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Scenario-based modelling of industrial energy demand and GHG emissions: A 2050 outlook for Slovenia

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ABSTRACT

Addressing GHG emissions in industrial sectors is crucial for developed nations' energy and environmental policies. European countries use diverse strategies to mitigate industrial GHG impacts, with energy models evaluating national objectives and supporting policy implementation. A new hybrid bottom-up technology-oriented simulation model has been developed for Slovenia's industrial sector, focusing on energy-intensive industries like paper, metal, chemical, and cement production. This model, linked with the macroeconomic GEM model, assesses the impacts of GHG reduction measures on the national economy. This paper introduces the Reference Energy System model for the industrial sector REES SLO, aiding Slovenia's NECP update. It details input parameters, model structure, proposed measures, peculiarities of energy-intensive industries, and calculation results. The findings indicate that decarbonizing Slovenia's industrial sector is feasible but demands immediate policy intervention, substantial investments, and a collaborative approach among stakeholders. Advanced technologies such as carbon capture, utilization, and storage (CCUS), hydrogen-based solutions, and enhanced energy efficiency measures are essential components of this transition. The integration of renewable energy sources (RES) and circular economy principles further strengthens pathways toward sustainability. The REES IND model underscores the importance of aligning industrial decarbonization strategies with broader economic and environmental objectives. It provides a comprehensive framework for policymakers to evaluate the effectiveness of proposed measures and their long-term impacts. Achieving these goals requires a phased approach, beginning with energy efficiency improvements and progressing to structural changes and advanced technologies. The model's insights pave the way for sustainable industrial transformation, aligning Slovenia's industrial sector with national and European Union climate objectives.

1. Introduction

The pressing need to mitigate climate change has driven global efforts towards reducing carbon emissions across various sectors. Among these, the industrial sector remains one of the largest contributors to global greenhouse gas (GHG) emissions, responsible for approximately 38 % of the total emissions according to the latest data from IEA for 2022. Industrial decarbonization refers to the process of reducing carbon dioxide (CO_2) and other GHG emissions from industrial activities. This involves the adoption of low-carbon technologies, energy efficiency measures, transition to renewable energy sources (RES) and shift to circular economy. The urgency of industrial decarbonization has been underscored by international agreements such as the Paris Agreement, which sets ambitious targets for limiting global temperature rise (UNFCCC, 2015). The challenges associated with industrial decarbonization are multifaceted, ranging from technological barriers to economic and policy considerations. Industries such as steel, cement, chemicals and paper, which are characterized by high energy intensity and process emissions, face significant hurdles in reducing their carbon footprints. These industries are typically reliant on fossil fuels not only for energy but also as feedstock, making the transition to low-carbon alternatives particularly challenging.

Recent advancements in industrial decarbonization include the development of carbon capture, utilization, and storage (CCUS) technologies, the integration of hydrogen as a clean energy carrier, and the electrification of industrial processes (IEA, 2023). Adopting greener

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production methods in industries, including the use of renewable energy and process optimization, is essential to meet the global carbon reduction targets as highlighted in (Zheng et al., 2022). Advanced materials, like **gradient porous electrodes**, enable high-efficiency energy storage and electrocatalysis, critical for renewable energy integration in industrial systems as reported by Wang J. et al. in (Wang et al., 2023a). Dye-sensitized solar cells have emerged as a promising alternative to conventional solar cells due to their cost effectiveness and ease of fabrication. In recent years, the integration of nanomaterials into dye-sensitized solar cells has garnered substantial attention, offering new avenues to enhance their photoelectric performance, as reported in (Zheng et al., 2024). Furthermore, the development of bio-based feedstocks is essential complementary strategy for industries where direct electrification and hydrogen use are challenging (Richardson-Barlow et al., 2022).

According to (Bhaskar et al., 2021) one of the most promising pathways for decarbonising the steel industry is the adoption of hydrogen-based direct reduction (H2-DR) technologies. H2-DR involves reducing iron ore using hydrogen instead of carbon, significantly lowering CO_2 emissions. Authors demonstrated the potential of integrating H2-DR with electric arc furnaces (EAF), highlighting the viability of both water electrolysis and methane pyrolysis as sources of hydrogen. In the steel industry, initiatives like the HYBRIT project in Sweden are pioneering fossil-free steel production by using hydrogen from electrolysis, aiming to replace traditional blast furnaces that rely on coke (Pei et al., 2020). Interesting study addressing hydrogen storage and transport by Hren et al. (2023) indicates that the production of hydrogen contributes the most to the GHG footprint, especially in the case where the produced hydrogen is shipped by pipeline (92.1 %). For all the other alternatives, the storage contributes more to the GHG footprint due to high electricity consumption for compression to the required pressure for gaseous hydrogen.

Also maximizing waste heat recovery in the steel industry not only enhances energy efficiency but also plays a vital role in reducing overall carbon emissions (Alshehhi et al., 2023). According to Isafiade et al. (2022), renewable energy supply chain can be integrated with not only industrial process heat demand, but also domestic heat. This can serve many purposes such as a point in an integrated energy system where utilities can be optimally distributed to multiple demand nodes considering not only economics but also environmental implications, which is a great example of sector coupling.

Textile industry, another significant emitter, is exploring decarbonization through energy efficiency improvements, renewable energy integration, and the adoption of sustainable materials (Román-Collado et al., 2023). Efforts in this sector include improving process efficiencies, switching to less carbon-intensive fuels, and incorporating circular economy principles to reduce waste and enhance recycling.

Chemical industry faces unique challenges in decarbonization due to its energy-intensive processes. According to de Faria et al. (de Faria et al., 2021), innovations in energy efficiency and alternative feedstocks are critical for reducing carbon emissions in this sector. The **direct synthesis of dimethyl carbonate (DMC)** from CO_2 and methanol exemplifies a green chemistry pathway according to (Cheng et al., 2023), efficiently utilizing CO_2 with minimal by-products, though catalyst improvements are needed.

Research work done by Norvaiša et al. (2023) reports that the successful implementation of decarbonization strategies in the chemical industry hinges on the integration of advanced technologies such as carbon capture and storage (CCS) and the shift towards sustainable raw materials. Cement industry is a significant contributor to CO_2 emissions, and targeted measures such as the use of CCSU and reducing the clinker-to-cement ratio and improving energy efficiency are vital for its decarbonization (Mikulčić et al., 2013). According to (Norvaiša et al., 2024), decarbonization options in the cement sector include the implementation of carbon capture and storage (CCS) technologies, which are considered crucial for reducing process-related emissions, especially in clinker production, where emissions are inherently high due to the calcination process. Additionally, fuel substitution, such as replacing coal or petrol coke with alternative low-carbon fuels like biomass or waste-derived fuels and enhancing energy efficiency through the adoption of dry clinker production processes can significantly lower carbon emissions in the cement industry. These strategies, coupled with innovative recovery and reuse systems, are essential for achieving sustainable production and lowering the sector's overall carbon footprint (Norvaiša et al., 2024).

