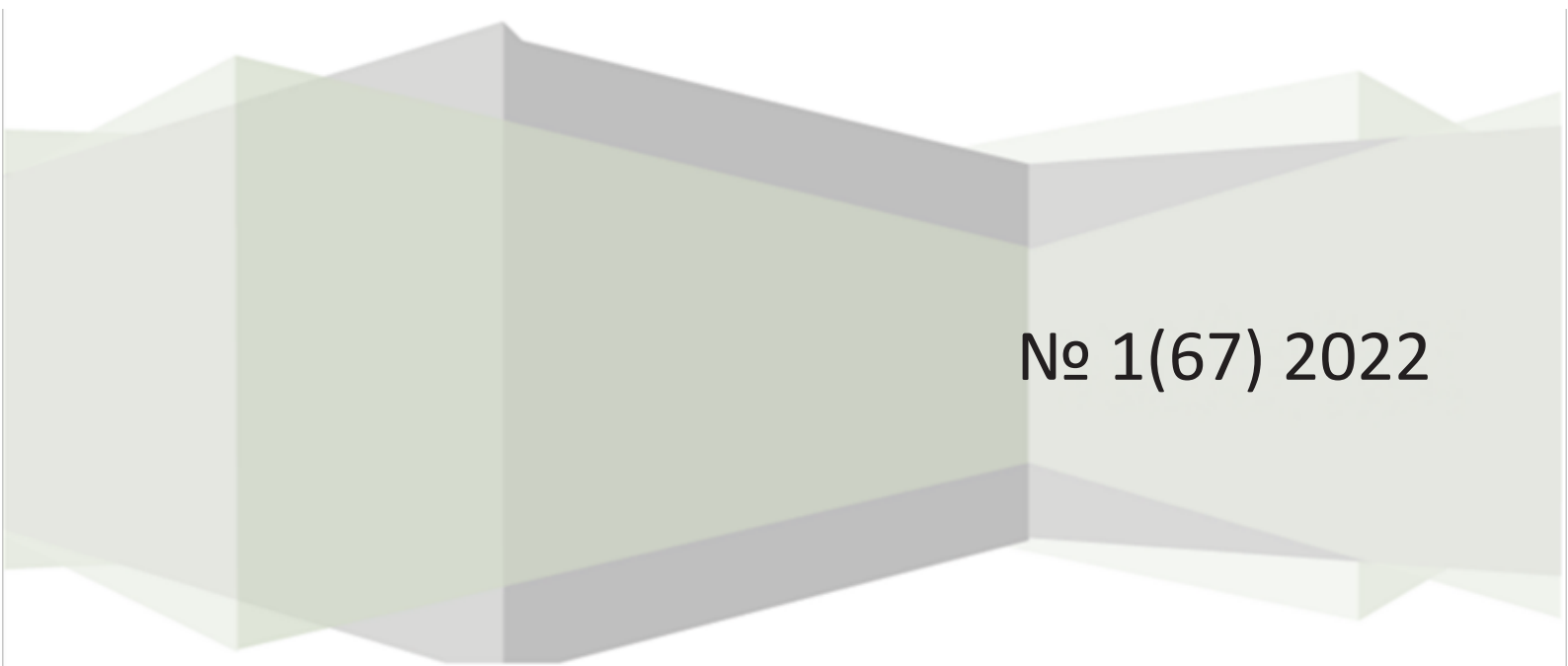


ISSN 1997-9347

# Components of Scientific and Technological Progress

*SCIENTIFIC AND PRACTICAL JOURNAL*



No 1(67) 2022

Paphos, Cyprus, 2022

Journal "Components  
of Scientific and Technological  
Progress"  
is published 12 times a year

**Founder**  
Development Fund for Science  
and Culture  
Scientific news of Cyprus LTD

The journal "Components of Scientific  
and Technological Progress" is included  
in the list of HAC leading peer-reviewed  
scientific journals and publications  
in which the main scientific results  
of the dissertation for the degree  
of doctor and candidate of sciences  
should be published

**Chief editor**  
Vyacheslav Tyutyunnik

**Page planner:**  
Marina Karina

**Copy editor:**  
Natalia Gunina

**Director of public relations:**  
Ellada Karakasidou

**Postal address:**  
**1. In Cyprus:**  
8046 Atalanta court, 302  
Paphos, Cyprus  
**2. In Russia:**  
13 Shpalernaya St,  
St. Petersburg, Russia

**Contact phone:**  
(+357)99-740-463  
8(915)678-88-44

**E-mail:**  
tmbprint@mail.ru

Subscription index of Agency  
"Rospechat" No 70728  
for periodicals.

Information about published  
articles is regularly provided to  
**Russian Science Citation Index**  
(Contract No 124-04/2011R).

**Website:**  
<http://moofrnk.com/>

Editorial opinion may be different  
from the views of the authors.  
Please, request the editors'  
permission to reproduce  
the content published in the journal.

## ADVISORY COUNCIL

**Tyutyunnik Vyacheslav Mikhailovich** – Doctor of Technical  
Sciences, Candidate of Chemical Sciences, Professor, Director of  
Tambov branch of Moscow State University of Culture and Arts,  
President of the International Information Center for Nobel Prize,  
Academy of Natural Sciences, tel.: 8(4752)504600,  
E-mail: vmt@tmb.ru, Tambov (Russia)

**Bednarzhevsky Sergey Stanislavovich** – Doctor of Technical  
Sciences, Professor, Head of Department of Safety, Surgut State  
University, laureate of State Prize in Science and Technology,  
Academy of Natural Sciences and the International Energy Academy,  
tel.: 8(3462)762812, E-mail: sbed@mail.ru, Russia

**Voronkova Olga Vasilyevna** – Doctor of Economics, Professor,  
Academy of the Academy of Natural Sciences, tel.: 8(981)9720993,  
E-mail: voronkova@tambov-konfcentr.ru, St. Petersburg (Russia)

**Omar Larouk** – PhD, Associate Professor, National School  
of Information Science and Libraries University of Lyon,  
tel.: +0472444374, E-mail: omar.larouk@enssib.fr, Lyon (France)

**Wu Songjie** – PhD in Economics, Shandong Normal University,  
tel.: +86(130)21696101; E-mail: qdwucong@hotmail.com,  
Shandong (China)

**Du Kun** – PhD in Economics, Associate Professor, Department of  
Management and Agriculture, Institute of Cooperation of Qingdao  
Agrarian University, tel.: 8(960)6671587,  
E-mail: tambovdu@hotmail.com, Qingdao (China)

**Andreas Kyriakos Georgiou** – Lecturer in Accounting, Department of  
Business, Accounting & Finance, Frederick University,  
tel.: (00357) 99459477 E-mail: bus.akg@frederick.ac.cy, Limassol  
(Cyprus)

**Petia Tanova** – Associate Professor in Economics, Vice-Dean of  
School of Business and Law, Frederick University,  
tel.: (00357)96490221, E-mail: ptanova@gmail.com, Limassol  
(Cyprus)

**Sanjay Yadav** – Doctor of Philology, Doctor of Political Sciences,  
Head of Department of English, Chairman St. Palus College Science,  
tel.: 8(964)1304135, Patna, Bihar (India)

**Levanova Elena Alexandrovna** – Doctor of Education, Professor,  
Department of Social Pedagogy and Psychology, Dean of the Faculty  
of retraining for Applied Psychology, Dean of the Faculty of Pedagogy

and Psychology of the Moscow Social and Pedagogical Institute; tel.: 8(495)6074186, 8(495)6074513; E-mail: dekanmospi@mail.ru, Moscow (Russia)

**Petrenko Sergey Vladimirovich** – Doctor of Technical Sciences, Professor, Head of Department of Mathematical Methods in Economics, Lipetsk State Pedagogical University, tel.: 8(4742)328436, 8(4742)221983, E-mail: viola@lipetsk.ru, viola349650@yandex.ru, Lipetsk (Russia)

**Tarando Elena Evgenievna** – Doctor of Economics, Professor of the Department of Economic Sociology, St. Petersburg State University, tel.: 8(812)2749706, E-mail: elena.tarando@mail.ru, St. Petersburg (Russia)

**Veress József** – PhD, Researcher in Information Systems Department, Business School of Corvinus University, tel.: 36 303206350, 36 1 482 742; E-mail: jozsef.veress@uni-corvinus.hu, Budapest (Hungary)

**Kochetkova Alexandra Igorevna** – Doctor of Philosophy and Cultural Studies (degree in organizational development and organizational behavior), PhD, Professor, Department of General and Strategic Management Institute of Business Administration of the Russian Academy of National Economy and Public Administration under the President of the Russian Federation, E-mail: dak6966@gmail.com, Moscow (Russia)

**Bolshakov Sergey Nikolaevich** – Doctor of Political Sciences, Doctor of Economics, Vice-Rector for Academic Affairs, Professor, Syktyvkar State University named after Pitirim Sorokin, tel.: 8(921)6334832, E-mail: snbolshakov@mail.ru, Syktyvkar (Russia)

**Gocłowska-Bolek Joanna** – Center for Political Analysis, University of Warsaw, tel. 48691445777, E-mail: j.gocłowska-bolek@uw.edu.pl, Warsaw (Poland)

**Karakasidou Ellada** – A&G, Kotanides LTD, Logistic, tel.: +99346270, E-mail: espavoellada9@gmail.com, Paphos (Cyprus)

**Artyukh Angelika Alexandrovna** – Doctor of Art History, Professor of the Department of Dramatic and Cinema Studies, St. Petersburg State University of Cinema and Television; tel.: +7(911)9250031; E-mail: s-melnikova@list.ru, St. Petersburg (Russia)

**Melnikova Svetlana Ivanovna** – Doctor of Art History, Professor, Head of the Department of Dramatic Art and Cinema Studies at the Screen Arts Institute of St. Petersburg State University of Cinema and Television; tel.: +7(911)9250031; E-mail: s-melnikova@list.ru, St. Petersburg (Russia)

**Marijan Cingula** – Tenured Professor, University of Zagreb, Faculty of Economics and Business, tel.: +385(95)1998925, E-mail: mcingula@efzg.hr, Zagreb (Croatia)

**Pukharenko Yury Vladimirovich** – Doctor of Technical Sciences, Professor, Head of the Department of Building Materials Technology and Metrology at St. Petersburg State University of Architecture and Civil Engineering, Corresponding Member of the Russian Academy of Architecture and Construction Sciences; tel.: +7(921)3245908; E-mail: tsik@spbgasu.ru, St. Petersburg (Russia)

