations. A thorough judgment requires considering the risks as well, and with different scenarios, managers can prepare for various outcomes.

Gap Analysis

This simple management tool analyzes the gap between the current and future state that the organization wants to reach. It starts with identifying the goals, followed by analysis of the processes and technologies at the company. In the previous steps managers have already done these tasks, so they have information to start to develop a plan to bridge the gap between these two states.

There can be different indicators that the organization might want to transform, and the direction of the change can be both positive (for example increasing workers' security or lengthening times between maintenance activities) or negative (e.g., decreasing the number of errors, delay times or the costs). The examples indicate that gap analysis can handle both qualitative and quantitative factors, and managers might want to change more than one indicator with implementing new technologies and processes, so a combination of these analyses can be used to evaluate the options. Murray continues the gap analysis process with a review of different levels within the company, and he argues that this way business units involved in the change will be more committed. He finishes the process with an audit, which will be introduced in the further steps of the implementation model. Furthermore, he describes that gap analysis can easily be applied to pilot projects before expanding new

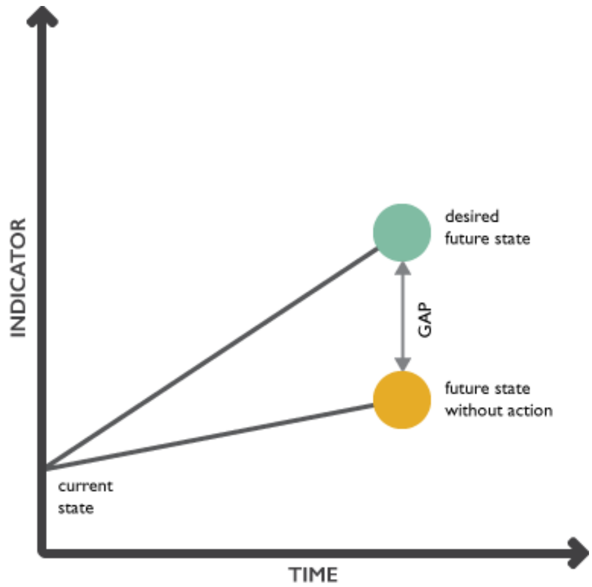

Figure 10 - Gap analysis (own figure based on Murray, 2000)

solutions to the whole company (Murray, 2000). As my research showed, implementation starts with small-scaled projects and gap analysis is used to verify their results.

Estimating Performance Measures and Other Returns

Performance measures are used to compare and evaluate investments. Managers can use these tools to support their decisions on implementing new technologies, as they usually require high initial investments and the company can only benefit from them during a longer period. Most of these measures consist of a formula that results in quantitative outcomes, usually based on financial variables. However, qualitative attributes should not be overlooked. For example, installing a new sensor might decrease delay times caused by a failure, so managers can calculate the monetary values of the beneficial factors, including continuous production, exploitation of human resources, the difference between the cost of replacement and cost of reparation. To translate qualitative benefits to financial values, managers frequently have to make estimations, which should represent reality as much as possible. They should try to include all aspects and they should calculate probabilities as well, to see the advantages of the investments (Brantley, Phillips, & Pulliam, 2011).

The most commonly used performance metric is ROI (Return On Investment). It is very simple, only the cost and gain of the investment is required for calculating it. It is a generic measurement that can be used for evaluating whole companies, but also individual projects.

$$\mathrm{ROI} = \frac{\text{Financial value} + \text{Cost of Investment}}{\text{Cost of Investment}}$$

It shows the financial benefits and returns of a project, that can help managers in making decisions about the execution of a project. During the calculation process, they might uncover new benefits (for example, predictive maintenance can increase the safety in some cases, which might result in decreasing compensation costs) (Brantley, Phillips, & Pulliam, 2011).

