Влияние технологий анализа данных на финансовые результаты компании (на примере энергетических компаний)

Арина Петрова, Валерий Смирнов

Финансовый университет при правительстве Российской Федерации, Москва, Россия

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Аннотация

Объем данных в каждой сфере жизни человечества постоянно растет, отсюда очевидно, что они требуют грамотного управления. Учитывая этот факт, высокоинновационные компании начали внедрять технологии и инструменты анализа данных в свои операционные процессы. Однако некоторые отрасли подвержены множеству ограничений в силу своей специфики. Одним из таких примеров является отрасль энергетики в России. Этот сектор выглядит достаточно консервативным и закрытым для применения аналитики. В статье основное внимание уделяется исследованию барьеров, препятствующих внедрению технологий. Посредством построения однокомпонентной эконометрической модели определено влияние инструментов анализа данных на чистую прибыль. Цель состояла в том, чтобы выяснить, существует ли статистически значимая связь между чистой прибылью компании, производящей энергию, и четырьмя элементами анализа данных. Основные выводы, полученные в ходе исследования, показывают, что применение инструментов анализа данных опосредованно влияет на чистую прибыль. Однако в будущем зависимость между ними может усилиться, так как в последние два года наметилась повышательная тенденция к этому.

Impact of Data Analysis Application on Competitive Performance: Case of Energy Generation Companies

Arina Petrova, Valeriy Smirnov

Abstract

The amount of data in each sphere of life of humanity is constantly growing, hence it is obvious that it requires proper management. Given this fact highly innovative companies started to introduce data analysis technologies and tools into their operational processes. However, certain industries are subject to many limitations due to their specific and, which slow down the process of innovation. One of such examples is energy generation in Russia. Though Russia is extremely energy intensive country the sector appears to be rather conservative and closed for analytics application.

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This paper focuses on the investigation of the barriers hampering technology introduction through relevant literature. Then data analytics instruments are divided into several components, and their influence on the net profits is examined through the construction of one-component econometric model. Aim was to find whether statistically significant relationship between net income of the energy generation company and four elements of data analytics exists. At first it is assumed that there is no such relationship. Data necessary to implement regression analysis was obtained through surveys and corporate policy studies. The main insights gained through this research show that the application of data analysis tools most likely impacts the net income indirectly which is proved by the case of Russian energy generation companies. However, the dependence between them may strengthen in future since there has been an upward trend towards this over the past two years. The results of the research may help energy generation companies understand that it is crucial to adapt to current path of data management. In addition, findings suggest it is possible to increase efficiency through enhancing qualitative innovations such as data analysis tools, nevertheless there is still a great field for future research as the model requires some improvements.

Introduction

The amount of information that firms must deal with during their daily operations has grown dramatically in recent years. The process of managing data becomes more and more complex, but at the same time it acquires a greater influence on the effectiveness of a business and its overall success. Data analysis nowadays may play a key role in helping companies improve the competitiveness of the firm and fit market specifics as data enabled technologies gives more power than the customer insights companies produced in the past (Hagiu & Wright, 2020). With this easily obtained knowledge of customers' needs the ability to meet their preferences also increases. analytics. Business Process Analysis (BPA) is an important field to improve business processes. BPA aims to provide organizations with suitable information to understand how their processes are currently being performed. This knowledge can then be used to detect gaps between what is determined and what is going on, so that organizations can improve processes and systems in accordance with their determined business objectives (Hassani & Gahnouchi). BPA includes a range of different tactics such as simulation and diagnosis, verification, and performance analysis of business processes, they become more and more used in different spheres of production and services. They appear to take place not only in finance and banking but in heavy industries too. However, at this point lack of innovation capacities in many fields of these industries is a cause for concern because these heavy productions are not modernized enough to use data analysis for their benefit. In this paper we will focus on the Russian energy generation sector as it has a great potential for data analysis application. However, the feasibility of this potential is substantially limited by several barriers reducing the desire of energy companies to apply it at all.