In paper industry the implementation of combined heat and power (CHP) systems and the utilization of waste materials like dregs, grits, and lime mud can significantly reduce carbon emissions by improving energy efficiency and enabling the production of sustainable construction materials.

Circular economy practices, including waste-to-energy systems and efficient water-energy-carbon (WEC) management, substantially reduce environmental footprints as reported by Wang, X. et al. in studies (Wang et al., 2021a), (Wang et al., 2023b) and (Wang et al., 2021b). Furthermore, regional cooperation addresses inequities in resource allocation and environmental burdens, with carbon compensation frameworks and resource-sharing mechanisms enhancing sustainability (Wang et al., 2022). Lifecycle assessments, exemplified by the rubber wood industry in (He et al., 2024), facilitate the identification of emission hotspots and inform strategies to improve energy efficiency and optimize industrial processes. These integrated strategies collectively advance decarbonization in industrial systems. Authors Irgolič et al. (2024) highlight, the use of hydrothermal degradation of various plastics sources as an environmentally friendly technique that requires no additional chemicals to recycle plastics, and that the obtained products (oils and gases) have enormous potential for use as fuels, or as a source of various chemicals.

Policy support and economic incentives are critical to overcoming barriers to decarbonization, such as high costs and technological uncertainties. Regulatory frameworks that promote innovation and provide clear guidelines for emissions reductions can accelerate the adoption of low-carbon technologies. For example, navigating the energy transition requires not only technological innovation but also coherent policies that address market and regulatory barriers, as highlighted in (Acheampong and Tyce, 2024). Effective policies can support the scaling of emerging technologies, making them economically viable and attractive to industry players. Additionally, the implementation of circular economy principles, where waste materials are recycled and reused, offers a promising pathway for reducing emissions. Policy frameworks and regulatory measures also play a crucial role in facilitating industrial decarbonization by setting emission reduction targets, providing financial incentives, and supporting research and development in clean technologies as addressed in (European Commission et al., 2021) and (Official Journal of the European Union).

The ongoing research in this field is focused on overcoming the technical and economic challenges associated with decarbonizing hard-to-abate sectors, optimizing the integration of renewable energy sources, and scaling up innovative solutions such as green hydrogen and CCUS. As industrial decarbonization becomes a central component of global climate strategies, it is imperative to explore and develop sustainable pathways that can be adopted at scale, ensuring a just transition for industries and workers alike.

To properly address the challenges in industrial sector and to assess the impact of future scenarios on energy consumption, material use and environmental impacts, various prediction models are used. By using energy models, opportunities for cost savings, efficiency improvements, and the integration of renewable energy sources can be identified. Such models are essential for long-term strategic planning and adapting to technological and policy changes in the industrial sector. As reported by Wiese and Baldini in (Wiese and Baldini, 2018) the decarbonization of industrial sectors requires a holistic approach, integrating technological advancements, policy frameworks, and market dynamics to achieve significant reductions in greenhouse gas emissions. To develop mitigation strategies and regulations, such as reducing single use plastics or improving the recycling infrastructure, a mathematical model to evaluate and predict plastic use and end-of-life fate in the future has been developed by Dokl et al. (2024) based on historical trends.

Recently various models and methodologies have been developed to accurately predict energy consumption in industrial settings, each with its strengths and application areas. One of the advanced methods for forecasting energy demand is the use of nonlinear autoregressive (NAR) neural networks. This approach leverages past time-series data to predict future energy consumption. A study by Abu Al-Haija et al. (Abu Al-Haija et al., 2023) demonstrated the effectiveness of NAR neural networks in forecasting global energy demand for the next decade, highlighting their robustness and ability to avoid overfitting while precisely following exponential trends in energy consumption. Deep learning techniques have also shown significant promise in energy demand forecasting as reported in (Anandavel et al., 2022). Authors validated several models for forecasting electricity demand in different regions of Australia. Their research demonstrated the potential of deep learning for precise energy demand predictions. Machine learning models such as Multiple Linear Regression (MLR), Decision Tree (DT), Recurrent Neural Networks (RNN), and Gated Recurrent Units (GRU) have been applied to predict energy consumption in industrial plants as reported by Bahij et al. (2022). Study concludes, that MLR was found to be the most effective forecasting method among the models evaluated, based on performance criteria.

To support the update of Slovenian National Energy and Climate Plan (NECP) (The Ministry of the Environment Climate and Energy, 2024a) a new hybrid bottom-up technology-oriented simulation model REES IND has been developed for Slovenia's industrial sector, focusing on energy-intensive industries like paper, metal, chemical, and cement production. To assess the impacts of GHG reduction measures on the national economy the model was linked with the macroeconomic GEM model. Presented research work is based on three key hypotheses: (i) that a sectoral disaggregated, soft-linked energy system model can provide robust and reproducible forecasts for industrial energy and emissions; (ii) that explicit inclusion of sectoral measures and policies reveals the scale of mitigation potential compared to baseline developments; and (iii) that high levels of research access through cooperation with the State Statistical Office and industry stakeholders increase the credibility and policy relevance of the results.

2. Methodology

2.1. REES IND model

The REES IND model serves as a primary tool for calculating long-term energy balances within the industrial sector, facilitating the analysis of various developmental strategies. This model operates within an integrated framework that encompasses a suite of simulation models, each addressing specific segments of the energy system with greater detail. The REES IND process-technology simulation model is instrumental in simulating and evaluating the impact of various policy instruments and strategic policy measures. For assessing the effects of these measures, a transparent model framework and a systematic approach to identifying instruments, measures, and their cumulative impacts across different industrial sectors has been developed. The integrated modelling approach necessitates the use of more detailed simulation models for individual segments of the energy system. These models are interconnected at the input/output level and are based on shared assumptions, which allows them to co-influence the overall calculations. Specifically, REES IND is designed to calculate prospective energy end-use balances for energy-intensive industries, including the manufacture of paper and paper products (C17), chemicals and chemical products (C20), other non-metallic mineral products (C23), basic metals (C24), as well as other industrial sectors. Schematic representation of the model is presented in Fig. 1.

The framework illustrated integrates technological, economic, and policy dimensions to assess energy demand, emissions, and resource use in the industrial sector. The model is structured into several interacting blocks, each representing a critical component of the system:

- **External Influence Parameters**; this block defines the contextual drivers of industrial activity, including gross domestic product (GDP), physical production in non-energy branches, industrial employment, and energy prices. These variables serve as the exogenous determinants of industrial output and energy demand, setting the boundary conditions for the subsequent modelling steps.
- **Resource Efficiency Measures**; this component captures measures aimed at reducing material and energy intensity through technological innovation, process optimization, recycling, and other circular-economy strategies. The resulting improvements are incorporated into the energy and emission model, thereby reducing overall energy requirements and associated emissions.
- **End-Use Technologies**; energy demand is further shaped by the characteristics and market penetration of end-use technologies. Technical parameters, such as efficiency and fuel type, are modelled in PET SLO (the technology penetration model), which simulates market adoption, equipment turnover, and diffusion of new technologies. Together, these define the future technology mix across industrial branches.
- **Energy and Emission Model**; at the core of the framework lies the REES IND model (Reference Energy and Emission System model for Industry), which computes energy demand, emissions, and resource flows based on production activity, technology mix, and efficiency levels. The model includes disaggregated representations of energy-intensive sectors (C17, C20, C23, C24) and other industrial branches, allowing for detailed sectoral analysis.
- **Economic Model**; the economic dimension is represented by a two-tier structure. The microeconomic model examines production costs, behavioural responses, and firm-level decision-making under different energy and policy scenarios. Its outputs feed into a macroeconomic model that assesses economy-wide impacts, including GDP growth, employment, investment, and energy price adjustments. The resulting energy prices are fed back into the external parameter block, establishing a dynamic feedback loop between economic conditions and energy demand.

