



## International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at <http://www.econjournals.com>

International Journal of Economics and Financial Issues, 2015, 5(Special Issue) 300-307.

Economics and Society in the Era of Technological Changes and Globalization



# Introducing Government Contracts to Technology Forecasting

Nikita Sergeyeovich Nikitinsky<sup>1\*</sup>, Dmitry Alexeyevich Ustalov<sup>2</sup>, Sergey Alexandrovich Shashev<sup>3</sup>

<sup>1</sup>NAUMEN, 47 Varshavskoye Highway, Moscow 115230, Russian Federation, <sup>2</sup>Ural Federal University, 19 Mira Street, Yekaterinburg 620002, Russian Federation, <sup>3</sup>Tsentr Razrabotki, LLC, 20/1 Pozharova Street, Sevastopol 299008, Russian Federation. \*Email: [nnikitinskij@naumen.ru](mailto:nnikitinskij@naumen.ru)

### ABSTRACT

Nowadays, technology forecasting has become a multidisciplinary field employing various methods for detecting patterns in data sources in order to forecast trends and future state of different technologies. Technology forecasting is widely used by decision-makers for evaluating grant and contract proposals. Although there are some production-grade systems for technology forecasting for English, Russian patent databases and citation indexes are isolated from the global ones. This makes technology forecasting in Russia more complicate. In this research, we introduce government contracts as new possible parameter for technology forecasting. We think that government contracts indicate government's interest in certain area of research or technology and thus may influence technology trends. We analyzed Russian government contracts; however, we consider this parameter suitable for technology forecasting systems in other languages as most of fundamental research conducted in most countries is sponsored by government. We study government contracts utilizing an information retrieval system pipeline exploiting latent semantic analysis and word2vec.

**Keywords:** Technology Forecasting, Information Retrieval, Government Contract, Trend Analysis

**JEL Classifications:** I38, O30

## 1. INTRODUCTION

Technology forecasting is aimed at predicting future technological capabilities, attributes and parameters, so it applies to understanding of the potential direction and effects of technological change, including invention, innovation, adoption and use. Technology forecasting can be used for analysis of emerging technologies, research areas and topics as well. For example, large commercial companies may use technology forecasting for R and D prioritizing, new product development planning and strategic decisions making.

Governmental structures also require technology forecasting for different purposes, such as contract or grant proposal evaluations in order to prevent plagiarism and conducting work, which has already been performed. Currently, the experts and decision-makers utilize diverse tools for the evaluation, including patent databases and citation indexes.

At the same time, governmental decisions to support certain technologies have a significant impact on technological innovation. For instance, Federal Targeted Programme for Research and Development in Priority Areas of Development of the Russian Scientific and Technological Complex for 2014-2020, issued in 2014, significantly boosted number of government contracts, papers and patents in some certain research areas.

In this paper, we studied the impact of government contracts on consensus trend built on the basis of patents and papers for a certain research topic. The research was conducted using the pipeline of the semantic information retrieval system we created for experts and decision-makers.

We managed to find out that contract trends are moderately correlated with patent and paper trends and statistically significantly influence consensus trends ( $P < 0.01$ ). In the research, we used only Russian data sources; nevertheless, we may suppose

that the results we obtained may be relevant for government contracts, papers and patents in other languages.

As the result, we consider contracts a promising feature for conducting technology analysis and forecasting as government contracts denote state interest in certain areas of research.

## 2. RELATED WORK

In this chapter, we will consider some certain aspects of technological forecasting, which has recently become a multidisciplinary field. In our previous study (Nikitinsky et al., 2015), we emphasized more on collection and analysis of data for technological forecasting, so we will only briefly outline the above-mentioned topics and elaborate more on trend analysis methods for making predictions based on collected data from the past and data visualization approaches for trend representation and visualization. Finally, we will describe some well-known publicly available systems that are often used for conducting technological forecasting and prior-art search.

To review the survey from the previous study, we must note that traditional data sources for technological forecasting are patents and research papers. Contemporary researchers address the information retrieval tasks using vector space models (VSM) and statistical measures of word importance evaluation (i.e. tf-idf), therefore content analysis methods for technological forecasting do often reduce this problem to the ranking problem. Some researchers apply alternative data sources in order to enhance quality of forecasting, i.e. Twitter data or materials published on technological companies' websites, which are said to be a good proxy for technological trend observations.

### 2.1. Trend Line Analysis

Since technological trends change over time, various general purpose regression methods are often used to make predictions. Choice of a method depends on time frame: For local changes it is sufficient to use a simple linear regression (LR) model, but more complex cases require dealing with seasonal effects, which are handled by models like autoregressive-moving average (ARMA), and so on (Hyndman and Athanasopoulos, 2013).