Being one of the most energy-intensive countries in the world, Russia has enormous potential for energy savings. The International Energy Agency (IEA) estimated that if each Russian economic sector used energy as efficiently as comparable Organization for Economic Co-operation and Development (OECD)-member countries, Russia could have saved more than 200 million tons of oil from its primary demand in 2008 (Roshchanka & Evans, 2016).

Every second CEO of the energy company confirms that his or her team is trying to effectively implement rapidly developing technologies. At the same time, only 9% of business leaders who participated in the survey said that their revenue and profit growth was achieved due to digitalization (Accenture research, 2019). Most of them blame lack of experiment culture and digital skills, insufficient data security and trust. At the same time, according to German-Japan Energy Transition Council data analysis usage may possibly provoke the following advantages:

– Possibility to collect smart meter data with high time resolution and improve forecasts.

– Safe data transmission as well as safe but easy data and consent management for energy services (Ninomiya & Thomas & Kolde & Sasakawa, 2021)

– Optimization of consumer bills.

– Up to +20% income growth (due to efficient demand-side and solar and wind generation management, optimized operation of energy storage and further flexibilities)

– 15% reduction in costs associated with improper forecasting.

Though the energy sector is not a pioneer in the usage of data analysis tools, limited awareness among the citizens still exists as the industry is of conservative nature. Nevertheless, it is worth finding whether data analysis applications have any effect on firm's competitiveness, does it help to increase the company's net profit. These are the issues we will focus on our work in a pursuit to facilitate the further discussion of this problem.

The paper is structured as follows: in section two existing literature is examined and assessed, in section three methodology of the research is explained, section 4 contains the analysis, results, suggestions for optimization and the list of references is the last section of this work.

Literature review

The literature review performed in this research has identified relevant papers related to the impact data analysis tools have on the competitive advantage of the firm which may be expressed in cost reduction, net profit growth, better forecasting, and many others.

The study of articles published from 2015 to 2021, searched in the Scopus and Web of Science databases, regarding big data and data analysis application in energy generation companies in Russia, indicated that Russia yet lacks research in this sphere, though for now it may adopt the experience of foreign countries. For example, the barriers of innovative technology adoption were examined by Maria Concepción Peñate-Valentína, María del Carmen Sánchez-Carreira and Ángeles Pereira in their article "The promotion of innovative service business models through public procurement. An analysis of Energy Service Companies in Spain". To achieve their goal – promote innovative service models in energy service companies – the authors have used multiple case study methodology conducting eight in-depth interviews of energy companies from different regions of Spain. After the description of the conditions of each case they have questioned the key agents of these firms to identify the limitations that discourage technology introduction. These barriers may be divided into four groups and all of them are summarized in Table 1.

It appears Russia and Spain have a lot in common when it comes to the reaction on the new technical achievements' adoption. Both markets are monopolized by the large size of awarded companies while the participation of small and medium-sized enterprises is limited. As well as in Spain, there are problems with the legislative process in Russia: issued laws often contradict each other and the regulatory environment may be suddenly changed and, unfortunately, not always for the better (Roshchanka & Evans, 2016). Additionally, the authorities do not always act in the interest of industry representatives.

Table 1

Types and examples of barriers

Type of barrier	Examples	References
Legal and political barriers	Unstable legislation. Contradictory government policy. Lack of understanding of the importance of the issue among the authorities	Bertoldi & Boza-Kiss (2017)
Institutional barriers	Insufficient technical capacities. Deficit of trained personnel. Lack of measurement tools. Poor security and lack of trust	Bertoldi & Boza-Kiss (2017) Lee et al. (2015)
Financial barriers	Limited market growth. Insufficient funding. High transaction costs	Hannon et al. (2015)
Informational barriers	The prejudice that this industry is well managed and does not require any innovative intervention	Bertoldi & Boza-Kiss (2017)

Source: Own elaboration based on work Maria Concepción Peñate-Valentína, María del Carmen Sánchez-Carreira, Ángeles Pereira (2021)

