

How to apply the ERP model for Smart Mining?

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Abstract. For a long time, and especially today, the energy crisis has been a limiting factor for the growth and development of the world economy. On the other hand, improving the reliability and readiness of energy production systems is becoming a first class priority for research and development institutions around the world. Therefore, the process of production, transport, distribution and usage of energy is increasingly becoming a very important part of smart systems, whose basic framework is Industry 4.0. Thus, starting from the analogies between industrial manufacturing and mining (i.e. "ore production"), the concept of smart mining is developed. This model has three dimensions: (i) application of advanced digital technologies (Cloud Computing and Internet of Things) with automated Cyber-Physical Systems (CPS), Adaptive Manufacturing Processes (depending on working conditions) and Control of Manufacturing Processes (with optimal resource usage); (ii) Smart Maintenance of CPS (for machinery and equipment); and (iii) Smart Supply Chains (procurement of materials and spare parts / delivery of final products). Deeper analyses have shown that most of the Industry 4.0 elements could be applied with some modifications in mining (there are 45 in total, and analyses have shown that 32 of them can be successfully applied in smart mining) – which was the starting point for the ERP model presented in this paper. The developed ERP model has three main parts: a virtual part based on the Cloud Computing model (SaaS model) and usage of Internet of Things to connect different business processes (procurement, sales, management, finance, warehousing, downtime monitoring etc.), the manufacturing part (coal production in open-pit mine) and the technology process part (monitoring and maintenance of auxiliary machinery). This paper presents the developed and partially implemented ERP model for Industry 4.0 in smart mining at one surface coal mine in the Republic of Serbia.

Keywords: Industry 4.0, Mining, ERP.

1 Introduction

Industry 4.0 is a new model of business automation, which is based on the application of new technologies (primarily in the field of ICT) that are data-driven and net-

worked through cyberspace, with decentralized management [1]. Based on these facts, it is extremely important for the application of the Industry 4.0 model to investigate the nature, type and size of databases, as well as to collect and analyze the Big Data (Big Data Analysis - BDA), which are used for product-level planning and management (PDM), plant (MES), factory (ERP) and supply chain (SCM) [2,3]. These questions are especially important for the topic of this paper, which refers to the surface coal mining and its production activities. Starting from the analogies with the manufacturing, in the paper [4] the Industry 4.0 model for surface mining was defined, where the key element of the concept is the machine systems maintenance. Because of this, the ERP model of the surface mining information system (maintenance and spare parts planning and management) has been developed and implemented, and at the moment its being transpoded to the Industry 4.0 model, which will be described in detail in this paper. Starting from the perspective of six technologies on which the data management model in Industry 4.0 is based (containing the elements of the ERP model), an analysis was performed according to the nature, type and volume of data as presented in Table 1 (adapted according to [1]), with special reference to mining.

Table 1. Correlation between the Industry 4.0 elements and the data used for them (adopted according to [1]).

	Nature of data	Data type	Data volume
Automation and manufacturing technology (including mining)	Prediction technology (Maintenance, Manufacturing, Spare parts)	Numerical, string, bits, symbolic	Medium. (Very large – big volume) ¹⁾
Data storage technology	Status and history of manufacturing equipment	Numerical, symbolic, string, time series, text	Very large. (Cloud computing) ¹⁾
Digitization technology	Artefact characterization, status	Numerical, symbolic, text	Large. (Digital twin) ¹⁾
Cloud computing technology	As-is data, transformed data, integrated data, models, algorithms	Potentially data of types determined by the cloud design	Very large. (SaaS) ¹⁾
Agent technology	Application specific (Maintenance planning and control)	Application specific	Low. (AI/ML) ¹⁾
Prediction technology	Application specific (Predictive maintenance)	Numerical, categorical, time series	Medium. (Intelligent Maintenance) ¹⁾

¹⁾Add characteristics of Industry 4.0 approach in mining.

If the concept from Table 1 is carefully reconsidered, it can be concluded that the key elements of Industry 4.0 technologies (simulation, big data, cloud computing, integration, AI and ML) are related to the development and implementation of the ERP mod-

els for mining, thus creating a smart mining framework. This analysis serves to design a model and structure of a decentralized database for surface mining and its ERP model.