ROI is measured as a percentage, so it is not applicable on its own to compare possible investments, as their costs are usually diverse. Managers also have to consider the timeframe when the projects break even, as their resources are very limited, especially these days when mining companies focus on cost reduction. A project that requires a shorter period to return might get approved even if it is more expensive than the others because after that point the investment will be more profitable than the other ones would be.

Decision about the Investment

When decision makers have all the information about the benefits, costs, applicability and risks of a possible technological upgrade, they have to choose whether to implement it or not. This is the first decision point of the implementation process, and managers can support it with the previously introduced techniques and performance measures, but they need to consider other factors and restrictions as well, including scarce resources, time, compatibility with future developments, or pressure from other stakeholders. To reduce the risks of the implementation, they usually start by applying the new technologies and processes in a selected mining operation as a pilot project.

An important aspect that needs to be considered is the existing level of big data analysis within the organization. It requires new job roles (data analysts) and processes in the company, maybe even new departments and if there have not been many projects where they utilize machine data, the initial investment can be remarkably higher. Employing new professionals and reorganizing the corporation can be intimidating for managers, and it could result in rejection of an otherwise promising project. However, they can outsource data analysis to external partners at the beginning. There are numerous companies who undertake data analysis and many times the machines' manufacturers also provide such services. The collection of data still has to be implemented by the mining enterprise, and the analysis might not be real-time, so when multiple projects use predictive maintenance and other IoT and big data solutions, setting up an analytics department should be preferred because of economies of scale, performance and reaction time, data integrity, etc.

Managers usually do not have all the knowledge needed to make technology-related decisions on their own. Therefore, they should rely on advises of the company's engineering team or other technical personnel, who have insights for current performance, possible optimizations and who can help evaluating if a project is feasible or not.

DEVELOPING IMPLEMENTATION AND INTEGRATION PLAN

Before the implementation could take place, managers have to translate their expectations about the project to the form of KPIs (Key Performance Indicators) or other business metrics that can be used to evaluate it. These measurements differ from project to project, and just as during the decision-making phase, they should not only focus on monetary values but on all aspects of the project. Usually, KPIs are developed from the factors used to evaluate the investment: if a newly implemented predictive maintenance solution is answering cost reduction issues by decreasing failure numbers and delay times, the related KPIs can measure how many unforeseen errors occur during a given period and how long do machines have to suspend their operations because of them.

