



Russian energy balance, energy efficiency, and energy-related GHG emission accounting system

Igor Bashmakov · Anna Myshak · Vladimir A. Bashmakov · Vladimir I. Bashmakov · Konstantin Borisov · Maxim Dzedzichuk · Alexey Lunin · Oleg Lebedev · Tatiana Shishkina

Received: 11 November 2022 / Accepted: 23 May 2023 / Published online: 26 July 2023
© The Author(s), under exclusive licence to Springer Nature B.V. 2023

Abstract This paper presents a newly developed Russian energy efficiency and energy-related GHG emission accounting system (EE-EGHG-AS) and discusses the results obtained. This system is designed to account for the energy efficiency progress as achieved in 12 sectors and 80 economic activities and to capture the impacts of 7 factors with a focus on the technological factor. It helped to reveal that in 2015–2021, the technological factor contributed to the 4.3% decline in GDP energy intensity (whereas the traditionally estimated GDP energy intensity was 3.6% up). If non-energy use is excluded, then energy intensity was 2.8% down, which brings the 2021 energy intensity level 15% below the traditional estimates. For some activities, the EE-EGHG-AS has demonstrated a limited ability to adequately assess the contribution made by the technological factor to crashing into, and recovering from, COVID-19-like crises, because the statistically reported data is scarce. With little progress towards energy efficiency improvements Russia is still one of the most energy-intensive countries in the world. Little progress in energy efficiency over the recent years has created the “super-coupling” effect for Russia in 2020–2021 and it is

extremely challenging to attain the country’s carbon neutrality target by 2060.

Keywords Energy balance · Energy efficiency accounting system · Energy efficiency indicators · GHG emissions · Decomposition analysis

Introduction

Ten years have passed since the first Russian energy efficiency accounting system (EEAS) was developed back in 2012 (Bashmakov & Myshak, 2014). It was used by the RF Ministry of Energy until 2014. That system was based on the log mean Divisia index (LMDI) methodology used to identify the contributions from various drivers and included 15 sectors and 44 activities (subsectors). It was based on annual Russian energy balances as assessed by CENEf-XXI¹ starting from 2000. Later, the responsibility for Russian energy efficiency policies was delegated to the Ministry of Economic Development of the Russian Federation (MED RF). By 2019, MED RF recognized that an effective set of indicators is needed to manage energy efficiency improvements and to identify the contribution from the technological factor to the evolution of Russian GDP energy intensity. CENEf-XXI then developed a new energy efficiency accounting system in 2019. The methodology for

I. Bashmakov (✉) · A. Myshak · V. A. Bashmakov · V. I. Bashmakov · K. Borisov · M. Dzedzichuk · A. Lunin · O. Lebedev · T. Shishkina
Center for Energy Efficiency – XXI (CENEf – XXI), 61 Novocheremushkinskaya St., 117418 Moscow, Russia
e-mail: bashmako@co.ru

¹ Center for Energy Efficiency – XXI.

this new accounting system was officially adopted by the Order of the MED RF No. 471 dated August 1, 2019, “On approval of the methodology for calculating the energy intensity of the gross domestic product of the Russian Federation and assessing the contribution of individual factors to the dynamics of energy intensity of the gross domestic product of the Russian Federation” (MED RF, 2019). This methodology includes guidelines for the development of Russian integrated energy balance tables. On the annual basis, CENEf-XXI develops an integrated fuel and energy balance (IFEB) and runs the energy efficiency accounting system to present the results in the annually published *State Report on the energy conservation and energy efficiency improvement in the Russian Federation* (MED RF, 2022). This accounting system has been in use for 4 years. In 2022, CENEf-XXI was requested to develop it further by adding the energy-related GHG accounting block to allow for monitoring mitigation effects related to the penetration of energy efficiency technologies. A similar model was previously in use by CENEf-XXI (Bashmakov & Myshak, 2012), but not as part of the official EEAS. In 2022, the Russian government has launched the development of a new national energy efficiency program, and the EE-EGHG-AS is a key to monitor this program’s progress. Late 2021, Russia made a 2060 carbon neutrality commitment. Analysis shows (Bashmakov et al., 2022) that improving energy efficiency of Russia’s economy (which is currently one of the least energy efficient economies in the world) is the key strategy to attain the carbon neutrality target.

The paper contributes to the literature in several ways. It highlights the importance of annual energy balances being developed as part of the decomposition system to effectively tailor energy use breakdown to better match the activity indicators; of extending the analysis from final to primary energy use; of using predominantly physical indicators for economic activities to better capture the effects of the technological progress; and of combining decomposition analysis of energy efficiency with both direct and indirect GHG emissions. It also highlights the need for additional indicators to adequately assess the contribution from the technological factor to crashing into, and recovering from, COVID-19-like crises.

This paper describes the approaches used in the new accounting system (“**Methodology**” section),

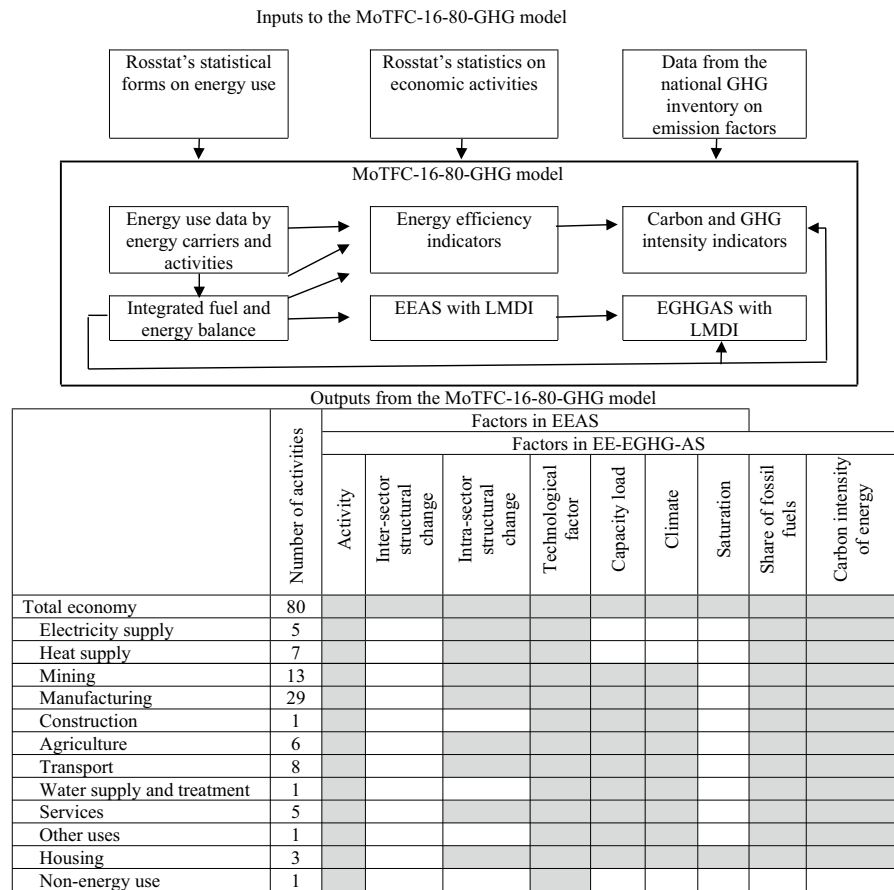
problems related to data collection and processing (“**Data**” section), and the system running results (“**Results**” section). It also discusses problems related to how the contribution from the technological factor is estimated in different sectors, including capturing the effects of the COVID-19 crisis (“**Discussion**” section). The major findings are presented in the “**Conclusions**” section.

Methodology

The new Russian energy efficiency and energy-related GHG emission accounting system (EE-EGHG-AS), like the previous one (see Bashmakov & Myshak, 2014), relies on the LMDI approach developed by Ang, Choi, Mu, Zhou, Su, and others (see Ang & Choi, 1997; Ang & Choi, 2010; Su and Ang, 2012; Ang & Choi, 2012). For an overview of various methods for calculating energy efficiency indices, see Ang and Choi (2010). A comprehensive review of dozens of papers presenting LMDI approaches and practices is given in Goh and Ang (2019). They conclude that LMDI-based energy efficiency accounting systems (EEASs) will be increasingly used to track energy efficiency trends and will become more sophisticated (Goh & Ang, 2019, p. 845). This prediction has come true. Decomposition analysis and EEASs have become regular tools used to monitor energy efficiency progress in many countries. They are used by the IEA (IEA, 2021a) and by many national statistical agencies (see for example Goh & Ang, 2019; Bin & Ang, 2012). Within the framework of the ODYSSEEMURE project, a tool has been created to decompose the change in end-use energy consumption in the EU countries (Enerdata, 2022a). There has been an increasing stream of evidence recently that LMDI is used for both EEASs and energy-related GHG emission accounting systems.

Application of the *direct aggregating* approach in LMDI to the whole economy is challenging, as activity indicators in all sectors are of different physical nature, measured in different units, and so do not sum up to the total activity index, for which GDP is often used as a proxy. This was why in the Russian EEAS the *unit consumption approach* was applied to the activities in different sectors estimated mostly in physical units (m², tons, t-km, kWh, etc.), which cannot be aggregated. It was demonstrated (Cahill &

Fig. 1 Architecture of the Russian EE-EGHG-AS.
Source: authors



Gallachóir, 2011) that physical and monetary output indicators may be jointly used in the decomposition analysis to capture the interplay of energy efficiency indicators based on both physical and value-added units. Lee and Kim (2021) applied decomposition analysis to the Korean manufacturing sector and concluded that the contribution from the technological factor to the energy efficiency evolution “seems to be overestimated when analyzed without physical output indicators” (p. 6192). They also concluded that the intensity effects are much lower, when primary, rather than final, energy consumption is used. These findings determine the use of primary energy and physical activity indicators in the Russian EEAS (where possible). GHG emission accounting systems have one unfortunate drawback: they build on the assumption that all of the factors used in the decomposition are independent. Koilakou et al. (2021) highlighted that further research should include checks on the causal relationships between GHG drivers. For

example, fuel switch to natural gas results in a lower emission factor and potentially higher generation efficiency, than coal. Solar and wind penetration bring down emissions and thermodynamic losses, since they are accounted in primary energy as being 100% efficient.

