Сведения об авторах

Юрий Евгеньевич Артамонов* – докторант кафедры «Химическая технология и экология»; Университет имени Шакарима города Семей, Республика Казахстан; e-mail: artamonov_kz@mail.ru. ORCID: 0000-0002-8038-7692.

Алексей Николаевич Кливенко – PhD, и.о. ассоц. профессора кафедры «Химическая технология и экология»; руководитель Научного центра радиоэкологических исследований; e-mail: alexeyklivenko@mail.ru. ORCID: 0000-0002-8971-686X

Елена Николаевна Артамонова – к.х.н., доцент кафедры «Химическая технология и экология»; e-mail: artlena2008@mail.ru. ORCID: 0000-0002-3316-9713.

Елена Петровна Евлампиева – к.б.н., руководитель отдела по управлению научной деятельностью; e-mail: elena_semei@mail.ru. ORCID: 0000-0003-1953-3686

Авторлар туралы мәліметтер

Юрий Евгеньевич Артамонов* – химиялық технология және экология кафедрасының докторанты; Семей қаласының Шәкәрім атындағы университеті, Қазақстан Республикасы; e-mail: artamonov_kz@mail.ru. ORCID: 0000-0002-8038-7692.

Алексей Николаевич Кливенко – PhD, м.а. ассоц. химиялық технология және экология кафедрасының профессор, Радиоэкологиялық зерттеулер ғылыми орталығының жетекшісі; e-mail: alexeyklivenko@mail.ru. ORCID: 0000-0002-8971-686X

Елена Николаевна Артамонова – х.ғ.к., химиялық технология және экология кафедрасының доценті; e-mail: artlena2008@mail.ru. ORCID: 0000-0002-3316-9713.

Елена Петровна Евлампиева – б.ғ.к., ғылыми қызметті басқару бөлімінің басшысы; e-mail: elena_semei@mail.ru. ORCID: 0000-0003-1953-3686

Information about the authors

Yuri Artamonov* – doctoral student, Department of "Chemical Technology and Ecology"; Shakarim University, Semey, Republic of Kazakhstan; e-mail: artamonov_kz@mail.ru ORCID: 0000-0002-8038-7692.

Alexey Klivenko – PhD, Acting Associate Professor of the Department of Chemical Technology and Ecology, Head of the Scientific Center for Radioecological Research; e-mail: alexeyklivenko@mail.ru ORCID: 0000-0002-8971-686X

Elena Artamonova – candidate of Chemical Sciences, Associate Professor, Department of Chemical Technology and Ecology; e-mail: artlena2008@mail.ru. ORCID: 0000-0002-3316-9713.

Elena Yevlampiyeva – PhD, Head of the Department for Scientific Activity Management; e-mail: elena_semei@mail.ru. ORCID: 0000-0003-1953-3686

Материал поступил в редакцию 20.02.2023 г.

DOI: 10.53360/2788-7995-2023-1(9)-2

IRSTI: 83.77.01

A. Zaidulla

Astana IT University,

010000, Republic of Kazakhstan, Astana, 55/11 Mangilik El Avenue

e-mail: adilhanzai@gmail.com

FORECASTING GREENHOUSE GAS EMISSIONS IN THE INDUSTRIAL PRODUCTION OF THE REPUBLIC OF KAZAKHSTAN

Abstract: *Excessive greenhouse gas (GHG) emissions are an environmental problem. Studies to determine cost-effective ways to reduce GHG emissions have revealed the need to model the dynamics of emissions of carbon dioxide, nitrous oxide, methane, and other gases. In this study, the calculation of CO2 equivalent emissions from industrial processes and production in the territory of the Republic of Kazakhstan was carried out. When forecasting, the data provided by the UN Framework Convention on Climate Change were used. To predict CO2 emissions from industrial production, tools for analysis and forecasting of time series were used: Prophet method, Cluster* *analysis of k-means time series, modern versions of ARIMA algorithms, exponential smoothing methods, and linear regression. This study presents comparative simulation results based on a baseline scenario with no action until 2045. This study compares four models to suggest an effective one for future CO2 emission forecasting. The accuracy comparison is conducted using various error measures, with the mean absolute percentage error (MAPE) chosen as the metric for comparison.*

Key words: *GHG emissions, artificial intelligence, machine learning, industrial processes, product use, CO2 emissions*.