**Przygoda Mirosław** – Dr. hab., Head of Institute of Economic Analysis and Planning, Department of Management, University of Warsaw, tel.: 225534167, E-mail: mirosławprzygoda@wp.pl, Warsaw (Poland)

**Recker Nicholas** – PhD, Associate Professor, Metropolitan State University of Denver, tel.: 3035563167, E-mail: nrecker@msudenver.edu, Denver (USA)

## Contents

### *Engineering*

- Maltsev M.V., Lobacheva N.N.** Laboratory-Scaleplant for Gases Wet Cleaningprocess  
Demonstration and Study ..... 5

### *Information Science*

- Albojwaid Dhurgham Abbas Mohsin** An Analytical Survey of Deep Learning Research  
Using Symbolic Mathematics..... 9

### *Economic Sciences*

- Nechaev K.A., Orlov M.A., Ivanov N.A.** Statistical Properties of PRNG-Algorithms ..... 18  
**Sharonova K.A.** Comparative Analysis of German and Russian Budgetary Systems.... 23  
**Voronkova O.V.** The Impact of the Pandemic on Macroeconomic Indicators ..... 27

## Содержание

### *Машиностроение*

- Мальцев М.В., Лобачева Н.Н.** Лабораторная установка для демонстрации и изучения  
процесса мокрой очистки газов ..... 5

### *Информационные технологии*

- Албоджваид Дхургхам Аббас Мохсин** Аналитический обзор исследований глубокого  
обучения с использованием символьной математики..... 9

### *Экономические науки*

- Нечаев К.А., Орлов М.А., Иванов Н.А.** Статистические свойства алгоритмов генера-  
торов псевдослучайных чисел ..... 18  
**Шаронова К.А.** Сравнительная характеристика бюджетных систем Германии и  
России ..... 23  
**Воронкова О.В.** Влияние пандемии на макроэкономические показатели ..... 27

UDK 66-5

## Laboratory Scale Plant for Demonstration and Study of the Process of Gas Wet Cleaning

M.V. Maltsev, N.N. Lobacheva

*Voronezh State University of Engineering Technologies,  
Voronezh (Russia)*

**Key words and phrases:** gases wet cleaning; laboratory scale plant; liquid film.

**Abstract.** The aim of the study was to create a laboratory scale plant for demonstration and research of gases wet cleaning process by students and carrying out laboratory work to study the dependence of gas cleaning degree on the operating modes of the above mentioned plant switchgears. The following tasks were completed to achieve the goal: the existing designs of laboratory scale plants of a similar purpose were examined and analyzed; the original design of the plant was proposed. The result of the study was the creation of the laboratory scale plant and its testing.

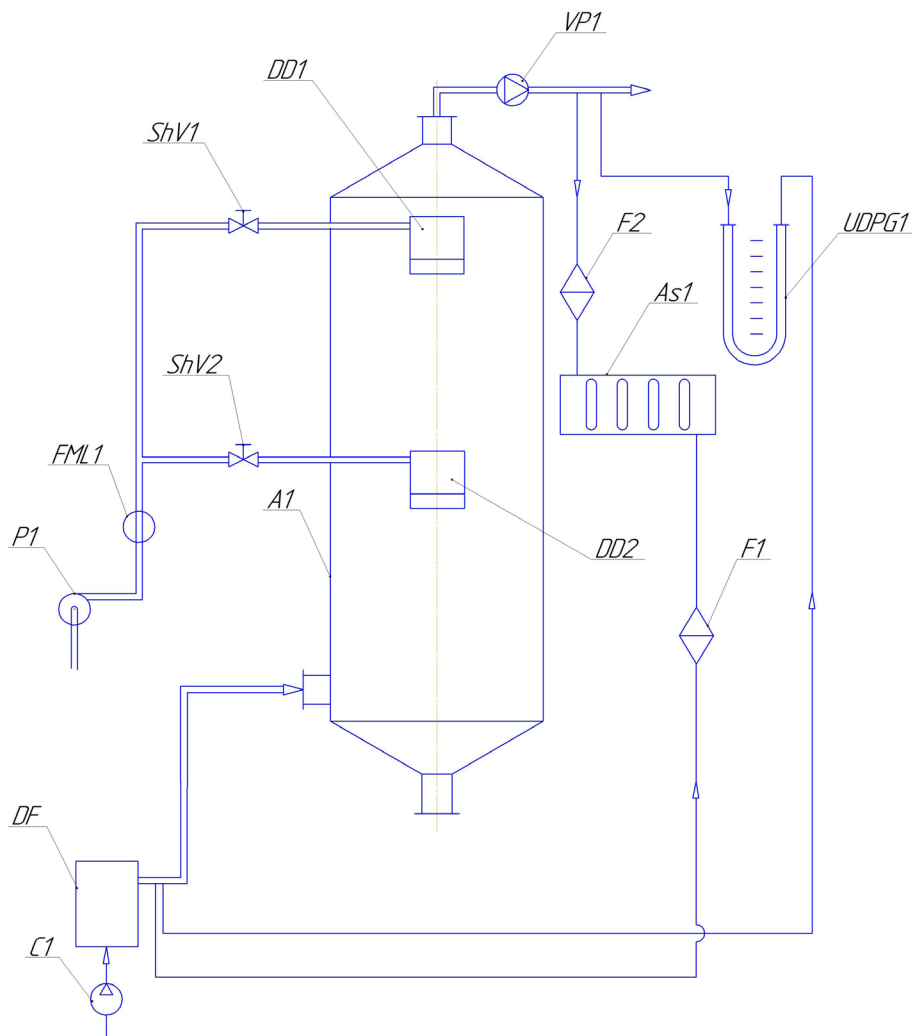
Industrial gas emissions are usually complex dispersed systems (aerosols), in which the continuous medium is a mixture of various gases, and suspended solid or liquid particles have different sizes and complex chemical composition.

The choice of apparatus for trapping suspended particles from gas and its calculation are carried according to physicochemical characteristics of the particles and the gas flow. The main characteristics of suspended particles are as follows: true and bulk density, dispersion, adhesive and abrasive properties, hygroscopicity and solubility, particles electrical charge, the ability of aerosols to spontaneous combustion and the formation of explosive mixtures with air. The main parameters of a dusty gas flow are: volumetric and mass flow, dust content, temperature, pressure and humidity.

The essence of wet dust collection is the deposition of solid particles from a hot gas stream on the surface of a liquid film. Cleaning is carried out due to the simultaneous action of two factors: particles trapping by a liquid film flowing down in a uniform layer along the apparatus walls; particles collecting in the collision of air and liquid flows. Purified hot gas can be used as a heat carrier [1].

The gas flow is tangentially fed into the apparatus. Larger particles are thrown to the walls of the apparatus and captured by the liquid film under the action of centrifugal forces, while the remaining particles are trapped as a result of inertial capture by the spatial liquid film. The speed of the particles must be high enough to overcome the resistance of the liquid after penetration into the film. The film thickness must be commensurate with the particle size.

The experimental plant consists of the following units: the main apparatus for wet air purification A1; vacuum pump VP1; dust feeder DF; pump P1; shut-off valves ShV1, ShV2;



**Fig. 1.** The experimental plant diagram

compressor C1; flow meter for liquid FML1; aspirator As1; filters F1 and F2; U-shaped differential pressure gauge UDPG1.

The gas cleaning apparatus A1 contains a cylindrical shell, consisting of glass inserts for the process visual viewing and steel sides, conical bottom and covers. Liquid distribution devices DD1 and DD2 are located inside the apparatus. One distributor is located in its upper part, and the other one is in the middle along the central axis of the apparatus. The plant provides for a tangential input of dusty gas. The liquid outlet is located at the bottom. The liquid distributor is an assembly unit. It consists of a cylindrical body with a flat-welded cover, on which a flexible cylindrical shell is fixed. The diaphragm providing a closed circuit with a flexible shell at a pressure less than or equal to the external one is located inside the sprinkler. Its shape is made in such a way as to direct the liquid jet to the apparatus walls. The diaphragm is rigidly welded to the switchgear cover.

Dust feeder DF1 is a cylindrical tank with branch pipes for air supply and exhaust. The grate, with which the dust is captured and does not spill, is fixed inside the container. Compressor C1 is attached to the bottom of the tank.

The main pipeline is brought to the inlet pipe of the apparatus A1 from the dust feeder.



**Fig. 2.** The experimental plant

Hoses for sensors: for aspirator As1; for filter F1 are connected to it. The filter is based on the principle of passing of certain air volume through an AFA paper filter.

The liquid flow meter LFM1 is built into the pipeline directly after the pump P1. The pipeline branches out and joins the switchgears. Shut-off valves ShV1, ShV2 and pressure gauges PG1, PG2 are built into each branch. The pipeline is brought to the outlet from the apparatus A1 and connected to the above mentioned aspirator As1. The filter F2 is built into it. Parallel to the hose leading to the aspirator As1, a hose is drawn leading to the U-shaped differential pressure gauge UDPG1.

The plant works as follows.

The dust with a known dispersion is in the dust feeder DF1. The dust is picked up by the flow and carried away into the apparatus under the influence of air pumped by compressor C1, passing through the dust feeder. The dust-laden air flow is directed tangentially through the inlet pipe into the apparatus A1, twisted and, is cleaned of dust in contact with the liquid film. Particles that are not captured by the liquid film flowing down the walls of the apparatus settle in the dome of the jet issued by the distributing device. Then the purified air is sent to the atmosphere through the outlet pipe. The vacuum pump VP1 is connected to it with an air flow rate  $QG = 0.4 \text{ m}^3/\text{s}$ .

The liquid fed by the pump P1 goes to the switchgears in the apparatus A1. The inclusion of one or two switchgears in the circuit is regulated by shut-off valves ShV1 and ShV2. Three types of liquid outflow from the liquid distributor are taken into account: jet-drip; unstable curtain; stable curtain. The studies were carried out when the upper switchgear was turned on and the lower switchgear was turned off, when the upper switchgear was turned off and the lower switchgear

was turned on and when the upper and lower switchgears were turned on at the same time. The liquid flow rate was determined through the lower fitting of the apparatus. The intake of purified air from the apparatus was carried out with the vacuum pump VP1 through the upper fitting of the gas cleaning apparatus.

The cleaning efficiency is determined as follows.

Aspirator C1 takes a certain and equal volume of air from the air inlet and outlet through hoses. Cases for replaceable filters F1 and F2, through which the air flow taken by the aspirator C1 passes, are mounted in hoses. AFA paper filters weighed in advance on an analytical balance are inserted into the housings for each experiment. The filters are again weighed on an analytical balance after the experiment. After that, the mass of dust laid-down on the filters is calculated. The cleaning efficiency of the A1 apparatus is calculated from this data.