The architecture of the Russian EE-EGHG-AS is shown in Fig. 1. The whole system was formalized and programmed as MoTFC-16-80-GHG model. The list of economic activities for the new Russian EE-EGHG-AS includes 12 sectors and 80 economic activities (subsectors) (see Attachment A), which is about twice as many as in the previous EEAS (44 activities). Only 12 activities (with multiple products, like electronic equipment, production of food, beverages, and tobacco) are represented by production indices (2016=100). The other 68 activities are represented by physical indicators. Some sectors, for example construction, include only one economic activity. In addition to the final energy use sectors,

all energy transformation processes are also considered, including power and heat generation, fuel processing, energy sector's own use, and transmission and distribution. Energy use in these sectors includes thermodynamic losses, process use, and transmission and distribution losses, and when all these are added to final energy use, bottom-up primary energy use is estimated. It differs from the top-down estimate of primary energy use (production less net export corrected by stock change) by statistical discrepancy. Maths for the LMDI-based approach used in Russia's first EEAS was presented in Bashmakov and Myshak (2014) and was only slightly modified in EE-EGHG-AS (see MED RF, 2019). Therefore, only a set of new equations used to supplement this EEAS with energy-related GHG emissions is presented in Attachment B.

In EE-EGHG-AS, the impacts of seven factors are assessed for the whole economy. The number of factors varies by sectors between 3 and 6, including activity, inter-sector structural change, intra-sector structural change, technological factor, capacity load, climate, and saturation. The latter factor is only used for the housing sector. In the EGHG-AS part, two more factors are added to each activity — the share of fossil fuels and carbon intensity of energy.

According to the IPCC classification, GHG sources are limited to the “energy” sector. A limited analysis is also provided for industrial emissions. GHGAS operates in two modes. The first mode aims to assess the change in direct GHG emissions for each activity. The reduction in GHG emissions resulting from power and heat savings is attributed to the power and heat sectors. The second mode allows for the accounting of indirect GHG emission reductions and attributes them to the activity, where power and heat savings originated. Emission reductions are estimated either for CO₂ only or for the sum of three GHGs — CO₂, CH₄, and N₂O.

Three factors in Russian EE-EGHG-AS are estimated using specific methods that need to be described: climate, capacity load, and saturation. Data on district heat use, as provided by the Russian statistics, break down by technology, space heating, and DHW — not only for buildings but also for a large variety of products and services. This allows it to correct specific energy use by heating degree-days as follows:

$$SEC_{it}^{HDD} = SEC_{it} + (SHHEC_i^t * \left(\frac{HDD_{2016}}{HDD_t} - 1 \right)) \quad (1)$$

where SEC_{it}^{HDD} is the specific energy use for activity i , corrected for heating degree-days; $SHHEC_i^t$ is the specific heat use for space heating only for activity i ; HDD is the heating degree-days.

There are no official statistical data on energy use for air conditioning, so cooling degree-days are not used in the climate correction algorithm.

Russian official statistics also breaks down electricity use in mining, manufacturing, and water supply by three components: (1) process use; (2) driving force use; and (3) total use for lighting at industrial facilities, own use at autoproducers' power plants and plant-level distribution losses. The assumption is that the latter component and heat use for space heating represent constant energy use, as these do not depend much on the output. Therefore, energy use for activity i corrected for heating degree-days and for the capacity load is calculated as follows:

$$SEC_{iPC}^{HDD} = SEC_{it}^{HDD} - (SEEFIX_i^t + SHHEC_i^t) * \left(\frac{Y_i^{2016}}{Y_i^t} - 1 \right) \quad (2)$$

where: $SEC_i^F = SEC_{iPC}^{HDD}$ is the specific energy use for activity i corrected for climate and for capacity load factor (for industrial, agricultural, transport, construction, and utility energy uses); $SEEFIX_i^t$ is the specific energy use for activity i for lighting production facilities, own needs of autoproducers' power plants and plant-level distribution losses i in year t ; Y_i^t is the indicator for activity i in year t .

This approach has a limitation: production capacities may go up from the 2016 level. But this has a limited impact in Russia, as its economy has been developing very slowly from 2008 onwards. It was important to account for the capacity load factor in years such as 2020, when the load was down. When it is not separated, one can drive to a wrong conclusion that industrial process energy efficiency is down.

The saturation factor in the housing sector captures the impacts of utility infrastructure development and household appliances saturation. Account is taken of residential space heating, DHW, and all other appliances according to the following formulas:

$$SEC_{ht}^{HDD} = SEC_{ht}^{HDD} * \frac{dSH_i^{2016}}{dSH_i^t} \quad (3)$$

$$SHWAC_t = SHWC_t * \frac{dHW_i^{2016}}{dHW_i^t} \quad (4)$$

$$SEAAC_t = SEAC_t * \frac{\sum_i as^i * ea_i^{2016}}{\sum_i as^{2016} * ea_i^{2016}} * \frac{ls^{2016}}{ls^t} \quad (5)$$

where: SEC_{htt}^{HDD} and $SHWAC_t$ are the specific energy consumption for space heating and DHW in the housing sector in year t , corrected for climate and public utilities saturation; SEC_{ht}^{HDD} is the specific energy consumption for space heating in the housing sector corrected for climate in year t ; $SHWC_t$ is the specific energy consumption for DHW in the housing sector in year t ; dSH_i^t is the share of housing stock connected to district heating systems in 2016 and in year t ; dHW_i^t is the share of population with centralized hot water supply in 2016 and in year t ; $SEAAC_t$ is the specific energy consumption by appliances per unit of housing area in year t corrected for appliances saturation; $SEAC_t$ is the specific energy consumption by appliances per unit of housing area in year t ; as_i^t is the appliances (i -type) saturation level for 100 households in 2016 and in year t ; ea_i^{2016} is the annual energy consumption by appliance i in 2016; and ls^t is the living area saturation per person in year t and in 2016.

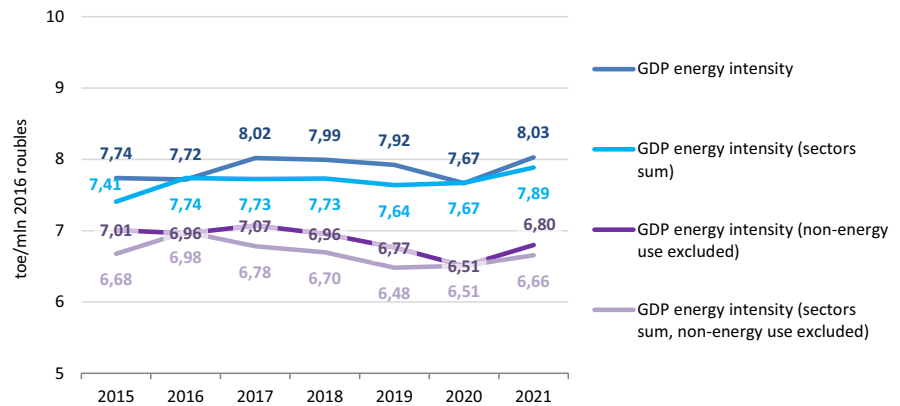
Data

Rosstat annually collects a variety of mandatory statistical forms for energy production and use (MED RF, 2019). Some of them are designed for large and medium enterprise reporting, others are filled in by energy utilities; all together, they show total energy use by all of the customers. However, the differences in sources and reporting requirements (including variations in coverage and boundaries) determine the indicator mismatches across the variety of the statistical forms. Seven major statistical forms with multiple tables are used all together as inputs to the MoTFC-16-80-GHG model. The information from these forms allows it to assess the energy use by 12 OKVED sectors (OKVED is the All-Russian classifier of economic activities, in fact the Russian equivalent of systems like ISIC, NACE, SIC, NAICS) and

100 activities within those sectors broken down by 21 fuels, plus electricity and heat, plus energy use for the housing sector broken down by energy carriers (with heat additionally broken down by space heating, DHW, and other uses), along with non-energy use. In many business activities, for statistical purposes, heat use is broken down by process use, space heating, and DHW, and electricity use is broken down by process use, driving force use, and total use for lighting at industrial facilities, own use at autoproducers' power plants and plant-level distribution losses.

The 80 economic activities selected are dominated by physical products, works, and services. However, some of the activities either include a large list of manufactured products (for example, "production of electrical equipment"), or do not provide any data on the energy use in core activities (for example, "railway transport" or "fishing and fish farming"). Where this is the case, the statistical basis is formed by the following algorithm. Total energy use is determined based on the data from OKVED files. Fuel consumptions by road transport (listed under given activity) and other non-core energy uses are identified. Total energy consumption less consumption by road transport and by non-core activities yields total energy consumption for the core activity. Information is processed in several sectoral blocks — mining, manufacturing, total industry, agriculture, construction, transport, water utilities, services, and other uses. In those blocks, as well as in MoTFC-16-80-GHG model, data on 23 energy carriers use is aggregated into seven groups: coal, crude oil, refinery products, natural gas, other solid fuels, electricity, and heat, which are then summed up for totals. In the IFEB (integrated fuel and energy balance) module, two more primary energy resources are added — nuclear and renewables (including hydro). Then, this information is organized by sectors and activities to form a basis for the development of the energy balance. At any stage of the data processing, the information in each cell of the energy balance sheet is clearly transparent and traceable up to the original statistical data provided by Rosstat. The country's statistical reporting system was modified significantly in terms of energy use starting from 2015. This is the reason why the analysis time frame is limited to 2015–2021. The results for 2000–2012 for a much

Fig. 2 Evolution of the Russian GDP energy intensity in 2015–2021. Source: calculated by the authors based on Rosstat data



smaller set of activities (44) were presented in Bashmakov and Myshak (2014).

Data on the economic indicators were also borrowed from Rosstat's official forms. They are used to estimate aggregated specific energy use and also by individual products and services. For the GHG emission, parts of the MoTFC-16–80-GHG model emission factors are borrowed from the 2022 National GHG Emission Inventory (IGCE, 2022). Much (yet not all) of the data used in the MoTFC-16–80-GHG model are available either from Rosstat's official website² or from Rosstat's EMISS database.³ Activities are mostly presented as physical indicators or physical indexes of production for aggregated activities, and by GDP in 2016 prices. Data on the energy balances developed using the MoTFC-16–80-GHG model and on the multiple energy efficiency indicators are available from annual *State reports on energy saving and energy efficiency in the Russian Federation* (MED RF, 2022). Since the EE-EGHG-AS is fully based on the official statistical data, all of the uncertainties are associated with the statistical accuracy of these data.