However, researchers are developing special trend line analysis models for forecasting. For instance, Inman proposed the TFDEA model for technology forecasting using data envelopment analysis that combines rates of changes from past technologies that have been superseded by superior technologies (Inman, 2004).

There are several approaches connected with various methodologies like technology life cycles (S-curves), which are used for forecasting purposes (Daim et al., 2006). De Godoy Daiha et al., showed that S-curves are particularly useful for assessing the importance of a research field by fitting the observed data to such a curve (de Godoy Daiha et al., 2015). Gao et al., used a nearest neighbor classifier for measuring the technology's life cycle stage, which resulted in better S-curve estimation (Gao et al., 2013).

### 2.2. Data Visualization

Previous sections show that technology forecasting deals with large amount of unstructured data, which have to be properly

summarized for making a correct decision. Various authors propose specialized data representation and visualization methods for different contexts.

Gartner, Inc., an information technology research and advisory firm, utilizes two well-known approaches for representing various aspects of technological trends: Magic quadrants (MQs) (Magic Quadrant Research Methodology 2015) and technology hype cycles (THCs) (Hype Cycle Research Methodology 2015, October 20). Particularly, MQs show technology players' positioning within a specific market, and THCs illustrate key phases of a technology's life cycle. Since that many methods operate with lines and their shapes, general purpose visualization techniques, including scatterplots and histograms, are suitable for trend visualization, too.

Morris, et al., proposed the DIVA system for exploring document databases for technology forecasting (Morris et al., 2002). Kim, Suh and Park proposed a graph-based method for visualizing patent databases by constructing a semantic network from the extracted keywords clustered by the k-means algorithm (Kim et al., 2008). Mahesh, Trumbach and Walsh provided a 3D version of the similar concept, but using publication data instead of patents (Mahesh et al., 2012). Cunningham and Kwakkel facilitated the popular TFDEA model with a non-linear visualization technique for preserving local structure in high-dimensional spaces of data (Cunningham and Kwakkel 2014).

### 2.3. Publicly Available Systems

Summarizing our survey, we have to conclude that state of the art methods use simple VSM for content analysis, general purpose regression methods or special domain-specific methods for trend line analysis, and either graph-based or plot-based representations of the final line.

There are several well-known production-grade systems for technological forecasting and related activities (Table 1). Those include Questel Orbit (Questel - Innovation, Invention, Patent, Licensing 2015, October 21), Web of Science by Thomson Reuters (Web of Science 2015, October 21), SciVal by Elsevier (SciVal - Welcome to SciVal 2015, October 21), Google Patents with Scholar search for English (Google Patents, 2015), Exactus Expert and Exactus Patent systems by ISA RAS for Russian (ISA RAS website - Homepage 2015). According to our analysis, the only available products working with Russian patents are Exactus, although these systems do not use contracts' data.

## 3. PROBLEM

From the Table 1 we may see that the majority of currently available systems for technological forecasting apply written

**Table 1: Systems for technology forecasting**

System	Patents	Papers	Contracts	Citations	Russian
Orbit	Yes	No	No	No	No
WoS	No	Yes	No	Yes	No
SciVal	Yes	Yes	No	Yes	No
Google	Yes	Yes	No	Yes	No
Exactus	Yes	Yes	No	No	Yes

artifacts to estimating the state of a research topic. The most widely used input data are patents and papers. At the same time, the influence of governmental funding on research areas is underestimated, according to our thoughts. In order to address this problem, we propose using government contracts' data as an additional input for technology forecasting.

We consider government contracts important for technology analysis and forecasting as state support currently plays a significant role in science. Traditionally, most of fundamental researches in most countries are conducted using budget funds. For example, in the USA 59% of fundamental researches are being financed from the federal budget. In Russia, the governmental influence on both fundamental and applied science is much higher. For instance, more than 56% of private-sector R&D projects in Russia are being financed by state (Makasheva, 2013).

Therefore, we suppose that government contracts denote governmental interest in certain areas of research and, as contracts often involve writing papers and patenting activity, change in the number of contracts may change the number of patents and papers with some time lag. Consequently, in this paper, we will analyze the degree of impact of government contracts to research intensity and their connection with papers and patents.

#### 4. DATA AND SYSTEM DESCRIPTION

We developed an information retrieval system for experts and decision-makers, which performs search over Russian patents, papers and government contracts data (Nikitinsky et al., 2015). The idea, on which the information retrieval system is based, is to extend a user query with context extensions (semantically similar terms) in order to retrieve broader results to the query and provide visualization of the results to the user.

The information retrieval system provides search over 1,119,689 invention patents from the Federal Institute of Industrial Property, 884,395 articles from the Russian Science Citation Index and 14,375 government contracts from Federal Target Programme "Research and Development." (Federal Institute of Industrial Property, 2015; Russian Science Citation Index, 2015; Directorate of Science and Technology Programmes, 2015).