U-shaped differential pressure gauge UDPG1, which allows measuring the apparatus A1 resistance, i.e. the pressure drop of the air flow at the inlet to apparatus A1 and at the outlet of it, is used to measure the apparatus resistance.

RF patent No. 2380141 "Gas cleaning apparatus" was received according to the number of solutions used in this plant.

### References

1. Panov, S.YU. Povyshenie effektivnosti apparata raspylitel'nogo tipa pri reshenii problem promyshlennoj ekologii / S.YU. Panov, M. KHimvinga, A.V. Zinkovskij // Vestnik VGUIT. – 2014. – № 1. – S. 160–164.

---

### Лабораторная установка для демонстрации и изучения процесса мокрой очистки газов

М.В. Мальцев, Н.Н. Лобачева

*ФГБОУ ВО «Воронежский государственный университет инженерных технологий»,  
г. Воронеж (Россия)*

**Ключевые слова и фразы:** лабораторная установка; мокрая очистка газов; пленка жидкости.

**Аннотация.** Цель – описать создание лабораторной установки для демонстрации и изучения процесса мокрой очистки газов студентами, проведения лабораторных работ по изучению зависимости степени очистки газов от режимов работы распределительных устройств установки. Для достижения поставленной цели были решены следующие задачи: изучены и проанализированы существующие конструкции лабораторных установок аналогичного назначения; предложена оригинальная конструкция установки. В результате работы была создана установка, проведена ее апробация.

---

© M.V. Maltsev, N.N. Lobacheva, 2022



UDK 004

# An Analytical Survey of Deep Learning Research Using Symbolic Mathematics

Albojwaid Dhurgham Abbas Mohsin

*South Ural State University, Chelyabinsk (Russia)*

**Key words and phrases:** deep learning; neural network; symbolic integration; symbolic mathematics.

**Abstract.** Whenever we apply a neural network in symbolic mathematics (in symbolic integration and solving differential equations), it typically produces solutions that are not easily explicable. Thus, we study the methods of generating expressions for symbolic mathematics as well as deep learning training methods. Furthermore, we analyze the use of symbolic techniques in deep learning, which makes it amenable to development and designing clear structures to teach the system to promptly find solutions to the integration of symbolic solving differential equations.

## Introduction

Despite their unpretentious appearances differential equations and integrations are often complex. The recent advancements in machine learning and deep learning, in particular, have made it easier to manage problems and find solutions that previously seemed unsolvable. Perhaps, it was the success of the neural network with its unique approach that prevented the use of deep learning in solving equations and symbolic integration. The recent research paper Simple and Charlton 2019 Deep Learning Solutions to Symbolic Mathematics provides an essential and rare contribution to the usage of methods in deep learning and the solution of differential equations and symbolic integration. Regrettably, deep learning is relatively underdeveloped to solve this mathematical notation. In this work, we present a study for generating symbolic solutions to differential and integral equations, in which we exploit the flexibility of deep learning through the power of its training to provide these solutions.

Furthermore, we study the proposals through seq2seq models representing mathematical expressions in symbolic integration to find solutions for differential equations and problems. We discuss the size and structure of the resulting problem space and explain how to create supervised learning datasets for first- and second-order differential equations.

## 1. Overview of deep learning

### 1.1 Deep learning

In recent years, artificial neural networks and machine learning (including recursive networks) have won many competitions in “machine learning and deep learning” pattern recognition. Learning can be unsupervised, partially supervised, or supervised. In many fields

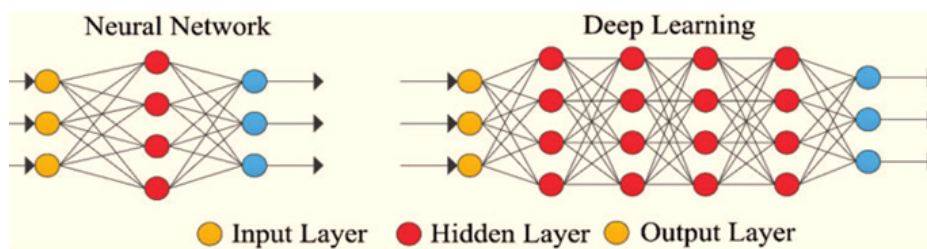


Fig. 1. Deep learning algorithm

such as machine translation, natural language processing, data analysis and processing, natural language processing, and medicine, deep learning architectures, such as deep belief neural networks and recurrent neural networks, have been applied. Programs for data analysis, imagery, and material validation have yielded results and, in some cases, exceed the capabilities of experts [1–3]. Deep structures consist of several levels of nonlinear operations, for example, in neural networks with lots of hidden layers or in complex proposed formulas that reuse many sub formats. Research dealing in parameter space for deep learning structures is complex. However, learning algorithms such as those of Deep Belief networks have been proposed to solve this problem with remarkable success, bypassing current developments in certain areas.

Fig. 1 shows the deep learning algorithm.

## 1.2 Deep learning architecture

Deep learning methods aim to reach goals through function hierarchies, from higher to lower levels, formed through function formation. Automatic job learning produces many inputs and outputs mapping levels without relying entirely on handmade jobs sourced directly from the data. People sometimes are unaware of how to explicitly define their path in terms of raw sensory inputs and outputs, especially when it comes to high-level abstractions. With the growth of data volumes, suites of applications, and software for machine learning technologies, the ability to automatically learn powerful features is becoming more and more crucial. Deep learning of the structure refers to a set of formation levels of non-linear operations in the acquired function. While most new learning algorithms agree with superficial structures (levels 1, 2, or 3), the mammalian brain is arranged in a deep learning architecture. It has a given input perception represented on the set of levels of abstraction, each level corresponding to a different region of the cerebral cortex. Often people describe these concepts in hierarchical ways from top to bottom with multiple levels of abstraction. It also appears that the human brain processes information through many stages of transformation and presentation. Inspired by the architectural depth of the human brain, neural network researchers have attempted to train multi-layer deep neural networks for decades [4; 5]. However, attempts were unsuccessful until 2006: the researchers reported positive experimental results. These were two or three levels (e.g., one or two hidden layers), frequently training deeper networks almost always yielded worse results. In 2006, something that could be considered a breakthrough happened: Hinton et al. at the University of Toronto introduced Deep Belief Networks (**DBN**) [6] with a learning algorithm that trains one level at one time. For each level, they provided an algorithm for unsupervised learning and used the Restricted Boltzmann Machine (**RBM**) [7]. Since that year, deep networks have proven successful in solving not solely classification problems but also those of regression, dimensionality reduction, texture modeling, and modeling motion. In this context, collaborative

filtering, robotics, object segmentation, and information retrieval are worth mentioning.

### 1.3 Symbolic mathematics with neural networks

Over seventy years ago, researchers in every field of AI research introduced neural networks as a revolutionary approach to understanding how the brain works. There are billions of networks in the human brain that connect neurons that process sensory information. The latter, in turn, allows people to learn from everyday experiences. In this regard, the neural network is also known for its ability to filter an enormous amount of data via connected layers to make predictions and differentiate patterns by following the rules they have learned. Nowadays, people regard neural networks as an artificial intelligence panacea capable of solving any technical problem. We consider it as a problem of pattern recognition. They can provide a natural language translation platform. Different photo applications exploit them to realize and differentiate duplicate faces in one's collection. In addition, programs that run on neural networks have beaten the world's top players at games such as go and chess. The neural networks have, however, always lagged in one notable area. An example for the latter includes solving complex symbolic math variable problems. These involve distinctive features of the mathematics courses that include both ordinary differential equations and integrals. In this regard, obstacles will generally arise from the root of the mathematics that necessitates precise solutions. For this, the neural networks solutions tend to excel at probability. Do they learn to recognize patterns, which Spanish translation sounds best, or how your face looks? And, as a result, they can create new ones. That changed at the end of last year. Then, two computer scientists, Guillaume Lamplais and François Charton, working for the Facebook artificial intelligence research group in Paris, presented a successful novel approach to address symbolic mathematical problems using neural networks. In its turn, their method employed neither numerical approximations nor calculations.

### 1.4 Computer training in mathematics

Numbers have always been easy for computers to calculate. Scores and even more algorithms are combined into predefined instructions in computer algebra systems. Typically, they are strict adherents of the rules. Simultaneously, no exceptions are allowed since they perform a specific operation. Their numerical solutions come close enough for engineering and physical applications for many symbolic problems. Neural networks function differently. It is not a rigid system. On the contrary, they use large datasets and statistics to calculate rather good approximations. In that case, there is no such thing as too much data. They determine which method is most effective as they go through the process. Programs that translate languages are unique in that they do not translate phrases literally but quite in the context of the whole text. According to Facebook researchers, this is a benefit when solving mathematical problems that rely on symbolic representations. As a result, the program can solve problems in its way. As mathematicians say, Differentiation is a mechanic, whereas integrating is an art. Therefore, finding a function's derivative is a straightforward process that requires just several defined steps. However, finding the integral will often require an intuitive approach rather than purely mathematical. Pattern recognition was suspected as a way to approximate this intuition at Facebook. Charton wrote, "Integration is a problem in mathematics that most closely resembles pattern recognition". Even though neural networks may not understand what functions and variables mean, they nevertheless form an instinct. Without understanding how it works, the

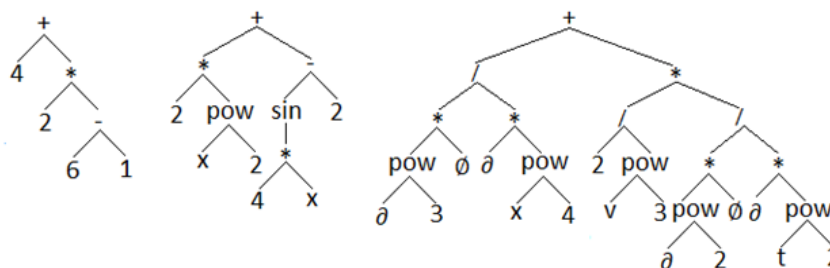


Fig. 2. Data Structures – Expression Tree

neural network becomes convinced it is working. For instance, a mathematician who needs to integrate an expression like  $yy' (y^2 + 1)^{-1/2}$  would instinctively believe the primitive, i.e., that expression differentiated to obtain an integral, to contain something like the square root of  $y^2 + 1$ . Charton and Lample commenced converting mathematical expressions into more usable forms so that the neural network could process symbols like mathematicians. As a result, they visualized them as trees in the form of diagrammatic phrases or statements. Adding, subtracting, multiplying, and dividing have become compounds in the tree.