Introduction

The purpose of this work is to apply various methods of statistical analysis and mathematical modeling to predict GHG emissions from the IPPU sector in Kazakhstan until 2045.

The task of the work is to collect and process data on CO2 emissions for industrial production in Kazakhstan and review the various methods used for forecasting time series, with a scenario analysis of the forecast of the dynamics of GHG emissions by 2045 in accordance with the rules of the UNFCCC (IPCCC).

In March 1995, Kazakhstan ratified the UN Framework Convention on Climate Change, under which Kazakhstan provides data on greenhouse gas emissions every two years. UNFCCC (United Nations Framework Convention on Climate Change) is an agreement on the general principles of action by countries on the problem of climate change, signed by more than 180 countries of the world, including all countries of the former USSR and all industrialized countries. The Convention was solemnly adopted at the "Earth Summit" in Rio de Janeiro in 1992 and entered into force on March 21, 1994.

According to UNFCCC studies, for 2020 Kazakhstan ranks 19th among countries in terms of CO2 and CO2 equivalent emissions in the Industrial Processes and Product Use sector, amounting to 22.3 thousand tons. In addition, it took 4th place in the index of growth in CO2 and CO2 equivalent emissions compared to the 2019 reporting year, demonstrating an increase of 6.8%.

GHG emissions in the IPPU sector will be mapped in accordance with the Kazakhstan GHG Inventory, which includes four main categories from the IPPU sector: emissions from the production of mineral materials, the chemical and metallurgical industry, the use of solvents and non-energy products from fuels.

The goal of the Convention is to stabilize the concentration of greenhouse gases in the atmosphere "at a level that would not allow dangerous anthropogenic, that is, human-induced, impact on the climate system".

Thus, Kazakhstan's progress in achieving emission reductions and removals related to its quantitative economy-wide emission reduction targets is assessed.

According to the development strategy of Kazakhstan, a presidential decree set the goal of achieving carbon neutrality by 2060. Ecology Minister Serikkali Brekeshev noted that the doctrine includes 2 scenarios: basic and carbon neutrality, where the base scenario is a path without measures to decarbonize the economy.

In this paper, a forecast of the baseline scenario of CO2 emissions will be presented.

Research methods

Time series – is a sequence of numbers ordered by time index. One of the features of time series is that it can be used to predict values based only on the time series itself.

We can represent the components of the y_t time series additively as:

$$y_t = S_t + T_t + R_t \quad (1)$$

Where: S_t – seasonal component;

T_t – trend component;

R_t – the remainder of the time series not covered by the seasonal or trend component.

Also, when predicting a time series, it is important to take into account autocorrelation and stationarity.

The term autoregression means regression applied to itself. In an autoregressive model, we predict a variable of interest using a linear combination of the variable's past values.

An autoregressive model of order p can be written as:

$$y_t = c + ф_1 y_{t-1} + ф_1 y_{t-2} + \ldots + ф_p y_{t-p} + ε \quad (2)$$

Where: ε – white noise.

An autoregressive model is similar to multiple regression, but with lagging y_t values as predictors. This model is commonly referred to as the p-order model.

Stationarity

A time series is called stationary if its statistical properties do not change over time. Thus, a time series with trend or seasonality is not stationary because trend and seasonality will affect the value of the time series at different times. On the other hand, white noise is stationary, as it looks the same at any moment.

Differentiation is one of the methods used to stabilize a time series. This method calculates the difference between successive members of a series. Differentiation is used to get rid of the moving average. Mathematically, the difference can be written as:

$$y'_t = y_t - y_{t-1} \quad (3)$$

Где: y_t – the value at time t.

When the difference series is white noise, the original series is called a non-stationary series of the first degree.

For forecasting the time series, 4 algorithms were chosen:

ARIMA (Box-Jenkins model) – is an abbreviation for AutoRegressive Integrated Moving Average and consists of the following components:

1) AR(p) – is an autoregression,
2) I(i)- represents the order of integration,
3) MA (q) – is a moving average.

The same conditions of stationarity and reversibility that are used for autoregressive and moving average models also apply to the ARIMA model.

The moving average equation is written as:

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} \quad (4)$$

Where: θ – free odds;

ε_t – white noise.

Combining all the components, the complete ARIMA model can be written as:

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots \theta_q \varepsilon_{1-q} + \varepsilon_t \quad (5)$$

Where: y'_t – it's a heterogeneous series.

The predictors on the right side include both lagging y'_t values and lagging errors.