Results

Energy efficiency accounting in Russia for 2015–2021

Energy intensity of the Russian GDP, when estimated for all primary energy, was 3.8% up in 2015–2021 and in 2021 amounted to 8.03 toe/million 2016 roubles,

which is the highest level seen since 2015 (Fig. 2). In the MoTFC-16–80-GHG model, primary energy is estimated not only using the resource method (output less net export and corrected for stock changes) but also as the sum of energy use and losses in all sectors. This helps avoid statistical discrepancy. The energy (the sum of all energy uses in all sectors) intensity of GDP amounted to 7.87 toe/million 2016 roubles in 2021, which is 6.5% above the 2015 level. The gap between 3.8 and 6.5% shows the uncertainty related to the accuracy of energy use data. The conclusion about the growth in Russia's GDP energy intensity in 2015–2021 is consistent with the range of estimates from other sources (Enerdata, 2022a; IEA, 2021b).

As some fuels are not used for energy purposes, the correct way of estimating energy intensity requires that non-energy use be excluded. For many countries, the share of non-energy use is limited to 3–7% of total primary energy use and is relatively constant. Therefore, taking account of non-energy use does not substantially affect either the comparative levels or the evolution of energy intensity. In Russia, non-energy use nearly doubled in 2015–2021, and its share in primary energy consumption was up from 9.4% in 2015 to 15.2% in 2021. Therefore, it needs to be subtracted to obtain robust estimates of GDP energy intensity.

Energy intensity of GDP (non-energy use excluded) is the key indicator of energy efficiency in the Russian EEAS. In 2021, it amounted to 6.8 toe/million 2016 roubles, which is 3% below the 2015 value and 15% lower, than the traditionally calculated energy intensity of GDP. Average annual rate of GDP energy intensity (excluding non-energy needs) decline in 2015–2021 was 0.5%. Energy intensity of GDP

² Federal Statistical Service (rosstat.gov.ru).

³ EMISS (fedstat.ru).

Table 1 Evaluation of contributions from individual factors to primary energy demand increments in 2015–2021 (1000 toe)*

Period	Total	Activity	Inter-sector structure	Intra-sector structure	Technology	Climate	Capacity load	Saturation
Whole economy								
2016/2015	27 291	1 130	12 148	−1 650	10 476	5 454	−352	85
2017/2016	−6 481	10 756	4 268	1 245	−19 121	−2 435	−876	−318
2018/2017	8 796	16 489	−809	−2 480	−6 561	2 777	−531	−91
2019/2018	−6 322	12 977	−2 444	587	−8 421	−8 831	−343	152
2020/2019	−13 423	−15 842	1 044	6 820	−4 735	−1 137	317	110
2021/2020	41 106	27 870	3 342	−1 405	1 964	10 278	−714	−230
2021/2015	50 967	53 381	17 549	3 117	−26 397	6 106	−2 498	−292
Power supply								
2016/2015	2 548	2 697		579	−728			
2017/2016	−712	380		756	−1 848			
2018/2017	305	2 353		319	−2 368			
2019/2018	−549	715		554	−1 818			
2020/2019	−6 253	−3 495		−1 426	−1 332			
2021/2020	9 720	7 638		910	1 171			
2021/2015	5 058	10 289		1 692	−6 922			
Heat supply								
2016/2015	3 404	938		32	2 433			
2017/2016	−640	−248		−445	54			
2018/2017	1 601	939		50	612			
2019/2018	115	−931		−255	1 300			
2020/2019	−1 564	−473		−169	−921			
2021/2020	2 751	2 139		378	234			
2021/2015	5 668	2 364		−409	3 712			
Mining								
2016/2015	5 495	1 106		2 245	2 085	269	−210	
2017/2016	−1 241	858		1 699	−3 707	−20	−71	
2018/2017	5 661	1 797		922	2 990	26	−74	
2019/2018	1 296	1 714		537	−756	−109	−90	
2020/2019	7 240	−3 712		598	10 145	15	194	
2021/2020	1 787	2 813		1 823	−2 921	128	−57	
2021/2015	20 238	4 576		7 824	7 837	309	−308	
Manufacturing								
2016/2015	4 577	1 288		−2 426	5 364	498	−146	
2017/2016	308	6 649		−3 371	−2 160	−214	−597	
2018/2017	490	4 247		−546	−3 030	240	−420	
2019/2018	−489	4 203		−1 958	−1 994	−583	−158	
2020/2019	−638	1 574		1 112	−3 125	−203	4	
2021/2020	4 922	5 905		−806	−443	773	−508	
2021/2015	9 170	23 865		−7 994	−5 387	511	−1 825	
Agriculture								
2016/2015	619	351		1 022	−867	87	27	
2017/2016	550	231		205	240	−39	−87	
2018/2017	−179	−17		409	−605	47	−13	
2019/2018	−272	338		−119	−349	−123	−20	

Table 1 (continued)

Period	Total	Activity	Inter-sector structure	Intra-sector structure	Technology	Climate	Capacity load	Saturation
2020/2019	118	103		−154	227	−45	−13	
2021/2020	956	−77		97	726	202	9	
2021/2015	1 793	930		1 460	−629	129	−97	
Transport								
2016/2015	7 964	1 419		−791	7 260	106	−30	
2017/2016	−5 275	5 753		1 456	−12 295	−56	−133	
2018/2017	−1 900	2 907		−3 600	−1 277	58	12	
2019/2018	−1 303	1 314		1 645	−4 040	−159	−63	
2020/2019	−8 697	−8 492		4 918	−5 163	−94	133	
2021/2020	6 609	6 655		−2 604	2 469	187	−98	
2021/2015	−2 602	9 556		1 023	−13 047	43	−178	
Services								
2016/2015	1 169	1 830		−785	−437	561		
2017/2016	207	639		−104	−70	−258		
2018/2017	497	350		9	−156	294		
2019/2018	−2 372	389		1	−2 012	−750		
2020/2019	−1 639	328		0	−1 688	−279		
2021/2020	2 791	539		−81	1 321	1 012		
2021/2015	653	4 075		−960	−3 042	580		
Housing								
2016/2015	2 650	2 000		−76	−2 949	3 590		85
2017/2016	−66	1 519		53	355	−1 674		−318
2018/2017	1 452	1 945		70	−2 378	1 906		−91
2019/2018	−3 610	2 043		383	−996	−5 191		152
2020/2019	−1 071	1 957		24	−1 301	−1 862		110
2021/2020	8 717	2 498		144	−1 017	7 323		−230
2021/2015	8 074	11 962		598	−8 286	4 092		−292

*A few one-activity sectors are not shown in this table, for example, construction, water supply and treatment, and other uses. Source: calculated by authors using the MoTFC-16–80-GHG model

(excluding non-energy use estimated as the sum of the energy uses by sectors) in 2021 amounted to 6.66 toe/million 2016 rubles, which is only 0.3% below the 2015 level. So despite some uncertainty, the conclusion is *very little progress has been achieved towards GDP energy intensity reduction in Russia after 2015*.

Primary energy consumption in 2021 reached 750 Mtoe, which is 9.7% up compared to the COVID-affected 2020. Many factors were driving energy use up by 51 Mtoe in 2015–2021. The key driver was the economic activity, which scaled up consumption by more than 53 Mtoe (Table 1). Structural changes, both across and within the sectors, contributed more than 20 Mtoe as additional energy demand. So economic development in these years was in favor of the energy

intense sectors and activities. Climate factor determined more than 6 Mtoe of additional energy use. Growing capacity loads counterbalanced the activity factor by reducing energy use by 2.5 Mtoe, and the saturation factor in the housing sector provided just a small impact.

Changes in energy use and energy intensity, related to the technological factor, are the key indicator to monitor the progress towards energy efficiency improvements. In 2015–2021, due to the technological factor, energy consumption was 26 Mtoe lower. In the power supply sector, technological factor was continuously contributing to energy demand reductions, except 2021, when for the first time since 2015, it provided the opposite effect, as the efficiency of

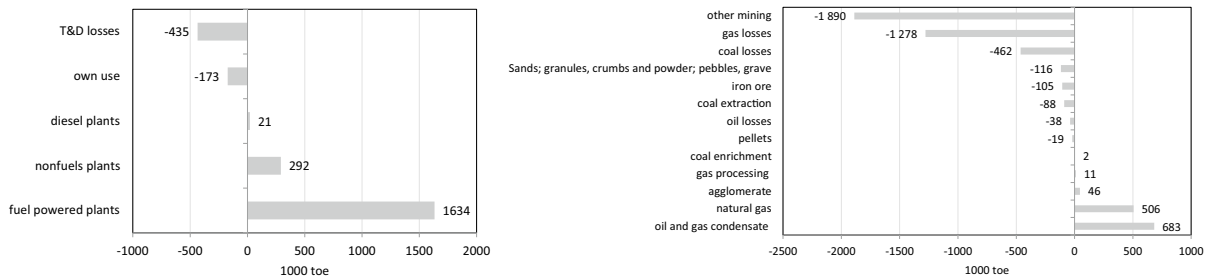


Fig. 3 Contributions from different activities to the impact of the technological factor in two sectors (2020/2021). Source: calculated by the authors using the MoTFC-16–80-GHG model

power generation by fuel-powered plants declined. This effect was only partly offset by a decline in the shares of power plants own use and transmission/distribution losses. The Russian EE-EGHG-AS allows for the visualization of the contribution from each activity towards the technological factor effects in each year (Fig. 3). In the heat supply sector, not only did the technological factor fail to halt energy use growth but even was ahead of the activity factor in driving it up. This was a result of heat generation efficiency reduction at CHPs and boiler houses, along with the growing share of district heat losses in 2015–2020.

The resultant multidirectional evolution of specific energy consumption (SECs) in the mining industry in 2015–2021 determined the negative contribution from the technological factor, as the mining conditions, especially in the oil and gas production, deteriorated. The balance of increasing and decreasing SECs of manufactured products made it possible to reduce the growth in energy consumption by more than 5 Mtoe in 2015–2021 due to the technological factor. In agriculture, the technological factor contributed 0.6 Mtoe to energy overruns in 2015–2021. The contribution of the technological factor in transport was responsible for nearly half (over 13 Mtoe) of the overall impact across the whole economy, mostly due to the decline in SECs for road transport measured as energy use per vehicle. The COVID-19 crisis and the lockdown have shown that this indicator has only a limited ability to reflect the energy efficiency evolution (see the “Discussion” section).