The primary purposes of the system are:

- To help users find the most experienced persons and organizations for certain scientific projects.
- To provide decision-makers with an ability to make a quick analysis of the specific research topic in terms of most competitive organizations, experts and actual contributions in that area.

Either, in the paper (Nikitinsky et al., 2015) we evaluated the information retrieval system on the basis of which we conduct experiments. We have performed some tests in order to evaluate the quality of context extensions, and then we compared our information retrieval system with the Baseline search system and evaluated our system on the test set gathered by experts.

According to our study, the results were as follows:

- Word2vec model showed fair results when tested on the AE2 and RT test sets from the Russian Semantic Similarity Evaluation Workshop (Panchenko et al., 2015).
- The system showed better recall and precision compared to the Baseline information retrieval system.
- The results of evaluating the system on a test set gathered by experts showed that applying context extensions to the user query improves precision of retrieved documents in comparison with the bare user query.

In this paper, we will analyze capabilities of the system to analyze trends, as it may be helpful for technology analysis and forecasting.

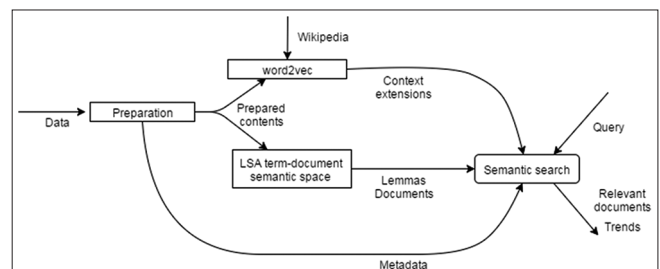
The process of the system data flow is shown at Figure 1 and consists of the following steps:

- Data Preparation: We prepare the data by extracting the documents' metadata, tokenize the contents and conduct morphological analysis, which consists of lemmatization and part-of-speech tagging.
- LSA term-document semantic space construction: LSA (Landauer et al., 2007), is a technique, which is often utilized in NLP and semantic search systems. LSA constructs a term-document matrix with rows representing unique words and columns representing documents. The term-document matrix is constructed with the help of dimensionality reduction technique called Singular Value Decomposition, which decreases the number of rows. As weighting function, we selected Log Entropy function, which is said to work fair in many practical studies (Deerwester et al., 1990). We also use LSA to extract key terms: For every document vector from term-document space we extract all the terms, vectors of which have cosine similarity with the document vector greater than 0.8.
- Building word2vec language model: Word2vec (Mikolov et al., 2013) is a tool for constructing a language model by computing vector representation of words. We train the model on all the data types we have (namely, contracts, patents and

**Table 2: Average correlation between data sources (raw data)**

Data Source	Patents	Papers	Contracts
Patents	1	0.42	0.28
Papers	0.42	1	0.32
Contracts	0.28	0.32	1

**Figure 1:** High-level schema of the data flow in the information retrieval system



papers) with addition of some Russian Wikipedia, using Skipgram neural network architecture.

- Constructing user interface of semantic search: User interface is constructed to let a user first to create a query, then extend the query with context extensions and convert the results into trends. A user can manually correct the extensions by removing unnecessary terms. The query is then projected into LSA semantic space to perform search and retrieve most relevant documents.

An example of automatic context extensions for the word “medicine” is depicted in a Figure 2. The picture shows the most relevant context extensions for the word “medicine” in Russian, including pharmacology, surgery, pathophysiology, endocrinology, dermatology, toxicology, pediatrics, immunology, medico-biological, etc.

Since we have metadata for all the documents in the system, including year of publication and type of the document (e.g., patent, paper or contract), we are able to build-time series plots of the most relevant documents to the query: On the X-axis, we put years and on the Y-axis we put number of documents. Thus, we can obtain three trend graphs for three types of documents - patents, papers and contracts (Figure 3). Since sizes of data sources for various data types we have differ significantly, we normalize the data in order to be able to compare trends (Section 5).

## 5. EXPERIMENTS

### 5.1. Sampling and Data Preparation

First, we randomly selected 20 different research topics from Federal Target Programme “Research and Development” priority directions, including oil and gas and information technologies (List of Federal Target Programme “Research and Development” (2014-2020) priority directions 2015, October 25).

Then, we created queries and extended them with contextually similar words and manually corrected the resulting extended queries.

The queries were created and corrected as follows:

- The name of research area is entered as query, e.g. polymer
- The query was automatically extended with contextually similar terms
- Some irrelevant terms (up to 4) were removed manually.

These queries were then converted into trends as described in Section 4.