SARIMAX (p, d, q) (P, D, Q)[S] – ARIMA-based model with an additional seasonal component.

Prophet – additive model-based algorithm uses adaptive regularization to model both linear components, such as trend, using linear regression, and non-linear components, such as seasonality, using a custom time transformation function.

Line regression with one parameter:

$$y = \omega_0 + \omega_1 x_1 \quad (6)$$

Where: y – target variable;

x – feature;

ω_0 – initial offset;

ω – model weight.

The following will be used as quality metrics:

$$MSE = \frac{\sum_{t=1}^{n}\left(y_t - y'\right)^2}{n} \quad (7)$$

$$MAE = \frac{\sum_{t=1}^{n}|y_t - y'|}{n} \quad (8)$$

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{y_t - y'}{y_t}\right|}{n}100 \qquad (9)$$

$$RMSE = \sqrt{MSE} \qquad (10)$$

$$R^2 = \sqrt{MSE} \qquad (11)$$

I. Data preparation

To conduct the study, data on CO2 emissions presented in the public domain on the UNFCC website for the period from 1990 to 2020[1] were used. The data represent specific emissions of air pollutants divided by major sectors. The IPPU sector was taken as the basis of the work. GHG emissions in the IPPU sector are presented according to the Kazakhstan GHG inventory which includes four main categories from the IPPU sector – emissions from the production of mineral materials (2.A), chemical industry (2.B), metallurgical industry (2.C), solvent use and non-energy products from fuel (2.D).

II. EDA

In Figure 1, CO2 emissions in Kazakhstan, according to the UNFCCC data, reached the level of 1990 in 2018, however, under the influence of Covid-19, the level of emissions decreased. At the same time, in the Industrial Processes and Use of Products (IPPU) sector, the quarantine of 2019 did not affect its growth. CO2 emissions from this sector exceeded 1990 emissions as early as 2014. Emissions from the metallurgical industry sector, although they occupy the largest part of emissions in the sector, however, over the past ten years, the share of emissions themselves has increased by only 23%. The mineral industry showed an increase of more than 2 times compared to 2010.