At the next level of database development for the presented model, information content is projected and the level and way of connecting the entities (their relation) is defined. In smart mining, these elements are implemented through the 2M (Man-Machine) model, supported by the AI / ML algorithms. In the smart mining model, information flows are realized through the cloud and physical layers. The cloud layer includes models and algorithms related to: management of manufacturing and maintenance operations, process and service models and condition monitoring, which, for example, at the surface mine, refer to: production volume, machine systems in operation / failure, condition monitoring of machine system elements, etc. The ERP covers the physical layer which includes equipment and sensors. In this way, shared virtual-physical systems, through cloud computing, share resources, which are managed through ERP models [4].

Planning of manufacturing and technological resources in the production management model (MRP / ERP), including mining, has a long history, and its development pursued two directions: (i) the business aspect – from stock planning at the factory (or surface mine) level to the whole chain (request for offer - delivery of the finished product) at the company level (surface mine as an enterprise), and (ii) the technological aspect (from software package to client server architecture). An overview of this model development is given in Table 2 [4-7,17], with added application characteristics for surface mining.

Table 2. History of ERP model development (adopted according [4-7,17]).

Year/model/Level	Characteristics of MRP/ERP model (in manufacturing)	Aspects of function (in manufacturing)	Application in mining
1960s/IC/ I level	Inventory management and control	Warehouse control	Spare parts control for maintenance
1970s/MRP I/ II level	Material Requirements Planning	Bill of product	Bill of equipment maintenance component
1980s/MRP II/ III level	Manufacturing Resources Planning	Bill of manufacturing process	Bill of technological component of equipment maintenance
1990s/ERP/ IV level	Enterprise Resource Planning	Integrate business activities across organization units	Enterprise Resource Planning for mining

2000s/ERP II/ V level	Enterprise Resource Planning by Internet	Services Oriented Architecture (SOA)	Enterprise Resource Planning by Internet for mining
2010s/Cloud based ERP/ VI level	Cloud based ERP	ERP as software a service (SaaS) model	Cloud based ERP for mining
2020s/Industry 4.0 ERP/ VII level	ERP of Industry 4.0 model	Industry 4.0 concept introducing	ERP of Industry 4.0 model for mining

ERP II, as the fifth level of development, uses Internet web browsers, with service-oriented architecture (SOA), supported by mobile devices. Cloud ERP, level VI, includes business applications that are delivered as a service model (SaaS), suitable for small and medium enterprises. Finally, the last level (seventh) refers to the ERP model for the Industry 4.0 model. Preliminary analysis has shown that the development of the first four levels of the ERP model is based on the development of information systems, and then the IC technology is involved in the development of the ERP model. The latest model is an Internet-oriented networking concept, based on cloud computing and AI tools in the Industry 4.0 model. The research presented in this paper refers to the last two levels.

The aim of this research is to develop a mining model [4] based on analogies with the ERP model in the context of the Industry 4.0 model.

This paper has several parts: (i) the introduction which gives a review of the development of the ERP model from the production point of view with defined analogies for the application of this model in smart mining, especially from the application aspect – in three key areas, as stated in the abstract; (ii) an analysis of different approaches is performed in the second part of the paper, (iii) the ERP model for smart mining is presented in the third part of the paper, where the basis of the developed model is partially implemented in practice, and (iv) the directions of future research are given, such as, for example, BDA with AI / ML support.

2 Literature overview

If the production (i.e. surface mining) is analyzed, the smart factory (i.e. smart surface mine) is based on four dimensions of Industry 4.0 basic technologies [4,8]: (i) cloud manufacturing, (ii) internet of things for production (mining), (iii) big data (for production / mining) and (iv) analytics (for production / mining).

The developed model creates a new business model for the organization in the circular economy - eco-sustainable smart manufacturing [9,10,19,24]. In this concept, the ERP model is a key element of the vertical integration model, but it is also a part of

smart chains and basic technologies for Industry 4.0 (simulation, big data, cloud computing, integration, AI and ML) of the organization that applies this model, which could also be a surface mine.