Overall, this integrated framework enables the simultaneous analysis of technological change, resource efficiency, and economic interactions, providing a consistent basis for projecting industrial energy demand and emissions under various policy scenarios. The model also estimates local electricity production based on the distribution of various technologies within the end-use structure and accounts for influential parameters. Additionally, REES IND allows for the separate analysis of measures applicable to sectors included in the European Emissions Trading Scheme (EU ETS).

A systematic workflow for the development of the REES IND model is presented in Fig. 2. The model construction followed a structured, iterative process that combined data collection, model formulation, calibration, and validation. Throughout this process, the State Statistical Office and representatives of energy-intensive industrial branches provided full institutional support and facilitated access to comprehensive datasets, including historical energy consumption, production statistics, and technology stock data. These high-quality datasets were instrumental for establishing the 2020 calibration baseline and for validating model outputs against observed trends.

Following the recommendations of Eisenhardt and Graebner (2007), such unusually high levels of research access represent a rare opportunity in empirical energy-economy modelling, significantly improving both the robustness of the model structure and the credibility of its assumptions. The collaboration with industry stakeholders also allowed

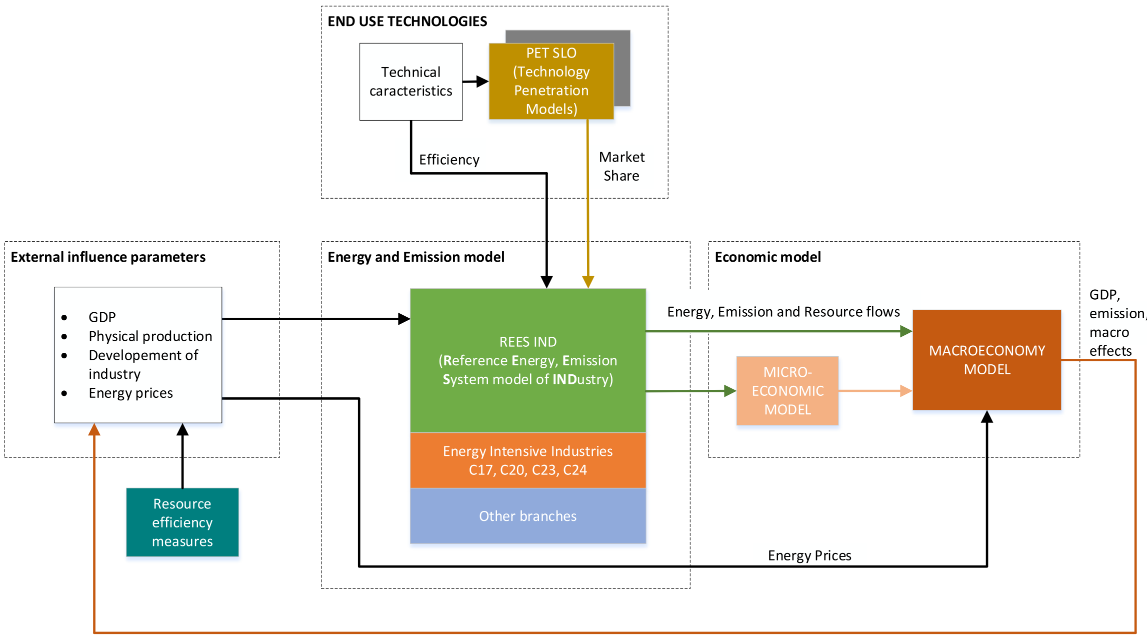

Fig. 1. Demonstration of the REES IND model concept and model-to-model connections.

for the integration of expert knowledge and sector-specific expectations, which strengthened the realism of production projections, efficiency improvement potentials, and technology adoption pathways. This comprehensive approach ensures that the REES IND model provides a reliable representation of industrial energy demand and emissions trajectories under various policy and technology scenarios.

2.2. Model structure

The core of the calculations is a dedicated commercial tool MESAP, which is a modern tool for the design of reference energy systems. It implements a reference energy system that describes the technical, economic, and environmental characteristics of energy conversions from the Slovenian energy system to simulate its responses to external influential parameters and aggregates calculations of detailed models of subsystems. In REES IND, the energy system is modelled up to the level of energy demand, allowing analysis of all energy policy measures, both on use and energy supply side. The reference energy system is a free structure, which means that the model is open to adapt to different analytical requirements, which allows modelling of new technologies and different decarbonization intensities. REES IND model calculates energy demand for four energy intensive branches and for other residual industries.

In parallel, standard and improved energy use technologies are modelled in segments where efficiency gains are the greatest. Based on technical, economic, and environmental characteristics, energy flows, costs and emissions are calculated in parallel for interchangeable technologies. This increases the transparency, consistency, and accuracy of estimates. The REES IND model calculates:

- energy use balances (useful, final and primary energy for the whole energy system and by sub-sectors, by energy sources, by technologies);
- emissions of harmful substances (SO_2, NO_x, CH_4, N_2O, dust particles) from energy conversions (by sectors, by energy sources, by technologies and by conversion levels and total emissions);
- costs related to the operation of the energy system and energy use (disaggregated by sectors or levels of conversion).

Several interconnected sub-models are incorporated within the analytical framework for assessing energy strategies. Energy efficiency measures in energy-intensive industries are modelled separately to capture their sector-specific impacts. Estimates of the market shares of individual technologies and their associated costs serve as key inputs for the REES IND model. The REES IND model then calculates prospective energy end-use balances with a particular focus on energy-intensive industries, including the manufacture of paper and paper products (C17), chemicals and chemical products (C20), non-metallic mineral products (C23), and basic metals (C24), as well as aggregated representations of other industrial branches. The model also estimates local electricity production based on the technology shares in the end-use structure and their interaction with key influencing parameters. Importantly, REES IND enables the separate treatment of measures for sectors covered by the European Emissions Trading Scheme (EU ETS), allowing for policy-specific analysis. The outputs from REES IND are subsequently fed into a macroeconomic model, which assesses the economy-wide impacts of the selected measures, including their effects on GDP, employment, and feedback loops on energy use and emissions. This integrated approach ensures that both sectoral and macroeconomic consequences of energy and climate policies are comprehensively evaluated.