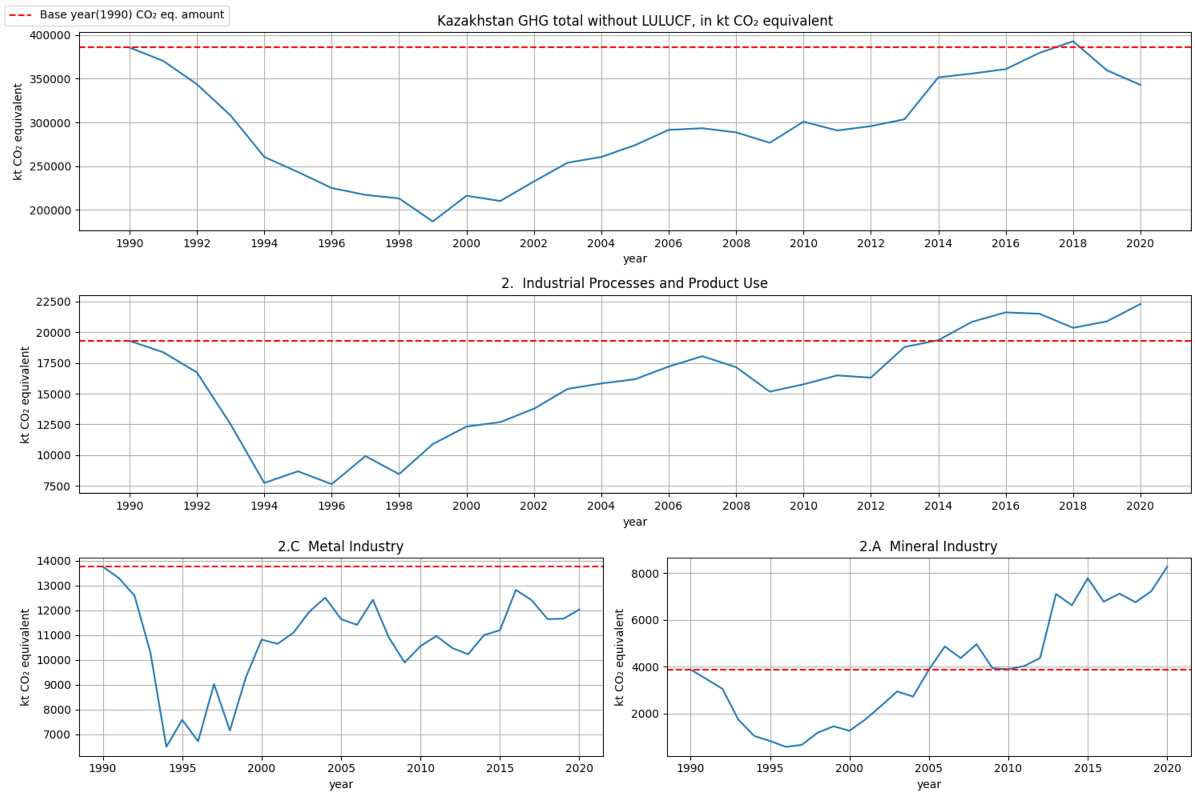

Figure 1 – Kazakhstan's CO2 emissions

According to the UNFCCC, Kazakhstan for 2020 ranks 6th among countries in terms of CO2 emissions in the 2.C Metal Industry sector, amounting to 12 thousand tons, and 10th in the 2.A Mineral Industry sector, amounting to 8.3 thousand tons. Also, Kazakhstan is one of the few countries that show a stable level of increase in CO2 emissions in the IPPU sector as presented in Figure 2. Over the previous year, Kazakhstan showed an increase of 6.8%.

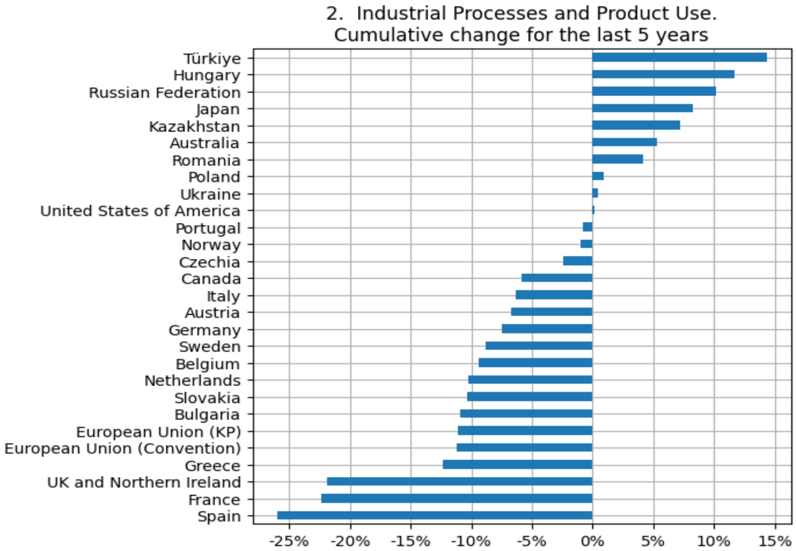

Figure 2 – Increase of CO2 emissions.

It is also particularly important for Kazakhstan to adopt the experience of other countries in reducing CO2 emissions in the IPPU sector. To find countries whose emissions are similar to those of Kazakhstan, the time series cluster analysis method was applied using the k-means algorithm. Chart 3 shows the distribution of countries into clusters.

For cluster analysis, the TimeSeriesKMeans algorithm was used - the time series clustering algorithm is based on the k-means algorithm. The distance between two time series is measured using DTW (Dynamic Time Warping). The algorithm starts by randomly selecting k time series as centroids and then iteratively assigns each time series to the nearest centroid and updates the centroids based on the assigned time series [2].

$$\mathrm{DTW}(x,y) = \min_{\pi} \sqrt{\sum_{(i,j)\in\pi} d\left(x_i, y_j\right)^2} \quad (12)$$

The outliers of Kazakhstan were grouped by the Euclidian k-means algorithms into cluster-4, DBA k-means into cluster-0 and soft-DTW k-means [3] into cluster-0, respectively. These algorithms showed the greatest similarity of emissions in Kazakhstan with emissions in Russia, Spain and Britain. You can also notice the outliers of Turkey, highlighted separately by each of the algorithms, presented on clusters 3-2-1 (Fig. 3).