### 1.5 Expression of the trees

The following mathematical expressions can be visualized as trees, functions as inner nodes with operators, variables as cards, numbers, constants, and operands as children.

$$4 + 2 \times (6 - 1), 2x^2 + \sin(4x) - 2, \frac{\partial^2 \emptyset}{\partial x^4} + \frac{2}{v} \frac{\partial^2 \emptyset}{\partial t^2}.$$

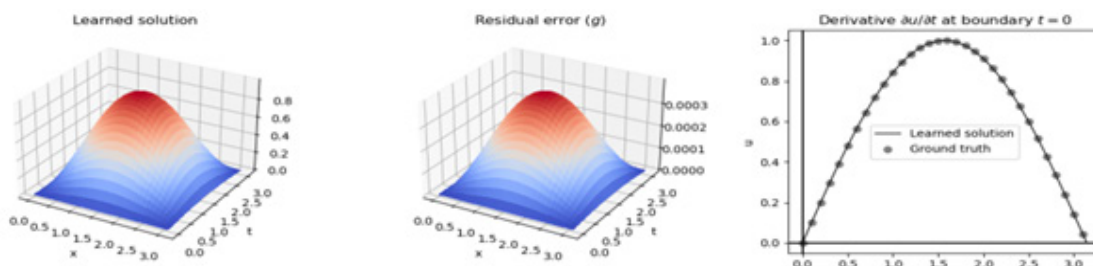
We consider mathematical symbols as expressions of sequences.  $1 + 4$  and  $4 + 1$  are different expressions. They are meaningful mathematical objects that represent most expressions. Mathematically, it is not necessarily logical.

Between the trees and expressions, there is a one-to-one match. Whereas, in the associated trees, the equality of expressions will be reflected as  $1 + 4 = 5 = 12 - 7 = 1 \times 5$ . These expressions are equivalent to the four corresponding trees.

We can reinterpret mathematical problems as operations on expressions or trees. For example, finding a shorter equivalent representation of the tree amounts to simplifying the expression. We consider two problems: solving differential equations and symbolic integration. Both come down to converting an expression into another, for example, mapping a tree of equations into a solution tree. We consider this a particular case of machine translation.

## 2. Deep learning with symbolic mathematics

Deep learning in the ancient tradition was based on statistical learning (Rumelhart et al., 1986). Besides, the neural network was at the end of its statistical development. In computer vision, the above authors achieve cutting-edge performance in an extensive spectrum of problems in statistical pattern recognition and natural language processing (NLP). However, networks in the symbolic computation are still considerably limited. Symbolic thinking has become a challenge to machine learning and persistent representations.



**Fig. 3.** The learned solution of the wave equation with residual error and boundary values

In their study titled “Symbolic solution of partial differential equations using deep learning” of November 16, 2020, the authors Maysum Panju, Kurosh Parand, and Ali Godsfi examine the neural method for generating explicit or approximate solutions of differential equations constituting math expressions.

The system they used returns symbolic forms which can be directly interpreted, unlike other neural methods. Their method optimizes user goals by using neural networks and mathematical expressions. Highly flexible, scalable, compact, and easily configurable, it is a perfect fit for a variety of tasks and configurations. The method is effective in finding the symbolic solutions to a wide range of differential equations with applications in natural sciences. As the authors demonstrate, their method can be used with partial differential equations in multiple variables as well as more complex boundary and seed conditions [8].

The authors start by telling the reader about the presented method for generating symbolic solutions to differential equations, which takes advantage of the flexibility and power of deep learning. Their method uses gradient-based backpropagation learning capabilities to provide symbolic solutions to differential equations which can be used and interpreted effortlessly and straight away. Based on the single variable model shown in [9], we focus on partial differential equations in multiple variables since these problems are more common and more complex than single-variable differential equations. We can, in fact, solve ordinary differential equations as a special case of our proposed method along with other symbolic mathematical problems such as integration, function inversion, and symbolic regression. As an added benefit, when their method cannot get an exact solution, including when a rudimentary solution doesn’t exist, it will return a symbolic function that approximates the proper solution rather than leaving you empty-handed:

$$L_2(f) = \sum_i \|f(x_i - y_i)\|^2.$$

Although neural networks do this naturally using backpropagation, it is not immediately clear how to perform this optimization for all symbolic functions. The motion of wave propagation in one spatial dimension in time can be modeled with a function  $u(x, t)$  that satisfies the PDE:

$$\frac{\partial^2 u}{\partial t^2}(x, t) = c^2 \frac{\partial^2 u}{\partial x^2}(x, t).$$

The article titled “Deep neural networks for handwritten mathematical character recognition on the Internet” was written by Hai Dai Nguyen, An Duc Le, and Masaki Nakagawa [10].

In this article, the author reviews a deep learning application that can recognize mathematical characters written by hand online. Several deep learning architectures have recently been

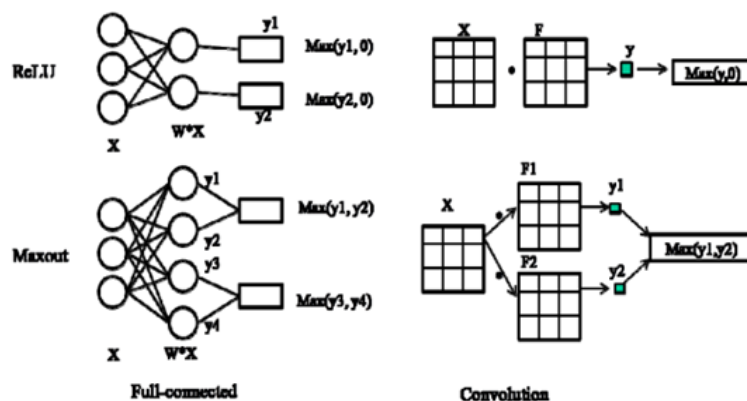


Fig. 4. The maxout layer diagram

applied in areas such as computer vision, speech recognition, and natural language processing, including deep neural networks (**DNN**), long short-term memory (**LSTM**), and convolutional neural networks (**CNN**). Our article applies CNN and BLSTM to a maximum number of image templates generated from online templates as well as original online templates with subsequent merging. The author compared them with MRF and MQDF, the traditional recognition methods. Furthermore, the author carried out several CROHME database experiments.

DMCN networks comprise a multiplicity of layers that launch activations by the Maxout function. As shown in Fig. 5, this function also aggregates the linear activations in the detection layer and transmits the greatest value in each group.

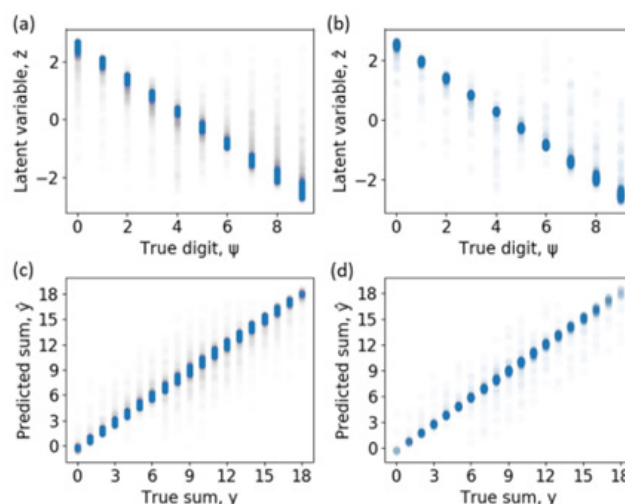
The author worked on the explored Deep Learning for handwritten mathematical character recognition online. Our CROHME database experiments have led us to the following conclusions.

- In contrast to MQDF, a deep neural network can extract broader yet specific features. The latter can contribute to the improvement of autonomous recognition of mathematical symbols.
- The advantage of BLSTM over MRF, as an online method, resides in the fact BLSTM can cater to the full context of an input sequence.
- The combination of interactive and offline recognition methods increases the classification efficiency by making the most of their advantages.

Samuel Kim, Peter Y. Lu, Srijon Mukherjee and Marin Solja wrote an article titled “Integration of Neural Network-Based Symbolic Regression in Deep Learning for Scientific Discovery” [11].

This article examines symbolic regression, one of the most powerful ways to uncover analytic equations related to specific patterns, potentially providing predictability and understanding of unseen data. Neural networks, on the other hand, achieve surprising levels of accuracy when processing NLP and image data. However, they are frequently viewed as black-box models with little ability to extrapolate. In this article, they use a neural network architecture with symbolic regression termed as the Equation Learning Network (**EQL**). Furthermore, the authors integrate it with alternative deep learning architectures which will allow the entire system to be trained using backpropagation.

Also, we note tremendous progress on developing neural network architectures that either provide for better interpretations or include inductive distortions more suitable for academic research. In search for mathematical expressions describing datasets, neural networks with specific activation functions were used to correspond to common scientific and technological functions [12; 13]. It was suggested that PDE-Net, a deep learning architecture, could be used



**Fig. 5.** Encoder's ability to distinguish between numbers

to predict the network as described by  $y = h_{L+1} = W_{L+1}h_L$ .

Fig 5 The encoder's ability to distinguish digits is evaluated by comparing the hidden variable  $z$  with the true digit  $\psi$  for the digits  $\chi$  sourced from the MNIST training dataset (a) and the test dataset (b). Coefficients of correlation are  $-0.985$  and  $-0.988$ , respectively. Based on the predicted sum  $\hat{y}$  vs. the true sum  $y$  for the digits  $\chi$  sourced from the MNIST training dataset (c) and test dataset (d), we can determine if the full architecture is able to match the label  $y$ .

Consequently, the authors demonstrated how symbolic regression could be integrated with deep learning architectures, allowing the entire system to be trained from start to finish employing the powerful deep learning methods developed in recent years. Specifically, their study shows that they can learn numeric arithmetic MNIST, which requires the system to learn to recognize images in an image recognition job while simultaneously finding a math expression that connects these numbers to the answer.

The article titled "Symbolic Techniques for Deep Learning: Challenges and Opportunities" is authored by Belinda Fang, Elaine Yang and Fei Xie [13].

Throughout this article, the authors focus on symbolic techniques along with various methods to build and implement neural networks. The author team explored Keras, MXNet, and TensorFlow that provided interfaces for symbolic programs and implementation. Deep learning efforts have focused on integrating symbolic and non-symbolic components due to the limitations of symbolic techniques. Hybridization, for instance, lets the Gluon API connect imperative programming to symbolic execution using Apache MXNet.

In addition, the author discusses the disadvantages of symbolic methods in that they do not function well for tree shapes, dynamic and recursive networks since the assembly forces the model to become static. Because neural networks do not lead to numerical computations, subsequently, generated graphs are implemented with separate functions. Comparatively to Python, users typically find prescriptive programming effortless to write and use. Using deep learning can be a better option for those who are new or who want to learn new ideas and become more experienced.