Financial limitation is mostly influenced by the lack of sufficient funding, which switches our attention to informational problems because having known the advantages of data analytics tools, the shareholders and, what is more important, the authorities would be interested in providing the industry with necessary investment. However, the biggest issue, to our opinion, is institutional one. Just like in Spain, many Russian energy companies are rather conservative and do not want to invest in something immaterial like a software they are not sure about. In addition, apart from investment into innovations, they need to educate personnel or hire already experienced specialists which causes additional line of expenses and thus does not act in favor of data analysis tools. All in all, this research has certain shortcomings. The opinion the authors have obtained from the questionnaire might be biased, so we think another research should be performed for example construction of a mathematical model using the same sample. Though it suggests the active role of government is important and we could not agree more.

Volha Roshchanka and Meredydd Evans, studying Russian Energy Service Companies (ESCOs), have concluded practically the same (Article "Scaling up the energy service company business: market status and company feedback in the Russian Federation"). Having used the Government's official public database, they find costly and risky tender procedures, uncertainty regarding repayment from public facilities, the inability to expand projects, and financing. The authors advise policymakers to adapt their approach.

These works lead us to the conclusion that the sphere in question needs improvement, but the fear of novelties exists. Why are data analysis tools still worth trying? That is brilliantly explained in the article "A framework for Business Process Data Management based on Big Data Approach". The authors, Asma Hassania and Sonia Ayachi Gahnouchia, claim big data analytics capability has a positive effect on three characteristics of a company: dynamic capabilities, marketing and technological and, thus, result in strengthened operational capabilities. They applied partial least squares-based structural equation modeling (PLS-SEM) analysis. Specifically, the software package SmartPLS 3 was used to conduct all analyses. It is finally stressed by the authors that the effect on performance is indirect and contingent upon how dynamic capabilities are exercised on operational capabilities. This finding raises several important implications for practice and research. A Big Data Analytics Capability (BDAc) is necessary but not a sufficient condition to lead to competitive performance remains subject to several internal and external factors. Since we think the fact that this study relies on top management respondents as key informants, sampling multiple respondents within a single firm may cause bias, we want to check whether their result applies to our case.

For more active digitalization of the energy industry in the Russian Federation, companies lack strategic goal-setting – a clear understanding of how to solve certain problems with the help of technology. Distrust of technology, unwillingness to take responsibility for the long term, a long decision-making cycle and the lack of an IT base: equipment, IT landscape and network resources also hinder (Maria Grigorieva, 2019). Thus, the question to be answered by this study is: How does the application of data analysis tools influence the profits of the Russian energy companies and their competitiveness? The objective is to review scientific literature and use the method of analysis we find the most suitable considering the research environment and obtain an answer to the question posed above.

Methodology

This research bases on literature review, interview method and construction of the mathematical model, seeking the benefits of data analysis tools applied in energy industry in Russia.

At first, it is necessary to choose the dependent (endogenous) variable and independent ones (exogenous). Then formulate the main hypothesis to be tested and the alternative one, construct the model according to the laws of econometrics and investigate this model performing regression and descriptive statistics.

It is necessary to consider that econometric model should fit the following four principles of specification:

- Specification of a model is a result of a translation of the economic laws into mathematical language. Linear mathematical equations are used to build the model whenever possible.
- Number of endogenous (dependent) variables should be equal to the number of equations in the system.
- All the variables should be dated; time periods should be clearly defined.
- Behavioral equations in the system should include disturbance term

Regression equations are obtained using the analysis of the same name and represent a description of the correlation dependence between the resultant and factor sign. This method constitutes the method of regression analysis. It is used in cases when it is necessary to find the exact type of X and Y dependence. In this case, it is assumed that independent factors are not random variables, but the effective indicator of Y has a constant, independent of the factors, variance, and standard deviation. Let's present the dependence of Y and X in the form of a linear equation of the first order:

$$Y = \beta_0 + \beta_1 * X + \varepsilon$$

We assume that the values of X are determined without error, β_0 and β_1 are the parameters of the model, and ε_t is the error, the distribution of which obeys the normal law with zero mean value and constant deviation σ^2. The values of the parameters β are not known in advance and need to be determined from a set of experimental values (X_i, Y_i, i= 1, …, n). So, we can write:

$\widehat{Y_i} = b_0 + b_1 * X_i$, i=1, …, n,

where Y_i – the model predicted value of Y for a given X, b_0 and b_1 are sample estimates of model parameters.