In 2015–2021, the technological factor pushed energy consumption in the services sector down by 3.3 Mtoe. The 2020 decline was almost in full offset in 2021. Here again, the drawbacks of the currently used energy efficiency indicators played a role. Heat demand in public buildings was not much affected by the 2020 lockdown; however, much of the 2020 decline and 2021 increase in electricity and hot water use in educational and healthcare facilities may be attributed to the building occupancy factor (which is not statistically monitored). Elimination of this factor in educational and healthcare buildings alone would reduce the impact of the technological factor in 2020 by 0.32 Mtoe.

In the housing sector, construction of new, more energy efficient, buildings, and retrofits of those in place, the increasing uptake of efficient DHW systems and appliances brought energy consumption down in 2015–2021 by substantial 8 Mtoe due to the technological factor. For this sector, climate factor is the most important driver. Its positive contribution in cold 2021 would have been even larger (just as the negative contribution from the technological factor), if SECs for other needs in the housing sector (total energy use less space heating and DHW) were corrected for the use of electric heating. The available statistical information does not allow for robust quantification of this effect. If the whole increase in SECs for other needs is fully attributed to the climate factor, its contribution will grow to 9.4 Mtoe, while the saving effect from the technological factor will scale up to 3 Mtoe. Analysis of how SECs depend

Fig. 4 Energy efficiency indexes for the whole economy and for the key sectors. Source: calculated by the authors based on Rosstat’s data

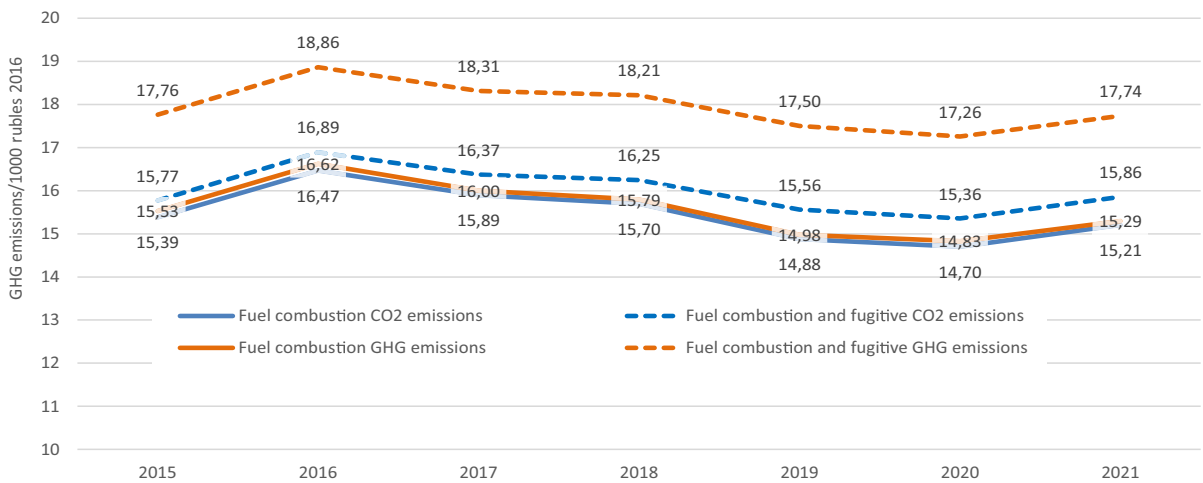
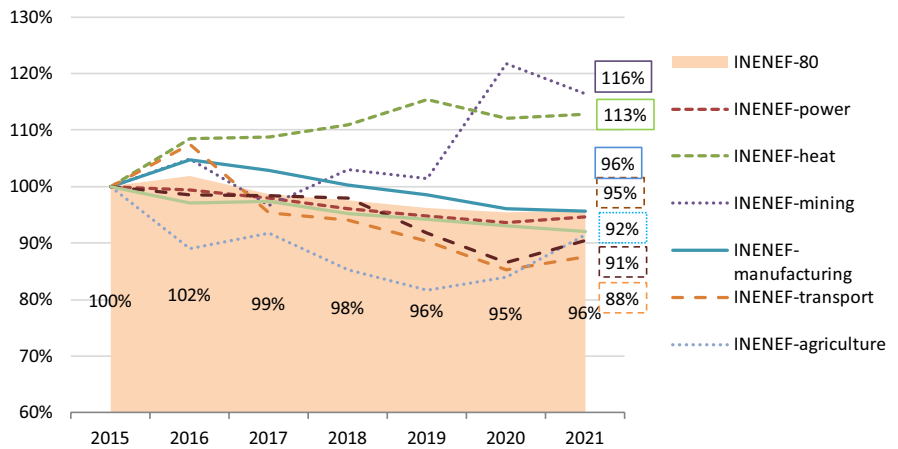


Fig. 5 GHG and carbon intensities of GDP evolution: 2015–2021. Source: calculated by the authors using the MoTFC-16–80-GHG model

on the number of heating degree-days only in cold years shows that over time, there is a declining trend due to the technological progress. Therefore, robust judgments on the contributions from different factors require more detailed statistical data which allow it to estimate appropriate energy efficiency indicators.

Decomposition analysis helps assess energy efficiency indexes (INENEFs) for the whole economy and by sectors (Goh & Ang, 2019). Energy efficiency index for the whole economy allows it to capture the contribution from the technological factor to the evolution of GDP energy intensity (Fig. 4). Due to this factor, energy intensity of GDP was up 0.4% in 2021. Over the past 6 years, such effect was also observed in 2016. Since the statistics can

only partially capture the effects of crashing into, and recovering from, COVID-19-like crises (see the “Discussion” section), contribution from the technological factor can be corrected to some 0,7 Mtoe. But even after this adjustment, it is still correct to say that in 2021, this factor contributed to the growth in GDP energy intensity.

In 2015–2021, due to the technological factor, GDP energy intensity was down 4.3%, or 0.7% per year.⁴ Over this period, heat supply and mining sectors noticeably slowed down the decline in energy

⁴ This is slightly less than in 2000–2012 (see Bashmakov and Myshak, 2014).

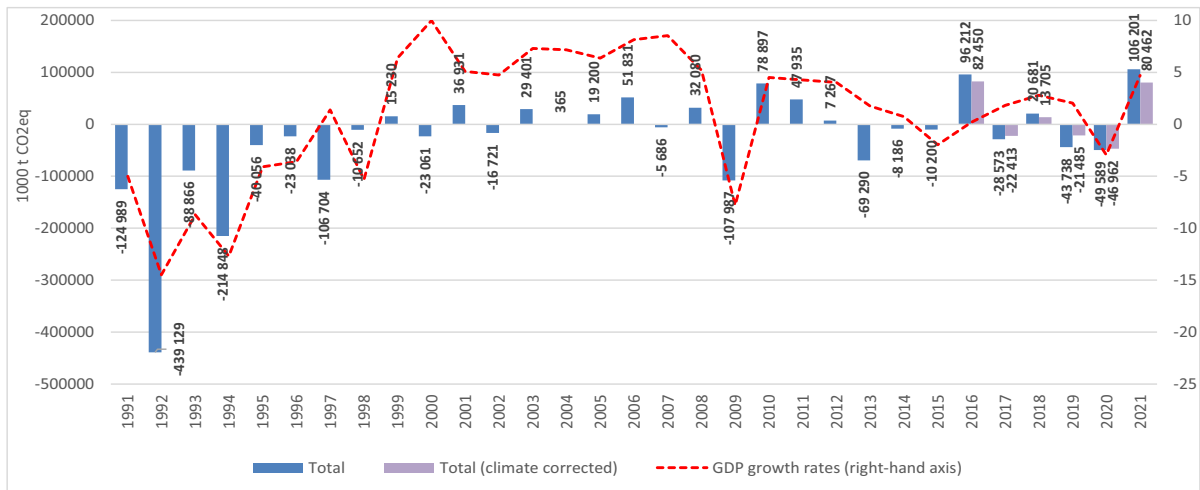


Fig. 6 Annual evolution of energy-related GHG emissions and GDP. Sources: calculated by CENEf-XXI based on the MoTFC-16–80-PG model; National report on the inventory of anthropogenic emissions from sources and removals by sinks

intensity of Russia’s GDP. Energy efficiency index for the whole economy shows that after 2015, there was little — and after 2019, nearly no technological progress in improving Russia’s energy efficiency (Fig. 4).

Energy-related GHG emission accounting

The MoTFC-16–80-GHG model was used to attribute the evolution of energy-related GHG emissions to different factors and to identify the role played by the technological factor. The model operates in six modes and allows it to estimate direct CO₂ and GHG emissions from either fuel combustion alone or with fugitive emissions; and to take account of direct or both direct and indirect emissions while allocating emissions from power and heat generation by end-use sectors. In 2015–2021, practically no progress was achieved towards reducing the carbon intensity of Russia’s GDP (Fig. 5). After an increase in 2016, carbon intensity was declining in 2017–2020. However, in 2021, it grew up again and nearly returned to the initial 2015 level.

In 2020–2021, the change in carbon intensity amounted to the following values (in parentheses as compared to pre-COVID-19 2019):

- Specific CO₂ emissions from fuel combustion per unit of GDP were up 3.5% (2.2%);

of greenhouse gases not controlled by the Montreal Protocol for 1990 – 2020, Moscow, 2022; SOCIO-ECONOMIC INDICATORS OF THE RUSSIAN FEDERATION IN 1991–2020, Statistical publications (rosstat.gov.ru)

- Specific CO₂ emissions from fuel combustion and fugitive emissions per unit of GDP were up 3.3% (1.9%);
- Specific GHG emissions from fuel combustion per unit of GDP were up 3.1% (2.1%);
- Specific GHG emissions from fuel combustion and fugitive emissions per unit of GDP were up 2.8% (1.3%).

The contribution from various factors in 2015–2021 resulted in GHG emission growth (depending on the accounting metric) by 101–138 million tons of CO₂eq., or by 8–10%. In other words, it was growing almost as fast as GDP. The economic activity played a major, even if a limited, role in driving GHG emissions — due to the slow economic growth over this period. Structural shifts were in favor of more carbon-intensive sectors, but within those sectors, in favor of less carbon-intensive economic activities. The role of the technological factor in slowing down GHG emissions (when calculated on the basis of direct GHG emissions) appeared to be quite modest, and when fugitive emissions are included, the technological factor was even driving the emissions up.