The following MXNet code examples demonstrate how a person unfamiliar with deep learning can feel more comfortable dealing with a deterministic program over a token.

The required version is more concise and readable, whereas the developers of the symbolic

Imperative programming (NDArray API)	Symbolic programming (Symbol API)
<pre> 1 import mxnet.ndarray as nd 2 a = nd.ones((4, 4)) 3 b = nd.ones((4, 4)) 4 c = a + b 5 print (c.asnumpy ()) </pre>	<pre> 1 import mxnet.sym as sym 2 import numpy as np 3 a = sym.Variable ('a', shape=(4, 4)) 4 b = sym.Variable ('b', shape=(4, 4)) 5 c = a + b 6 exe = c.simple_bind(ctx=mx.cpu()) 7 exe.forward(a=np.ones((4, 4))) 8 print(exe.outputs[0].asnumpy()) </pre>

**Fig. 6.** A side-by-side comparison of an imperative and symbolic program in MXNet

version have to do additional work to compile the port (line 6) and subsequently run it (line 7). Understanding the advantages and disadvantages of deep learning frameworks can be accomplished by considering and modifying particular symbolic techniques resulting in the most efficient use of and adaptations to them.

### Conclusion

The purpose of the research was to review the existing methods for symbolic solving of partial differential equations as well as symbolic integration over many variables using deep learning techniques.

According to current research on deep learning techniques, datasets trained with this simple transformer model are capable of performing very well in symbolic integration of computing functions, as well as solving differential equations.

However, they outperform the advanced mathematical frameworks like Mathematica or Matlab that rest on numerous algorithms and heuristics. Deep learning has demonstrated its capability and potential. Although the symbolic function learner is multivariate, it seeks to improve symbolic functions with all algorithms. The major search space problem poses a great challenge to contemporary researchers. Hopefully, symbolic mathematics will benefit from more deep learning applications entering the market, which will undoubtedly be a positive step in that direction.

### References

1. Schmidhuber, J. Deep Learning in Neural Networks: An Overview / J. Schmidhuber // *Neural Networks*. – 2015. – Vol. 61. – P. 85–117.
2. Bengio, Y. Deep Learning / Y. Bengio, Y. LeCun, G. Hinton // *Nature*. – 2015. – Vol. 521(7553). – P. 436–444. – DOI: 10.1038/nature14539.
3. Hu, J. Voronoi-Based Multi-Robot Autonomous Exploration in Unknown Environments via Deep Reinforcement Learning / J. Hu, H. Niu, J. Carrasco, B. Lennox, F. Arvin // *IEEE Transactions on Vehicular Technology*. – 2020. – Vol. 69(12). – P. 14413–14423. – DOI: 10.1109/TVT.2020.3034800.
4. Bengio, Y. Scaling learning algorithms towards AI / Y. Bengio and Y. LeCun; eds. L. Bottou, O. Chapelle, D. DeCoste, J. Weston // *Large Scale Kernel Machines*. – MIT Press, 2007.
5. Utgoff, P.E. Many-layered learning / P.E. Utgoff, D.J. Straczuzi // *Neural Computation*. – 2002. – Vol. 14. – P. 2497–2539.



6. Hinton, G.E. A fast learning algorithm for deep belief nets / G.E. Hinton, S. Osindero, Y. Teh // *Neural Computation*. – 2006. – Vol. 18. – P. 1527–1554.
7. Freund, Y. Unsupervised learning of distributions on binary vectors using two layer networks / Y. Freund, D. Haussler. – Technical Report UCSC-CRL-94-25, University of California, Santa Cruz, 1994.
8. Panju, M. Symbolically Solving Partial Differential Equations using Deep Learning / M. Panju, K. Parand, A. Ghodsi, 2020.
9. Panju, M. A neuro-symbolic method for solving differential and functional equations / M. Panju, A. Ghodsi, 2020.
10. Martius, G. Extrapolation and learning equations / G. Martius, C.H. Lampert, 2016 [Electronic resource]. – Access mode : <http://arxiv.org/abs/1610.02995>.
11. Sahoo, S.S. Learning equations for extrapolation and control / S.S. Sahoo, C.H. Lampert, G. Martius, 2018 [Electronic resource]. – Access mode : <http://arxiv.org/abs/1806.07259>.
12. Choromanska, A. The loss surfaces of multilayer networks / A. Choromanska, M. Henaff, M. Mathieu, G.B. Arous, Y. LeCun // *Journal of Machine Learning Research*. – 2015. – Vol. 38. – P. 192–204.
13. Fang, B. Symbolic Techniques for Deep Learning: Challenges and Opportunities / B. Fang, E. Yang, F. Xie, 2020.

---

### Аналитический обзор технологий глубокого обучения с использованием символьной математики

Албоджваид Дхурghам Аббас Мохсин

ФГАОУ ВО «Южно-Уральский государственный университет»,  
г. Челябинск (Россия)

**Ключевые слова и фразы:** слова: нейронная сеть, символьная математика, символьная интеграция, глубокое обучение.

**Аннотация.** Всякий раз, когда мы применяем нейронную сеть в символьной математике (при символьном интегрировании и решении дифференциальных уравнений), она обычно дает решения, которые нелегко объяснить. Таким образом, мы изучаем методы генерации выражений для символьной математики, а также методы обучения глубокому обучению. Кроме того, мы анализируем использование символьных методов в глубоком обучении, что делает его поддающимся разработке и проектированию четких структур, чтобы научить систему быстро находить решения для интегрирования символьных решений дифференциальных уравнений.

---

© Albojwaid Dhurgham Abbas Mohsin, 2022

UDK 004.056

## Statistical Properties of PRNG-Algorithms

K.A. Nechaev, M.A. Orlov, N.A. Ivanov

*National Research Moscow State University  
of Civil Engineering, Moscow (Russia)*

**Key words and phrases:** measure of randomness; pseudo-random number generators; statistical properties; test.

**Abstract.** This article is the second in the series of papers devoted to using pseudo-random number generators to solve simulation modeling problems and ensure the storage and transmission of information in the construction industry. The purpose of this work is to determine the quality of the obtained pseudo-random sequence, namely the randomness measures for the four most commonly used PRNGs: the Mersenne Twister, the linear congruential generator, the Blum-Blum-Shub, and the Fortuna. The instrumental basis of the study is the NIST statistical test suite developed by the Information Technology Laboratory (ITL) unit of the National Institute of Standards and Technology. The experiments were conducted using the values of the generator parameters selected by the authors at the first stage of the study. The results obtained during the experiments allow us to conclude that the first three of the four generators generate sequences with a high degree of randomness at a good operating speed. Therefore, they are perfect for building mathematical models under simulation modeling. However, good statistical properties do not guarantee the effectiveness of generators in cryptographic security requirements. The following article of the series will be devoted to this issue.

A group of statistical properties can describe any pseudo-random set [1]. These properties allow us to determine the quality of the resulting pseudo-random sequence, namely the measure of randomness.

Test suites are used to analyze statistical properties. One of them is the National Institute of Standards and Technology (NIST) Statistical Test Suite. It contains 15 different tests that determine the measure of randomness for the resulting pseudo-random set [2]. It includes the tests listed in column 2 of Table 1.

The main parameter values (the block lengths) recommended by the NIST were used for the test conducting. Values of this parameter are presented in Table 2.

In the previous article of the series [3], we analyzed in detail the most popular pseudo-

**Table 1.** Results of statistical NIST tests of pseudo-random number generators

# based on the results of experiments	Name of the test	MT19937	LCG	BBS	Fortuna
		Success rate	Success rate	Success rate	Success rate
1	1. Monobit	1	1	1	1
2	2. Frequency Within Block	1	0.9	1	1
3	13. Cumulative Sums	1	1	1	1
4	3. Runs	1	1	1	1
5	4. Longest Run Ones in a Block	1	1	1	1
6	5. Binary Matrix Rank	1	1	1	1
7	6. Discrete Fourier Transform	1	0.1	1	1
8	7. Non-Overlapping Template Matching	0.9912	0.9851	0.9946	0.9926
9	8. Overlapping Template Matching	1	1	1	1
10	9. Maurers Universal	1	1	1	1
11	12. Approximate Entropy	1	0.9	1	1
12	14. Random Excursion	0.9861	0.9444	1	1
13	15. Random Excursion Variant	0.9877	1	1	0.9352
14	11. Serial	1	1	0.9	1
15	10. Linear Complexity	1	1	1	0.9

**Table 2.** Values of the “block length” parameter

Test name	Parameter value
Frequency Within Block	128
Non-Overlapping Template Matching	9
Overlapping Template Matching	9
Approximate Entropy	10
Serial	16
Linear Complexity	500

random number generators (**PRNG**): the Mersenne Twister (MT19937), the linear congruential generator (**LCG**), the Blum-Blum-Shub (**BBS**), the “Fortuna” (Fortuna). It was these algorithms that were chosen to continue research/experimentation.

It was necessary to generate pseudo-random sequences using the presented generators to study the statistical properties. To ensure the accuracy of statistical results, the length of such sequences was taken to be 8000000 bits. Ten tests were performed for each pseudo-random bit generation algorithm (that is, exactly 80000000 bits participated in the tests in total). The results presented in columns 3–6 of Table 1 were obtained based on testing.

It is possible to conclude the quality of the output sequence of each of the considered generators based on the conducted statistical tests.

First, we focus on the tests passed by algorithms with varying degrees of success (lines

8–15 of Table 1). As can be seen, some of the tests in Table 1 do not follow the order given in the NIST STS documentation [2] (the documented order of the tests is shown before their names). For clarity, the tests were sorted so that, from the authors' point of view, the more significant tests for the quality of the sequence were higher in Table 1.

In our opinion, you cannot evaluate the results of all tests in the same way. Each of them allows you to assess the quality of the bit sequence in different aspects, which makes it possible to reasonably assume which test results will have a more substantial impact on the final evaluation of the generators.

Having analyzed the results, one can see that the MT [4] generator performed well on all tests. The algorithm showed weak results in tests 14 and 15. The test for random excursion (line 12) shows the uneven distribution of zeros and ones on partial sums (cycles) with cumulative sums from  $-4$  to  $+4$ . The "Random Excursion Variant" test (line 13) works with a broader range of cumulative sum values, namely from  $-9$  to  $+9$ .