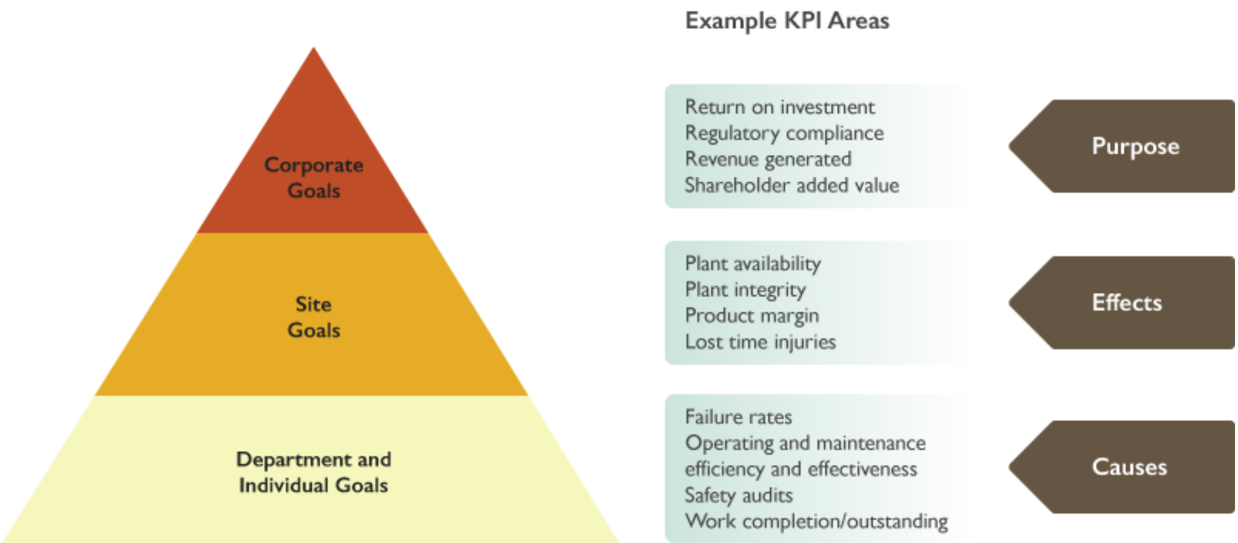

Figure 11 - Control Pyramid of Business Objectives (Sondalini, 2013)

Figure 11 shows how different KPIs can be applied on the different levels of the organization, developed by Mike Sondalini (2013). He also argues that each level can be divided into further groups, and each group can have several measures. For example, on the operational level these groups can be equipment reliability, process reliability, equipment maintainability; while on the site level plant downtime and plant reliability can be evaluated (Sondalini, 2013). He proposes several KPIs for each group in each level, such as *total maintenance cost*, *mean time between failure*, *emergency work %, uptime %*. However, these metrics differ based on the project's individual attributes and requirements (Sondalini, 2013). Appendix A presents sample KPIs that are relevant for maintenance in a mining company, structured by the goals and objectives of the different corporate levels.

Besides the integration of new technologies, managers have to remember that implementing new business processes and changing corporate behavior can result in resistance from the employees. They have to consider these threats already at this planning phase, and they have to forge solutions for them.

EXECUTING THE CHANGE

The third big phase of the implementation process is executing the change itself: integrating new technologies, incorporating new tasks, processes, altering the organization structure. This is the part where everything materializes that was just a plan before. Therefore, this is the stage, where most of the obstacles can emerge that decision makers did not consider previously. Consequently, the process of moving to a new state requires a close attention from the management.

Pilot Projects

In some cases, it can be too risky to implement a brand new technology across all mining sites at the same time: there is little information about feasibility, and time, cost and benefits are all based on estimations rather than facts. However, if the technology seems appealing, it would be irrational not to test its results in the real life. Therefore, as I learned during my research, most companies start execution with small-scale pilot projects, usually in a single mining field (and maybe even on a single machine). This way managers can limit the risks: they do not have to spend large amounts of money, they only invest in the equipment that is minimally required. As a consequence, the benefits of the project will also be lower as if it would have been applied across the whole company; the goal of the pilot project is not solely to create benefits for the organization but to help to evaluate the investment by matching these benefits with real life expenditures and complications. Pilot projects can help discovering employee behavior (especially resistance against the change), unveiling unexpected problems and they can be used in polishing the integration process for further implementations.

The execution of the project involves the procurement and setup of new technologies, sensors or machines, usually supervised by engineers. Communication methods can be upgraded to support the new equipment, if necessary. Site workers' assignments and responsibilities are expanded to include the new tasks, and they might have to take training to learn about the new technologies. The company's information systems have to be prepared to handle the new data, documents and reports. Internal or external analyst teams and engineers have to be able to work with these data to examine trends, history and make predictions. They might also need to be educated about their new tasks. Finally, the performance of the new equipment should be incorporated to the management reports so that they can evaluate them.

Addressing Resistance

Change is usually anticipated and welcomed in different ways across organizations. The management who designs and implements it has high expectations about it, but employees at the operational level might think of it as unnecessary actions. They might feel that they have to deal bothered that they have to deal with new tasks, or they might feel intimidated, fearing that new technologies might threaten their jobs. A resistance can develop from their side, which could slow the project or even stop it altogether. The leaders of the company have to address this opposition to integrate successfully the new technologies and processes to the organization's life.

