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Advanced text-mining for trend analysis of Russia's Extractive Industries

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ABSTRACT

The world economy relies on access to industrial metals, oil and gas for maintaining its critical industrial infrastructure. Although demand is likely to remain high, the most accessible deposits have been depleted. Future capacity growth will be facilitated through further technological developments. Russia as a leading producer is paying great attention to strengthening its competitive edge in global markets. This paper reports on a large-scale technology foresight study of the Russian extractive sector (including oil and gas), which combined expert-based foresight activities with statistical analyses and text-mining techniques based on artificial intelligence and machine learning technologies. The presented methodology helped to link the technologies to dominant discussions (e.g. climate change vs rural development) and to flag key trends. Furthermore, quantitative estimates can be identified quickly. The study's methodology should function as an example for similar studies to support policy planning and investment decisions based on text-mining techniques.

1. Introduction

The extractive industries have greatly improved their productivity over the past few decades (e.g. Tilton & Lagos, 2007; Bartos, 2007; Gstraunthaler & Proskuryakova, 2012). The most accessible deposits, though, have been depleted (Arndt et al., 2017), which imposes technical and economic limits on long-term supply (Gokhberg, 2016; Lindholt, 2015; Rimos, Hoadley, & Brennan, 2015; Rosenau-Tornow, Buchholz, Riemann, & Wagner, 2009). Especially technologically advanced products, such as photovoltaic cells or batteries, rely on the supply of critical metals (e.g. platinum group metals, silver and cobalt, rare earth metals and other critical metals) (Andrews et al., 2015; Grandell et al., 2016). In the fuel and energy sectors, new opportunities are seen in hard-to-recover (tight) oil and gas deposits (Chengzao, Yongfeng, & Xia, 2014), shale oil and gas (Manescu & Nuno, 2015), new offshore deep-water deposits (Slatt, 2013), the Arctic (Ermida, 2014), as well as unconventional sources of hydrocarbons, such as methane hydrates or clathrates (Chong, Yang, Babu, Linga, & Li, 2016). The Arctic holds undiscovered reserves of conventional hydrocarbons of about 90 billion barrels (13 billion tons) of oil, 44 billion barrels (6.5 billion tons) of gas condensate and 47 trillion cubic metres of natural gas – according to the US Geological Survey for 2014. This share equals 13% of all known deposits in the world of oil, 30% of natural gas and 20% of the world's gas condensate reserves. Another area which holds great unexploited deposits is the ocean grounds (Hein, Mizell, Koschinsky, & Conrad, 2013; Shahmansouri, Min, Jin, & Bellona, 2015). Deep-sea drilling happens in water depths of 1,500 m and deeper, under enormous pressure and challenging temperatures. Although economically viable mining projects of metallic mineral resources from the seabed are few, the technological capacity is increasing. The main technical problem is the development

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of a supply chain for providing transportation of solid ore, its refinement and water treatment. Another interesting frontier is the extraction of ore on asteroids. The required technologies are being developed, and commercial projects will be implemented in the next decades (Andrews et al., 2015; Elvis, 2014). In the metals sector, most attention is paid to declining ore grades and the search for new deposits of uranium (Gabriel, Baschwitz, Mathonniere, Eleouet, & Fizaine, 2013).

Mining ranks, together with oil and gas exploration, among the most prominent pillars of Russia's economy. Russia produced 546 million tons of oil liquids (around 12% of world crude oil, natural gas liquids and other hydrocarbons) in 2016, ranking third among the top producers in the world after the United States and Saudi Arabia. Russia was the second largest natural gas producer (644 billion cubic metres or 18% of the global production in 2016) (IEA, 2017b), the third largest coal exporter (171 million tons) and the second largest lignite producer in the world (74 million tons) in 2016 (IEA, 2017a). Russia is also among the world leaders in minerals production: total minerals production in 2014 reached 1,5 billion metric tons (or 8,5% of the respective world total, with a total value of $566 billion, excluding diamonds).

Due to the importance of the extractive industries for Russia's economy, the national government leverages its mineral resource wealth through earmarked policies (Bouzarovski & Bassin, 2011; Wilson, 2015). To identify technological developments at an early stage, Russia is increasingly building competencies around long-term foresight activities to strengthen its economic competitiveness (see for example the report "Russia 2030: Science and Technology Foresight" (Gokhberg, 2016)). Foresight had globally gained popularity during the previous decade (Popper, 2012) and has been widely used in connection with public policy making (Georghiou, 2008; Keenan & Popper, 2008; Calof & Smith, 2010; Miles, Saritas, & Sokolov, 2016) and corporate planning activities (Daheim & Uerz, 2008; Costanzo & MacKay, 2008; Rohrbeck & Gemünden, 2011; Daim & Pilkington, 2018). Sectoral foresight activities, such as the one presented in this paper, build on a sector-specific knowledge base and on sectoral levels of supply and demand for technologies (e.g. Malerba, 2002). These sectoral specificities result in different technological opportunities and in different sources of knowledge provision (see Andersen, Andersen, Jensen, and Rasmussen (2014)), for a foresight exercise on the Scandinavian facilities management sector or Gokhberg, Kuzminov, Chulok, and Thurner (2017)) for a foresight exercise on the Russian agriculture and food sector). For work on sectoral innovation systems in Russia, see Gokhberg et al. (2017), Thurner and Zaichenko (2014a, 2014b), or Thurner and Proskuryakova (2014).