The LCG [5] was weakest on tests 2, 6, and 12. "Frequency Within Block" test (line 2) showed that in 10 % of sequences that passed the test, there are blocks of 128 bits by the parameters of the test being conducted, having an approximately unequal number of zeros and ones. The results of passing the "Discrete Fourier Transform" test (line 7) were the lowest for each generator. Only one set of ten sets generated by LCG passed this test. The "Discrete Fourier Transform" test shows that the entire set has so-called frequency peaks that exceed the amplitude threshold of 95 % in more than 5 % of the set. The "Approximate Entropy" test (line 11) shows how much the frequency of various samples of blocks with a length of  $m$  and  $m + 1$  bits (in our case 10 and 11 bits, respectively) deviates relative to the benchmark, that is, the calculated Chi-squared value ( $\chi^2$ ).

The weakest side of the BBS algorithm [6] turned out to be the "Serial" test (line 14), which examines samples of long  $m$  bits  $2^m$  times. In the study, the value of  $m$  was chosen equal to 16. Thus, the frequency of occurrence of blocks with a length of 16 bits is checked, based on which the P-value is calculated (a probabilistic value reflecting the quality of the set relative to the significance level of 0.01). Experiments have shown that after passing the test, one of the ten generated sequences has a P-value less than 0.01.

The Fortuna generator [7] performed worst in the "Linear Complexity" test (line 15), which represents the resulting sequence of pseudo-random values with a length of  $m$  bits (in this example,  $m = 500$ ) as a sequence obtained using LFSR. The test finds the estimated size of the LFSR, based on which it calculates the Chi-squared value ( $\chi^2$ ) and P-value parameters, to do this. One out of ten sets generated using the Fortuna algorithm has a P-value of less than 0.01.

The "Non-Overlapping Template Matching" test (line 8) is worth mentioning separately since none of the generators considered could pass this test 100 %. This test finds patterns with a length of  $m$  bits (in the test under consideration, the pattern length is 9 bits, NIST offers 148 patterns) and goes through the sequence without crossing the already found patterns if any. For small parameter  $m$ , a concise pattern will be taken, which will be easier to detect in a binary sequence. To get values close to "1", it is necessary to specify the length of the template  $m$  as much as possible. As a result, the number of found samples is counted, based on which the P-value is calculated.

Speaking about the experiment results in general, we can confidently say that all the algorithms considered have good statistical properties. This is reflected in our proposed version of the priority distribution of tests (column 1 of Table 2).

The tests' values are equal to one for almost all generators in most of the table (lines 1–7, 9–10). The exception is the results of the "Frequency Within Block" test (line 2) of the LCG,

**Table 3.** Pseudo-random sequence generation time

№	Name of the generator	Time
1	Mersenne Twister	61 sec.
2	Linear congruential generator	63 sec.
3	Blum-Blum-Shub	66 sec.
4	Fortuna	23 400 sec.

which were discussed above.

Significant differences begin to appear from line 11, reflecting the weaknesses of one or another algorithm. However, the BBS and Fortuna have non-one values lower in the table than the other two algorithms, and hence they produce better quality pseudo-random sequences.

In addition to good statistical properties, the presented PRNGs should also have an acceptable rate of random bit generation. The results of the time spent generating 80 000 000 bits for each of the PRNGs are presented in Table 3.

It is essential to consider that the data is valid only for some parameters included in the algorithms. For example, the LCG algorithm is sensitive to initial values, significantly complicating their selection to generate a sequence with good statistical properties.

Completing the analysis of the results obtained, we can conclude that the algorithms “Mersenne Twister”, BBS, and the linear congruential generator show good statistical results, giving out, according to the NIST tests’ developers, good sequences with a high degree of randomness. At the same time, unlike the Fortuna algorithm, the mentioned algorithms generate bits with good speed. That’s why such PRNGs are perfect for building mathematical models under simulation modeling.

However, good statistical properties are not enough when using sequence generation algorithms in cryptography. Another important property is the cryptographic strength of the algorithm. The following article of the series will be devoted to this issue.

### References

1. Ivanov, M.A. Teoriya, primeneniye i ochenka kachestva generatorov psevdosluchajnykh posledovatel'nostej / M.A. Ivanov, I.V. CHugunkov. – M. : KUDIC-OBRAZ, 2003.
2. National Institute of Standards and Technology Special Publication 800-22 revision 1a Natl. Inst. Stand. Technol. Spec. Publ. 800-22rev1a, 131 p. (April 2010).
3. Orlov, M.A. Issledovanie sposobov formirovaniya psevdosluchajnykh chisel s bol'shim periodom / M.A. Orlov, K.A. Nechaev, N.A. Ivanov // Nauka i biznes: puti razvitiya. – M. : TMBprint. – 2022. – № 1(127).
4. Matsumoto, M. Mersenne twister: a 623-dimensionally equidistributed uniform pseudo-random number generator / M. Matsumoto, T. Nishimura // ACM Transactions on Modeling and Computer Simulation. – 1998. – Vol. 8(1). – P. 3–30. – DOI: 10.1145/272991.272995.
5. Lehmer, D.H. Mathematical methods in large-scale computing units / D.H. Lehmer // Proceedings of 2nd Symposium on Large-Scale Digital Calculating Machinery, 1951. – P. 141–146.
6. Blum, L. A Simple Unpredictable Pseudo-Random Number Generator / L. Blum, M. Blum,

M. Shub // SIAM Journal on Computing. – 1986. – Vol. 15. – Iss. 2. – P. 364–383 [Electronic resource]. – Access mode : <https://doi.org/10.1137/0215025>.

7. Ferguson, N. Cryptography Engineering: Design Principles and Practical Applications / N. Ferguson, B. Schneier, T. Kohno. – Wiley Publishing, Inc., Indianapolis, Indiana, 2010.

---

### Статистические свойства алгоритмов генераторов псевдослучайных чисел

К.А. Нечаев, М.А. Орлов, Н.А. Иванов

*ФГБОУ ВО «Национальный исследовательский  
Московский государственный строительный университет»,  
г. Москва (Россия)*

**Ключевые слова и фразы:** генератор псевдослучайных чисел; мера случайности; статистические свойства; тест.

**Аннотация.** Настоящая статья является второй в цикле работ, посвященных проблематике применения генераторов псевдослучайных чисел (ГПСЧ) в рамках решения задач имитационного моделирования и обеспечения хранения и передачи информации в строительстве. Целью настоящей работы является определение качества получаемой псевдослучайной последовательности, а именно меры случайности для четырех наиболее часто используемых ГПСЧ: алгоритм «Вихрь Мерсенна», линейно конгруэнтный алгоритм, алгоритм «Blum-Blum-Shub», алгоритм «Fortuna». Инструментальной основой исследования выступает статистический тест NIST, разработанный лабораторией информационных технологий Национального института стандартов и технологий. Эксперименты проводились с использованием значений параметров генераторов, подобранных авторами на первом этапе исследования. Полученные в ходе экспериментов результаты позволяют сделать вывод о том, что первые три из четырех генераторов формируют последовательности с довольно высокой степенью случайности при хорошей скорости работы. Следовательно, они идеально подходят для построения математических моделей в рамках имитационного моделирования. Однако это совсем не гарантирует их эффективности с точки зрения требований криптостойкости. Этому вопросу будет посвящена следующая статья цикла.

---

© К.А. Nechaev, М.А. Orlov, Н.А. Ivanov, 2022

UDK 336.14

## A Comparative Analysis of German and Russian Budgetary Systems

K.A. Sharonova

*Samara State University of Economics, Samara (Russia)*

**Key words and phrases:** budget; budget system; fiscal equalization; inter-budget relations; tax system.

**Abstract.** This article presents the analysis of Russian and German fiscal systems. The sequence of financial resources generation and expenditure in Germany's budget system is of great interest. System of inter-budget equalization in Germany bears a specific character. The purpose of this study is to estimate the efficiency of its function of Germany's budget system and feasibility of application of certain postulates in Russian Federation's budget system. To conduct this study, first of all, the necessary information was searched. The main method in this study is analysis. Using the estimation the efficiency of its function we can select the advantages Germany's budget system and apply them in Russian Federation's budget system, which solves the assigned tasks.

The relevance of the study lies in the fact that Russia has a similar fiscal system compared to Germany. An important fact is that due to the tax system established in Germany, a very high level of economic growth and well-being of the population was reached.

Russia, as well as Germany, strives to provide the population with equal social services. Meanwhile in Russia, approximately only 30 % of budget expenses goes to social investment, while in Germany this number reaches 60 % [2, p. 92].

In Germany, as well as in Russia, financial well-being of territories is differentiated. Due to this reason, means of vertical and horizontal equalization are applied to administrative-territorial units. Tax revenues and insurance fees are distributed in different proportions between the national budget and territories.

Germany itself presents a parliamentary republic with federal administrative-territorial structure. In this case, some common features are apparent compared to Russia. In our country also takes place a separation into territorial entities, which govern certain matters, while tax legislation is also in part being governed by territorial entities. In Germany certain matters also being governed by the Lands, but their list is different. Clearly, the ability to refer some matters from federal to regional level has undeniable advantages. This allows for an increase of budget's policy efficiency and distribution of the taxation burden considering the economic characteristics of territories.

The budget system in Germany, as well as in Russia, has a three-leveled structure, but the Basic Law of Germany only stipulates the two level of authority – that of federation and the

Lands. Communities are a part of the Lands, therefore, self-governance in Germany has a very limited nature.

In Germany, as well as in Russia, there are federal, regional and local taxes, which are credited to budgets in different proportions.

In Germany, the tax system includes more than 40 types of taxes, their number depends on the region. In Russia there are only 15 types of taxes. By provision of tax revenues, 70 % of Germany's national budget is formed. In exchange, the Government provides population with reliable social guarantees.

The German basic law governs the applicability of different types of tax rates. There are progressive, retrogressive, and proportional tax rates. In Germany's tax system, taxes with progressive rates prevail. The value of the rate depends on the income level of the population and a well-being level of the area. Due to higher tax rates of more developed territories, the government of the country provides financial support to less developed territories.

The tax burden on population in Germany and Russia was calculated by N. Zotikov, O. Arlanova and M. Lvova in their study [4, p. 78–87]. The tax burden on a single worker in Germany amounts to 36.9 %, while in Russia it amounts to 13 % (on the level of personal income tax rate).

According to this, the tax burden on a worker in Germany is 2.8 times higher than in Russia, but in Germany wages are also higher. In accordance with calculations, wages in Germany are 11.9 times higher, and the amount of take-home pay is 8.6 higher.

Also, in Russia, there is an option to receive personal income tax deduction, in which case the tax burden will be even less than 13 %.

To date, the main taxes in Germany's tax system are income tax and VAT. At that, income tax credits into budget not less than 40 % of total budget income.

