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# COMPARISON OF APPROACHES TO ASSESSING ENERGY EFFICIENCY OF TECHNOLOGICAL PROCESSES

*This paper examines the issues of assessing the energy efficiency of technological processes to ensure sustainable development and rational management of mining enterprises in accordance with international standard ISO 50001. The main idea of the work is a comparative analysis of the traditional approach based on the calculation of specific energy consumption (SEC) values, used by many domestic and foreign enterprises as a key indicator of efficiency, and an approach based on the stochastic frontier analysis (SFA) methods. The rationale for the need to assess energy efficiency is given, taking into account the nonlinearity and stochasticity of technological processes of mining enterprises, as well as the features of the technical and operational characteristics of individual energy-consuming objects and environmental conditions. During the work, the computational experiments were carried out as a case-study of production activities of EKG-10 excavators for 2021–2023. Based on the results of the work, the nonlinear relationship between the key parameters of energy efficiency monitoring and the adequacy of the proposed method for solving the problem is proved. The comparative estimates of potential energy losses with different approaches to analyzing the activities of enterprises are presented, showing potential hidden energy losses when using SEC of more than 30% of the total volume.*

***Keywords:*** *specific energy consumption, SEC, stochastic frontier analysis, SFA, Cobb–Douglas production function, opencast mining enterprises, energy efficiency, ISO 50001:2018, excavator, sustainable development*

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## Introduction

Energy efficiency of technological processes remains one of the critical objectives of smart production management for over half a century [1–4]. An essential advance in the sphere of energy efficiency became possible with the advent of the energy management concept in the 1980s. The concept of energy management included a system approach to resource management in industry owing to the development of procedures for the energy consumption measurement and analyses at different stages of production. An important element of this approach was the introduction of energy audits which estimated current energy costs and revealed bottle necks in enhancement of energy efficiency [5, 6]. At the turn of the 1990s and 2000s, the international standards of energy management began developing to ensure a systematized approach to energy consumption control in industry. One of the highlights in this sphere was international standard ISO 50001 accepted in 2011. The standard defined the general principles and requirements for the energy management systems to help industries control and reduce consumption using measurable indicators. ISO 50001 uses the plan–do–check–act cycle (PDCA), which assumes persistent improvement of energy control. The standard became a framework for the long-term energy saving strategies at many Russian and foreign mining companies [4, 5, 7–10]. The results of the standard introduction are not only the reduction of expenditures connected with energy but the increased resistance to fluctuations of the market of energy sources.

Today the energy efficiency management systems enjoy a great advance thanks to the active automation. Modern mines possess as a rule all necessary facilities of technological information acquisition and processing; these facilities allow real-time tracing of energy consumption and production factors [11, 12]. Industry 4.0 technologies have opened up new vistas for the energy consumption analysis and disclosure of hidden resources for the energy efficiency enhancement. For example, predictive analytics and machine learning enable forecasting peak loads and preplanning energy consumption, which allows minimization of costs of electric energy when its price is on the rise [13]. Furthermore, intersystem integration of energy consumption data and industrial production figures enables more accurate planning and control of energy consumption. The introduction of automated systems of centralized energy efficiency management at mines facilitates the real-time response to changes in process flows and makes it possible to prevent accidents connected with overloads or inadequate performance of equipment.

The critical component of such systems is continuous monitoring and analysis of the key energy efficiency indicators. In the context of the mining industry and many related sectors, such indicator is traditionally the specific energy consumption (SEC) [11]. SEC is understood as a linear value of volume ratio of consumed energy to work performed. The range of the efficient energy consumption, as a predictive estimate of planned performance at individual energy-consuming objects (ECO) and processes, is determined at each individual mine and has no strictly formalized and substantiated principles of calculation. Moreover, the use of the value of SEC for the analysis of production process at the absence of statistically significant ranges of efficiency disregards some factors and features of mining production, which can lead to potential economic losses. Thus, the aim of this study is the comparative analysis of approaches to the energy efficiency evaluation in the mining industry using the conventional approach with SEC and the approach based on the econometric method of the Stochastic Frontier Analysis (SFA) having a good account of solving problems connected with evaluation of efficiency of nonlinear processes [14–16].

