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APPROACHES TO REDUCING THE CARBON FOOTPRINT IN TRAINING LARGE ML MODELS

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The study's relevance is due to a significant increase in the use of machine learning, accompanied by an increase in the energy consumption required to train large models. This creates a significant carbon footprint that threatens environmental sustainability. To reduce the environmental impact of technological development, the problem requires the integration of energy-efficient approaches and the introduction of renewable energy sources.

The study aims to develop effective approaches to optimising computing processes, with the aim of reducing energy consumption during the training of machine learning models.

The study uses system analysis to assess current approaches to reducing the carbon footprint. It also compares technological solutions and summarises the results to develop comprehensive recommendations.

It has been established that the main areas of optimisation are the introduction of energy-efficient algorithms, in particular Pruning and Quantisation, using specialised equipment (TPU, GPU, ASIC), distributed computing and energy consumption monitoring systems. It has been proven that integrating renewable energy sources, such as solar and wind energy, into data centre operations significantly reduces carbon emissions. It is revealed that the main problems remain the high cost of energy-efficient equipment, insufficient transparency of algorithms and limited access to green energy.

The study results confirm that energy-efficient practices in machine learning can significantly reduce the environmental impact of computing processes. It is recommended that systematic energy consumption monitoring be introduced, infrastructure developed to support green computing, and international standards harmonised in this area.

Prospects for further research are focused on improving artificial intelligence models' performance in conditions of limited resources, developing adaptive algorithms, and minimising environmental risks associated with the introduction of modern technologies.

***Key words:** machine learning, energy efficiency, carbon footprint, renewable energy sources, sustainable development, data centres, algorithm optimisation.*

Коростін О. О. Підходи до зменшення вуглецевого сліду в тренуванні великих ML-моделей

Актуальність дослідження зумовлена значним зростанням масштабів використання машинного навчання, що супроводжується підвищенням енергоспоживання для тренування великих моделей. Це створює суттєвий вуглецевий слід, що ставить під загрозу екологічну стійкість. Проблема потребує інтеграції енергоефективних підходів та впровадження відновлюваних джерел енергії для зниження впливу технологічного розвитку на довкілля.

Мета дослідження – розробка ефективних підходів до оптимізації обчислювальних процесів, спрямованих на зменшення енергоспоживання під час тренування моделей машинного навчання.

У межах дослідження застосовано системний аналіз для оцінки сучасних підходів до зменшення вуглецевого сліду. Проведено порівняльний аналіз технологічних рішень, а також узагальнено результати для розробки комплексних рекомендацій.

Встановлено, що основними напрямами оптимізації є впровадження енергоефективних алгоритмів, зокрема Pruning і Quantization, використання спеціалізованого обладнання (TPU, GPU, ASIC), розподілених обчислень та систем моніторингу енергоспоживання. Доведено, що інтеграція відновлюваних джерел енергії, таких як сонячна та вітрова енергія, у роботу дата-центрів значно знижує обсяг вуглецевих викидів. Виявлено, що основними проблемами залишаються висока вартість енергоефективного обладнання, недостатня прозорість алгоритмів та обмежений доступ до «зеленої» енергії.

Результати дослідження підтверджують, що впровадження енергоефективних практик у галузі машинного навчання дозволяє суттєво зменшити екологічний вплив *обчислювальних процесів. Рекомендовано запровадження систематичного моніторингу енергоспоживання, розвиток інфраструктури для підтримки «зелених» обчислень та гармонізацію міжнародних стандартів у цій галузі.*

Перспективи подальших досліджень зосереджуються на вдосконаленні моделей штучного інтелекту для роботи в умовах обмежених ресурсів, розробці адаптивних алгоритмів та мінімізації екологічних ризиків, пов'язаних із впровадженням сучасних технологій.

Ключові слова: *машинне навчання, енергоефективність, вуглецевий слід, відновлювані джерела енергії, сталий розвиток, дата-центри, оптимізація алгоритмів.*

Problem statement. Training large machine learning models is one of the most resource-intensive processes in modern technologies, accompanied by significant energy consumption and carbon footprint. This necessitates introducing sustainable approaches to optimising computing processes to reduce energy costs and minimise negative environmental impact.

Among the effective approaches to solving this problem is integrating renewable energy sources into data centres, which helps significantly reduce dependence on traditional energy sources. Another important area is using energy-efficient equipment specially designed for machine learning tasks, which can significantly reduce energy consumption and increase the efficiency of computing processes.