The REES IND model provides a technologically oriented framework designed for a consistent and systematic approach to identifying instruments, measures, and their resultant impacts across diverse industrial sectors. By integrating horizontal technologies within industry-specific contexts, the model enables detailed quantitative analyses of the implications of energy efficiency strategies. Each technology is parameterized using different technical specifications, facilitating high-resolution modelling and simulation. In aluminium production, the electrolysis process is parameterized by specific energy consumption per ton of aluminium. For electric arc steel furnaces, the model incorporates energy input per unit mass of steel, thermal processes and non-energy applications are characterized by process-specific heat demands and thermal conversion efficiencies. Compressed air systems are modelled with parameters such as compressor efficiency, leakage rates, and system pressure levels. Electric motors with variable frequency drives are defined by operational load profiles, drive efficiency, and power factor enhancement capabilities. Space heating and boiler systems are represented by fuel-to-thermal energy conversion efficiencies, insulation performance, and boiler efficiency profiles. For cogeneration systems,

Fig. 2. A systematic workflow for REES IND model development.

the model captures critical parameters, including electrical and thermal conversion efficiencies, fuel input characteristics, and energy distribution profiles. This parameterization within the REES IND model facilitates simulations, enabling an in-depth evaluation of the operational, economic, and environmental impacts of deploying advanced energy efficiency measures, and technology switch in industrial processes. The model's structure and bottom-up approach ensures its applicability to national energy systems and its utility in policy and decision-making frameworks. Fig. 3 presents the technology categories modelled in the REES IND framework, illustrating the disaggregation of industrial energy demand into technology-specific components used for calculating final energy requirements for heat and electricity.

The model disaggregates final energy consumption into distinct technology categories, including non-energy use, electrolysis, electric arc furnaces for steel production, electrical motors and compressed air systems, process and appliance electricity, boilers, thermal process heat,

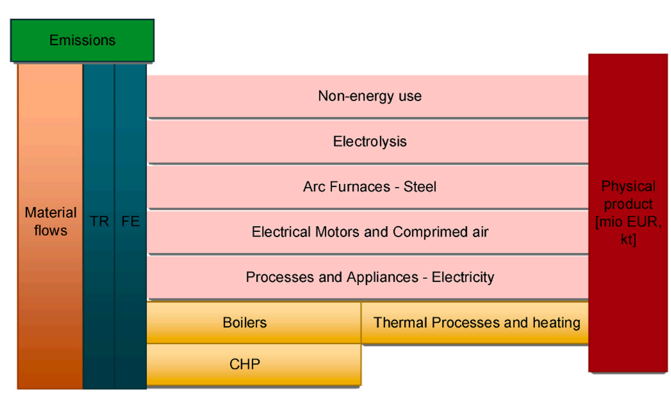

Fig. 3. Technology categories modelled in REES IND.

and combined heat and power (CHP) systems. This detailed segmentation enables technology-specific calculation of energy requirements for both heat and electricity. Each technology is characterized by dynamic efficiency parameter, which evolve over time to reflect improvements in energy performance due to retrofits, equipment replacement, and adoption of best-available technologies.

These efficiency improvements reduce the amount of energy input required for a given level of physical production, while market penetration modelling captures the rate at which new, more efficient, or low-carbon technologies enter the stock and displace older ones. The technologies determine the quantity and type of fuel consumed, while greenhouse gas (GHG) emissions are calculated by applying fuel-specific emission factors (e.g., CO_2 per GJ of natural gas or coal). This modelling approach allows REES IND to simulate both technological progress and fuel decarbonization pathways, providing a robust framework for assessing mitigation measures and their impact on industrial heat and electricity demand as well as emissions.

2.3. Model equations and relationships

The REES IND model is a technology-explicit, bottom-up simulation framework that links sectoral activity to useful energy demand, final energy consumption, and greenhouse gas (GHG) emissions. Its modular architecture ensures transparency and reproducibility: each module exchanges well-defined data flows as presented in Fig. 1, allowing consistent calibration, validation, and scenario analysis.

1. From Activity to Useful Energy

The modelling process begins by quantifying sectoral activity $Q_{s,t}$ for each sector s and year t. Activity is expressed as physical production (for energy-intensive sectors such as cement, steel, and paper) or value added (for heterogeneous sectors such as chemicals and other manufacturing). The useful energy demand $U_{s,t}$ is then calculated as:

$$U_{s,t} = Q_{s,t} \cdot SEC_s^{base} \cdot \left(1 - \Delta EE_{s,t}\right)$$

where SEC_s^{base} is the baseline specific energy consumption and $\Delta EE_{s,t}$ captures cumulative efficiency improvements over time (Table 2). This step integrates energy efficiency measures, retrofits, and technology upgrades as key policy levers.

2. Technology and Fuel Allocation

The next step is to allocate useful energy across technologies and fuels in a bottom-up manner. For each technology f, useful energy is calculated as:

$$U_{s,f,t} = U_{s,t} \cdot share_{s,f,t}$$

where $share_{s,f,t}$ represents the market penetration of technology f in sector s and year t. These shares are dynamic, reflecting technology adoption, stock turnover, and fuel-switching assumptions (e.g., replacement of natural gas boilers with electric boilers or hydrogen-ready systems).

The final energy demand per technology is then derived by applying the technology efficiency $\eta_{s,f,t}$:

$$FE_{s,f,t} = \frac{U_{s,f,t}}{\eta_{s,f,t}}$$

This formulation ensures that efficiency improvements directly reduce energy inputs, while fuel-switch scenarios adjust the fuel mix used by each technology. As a result, the model can capture simultaneous impacts of efficiency gains, electrification, and substitution of fossil fuels with CO_2-neutral fuels. After technology-level calculations are complete, final energy is aggregated per fuel carrier (electricity, natural gas, biomass, coal, hydrogen, etc.) to produce sectoral energy balances.

3. Conversion from Useful to Final Energy

For processes that rely on multiple energy carriers (e.g., hybrid systems or CHP), final energy demand is computed separately for each carrier before aggregation. This allows the model to explicitly capture fuel-switching dynamics over time and their effects on total energy consumption.

4. Emissions Calculation

Emissions are calculated in two steps: combustion emissions and process emissions.

Combustion emissions are computed as:

$$E_{s,t}^{comb} = \sum_f FE_{s,f,t} \cdot EF_f$$

where EF_f is the fuel-specific emission factor (e.g., CO_2 per GJ of natural gas, coal, or biomass). Because emissions are fuel-linked, any shift in fuel mix, such as electrification or substitution with hydrogen, directly affects emission levels.

Process emissions are calculated separately because they arise from chemical transformations rather than fuel combustion. They are proportional to the level of process-relevant activity $A_{s,t}$:

$$E_{s,t}^{proc} = A_{s,t} \cdot EF_s^{proc} \cdot \left(1 - capture_{s,t}\right)$$

where $A_{s,t}$ represents the process activity level for sector s and year t (e.g., clinker production in cement, output of steel, or aluminium production). EF_s^{proc} is the process emission factor, expressed per physical unit of output and $capture_{s,t}$ reflects the fraction of emissions abated by carbon capture, utilization, and storage (CCUS) technologies.