There are three concepts of integration in the Industry 4.0 model [6,11,12,18]: (i) vertical integration (from process - sensor, to organization (corporate planning) - ERP). The center of integration at this level is the cyber-physical system (CPS, for example - excavator), whose production is realized; (ii) horizontal - from the request for offer to the delivery note of the finished product (marketing, design, manufacturing, delivery); the integration center is an intelligent product, with added value; this approach is a classic example for manufacturing organizations in the field of production engineering; and (iii) supply chains and sustainable manufacturing with a Customer Relationship Management (CRM) center. This approach is also a good example for manufacturing organizations, but not for mines.

In the case relevant for this paper, the open pit mine company is implementing a new business model of Industry 4.0 concept, centered on a large database and its reporting, with the ERP model playing a key role, especially for planning and management of machine systems maintenance.

3 ERP model for SM (Smart Mining)

3.1 Model of digital ERP mining

Planning and management of maintenance resources at the surface mine is performed according to the ERP model [13,14] in this concept, which was tested in the presented research and represents an upgrade of the existing information and communication system (ICS), previously applied at the surface mine, Figure 1 [4,8,13,20,21,23].

In the real-life ore production at the surface mine, data on operation and maintenance are generated through work orders, downtime maps, maintenance plans, inspection of spare parts stocks, etc. Based on the digital twin model, which connects to the real world through agent technology, for each agent the following is defined: identification, authorization, configuration, capacity, status and metadata. The cloud data warehouse (SaaS model) is an information center that stores and exchanges all production data from the mine. It creates, stores, retrieves, and analyzes the model uncertainty, using machine learning models, statistical, or stochastic concepts, based on the mathematical functions required to create data-driven models, as provided by the ERP model concept [19,20]. Each agent takes over such models through intermediaries and decides on predictive operations and controls of machine systems and their components, based on the results that those models generate.

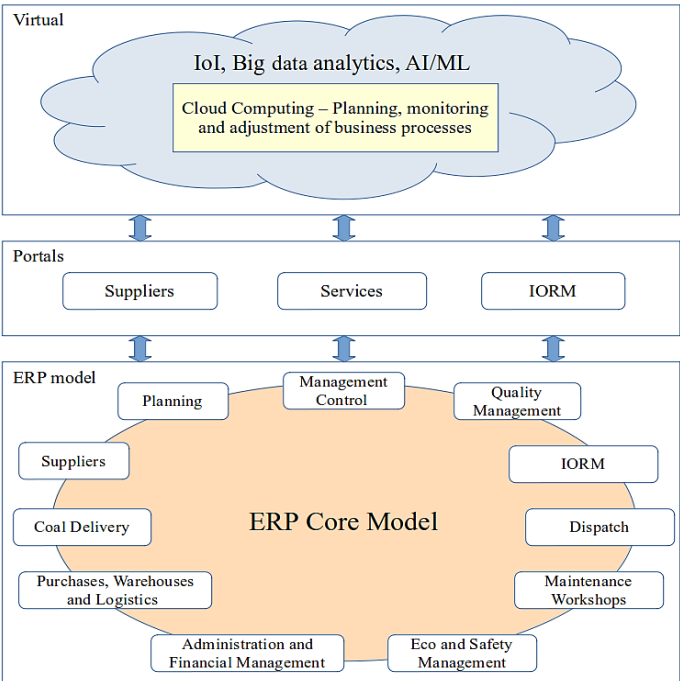


Fig. 1. ERP Industry 4.0 model for mining (adopted according [4,8,13,20,21]); *IORM - intra-organizational relationships management

The proposed model has three parts [4,13,14,22]: (i) a virtual part based on the cloud computing (SaaS) model, which contains a virtual model of ERP system that uses IoT to connect business processes (procurement, sales, management, finance, warehouse, downtime), production (in the presented case: ore production) and technological processes (in the presented case: monitoring and maintenance of auxiliary machinery). The ERP procedures in use generate a large database. The data obtained from the database is analyzed and synthesized, and, along with the machine learning and AI tools, used to optimize decisions on maintenance, downtime planning and spare parts inventory management, interface and the core model of ERP. The function of interface (suppliers, services and maintenance management) is to provide online maintenance managers with the capability to monitor the entire system. The core model of ERP, in addition to the previously listed functions, includes other business-technical and management functions of surface mines.