When indirect GHG emissions are allocated by sectors, the contribution of the technological factor becomes more meaningful: in 2015–2020, it drove

Table 2 Evaluation of contributions from different factors to energy-related GHG emissions (including fugitive emissions from fuels with indirect emissions attributed to end-use sectors) in 2015–2021 (1000 tCO₂eq)*

	Total	Activity	Inter-sector structure	Intra-sector structure	Technology	Climate	Capacity load	Saturation	Carbon intensity
Total									
2016/2015	96,212	2655	27,544	−13,445	37,071	13,762	−871	232	29,264
2017/2016	−28,573	25,463	14,143	−1760	−47,102	−6160	−2361	−773	−10,024
2018/2017	20,681	38,838	−1743	−8282	−28,127	6975	−1470	−200	14,688
2019/2018	−43,738	30,254	−2663	−406	−25,826	−22,253	−929	417	−22,333
2020/2019	−49,589	−36,320	168	13,387	−15,000	−2627	761	295	−10,253
2021/2020	106,201	63,719	6461	−3887	7566	25,739	−1936	−458	8998
2021/2015	101,193	124,609	43,911	−14,393	−71,417	15,437	−6805	−487	10,339
Power									
2016/2015	7456	468		3836	2344				807
2017/2016	−5973	4393		−3066	−6822				−477
2018/2017	−1186	6624		−1214	−5224				−1372
2019/2018	−4775	5137		−3818	−5032				−1063
2020/2019	−19,610	−6046		−14,405	−587				1428
2021/2020	19,831	10,396		10,271	3089				−3925
2021/2015	−4257	20,972		−8396	−12,231				−4602
District heat									
2016/2015	3953	75		1259	2633				−15
2017/2016	−1529	727		−2193	79				−142
2018/2017	−2818	1054		369	−3860				−381
2019/2018	2453	824		−2634	4129				133
2020/2019	1647	−1079		−76	2646				157
2021/2020	4057	1986		1761	−23				334
2021/2015	7764	3588		−1514	5604				86
Mining									
2016/2015	12,625	123		1584	10,877	638	−490		−107
2017/2016	1491	1293		530	268	−50	−165		−384
2018/2017	21,080	2260		2024	3840	73	−193		13,075
2019/2018	−15,291	1848		3009	−4382	−285	−203		−15,279
2020/2019	11,226	−2244		−1430	16,534	31	444		−2109
2021/2020	−774	4120		620	−2229	293	−129		−3450
2021/2015	30,358	7400		6337	24,908	701	−734		−8254
Manufacturing									
2016/2015	36,421	658		−3656	14,678	1351	−400		23,789
2017/2016	−162	6501		3317	−6937	−602	−1669		−772
2018/2017	425	9944		−20	−10,366	671	−1182		1379
2019/2018	−4490	7759		−1719	−8863	−1638	−478		450
2020/2019	−6549	−9499		17,054	−8538	−559	14		−5021
2021/2020	23,442	16,720		−1726	−2036	2171	−1440		9754
2021/2015	49,088	32,083		13,251	−22,062	1395	−5157		29,578
Agriculture									
2016/2015	1739	39		3601	−2211	223	68		19

Table 2 (continued)

	Total	Activity	Inter-sector structure	Intra-sector structure	Technology	Climate	Capacity load	Saturation	Carbon intensity
2017/2016	5237	428		800	730	-106	-223		3609
2018/2017	-1299	714		352	-1848	134	-31		-620
2019/2018	-875	537		231	-1226	-338	-63		-15
2020/2019	-426	-649		546	376	-124	-36		-539
2021/2020	3375	1183		-1232	2086	537	27		775
2021/2015	7751	2252		4297	-2093	326	-260		3228
Transport									
2016/2015	22,633	552		1131	21,475	267	-73		-718
2017/2016	-19,576	5181		14,237	-36,569	-138	-333		-1953
2018/2017	-4228	7614		-8508	-4669	144	26		1165
2019/2018	-4163	5893		1989	-9676	-389	-155		-1826
2020/2019	-20,653	-6973		-2418	-14,082	-234	341		2713
2021/2020	12,205	11,774		-349	4540	471	-254		-3978
2021/2015	-13,782	24,041		6082	-38,981	120	-448		-4597
Services									
2016/2015	3957	146		2223	-822	146	1459		951
2017/2016	-837	1397		-132	140	1397	-667		-1576
2018/2017	1308	2142		-1269	-712	2142	750		395
2019/2018	-6869	1616		-662	-5047	1616	-1911		-865
2020/2019	-6520	-1834		2622	-4194	-1834	-706		-2409
2021/2020	8243	3185		-2140	2964	3185	2578		1657
2021/2015	-718	6653		642	-7670	6653	1504		-1847
Housing									
2016/2015	9010	486		4287	-7372	8868		232	2510
2017/2016	-4908	4578		-699	863	-4125		-773	-4752
2018/2017	4755	7003		-2066	-5907	4659		-200	1266
2019/2018	-11,782	5423		508	-2641	-12,677		417	-2812
2020/2019	-7319	-6476		11,244	-3200	-4516		295	-4666
2021/2020	26,313	11,561		-5191	-2900	17,953		-458	5348
2021/2015	16,069	22,574		8082	-21,157	10,162		-487	-3105

*A few one-activity sectors are not shown in this table, for example, construction, water supply and treatment, and other uses. Source: calculated by authors using the MoTFC-16-80-GHG model

the emissions down by 39–70 Mt CO₂eq, and thus offset 27–57% of the increment determined by the economic activity. The contribution of the technological factor is more adequately captured through a calculation for both direct and indirect emissions, thus reflecting the progress towards improving end-use power and heat efficiency.

In 2020 and 2021, Russia demonstrated the “super-coupling” effect. Extensive economic growth in 2021 along with a noticeable loss of interest in energy efficiency policies led to the

largest increase in total energy-related GHG emissions observed since 1990 (Fig. 6). In 2021, for the first time since 2017, the technological factor was supporting, rather than restraining, GHG emission growth (Table 2).

If only direct emissions are discussed, the decline in energy efficiency in 2021 ensured the contribution from the technological factor to GHG emission growth in the power sector in the amount of 5.3 Mt CO₂eq. and in heat supply of 5.4 Mt CO₂eq. When indirect emissions are also taken into account, the

energy efficiency decline drove up GHG emissions in agriculture by 2.1 Mt CO₂eq., in transport by 4.5 Mt CO₂eq., in the services sector by almost 3 Mt CO₂eq. In 2021, the improvement in the technological parameters of energy efficiency brought GHG emissions from the mining industry down by 2.3 Mt CO₂eq., from the manufacturing industry by 2 Mt CO₂eq., and in the housing sector by 2.9 Mt CO₂eq. The technological factor stimulated growth in construction and worked towards emission reduction in water supply and sanitation. In 2021, the rise in emissions from industrial processes was determined mainly by the economic activity, which was growing unevenly, and so the structural factor slowed down the emission growth with practically zero contribution from the carbon intensity factor.

Discussion

The above results could be discussed in several ways. First, what are the advantages of the Russian EE-EGHG-AS compared to other systems? Second, what indicators should be used to better capture the progress towards energy efficiency? Third, to what extent do the available data allow for capturing the energy efficiency evolution during deep crises? Forth, what are the reasons for a substantial slowdown in progress towards technological energy efficiency improvements in Russia after 2015? Fifth, what indicators should be used in cross-country comparisons of energy efficiency, and where does Russia stand compared to other countries and regions? Sixth, what lens allow to better capture the impact of technological progress towards GHG emission reduction?

Analysis of the discussed above Russian EE-EGHG-AS versus other decomposition systems (Goh & Ang, 2019) highlights its seven advantages:

1. Faster obtained results: the results can be obtained in just 9–10 months versus 2–3 years in many other systems. Annual energy balance is developed at the same time as the decomposition and within one system, so there is no delay in getting energy use data.
2. The development of the IFEB (with full reliance on the official statistics and 100%-traceabil-

ity of each assessed indicator) is combined with decomposition analysis. This helps effectively tailor energy use breakdown to the activities breakdown, which is shown mostly by products, works and services, rather than by value-added aggregates.

3. The level of energy consumption coverage. In many systems, analysis is carried out for final energy, while the Russian EEAS also allows it for primary energy. Therefore, the whole energy use is in the focus.
4. High level of detail. The Russian EEAS covers 12 sectors and 80 activities (certain types of products, works and services). Many other EEASs are limited by the statistical breakdown of energy use by aggregated industries.
5. The use of mostly physical indicators helps better capture the technological progress, than the EEASs based on value-added indicators, adding to the reliability of assessments of the technological factor contribution. Physical indicators can be easily interpreted and provide a more sound basis for the communication with the business community and institutions responsible for EE and mitigation policies.
6. EEAS can monitor more than 100 integral and partial, primarily technological, energy efficiency and that many carbon intensity indicators for all sectors and all covered products, works and services. Therefore, this EE-EGHG-AS provides a comprehensive set of EE and GHG indicators to monitor the effectiveness of EE and mitigation policies at the national, sectoral, and activity levels.
7. EE-EGHG-AS combines decomposition analysis for energy efficiency and GHG emissions, for both direct and indirect GHG emissions. This allows for effective and detailed monitoring of the progress towards Russia's carbon neutrality target.

In 2020 and 2021, EE-EGHG-AS faced some problems with the assessment of contributions from the technological factor. For example, fuel consumption per 1 car is the energy efficiency indicator for road transport. With a relatively stable average annual mileage, it shows the energy efficiency of the entire car fleet. In 2020, this indicator was 7% down in Russia. In fact, the technological efficiency

did not improve that much. In 2020, average mileage dropped dramatically in many countries, which was taken as SEC reduction and so demonstrated “energy efficiency improvements.” A more accurate assessment of the contribution from the technological factor requires specific fuel consumption per unit of total car mileage. However, unlike the EU and the USA, Russia has no statistics on average annual car mileage. In the USA, average car mileage was 16% down in 2020, fuel consumption per 1 car declined by 20%, while average mileage per gallon of fuel increased by nearly 5% in 2020, partly due to the increased share of electric vehicles (EIA, 2022). In 2011–2019, average mileage per car was fairly stable ($\pm 2\%$) in the USA, so fuel use per car was an adequate indicator of the car fleet energy efficiency. In 2021, average mileage increased in many countries as SEC per vehicle. Formally, this effect is captured as increase in energy intensity, yet physical efficiency showed no decline. Scarce data on mileage does not allow for adequate estimates of the contribution from the technological factor, where this factor is subject to dramatic fluctuations. The situation is similar to what is seen in the service and the housing sectors. In 2020, lockdown-caused reduction in electricity consumption per 1 m² of public buildings formally showed energy efficiency improvement, while the 2021 increase indicated its decline. In fact, technological energy efficiency was not changing much. This fact could be proved by appropriate data on the buildings use, but this information is not collected by Rosstat. For the lack of the required statistical data, change in capacity load is interpreted as change in energy efficiency. During the lockdown, people spent a lot of time at home, and so residential electricity consumption per 1 m² went up. However, this is no indication of any change in energy efficiency. Additional information (such as commercial buildings use rates or average mileage per car) is required to more accurately assess the energy efficiency evolution during crises, such as COVID-19 economic crisis, and to reduce the uncertainty in the evaluation of the contribution from the technological factor.