In recent times, the studies that cover the Russian oil and gas sector have been mainly dominated by institutional and macroeconomic perspectives. Paltsev (2014), for example, approaches the economic opportunities of Russia's natural gas exports through possible scenarios until 2050, including threats to Russian exports, such as the emerging shale gas technologies development across the globe, the EU energy policy (nuclear, non-nuclear, renewable), and the transformation of liquefied natural gas markets. Shadrina (2014) and Mareš and Laryš (2012) describe the prospects of Asian markets for Russian gas in detail. Gubaidullina and Yakupov (2015) analysed the export potential of Russia's regions (including in industries related to mineral resources) in the context of the World Trade Organization rules and relevant Russian commitments. For foresight studies in resource governance see e.g. Prior, Daly, Mason, and Giurco (2013) for general resource governance; Scheraz (2014) for sustainable development of Afghanistan's mineral sector, Dufva, Konnola, and Koivisto (2015) for regional resource-related policies in Chile or Lieder and Rashid (2016) for a resource-based circular economy approach for the manufacturing industry). Still, insights into how such studies connect with policy decisions are surprisingly limited. For example, Hafezi, Akhavan, and Pakseresht (2017) analysed historical strategies, while Sykes and Trench (2016) applied a scenario approach. Still, the Delphi method with expert panels remains the most widely used method in foresight (Daim et al., 2009). However, interest in new complex methods of scanning for strategic intelligence is on the rise as information is hard to come by and difficult to access. Data-driven methods help to overcome bias that is often inherent in qualitative data analysis. Among the quantitative approaches that are favoured to identify future developments in the extractive industry rank the mining of bibliometric or patent data (Choi & Park, 2009; Deorsola et al., 2013; Wei, Kang, Yu, Liao, & Du, 2017 for the future of shale gas) or science and technology databases (Bengisu & Nekhili, 2006). In the field of energy, the expected development of associated costs of future technologies for power generation has proven insightful (Neij, 2008). With the rise of Web 2.0, new ways emerged to extend the group of participants. For example, Zeng (2018) uses online community members to extract relevant information regarding renewable energies.

The existing methods for the processing of large amounts of textual information rely on operations with words and phrases in sentences (see, for instance, Altuntas, Dereli, & Kusiak, 2015; Carvalho, Winter, & de Souza Antunes, 2015; Daim et al., 2016; Ena, Mikova, Saritas, & Sokolova, 2016). Through statistical approaches, computer linguistics and principles of machine learning, linguistic patterns are identified. While these approaches help to identify and monitor global technological trends, the quality of the results of such an analysis very much depends on the terminology used in the documents under study. Thus, at least two problems stand out that reduce the effectiveness of this type of research on trends in science and technology:

- new technologies with a rapidly emerging terminology cannot be sufficiently detected by traditional methods of big data mining, since each separately presented term is statistically insignificant to characterize the trend (false negative);
- many new trends are often based on preexisting ideas and approaches (for example, research on machine learning algorithms started in the 1960-70 s), but over the years they undergo a social career (like "digital economy", etc.). Thereby, a term can be picked up as a completely new area of R&D (false positive).

To solve the problems described, we apply advanced semantic analysis based on distributive semantics and vector representations of words and phrases (Bojanowski, Grave, Joulin, & Mikolov, 2016; Mikolov, Chen, Corrado, & Dean, 2013; Pennington, Socher, & Manning, 2014). The main idea is to create a model that predicts the context in which each word is embedded (skip-gram model, see for example Liu, Qiu, and Huang (2015)), or predicts the occurrence of a keyword based on the surrounding semantic context

(Continuous Bag of Words model, Köper, Scheible, & im Walde, 2015; Xie, Liu, Jia, Luan, & Sun, 2016). The integration of deep machine learning and neural networks based on such algorithms for example, word2vec can greatly improve the analysis of sectoral science and technology (S&T) trends.

2. Methodology

The present paper reports on technology foresight studies of the extractive industries implemented in Russia recently (for an overview of Russia's long history of foresight studies, see Gokhberg & Sokolov, 2017). The first part of the study is based on desk research of global socio-economic and technological trends in the mineral sector. Particular attention was devoted to the detection of long-term technological transformations that cause structural changes in the industry (the sectoral context).