Instead of sales and CRM, the ERP core model for coal mining relies on coal delivery and intra-organizational relationships management (IORM). These elements are suitable when a coal mine is a part of a larger enterprise, so the coal consumers, such as thermal power plants, are within the same enterprise (e.g., different sectors or branches). In addition, the given ERP core model contains two important elements specific to mining, which is heavily dependent on machinery: fleet dispatch (and management) and maintenance workshops.

In this way, the presented model for surface mines includes the following main elements of the Industry 4.0 concept: Cyber Physical System (CPS), Industrial Internet of Things (IIoT), Cloud Computing (CC), Big Data and Analytics (BDA) and horizontal and vertical integration and simulation [4].

3.2 Implementation of ERP model

Due to the complexity and specifics of basic and auxiliary mining operations, as well as of the encompassing business processes, the developed model implementation was carried out gradually over several years and can be still considered as an ongoing process. The model implementation efforts so far have primarily addressed the VI level (see Table 2) of the ERP model development, but have also laid the foundation for the VII level in terms of building capacities for big data collection.

To illustrate the model through phases of digital planning and management, the process of fuel management and the process of technical fluids and lubricants management will be primarily addressed further on in the paper. These are some of the priority processes for which significant direct cost-saving potential has been identified in the initial business analysis. This analysis has been largely based on interviews with middle / lower-level management and domain experts, as well as on the analysis of inputs / outputs of the as-is business processes. Due to their interconnectivity with other processes such as annual / daily planning of operations and scheduling of workers / machines, maintenance, KPIs-based analytics, etc., the other implemented processes will be touched upon.

The procurement of fuel, technical fluids and lubricants is planned based on consumption in the previous period, as well as on the volume and types of work planned for the next one. Therefore, digital data and reports available in the MES (Mining Execution System) provide critical input for the procurement planning process. In this particular case, the MES is a Web-based information system that has been custom-developed for the sector of auxiliary mining operations. It has covered end-to-end business processes of operations management in the first phase, and maintenance management in the second phase of implementation [15]. In this way, the digital platform has connected two departments - Operations and Maintenance, with many deeply interconnected or output-dependent business processes. As a result, the business processes have been simplified, with reduced paper flows and information being delivered more quickly. One of the ultimate goals is a paperless work environment.

The third phase has introduced a fleet monitoring system (with a Web-based geo-tool), whose primary purpose is to support fleet dispatch and management. In addition, the system is beneficial to broader operations management, as well as to maintenance management. It relies on GPS / GPRS and GIS technologies and is integrated with the MES. The system has encompassed all machinery for auxiliary operations

(e.g., bulldozers, backhoe loaders, graders) and some of the machinery for basic operations (e.g., bucket-wheel excavators, dragline excavators). Inter alia, it allows for monitoring the positions of machines in real-time on the open pit area map; monitoring the machines' / vehicles' parameters (such as the GPS position, engine operating time, device operating time, fuel volume in the tank in liters and percentage, time of the last message, time of the last panic alarm); reporting on the history of the machine / vehicle movement (route analysis and visualization), fuel consumption, working hours, mileage, geofence breaches, etc.

Figure 2 shows the main page of the geo-tool. Both in this figure and all the subsequent figures, the labels are in English, while the data are in Serbian as entered into the system.