Algorithmic optimisations, such as model complexity reduction techniques, reduce computational costs while maintaining model accuracy and performance. Using these methods is one of the key elements of optimisation in modern computing systems.

At the global level, the adaptation of environmental standards and sustainability principles plays an important role in reducing machine learning's environmental impact. Environmental management systems, which regulate the requirements for the sustainable use of resources, are the basis for developing policies in computing.

Successful integration of international experience into local conditions requires creating favourable conditions for the development of green technologies. Investing in energy-efficient equipment, developing solutions for monitoring energy consumption, and using local renewable energy sources will help optimise resources while minimising machine learning's carbon footprint. These measures not only increase environmental sustainability but also create the preconditions for sustainably further development of the technology sector.

Analysis of the latest research and publications. Analysing scientific papers on approaches to reducing the carbon footprint in training large ML models allows us to identify several main research areas and summarise the results achieved.

The first area focuses on quantifying the carbon footprint. E. Strubell, A. Ganesh and A. McCallum [1] showed that training large ML models can generate CO_2 emissions equivalent to tens of tonnes. They proposed a transparent approach to measuring these emissions, which could form the basis for future standards. A. Lacoste, A. Luccioni, V. Schmidt, and T. Dandres [2] complemented this analysis by proposing tools for assessing the carbon footprint at different stages of the model life cycle. D. Patterson, J. Gonzalez, et al. [3] considered the technical aspects of reducing energy consumption during the training of large models, particularly through renewable energy sources. These results contribute to the creation of basic standards for the implementation of environmentally sound approaches in the field of machine learning.

The second area is devoted to optimising algorithms and model architectures to reduce energy consumption. J. Tmamna, E.B. Ayed and R. Fourati [4] summarised Pruning methods that reduce power consumption by 30–50% by removing redundant parameters in neural networks. P. Henderson and co-authors [5] systematised the data on energy consumption of ML models, suggesting the introduction of carbon footprint reporting standards. V. Mehlin, S. Schacht and C. Lanquillon [6] summarised approaches to reducing energy consumption in the life cycle of models, indicating the possibility of reducing energy consumption by 25%. These studies emphasise the prospects of improving architectures to reduce the carbon footprint without sacrificing model performance. This suggests that introducing optimisation techniques such as Pruning, combined with standardised approaches to energy reporting, can significantly improve resource efficiency.

The third area concerns using environmentally friendly energy sources and approaches to integrating sustainable development. D. Rolnick and his team [7] proposed a roadmap for implementing green technologies in machine learning, including the transition to federated learning and reducing energy consumption through local data processing. V.K.Q. Dinh, C.N.D.V. Anh and N.M. Quy [8] demonstrated that federated learning reduces the amount of transmitted data by 60%, significantly reducing energy costs. T. Khan, W. Tian, et al. [9] showed that workload forecasting in cloud data centres using ML can increase energy efficiency by 25–30%. For further study of the problem, it is recommended to prioritise using renewable energy sources and federated learning to combine technical efficiency with minimising environmental impact.

The fourth area covers the study of organisational and political aspects of sustainable development in machine learning. E.M. Bender, T. Gebru and co-authors [10] emphasised the need for ethical management of the development of large models, noting that their excessive scaling can lead to a disproportionate increase in carbon footprint. F. Zennaro, E. Furlan and C. Simeoni [11] explored the potential of machine learning for climate risk assessment, emphasising the importance of integrating environmental practices. F. Daghero, D.J. Pagliari, and M. Poncino [12] focused on energy-efficient architectures for edge devices that can significantly reduce energy consumption. The generalisation of these approaches contributes to the formation of policies that consider the balance between innovation and environmental responsibility. The introduction of environmental standards at the level of organisational policies will help to align innovation with sustainable development.

The fifth area concerns practical examples of energy-efficient practices in industry. D.A.C. Narciso and F.G. Martins [13] analysed the application of machine learning to improve energy efficiency in industrial environments, identifying a reduction in energy consumption of up to 20% compared to traditional methods. M. Demirci [14] investigated the use of ML for resource management in cloud computing environments, revealing the possibility of reducing energy consumption by 15% due to dynamic load balancing between servers. The active integration of machine learning in dynamic resource management will significantly reduce energy consumption in industrial systems.