The study made use of openly available published material from:

- multinational organisations and national agencies: the Organisation for Economic Co-operation and Development (OECD) and the International Energy Agency (IEA), the European Commission, the Organization of Petroleum Exporting Countries (OPEC), the US Energy Information Agency, the National Energy Agency of Japan, and non-profit organisations (e.g., Greenpeace);
- major energy companies: BP, Royal Dutch Shell, ExxonMobil, Lukoil, Gazprom Neft, Rosneft;
- foresight studies published by analytical centers: University of Manchester, HSE, ICESE, Garrett Hering, Institute of Energy Strategy, INEI RAS;
- consulting firms and investment banks: BCG, EY, Accenture, AT Kearney, BAIN, Platts, IHS, McKinsey and Company, BCG, Carbon Tracker, PwC, Douglas Weston, Deloitte, Citygroup, Kepler, Goldman Sachs;
- sectoral and regional long-term strategies and programmes.

Simultaneously, we performed a text-mining analysis[1] (see Porter, 2009; Bakhtin & Saritas, 2016) based on Ngram and stem analysis, together with specific contexts retrieval and clustering of the following data sources:

- a stratified random sample of summaries and metadata of around 2 million internationally top-cited research articles for a 10-year period, acquired from the open citation indexes and other open data sources;
- a stratified random sample of summaries and metadata of around 2 million international patents for a 10-year period, acquired through open access sources of WIPO PCT patents;
- around 15 million newsfeed items from the best of the global news portals with a S&T focus ranked in Alexa.com and SimilarWeb.com;
- more than 200 000 analyses and forecast reports, proceedings and other documents, openly accessible via web search engines and institutional web sites, including the websites of UN organisations.

The processing and the analysis of collected text data regarding the mineral sector consisted of four main stages: *primary natural language processing, syntactic-semantic analysis, topic modeling, classification and clustering*. At the first stage, *primary natural language processing*, large arrays of unstructured textual data were converted into structured tables, arrays and vector representations. Each document was split into separate sentences, words and phrases with different linguistic characteristics. The next stage – *syntactic-semantic analysis* – included an in-depth analysis of the text in order to identify its semantic meaning based on a syntactic analysis of the links between words in the sentence.

The emerging *topic models* for documents and terms calculated on the probability with which a particular term or document refers to a topic provide a categorisation in the absence of adequate expert opinions[2] . We used relative statistics for the clustering and classification of the results. All calculations center on the *relative frequency* (f_{term}) *of occurrence* of terms in relevant documents, which is calculated as shown below:

$$f_{term} = \frac{\sum_{i=1}^{m=amount\ of\ documents} SentOcc_i)}{N}$$

i – document's number,
$SentOcc_i$ – the number of sentences in the i-th document, in which a term has occurred,
N – the number of sentences in the corpus,

$$0 \le f_{term} \le 1$$

Other core measures included the specificity of terms (general vs specialised terms), and the *average annual growth rate* (AAGR) of the relative occurrence of the term to capture dynamics and trends. This allowed us to search for:

[1] Semantic analysis algorithms described in this article are proprietary to the National Research University Higher School of Economics (Moscow, Russian Federation). For more details about semantic analysis approaches and procedures developed see Bakhtin et al. (2017).

[2] Thematic modeling in iFORA employs a words and phrases embedding technique (Word2Vec) which is based on the analysis of the joint occurrence of terms in the context of a large number of sentences with the purpose of revealing words similar topic-wise, as well as synonyms.

- *growth leaders* – a class of terms with a relatively high average annual growth rate and a high relative frequency of occurrence;
- *weak signals* – a class of terms with a relatively high average annual growth rate and a low relative frequency of occurrence;
- *stable areas* – a class of terms with a relatively low average annual growth rate and a high relative frequency of occurrence;
- *niche areas* – a class of terms with a relatively low average annual growth rate and a low relative frequency of occurrence.

In order to filter specific technological and sectoral terms we developed a simple *specificity index* calculated as below:

$$Spec_{term} = f_{term} \times \frac{sents_{term}}{sents_{term\,(corpus)}},$$

- f_{term} – the relative frequency of occurrence of the term within the area of study, e.g. in the documents' corpus (context) in which the research query occurs (in this case it was "oil" OR "gas" OR "coal" OR "fuel" OR "minerals" OR "extractive" OR "mining" OR "drilling"), and not in the whole database of the iFORA system;
- $sents_{term}$ – the number of sentences in which the term occurred within the area of study
- $sents_{term\,(corpus)}$ – the number of sentences in which the term was found throughout the whole corpus of documents.

We used the networks of joint occurrence of terms to determine the main semantically related elements and to evaluate the joint usage of terms in the texts. The preliminary results of both the text-mining exercise and the desk-research were discussed (in three workshops) with 66 experts from businesses and industrial associations, governmental officials, research scholars, and environment protection groups to produce SWOT and STEEPV analyses of the identified technologies development. Subsequently, the discussions continued in smaller moderated panels to validate a list of critical sectoral technologies[3] . The participants were selected on the basis of bibliometric analysis of scientific publications and experts' co-nomination. More details of our methodology and obtained results are described in Table 1.