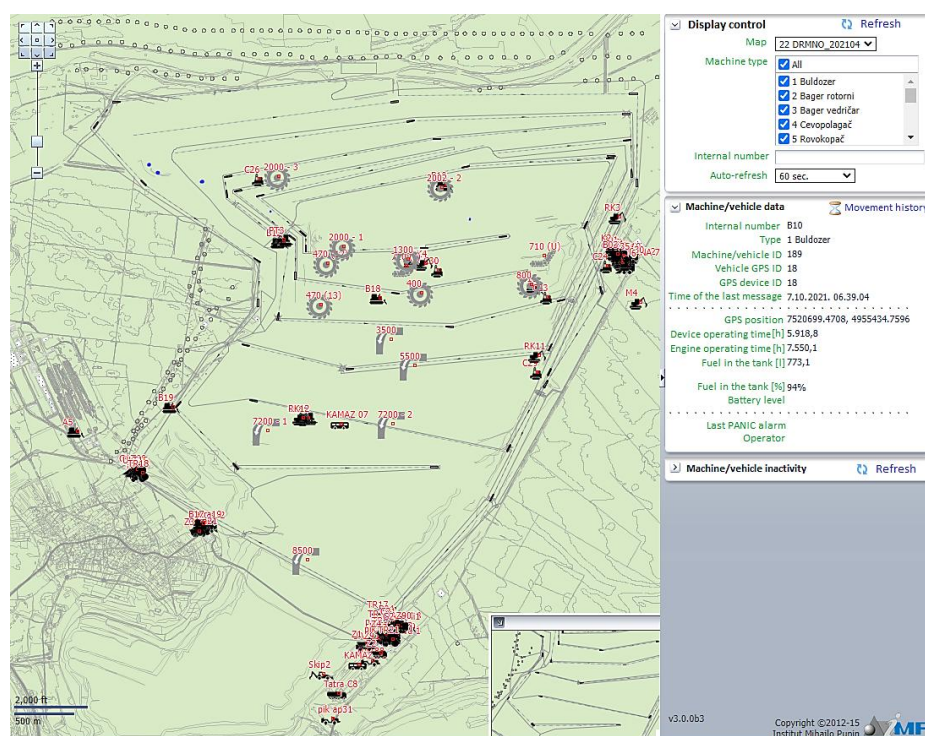


Fig. 2. The web-based geo-tool for supporting fleet dispatch and management

On the one hand, digital reports have been obtained on the basis of work / maintenance orders and fuel, lubricants and technical fluid orders from MES. On the other hand, digital reports have also been obtained on the basis of data collected from machine / vehicle sensors and stored in the fleet monitoring system. Comparative reviews of such reports (e.g. on working hours, fuel consumption, etc.) from alternative data sources have significantly improved the quality of input for operations and maintenance management, and accordingly for the procurement process. Any major

deviation in the data from these two sources is an alarm for close checking. Such close checking has revealed some causes of data inaccuracy, such as human error in the delayed entry of data from paperwork / fuel orders into digital MES or negligence of some employees in filling out paper forms. Namely, paper forms have been used initially when refueling of machines / vehicles is carried out at the place of operation or in workshops.

Accordingly, the next step towards the implementation model has been the introduction of industrial PDA (Personal Digital Assistant) devices with an easy-to-use application for keeping digital records on refueling machines and vehicles [15, 16]. PDAs do not have a keyboard; data entry is enabled via screen as with tablets and mobile phones, which are familiar to employees. PDAs are used by maintenance workers in workshops, operators in a warehouse of technical fluids and lubricants (the Maintenance department), as well as by fuel tank operators (the Operations department). Namely, lubricants and technical fluids are used in emergency maintenance (at the place of operation), as well as in preventive maintenance (in workshops). Thanks to the fleet monitoring system, a dispatcher can propose an optimal route for reaching machines and vehicles at the place of operation.

The mobile application is integrated with the central MES so that data obtained in this way are combined with other relevant data using the number of the operator's work / maintenance order. Several reports / KPIs have been provided based on these data, including an overview of shift activities, average consumption, the ratio of average to normative consumption in percentage, consumption of fuel / lubricants / technical liquids according to a time period, a machine / vehicle, working hours or mileage, etc. Consequently, timely and more accurate monitoring has been enabled, leading to better control and planning of fuel / lubricants / technical liquids consumption on a daily, monthly and annual basis, better procurement planning and finally cost reduction.

Fig. 3 shows an example of a dynamic digital report with KPIs on the daily operation of the machine between two given dates. More specifically, the report shows the ratio of average to normative fuel consumption of the machine (in percentage), as well as the ratio of the time when the machine is not moving and the operation time (OT) of the machine (in percentage). The report also shows individual data that are necessary for the calculation of the given KPIs. The report is dynamic based on suitable report parameters that allow for controlling report data and varying report presentation.