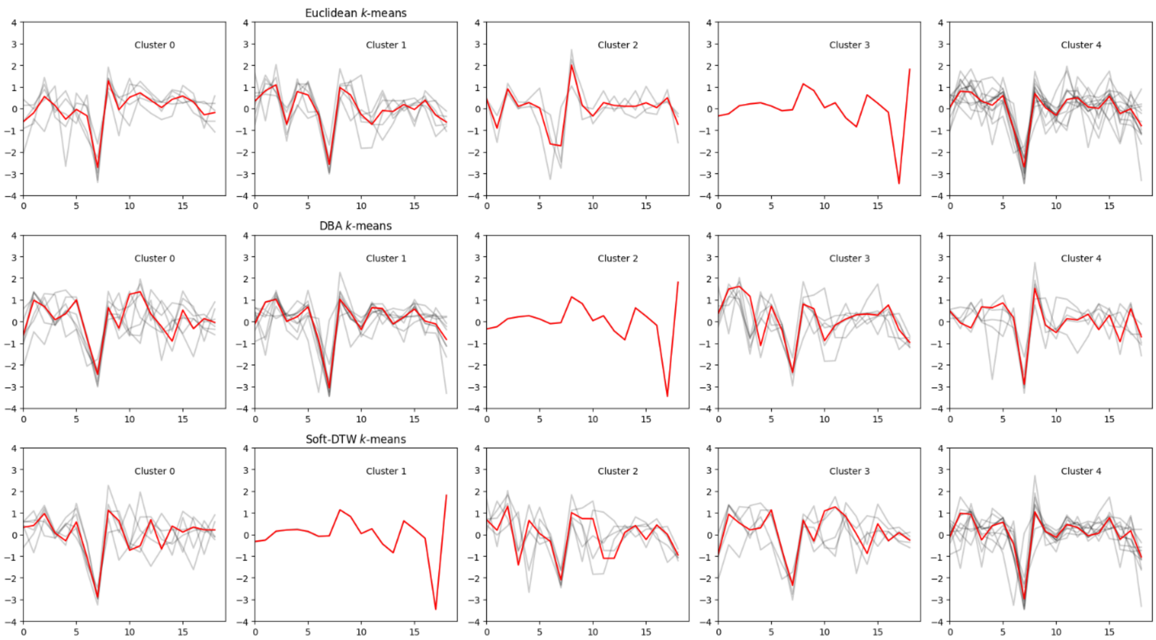

Figure 3 – IPPU time series clustering

III. Data Processing

For forecasting, the time series was reduced to a stationary time series by differentiation, and the Dickey-Fuller test is also carried out to test stationarity. Since heteroscedasticity is not observed in the time series, no methods were applied to it to reduce the inhomogeneous variance. However, some modern machine learning models (such as prophet) automatically flatten the data.

For the period from 1990 to 2000, the data show a downward trend in CO2 emissions, which characterizes the subsequent periods poorly. To improve the quality of the models, it was decided to use extrapolation for the period from 1990 to 1999. To prevent leakage of the validation sample, extrapolation was carried out on the training sample from 2000-2015.

IV. Model validating

To assess the quality of the models, the time series was divided into training and validation sets. The period from 2015 to 2020 was used as a validation sample. Figure 4 shows the predictions of the ARIMA (p=0,d=2,q=1) SARIMAX(p=0,d=2,q=1),(P=1,D=1,Q=0)(S=12) linear regression models and prophet. The confidence interval and the forecast itself are highlighted in green.

Figure 4 – Models forecasts

	Prophet	ARIMA	SARIMA	Linear
MSE	2 250 953,06	4 102 515,79	5 158 242,71	1 994 645,54
RMSE	1500.318	2025.467	2271.177	1412.319
MAE	1 230,60	1 669,52	1 774,83	1 188,08
r2_score	-4,65	-9,297	-11,947	-4,006
MAPE	5,70%	7,90%	8,50%	5,50%

Chart 1 – Models quality metrics

Chart 1 presents model quality metrics. All showed relatively similar results.

V. Results

Figure 5 presents the projection of CO2 emissions for the IPPU sector until 2045. Due to good pre-processing of extrapolation data and hyperparameter fitting, all compared models showed relatively similar results. The largest number of emissions is predicted by the ARIMA model 42.5 thousand CO2, while all other algorithms predict emissions in the range of 31.5-34.6 thousand CO2. It can also be seen that the SARIMAX and Prophet algorithms, being able to regulate the order of seasonality of the time series themselves, reduced its influence to a minimum, since fluctuations in emissions are associated with domestic political and economic events.