## Approaches to energy efficiency evaluation

This study uses the analysis of data on performance of individual ECOs at operating opencast mines in Russia. The data were obtained with the help of the automated energy efficiency measurement system integrated in operation of the test mines. **Figure 1** presents the conceptual architecture of this system described by the authors earlier [17].

The feature of this system is integration of production data from heterogeneous information systems operated at mines, and their further complexing for the analysis of performance of individual ECOs and production processes. In conformity with the adopted practices at mines, the system can evaluate specific energy consumptions per different time intervals (hour, shift, month, year). The value of the actual specific energy consumption $SEC$ is to be compared with the effective specific energy consumption limit $\widehat{SEC}$ set by the mine engineers on the basis of their expert estimates, from the nonformal retrospective analysis of the mine performance with regard to only integral volume of spent energy resources and planned volume of work. The accumulative values are averaged as per the number of energy consuming objects (dump trucks, excavators and other equipment) for each type of energy resources, and are then assumed as predicative plane evaluations for the comping production periods. In a general form, this procedure can be written as follows:

$$\begin{cases} \left(SEC_{n_m} = \dfrac{E_{n_m}}{V_{n_m}}\right) \le \left(\widehat{SEC}_{n_m} = \dfrac{E_{n_m}}{V_{n_m}}\right) \to \\ \to (\textit{efficiently}) \text{ and } \Delta E^{+}_{n_m} = E_{n_m} - E_{n_m}; \\ \left(SEC_{n_m} = \dfrac{E_{n_m}}{V_{n_m}}\right) > \left(\widehat{SEC}_{n_m} = \dfrac{E_{n_m}}{V_{n_m}}\right) \to \\ \to (\textit{inefficiently}) \text{ and } \Delta E^{-}_{n_m} = E_{n_m} - E_{n_m}, \end{cases}, \qquad (1)$$