Total emissions are then given by:

$$E_{s,t} = E_{s,t}^{comb} + E_{s,t}^{proc}$$

This formulation captures the combined effect of efficiency improvements, fuel substitution, electrification, and CCUS deployment on industrial emissions.

2.4. Model inputs and influencing factors

Economic activity, particularly the evolution of physical production, constitutes one of the principal drivers in the REES IND model. For energy-intensive industries, namely the production of paper and paper products (C17), non-metallic mineral products (C23, cement), and metals (C24), explicit projections of physical production were developed. Conversely, for the production of chemicals and chemical products (C20), other non-metallic mineral products (e.g., glass, ceramics, excluding cement), and the remaining manufacturing activities, projections were expressed in terms of value added (VA) rather than physical output, reflecting the heterogeneity of product groups.

The modelling framework was calibrated to 2020 as the baseline year, using observed production data to ensure consistency with historical developments. Projections of future industrial activity were prepared following an extensive process that combined expert recommendations, site visits and consultations with representatives of energy-intensive companies, and a detailed review of sector-specific characteristics. For sectors C17, C23 (cement), and C24, production forecasts were expressed in physical units (kilotons), allowing the model to incorporate technology- and process-specific energy intensities. For sectors with diverse product portfolios (C20 and C23 excluding cement), VA projections in monetary units were employed as the leading indicators of activity. All remaining industrial branches were aggregated, with VA used as the principal influencing parameter.

Table 1 presents the resulting assumptions for the growth of economic activity in selected industries and aggregated sectors. Physical production trajectories were derived from structured interviews and consultations with industrial stakeholders, ensuring that the model reflects realistic production trends, including the gradual phase-out of primary aluminium production and the anticipated increase in secondary aluminium output. In contrast, projections of value added for sectors such as C20 and non-cement C23 were aligned with the European Commission's EU Reference Scenario, thereby ensuring consistency with broader EU-level macroeconomic and energy policy frameworks.

Overall, the projections for the period 2020–2030, with an outlook to 2050, combine historical trends, the 2020 baseline, and industry expectations regarding capacity expansions, enabling a robust representation of the drivers of industrial energy demand and emissions within the REES IND model.

2.5. Sectoral measures and policies – key assumptions

Sector-specific measures and key assumptions embedded in the REES IND model, as used in the Slovenian NECP update (The Ministry of the Environment Climate and Energy, 2024b) are summarised in Table 2. The development of these measures relied on multiple complementary knowledge sources to ensure technical and policy coherence. Data from industrial energy audits were particularly valuable in quantifying the potential for waste heat recovery, energy efficiency improvements, and fuel substitution measures. The draft National Hydrogen Strategy informed assumptions on the gradual replacement of natural gas with hydrogen, biomethane, and synthetic gases, as well as the increasing electrification of process heat, particularly in glass, steel, and chemical production.

In addition, the assumptions incorporate the deployment potential of carbon capture and storage/utilization (CCUS) technologies, especially for process emissions in cement production post-2040. The modelling framework was further aligned with national industrial policy guidelines and long-term decarbonization objectives, ensuring consistency with strategic climate targets. Finally, close collaboration with the national chamber of commerce and sectoral industry representatives provided essential insights into the technical feasibility, timing, and expected adoption rates of the measures, thereby improving the realism and credibility of the projections.

The portfolio of measures to reduce industrial energy consumption and greenhouse gas (GHG) emissions was systematically identified and evaluated based on multiple knowledge sources. These included the first NEPN, Slovenia's Long-Term Climate Strategy until 2050, the Slovenian Industrial Policy, and recent studies and international literature, most notably analyses by the International Energy Agency (IEA), as well as detailed data on energy use in Slovenian industry. This comprehensive approach ensured that the measures considered are both technically feasible and aligned with national and international decarbonization objectives.

In addition to the sector-specific measures outlined above, other

Table 2
Sectoral measures and key assumptions included in the REES IND model.

Industrial sector	Measures
Paper and Paper Products (C17)	- reduce specific heat consumption by 10 % by 2030 and 23 % by 2050 through waste heat recovery and technological upgrades; - replace fossil fuels with CO_2-neutral fuels (e.g., coal to biomass, natural gas to synthetic gas/biomethane/hydrogen); - shift to electricity with a potential of 10 % of natural gas use; - implement combined heat and power (CHP) systems.
Production of Non-Metallic Mineral Products (C23, Cement)	- improve energy efficiency by 7 % by 2030 and 15 % by 2050 through waste heat recovery and increased use of alternative fuels (e.g., biomass, waste); - implement CCUS technologies post 2040, aiming to capture 700 kt of process emissions by 2050; - reduce clinker content in cement production.
Other Non-Metallic Mineral Sectors (e.g., Glass, Ceramic)	- improve energy efficiency by 7 % by 2030 and 15 % by 2040 through waste heat recovery and increased use of alternative fuels; - shift from natural gas to electricity in glass production, with 25 % of potential realized by 2030 and 100 % by 2040; - increase recycling and material efficiency.
Production of Metals (C24, including Aluminium)	- increase secondary aluminium production by 45 % by 2030 and 94 % by 2050; - continue reducing energy intensity in steel production with furnace upgrades, oxygen injection, and preheating; - shift 33 % of natural gas use to electricity in steel and foundry processes by 2030 and 100 % by 2040; - utilize excess heat and increase recycling efforts.
Production of Chemicals and Chemical Products (C20)	- reduce specific heat consumption by 3 % by 2030 and 12 % by 2050 through waste heat recovery and technological modernization; - replace natural gas with CO_2-neutral fuels (e.g., biomass, synthetic gas/biomethane/hydrogen); - shift 15 % of natural gas use to electricity by 2030, expanding to 20 % post 2030; - implement CHP systems and improve material efficiency.
Other Manufacturing Sectors	- reduce specific heat consumption by 1 % annually through organizational measures, energy management, and technological upgrades; - shift from natural gas to electricity in heating and drying processes; - increase the use of CO_2-neutral fuels and renewables; - improve energy efficiency in compressed air systems and industrial boilers.

Table 1
Assumptions about the growth of economic activity in selected industries.

