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Soft-linking a national computable general equilibrium model (ThreeME) with a detailed energy system model (IESA-Opt)

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ABSTRACT

Top-down CGE models are used to assess the economic impacts of climate change policies. However, these models do not represent the technologies and sources of greenhouse gas emissions as detailed as bottom-up energy system models. Linking a top-down CGE model with a bottom-up energy system model assures macro-economic consistency while accounting for a detailed representation of energy and emission flows. While there is ample literature regarding the linking process, the corresponding details and underlying assumptions are barely described in detail. The present paper describes a step-by-step soft-linking process and its underlying assumptions, using the Netherlands as a case study. This soft-linking process increases the Dutch energy demand levels in 2050 by 19.5% on average compared to assumed exogenous levels. Moreover, the GDP in 2050 reduces by 5.5% compared to the baseline economic scenario. Furthermore, we identified high energy prices as the primary cause of this GDP reduction in the soft-linking process.

1. Introduction

Providing an effective climate mitigation policy advice requires insights that take both top-down (TD) and bottom-up (BU) effects of such policies (and their interactions) into account. Such an approach has been used to present an in-depth analysis of global decarbonization scenarios in several studies, such as the climate change report of IPCC AR6 (Shukla et al., 2022), the global energy and climate outlook of JRC (Keramidas et al., 2021), and the world energy outlook of IEA (International Energy Agency, 2021).

Computable general equilibrium (CGE) models are used to assess top-down effects of climate polices. However, these models oversimplify the energy system and are unable to represent the technological characteristics of the greenhouse gas emission sources. For instance, in CGE models (CGEMs), household energy consumption and emitted emission are often directly related to the household income, whereas in reality, they highly depend on the energy carrier, technology choices, and insulation levels.

CGEMs often represent energy consumption through a simplified and abstract production function where substitution possibilities between energy and capital, as well as between individual energy sources, are modeled assuming a Constant Elasticity of Substitution (CES). Technology is often included in these macroeconomic models as a separate coefficient in the production function. Examples of these models are MERGE (Manne et al., 1995), CETA (Peck and Teisberg, 1992), DICE (Nordhaus, 1993), and RICE (Nordhaus, 2010). Some models represent technologies in higher detail by incorporating endogenous technological progress (e.g., DEMETER (Van Der Zwaan et al., 2002)). Some others reformulated the equilibrium problem as a mixed complementarity problem to represent technologies with higher details (Böhringer and Rutherford, 2009). Some integrated assessment models (e.g., FUND (Link et al., 2010)) account for energy consumption through economic

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and environmental parameters such as income, population, and temperature. However, current CGEMs represent far lower technological detail than state-of-the-art BU energy system models.

In contrast, BU energy system models (ESM) provide higher technological, temporal, and spatial details. They include many technological options (e.g., >1000) with the corresponding costs, emissions, and physical attributes (e.g., potentials and constraints). Additionally, ESMs can compute on hourly temporal resolution across several regions. However, since ESMs merely compute the partial equilibrium, they are highly dependent on the exogenous general equilibrium state of the system (e.g., energy demand drivers). Consequently, BU models are not capable of performing economy-wide analyses.

Hybrid models can combine the technological explicitness of BU models with the economic richness of TD models through model linking (Böhringer and Rutherford, 2008). Various efforts have been made on different energy-economy model linking methods after it was first demonstrated by Hoffman and Jorgenson in 1977 (Hoffman and Jorgenson, 1977). This allows for improving the analysis: (1) it assures the macroeconomic consistency of the system regarding the aggregate energy demand, inflation, and revenue of agents, (2) it accounts for the indirect effects of the energy transition on the rest of the economy by ensuring the general equilibrium.

Hybrid models are classified in several manners. Wene (Wene, 1996) classifies model linking as soft-linking (user controlled) versus hard-linking (computer controlled). Holz et al. (Holz et al., 2016) divide model linking into three subcategories: 1) soft-linking in which the processing and transfer of information is controlled by the user. 2) hard-linking in which all information processing and transfer is handled by a computer program. 3) integrated modeling in which a unified mathematical approach is used (e.g., applying mixed complementarity problems (Böhringer and Rutherford, 2009)). Böhringer and Rutherford (Böhringer and Rutherford, 2008) define three categories: 1) coupling of existing large-scale models (i.e., soft-linking), 2) having one main model complemented with a reduced form of the other, and 3) combining the formulation of the models as mixed complementarity problems. The present paper adopts the term “soft-linking” as defined by Fragkos and Fragkiadakis (Fragkos and Fragkiadakis, 2022), where large-scale independently developed TD and BU models are linked through specific variables and an iterative process to ensure convergence. Subsequently, the term “hard-linking” refers to the approach where the TD model (e.g., CGE) is extended to include detailed BU representation (of the energy system).