In Germany, the income tax is distributed between budgets as follows: 42.5 % is being credited to central budget, 42.5 % – to the budget of the lands, 15 % – to the communities budget.

VAT is distributed between the budgets of Germany's budgetary system the following way: 48 % is being credited to central budget, 34 % to the budget of the lands, and 13 % to the communities' budget. This reinforces the control function laid upon German taxes and increases the social focus of the Germany's tax system.

In Russia, currently, the amount of tax revenues prevails in the federal budget. This means that the most significant taxes are assigned to federal budget of the nation. In tax system of Russia, taxes are not distributed among all three budgets of the budgetary system simultaneously. The legislation provides for a distribution of several taxes into the federal budget and budgets of territorial entities of Russian Federation. Only a critically small amount of tax revenues is credited to local budgets. In Russia, total amount of VAT is credited to federal budget, this means that in VAT a fiscal function prevails, while regulating function is completely absent. With this, income tax is not credited at all to budgets of municipalities. These conditions lead to subsidization of almost all budgets of territories and widespread use of non-reimbursable revenues for compensation of budget deficits in the country's budgetary system.

Germany is characterized by a three-tier system of inter-budgetary control. With VAT being credited to regional budgets, an income-equalization is performed, which means that re-distribution of finance resources among regional budgets is performed without an active involvement of the federation in this process.

Unlike Russia, in Germany, the tax income via federal budget is re-distributed from more developed to less developed territories. This way, in Germany a vertical and horizontal



equalization of budgets is performed, with the most important aspect – tax potential equalization of territories via system of horizontal transfers.

The main instrument of the vertical equalization is the re-distribution of income from VAT between federal and total budget of federation entities [3, p. 37–40]. For horizontal equalization, general taxes are applied, credited to budget of the entities. Besides, 2 % of the income from portion of VAT, credited to federal budget is used as additional subsidies for the lands with low level of tax income [1].

In Russia, functions a system of inter-budgetary transfers, which essentially represent the same system of financial equalization, as in Germany. However, there are differences between the structure of inter-budgetary relations between Russia and Germany. In Germany horizontal equalization does not lead to transition of recipient-entity to the “middle” status, and transfers of donor-entities should not significantly weaken their social-economic standing. Main part of transfers comes from the federation budget, which allows to maintain a balance of social-economic standing of the lands. It is important to note, that the lands do not issue target payments, as it is customary in Russia.

A detailed review of German fiscal system may turn out to be useful for possible application of its postulates in Russian budget system. Germany, as well as Russia, has an extensive experience of changing the economic and political structure of the country, it also arose from the devastation of the world wars; nevertheless, Germany became the economically strong nation with a greater focus on social orientation.

The fiscal systems of Germany and Russia are similar in regards to the fact, that taxes are used as the main way of influence on development of nation’s economy. They form approximately 70–80 % of federations budget income. Ministry of Finance in Germany, as well as in Russia, drafts a plan of income and expenses of the federal budget for the five year period of time.

The German fiscal system is different from the Russian fiscal system in that it burdens the population with high taxes, especially people with high income. In Russia, taxpayers pay the equal part of their income. Meanwhile Germany has a highly developed uniformity of social services provided for the population.

It should be noted that progressive tax rates bring Germany great results. In Russia, introduction of a progressive tax had been debated often. At that, a big advantage for Russian population presents the fact that the rate of income tax in Russia is one of the lowest in the world, which contributes to development of small and medium-sized businesses.

The question of the efficiency of introduction of progressive tax rates in Russia is controversial. However, the most researchers favor the introduction of the progressive tax. It should be noted, that the most of developed countries effectively use the progression tax rates for the benefit of corporate organizations [6, p. 95–97].

Germany’s budget system not only applies vertical, but also horizontal equalization of income. The most influential taxes in Russia are credited to federal budget, while tax revenues assigned to budgets of territorial entities of Russian Federation and budgets of municipalities do not cover the required obligation which need to be fulfilled. Highest taxes in Germany are credited to budgets of all levels of the budget system in accordance with regulated standards, this provides the nation with necessary finance resources to fulfill the obligations of all levels of government.

Decentralization is based on the right of territorial authorities to a certain degree of independence in relation to defining the taxes on their level. This implies that they have a responsibility related to performing obligations on provision of social services for the population. [5, p. 7–15].

Therefore, positive experience of taxation in Germany may be partially applied in Russian economy. It is necessary to pay attention to tax distribution among the budgets of the budget system and experience of progressive taxation scale application.

### References

1. Trading Economics [Electronic resource]. – Access mode : <https://ru.tradingeconomics.com/country>.
2. Balashev, N.B. Sravnitel'naja karakteristika bjudzhetnyh sistem Rossii i Germanii / N.B. Balashev, Ju.A. Zhivotnikova // Izvestija Tul'skogo gosudarstvennogo universiteta. Jekonomicheskie i juridicheskie nauki. – 2019. – № 1–1. – S. 87–94.
3. Belostockij, A.A. Modeli mezhbjudzhetnogo vzaimodejstvija zarubezhnyh stran / A.A. Belostockij // Norwegian Journal of Development of the International Science. – 2019. – № 12–2(37). – S. 37–40.
4. Zotikov, N.Z. Osobennosti nalogovo-bjudzhetnogo regulirovanija v Germanii / N.Z. Zotikov, O.I. Arlanova, M.V. L'vova // Vestnik Cheljabinskogo gosudarstvennogo universiteta. – 2020. – № 10(444). – S. 78–87. – DOI: 10.47475/1994-2796-2020-11009.
5. Kravcova, N.I. Nalogovaja decentralizacija kak osnova formirovanija jeffektivnoj bjudzhetno-nalogovoj politiki regiona / N.I. Kravcova, R.M. Magomedova, M.M. Sulejmanov // Regional'naja jekonomika: teorija i praktika. – 2014. – № 10. – S. 7–15.
6. Mandroshhenko, O.V. Zarubezhnyj opyt nalogooblozhenija pribyli i ego ispol'zovanie v nalogovoj sisteme Rossii / O.V. Mandroshhenko; pod obshh. red. E.P. Tkachevoj // Strategicheskie napravlenija razvitija nauki, obrazovanija, tehnologij : sb. nauch. tr. po materialam Mezhdunar. nauch.-prakt. konf. : v 4 ch. – Penza : Nauka i prosveshhenie, 2017. – S. 95–97.

---

### Сравнительная характеристика бюджетных систем Германии и России

К.А. Шаронова

*ФГАОУ ВО «Самарский государственный экономический университет»,  
г. Самара (Россия)*

**Ключевые слова и фразы:** бюджет; бюджетная система; бюджетное выравнивание; межбюджетные отношения; налоговая система.

**Аннотация.** В данной статье сравниваются налогово-бюджетные системы России и Германии. Порядок формирования и расходования финансовых ресурсов в бюджетной системе Германии представляет большой интерес. Система межбюджетного выравнивания страны тоже является достаточно специфичной. Целью данного исследования является оценка эффективности функционирования бюджетной системы Германии и целесообразности применения некоторых ее постулатов в бюджетной системе РФ. Для проведения данного исследования, прежде всего, был произведен поиск необходимой информации. Основным методом в данном исследовании выступает анализ. С помощью оценки эффективности функционирования можно выделить достоинства бюджетной системы Германии и применить их в бюджетной системе РФ, что решает поставленные задачи.

---

© К.А. Sharonova, 2022

UDK 337

## The Impact of the Pandemic on Macroeconomic Indicators

O.V. Voronkova

*Russian State Hydrometeorological University;  
Peter the Great Saint Petersburg Polytechnic University,  
St. Petersburg (Russia)*

**Key words and phrases:** COVID-19 pandemic; economic activity; economic sectors; global GDP decline; relaxation of quarantine restrictions; business activity.

**Abstract.** In order to study the consequences of the COVID-19 pandemic, which had an impact on the economic activity of all countries without exception, an analysis of the dynamics of the activities of many sectors of the economy was carried out. As a result of the economic review presented in the article, some directions of the decline in global GDP and the decline in revenue of companies around the world are outlined. There are also signs that as quarantine restrictions are eased, business activity in many industries has begun to resume.

In 2020, global GDP growth slowed significantly. This phenomenon was influenced by two factors:

- the “late” stage of the economic cycle of development in developed markets;
- the COVID-19 pandemic.

The COVID-19 pandemic has had an impact on the economic activity of all countries without exception. Governments of many countries have introduced fiscal stimulus measures for the population and commercial enterprises, as well as monetary stimulus measures, including reduction of credit rates and cash injections. The restrictions affected many sectors of the economy: transport, construction and manufacturing, which eventually led to a drop in global GDP and a decrease in the revenue of companies around the world.

As quarantine restrictions eased, business activity began to resume. In 2020, due to two waves of COVID-19, GDP growth slowed in the USA to –3.4 % and in the EU it slowed to –7.2 %, in India a decrease was by 8 %. The only country that showed GDP growth is China, where growth decreased from 6 % to 2.3 %. Against the background of these crisis phenomena, global steel demand fell by 2.4 %. Demand in the EU decreased by 15.2 %, and in India steel consumption decreased by 20.2 %. Steel consumption increased in China by 8 %, thanks to measures to support infrastructure and a stable situation in the real estate market. A drop in demand for steel was observed in the first two quarters, and in the third and fourth quarters of 2020, deferred demand accelerated the growth rate against the background of easing quarantine restrictions. The prospects for global economic growth are linked to the development of vaccines against COVID-19 and the restoration of world trade. The forecast for steel demand

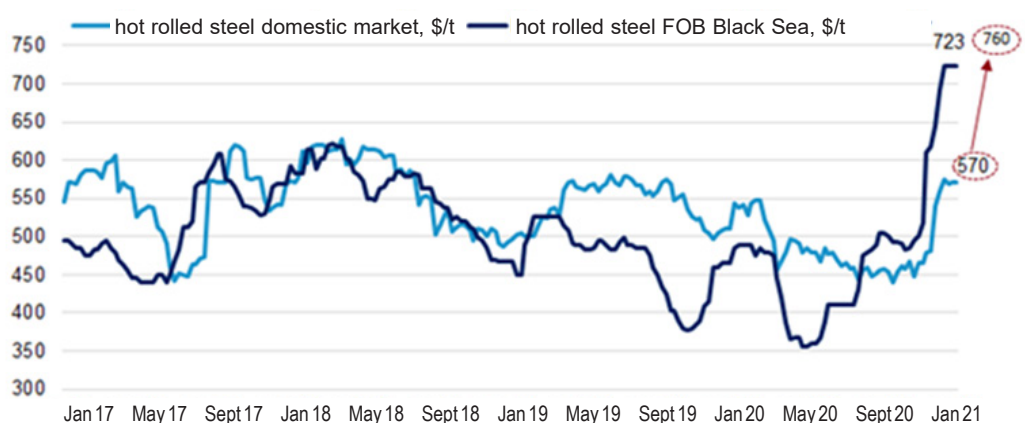


Fig. 5. Encoder's ability to distinguish between numbers

growth is 4.1 % in 2021, which is slightly higher than in 2019, the estimate is based on the growth of steel consumption by developing countries – India and ASEAN countries, as well as the expectation of a recovery in demand in the EU. In particular, the forecast is based on the recovery of car production. It is expected that the level of steel consumption in China will remain high, as the government will continue infrastructure projects launched in 2020, the main factor of unstable demand from China is the unstable state of developers, who account for a large share of steel consumption.