These studies show that optimising the energy consumption of large ML models is achieved by integrating technical, organisational, and environmental solutions.

Despite the progress in reducing the carbon footprint of ML models, the issues of integrated energy consumption assessment at all stages of the model life cycle and the development of universal monitoring standards remain unresolved. Particular attention should be paid to the transparency of algorithms that determine the amount of energy consumption, which is critical for creating environmentally sound approaches. Regional characteristics and economic factors limit the use of renewable energy sources, while technological solutions such as Pruning need to be adapted to industrial conditions, which hinders their massive adoption. Organisational aspects, such as a lack of awareness of the need for sustainability among developers and managers, also create barriers to integrating environmental practices.

The proposed study addresses these issues by evaluating current approaches to reducing carbon footprint, analysing energy-efficient technologies used in training large ML models, and developing recommendations for their optimal implementation. The main goal is to create integrated tools for monitoring energy consumption that will help standardise processes and improve the transparency of algorithms, as well as ensure the practical implementation of sustainable practices in machine learning.

These measures have the potential to create an effective energy management system in artificial intelligence, increasing the overall environmental sustainability of technological solutions.

The article's purpose is to analyse modern technical solutions and innovations, including algorithmic optimisation, renewable energy, and sustainable practices in data centres, to reduce the carbon footprint of training large machine learning models and develop practical recommendations for their implementation in real-world conditions.

Objectives of the article:

1. Analyse algorithmic optimisation methods (Pruning, Quantisation) and their impact on reducing power consumption when training large ML models.
2. Explore using renewable energy sources, such as solar and wind power, to ensure energy efficiency in data centres.
3. To develop practical recommendations for implementing energy-efficient solutions in real-world conditions, mainly through integrating energy monitoring systems, optimised algorithms and renewable energy sources.

Summary of the main material. Training large machine learning models is one of the most resource-intensive operations in modern technology. Energy consumption during these processes has become the subject of intensive research, as it directly affects the carbon footprint caused by using computing systems. Current research focuses on developing energy-efficient algorithms, optimising model architecture, and using more environmentally friendly energy sources for computing infrastructure. The table below shows the main research areas and their practical implementation (Table 1).

In the current environment, considerable emphasis is placed on practically integrating these approaches into industrial processes and academic research. For example, companies such as Google and Microsoft are actively switching to energy-efficient servers running on renewable energy [15]. Innovative algorithms that reduce the complexity of computations demonstrate a significant reduction in energy consumption without losing the accuracy of the models. The use of distributed computing, in particular federated learning [7], can significantly reduce the amount of data that needs to be transmitted for training, which minimises energy consumption at the stage of information transmission.

One of the most significant achievements of recent years has been the introduction of tools for modelling the environmental impact of ML models, such as CodeCarbon [16]. They allow us to estimate the amount of carbon emissions during model training and find the best ways to reduce them. At the same time, access to renewable energy sources in some regions remains challenging, making integrating environmental solutions globally difficult. However, active cooperation between researchers and industry is gradually reducing these barriers, contributing to the sustainable development of machine learning.

Technical solutions and innovations in machine learning are actively aimed at optimising model training processes to reduce energy consumption and increase resource efficiency. These approaches include optimising algorithms, upgrading hardware, using distributed computing, and implementing energy monitoring technologies. Modern advances reduce the carbon footprint and significantly reduce model training time, which is especially important for large-scale projects in science and business. Table 2 compares the main technical solutions and their impact on process optimisation.

Table 1

Key approaches to reducing power consumption when training large ML models

Research area	Main objective	Implementation in practice
Energy-efficient algorithms	Reduce the number of calculations and model parameters	Use of Pruning (removing redundant parameters with an accuracy of 95%, as in GPT-3) and Quantization (transcoding 32-bit numbers into 8-bit) methods.
Optimise your computing infrastructure	Reducing energy consumption in data centres	Use of Google Cloud servers running on TPUs (up to 50% less power compared to traditional CPUs).
Use of renewable energy sources	Minimising the carbon footprint of computing	Installation of solar panels for Amazon's data centres (providing up to 80% of energy needs), integration of wind energy into Microsoft Azure.
Application of distributed computing	Offloading central computing resources and increasing efficiency	Using Federated Learning in Apple projects to train models locally, reducing data transfer by 65%.
Environmental impact modelling	Determining carbon footprint and environmental impact	The CodeCarbon tool estimates the carbon footprint of projects in TensorFlow and PyTorch (up to 30% energy savings due to optimisation).