On average, the technological factor contributed about 0.6% to Russia’s GDP energy intensity decline (excluding non-energy use) in 2015–2021. During 2016–2021, in the global economy, the structural factor was also contributing to energy demand growth, but the technological factor was driving the

demand down on average by about 1.4% per year⁵ (IEA, 2022b). For the EU, in 2013–2019, the technological factor was contributing 0.9% per year to the energy intensity decline⁶ Therefore, the conclusion that Russia failed to bridge the technological gap with advanced economies (Bashmakov & Myshak, 2014) is still valid

After 2014, the technological contribution to energy efficiency in Russia slowed down for clearly weaker business incentives and declining attention to energy efficiency improvements on the federal and regional levels. The economic growth in Russia has been quite weak after 2014 (slightly below 1% GDP growth in 2014–2021), which can be seen from very moderate new capacity additions. The share of government-owned and controlled businesses and monopolies is high, abating the pressure of competition and reducing the incentives to improve energy productivity. In addition, energy prices are under control at a low level. Because of the energy inefficiency, energy prices can only increase at the cost of going beyond the economic affordability thresholds. For this reason, energy utilities are short of funds to invest in their facilities upgrades.

After 2014, there was a 50-fold drop in federal budget spending on promoting energy efficiency improvements. This caused a chain reaction, including a decline in financial support for energy efficiency improvements at the regional and municipal levels. According to IEA, back in 2011 Russia spent \$US5.7 billion on energy efficiency. Bashmakov (2014) estimated this spending at \$US5.2–5.9 billion. MED RF (2022) estimated this investment at about \$US2.5 in 2016–2017 and about \$US3 billion in 2018. In other words, energy efficiency investments in Russia nearly halved over the last decade. The scale of EE investments can be taken for an indicator of the country’s interest in EE improvements.

Energy intensity of Russia’s GDP is the highest among the G20 countries (IEA, 2022a;

⁵ The results are not strictly comparable, because the IEA study only assesses the contribution of 4 factors to explain the final energy evolution.

⁶ ODYSSEE-MURE Decomposition tool. Energy efficiency factors tool that have consequences in the energy consumption | ODYSSEE (odyssee-mure.eu). The sample ends in 2019. This result doesn’t change much, if the starting year is selected between 2013 and 2015.

Enerdata, 2022b). When calculated using the exchange rate, energy intensity of Russia's GDP is 3.1 times the world average, 4.8 times that in the USA, 5.9 times in Japan, and 6.5 times in Germany. For 2021, if calculated using the purchasing power parity (PPP), the corresponding gaps in GDP energy intensity are still significant: 1.3 times compared with Canada, 1.4 times with China, 1.9 times compared with the global GDP energy intensity, 2 times with the USA, 2.8 times with Japan, and 2.9 times with the EU. The persistence of this gap works to slow down the economic growth. The conclusion that Russia is one of the most energy-intensive countries in the world remains true. According to the IEA data for 2019, Russia ranks 136th among 149 countries in terms of GDP energy intensity (purchasing power parity), or 140th (exchange rates) (IEA, 2022a). If energy intensity of GDP is used in cross-country comparisons, then non-energy use needs to be extracted, and the gap with the global average comes down to 1.8. National estimates of primary energy consumption, both including and excluding non-energy use, substantially differ from the ones made by IEA. In the 2019 Russian IFEB, the former is 6% below the IEA's estimate, and the latter is 11% below the relevant IEA's estimate. Therefore, the gap in energy intensity is lower, than that reported by the IEA. Using the above adjustments, Russian GDP energy intensity (PPP) equals that of Canada, but it is still large compared to other countries, and has not been shrinking since 2015. In Russia, it is commonly believed that this gap is mostly determined by a colder climate. The EE-EGHG-AS allows to test this hypothesis. If average 2021 HDD for Russia is replaced with that for EU, primary energy use is only 2.5% down leaving a twofold gap (computed with PPP, non-energy use extraction, and energy balance data).

For the purpose of cross-country comparisons of the progress towards energy efficiency improvement, GDP energy (excl. non-energy use) intensity reduction due to the technological factor, as calculated based on INENEFs for the whole economy, is more informative, than GDP energy intensity average annual growth rates. With better harmonization across EEASs, this approach may allow for much more robust findings.

When indirect GHG emissions are allocated by sectors, contribution of the technological factor

becomes more important, as it allows to capture progress towards improving the efficiency of power and district heat use. These lenses of analysis become more important, as electrification progresses. In the marginal case, when the entire sector is fully electrified, this leaves the only chance to capture energy efficiency impacts on the evolution of GHG emissions.

Conclusions

The new Russian energy efficiency and energy-related GHG emission accounting system (EE-EGHG-AS) is one of the most detailed EEASs. It is designed to account for 12 sectors and 80 economic activities represented mostly by physical parameters: products, works, and services. Contributions from 7 factors are assessed for the whole economy, and from 3 to 6 factors for individual sectors.

Comparison between EE-EGHG-AS and other EEASs allows it to highlight a few advantages, including the development of the energy balance in the same system as the decomposition analysis, to ensure a good match between energy use and activity indicators; and the use of primarily physical indicators to better capture the effects of the technological progress compared to the EEASs based on value-added activity indicators.

Russian GDP energy intensity estimated for 2015–2021 using a traditional approach showed a 3.6% rise. In order to have a more adequate indicator, non-energy use was excluded resulting in a 2.8% decline in this modified energy intensity and bringing the 2021 level 15% below the traditional estimates. The results of the EE-EGHG-AS use show that due to the technological factor, energy intensity of GDP declined in 2015–2021 by 4.3%.

EE-EGHG-AS, as probably many other EEASs, has only a limited ability to capture the effects of crashing into, and recovery from, crises, such as COVID-19 economic crisis. Additional information (such as commercial buildings use rates or average mileage per car), which is not reported in Russian official statistics so far, is required to more accurately capture the contribution from the technological factor.

Taking non-energy use away from GDP energy intensity estimations allows it to narrow the gap in energy efficiency with the leading nations; however,

it is still true that Russia is one of the most energy-intensive countries in the world and is not actually progressing. After 2014, this has been determined by obviously weaker business incentives and declining attention to energy efficiency improvements on the federal and regional levels.

Very little progress in energy efficiency over the recent years has determined a “super-coupling” effect for Russia in 2020–2021: GHG emissions elasticity was much above unity. This makes it extremely challenging to attain Russia’s carbon neutrality target by 2060. This goal can only be achieved by switching from the recently selected *4S* — *Stagnation, Sanctions, Self-Sufficiency pathway, which may be also titled Forward-to-the-Past* (as the opposite to the *Back-to-the-Future*) to *4D* — *Development Driven by Decarbonization and Democratization*, which can bring Russia back to the global economy (Bashmakov et al., 2022) to at least partly compensate for the two decades that will likely be wasted — the 2020s and 2030s. This period will have the crucial role in accumulating the know-how and developing skills related to the technologies with high GHG mitigation potential.

Author contribution All authors contributed to the study conception and design. Development of the EE-EGHG-AS methodology and integration of results by Igor Bashmakov. Programming of the model to assess the contribution of the technological factor to reduce energy intensity of GDP and GHG emissions (*MoTFC-16–80-GHG*) and development of the attachments by Anna Myshak. Processing the statistical data for different sectors to be used in *MoTFC-16–80-GHG* by Vladimir A. Bashmakov, Vladimir I. Bashmakov, Konstantin Borisov, Maxim Dzedzichak, Alexey Lunin, and Oleg Lebedev. Writing by Igor Bashmakov and Tatiana Shishkina. Editing by Tatiana Shishkina. All authors have read and approved the final manuscript.

Funding Partial financial support for this research was provided by the RF Ministry of Economic Development.

Data availability The data that support the findings of this study, including a variety of Russian statistical forms on energy production, foreign trade, transmission, distribution, and use, are available from the RF Statistical Service (Rosstat) and the RF Customs Service (FTS), but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. The data are, however, available from the authors upon reasonable request and with permission of Rosstat and FTS.

Declarations

Competing interests The authors declare no competing interests.

Appendix A

Energy use sectors and activities and relevant economic indicators, which are integrated in the estimation of technological contribution to the energy use dynamics in the Russian Federation and the country’s GDP energy intensity reduction.