In addition, to obtain the best results from this method the variance of random deviation should be constant, and the mathematical expectation of a random deviation is zero.

After choosing the linear regression equation and estimating its parameters, statistical significance of both the equation as a whole and its individual parameters is assessed. The coefficient of determination R^2 is the fraction of the variance of the dependent variable explained by the model under consideration, that is, explanatory variables. The coefficient of determination always lies between 0 and 1. The closer R^2 to 1, the more accurate the model is, however, too high value of R^2 could be a signal of multicollinearity.

All in all, this technique was chosen to achieve more comprehensive information in this study, and to allow for a more exhaustive study of specific topics in future research.

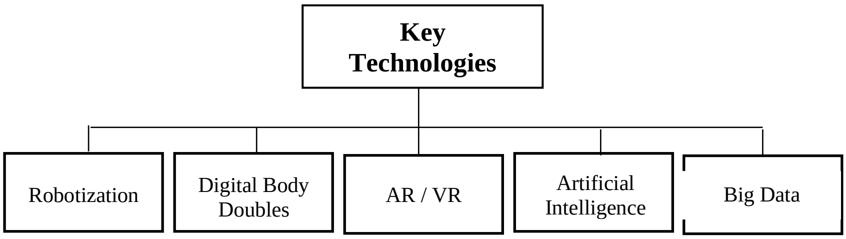
Analysis and discussion

In this section we will try to answer the questions that have arisen ate the initial stages of this research, formulate the hypothesis, and test it in accordance with chosen method of analysis.

4.1. Sample and variables

The sample of 15 largest Russian energy generation companies listed on the website of the Ministry of Energy were chosen to be investigated in 2 years, 2019 and 2020, so this list is comprised of Inter Rao Group, ROSENERGOATOM, RusHydro, Gazprom Energoholding, PJSC Unipro, PJSC Enel, Fortum, PJSC Quadra, Eurosibenergo, PJSC ROSSETI, Grid Company Group, JSC BESK, JSC Regional electric networks, IESK (Irkutskenergo), PJSC SUENCO.

The dependent variable is net income, but when it comes to the choice of independent variables, it is rather hard to measure the data analysis influence, whether it should be showed by the number of technical applications, their quality, their resultant factors, or everything at once. Of course, it is better to combine all such elements in order to get a complex picture, so we have addressed the Accenture research (2019), where the authors have identified several key technologies that can increase capitalization in the energy sector, split them into 4 (Pic 1) and calculated the share of increase: robotics – 8%, the use of digital twins – 8%, augmented and virtual reality (AR/VR) – 28%, artificial intelligence – 12%, big data – 27%. Many energy generating companies are already dealing with big data that implies software tools for analyzing, processing, and extracting data from an extremely complex and large data set with which traditional management tools can never deal (Pappas & Mikalef & Giannakos & Krogstie & Lekakos, 2018), robotization is also coming to use in many industries, generation companies are no exception (Ninomiya & Thomas & Kolde & Sasakawa, 2021). As for digital doubles, there are few scaled solutions in this direction yet. To use the technology, it is necessary to focus on collecting analytics first. Nevertheless, many energy companies in Russia are actively making prototypes and are already trying to use digital doubles (Accenture research, 2019). AR/VR technologies are also actively developing, mainly for employee training. As for the business application, so far, we may talk only about many pilots and testing of virtual and augmented reality.