Lewin – besides his model of change – introduced Force Field Analysis tool (Lewin, 1951). This framework classifies the forces that affect the change in two categories. He wrote, "An issue is held in balance by the interaction of two opposing sets of forces - those seeking to promote change (driving forces) and those attempting to maintain the status quo (restraining forces)" (Lewin, 1951). In the initial state the opposed forces equalize each other, there is an equilibrium between the two sides. Lewin describes that this equilibrium will change if the driving forces become stronger than the restraining forces (Lewin, 1951). To successfully implement a change in the organization, managers have to examine these forces and either try to strengthen the driving ones or reduce the impact of the ones that cause resistance.

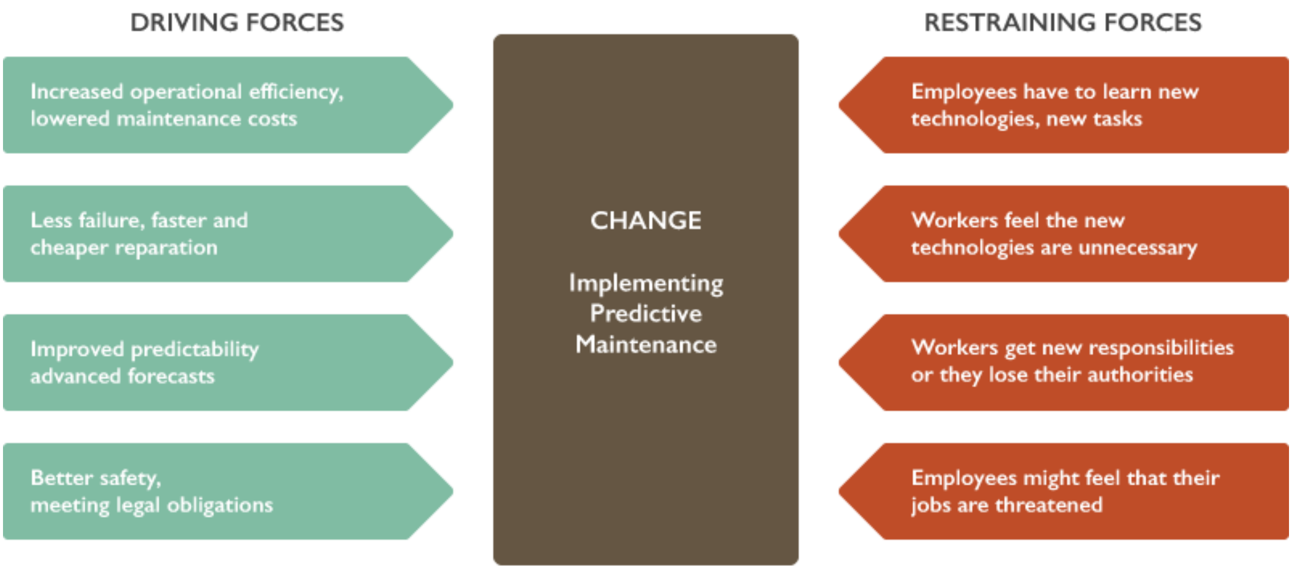

Figure 12 - Force Field Analysis (Lewin, 1951)

Figure 12 presents an example application of Lewin's Force Field Analysis in the case of implementing a predictive maintenance solution in a mining site. The driving forces have been identified already in the previous phases of the implementation process, and ideally, managers considered many of the restraining ones as well. However, it is advised to use this tool at the initial stage of executing the change so they can be prepared for the unforeseen complications.

The previous technique helps in understanding resistance but does not give a solution for eliminating it. Palmer introduced several tools to decrease the opposition, which can be generally applied to any change where sufficient support from stakeholders is needed to make it successful (Palmer, 2003). He states that in order to mobilize commitment key influence agents have to be identified and converted, sources of possible resistance have to be determined, and a coalition of committed supporters has to be obtained. He provides several tools that can help smooth changes, of which many can be applied in the case of implementing predictive maintenance technologies:

- Understanding and managing resistance: Palmer states that around 25% of an organization supports a change, 50% is neutral, and 25% opposes it. He suggests to locate the supporters and involve them in the implementation as they are already dedicated, and they can help transforming the neutral ones. He advises to start a dialogue with the people against the change to understand their reasons. However, there will always be someone who cannot be convinced. In the practical case of new predictive maintenance technologies, managers can involve passionate employees in the implementation process from all levels of the organization, who then can help in mobilizing commitment from their peers.
- Key constituents map: this technique looks for clusters of people who are affected by the change, to see who has to be won over to make the implementation successful. In the current case site workers are the biggest group, but data analysts, engineers, and logistics personnel are also represented. These groups are differently affected by the new technologies and processes, so the management should approach them distinctively.
- Stakeholder analysis for change: this tool goes one step further and tries to identify the individual stakeholders in the previously defined groups. This way managers can determine who is critical to the success of the project, and what are those people's current attitude. For example, if one of the key engineers opposes the implementation of new

technologies, his opinion is more important than many others', so he needs additional attention to converting his viewpoint.

- Technical-political-cultural analysis: this technique helps to understand the resistance, and it also uses the groups defined in the key constituents map. In each one of them, managers have to classify the reasons that can cause resistance: technical issues can be the lack of critical resources or even skills from machine operators or data analysts; political reasons can be the issues of power and authority or responsibilities; and cultural aspects include norm, old mindsets, and habits. Palmer argues that this technique can be used to acknowledge individuals' or groups' concerns and if possible, demonstrate that those are unsubstantiated.
- Developing an influence strategy: this exercise uses the key stakeholders identified in the previous techniques and record their primary issues and concerns. Palmer advises to list all stakeholders whose influence is important to the project, even if they are already supportive because they might still have issues. During this process practical and actionable steps can be determined to address these people's concerns and convert them to be supportive. For example, workers who are responsible for fixing machines might feel threatened that they could lose their jobs because of improved predictive maintenance. This fear can be eliminated by starting a dialogue with them.
- Resolving differences and conflicts: this approach is used to negotiate with opposed stakeholders. Managers should ask the resistant ones about their positions and then explain their own. They should try to find a common ground by confirming that the overall goals are similar or looking for areas that they already agree on. This way they can filter the areas of disagreement so both sides can realize how narrow their differences are. If, for example, an engineer insists on continue using preventive maintenance, he might still want the best for the company because he is aware of how expensive failures are. Therefore, he wants a scheduled evaluation of the parts instead of depending on sensor data. He agrees with the goals of the change, but he has a different perspective, or maybe he does not trust the unfamiliar technologies.
- Communicate effectively: Palmer names communication as one of the most important factors for a successful change. He describes that different interest groups should be addressed differently, but all from a very early stage of the change process. Managers should define the goals of communication for each group (e.g., informing IT department,

persuading on-site workers), and based on these objectives frequently address the participants (Palmer, 2003).

There are numerous other literature (Harvey & Broyles, 2010) (Hultman, 1998) that gives practical advice on how to implement change successfully in an organization; as long as managers pay attention to resistance, they can eliminate most oppositions by recognizing them and making actionable plans to convert them.

Evaluating the Implementation

Before making the change a permanent part of the company's processes, culture and practices, managers have to evaluate its outcomes and compare them with the previously defined metrics and requirements. There are different aspects that need to be assessed besides the performance of new technologies, such as validating new process integration, data validity, employee's attitude for the change and their knowledge about the new equipment. The information needed for these evaluations might come from different sources: engineers can provide performance measurements that can be used to compare efficiency with historical data, while assessment surveys, dialogues with stakeholders and interviews can help understanding qualitative attributes of the change.

Both pilot projects and company-wide implementations should be evaluated after executing the change, and continuously afterward. The time of different assessments can be different: managers should give enough time for the change to settle, but the evaluation process should not happen too late, so improvements can be carried out if needed.