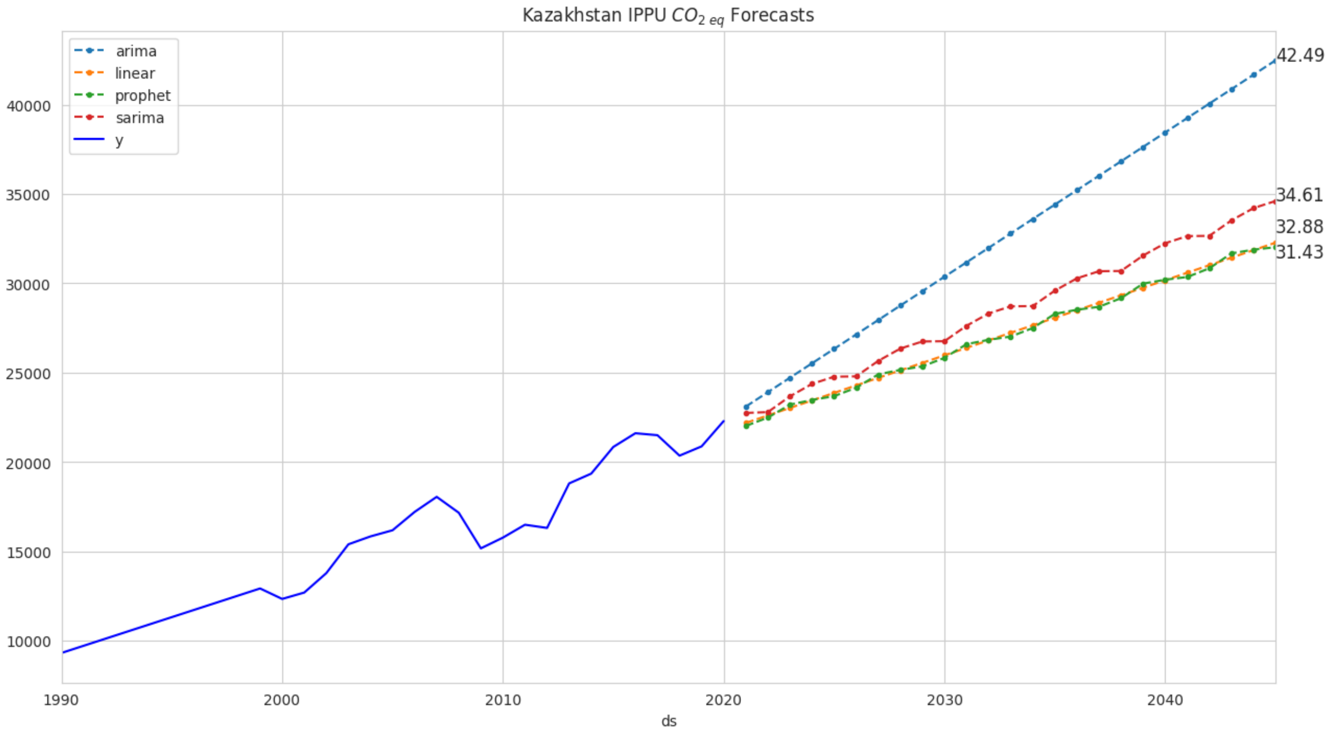

Figure 5 – Forecast of CO2 emissions in the IPPU sector until 2045

Conclusion

In the absence of any measures taken by the government and industrial production, the average value of the three forecast values at the end of 2045, CO2 emissions from the IPPU sector in the Republic of Kazakhstan alone, will amount to 35 million tons.

In this study, a forecast was presented based on the baseline scenario without taking any measures to decarbonize the economy of the Republic of Kazakhstan. The data was taken from official open sources of the UNFCCC.

Data Availability Statement: Data used in this article is cited in the reference section. More curated data is also available by a request to the corresponding author.