Picture 1. Key technologies to increase capitalization for energy generation companies, *Source:* Accenture Research (2019)

These technologies seem to comprise the essence of analytics application, hence, we decided to choose these 4 components as independent variables. Questioning firms' managers and consulting their websites we have assessed if mentioned technologies were present in 2019 (Answer "Yes' – 1, answer "No" – 0), did they appeared in 2020 and if so, what impact they would possibly have. All information about the variables is summarized in Table 2.

Table 2

Description of the variables

Name of the variable	Short form	Type	Format and possible value range	Source
Net income	NI	Endogenous	Millions of rubles	Financial statements
Robotization	R	Exogenous	No = 0; Yes = 1	Annual reports
Usage of digital body doubles	D	Exogenous	No = 0; Yes = 1	Annual reports
AR/VR	V	Exogenous	No = 0; Yes = 1	Annual reports
Artificial intelligence	AI	Exogenous	No = 0; Yes = 1	Annual reports
Big Data	BD	Exogenous	No = 0; Yes = 1	Websites

Source: Own elaboration

4.2. Description of the model

In accordance with investigated literature and our own research the null hypothesis may be written as follows:

H_0. There is no statistically significant relationship between net income of the generation company and the implementation of four elements of data analytics: robotization, digital body doubles, artificial intelligence, and big data.

If this hypothesis is proved to be wrong using the significance level of 90% that we have chosen, the alternative hypothesis should be accepted:

H_1. There is statistically significant relationship between net income of the energy generation company and the introduction of four elements of data analytics.

To test these hypotheses, we constructed in the following model:

$$\begin{cases} NI_t = \alpha_0 + \alpha_1 \cdot R_t + \alpha_2 \cdot D_t + \alpha_3 \cdot V_t + \alpha_4 \cdot AI_t + \alpha_5 \cdot BD_t + \varepsilon_t \\ E(\varepsilon_t) = 0 \\ \sigma(\varepsilon_t) = const \end{cases}$$

Where $\alpha_0, \alpha_1, \ldots\ \alpha_5$ are the parameters; ε_t is error; $E(\varepsilon_t)$ is mathematical expectation; $\sigma(\varepsilon_t)$ is a variance of random deviation.

4.3. Results

Table 3 presents the means, standard deviations values of exogenous variables of the model.

Table 3

Descriptive statistics

	2019		2020	
	Std. dev	*Mean*	*Std. dev*	*Mean*
Robotization	0.4880	0.33	0.5071	0.6000
Usage of digital body doubles	0	0	0.4577	0.2667
AR/VR	0	0	0.4577	0.2667
Artificial Intelligence	0.5071	0.4000	0.5071	0.4000
Big data	0.4577	0.7333	0.4577	0.7333
R^2	0.7962		0.8294	

Source: Own elaboration

At first, it is necessary to look at the R^2 to assess the overall quality of the model and its reliability, it is not high in both cases – 0.7962 in 2019 and 0.8294 – in 2020, but still may be accepted. F calculated is greater than F-critical, meaning R^2 is non-random, and the quality of model specification is high.

For 2019 we resulted in the following system:

$$\begin{cases} NI_t = 4{,}282{,}377 + 188.39 \cdot R_t + 0 \cdot D_t + 0 \cdot V_t + 15.38 \cdot AI_t + 49.07 \cdot BD_t + \varepsilon_{1_t} \\ \quad (15{,}713{,}169) \qquad (1723) \qquad (0) \qquad (0) \quad (19.02) \qquad (20.29) \quad (3{,}021.25) \\ R^2 = 0.7962 \end{cases}$$

In 2019 p-values of the variables are statistically nonsignificant (p-values > .1), thus, there is strong evidence for the null hypothesis, meaning the correlation between net income and data analysis technologies in case of Russian generation companies does not exist with a probability of 90%. Then we ran regression analysis again using changed data sample, as some companies have introduced new tools of data analytics, to check whether this change influences net profit of given companies. For 2020 the model obtained the following form:

$$\begin{cases} NI_t = 6{,}662{,}481 + 95.43 \cdot R_t + 1.74 \cdot D_t + 1.19 \cdot V_t + 39.22 \cdot AI_t \\ \qquad - 152.35 \cdot BD_t + \varepsilon_{1_t} \\ (14{,}829{,}672) \; (187.34) \; (1.87) \; (2.11) \; (19.38) \; (212) \; (28{,}141) \\ R^2 = 0.8294 \end{cases}$$