Many other reports have been enabled in this way, targeting specific operations / maintenance KPIs and parameters. Likewise, MES provides a configurable overview of operations / maintenance orders including some performance KPIs, such as time assigned and time spent in conducting operations / maintenance activities. Figure 4 shows an overview of the maintenance orders for the selected period of time.

Diagnostics precedes the issuance of a maintenance order and provides inputs for planning subsequent maintenance activities. Figure 5 shows an overview of machinery diagnostics for the selected period.

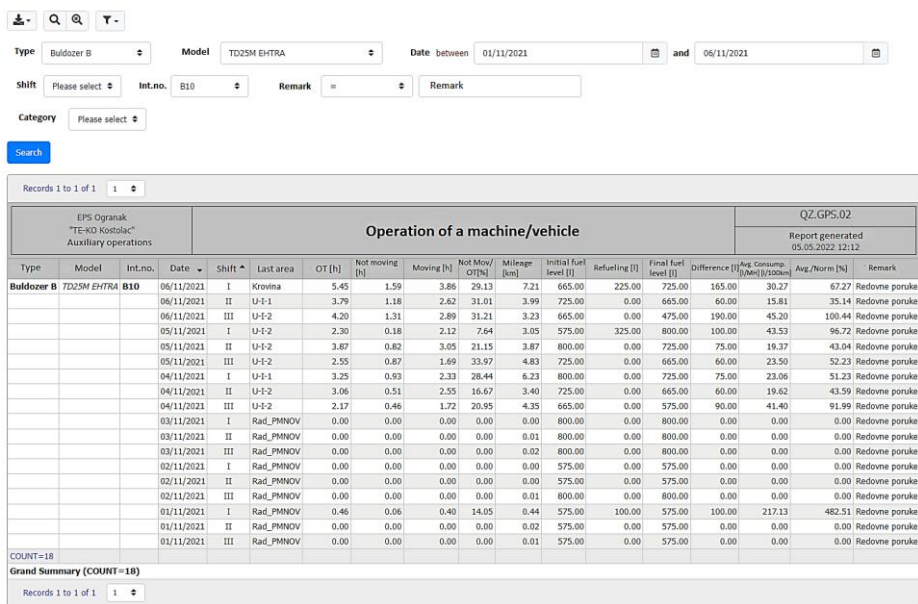


Fig. 3. A digital report with KPIs on the daily operation of the machine

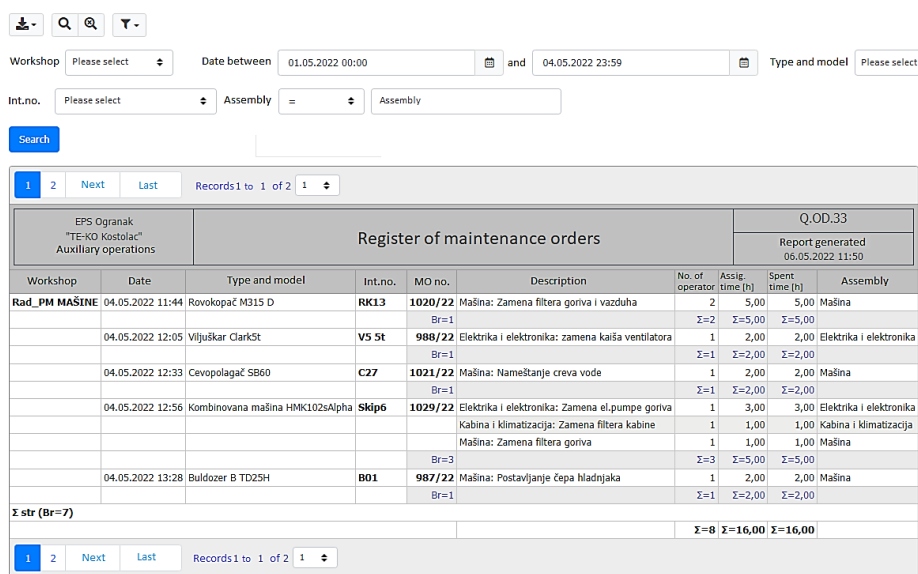


Fig. 4. Register of maintenance orders

Software support for inventory management, administration and financial management is provided in a branch-level traditional ERP. Therefore, MES and the traditional ERP need to share data on inventory such as fuel and spare parts to support inventory planning, inventory issuing and other inventory management sub-processes. Furthermore, these information systems need to share data for procurement management, as well as for cost management. This is why both information systems use the same labeling system for tracking fixed assets and consumable inventory. Integration of MES with the traditional ERP has enabled sharing of data on relevant inventory items (e.g., item type, subtype, technical details), warehouse input/output logistics, warehouse stock status and inventory items cost. Figure 7 shows a report on costs of the selected machine.