References

1. Framework Convention of Organizations Arises Out of Climate Consumption (UNFCCC), 1994. – URL: https://di.unfccc.int/detailed_data_by_party
2. F. Petitjean, A. Ketterlin & P. Gancarski. A global averaging method for dynamic time warping, with applications to clustering. Pattern Recognition, Elsevier, 2011.
3. M. Cuturi, M. Blondel "Soft-DTW: a Differentiable Loss Function for Time-Series," ICML 2017.
4. Singh, P.K.; Pandey, A.K.; Ahuja, S. Multiple forecasting approach: A prediction of CO2 emission from the paddy crop in India. Environ. Sci. Pollut. Res. Vol. 2022.
5. Demir, A.S. Modeling and forecasting of CO2 emissions resulting from air transport with genetic algorithms: The United Kingdom case. Theor. Appl. Climatol. 2022.
6. Ahn, K.U.; Kim, D.W.; Cho, K.; Cho, D.; Cho, H.M.; Chae, C.U. Hybrid Model for Forecasting Indoor CO2 Concentration. Buildings 2022.
7. Chang, C.L.; Ilomäki, J.; Laurila, H.; McAleer, M. Causality between CO2 emissions and stock markets. Energies 2020.
8. Libao, Y.; Tingting, Y.; Jielian, Z.; Guicai, L; Yanfen, L.; Xiaoqian, M. Prediction of CO2 Emissions Based on Multiple Linear Regression Analysis. Energy Procedia 2017.
9. Box, G. A Very British Affair Box and Jenkins: Time series analysis, forecasting and control. In A Very British Affair; Palgrave Macmillan: London, UK, 2016.

Ә.А. Зайдулла
Astana IT University,
010000, Республика Казахстан, г.Астана, ул. Мангилик ел, 55/11
e-mail: adilhanzai@gmail.com

ПРОГНОЗИРОВАНИЕ ВЫБРОСОВ ПАРНИКОВЫХ ГАЗОВ В ПРОМЫШЛЕННОМ ПРОИЗВОДСТВЕ РЕСПУБЛИКИ КАЗАХСТАН

Чрезмерные выбросы парниковых газов (ПГ) являются экологической проблемой. Исследования по определению экономически эффективных способов сокращения выбросов парниковых газов выявили необходимость моделирования динамики выбросов углекислого газа, закиси азота, метана и других газов. В данном исследовании был проведен расчет выбросов СО2 в эквиваленте от промышленных процессов и производства на территории Республики Казахстан. При прогнозировании использовались данные, предоставленные Рамочной конвенцией ООН об изменении климата.

Для прогнозирования выбросов СО2 от промышленного производства использовались инструменты анализа и прогнозирования временных рядов: метод Prophet, кластерный анализ временных рядов k-средних, современные версии алгоритмов ARIMA, методы экспоненциального сглаживания и линейной регрессии. В этом исследовании представлены результаты сравнительного моделирования временных рядов, основанные на базовом сценарии, который не предусматривает никаких действий до 2045 года. В этом исследовании сравниваются четыре модели, чтобы предложить наиболее эффективную модель для прогнозирования выбросов СО2 в будущем. Сравнение точности проводится с использованием различных мер погрешности, при этом в качестве метрики для сравнения выбрана средняя абсолютная процентная ошибка (MAPE).

***Ключевые слова**: выбросы парниковых газов, искусственный интеллект, машинное обучение, промышленные процессы, использование продукции, выбросы СО2.*

Ә.А. Зайдулла
Astana IT University,
010000, Қазақстан Республикасы, Астана қ., Мангилик ел к-сі, 55/11
e-mail: adilhanzai@gmail.com

ҚАЗАҚСТАН РЕСПУБЛИКАСЫНЫҢ ӨНЕРКӘСІП ӨНДІРІСІНДЕГІ ПАРНИКАЛЫҚ ГАЗДАР ШЫҒАРУЛАРЫН БОЛЖАУ

Парниктік газдардың (ПГ) шамадан тыс шығарындылары экологиялық проблема болып табылады. Парниктік газдар шығарындыларын азайтудың үнемді әдістерін анықтау бойынша зерттеулер көмірқышқыл газы, азот оксиді, метан және басқа газдар шығарындыларының динамикасын модельдеу қажеттілігін анықтады. Бұл зерттеуде Қазақстан Республикасының аумағындағы өнеркәсіптік процестер мен өндірістің баламасында СО2 шығарындыларын есептеу жүргізілді. Болжам жасау үшін Біріккен Ұлттар Ұйымының Климаттың өзгеруі туралы негіздемелік конвенциясы ұсынған жалпыға қолжетімді деректер пайдаланылды.