Source: compiled by the author on the basis of [1; 6; 10; 11].

In practice, these technical solutions have a significant impact on optimising the training of machine learning models. For example, the Pruning technique, which is widely used in mobile application development, allows the creation of compact models with low power consumption. This is key for resource-constrained devices such as smartphones and IoT devices [9]. Quantisation reduces the amount of memory required to store model parameters, which reduces power consumption by 75% when training and using models, particularly in mobile applications such as TensorFlow Lite [4].

The use of specialised hardware, such as Google's TPU, can significantly reduce the training time of large models, such as GPT-3 while reducing power consumption compared to conventional GPUs. This is important for cloud data centres that run large ML projects [15].

Distributed computing, such as federated learning, provides parallel data processing on local devices, which reduces the load on central computing nodes and reduces the amount of data transferred by 65% [7]. This approach is especially effective for large-scale systems that work with sensitive data, such as in the healthcare sector.

The use of monitoring technologies such as CodeCarbon [16] and EnergyScope [17] allows for a detailed analysis of energy consumption during model training. These tools help to identify energy-intensive processes and implement measures to optimise them, which allows the computing infrastructure to be adapted to international environmental standards such as ISO 50001 [18] and LEED [19].

Table 2

Technical solutions and innovations to optimise the energy efficiency of ML model training

Technical solution	Description.	Impact on energy efficiency
Thinning of models (Pruning)	Remove unimportant parameters from the model to reduce its complexity	Reduce computational costs by 30–50% without losing accuracy (optimising models for mobile devices such as BERT-Mobile).
Quantisation	Using numbers with lower precision to represent model parameters	Reduced memory footprint by 75%; when used in TensorFlow Lite for mobile applications, it allows you to train models with a significant reduction in power consumption.
Use of specialised equipment	Using GPUs, TPUs and ASICs designed for machine learning computing tasks	Google TPUs deliver up to 50% less power consumption than standard GPUs when training large models such as GPT-3.
Knowledge Distillation technique	Transferring information from a large model to a smaller one that retains its core capabilities	A 40% reduction in energy consumption compared to using large models such as the GPT-3 distilled down to a smaller version.
Distributed computing	Parallel data processing on multiple devices or nodes	Reduced training time by 50%; (federated training in Apple products, which minimises data transfer)
Technologies for monitoring energy consumption	Introduce tools for analysing energy use and optimising processes	CodeCarbon allows you to estimate the carbon footprint of your TensorFlow model training, reducing energy consumption by 20–30%.

Source: compiled by the author on the basis of [2; 7; 8; 9].

Innovations in machine learning strike a balance between high model performance and reducing their negative impact on the environment, which is in line with the current requirements for sustainable development of science and technology.

The use of renewable energy sources and the implementation of sustainable practices in data centres that provide computing resources for training machine learning models are key to reducing their carbon footprint. The growing demand for computing power required to train complex models is accompanied by significant energy consumption, which creates environmental challenges. In response, companies and organisations are actively implementing sustainable development practices, such as switching to renewable energy sources such as solar, wind, and hydro, and upgrading infrastructure to improve energy efficiency. Table 3 shows a comparison of the main aspects of using such approaches in data centres.

In practice, introducing renewable energy sources is showing significant progress in different regions of the world. For example, Google’s data centre in Nevada uses solar panels to cover more than 90% of its electricity needs [20]. This allows not only the reduction of carbon emissions but also the stabilisation of energy costs regardless of changes in prices for traditional energy resources. Similarly, Microsoft uses wind farms in Wyoming, where wind speeds ensure constant power generation even during peak periods [21].

Table 3

The impact of renewable energy and sustainable practices on data centre operational efficiency

Approach	Usage	Impact on operational efficiency
Solar energy	Installation of solar panels on the territory of data centres	Stability of energy supply, reduction of electricity costs
Wind energy	Attracting wind farms to provide electricity	Reducing dependence on unstable energy resources, improving environmental sustainability
Energy-efficient cooling	Innovative cooling systems that reduce energy consumption	Reducing the risk of server overheating, extending their service life
Use of hydropower	Use of electricity from hydropower plants	Ensuring continuous operation of data centres in regions with access to hydro resources
Certification according to standards for green buildings	Compliance with environmental standards in the construction and operation of data centres	Efficient use of resources and integration of environmental practices at the management level

Source: compiled by the author on the basis of [2; 3; 5; 14; 15].