3. Findings

In a first step, we used the specific technological terms that were automatically extracted by the AI system and ranked them according to the number of times mentioned, normalised average annual growth rate of references, patent activities and S&T news coverage (Table 2). Thereby, we developed an overview of trending topics on the development of the sector which we discussed with the group of stakeholders and experts. Drilling fluids lead the list in patent databases and rank similarly high in S&T news archives, mainly because of their key role in fracking. The term 'oil recovery' is intensively covered in S&T news, as many pits are usually closed prematurely due to the high costs associated with accessing the last quarter of the oil reserves. Some technologies, such as 'dust suppression', are notable for increasing patent activities, which is an indicator for future commercial activities.

Table 3 presents the table of relations of identified technological subareas with the World Bank Global Sustainable Development Goals (World Bank, 2017). The application of a sophisticated text-mining approach (word2vec) allowed to track the conceptual context of these entities, not just to number particular terms. Thereby, we can show how sectoral technologies relate to agreed long-term development targets. The majority of the technologies associated with extractive industries are connected with industrial and infrastructural development opportunities. Pollution issues and entrepreneurial activities are linked to a broader range of technologies than, for example, poverty or problems related to biodiversity loss. Although the area is well suited for start-ups to introduce disruptive technologies, entrepreneurial activities in a market that is dominated by large state-owned enterprises are difficult to establish (e.g. Thurner & Proskuryakova, 2016). Climate change is comparatively often mentioned in the context of offshore and shale mining technologies, while mining and extraction co-occur more frequently with work-related issues. This information helps to identify the relevance of specific technologies in the light of the Russian context and local peculiarities. Also, this analysis is helpful in identifying the associated topics for particular technologies, which is also relevant for choosing the right set of experts. Furthermore, this step indicates potential international partner agencies to support the local development of the technologies.

In a first step, we conducted desk-research into both foresight and strategy documents and processed statistical data to derive information about major sectoral technology trends in Russia. The aim was to identify future drivers of demand and to estimate market sizes through various estimates.

Finally, we ran a full text-mining exercise (for a detailed description of the syntactic rules and heuristics see Kuzminov, Bakhtin, Khabirova, Kotsemir, & Lavrynenko, 2018). Thereby, we compiled a complete list of sectoral technological trends in Russia which we subsequently enriched with more details for expert panel validation (building consensus and identifying dissensus on disputable issues like renewable and alternative energy (for more details see Ratner and Nizhegorodtsev (2017)) and used as a guideline for structured discussions of the results with our stakeholders. This analysis connects expert-based foresight with statistical analysis and AI supported text-mining techniques and machine-learning technologies. In the next step we connected the identified technologies to Russia's own technological strengths and weaknesses and corresponding market estimates. On the basis of this collected information, the selected areas of technological development are presented in Table 4.

[3] For more foresight studies of the HSE Institute for Statistical Studies and Economics of Knowledge, including the foresight approach developed, we refer the reader to "Russia 2030: Science and Technology Foresight" (Gokhberg, 2016).

Table 1
Methodological stages and provisional results.
Source: compiled by the authors.

Stage	Methods	Provisional results
Building an information base for the study	Mobilising stakeholders: ● Stakeholders matrix (method of systematic collection and analysis of quantitative and qualitative information to identify actors whose interests should be taken into account in the study, and strategies for interactions with them) ● Bibliometric analysis of Russian scientific publications related to industry issues in order to select the most authoritative experts ● Experts' co-nomination (selection of experts based on the recommendations of other experts)	A group of stakeholders and experts interested in the topic from businesses and industrial associations, government officials, research scholars, and environment protection groups
	Collecting and systematising data: ● Desk-research of the foresight and strategic documents in the sector, both on the national level and worldwide ● Analysis of best practices and requirements in sectoral S&T foresight ● Collection and systematisation of the data for the subsequent text-mining analysis	A preliminary set of hypotheses on global socio-economic and technological trends in the mineral sector, threats and opportunities specific to the Russian mineral sector caused by global technological trends, lists of promising technologies, emerging markets and emerging new products Semantic database of around 19 million documents (research articles, patents, S&T newsfeed items, documents of international organisations)
Conceptual development of the research area	Text-mining methods to verify desk-research hypotheses: Ngram analysis and term clustering, text-mining of quantitative forecast estimates	Statistical rankings of global challenges, trends, drivers, national specificities, markets (supply and demand)
	Expert procedures to further develop the hypotheses and text-mining results: set-up of expert panels, panel scenarios development, on-site expert procedures (including SWOT and STEEPV analyses)	Structured lists of global challenges, trends, drivers, national specificities, markets (supply and demand)
	In-depth desk-research to verify the novelty of the results	Results of gap-analysis of recent publications on geology and mining trends
Validation of the results	Structured discussion of the results with representatives of the stakeholders	Validated lists and characteristics of trends, traditional and new markets, threats and opportunities

Table 2
Patent activities and S&T news coverage of identified sectoral technologies (extracted technological terms).
Source: Calculated by the authors on the basis of the extracts from openly available published materials with the use of developed text-mining instruments.