Sector	No	Energy uses	Units
1. Power sector			
	1	Electricity supply by fossil fuel power plants	Million kWh
	2	Electricity supply by diesel fuel power plants	
	3	Electricity supply by non-fuel power plants	
	4	Own use for power production	
	5	Transmission and distribution losses	
2. Heat sector			
	6	Heat supply by fossil fuel power plants	Thou. Gcal
	7	Heat supply by non-fuel power plants	
	8	Heat supply by boiler houses	
	9	Heat supply by electric boilers	
	10	Heat supply by heat recovery units	
	11	Own use for heat production and supply	
	12	Distribution heat losses	
3. Mining			
	13	Oil and gas condensate production	Thou. tons
	14	Natural and associated gas production	Million m3
	15	Gas processing	Million m3
	16	Oil losses	Thou. tons

Sector	No	Energy uses	Units	Sector	No	Energy uses	Units	
4. Processing industries	17	Gas losses	Million m3	5. Construction	47	Construction bricks	Million conv. bricks	
	18	Coal production	Thou. tons		48	Ceramic tiles and plates	Million m2	
	19	Coal processing (enrichment)	Thou. tons		49	Food, beverages, and tobacco production	Index of production	
	20	Coal losses	Thou. tce		50	Computers, electronic and optic components production		
	21	Iron ore; iron ore concentrate	Thou. tons		51	Electric equipment production		
	22	Iron ore agglomerate			52	Production of equipment and machinery not included in other groups		
	23	Iron ore sinter			53	Production of vehicles, trailers and semi-trailers		
	24	Natural sands; particles, chips, and powder; pebbles, gravel			54	Other processing industries		
	25	Other mining	Index (2016 = 100%)		55	Construction		
	26	Coke production	Thou. tons		56	Cattle, sheep and goats; swine and poultry for meat	Centners	
	27	Oil refinery, including gas condensate			57	Greenhouses: power and heat supply to the greenhouses	m3	
	28	Pig iron			58	Water pumping for irrigation and water supply	Thou. m3	
	29	Steel			59	Agricultural tractors and harvesters	Conv. ha	
	30	Aluminium			60	Fishing and fishery	Index of production	
	31	Copper			61	Other agriculture		
	32	Rolled products			62	Railroad	Revenue ton-km	
	33	Steel pipes			63	Oil and oil products pipeline	Thou ton-km	
	34	Synthetic ammonia			64	Gas pipeline	Million m3-km	
	35	Acyclic hydrocarbons			65	Urban electric	Billion pass.-km	
	36	Sodium bicarbonate			66	Road	Thou. cars	
	37	Potassium fertilizers			67	Water	Revenue ton-km	
	38	Phosphate fertilizers			68	Air		
	39	Nitrogen fertilizers			69	Other transport		
	40	Synthetic rubber						
	41	Compressed fiber boards of wood or other woody materials	Million conv.m2		7. Transport	62	Railroad	Revenue ton-km
	42	Compressed fiber boards	Thou. conv.m3			63	Oil and oil products pipeline	Thou ton-km
	43	Pulp	Thou. tons			64	Gas pipeline	Million m3-km
	44	Paper and cardboard				65	Urban electric	Billion pass.-km
	45	Cement				66	Road	Thou. cars
	46	Clinkers				67	Water	Revenue ton-km

Sector	No	Energy uses	Units
8. Utilities	70	Sewage, water treatment and distribution, wastewater collection and treatment, waste collection and management	Index of production
9. Commercial sector	71	Wholesale and retail trade	Million m2
	72	Education	
	73	Health care	
	74	Other public organizations	
	75	Other commercial organizations	
10. Other energy uses	76	Other energy uses	GDP in 2016 prices
11. Residential sector	77	Space heating	Million m2
	78	DHW	Thou. people
	79	Other uses	Million m2
12. Non-energy use	80	Non-energy use	Index of chemical production

Appendix B

GHG emissions are estimated as the total for 80 activities according to the formula:

$$\begin{aligned}
 C &= \sum_i C_i = \sum_i A_i * CARB_i * SEC_i = A * \sum_i Sh_i \\
 &* (C_i/F_i) * (F_i/E_i) * (E_i/E_i^{HDD}) \\
 &* (E_i^{HDD}/E_i^F) * (E_i^F/A_i) \tag{6}
 \end{aligned}$$

where:

- C and C_i are GHG (or CO₂ only) emissions across the whole economy and for activity i ;
- F_i is fossil fuel consumption for activity i ;
- E_i is total energy consumption for activity i ;
- A is GDP;
- A_i is activity i value;

$CARB_i$ is direct carbon intensity of energy use for activity i (the ratio of GHG or CO₂ only emissions to the total energy use);

$E_i^{HDD} = (A_i * SEC_i^{HDD})$ is energy use for activity i adjusted for climate; it equals the economic activity value multiplied by specific energy use adjusted for climate;

$E_i^F = (A_i * SEC_i^F)$ is energy use for activity i adjusted for climate and capacity load (for industrial, agricultural, transport, construction, and water utility energy uses it is estimated as $SEC_i^F = SEC_{iCAP}^{HDD}$), or for public utilities and appliances saturation (for the residential sector it is $SEC_i^F = SEAAC_i$);

$Sh_i = (A_i/A)$ is the ratio of activity i indicator to GDP to capture the contribution from the structural factor.

Changes in GHG emissions are decomposed using the following multiplicative formula:

$$D_{TOT}^t = \frac{C^t}{C^{2015}} = D_A^t * D_S^t * D_{C/F}^t * D_{F/E}^t * D_{HDD}^t * D_F^t * D_{tech}^t \tag{7}$$

where:

C^t and C^{2015} are economy-wide GHG (or CO₂ only) emissions in 2015 base year and in year t ;

D_{TOT}^t is total GHG emissions in year t divided by GHG emissions in the base year;

D_A^t is the activity changes effect;

D_S^t is the structural changes effect;

$D_{C/F}^t$ is carbon intensity of fuels effect, when the share of fossil fuels factor is included, or otherwise change in the carbon intensity of total energy consumption;

$D_{F/E}^t$ is the fossil fuels share in the energy use change effect (if the factor of fossil fuels share is included in the analysis). If it is not included, this multiplier is removed from the equation;

D_{HDD}^t is the heating degree days change effect;

D_F^t is the capacity load change effect in the industrial, agricultural, transport, and water utilities sectors, or saturation factor in the residential sector;

D_{tech}^t is the technological factor change effect. This component shows the contribution from the technological factor to the emissions dynamics.

Changes in GHG emissions are decomposed using multiplicative formulation and LMDI either

by formula (8a) or (8b): if changes to the share of fossil fuels are included in the analysis:

$$\begin{aligned} \frac{C^t}{C^{2015}} = & \exp \sum_i w_i * \ln \frac{A^t}{A^{2015}} * \exp \left(\sum_i w_i * \ln \frac{Sh_i^t}{Sh_i^{2015}} \right) \\ & * \exp \left(\sum_i w_i * \ln \frac{C_i^t / F_i^t}{C_i^{2015} / F_i^{2015}} \right) * \exp \left(\sum_i w_i * \ln \frac{F_i^t / E_i^t}{F_i^{2015} / E_i^{2015}} \right) \\ & * \exp \left(\sum_i w_i * \ln \frac{E_i^t / E_i^{HDDt}}{E_i^{2015} / E_i^{HDD2015}} \right) * \exp \left(\sum_i w_i * \ln \frac{E_i^{HDDt} / E_i^{Ft}}{E_i^{HDD2015} / E_i^{F2015}} \right) \\ & * \exp \left(\sum_i w_i * \ln \frac{E_i^{Ft} / A_i^t}{E_i^{F2015} / A_i^{2015}} \right) \end{aligned} \tag{8a}$$

if changes to the share of fossil fuels are excluded from the analysis:

$$\begin{aligned} \frac{C^t}{C^{2015}} = & \exp \sum_i w_i * \ln \frac{A^t}{A^{2015}} * \exp \left(\sum_i w_i * \ln \frac{Sh_i^t}{Sh_i^{2015}} \right) \\ & * \exp \left(\sum_i w_i * \ln \frac{C_i^t / E_i^t}{C_i^{2015} / E_i^{2015}} \right) * \exp \left(\sum_i w_i * \ln \frac{E_i^t / E_i^{HDDt}}{E_i^{2015} / E_i^{HDD2015}} \right) \\ & * \exp \left(\sum_i w_i * \ln \frac{E_i^{HDDt} / E_i^{Ft}}{E_i^{HDD2015} / E_i^{F2015}} \right) * \exp \left(\sum_i w_i * \ln \frac{E_i^{Ft} / A_i^t}{E_i^{F2015} / A_i^{2015}} \right) \end{aligned} \tag{8b}$$

where:

A^{2015} and A^t are GDP in constant prices in the base year and year t ;

A_i^{2015} and A_i^t are activity i values in the base year and year t ;

Sh_i^{2015} and Sh_i^t are ratios of activity i to GDP in the base year and year t ;

C_i^{2015} and C_i^t are GHG emissions from activity i in the base year and year t ;

F_i^{2015} and F_i^t are fossil fuels consumption for activity i in the base year and year t ;

E_i^{2015} and E_i^t are energy consumption for activity i in the base year and year t ;

$E_i^{HDD2015}$ and E_i^{HDDt} are energy use for activity i adjusted for climate in the base year and year t ;

E_i^{F2015} and E_i^{Ft} are energy use for activity i adjusted for climate and capacity load (for industrial, agricultural, transport, construction, and utility energy uses), or for public utilities and appliances saturation (for the residential sector) in the base year and year t . Energy use levels for each activity adjusted for the factors as mentioned above are calculated based on specific energy consumption values adjusted for corresponding factors using the method described in the main article (Eqs. 1–5), and activity levels; w_i^* is logarithmic mean share of GHG emissions for activity i in total emissions over a specified time interval, which is estimated as follows:

$$w_i^* = \frac{L(C_i^t; C_i^{2015})}{L(C^t; C^{2015})} = \frac{(C_i^t - C_i^{2015}) / (\ln C_i^t - \ln C_i^{2015})}{(C^t - C^{2015}) / (\ln C^t - \ln C^{2015})} \tag{9}$$

where:

C^{2015} and C^t are GHG emissions across the whole economy in the base year and year t ;

C_i^{2015} and C_i^t are GHG emissions for activity i in the base year and year t .

Contributions from individual factors to the change in total GHG emissions in the additive form across the whole economy or in sector j between 2015 and T are estimated using the multiplicative values obtained through formula (8), in the same manner for all sectors, according to the formula:

$$\Delta C_F = \ln(D_F) * \left(\frac{C^T - C^{2015}}{\ln(C^T / C^{2015})} \right) \tag{10}$$

where:

ΔC_F is the additive form of a factor’s contribution; D_F is the multiplicative form of a factor’s contribution;

C^T and C^{2015} are total emission in year T and in 2015 base year.

The multiplicative form of contribution from the technological factor to the change in GHG emissions is estimated as follows:

$$D_{Tech}^t = \exp \left(\sum_i w_i * \ln \frac{E_i^{Ft} / A_i^t}{E_i^{F2015} / A_i^{2015}} \right) \tag{11}$$

Where:

D_{Tech}^t is the change in GHG emissions in year t against GHG emission in 2015 base year, as determined by the technological factor; w_i^* is logarithmic mean share of GHG emissions for activity i in total GHG emissions over a specified time interval;

E_i^{F2015} and E_i^{Ft} are energy use for activity i adjusted for climate and capacity load (for industrial, agricultural, transport, construction, and utility energy uses), or for public utilities and appliances saturation (for the residential sector) in 2015 base year and in year t ;

A_i^o and A_i^t are economic activity values for activity i in 2015 base year and in year t .