Export prices for hot-rolled sheet increased by 2 % in 2020, reaching an annual average of 475 US dollars per ton. Pressure on the metal products market was associated with a drop in global demand in the first half of 2020. Due to a sharp drop in demand, the operation of blast furnaces with a capacity of 70 million tons was suspended. The second half of 2020 was held under the motto “deferred demand”, which influenced the price increase and during this period companies began to resume the operation of blast furnaces (Fig. 1).

In 2020, China became a net importer of steel for the first time since 2009. This is due to the rise in steel prices in Southeast Asia.

The dynamics of steel prices in 2021–2022 will be determined by a positive demand forecast and trends in raw material prices. A recovery in demand in countries such as Turkey and an increase in demand in the Middle East due to the expected increase in oil prices and consumption growth in the EU will support export prices for Russian hot-rolled sheet.

The negative market situation in 2020 had a detrimental impact on the coking coal market due to the downtime of blast furnaces. The degree of political tension between Australia and China has intensified, and China has imposed a strict ban on coal imports from Australia – this has led to a 31 % reduction in coking coal prices in 2020.

Iron ore prices have had a steady upward trend since April 2020, averaging US\$ 108 per ton, and in May 2021 they reached US\$ 220 at the moment. The steady increase in prices was supported by a noticeable increase in steel production by Chinese enterprises and an increase in the production capacity of blast furnaces compared to 2019 and 2020. Amid downtime due to the COVID-19 pandemic, shipments from Australia and Brazil were reduced in the first half of 2020. The demand that decreased during the year in foreign markets was offset by an increase in consumption in China itself. Iron ore prices are well above the break-even level, which is explained by the high level of consumption in China. Analysts in forecasts for 2022 are based on the fact that ore prices will be determined by the dynamics of consumption in China.

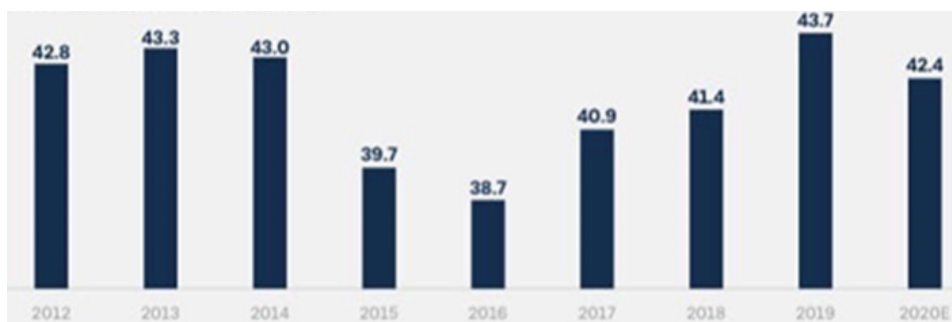


Fig. 2. Russian demand for steel, mln tons

World GDP in the pandemic year lost 4.3 %, following global trends, Russia's GDP decreased by 3.9 %, which is slightly better than the world. The slowdown in economic growth mainly occurred in the second quarter of 2020 due to quarantine restrictions. Economic activity began to recover only with the weakening of quarantine measures. Industrial production fell by 2.9 %, capital investment decreased by 6.6 %, and personal consumption decreased by 5.7 % in 2020.

In the Russian Federation, the Government has formed and implemented a set of measures to stimulate the economy to mitigate the consequences of the economic crisis. Fiscal stimulus measures were taken to support the population and businesses. The Central Bank of Russia lowered the key rate to 4.25 %. The inflation rate at the end of 2020 was 4.9 %. GDP growth was expected to be 4.5 % in 2021 and 2.5 % in 2022. The potential for growth is due to deferred exports and domestic demand. The easing of monetary policy and the implementation of the national economic recovery plan in the amount of 6.4 trillion rubles should accelerate investment in infrastructure projects, providing support for GDP growth, which will spur demand for metals. In 2020, the demand for steel fell by 3 %, while in 2021 it was expected to recover by 3–4 % (Fig. 2).

The main incentives for the growth of demand for steel in Russia will be an increase in business activity and the implementation of the "National Projects" program. The implementation of the mortgage lending program on preferential terms will stimulate the development of construction.

## References

1. Sidorov, V.A. *Ekonomicheskaya teoriya : uchebnik dlya vuzov* / V.A. Sidorov, 2018.
2. Nikiforova, E.V. *K voprosam ustojchivogo razvitiya ekonomicheskikh subektov* / E.V. Nikiforova // *Balkanskoe nauchnoe obozrenie*. – 2019. – T. 3. – № 2(4). – S. 106–111.
3. Voronkova, O.V. *Priorities of Russia's Foreign Economic Activity* / O.V. Voronkova // *Components of Scientific and Technological Progress*. – 2020. – № 12(54). – P. 22–25.
4. Voronkova, O.V. *Dynamics of Russia's Main Economic Indicators at the Time of the Pandemic* / O.V. Voronkova // *Components of Scientific and Technological Progress*. – 2020. – № 4(46). – P. 24–28.

**Влияние пандемии на макроэкономические показатели**

О.В. Воронкова

*ФГБОУ ВО «Российский государственный гидрометеорологический университет»;  
ФГАОУ ВО «Санкт-Петербургский политехнический университет Петра Великого»,  
г. Санкт-Петербург (Россия)*

**Ключевые слова и фразы:** деловая активность; ослабление карантинных ограничений; отрасли экономики; падение мирового ВВП; пандемия COVID-19; экономическая активность.

**Аннотация.** С целью изучения последствий пандемии COVID-19, которая оказала влияние на экономическую активность всех без исключения стран, был проведен анализ динамики деятельности нескольких отраслей экономики. В результате экономического обзора, представленного в статье, обозначены некоторые направления падения мирового ВВП и снижение выручки компаний по всему миру. Показаны также признаки того, что по мере ослабления карантинных ограничений деловая активность во многих отраслях начала возобновляться.

---

© O.V. Voronkova, 2022

## List of Authors

**Maltsev M.V.** – Candidate of Science (Engineering), Associate Professor, Department of Industrial Ecology, Equipment for Chemical and Petrochemical Industries, Voronezh State University of Engineering Technologies, Voronezh (Russia), E-mail: max\_proekt@mail.ru

**Мальцев М.В.** – кандидат технических наук, доцент кафедры промышленной экологии, оборудования химических и нефтехимических производств Воронежского государственного университета инженерных технологий, г. Воронеж (Россия), E-mail: max\_proekt@mail.ru

**Lobacheva N.N.** – Candidate of Science (Engineering), Associate Professor, Department of Foreign Languages, Voronezh State University of Engineering Technologies, Voronezh (Russia), E-mail: naloni@mail.ru

**Лобачева Н.Н.** – кандидат технических наук, доцент кафедры иностранных языков Воронежского государственного университета инженерных технологий, г. Воронеж (Россия), E-mail: naloni@mail.ru

**Albojwaid Dhurgham Abbas Mohsin** – Postgraduate Student, South Ural State University, Chelyabinsk (Russia), E-mail: alkafiethargham3@gmail.com

**Албоджваид Дхурghам Аббас Мохсин** – аспирант Южно-Уральского государственного университета, г. Челябинск (Россия), E-mail: alkafiethargham3@gmail.com

**Nechaev K.A.** – Undergraduate Student, National Research Moscow State University of Civil Engineering, Moscow (Russia), E-mail: knecaev1@gmail.com

**Нечаев К.А.** – студент Национального исследовательского Московского государственного строительного университета, г. Москва (Россия), E-mail: knecaev1@gmail.com

**Orlov M.A.** – Undergraduate Student, National Research Moscow State University of Civil Engineering, Moscow (Russia), E-mail: orlov.mikhail.alekseevich@mail.ru

**Орлов М.А.** – студент Национального исследовательского Московского государственного строительного университета, г. Москва (Россия), E-mail: orlov.mikhail.alekseevich@mail.ru

**Ivanov N.A.** – Candidate of Science (Engineering), Assistant Professor, Department of Information Systems, Technologies and Automation in Construction, National Research Moscow State University of Civil Engineering, Moscow (Russia), E-mail: IvanovNA@mgsu.ru

**Иванов Н.А.** – кандидат технических наук, доцент кафедры информационных систем, технологий и автоматизации в строительстве Национального исследовательского Московского государственного строительного университета, г. Москва (Россия), E-mail: IvanovNA@mgsu.ru

**Sharonova K.A.** – Postgraduate Student, Samara State University of Economics, Samara (Russia), E-mail: ksh1995@yandex.ru

**Шаронова К.А.** – аспирант Самарского государственного экономического университета, г. Самара (Россия), E-mail: ksh1995@yandex.ru

**Voronkova O.V.** – Doctor of Economics, Professor, Department of Environmental Management Economy and Accounting Systems, Russian State Hydrometeorological University; Professor, Institute of Industrial Management, Economics and Trade, Peter the Great Saint Petersburg Polytechnic University, St. Petersburg (Russia), E-mail: journal@moofrnk.com

**Воронкова О.В.** – доктор экономических наук, профессор кафедры экономики предприятия природопользования и учетных систем Российского государственного гидрометеорологического университета; профессор Института промышленного менеджмента, экономики и торговли Санкт-Петербургского политехнического университета Петра Великого, г. Санкт-Петербург (Россия), E-mail: journal@moofrnk.com



**FOR NOTES**

---

**COMPONENTS OF SCIENTIFIC AND TECHNOLOGICAL PROGRESS**  
**№ 1(67) 2022**  
SCIENTIFIC AND PRACTICAL JOURNAL

---

Manuscript approved for print 21.01.22  
Format 60.84/8  
Conventional printed sheets 3.95  
Published pages 2.06  
200 printed copies

16+

Printed by Zonari Leisure LTD. Paphos