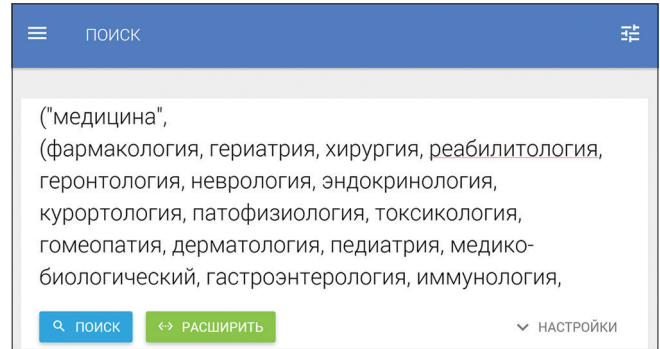
In order to allow the comparison of corresponding values for different data sets, we normalized the data as the ratio of the number of obtained documents to the total number of documents in a corpus per year. Thus, we obtained the percentage of documents for certain research topic to all documents issued that year.

### 5.2. Analyzing Trend Correlation

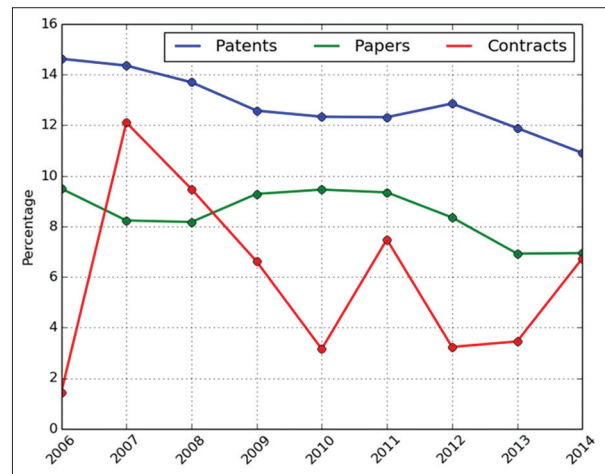
The normalized data (Figure 3 and Table 2) still have some outliers, especially in the contracts subset. To get rid of them,

we apply smoothing techniques to the data. We experimented with third order polynomial (Figure 4 and Table 4) and locally

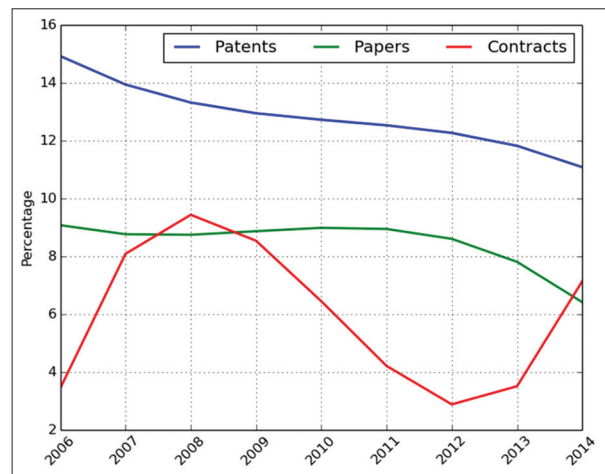
**Figure 2:** Context extensions for medicine research area (Russian language)



**Figure 3:** Normalized data for medical technologies research area



**Figure 4:** Trends smoothed by polynomial for medical technologies research area



**Table 3:** Average correlation between data sources (polynomial)

Data source	Patents	Papers	Contracts
Patents	1	0.50	0.28
Papers	0.50	1	0.48
Contracts	0.28	0.48	1

**Table 4: Average correlation between data sources (LOWESS)**

Data source	Patents	Papers	Contracts
Patents	1	0.41	0.41
Papers	0.41	1	0.47
Contracts	0.41	0.47	1

LOWESS: Locally weighted scatterplot smoothing regression

weighted scatterplot smoothing regression (LOWESS, Figure 5 and Table 5) with smoothing span equal to 2/3 and the number of fitting iterations equal to 3.

Locally weighted scatterplot smoothing regression (LOWESS) (Cleveland and Devlin, 1988) is a non-parametric method based on linear and nonlinear least squares regression. The general idea is to start with a local polynomial (a k-NN type fitting) least squares fit and then to use robust methods to obtain the final fit. We used LOWESS in the study since it has many advantages over other methods, often used for smoothing, including flexibility of the method and the fact that it does not require the specification of a function to fit a model to the data.