	2020	2025	2030	2035	2040	2045	2050
Growth of physical production volume (2020 = 100 %)							
C17 production of paper and paper products	100 %	103 %	105 %	106 %	108 %	109 %	111 %
C23 production of non-metallic mineral products: cement	100 %	112 %	115 %	117 %	118 %	120 %	120 %
C24 production of metals: steel	100 %	119 %	128 %	130 %	131 %	132 %	134 %
C24 production of metals: primary aluminium	100 %	0 %	0 %	0 %	0 %	0 %	0 %
C24 production of metals: secondary aluminium	100 %	129 %	145 %	161 %	194 %	194 %	194 %
Growth of value added (2020 = 100 %)							
C20 production of chemicals and chemical products	100 %	110 %	112 %	115 %	117 %	118 %	121 %
C23 production of other non-metallic mineral products excluding cement	100 %	106 %	112 %	117 %	123 %	127 %	131 %
Other sectors (residual)	100 %	118 %	130 %	140 %	149 %	157 %	165 %

measures in line with the principles of a low-carbon circular economy were also included in the model. The decarbonization of the industrial sector, particularly in the long term, relies heavily on the development of new technologies, such as power-to-X technologies, energy storage technologies, and carbon capture and utilization (CCUS). These technologies and varying degrees of their penetration are included in the modelled scenarios, depending on the ambition level of each scenario. The use of renewables and low-carbon gases in industry assumes the appropriate development of technologies and the establishment of infrastructure and a suitable regulatory framework. Also, the integration of industrial enterprises with district heating systems is envisaged to support heat consumption reduction and increase the utilization of waste heat. Furthermore, intensive implementation of pilot projects is expected, especially in areas such as waste heat utilization, circular economy, and low-carbon technologies. The EU Emissions Trading System (EU ETS) and various financial incentives are expected to play a crucial role in encouraging the industry to progressively reduce emissions and adopt renewable energy technologies.

3. Results and discussion

3.1. Final energy consumption

The final energy consumption in the industrial sector, encompassing electricity and other energy sources, is projected to reach 15.8 TWh by 2030 under the With Existing Measures (WEM) scenario, reflecting a 12 % increase compared to the base year 2020. In contrast, the With Additional Measures (WAM) scenario anticipates a consumption level of 14.8 TWh in 2030, corresponding to a 5 % increase from 2020 as shown in Fig. 4.

By 2050, energy consumption is expected to rise to 17.9 TWh under the WEM scenario, whereas the WAM scenario projects an increase to 16.1 TWh, which is 14 % higher than in 2020. These projections indicate that, despite the ambitious implementation of energy efficiency measures, significant reductions in energy consumption within the industrial sector, are not observed, given the anticipated growth in production and added value in these sectors. Under the WEM scenario, the share of renewable energy sources (RES) is forecasted to be 10 % in 2030 and declines to 7 % by 2050. Conversely, the WAM scenario predicts a substantial increase in the RES share, rising to 29 % in 2030 and reaching 89 % by 2050. The RES share calculations incorporate contributions from renewables, hydrogen, synthetic gases, and biomethane. Additionally, the share of waste heat is estimated to constitute 10 % of the required thermal energy in 2030, increasing to 14 % by 2050 under the WAM scenario. The WAM scenario also emphasizes the substitution of natural gas with synthetic gases, biomethane, and hydrogen. Specifically, the scenario projects that "green" gases (RES and low-carbon gases) will comprise 10 % of gaseous fuel consumption by 2030, expanding to 40 % by 2040, and ultimately reaching 100 % by 2050. By 2050, the consumption of gaseous fuels (RES and low-carbon gases) under the WAM scenario is expected to amount to 4.2 TWh, representing 48 % of the final energy consumption for thermal purposes in industrial sector. Table 3 shows the projection of energy consumption in industrial sector for the period from 2020 up to 2050.

Electricity consumption in Slovenian industrial sector is increasing, amounting to 5.8 TWh in 2020. Under the WEM scenario, electricity consumption is projected to increase by 6 % by 2030 and by 25 % by 2050; under the WAM scenario, it is expected to increase by 12 % by 2030 and by 34 % by 2050 (excluding electricity consumption for primary aluminium production in the base year, electricity consumption is projected to increase by 21 % by 2030 and by 54 % by 2050). Both scenarios consider the cessation of primary aluminium production starting from 2023. The share of electricity in final energy consumption is projected to be around 40 % by 2050 under the WEM scenario, while in the WAM scenario, it is expected to be 44 % in 2030 and 49 % in 2050. The WAM scenario anticipates a shift from the use of natural gas (for thermal purposes) to electricity, with electricity consumption for these purposes amounting to 0.5 TWh in 2030 and 1.2 TWh in 2050. Fig. 5 shows the final energy consumption by industrial sector for the WEM and WAM scenarios.

Among the energy-intensive sectors, the largest share of final energy consumption is attributed to sector C24 - Manufacture of basic metals (22 %), followed by C23 - Manufacture of other non-metallic mineral products (16 %), C17 - Manufacture of paper and paper products (13 %), C20 - Manufacture of chemicals and chemical products (8 %), with other residual industry sectors accounting for 40 % of the share.

3.2. GHG emissions

Greenhouse gas (GHG) emissions in industrial sector amounted to 2744 kt CO_2 equivalent in 2022, which is 4 % less than the records from 2021. Under the WEM scenario, total GHG emissions in industrial sector are expected to increase by 1 % by 2030 and by 8 % by 2050, compared to the base year 2020. Under the WAM scenario, emissions in industrial sector are projected to decrease by 16 % by 2030 and by 80 % by 2050, compared to the base year 2020. In 2030, GHG emissions decrease significantly due to the cessation of solid fuel (brown coal) use in CHP units in the paper industry. The substantial reduction is due to the utilization of waste heat, the transition of some gas technologies to electricity, the use of renewable gases, and the implementation of carbon capture technologies after 2040. It is important to emphasize that the addressed emissions are total industrial emissions, meaning emissions resulting from fuel use and process emissions, including F-gas emissions. In 2050, process emissions account for 84 % of the remaining emissions.

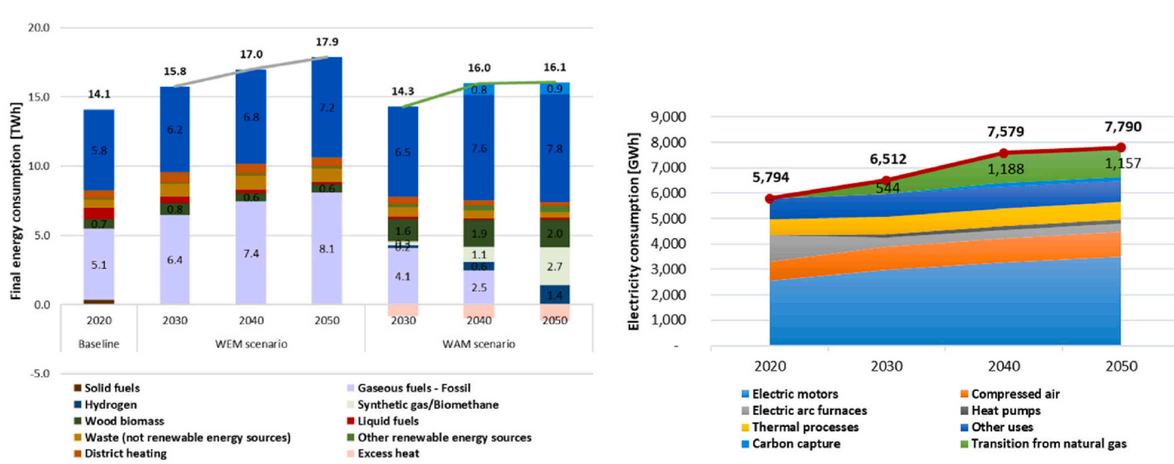

Fig. 4. Final energy consumption (left) and electricity consumption by type of use for WAM scenario (right) for the industrial sector.