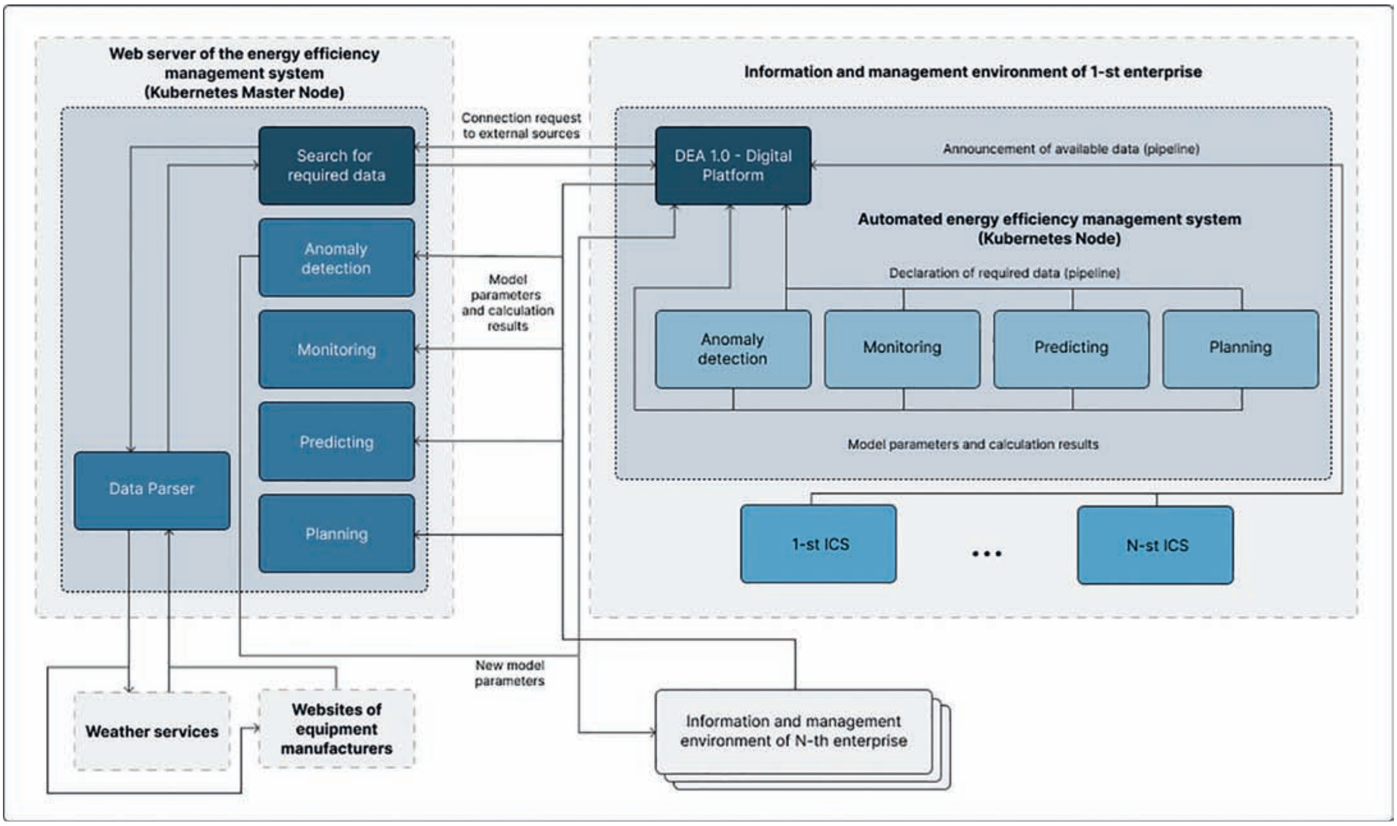

**Fig. 1. Conceptual architecture of automated energy efficiency management system of a mine**

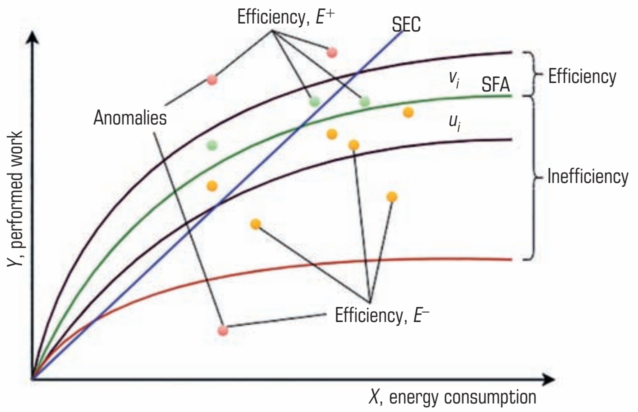

**Fig. 2. Illustration of SFA/Cobb–Douglas function application in energy efficiency analysis**

where $SEC_{n_m}$ is the current specific energy consumption for an n-th ECO in an m-th interval of time (shift or month); $E_{n_m}$ is the current volume of spent energy resources; $V_{n_m}$ is the current volume of executed work; $\widehat{SEC}_{n_m}$ is the set limit of the effective specific energy consumption; $E_{n_m}$ is the predicted heuristic estimate of energy consumption; $V_{n_m}$ is the planned volume of work; $\Delta E^{+}_{n_m}$ is the volume of saved energy resources; $\Delta E^{-}_{n_m}$ is the volume of overspent energy resources.

Evidently, this approach has some shortages, namely:

1. First, the estimate of the planned energy consumption is based on the experience of a decision-maker, and this approach lacks guaranteed relevance of information at hand and features risk of human error.