Technological term	Times mentioned in the patents database sample	AAGR[a] in the patents database sample	Classification group based on the patents database	Times mentioned in the S&T news archive	AAGR in the S&T news archive	Classification group based on the S&T news archive
drilling fluid	6970	0,14	stable areas	151	0,40	growth leaders
propants	6931	0,54	growth leaders	75	2,53	growth leaders
heat transfer fluid	3612	0,26	stable areas	20	0,56	weak signals
gas treatment	2873	0,15	stable areas	49	0,65	growth leaders
oil recovery	2681	0,28	stable areas	350	0,29	stable areas
drilling mud	1767	0,21	stable areas	99	1,07	growth leaders
chemical injection	463	0,53	growth leaders	52	0,30	growth leaders
seismic exploration	337	0,49	weak signals	23	0,32	growth leaders
gravity separation	234	0,17	niche areas	9	−0,17	niche areas
dust suppression	186	1,34	weak signals	18	0,26	niche areas
wellhead system	78	0,75	weak signals	7	0,12	niche areas
seal oil	68	0,72	weak signals	6	0,00	niche areas
in-situ leaching	46	0,69	weak signals	14	0,08	niche areas

[a] Average Annual Growth Rate of times mentioned normalised to the overall number of analysed documents in the iFORA database for each year.

3.1. Technologies supply

Many key technologies have been developed outside mining and geology. Among them rank, for example, advancements in information and communication technology which have had a profound impact on all sectors of the economy. The application of remote sensing technologies and digital geological information has greatly improved drilling activities, while automation technologies raised efficiency in the processing of ore (Ralston, Reid, Hargrave, & Hainsworth, 2014). Advancements in aviation and space technologies provide the information and communication infrastructure for complex mining management systems which significantly improve searching, exploration, production and transportation of resources (Bokov et al., 2014). Biotechnology makes mining

Table 3
Specific technologies and their relation to the World Bank Sustainable Development Goals (times mentioned together in the S&T news archive).
Source: calculated by the authors on the basis of the openly available published materials with the use of the developed text-mining instruments.

	Industry, innovation, and infrastructure	Responsible consumption and production	Climate action	Life on land	Partnership for global development	Reduced inequalities	Good health and well-being	Decent work and economic growth	No poverty	Life below water
drilling technology	134	33	12	3	2	2	6	3	4	2
offshore technology	111	14	18	2	15	1	1	12	4	5
fracking technology	6	12	5	1	2	3	6		1	
Deep-drilling technology		4	2	1		1	1	1	2	1
leach technology	4	8			1			1		
shale technology	11	6	16	1						
underground mining technology	11	2			1					
CO re-use technology	1	1		1						
underground gasification technology	1	1	5							
radioactive disposal technology		4						2		

Table 4
Major sectoral technological trends in Russia.
Source: compiled by the authors on the basis of the extracts from openly available published materials.

Areas of technological development	Future drivers of demand	Markets and market opportunities	Relevant estimates
• Integrated systems for deep-level mining • Increasing the size of mining equipment • The emergence of "smart mines" • Technology to extract valuable components of associated gas • Development of equipment for unconventional hydrocarbons extraction	• Growing demand for a wider spectrum of chemical elements • Exploration under extreme conditions	• Development and production of oil and gas equipment • Oilfield reagents for exploration and drilling • Risk management and forecasting services • Services in engineering and permafrost investigations, monitoring and related types of work	• Currently, the expenses for oil and gas equipment accounts for 25-40% of recovered oil and gas. Drilling equipment accounts for 12-17% of the total Russian oil and gas equipment market. Russian rig producers control about 30% of the value, and their market share is rising. The value of the Russian oil and gas field equipment is now estimated to be up to $6-7 billion. In the medium term, the domestic market is expected to develop synchronously to the global one. • The value of reagent production for the oil industry reaches around $150 million in Russia and is growing at the annual rate of about 5%. • The market for engineering services has great potential in Russia and might well reach up to $7 billion by 2020, with a growth rate of 5%-7% per year. By 2020-2030, annual growth rates are likely to increase and may exceed 10%-15%.
• Increase in oil recovery • The use of bioleaching • Methods for increasing the rate of oil extraction in depleted hydrocarbon fields and low-pressurised gas fields	• Shift to renewable energy technologies in major consumer markets • Liquefied natural gas • Gasification of solid fuel	• Enhanced oil recovery (EOR) technology market • Production of liquid hydrocarbons • Market equipment and materials to improve recovery rates of minerals of existing fields	• In the Russian oil and gas industry, the EOR methods provide about 12% of the additional enforcement of oil produced. Thermal methods account for 22% and chemical methods for about 30% (chemical methods are also prominently used on a global scale). A large number of technological solutions for acoustic and seismic impact on the hydrocarbon reservoirs and components increased yields up to 15%. • The process of natural gas liquification reduces the volume and hence increases the energy density of natural gas up to 2.4 times that of compressed natural gas. Global production of LNG reached 246 million tons in 2014, or 30% of the global gas market.
Increased use of waste and recycled materials	Constant tightening of international environmental standards	Technologies for the detection and elimination of oil spills Equipment for the recovery of damages to the natural environment Services in environmentally sound waste management, mineral waste recycling technologies	The worldwide market value of microbiological methods is estimated at $500 million. The Russian market for refining by microbiological methods is so far evaluated at the level above $10 million. The market capacity of sorbents, oil and non-concentrating petroleum products in Russia is $1.5 billion. Market growth is expected to top 10% per year. The average cost of the application of technologies of forecasting, assessment and prevention of emergencies ranges from 1% to 5% of the potential damage. In Russia, the annual losses from disasters are expected to reach $450-900 million.