Judging by the p-values received in the regression analysis process Robotization, Big data and Artificial Intelligence appeared to be significant for the model whereas usage of digital body doubles and alternative reality if introduced in 2020 still did not influence the dependent variable which is net income. It is hard to say for certain what is the result of hypothesis testing but most likely the null hypothesis is rejected, and the alternative hypothesis should be accepted assuming there is a relationship between data analysis tools and net profit of the generation companies in Russia.

Table 4

Levels of statistical significance

p-value	Robotization	Usage of digital body doubles	AR/VR	Artificial Intelligence	Big data
2019	.3045	-	-	-	.8143
2020	.0723	.3769	.5851	.08442	.0991

Source: Own elaboration

Apart from the quality of the model we were interested in the reduction of p-value over time (Table 4) that occurs due to the introduction of the data analysis components in some companies which will prove the relationship between these components and net income exists. Yet it seems to be indirect for it has a small influence on the results of significance testing. Moreover, such components as usage of digital body doubles and AR/VR could be excluded from the model as they appear to be insignificant at all. Nevertheless, p-values of other elements have decreased indeed meaning that the effect of data analysis tools application on net income of considered companies strengthens, which could be considered as a positive output of this research.

5. Conclusions

5.1 Practical implications

The results of this research show that data analytics application in Russia currently have only an indirect effect on the operational results of energy generation companies, but the positive trend is observed so in the nearest future it may significantly affect the profits of firms and for sure contribute to their competitiveness.

Though in practice not all technologies at a firm's disposal are related to its current line of a business (which is proven 2 components in our model appearing to be unimportant), benefits data analysis may bring to a company in the energy sector outweigh possible drawbacks mentioned in first 2 sections and show that the development of analytics tools is crucial for firms that seek to be successful.

Basing on our research we would advise companies of the considered sector to apply such technologies as robotization, data mining and data management schemes that comprise big data and artificial intelligence. All these, if it does not affect the financial results of the company positively, will improve the automatization of the daily processes, understanding of the environment and help make business decisions.

5.2 Limitations and suggestions for further studies

This research study has some limitations that should be mentioned. First, as noted already the sample is too small and data used to test the research hypotheses is self-reported. Even though considerable efforts were undertaken to confirm data quality, the potential of biases cannot be excluded. Secondly, it was hard to find the information about the investment into data analysis tools in financial statements of the businesses and the exact time when this tool was brought into. Hence, future studies should focus on expanding the data sample with other companies, substituting some variables in the model (AR/VR, digital body doubles) to increase its accuracy. Avoiding bias caused by inability to verify information given on firms' websites is also essential for improvement of the overall quality of the work.

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Сведения об авторах / About authors

Смирнов Валерий Валерьевич, кандидат экономических наук, доцент кафедры КПМГ, Финансовый университет при Правительстве Российской Федерации. 125167 Россия, Москва, Ленинградский проспект, 49. *E-mail: VSmirnov@fa.ru*
Valery V. Smirnov, Candidate of Economic Sciences, Associate Professor of the KPMG Department, Financial University under the Government of the Russian Federation. 125167 Russia, Moscow, Leningradsky prospect, 49. *E-mail: VSmirnov@fa.ru*

Петрова Арина, студент, Финансовый университет при Правительстве Российской Федерации. 125167 Россия, Москва, Ленинградский проспект, 49.
Arina Petrova, Student, Financial University under the Government of the Russian Federation. 125167 Russia, Moscow, Leningradsky prospect, 49.

Адрес сайта в сети интернет: http://jem.dvfu.ru