The additive form of contribution from the technological factor to the change in GHG emissions is estimated as follows:

$$\Delta C_{techj} = in(D_{Ctech}) * \frac{C^T - C^j}{in(C^T/C^{2015})} \tag{12}$$

where:

ΔC_{tech} is the additive form of contribution from the technological factor to the change in GHG emissions.

The energy performance index-GHG captures the change in GHG emission obtained through a technological change alone and is calculated using the additive form of contribution from the technological factor as obtained in (12) according to the formula:

$$EPIGHG^{2015,T} = \left(\frac{C^T}{C^{2015}}\right) \wedge \left(\frac{\Delta C_{tech}^T}{C^t - C^{2015}}\right) \tag{13}$$

where:

$EPIGHG^{2015,T}$ is energy performance index-GHG;
 ΔC_{tech}^T is the additive form of contribution from the technological factor to the change in GHG emission;
 C^{2015} and C^T are total emissions in 2015 base year and in year T .

Similarly, contributions from the carbon intensity factor (carbon intensity index-GHG, GHG-Int) and from the share of fossil fuel (fossil fuel index-GHG, FF-Int) are calculated according to formulas (14) and (15):

$$GHG - Int^{2015,T} = \left(\frac{C^T}{C^{2015}}\right) \wedge \left(\frac{\Delta C_{C/F}^T}{C^t - C^{2015}}\right) \tag{14}$$

$$FF - Int^{2015,T} = \left(\frac{C^T}{C^{2015}}\right) \wedge \left(\frac{\Delta C_{F/E}^T}{C^t - C^{2015}}\right) \tag{15}$$

GHG emissions are estimated using a method based on fuel combustion data and emission factors from the national inventory (IGCE, 2022); fugitive emissions are estimated similarly. For each GHG (and also for all GHG), this approach is represented by the following equation:

$$C_{ii}^{direct} = \sum_a (F_{ati} * EF_a) \tag{16}$$

where:

C_{ii}^{direct} is estimated direct emissions from fuel combustion in activity i in year t ;

F_{ati} is the use of fuel a for activity i in year t ;

EF_a is specific emission factor used in the national inventory for fuel a (for carbon dioxide and for the total of three GHG).

Factors for fugitive emissions are borrowed from (IGCE, 2022). If the option to include fugitive emissions is selected, fugitive emissions are added to the corresponding sectors. This methodology allows for attributing the reductions in indirect GHG emissions to locations where electricity and heat savings were obtained, according to the formula:

$$C_{it}^{ind} = EL_{it} * EF_t^{EL-ind} + H_{it} * EF_t^{H-ind} \tag{17}$$

where:

C_{it}^{ind} is indirect emissions from activity i in year t ;
 EL_{it} and H_{it} are electricity and heat use for activity i in year t respectively;

EF_t^{EL-ind} and EF_t^{H-ind} are specific indirect emission factors for electricity and heat generation in year t respectively, and are estimated by formula (22–23) per unit of electricity and heat supply for activity i .

Direct carbon intensity in (6) is replaced with the sum of direct and indirect carbon intensity according to the formula:

$$CARB_i^{full} = CARB_i + C_{it}^{indir} \tag{18}$$

where: $CARB_i$ is direct carbon intensity of energy use with an account of indirect GHG emissions reduction through electricity and heat savings (the ratio of GHG emissions to energy use); C_{it}^{indir} is indirect emissions with an account of indirect GHG emissions reduction through electricity and heat savings in year t .

Then calculations are made by formulas 6–15 using $CARB_i^{full}$.

Direct emissions C_{ii}^{dirEL} and C_{ii}^{dirH} are estimated for four electricity and heat generating activities: electricity generation (by fossil plants and by diesel fuel plants), and heat production (by boiler houses and by power plants).

$$C_{ii}^{dirEL} = C_{ii}^{combEL} * \frac{E_{ii}}{F_{ii}}, C_{ii}^{dirH} = C_{ii}^{combH} * E_{ii}/F_{ii} \tag{19}$$

where:

F_{ii} is fuel use in activity i of the four activities specified above;

E_{ti} is thermodynamic losses of primary energy in heat and electricity generation in activity i of the four activities specified above (in other words, the difference between energy use and energy production); C_{ii}^{combEL} and C_{ii}^{combH} are emissions estimated from fuel combustion in activity i of the four activities specified above.

Indirect emissions from electricity generation as attributed to final energy uses are estimated according to the formula:

$$C_t^{indEL} = \sum_i (C_{ii}^{fullEL} - C_{ii}^{dirEL}) \quad (20)$$

The emissions from electricity generation at fossil plants and diesel fuel plants are summed up. Likewise, indirect emissions from heat production, which are attributed to final energy uses, are estimated as follows:

$$C_t^{indH} = \sum_i (C_{ii}^{fullH} - C_{ii}^{dirH}) \quad (21)$$

And similarly, the emissions from heat production at fossil plants and diesel fuel plants are summed up.

Then emission factors are calculated based on the estimated indirect emissions:

$$EF_t^{EL-ind} = C_t^{indEL} / E_t \quad (22)$$

where:

E_t is total electricity consumption in year t by all end-use sectors, to which indirect emissions from electricity generation will be attributed.

Likewise for heat production:

$$EF_t^{H-ind} = C_t^{indH} / H_t \quad (23)$$

where:

H_t is total heat consumption in year t by all end-use sectors, to which indirect emissions from heat production will be attributed.

Therefore, if indirect emissions for electricity and heat end-use sectors are estimated according to (17), and direct emissions are used for four heat- and electricity generation options (formula 19), then total emissions are equal to the one based on direct emissions.

EEAS-GHG for informational purposes also allows for the analysis of the evolution of industrial GHG emissions for the following products: cement,

ammonia, steel, cast iron, iron ore agglomerate, iron ore pellets, and aluminum. The algorithm of estimating the contribution of individual factors to industrial processes only allows it to estimate the effects for three factors, namely, output, carbon intensity of production, and the structural factor. Formula (6) is therefore reduced to:

$$C = \sum_i C_i = \sum_i A_i * CARB_i * SEC_i = A * \sum_i Sh_i * (C_i/A_i) \quad (24)$$

References

- Ang, B. W., & Choi, K. H. (1997). Decomposition of aggregate energy and gas emission intensities for industry: A refined Divisia index method. *The Energy Journal*, 18(3), 59–73.
- Ang, B. W., & Choi, K. H. (2010). Accounting frameworks for tracking energy efficiency trends. *Energy Economics*, 32(2010), 1209–1219.
- Ang, B. W., & Choi, K. H. (2012). Attribution of changes in Divisia real energy intensity index – An extension of index decomposition analysis. *Energy Economics*, 34(2012), 171–176.
- Bashmakov, I. (2014). Who, where, and how much spends on energy efficiency? Analysis of foreign practices and recommendations for Russia. *Akademia energetiki (Energy Academy). No., 1*, 68–81.
- Bashmakov, I., & Myshak, A. (2014). Russian energy efficiency accounting system. *Energy Efficiency*, 2014(7), 743–759. <https://doi.org/10.1007/s12053-014-9252-z>
- Bashmakov I.A., Myshak A.D., 2012. Factors behind the evolution of greenhouse gas emissions in Russia's the energy sector. Analysis based on the national inventory data. Moscow, ANO "Roshydromet meteorological agency". 131 p.
- Bashmakov I., V. Bashmakov, K. Borisov. M. Dzedzichok, A. Lunin, I. Govor, 2022. Russia's carbon neutrality: Pathways to 2060. CENEF-XXI. <https://cenef-xxi.ru/articles/russia's-carbon-neutrality:-pathways-to-2060>.
- Bin Su., & Ang, B. W. (2012). Structural decomposition analysis applied to energy and emissions: Some methodological developments. *Energy Economics*, 34(1). <https://doi.org/10.1016/j.eneco.2011.10.009>
- Cahill, C. O., & Gallachóir, B. P. (2011). Combining physical and economic output data to analyse energy and CO2 emissions trends in industry. *Energy Policy*, 49, 422–429.
- EIA, 2022. The Monthly Energy Review (MER). *U.S. Energy Information Administration*. July 2022.
- Enerdata, (2022a). *ODYSSEE-MURE decomposition tool*. Energy efficiency factors tool that have consequences in the energy consumption | ODYSSEE (odyssee-mure.eu).
- Enerdata. (2022b). *World Energy & Climate Statistics – Yearbook 2022*. *World energy statistics | Enerdata*.
- Goh, T., & Ang, B. W. (2019). Tracking economy-wide energy efficiency using LMDI: Approach and practices. 2019.

- Energy Efficiency*, 12, 829–847. <https://doi.org/10.1007/s12053-018-9683-z>
- IEA, 2021a. Energy Efficiency 2021a.
- IEA, 2021b. World energy balances. <https://www.iea.org/data-and-statistics/data-product/world-energy-balances>. (Accessed October 29, 2020).
- IEA, 2022a. KEY WORLD ENERGY STATISTICS. 2021.
- IEA, 2022b. Energy Efficiency 2022b.
- IGCE, 2022. National report on the inventory of anthropogenic emissions from sources and removals by sinks of greenhouse gases not controlled by the Montreal Protocol for 1990–2020.
- Koilakou, E., Hatzigeorgiou, E., & Bithas, K. (2021). Carbon and energy intensity of the USA and Germany. *A LMDI Decomposition Approach and Decoupling Analysis*. <https://doi.org/10.21203/rs.3.rs-1119478/v1>
- Lee, J., & Kim, J. (2021). A decomposition analysis of the Korean manufacturing sector: Monetary vs. physical outputs. *Sustainability*, 13, 6192. <https://doi.org/10.3390/su13116192>
- MED RF, 2019. Order of the Ministry of Economic Development of the Russian Federation dated August 1, 2019, No. 471 “On the approval of the methodology for calculating the energy intensity of the gross domestic product of the Russian Federation and assessing the contributions from individual factors to the evolution of energy intensity of the gross domestic product of the Russian Federation”.
- MED RF, 2022. State report on energy saving and energy efficiency in the Russian Federation for 2020. *State report on energy saving and energy efficiency in the Russian Federation for 2020.pdf (gov.spb.ru)*.

Publisher’s Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.