**Table 1. Integral SEC-based analysis of ECO performance**

| Indicator | Excavator 1 | Excavator 2 | Excavator 3 |
|---|---|---|---|
| Efficient shifts, % | 99.9 | 11 | 100 |
| Inefficient shifts, % | 0.1 | 89 | 0 |
| $\Delta E^{+}_{\Sigma}$, kWh | 2,288,950.83 | 79,890.83 | 3,599,419.88 |
| $\Delta E^{-}_{\Sigma}$, kWh | –26.75 | –6,897,425.81 | 0 |
| $\Delta E^{total}_{\Sigma}$, kWh | 2,288,924.08 | –6,817,534.98 | 3,599,419.88 |

**Table 2. Integral SFA-based analysis of ECO performance**

| Year | Indicator | Excavator 1 | Excavator 2 | Excavator 3 |
|---|---|---|---|---|
| 2021 | Effective shifts, % | 11 | 20 | 9 |
| | Ineffective shifts, % | 89 | 80 | 91 |
| | $\Delta E^{+}_{\Sigma}$, kWh | 11,510.24 | 153,492.71 | 9,287.76 |
| | $\Delta E^{-}_{\Sigma}$, kWh | –187,310.98 | –1,069,493.05 | –247,858.04 |
| 2022 | Effective shifts, % | 10 | 7 | 11 |
| | Ineffective shifts, % | 90 | 93 | 89 |
| | $\Delta E^{+}_{\Sigma}$, kWh | 9,865.12 | 56,010.38 | 13,013.71 |
| | $\Delta E^{-}_{\Sigma}$, kWh | –206,765.25 | –2,358,288.75 | –178,618.75 |
| 2023 | Effective shifts, % | 12 | 12 | 8 |
| | Ineffective shifts, % | 88 | 88 | 92 |
| | $\Delta E^{+}_{\Sigma}$, kWh | 9,377.09 | 60,692.46 | 4,690.23 |
| | $\Delta E^{-}_{\Sigma}$, kWh | –123,555.1 | –723,623.05 | –143,747.92 |
| $\Delta E^{total}_{\Sigma}$, kWh | | –486,878.88 | –3,881,209.3 | –543,233.01 |

2. The uniform averaging of the planned energy consumption for the same-type ECOs disregards specifics of the initial operating data of equipment and variation of these data in the course of equipment operation.

3. Specifics of certain types of work is neglected while their SECs can differ greatly.

4. And, chiefly, it is initially assumed that the functional connection between the key technological parameters is the deterministic linear dependence, which is not a statistically proved property of mineral mining processes which feature the nonlinear behavior and stochastic variation of service conditions of ECOs and production environment.

Thus, in the framework of this research, it was hypothesized to be necessary to revise the energy consumption efficiency evaluation approach with regard to the nonlinearity and stochasticity of process flows, individual calculation of indicators of individual ECO and types of works to be executed, as well as with the use of the key monitoring parameters—volumes of implemented works and spent resources.

In conformity with the hypotheses, the base approach was selected to be a group of econometric methods of the stochastic frontier analysis (SFA). This group of methods is sufficiently studied and appears to be many times efficient in calculation of the efficiency limits for the production processes in different sectors of economy [18, 19]. The main idea of SFA is the nonlinear modeling of the production volume as function of the volume of spent resources with regard to various errors [20–22]. The shape of such nonlinear function is undetermined beforehand and can be selected in conformity with the initial conditions of the problem and with the estimated accuracy calculated empirically using specific experimental data. The present study authors select a function of support to be the well-known Cobb–Douglas function [2, 24] which possesses the best interpretability of the results. The pattern of the stochastic production function on the basis of the SFA and Cobb–Douglas model is determined as follows:

$$y_i = A \cdot x_i^{\beta} \cdot \exp(v_i) \cdot \exp\left(-u_i\right), \qquad (2)$$

where $y_i$ is the executed work volume $V_{n_m}$ (1) in excavation and haulage of rocks; $x_i$ is the spent energy volume $E_{n_m}$ (1); $A$ is the production scale factor; $\beta$ is the cost elasticity factor; $v_i$ is the accidental variation in the spent energy volume, explained by stochastic or unformalizable factors of variation in production processes; $u_i$ is the variation in the spent energy volume due to ineffective work execution.