Table 3
Projection of energy consumption in manufacturing industries for the years 2030, 2040, and 2050 compared to the situation in 2020 by energy sources.

Fuels	Unit	2020		2030		2040		2050	
		WEM	WAM	WEM	WAM	WEM	WAM	WEM	WAM
Solid fuels	TWh	0.4	0.1	0.0	0.0	0.0	0.0	0.0	0.4
Gaseous fuels - fossil	TWh	5.1	6.4	4.1	7.4	2.5	8.1	0.0	5.1
Syn. gas/Biomethane	TWh	0.0	0.0	0.3	0.0	1.1	0.0	2.7	0.0
Wood biomass	TWh	0.7	0.8	1.6	0.6	1.9	0.6	2.0	0.7
Liquid fuels	TWh	0.8	0.4	0.2	0.3	0.1	0.2	0.1	0.8
Waste (non-RES)	TWh	0.6	0.9	0.7	1.0	0.6	1.0	0.4	0.6
Other RES	TWh	0.1	0.1	0.2	0.1	0.3	0.1	0.4	0.1
District heating	TWh	0.6	0.8	0.5	0.7	0.4	0.7	0.3	0.6
Waste heat	TWh	0.0	0.0	−0.8	0.0	−1.0	0.0	−1.2	0.0
Hydrogen	TWh	0.0	0.0	0.2	0.0	0.6	0.0	1.4	0.0
Electricity	TWh	5.8	6.2	6.5	6.8	7.6	7.2	7.8	5.8
Total	**TWh**	**14.1**	**15.8**	**14.3**	**17.0**	**16.0**	**17.0**	**17.9**	**16.1**

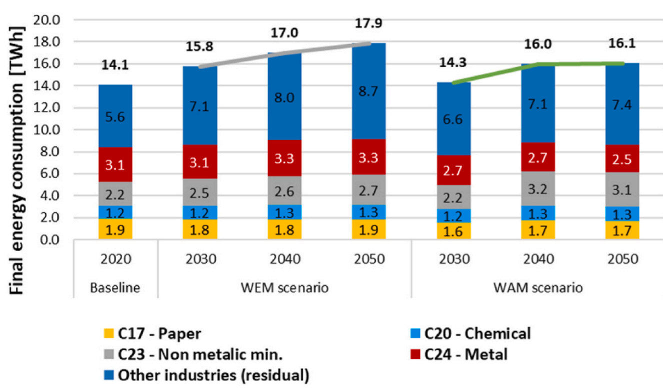

Fig. 5. Final energy consumption by sectors of the manufacturing industry.

The projection of total GHG emissions by sector in industrial sector is shown in Fig. 6.

Table 4 provides a comparison of values of total GHG emissions in industrial sector.

3.3. Assessment of investments in industry

For the assessment of industrial investments, a critical component of the European Union's strategy to decarbonize the industrial sector (Europe's net-zero technology manufacturing ecosystem, previously known as Net Zero Industry Act) has been taken into account. Regulation is designed to establish a stable and streamlined regulatory framework that incentivizes investments necessary for achieving the EU's climate neutrality targets. According to the estimates provided by the regulation, investments in green technologies within the EU for the period 2023–2030 are projected to reach approximately EUR 92 billion. This contrasts with the current investment levels under the With Existing Measures (WEM) scenario, which are estimated at around EUR 52 billion. Furthermore, planned investments under the REPowerEU program have also been incorporated into these projections. Fig. 7 illustrates the historical values and future projections for investments in fixed assets within the Slovenian industry across different scenarios.

Under the With Additional Measures (WAM) scenario, the annual investment volume in the industrial sector is expected to double by 2030 compared to the current WEM scenario. Specifically, investments in fixed assets within Slovenian industry totalled EUR 1.365 billion in 2020, with a cumulative investment of slightly over EUR 17 billion in the period from 2010 to 2022. Projections indicate that under the WAM scenario, cumulative investments for the period 2020–2030 will amount to approximately EUR 30 billion, whereas under the WEM scenario, they will total EUR 18 billion. This results in a cumulative difference of EUR 12 billion between the two scenarios for the 2020–2030 period.

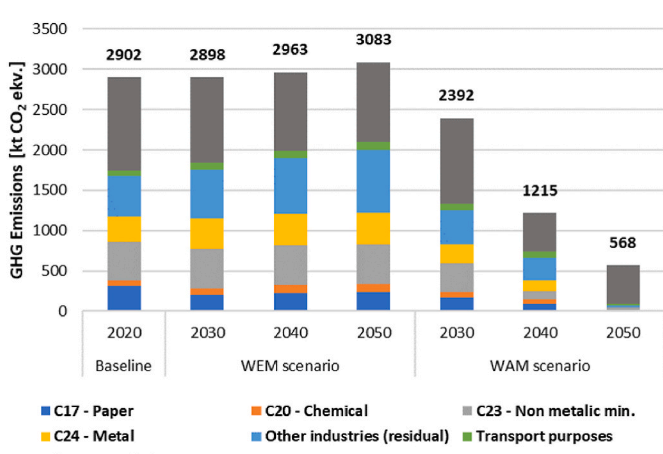

Fig. 6. Total GHG emissions by sector in industrial sector up to 2050.

4. Discussion

The presented research confirms that designing reliable models of industrial energy demand is inherently challenging, due both to the extensive data requirements and to the complexity of relationships among diverse stakeholders and their roles in the energy system. Despite these challenges, the results obtained provide robust evidence in support of the three hypotheses formulated at the outset of this work.

First, the model reliability hypothesis was validated through successful calibration against official statistics and historical energy balances, as well as through sensitivity tests. These results demonstrate that the soft-linked REES IND framework, when properly parameterized, is capable of delivering reproducible and policy-relevant forecasts of industrial energy demand and emissions. Second, the policy impact hypothesis was confirmed by the scenario analysis, which revealed pronounced differences between the WEM and WAM pathways. The inclusion of sector-specific measures and policies led to significantly lower energy demand and emissions trajectories, underscoring the decisive role of policy design in shaping industrial decarbonization outcomes. Finally, the stakeholder integration hypothesis was supported by the exceptionally high quality of research access, which was made possible through the full cooperation of the State Statistical Office and active engagement of representatives from energy-intensive industries. In line with Eisenhardt and Graebner (2007), this level of access provided a unique opportunity to obtain high-resolution data and to ensure that assumptions reflect real sectoral dynamics.

At the same time, several limitations of the proposed approach must be acknowledged. The model is highly data intensive: reliable calibration and scenario design require detailed sectoral statistics, energy

Table 4
Projection of GHG emissions in industrial sector for the years 2030, 2040, and 2050 compared to the situation in 2020 by emission sources.