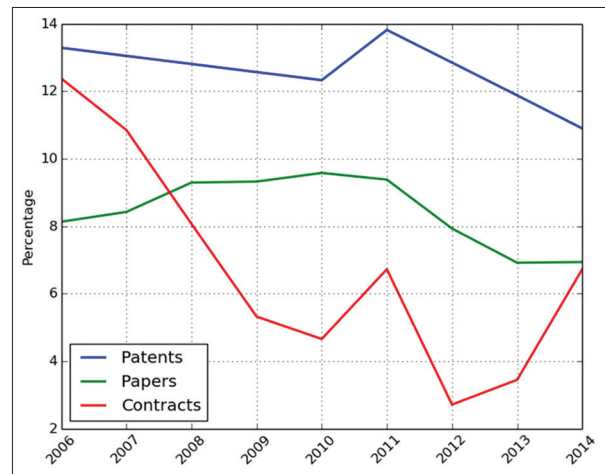
Below, we compared correlations between data types when applied two types of smoothing and raw data.

For the raw data, patents and papers correlate better than contracts with papers or patents. At the same time, contracts and papers correlate better than contracts and patents. When applied smoothing techniques, we could see that patents and papers smoothed by LOWESS correlated slightly worse than the ones smoothed by polynomial, but correlation of contracts and patents smoothed by LOWESS was significantly higher than the ones smoothed by polynomial. In further experiments, we consider using raw data and LOWESS-smoothed data.

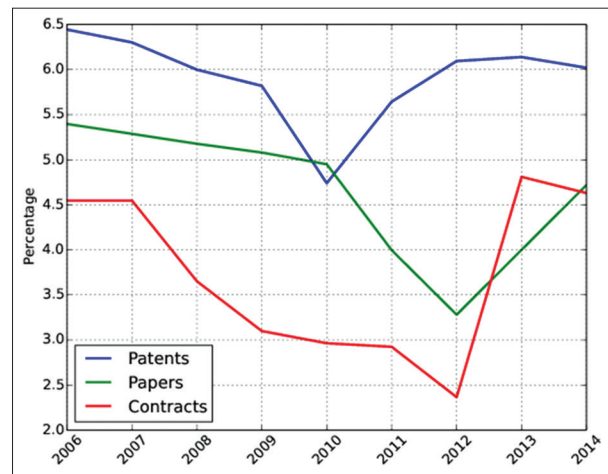
The higher correlation (0.32-0.48 depending on smoothing type) between contracts and papers than between contracts and patents (0.28-0.41) may tell us that contracts impact scientific publication activity more than patenting activity. It may be caused by the fact that more contracts involve writing papers than patenting new inventions. However, it should be noted that we have only part of Federal Institute of Industrial Property database, namely FIPS: Inventions and the correlation of contracts may differ for the whole FIPS database.

It is also worth noting that publication and patenting activity may be affected by various sources, so we are not likely to expect very high correlation of contracts with paper and patent trends for every research area. Nevertheless, for research areas, which are almost totally dependent on government sponsorship in Russia, for example, oil and gas technologies (Figure 6), we may see obvious correlation between contracts, patents and papers, considering a time lag. Some research areas (Figure 7) may show better correlation of contracts with patents, than of contracts with papers; this may be the case for research topics, where most theoretical work has already been carried out and currently R and D work is primarily conducted (as we remember, 56% of applied research in Russia is sponsored by government). Correspondingly, we may suppose that contracts are likely to be more important as parameter for research areas with stronger state presence.

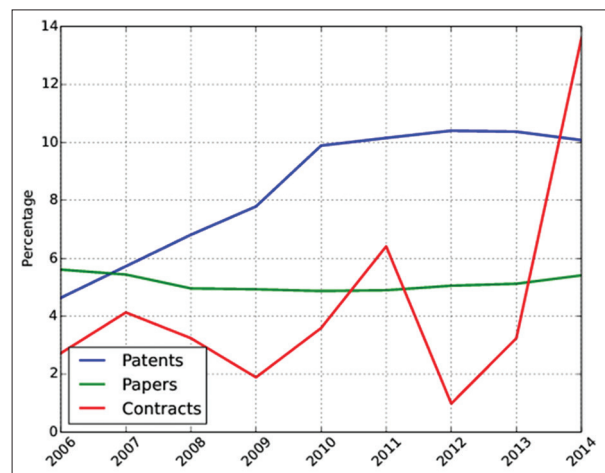
**Figure 5: Trends smoothed by LOWESS for medical technologies research area**



**Figure 6: Trends smoothed by LOWESS for oil and gas technologies research area**



**Figure 7: Trends smoothed by LOWESS for information technologies research area**



**5.3. Analyzing Time Lag Hypothesis**

Considering the assumption that it takes much more time to issue a patent than to publish a paper, many contracts involve publishing, and patenting activity, we made a supposition that

there may be time lag between year of concluding a contract and year of issuing a patent.

In order to research the time lag hypothesis we split the data set into two offsets O1 (data from 2006 to 2010) and O2 (data from 2010 to 2014) and conducted correlation analysis of contracts-to-papers and contracts-to-patents subsets within the offsets. According to the hypothesis, we expect papers from offset O1 to correlate more with the contracts from the same offset and patents from O2 to correlate more with contracts from O1.