For calculating parameters of the stochastic energy efficiency function, it is required to use a logarithmic likelihood function [20–22] which is optimized with the help of BFGS algorithm (Broyden–Fletcher–Goldfarb–Shanno algorithm). In this case, in view of a lot of anomalous values present in the input data, which are described by the authors in the earlier research [17], these data are withdrawn from the efficiency limit modeling but are included in the final analysis of the mine performance.

**Figure 2** offers a visual interpretation of application of the stochastic production function, where SFA is the calculable limit of efficiency for a certain ECO per certain type of work implemented. The values in the line of SFA and above it are interpreted as the energy-efficient performance of ECO, while the values above the line are explained by the stochastic error $v_i$. The values under the line SFA are interpreted as the inefficient performance of ECO and are explained by the ineffectiveness error $u_i$.

## Calculated results of energy efficiency

During the experimental research to compare the conventional SEC-based approach with the proposed approach to energy efficiency, the energy-consuming objects implementing the same-type works were selected at a mine.

**Figure 3** shows the shift-by-shift patterns of the actual specific energy consumption relative to the calculated limit of the efficient energy consumption for three excavators EKG-10 for 2021–2023. **Table 1** gives

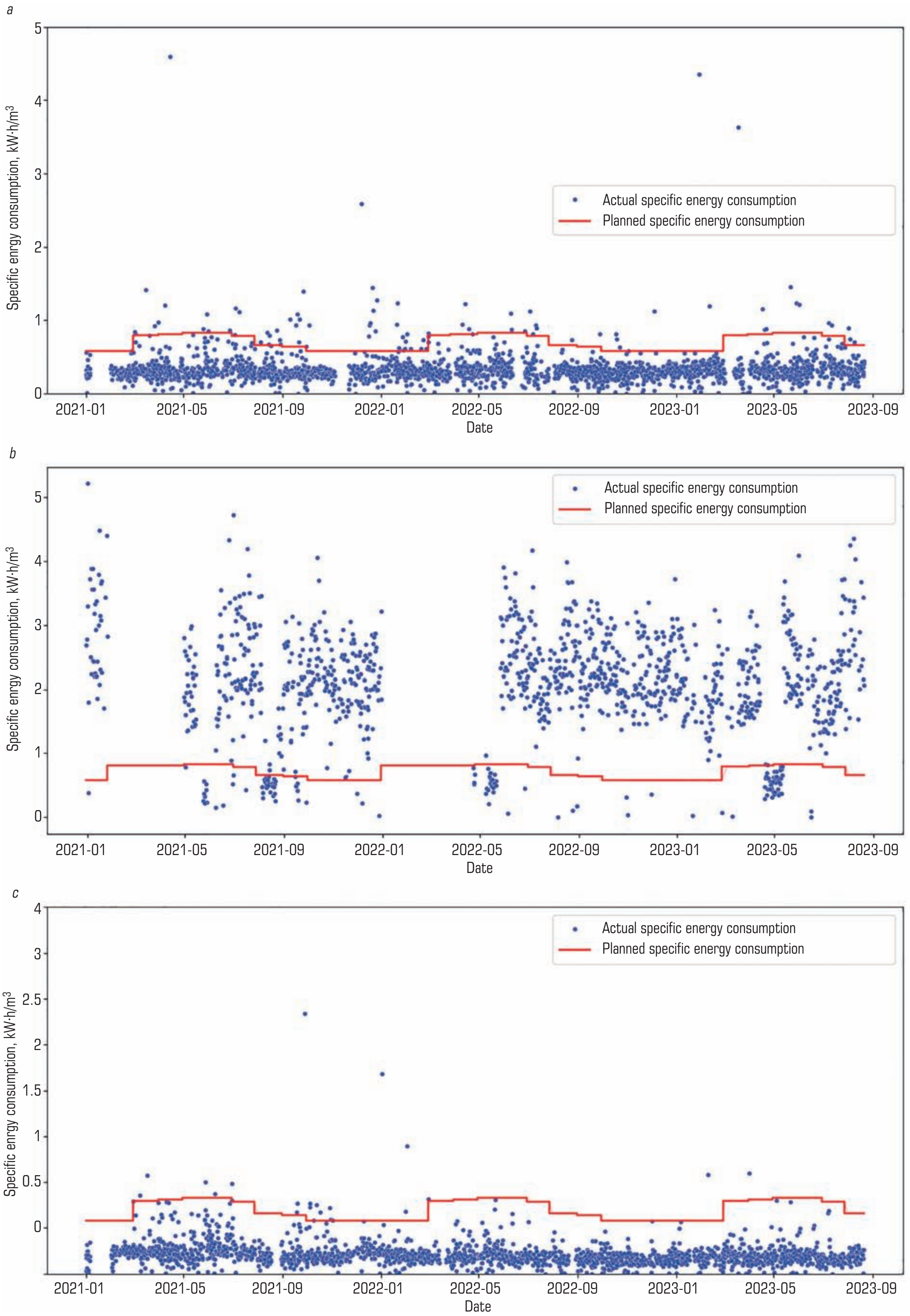

**Fig. 3. Visualization of patterns of actual and planned SEC:**
*a* – Excavator 1; *b* – Excavator 2; *c* – Excavator 3