Evaluating the change can be useful to justify its success towards higher management, or to raise awareness about errors and if the implementation did not result in the expected performance increase or other benefits (Anderson, 2003). Because this step is not in Lewin's Freeze phase, the evaluation can be used as a basis for modifying plans and processes (especially if they are in a pilot project that does not involve the whole company) and fine-tune them until reaching the required outcomes. It also provides input for the learning curve of the company, so they will not make the same mistakes again in future projects.

TRANSFORMING CHANGE INTO BUSINESS AS USUAL

After a successful pilot project, the company can decide to extend the technology to all of its mining sites. The transformation ended if the technical upgrades have been implemented, tested and evaluated, the new tasks, job descriptions and responsibilities are clearly defined, and a stable organizational structure is in place (Lewin, 1947). Refreezing the new state has long-lasting effects on the company, so leaders have to carefully contemplate if everything works according to their original conception and requirements.

The primary function of the freeze phase is to create stability in the organization and incorporate the changes to the company's everyday life. Some might argue that this step loses its validity in our global and digital age, as businesses should adapt quickly and freezing a state may reduce their flexibility (Graetz, et al., 2005). However others defended the model, indicating that it should not be used so rigidly, and there are several examples where refreezing did not result in competitive disadvantage even in fast-paced environments (McAleese, Creed, & Ambika, 2013). In the case of mining operations incorporating new technologies can be beneficial for the company, if they result in a generic increase in performance, reliable predictions about failures and if they reduce maintenance costs. To assure that the company can respond to new innovations or challenges, the organization should continuously evaluate its processes and analyze feedbacks coming from its stakeholders.

Another important part of this step is to make a definite closure of the change process. Employees should celebrate success, and get a positive reassurance that their efforts were valuable for the organization. If the ending of the transition has been declared, even people with oppositions have to reduce their resistance, as they accept that the current state is the new norm.

CONTINUOUS EVALUATION

The process does not end when the implementation has been executed, and the change has been frozen. New challenges might emerge, new technologies might appear. As big data increases, the predicting models can be more accurate. However, managers, engineers, analysts, field workers and all stakeholders should continuously evaluate new situations since different factors can appear (e.g., new legal requirements for safety, new mining sites, new sensors are installed on existing machines or new associations are discovered between data and specific events, etc.). To address the critiques of Lewin's model about the freeze step and fast-paced business environment (Graetz, et al., 2005), companies should constantly consider new opportunities and they should be able to react quickly to new threats and issues. Just as an enterprise should operate as a going-concern, it should also alter its processes whenever needed to keep up the pace of the global industry.

SUPPORTING THE MODEL

Implementing changes in a mining company is not a novelty. Knowles (1998) mentions that the industry already started applying management philosophies at the end of the 1990s. These changes were also executed to improve efficiency, streamline processes and transition the companies to a new era (Knowles, 1998).

Knowles also discusses the challenges of management changes within mining industry (as they appear in the Sensitize phase in my model), and though his findings were more business related, they show similarities to the model I constructed. He also starts the change process with external and internal challenges, which were slightly different at the time of his research. He mentioned increasing global competition as the major threat for companies, but high costs and static commodity prices also played a key role in his study. Overall, the market of minerals was more balanced, so the pressure on leadership was less about constant innovation. However, the emergence of new technologies increased productivity by 5-9% a year, which could not have been ignored.

Knowles analyzed concepts like business process reengineering or corporate transformation to build a framework that can be applied to mining companies.

Giving meaning of these market signals were followed by creating a vision. He provided examples of effective visions, like "Be the lowest cost producer in NSW" or "Increase production by 30% in two years (...)" (Knowles, 1998). He also considered distributing these phrases to all levels of the organization so employees can relate to them.

Another similarity to my model is the importance of measurement systems. There are two main differences between his approach and my model: He suggest to define KPIs and measures already, even though the assessment of existing technologies and processes has not happened yet. And while I demonstrated how KPIs can be built up from operational levels to overall corporate performance, he does not detail how it should be done, but he also explains that managers should break the vision into actionable tasks and translate high-level objectives into concrete measures (Knowles, 1998).