According the results from Tables 5 and 6 we could see that contracts from the offset O2 indeed correlated more with patents from offset O2 than with patents from the same offset both for raw and LOWESS-smoothed data. However, surprisingly, we could see a moderate correlation of contracts (O1) with patents (O2), which may indicate that decision-makers could use the information about the issued patents in order to make decisions about concluding new contracts in certain area of research.

For papers, we could see the expected results - they correlated more with contracts from the same offset.

Correspondingly, we suppose that a time lag between contracts and patents may exist and can be used as additional information for technology forecasting.

**5.4. Comparing Consensus Trends**

In order to examine the influence of contract data to the overall trend, we compare two trend lines: Patents + papers consensus trend (PP-trend) and patents + papers + contracts consensus trend (PPC-trend). An example of the trends can be seen at Figure 8.

- To make the consensus PP-trend, for every point on the plot, we computed the mean for patents and papers values.
- To make the consensus PPC-trend, for every point on the plot, we computed the mean for patents, papers and contracts values.

Then, we conducted correlation analysis on PP-trends and PPC-trends obtained for every research area in our sample. The experiment showed high correlation between trends smoothed by LOWESS ( $r > 60$ ), a 95% confidence interval is (0.40, 0.84). After that, we conducted a t-test on PP- and PPC-trend lines smoothed by LOWESS and found out that the contracts data do influence the trend line with  $P < 0.01$ .

One may think that contracts data make trends more biased. This may occur as contracts are heavily influenced by different external factors, and the dominant factor is state science policy. For instance, issuing a new Federal Programme may boost number of new government contracts in some certain research areas while decreasing number of new contracts in others. We suppose this factor should be considered in future research in order to be able to construct less biased contracts' trend line.

We also conducted some experiments in order to extrapolate trends into future and see if trends may be predicted precisely enough.

We tried two models for trend prediction: (1) Classic LR and (2) ARMA.

**Table 5: Average correlation between offsets O1 and O2 (raw data)**

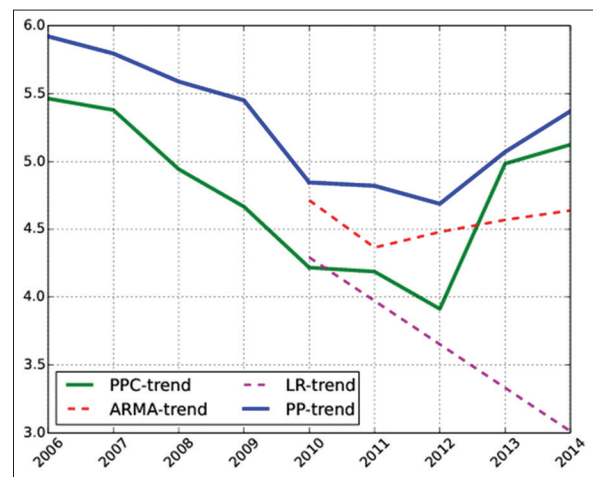
Offset	Contracts (O1)	Contracts (O2)
Patents (O1)	0.26	0.49
Patents (O2)	0.43	0.3
Papers (O1)	0.47	0.33
Papers (O2)	0.23	0.46

**Table 6: Average correlation between offsets O1 and O2 (LOWESS)**

Offset	Contracts (O1)	Contracts (O2)
Patents (O1)	0.53	0.7
Patents (O2)	0.6	0.34
Papers (O1)	0.71	0.42
Papers (O2)	0.33	0.66

LOWESS: Locally weighted scatterplot smoothing regression

**Figure 8:** Patents + papers and patents + papers + contracts trends for oil and gas technologies research area and trend predictions with autoregressive-moving average and linear regression



ARMA (Brockwell and Davis, 2009), is a tool for predicting future values of given time series. The tool consists of two parts called AR and MA. ARMA is often referred to as ARMA ( $p, q$ ) where  $p$  is the order of the AR part and  $q$  is the order of the MA part. Classic ARMA notation is expressed as:

$$X_t = \mu + \epsilon_t + \sum_{i=1}^p \phi_i X_{t-i} + \sum_{i=1}^q \theta_i \epsilon_{t-i}$$

Where  $\phi_1 \dots \phi_p$  are parameters for AR part of the model,  $\theta_1 \dots \theta_q$  are parameters for MA part of ARMA,  $\mu$  is a constant,  $\epsilon_t$  and  $\epsilon_{t-i}$  are error terms representing white noise.