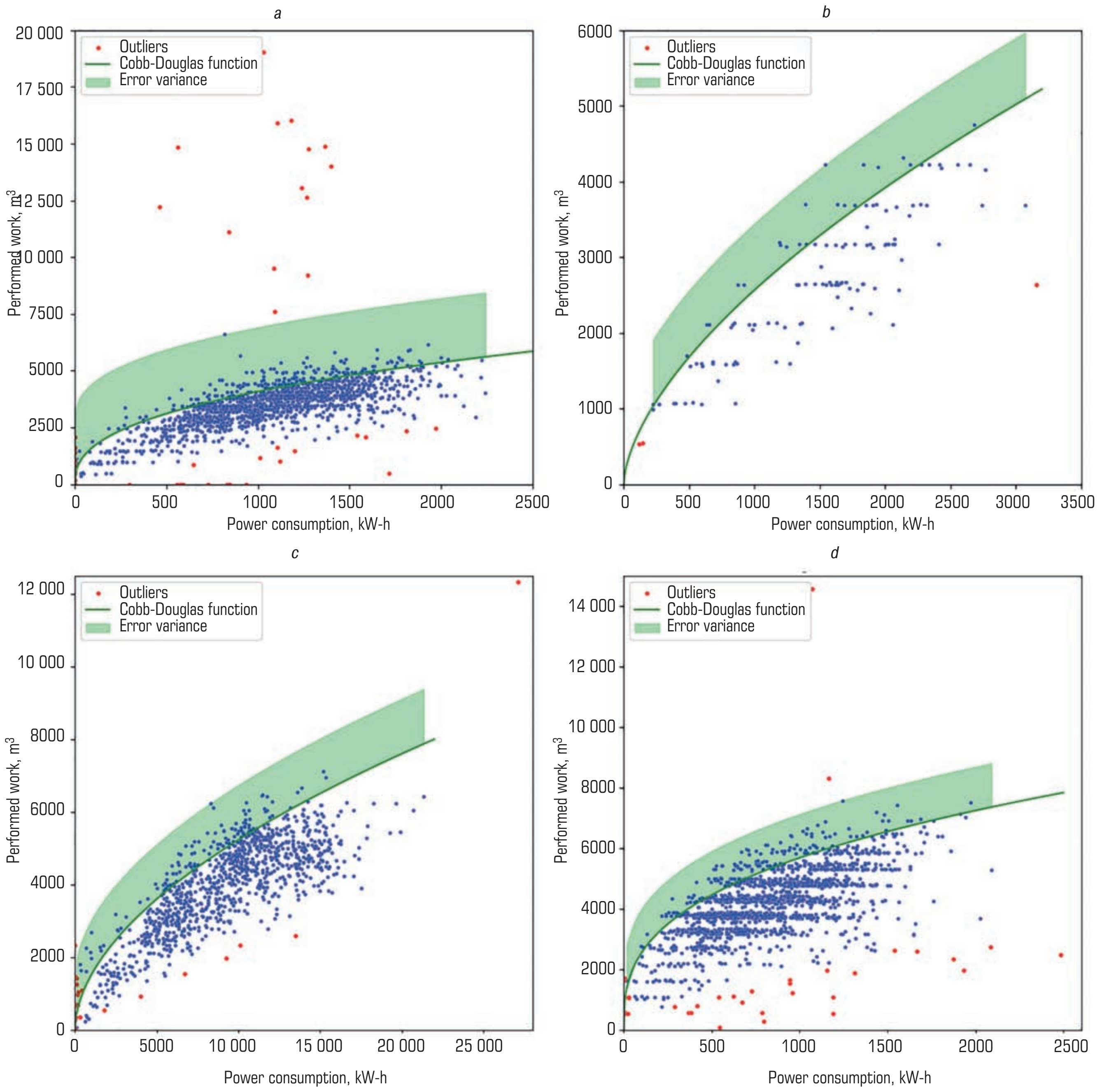

**Fig. 4. Plotting of stochastic production functions of energy efficiency for certain ECOs per certain types of work performed:**
*a* – Excavator 1: Technological work 4; *b* – Excavator 2: Technological work 2; *c* – Excavator 2: Technological work 3; *d* – Excavator 3: Technological work 4

**Table 3. Comparison of integral energy efficiency evaluations**

| Indicator | SEC | SFA/Cobb–Douglas |
|---|---|---|
| Effective shifts,% | 77 | 11 |
| Ineffective shifts, % | 23 | 89 |
| $\Delta E_\Sigma^+$, kWh | 5,968,261.54 | 327,939.71 |
| $\Delta E_\Sigma^-$, kWh | –6,897,452.56 | –5,239,260.89 |
| $\Delta E_\Sigma^{total}$, kWh | –929,191.02 | –4,911,321.18 |
| Total energy loss, % | 7 | 37.4 |

the calculated data on percent of effective and ineffective shifts, volumes of saved and overspent energy sources (electric power), as well as the integral energy consumption $\Delta E_\Sigma^{total}$ for the whole observation period.

**Figure 4** depicts plotting of the SFA/Cobb–Douglas production function for the test excavators. The calculations disregarded anomalous values in the data (red spots), which were revealed using the known Isolation Forest algorithm [25, 26]. Later on, these data were included in the integral performance estimation in terms of saved and overspent electric power (**Table 2**).

## Results and discussion

The conclusions drawn on the ground of the accomplished computational experiments are presented below.