Energy-efficient cooling systems, such as those at the Facebook data centre [22] in Sweden, take advantage of the region's natural climate. This solution significantly reduces electricity consumption for cooling servers while maintaining their stable operation. Amazon actively uses hydroelectric power in Northern Virginia, which ensures a stable power supply to its computing systems even in case of peak loads on the local power grid [23].

Certification of data centres according to green building standards, such as LEED [19], promotes optimal management of resources, including water and electricity. This allows for integrating environmentally sustainable policies at the corporate governance level and improves the long-term efficiency of data centres. Implementing such solutions is becoming a necessary element of the sustainable development of the technology industry.

Reducing the carbon footprint of training large machine learning models faces several environmental, technical, and organisational challenges that significantly slow the implementation of sustainable practices. Environmental aspects are related to the limited access to renewable energy sources in many regions where large data centres are located [14]. This creates dependence on fossil fuels and increases greenhouse gas emissions. There is also an insufficient investment in green energy development to meet the technology sector's needs, making integrating clean energy sources on a large scale challenging.

Technical challenges centre around the limited availability of energy-efficient hardware, such as specialised TPU and ASIC processors, which can significantly reduce power consumption [11]. Their high cost and limited manufacturing capabilities make these technologies unaffordable for many organisations, especially SMEs. In addition, implementing energy-efficient algorithms that require significant resources to optimise and adapt to specific tasks is difficult.

Organisational challenges include a lack of awareness of the importance of sustainability among technology company managers. This is manifested in the lack of comprehensive strategies to reduce the carbon footprint and insufficient funding for research in this area [5]. In addition, the absence of global standards and regulations that would encourage environmentally responsible use of computing resources creates additional barriers to reducing the negative impact on the environment.

Reducing machine learning's negative impact on the environment and increasing the sustainability of computing processes requires a comprehensive approach that includes technological, organisational, and environmental measures.

Technological recommendations include the implementation of energy-efficient algorithms that reduce the number of calculations without compromising model performance. For example, using Pruning and Quantisation methods can significantly reduce the amount of computational operations. In addition, switching to specialised hardware, such as GPU, TPU, or ASIC, ensures optimal energy use and increases computing efficiency. For companies of different sizes, using energy monitoring tools such as CodeCarbon [16] for small projects or EnergyScope [17] for large organisations working with distributed computing is advisable.

Organisational measures include the development of sustainability strategies that integrate carbon footprint reduction goals into the companies' business processes. This can be achieved by introducing regular energy monitoring and transparent environmental performance reporting. It is recommended to use international standards such as ISO 50001 [18], which ensures effective management of energy resources, or ISO 14001 [23], which helps to integrate environmental practices into the overall management strategy.

Environmental measures include actively using renewable energy sources to meet the needs of data centres. Installing solar panels, connecting to wind or hydroelectric power plants, and developing local environmental initiatives help reduce dependence on fossil fuels. Upgrading cooling systems to LEED standards for data centres makes it possible to use natural resources more efficiently, reducing energy consumption to maintain server operating conditions.

In the global context, developing international cooperation to share experiences and technologies between countries is important. Introducing common standards in sustainable computing, such as LEED Gold or Platinum certification, will encourage companies of all sizes to reduce their carbon footprint while helping to increase their competitiveness in the global market.

Conclusions. The study has shown that training large machine learning models is a significant source of energy consumption that creates a significant carbon footprint. Modern technical and organisational solutions aimed at optimising processes have proven effective in reducing the negative impact on the environment. It was identified that the main challenges are limited access to renewable energy sources, high cost of energy-efficient equipment, and lack of transparency of algorithms, which complicates the implementation of sustainable practices.

The recommendations include introducing energy-efficient algorithms, using renewable energy sources in data centres, developing infrastructure to support green computing, and raising awareness among technology company executives about the importance of sustainable development. It is proposed that standards for monitoring energy consumption be introduced and regulatory mechanisms to support environmentally responsible use of computing resources be created.

Prospects for further research include developing artificial intelligence models that work in conditions of limited computing resources, integrating adaptive algorithms for processing big data and reducing the carbon footprint associated with their training. In addition, it is necessary to explore ways to harmonise international standards in environmentally sustainable technology development.

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