We split each PPC-trend line in data set into train and test parts with proportion of 3:2. For each algorithm, we measured root mean squared error (RMSE). Although ARMA (1, 0) showed better results for predicting PPC-trend line than LR in terms of RMSE (1.37 vs. 1.82), we could not consider the results reliable enough due to the lack of data - the time series we worked with consisted only of 10 points as we had contracts only for time period from 2005 to 2014 inclusive. Nevertheless, ARMA (1, 0) trend

was able to indicate the type of the real future trend (i.e. uptrend or downtrend) correctly. An example of prediction can be seen at Figure 8.

## 6. RESULTS AND DISCUSSION

In this study, we analyzed the factors influencing scientific trends and studied impact of government contracts to consensus research trend.

We showed that for Russia, the government contracts influence research trend significantly ( $P < 0.01$ ) and may be considered an important factor for research trend analysis.

The contracts show governmental interest in certain area of research and growing number of contracts in certain research topic may cause growth of number of papers and, possibly, patents for the topic with some time lag as many contracts assume publishing papers and patents as part of contract work - we found out good positive correlation of contracts with papers (0.47-0.48, depending on smoothing algorithm) and moderate positive correlation of patents with contracts (0.28-0.41, depending on smoothing algorithm).

Certainly, our study possesses some limitations. For example, we found out that there are some external factors influencing patenting, publishing and contract activity and making it difficult to predict the trend precisely enough. For instance, Federal Targeted Programme for Research and Development in Priority Areas of Development of the Russian Scientific and Technological Complex for 2014-2020, issued in 2014, significantly boosted the number of government contracts in some certain research areas.

In this study, we employed general queries in order to show that the approach we introduced can be applied to encompass trends in broader research areas. The application of the approach, which we introduced in the paper, to the more specific topics may lead to a better picture. We consider researching the more specific topics in a future study.

## 7. CONCLUSION AND FURTHER RESEARCH

To conclude, we may say that in this paper we proposed government contracts as significant parameter influencing consensus research trend. We suppose that the number of contracts denotes the level of governmental interest in certain research area.

To the best of our knowledge, this paper is the first attempt of proposing government contracts for technology forecasting and analysis.

In this study, we used data in Russian language from Russian sources (Federal Institute of Industrial Property, Russian Science Citation Index, Directorate of Science and Technology Programmes), but we think that government contracts may influence research trends in most countries, as state plays significant role in science, at least

in fundamental research. In addition, we suppose, that influence of contracts on research trend is higher in countries with stronger governmental presence in science.

Our study showed that the combination of trends for three different artifacts (patents, papers and contracts) differs significantly from the combination of trends for patents and papers and may reflect the situation in certain research area better, but more work on this is needed. In particular, we suppose, that it is essential to consider external factors influencing contracting activity.

For a future study, we suggest:

- Obtain and consider data for lesser time frames in order to be able to conduct more reliable time series analysis.
- Create a model considering external factors influencing contracting activity.
- Elaborate more on special features of government contracts and types of research areas where contracts impact on results more.
- Analyze possible influence of government contracts on research trends for other languages.

In addition, in the more thorough study, one may focus on contracts for fundamental research, such as grants of Russian Fund for Basic Research, in order to verify the idea of using government contracts for technology forecasting. Most probably, the time lags in that case are likely to be even bigger, but this can sometimes be used as an “early warning” system for some emerging technologies.

It also seems like a good idea to extract the information about the ending dates of contracts and on how many papers and patents (and in which years) are expected as the result of the contract work. This information can be a significant additional factor for technology forecasting.

## 8. ACKNOWLEDGMENT

We acknowledge the Directorate of Science and Technology Programmes and personally Petrov A. N. for providing us with government contracts' data for this study. Research reported in this publication was supported by Ministry of Education and Science of the Russian Federation under contract number 14.579.21.0091

## REFERENCES

- Brockwell, P.J., Davis, R.A. (2009), *Time Series: Theory and Methods*. 2<sup>nd</sup> ed. New York: Springer. p273.
- Cleveland, W.S., Devlin, S.J. (1988), Locally-weighted regression: An approach to regression analysis by local fitting. *Journal of the American Statistical Association*, 83(403), 596-610.
- Cunningham, S.W., Kwakkel, J.H. (2014), Technological frontiers and embedding's: A visualization approach. In: *Proceeding 2014 Portland International Conference on Management of Engineering and Technology (PICMET)*. p2891-2902.
- Daim, T.U., Rueda, G., Martin, H., Gerdstri, P. (2006), Forecasting emerging technologies: Use of bibliometrics and patent analysis. *Technological Forecasting and Social Change*, 73(8), 981-1012.
- Deerwester, S., Dumais, S.T., Furnas, G.W., Landauer, T.K., Harshman., R. (1990), Indexing by latent semantic analysis. *Journal of the American*