The next step in Knowles' framework is obtaining an understanding of the industry with all the possibilities, similarly to my model. Although he also mentions the assessment of current technologies and benchmarking, he does not consider the related processes, job roles, and responsibilities. He also ignores the decision-making step with evaluating various options, which is an important part of the change process, as that defines how to move further (Knowles, 1998). In my model, KPI construction happens after the decisions have been made, as the last step of the unfreeze part.

During the change phase, Knowles focuses on the actions that have to be taken to address the requirements, and he also touches the topic of resistance but he does not provide techniques for resolving the issues. However, he also describes that change is not just implementing new equipment, but it requires new processes, responsibilities and education of the employees. Finally, he states that rewarding system should also be aligned to support the corporate vision. One of the big differences between Knowles' work and my model is that I followed practical cases and recommended a step-by-step implementation - preferably through pilot projects, to reduce risk, while in Knowles' framework management commits itself to the change, and evaluation only happens at the end of the process (Knowles, 1998).

Even though there are slight differences between the two frameworks, his study and the interviews I conducted support my model and makes it generally applicable for change management processes in mining companies, especially if they involve new technologies and processes.

OUTLOOK AND CONCLUSION

The mining industry has had several challenges in the last years, that tried even the largest players. As it was pointed out, most of these problems come from the same source: commodity prices have dropped to record lows while the big and slow enterprises could not align their expenditures to these new trends. Managers had to recognize the need for change, and this time, one of the most convenient ways to decrease their costs was to improve maintenance, that account for the largest portion of their expenses. As the examples showed, many of them already started experiencing and implementing new technologies that saves them money, but there are still a lot of opportunities in this area.

FURTHER UTILIZATION OF BIG DATA AND IOT

However, there are many other fields where mining companies can utilize big data, data mining and Internet of Things, in various phases of the mining operations process.

Exploration

Mining area exploration can be enhanced by drones and data analytics. As it was mentioned, new mines are usually located in distant, remote locations, so it is a complicated and expensive process to send out geologist professionals so they can take samples – especially when only a small portion of the attempts result in positive outcome. With the rise of drones and small, high-resolution cameras, explorers can have an overview of the landscape from above, and they can process these recordings to generate a 3D blueprint of the area. This way they can discover near surface mineralized structures under the soil, based on anomaly detection. After the initial findings they still have to take ground samples, but the pre-evaluation process dramatically increases the chances of locating rich mining fields. As Shawn Ryan (Prospector of Dawson City, Klondike mining area) described: “We can now pursue a high-quality target with a handful of permits”, referring to all the complicated (and expensive) bureaucratic processes that preceded field exploration. With these advancement companies can save 80% while locating new mines, compared to traditional methods. Moreover, data derived from these recordings can be used in latter reclamation programs, where they have to re-establish the natural environment of the area (Fiscor, 2015).

Measuring Stockpile Sizes

Managers need to have an accurate knowledge of their inventory of their materials to plan transportation, exploitation, workload and inventory areas. Traditionally employees had to measure these piles with techniques similar to cartography methods. However, this process is very time-consuming, and the results are not permanent: as new materials are excavated the stockpiles' sizes increase while after transporting them they shrink. Kespry, a California-based company, invented a drone system to measure stockpile volumetric. John P. Davenport, a project manager at Madison Materials, describes that data collection took two weeks of manual labor, but with drones and data mining technology the same piles can be assessed in two days. He even mentions safety concerns: traditionally someone had to climb on top of the piles, and it was not unusual that rocks rolled out from under their feet, and they slid and fell. Drones can fly over any size of hills, and their collected data can be processed by a handheld device. Moreover, the data analysis technologies can provide more accurate results that were possible beforehand (Kespry Inc., 2015).