processes eco-friendly, e.g. through the usage of biological leaching, replacing more hazardous chemicals (Hennebel, Boon, Maes, & Lenz, 2015). Advances in biotechnology also provide solutions to cleaning the soil from waste materials caused by intensive mining (Johnson, 2014). Another highly-promising area of growth is the usage of new materials and the development of nanotechnologies in mining for light, ultra-strong, heat-resistant materials, as mostly applied in modern mining equipment.

The following list includes general technologies identified in the framework of our foresight exercises that will shape the future of the industry:

3.1.1. Integrated systems for deep-level mining

The energy saving potential of variable water flow systems is estimated at up to 33% of the total electricity usage of a deep mine (Du Plessis, Arndt, & Mathews, 2015). Furthermore, an additional 30% of a deep-level mine's electricity cost stems from power usage during peak hours (Pelzer, Mathews, Le Roux, & Kleingeld, 2008). The introduction of new processing technologies will lower the unit costs of water by 15%–20%, and the cost of electricity and reagents by 30%–50%.

3.1.2. Bioleaching

Bioleaching involves living organisms in the extraction of metals from ores. The process is much cleaner than traditional heap leaching based on cyanides, and primarily used for copper, zinc, lead, arsenic, antimony, nickel, molybdenum, gold, silver and cobalt extraction. Various groups of micro-organisms are suitable to perform bioleaching, and the true potential of this technology remains yet to be seen (for a review, see Vera, Schippers, & Sand, 2013).

3.1.3. Increasing the size of mining equipment

The mining industry has improved productivity through increasing the size of the mining equipment, both stationary and mobile (Mazumdar, 2013). In the 1990s, mining hoisting capacity of 120 tons was seen as very large. Today, 240-ton dump trucks are standard, and 360-ton trucks are being introduced. The proliferation of more powerful technologies reduces unit costs, in terms of fuel and maintenance costs as well as labour costs. Among the world leaders in the production of heavy mining technologies are such companies as Caterpillar (USA), Hitachi (Japan), Komatsu (Japan), and Liebherr (Germany). Still, due to the declining commodity prices, Caterpillar has already announced plans to shed 10,000 jobs as demand for mining and energy equipment is declining.[4]

3.1.4. Smart mines

This pilot project, funded by the European Union, functions as a technology platform to integrate various technologies that optimise the workflow and data management in underground mines[5] . Smart mines achieve higher degrees of ore extraction with increased levels of energy efficiency, while producing almost no carbon dioxide. The bulk of mining personnel works via telemechanics in major cities' off-site production zones.

3.1.5. Increasing oil recovery

New methods of enhanced oil recovery increase the share of recoverable reserves – especially at the end of the commercially useful life of a pit. Next to classical hydrodynamic methods of stimulation, enhanced oil recovery or tertiary oil recovery methods are increasingly used (Sheng, 2013). The methods include the injection of gases, such as natural gas or nitrogen, or thermal methods, such as stimulation with steam. Chemical methods displace oil with other substances, such as polymers, thickening agents, foam systems or alkaline solutions. A Russian technology, entitled Plasma-Pulse[6], allows upscaling the existing well production by 50%. Leading nations, along with Russia, in the development and usage of new methods are the United States, Canada, Venezuela and Indonesia. China places great emphasis on the active development and testing of these new technologies, as limited own oil reserves leave the country highly dependent on energy imports (Wang & Xu, 2015). However, the technologies for enhancing oil recovery remain expensive and, again, energy intensive.