Өнеркәсіптік өндірістен СО2 шығарындыларын болжау үшін әртүрлі уақыттық қатарларды талдау және уақыт қатарларын болжау құралдары пайдаланылды: Пайғамбар әдісі, k-меанс уақыттық қатарларды кластерлік талдау, маусымдық түзетілген ARIMA алгоритмдерінің заманауи нұсқалары, экспоненциалды тегістеу және бір жақты сызықтық регрессия әдістері. Бұл зерттеу 2045 жылға дейін ешқандай әрекетті қамтымайтын негізгі сценарийге негізделген салыстырмалы модельдеу нәтижелерін ұсынады. Бұл зерттеу болашақ СО2 шығарындыларын болжау үшін машиналық оқытудың ең тиімді моделін табу үшін осы төрт модельді салыстырады. Дәлдік салыстыру әртүрлі қате өлшемдерін қолдану арқылы жүргізіледі, салыстыру үшін көрсеткіш ретінде орташа абсолютті пайыздық қате (MAPE) таңдалады.

***Түйін сөздер:** парниктік газдар шығарындылары, жасанды интеллект, Машиналық оқыту, өндірістік процестер, өнімді пайдалану, СО2 шығарындылары.*

Information about the author

Adilkhan Zaidulla* – Master student of the department "Information and Communication Technologies"; Astana IT University; The Republic of Kazakhstan; e-mail: adilhanzai@gmail.com. ORCID: 0000-0002-9257-5797.

Сведения об авторе

Әділхан Абзалұлы Зайдулла* – Магистрант кафедры «Информационно-коммуникационные технологии»; Astana IT University; Республика Казахстан; e-mail: adilhanzai@gmail.com. ORCID: 0000-0002-9257-5797.

Автор туралы мәлімет

Әділхан Абзалұлы Зайдулла* – «Ақпараттық-коммуникациялық технологиялар» кафедрасының магистранты; Астана IT университеті; Қазақстан Республикасы; электрондық пошта: adilhanzai@gmail.com. ORCID: 0000-0002-9257-5797.

Material received on 03.04.2023 г.

DOI: 10.53360/2788-7995-2023-1(9)-3

МРНТИ: 44.31.29

М.В. Ермоленко[1*], О.А. Степанова[1], Н.А. Демин[1,2], Т.Н. Умыржан[1], Ж.К. Алдажуманов[1]

[1]Некоммерческое акционерное общество «Университет имени Шакарима города Семей»,
071412, Республика Казахстан, г. Семей, ул. Глинки, 20 А,
[2]Государственное коммунальное предприятие «Теплокоммунэнерго»,
071417, Республика Казахстан, г. Семей, пр. Ауэзова, 111
[*]e-mail: tehfiz@mail.ru

ИССЛЕДОВАНИЕ ВЛИЯНИЯ ТЕПЛОПРОИЗВОДИТЕЛЬНОСТИ И ПАРОПРОИЗВОДИТЕЛЬНОСТИ КОТЕЛЬНОГО АГРЕГАТА НА КПД БРУТТО И РАСХОД УГЛЯ

Аннотация: *Несмотря на то, что в настоящее время во всем мире все больше внимания уделяется развитию нетрадиционной и возобновляемой энергетики, для Республики Казахстан угольная промышленность продолжает оставаться одной из важнейших отраслей. В Казахстане представлены все основные отрасли угольной промышленности: добыча и переработка. В Республике сосредоточены 3,3 процента мировых запасов угля. В данной работе представлено исследование процессов сжигания каражыринского угля марки Д (низшая теплота сгорания находится в пределах от 18855 до 21788 кДж/кг), который является непроектным топливом. Исследования проводились на действующем котле Е-90-3,9/440 при различной паропроизводительности для составления режимной карты котла. Данный уголь используется не только в области, но и за ее пределами. В ходе проведенного исследования были установлены зависимости коэффициента полезного действия (КПД) брутто котельного агрегата от теплопроизводительности и паропроизводительности.*

В результате проведенной математической обработки полученных экспериментальных данных (для трех тепловых нагрузок 50 т/час, 75 т/час, 90 т/час), были получены аналитические зависимости, которые описывают изменение КПД брутто и расхода угля в зависимости от теплопроизводительности и паропроизводительности котла, при этом коэффициент детерминации находится в допустимых пределах.

Ключевые слова: *котел, КПД брутто, паропроизводительность, потери, тепловая электростанция, каменный уголь, теплопроизводительность, расход топлива.*

Введение

В последние годы отмечается интенсивное развитие нетрадиционной энергетики. Тем не менее, большая часть производимой в мире электроэнергии, в том числе и в Казахстане,