Vehicle Collision Avoidance

Underground mines have more safety concerns as open pit mines, and most of the accidents happen in the tunnels. By the end of November 2015, 13 workers died in Australian mines, even though this country is one of most regulated (Safe Work Australia, 2015). IoT with RFID can significantly increase safety by enabling communication between machines, vehicles, and personnel. This wireless communication can be enhanced by infrared, radar and video systems, and they can notify the operators about obstacles or automatically prevent the collision (Lee & Prowse, 2014).

CONCLUSION

In the previous chapters, I tried to find answers about *how can mining companies can utilize machine-generated big data in their operations*. To respond to this question, big data, data mining had to be introduced with the most relevant techniques to analyze data related to mining operations. The concept of machine-generated data was also necessary for the further parts, as log files and reports from mining equipment are used in the data analyses. Internet of Things, an emerging area, was also presented, with examples of its industrial applications. The paper briefly described the current situation of mining industry, focusing on its challenges, and also mentioning some of its other unique attributes. I explained that the location and the mineral do not have a significant effect on the operational processes, and underground and open pit mines work very similarly, so I did not restrict the scope of my thesis in any particular area. However, after examining the cost structure of mining enterprises, I narrowed my research to predictive maintenance. I found that companies could benefit from improving it, as it is the largest contribution to their expenditures, and one of my sub-questions was also related to operational processes optimization.

My research included numerous steps: I interviewed a company that has several mining sites across Australia (both underground and surface mines), and analyzed their practices. Based on my findings and the theories from the first parts of the thesis, I constructed an optimal structure of mining companies, that utilizes big data, machine-to-machine communication and data mining techniques to improve maintenance processes by better predictive analytics and faster (immediate) access to all the relevant information about the equipment.

This setup requires new processes, modern technologies and a shift of mindset: most mining companies followed old traditions, and though exploitation was already done by machines, maintenance techniques are still old-fashioned and not efficient in most cases. Therefore, I developed a model about transitioning to predictive maintenance techniques. I used Lewin's Change Management Model, and I have built my framework around it while I was constantly considering mining industry's unique attributes.

I presented different cases from various locations to support my results, and I found proof that predictive maintenance brings economical benefits for a mining enterprise, and that an integrated and connected company can operate more efficiently.

Finally, I demonstrated that there are many other areas where mining-related processes can be improved by utilizing big data, IoT and data mining.

Mining companies followed traditional paths before with their long-established operational processes, and they were reluctant about innovations, as mining is an ancient industry. However, today's tight competition and unfavorable market conditions force them to react quickly to changes and optimize their operations. The transformation will require determined leaders and well-qualified professionals, as in the future mining companies will not be successful only because they exploit more minerals, but because they do it in a smarter and more efficient way.

APPENDIX A – MAINTENANCE RELATED KPIS IN MINING

Level	KPI	Sample target
Corporate level (general)	Return on Investment	> 300%
	Time until break-even point	6 months
	Decrease of corporate costs	< -10%
Site level (general)	Uptime	> 90%
	Inventory size	< 16M $
	Total maintenance cost	2% - 2.5%
Site level (reliability of equipment)	Professionals per machine	1 : 5-6
	Mean time between failures	increasing 10% / year
	Reactive maintenance (failures)	< 20%
	Replacement value	< 60M $
	Buy-back value	> 18M $
Site level (quality and speed)	Planned work	> 80%
	Mechanics per engineer	20-25 : 1
	Predictive / scheduled (value)	1 : 3
	Re-occurring failures	< 5%
Site level (maintenance costs)	Overtime	10-12%
	Maintenance labor cost / total m. cost	20-25%
	Not utilized inventory at EOY	< 5M $
Machine level (e.g. escavator)	Hours of usage	5400
	Lifetime	increasing 4% / year
	Maintenance frequency	12
	Number of critical failures	< 4
	Total Maintenance Cost	< 10M $
	Halt time	< 5%

The table shows the different levels that are affected by improved maintenance technologies. It is based on Sondalini's work (2013), but customized to mining companies, emphasizing predictive maintenance related KPIs.

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