3.1.6. Technology to extract valuable components of associated gas

The total depletion of oil and natural gas deposits has triggered attempts to increase the usage of available hydrocarbon resources, particularly associated petroleum gas (APG). The major hotspots of mining and processing of APG are – besides Russia – the United States, Saudi Arabia, Canada, Mexico, United Arab Emirates (Abu Dhabi), Iran, Venezuela, and Algeria (WWF & KPMG, 2011). The use of associated gas is also fostered by specific policies. For instance, Norway requires its gas producers to account for flared associated gas at market prices[7] . APG has been treated as a waste product of petroleum extraction, which previously had simply been burned off and attracted increasing criticism due to environmental concerns. Opportunities that arise from the usage of this gas are plentiful and range from electricity production to utilisation in the petrochemical industry.

3.1.7. Increased use of waste and recycled materials

In developed countries, primarily in the European Union, material consumption is falling steadily (by more than 1% per year) due to the penetration of more resource-efficient manufacturing technologies and equipment (Eurostat, 2015). At the same time, recycling technologies (in particular, intelligent sorting, plasma incineration or biodegradation) are also improving.

3.2. Demand for technologies

The above-mentioned technologies are certainly powerful, but to ensure commercial success, they need to meet the respective demand that becomes more and more sophisticated due to a variety of socioeconomic and environmental factors. Groundbreaking technological developments often transform global minerals and energy markets, and demand may well arise in the earlier

[4] URL: http://www.caterpillar.com/en/news/corporate-press-releases/h/building-for-a-stronger-future-caterpillar-announces-restructuring-and-cost-reduction-plans.html (date last accessed 01/10/18).
[5] URL: http://www.i2mine.eu/ (date last accessed 01/10/18).
[6] URL: https://www.wallstreetdaily.com/2016/08/10/oil-plasma-pulse-technology/ (date last accessed 01/10/18).
[7] URL: http://www.worldbank.org/en/news/press-release/2015/04/17/countries-and-oil-companies-agree-to-end-routine-gas-flaring (date last accessed 01/10/18).

unexpected areas. Hence our exercise looked at hotspots of changing demand in the near future. Based on the text-mining analysis and the expert opinions we collected, the following areas have been identified as drivers of future demand during consensus-building at three conducted expert panels:

3.2.1. Shift to renewable energy technologies in major consumer markets

The share of renewable energies in the EU energy balance continues to grow (European Commission, 2017). While this is probably bad news for traditional commodity exports, there are also many and diverse new commercial opportunities to consider. The intensive use of renewable energy will require new energy storage systems, as well as increased flexibility in hydro and gas generation, capable of providing backup systems in the absence of suitable conditions for electricity production.

3.2.2. Growing demand for a wider spectrum of chemical elements

Manufacturing demand for metal and nonmetal elements is expanding, especially for rare earth metals (ABN AMRO, 2014; Goodenough, Wall, & Merriman, 2018). The main drivers of demand are energy producers (particularly wind energy, nuclear technology) and the electronics industry. Other growth areas are metal treatments (alloying of steel, chromium, aluminium), chemical catalysts or inhibitors, and space research (materials with unique properties, including effective lubrication in a vacuum).

3.2.3. Gasification

The process of coal gasification provides multipurpose clean methods of turning coal into electricity, hydrogen, or other products used in the chemical industry. Instead of burning coal directly, the thermo-chemical process of gasification breaks down coal into its basic chemical constituents. The gasification and liquification of coal for synthetic fuel production is a vital technological process that has already become economically promising for energy supply in many world regions (Guo & Xu, 2018). Three processes of converting coal into synthetic fuels are in use in Russia: pyrolysis, direct and indirect hydrogenation. Until the 1990s, underground and pulverised gasification of coal and the Fischer-Tropsch process had been steadily improved; however, since then the business interests have begun to decline.

3.2.4. Liquefied natural gas

Natural gas has increasingly attracted interest as an energy carrier that provides an alternative to nuclear energy. In addition, liquefied natural gas (LNG) can be transported by special vessels to consumer markets to which no pipeline connection has yet been established. Here, Russia may fill an important niche in the international LNG market. Russia's LNG hubs are connected with reserves located in geographically very remote areas of Eastern Siberia and the Arctic North, which leaves Russia in a disadvantageous position in comparison to other suppliers (e.g. Australia or Qatar). In the past decade, amid rising production and consumption of oil in developing countries, production capacity in developed nations fell from 83% in 2000 to less than 78% in 2014 (engaged experts' evaluation). Also, the demand for energy carriers, e.g. natural gas from China, triggered neighbouring countries, such as Australia and Vietnam, to invest in LNG capacities as well.