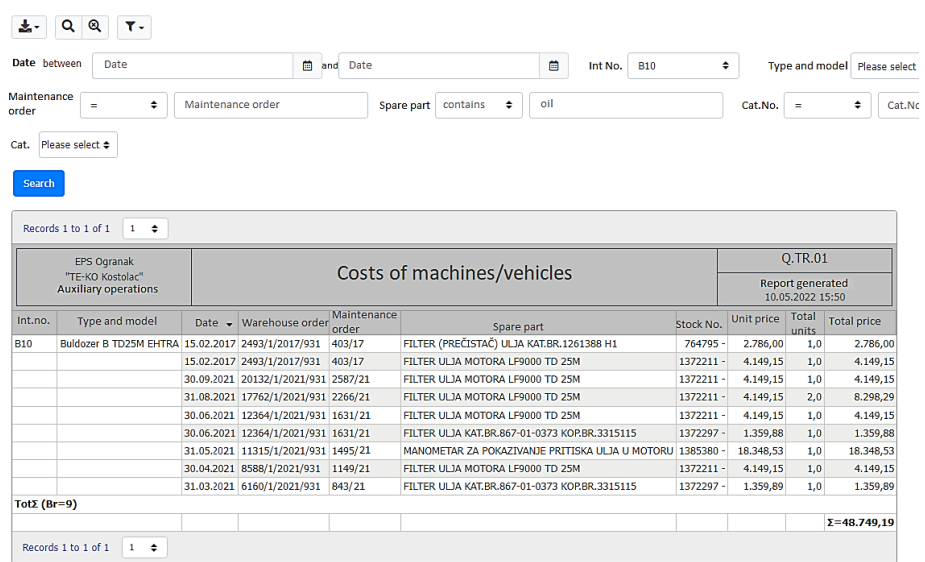


Fig. 7. Digital report on costs of a machine

There is much space for improvements towards smart mining, but it mostly requires substantial investment (renewal of machines/vehicles with additional and more reliable sensors, expansion and upgrades of the ICT platform, etc.). Predictive maintenance, which was envisioned years ago, would be a major step forward. An example in the given context would be the analysis and control of machine wear, lubricant contamination and related condition-based maintenance and failure prediction. Predictive maintenance reduces labor and material costs, and keeps machines in optimum settings. Withal, keeping machines in optimum operating condition has positive implications for human safety and the environment.

4 Conclusions and future research plans

Although partially implemented, the model has made it possible to significantly speed up decision-making and facilitate management activities at operational, sectoral and branch levels. The covered business processes have been improved in terms of KPIs and a substantial cost reduction has been achieved. In addition, the redesign of some business processes has removed tedious activities such as data entry from paper forms and led to better working conditions. The basis for the next steps towards smart mining has been laid.

Future research and development should consider technological upgrades to support smart analytics such as different trends and prognoses (e.g., work volume, resources consumption, service life and failures of machinery), as well as alerts (e.g., in predictive maintenance). To this end, further support for IORM and ‘ERP extended board’ or a single board for monitoring smart analytics (and analytics that are already available) based on Big Data coming from various connected systems would be highly beneficial. Predictive maintenance is in itself one of the ultimate goals. In addition to smart/predictive analytics, it requires an extension of sensor coverage and improvement of sensor reliability.

To this end, there are intentions to include the remaining machinery in IoT and to expand and improve the data set collected via the IoT (e.g., status data, engine parameters). However, the renewal of some of the machinery may have to precede since only newer machinery is equipped with modern sensors that allow for collecting a richer and more reliable data set. This is a substantial investment even for much richer economies and therefore can only be realized in phases.

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