1. The conventional SEC-based approach fortifies the initial doubts. The estimates obtained for the same-type ECOs seem mistrustful in terms of relevance of the unified averaged limits of the effective specific energy consumption without regard to the implemented operations and actual operational parameters of the employed equipment.

2. Although high heteroscedasticity of initial data, with highly scattered values at the SFA efficiency limit, the calculated stochastic production function proves the nonlinear interaction between the test parameters. This fact also confirms the initial hypothesis made within the research, and suggests the need to revise the existing strategies of the energy efficiency evaluation in the mining industry with the linear parameter SEC.

**Table 3** compares the integral energy efficiency evaluations obtained for the performance of test ECOs during the whole test period.

### Conclusions

Based on the comparative analysis of the two approaches, the SEC-based approach currently conceals huge potential losses of energy. For instance, at the overall spent energy by three excavators over the whole test period in amount of 13,131,100.048 kWh, the difference in the overspent energy estimate is 3,982,130.16 kWh, or more than 30%. It is worthy of mentioning that this research avoided finding the most precise SFA model, and, in case of using other functions, such as translog, the accuracy of the obtained evaluations can be improved within 1–7%. Furthermore, the proposed approach, owing to the retrospective data analysis, informs only about potential losses of energy, while their actual elimination can only be achieved thanks to efficient production management using the proposed computational apparatus.

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