3.2.5. Exploration under extreme conditions

Despite recent setbacks, deposits in the Arctic Circle and the deep-sea will continue to attract attention. As there is almost no experience with large-scale extraction under such circumstances, technologies that support such extraction activities in both safe and commercially viable forms are in dire need. The true importance of the Arctic and deep-sea deposits can best be demonstrated with the Russian example. Since the collapse of the Soviet Union, no new deposits of rare elements and metals have been detected, and previously discovered deposits remained unexplored. With respect to oil and gas, the exploration of new fields and deposits will result in a 15%–20% increase in hydrocarbon reserves (Ministry of Natural Resources & Environment of the Russian Federation, 2018). According to long-term state programs, and based on balancing consumption and reproduction of mineral raw materials for the period 2011–2020, funding of more than $5,3 billion annually (at 2007 prices) has been provided for exploration work. The ratio of company investments to federal support in recent years varied in the range of 1: 9–1: 8 (Ministry of Natural Resources and Environment of the Russian Federation, 2017a).

4. Discussion and conclusion

This paper presents the methodology and findings of a major foresight study for the extractive industry in Russia. Easily accessible deposits of hydrocarbons and other important natural resources (phosphate, rare earth metals) are being depleted rapidly, and tapping into new deposits requires more advanced technologies. The current macroeconomic situation – low oil price and low valuation of the ruble – puts additional pressure on Russia's extractive industry to replace expensive imports of new technologies, construction materials and equipment for offshore drilling rigs and platforms with domestic products and technological know-how, especially for underwater production systems. Due to Russia's knowledge base in the extractive industries, the current situation offers opportunities for her to become a prominent provider of specialised equipment and services for the production of unconventional oil (heavy and super-heavy oil, oil sands and bitumen, and oil from low-permeability rocks) and unconventional gas deposits (such as coal bed methane, shale gas, gas low-permeability rocks, deep levels of gas, and gas hydrates).

The methodology used in this study demonstrates a way of combining expert opinions with a text-mining approach. Putting together the accumulated desk-research materials and opinions of expert workshop participants with a quantitative study raises both coverage and overall reasonableness of the foresight exercise. Furthermore, the method creates opportunities for monitoring and updating the study through newly published documents, which is crucial for technology mapping and market trend analysis. The instrument also provides a testing procedure for the perspectives, hypotheses and desk-research results through subsequent expert discussions, and allows for the identification of gaps in the coverage of important sectoral development issues. By means of the presented methodology the technologies were linked to dominant discussions on global problems (e.g., climate change vs rural development) and identified key trends.

The application of the implemented hybrid expert-machine learning interaction approach reduces to a significant extent the subjectivity, bias and incompleteness of the expert knowledge as opposed to traditional (un-augmented) desk-research and expert-panel approaches in technology foresight studies. While the foresight study identified a great number of commercially promising technologies, the question regarding businesses interested in and capable of pursuing them has been a major limitation to previous foresight studies. Here, the text-mining study helped to identify potential sponsors and partner institutions based on the context of certain technologies.

Our research also highlights certain limitations of a text-mining approach for future studies. In addition to obviously finite number of already articulated future trends, new narratives about sectoral prospects on the basis of structured results (lists, tables, diagrams) of analysis of unstructured data (big arrays of texts) can emerge. In order to provide a sufficient grounding for such arguments, expert knowledge for the contextual analysis is needed. Especially “black swans” or “wild cards”, events with a low probability of occurring and a high potential impact, are hard to identify (Popper, 2008; Saritas & Smith, 2011; Taleb, 2007). Still, new text-mining applications have started to focus on this area already (Kuzminov, Loginova, & Khabirova, 2018).

Moreover, text-mining has several practical weaknesses that should be carefully addressed. Firstly, any text-mining study faces the challenge of processing and analysing a comprehensive amount of information and sufficient coverage of its relevant sources. Like any other empirical research, text-mining is sensitive to input data quality, and a biased text corpus can result in an inaccurate output. Therefore, the most promising research strategy is to build on vast databases of texts, which can guarantee the necessary heterogeneity of raw input data. Such demand for large collections of texts results in substantial data storage capacities and appropriate computational resources, which require advanced methods and algorithms along with expensive high-performance server infrastructures. An alternative to the development of proprietary text- mining systems is the use of well-known text-mining software, such as VantagePoint[8] or TechWatchTool[9] . However, working with these tools usually requires a large amount of manual cleaning efforts, filtering and grouping of keywords in order to evaluate the presented information. Furthermore, these systems, like many others of the same type, are limited to standard data representations, and do not allow deep analysis of dependencies between different types of data (for example, building multidimensional relationships).

Our approach described in this article can be further refined by adding text-mining proxies of technology and market trends. For instance, the proposed measure of relative frequency of occurrence of terms has limitations due to a varying term popularity and several other factors connected with peculiar properties of each type of information sources. Every time a term is criticised or named as false, its popularity measure rises. Other examples include ‘hypes’ around certain keywords due to media attention, promotion by PR agents or other interested stakeholders. Additional analytical tools, such as sentiment analysis or life cycle analysis, which have already become an integral component of our toolkit, will enrich further foresight studies.

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