		2020	2025	2030	2035	2040	2045	2050
GHG emissions [kt CO_2 ekv]								
Industry - fuel combustion	WEM	1748	1843	1847	1916	1990	2048	2104
	WAM	1748	1603	1334	903	740	517	90
Industrial processes	WEM	1154	1097	1052	997	971	974	979
	WAM	1154	1103	1059	502	475	471	478
Total	**WEM**	**2902**	**2940**	**2899**	**2913**	**2961**	**3022**	**3083**
	WAM	**2902**	**2706**	**2393**	**1405**	**1215**	**988**	**568**

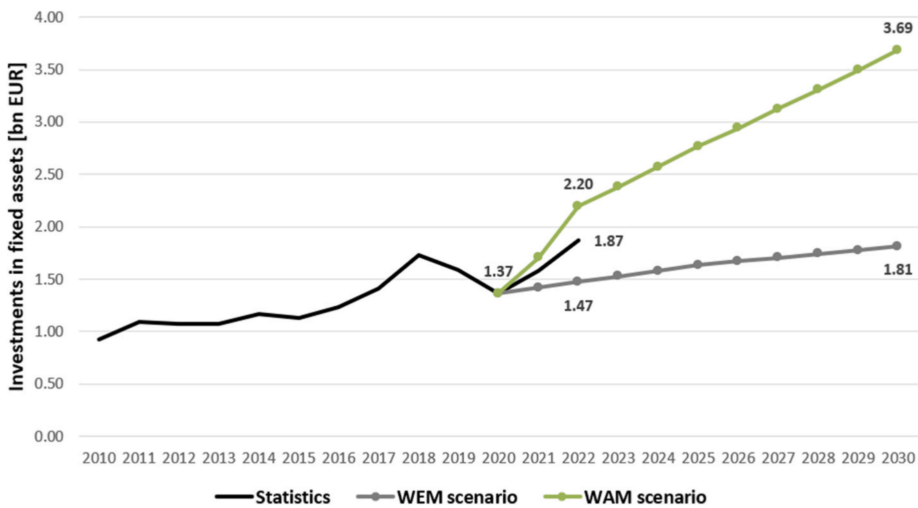

Fig. 7. Historical values and investment projections in fixed assets in the Slovenian industry by scenario.

balances, and process-level data, which may not be available or consistent in all contexts. The REES IND model requires constant updating and adaptation in line with improvements in statistical data availability, technology development, and evolving external drivers. Several research challenges have been identified for future model development:

- Integration of circular economy, resource efficiency, product design, and sustainability aspects;
- Evaluation of socio-economic effects, such as energy poverty and behavioral changes;
- Consideration of shifts in economic and social paradigms (energy efficiency versus energy sufficiency);
- Assessment of scenario impacts on the structure of the economy in support of national development strategies.

Future model upgrades should also improve sector coupling and achieve greater spatial and temporal resolution. A key barrier remains the lack of a national strategic basis for long-term industrial development, which constrains scenario development. The introduction of economic optimization routines into technology selection, as well as the development of novel modelling frameworks that move beyond climate neutrality, such as those proposed by Potrč et al. (2022), will be important steps forward.

Moreover, the development of regression-based relationships and technology assumptions relies on substantial expert knowledge, which, while indispensable, introduces a degree of subjectivity that needs to be managed transparently. Finally, although stakeholder engagement enhances credibility and policy relevance, it may also introduce biases depending on the perspectives represented.

Additionally, the proposed modelling approach could be further enhanced by extending the framework to a full life-cycle perspective, incorporating a broader range of stakeholders such as supply chains, regulatory bodies, and transportation stages. Such an expansion would also allow the assessment of environmental factors beyond GHG emissions, for example, resource use, air pollutants, or water impacts, as suggested by Si et al. (2024). In addition, the choice of modelling approach should always be guided by the specific goals of the forecast, the availability and quality of data, and the complexity of the energy system under analysis. Combining insights from multiple complementary models could provide a more comprehensive understanding of future industrial energy demand and strengthen the evidence base for effective policy and investment decisions. Similar to Bahij et al. (2022), this research work provides a robust methodological foundation for further research and offers a transparent, policy-relevant instrument to support industrial energy and emissions forecasting.

5. Conclusion

Achieving industrial decarbonization requires a multifaceted approach that combines technological innovation, supportive policy frameworks, and cross-sector collaboration. This paper presented the Slovenian REES IND model, which has been used to support the update of the Slovenian NECP. Energy-intensive industries were modelled separately, enabling detailed calculation of branch-specific energy demand and emissions flows. The model was soft-linked with a macroeconomic framework, representing a methodological first in Slovenia's modelling environment and providing a more holistic perspective on energy-economy interactions.

The presented research confirmed that a sectoral disaggregated, soft-linked modelling approach can generate robust and reproducible forecasts of industrial energy demand and emissions in relatively small energy systems such as Slovenia's. The results also confirmed the decisive role of policy measures and stakeholder integration in shaping credible scenarios, thereby validating the three key hypotheses set at the outset of the study. The analysis highlights the particular importance of the manufacturing sector, which is both a cornerstone of Slovenia's export-oriented economy and a major consumer of materials, energy, and water, as well as a significant generator of waste. This dual role underscores the need for circular business models and value chains that integrate eco-design, innovative materials, energy efficiency, maintenance and refurbishment, and recycling. Embedding these aspects into the model remains one of the most important challenges for future research. The transition towards low-carbon technologies in Slovenia's industrial sector is expected to occur in phases, consistent with earlier findings by Mikulčić et al. (2013), albeit with a slightly refined time horizon. Energy efficiency will pave the way, followed by structural changes, and eventually the widespread adoption of emerging technologies such as green synthetic gases, biomethane, and hydrogen after 2030. The results of the REES IND model demonstrate that industrial decarbonization in Slovenia is feasible, but it requires immediate action, increased investment, and sustained collaboration among stakeholders. Looking forward, continued research and development, coupled with policies that incentivize and facilitate the adoption of sustainable practices, will be decisive in ensuring that industry contributes effectively to national and global climate goals.

CRediT authorship contribution statement

Matevž Pušnik: Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Boris Sučić:** Writing – review & editing, Validation, Supervision, Formal analysis, Conceptualization. **Matjaž Česen:** Validation, Methodology, Formal analysis, Data curation. **Fouad Al-Mansour:** Supervision, Methodology, Data curation, Conceptualization. **Stane Merše:** Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Nomenclature

C	Classification Code (used to denote industry sectors)
CCUS	Carbon Capture, Utilization, and Storage
CHP	Combined Heat and Power
EAF	Electric Arc Furnace
EU	European Union
ETS	Emissions Trading System
FE	Final Energy
GEM	General Equilibrium Model
GHG	Greenhouse Gas
H2-DR	Hydrogen-Based Direct Reduction
MESAP	Modular Energy System Analysis and Planning Tool
NECP	National Energy and Climate Plan
REES IND	Reference Energy System for Industrial Sector
REES SLO	Reference Energy System for Slovenia
RES	Renewable Energy Sources
TR	Transformations
WAM	With Additional Measures
WEM	With Existing Measures

Data availability

Data will be made available on request.

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