- Society for Information Science, 41(6), 391-407.
- Directorate of Science and Technology Programmes. Available from: <http://www.fcntp.ru/>. [Last retrieved on 2015 Oct 23].
- Federal Institute of Industrial Property. Retrieved from: [http://www.fips.ru/wps/wcm/connect/content\\_en/en/](http://www.fips.ru/wps/wcm/connect/content_en/en/). [Last accessed on 2015 Oct 23].
- Gao, L., Porter, A.L., Wang, J., Fang, S., Zhang, X., Ma, T., Wang, W., Huang, L. (2013), Technology life cycle analysis method based on patent documents. *Technological Forecasting and Social Change*, 80(3), 398-407.
- Google Patents. Retrieved from: <http://www.patents.google.com/>. [Last accessed on 2015 Oct 21].
- Hyndman, R.J., Athanasopoulos, G. (2013), *Forecasting: Principles and Practice*. O Texts.
- Hype Cycle Research Methodology Gartner Inc. Retrieved from: <http://www.gartner.com/technology/research/methodologies/hype-cycle.jsp>. [Last accessed on 2015 Oct 20].
- Inman, O.L. (2004), *Technology Forecasting Using Data Envelopment Analysis*. Portland, OR, USA: Portland State University.
- ISARAS Website - Homepage. Retrieved from: <http://www.isa.ru/index.php?lang=en>. [Last accessed on 2015 Oct 21].
- de Godoy Daiha, K., Angeli, R., de Oliveira, S.D., Almeida, R.V. (2015), Are lipases still important biocatalysts? A study of scientific publications and patents for technological forecasting. *PLoS One*, 10(4), 1-20.
- Kim, Y.G., Suh, J.H., Park, S.C. (2008), Visualization of patent analysis for emerging technology. *Expert Systems with Applications*, 34(3), 1804-1812.
- Landauer, T., McNamara, D.S., Dennis, S., Kintsch, W. (2007), *Handbook of Latent Semantic Analysis*. Mahwah, NJ: Lawrence Erlbaum Associates.
- List of Federal Target Programme Research and Development. (2014-2020), Priority Directions. Retrieved from: [http://www.fcpir.ru/about/priorities\\_and\\_critical\\_technologies/critical\\_technologies/](http://www.fcpir.ru/about/priorities_and_critical_technologies/critical_technologies/). [Last accessed on 2015 Oct 25].
- Magic Quadrant Research Methodology Gartner Inc. Retrieved from: <http://www.gartner.com/technology/research/methodologies/magic-quadrant.jsp>. [Last accessed on 2015 Oct 20].
- Mahesh, S., Trumbach, C.C., Walsh, K.R. (2012), Visualizing technology mining results on life cycle axes: A study of server virtualization. *Information Knowledge Systems Management*, 11(3,4), 321-343.
- Makasheva, N.P. (2013), Gosudarstvennaya podderzhka i finansirovaniye innovatsionnoi deyatelnosti v Rossii i stranah mira [State support and sponsoring of innovative activity in Russia and countries worldwide]. *Tomsk State University Herald. Economy*, #3 (23), Federal Institute of Industrial Property. Retrieved from: [http://www.fips.ru/wps/wcm/connect/content\\_en/en/](http://www.fips.ru/wps/wcm/connect/content_en/en/). [Last retrieved on 2015 Oct 23].
- Mikolov, T., Sutskever, I., Chen, K., Corrado, G.S., Dean, J. (2013), Distributed representations of words and phrases and their compositionality. *Neural Information Processing Systems*, 26, 3111-3119.
- Morris, S., De Yong, C., Wu, Z., Salman, S., Yemenu, D. (2002), DIVA: A visualization system for exploring document databases for technology forecasting. *Computers and Industrial Engineering*, 43(4), 841-862.
- Nikitinsky, N., Ustalov, D., Shashev, S. (2015), An information retrieval system for technology analysis and forecasting. In: *Proceedings of the AINL-ISMW FRUCT Conference 2015*, 52-59.
- Panchenko, A., Loukachevitch, N.V., Ustalov, D., Paperno, D., Meyer, C.M., Konstantinova, N. (2015), RUSSE: The First Workshop on Russian Semantic Similarity. In *Computational Linguistics and Intellectual Technologies: Papers from the Annual Conference. Dialogue*, 2, 89-105.
- Questel - Innovation, Invention, Patent, Licensing. Retrieved from: <http://www.questel.com/index.php/en/>. [Last accessed on 2015 Oct 21].
- Russian Science Citation Index. Retrieved from: <http://www.elibrary.ru/>. [Last accessed on 2015 Oct 23].
- SciVal - Welcome to SciVal. Retrieved from: <http://www.scival.com/>. [Last accessed on 2015 Oct 21].
- Web of Science. Retrieved from: <http://www.webofknowledge.com/>. [Last accessed on 2015 Oct 21].