Each linking approach has its own advantages. Soft-linking requires minimum change to the models. Therefore, the high level of detail of both models can be maintained. However, soft-linking raises several issues, such as the consistency of both models (e.g., data calibration: physical versus monetary flows) and the risk of overlap (e.g., both models define endogenous emissions, energy consumption, and prices). Hard-linking eliminates the consistency problem of soft-linking. However, the level of detail of models is considerably lower than in the soft-linking approach. Since we aim to keep the high level of detail of both models, the present paper focuses on the soft-linking approach.

The gap between the TD and BU modeling approaches has already discussed three decades ago (Wilson and Swisher, 1993). Since then, several efforts have combined both approaches in climate mitigation analyses (Hourcade et al., 2006); however, they hardly describe the details and underlying assumptions regarding the linking process. Manne and Wene (Manne and Wene, 1992) demonstrate a generic soft-linking approach for the MARKAL and ETA-MACRO models. Wene (Wene, 1996) links the MESSAGE III and ETA-MACRO models by further elaborating connection points. Messner and Schrattenholzer (Messner and Schrattenholzer, 2000) automate the link between MESSAGE and MACRO models. Labriet et al. (Labriet et al., 2010) describe the linking algorithm and convergence criteria in soft-linking two global models, GEMINI-E3 and TIAM. Glynn et al. (Glynn et al., 2015) summarize several model linking efforts for different case studies at national levels. Fortes et al. (Fortes et al., 2013) link the TIMES-PT and GEM-E3 (Capros et al., 2013) models for the case study of Portugal. Bulavskaya and Reynès (Bulavskaya and Reynès, 2018) investigate the impact of the energy transition on job creation by soft-linking the ETM and ThreeME models. JRC soft-links POLES-JRC (Keramidas et al., 2023) and JRC-GEM-E3 (Garaffa et al., 2022); however, since the models have a global perspective, they offer lower detail level compared to national models.

The study by Krook-Riekkola et al. (Krook-Riekkola et al., 2017a) is one of a few that emphasize on soft-linking transparency by describing their linking process and the simulation procedure in detail. They soft-link the TIMES-Sweden (Krook-Riekkola et al., 2017b) and EMEC (Östblom and Berg, 2006) models and demonstrate the importance of soft-linking in assessing national energy and climate policies.

Due to the growing national policy-driven demand for analyzing socially optimal energy transition pathways (Kragt et al., 2013) and the lack of scientific literature on linking details, there is a need for a transparent national model linking process and its underlying assumptions. Moreover, the detail level of soft-linked models can be improved by using state-of-the-art TD and BU models. However, only a few studies provide transparency on their soft-linking approach.

After identifying several energy system modeling challenges, Fattahi et al. propose the IESA framework (Fattahi et al., 2020) to better analyze the transition towards a low-carbon energy system. This framework employs highly detailed models to assess net-zero greenhouse gas (GHG) emission scenarios with high shares of variable renewable energy sources (VRES). For this purpose, the highly detailed and open-source IESA-Opt energy system model is developed (Sánchez Diéguez et al., 2022), calibrated to the Netherlands (Sánchez Diéguez et al., 2021), and its capabilities are tested (Fattahi et al., 2021). Moreover, to address the impact of these scenarios on the economy, the IESA framework suggests soft-linking the core ESM (i.e., IESA-Opt) with a CGEM.

The present paper aims to provide a transparent soft-linking approach for a highly disaggregated ESM and CGEM at a national scale; and subsequently analyze and demonstrate the relevance of various linking parameters on results, such as energy demand drivers and GDP. In this regard, we choose the IESA-Opt and ThreeME models for their high level of detail in the energy system and economy, respectively. Then, firstly, we demonstrate the soft-linking process of IESA-Opt and ThreeME, its steps, and underlying assumptions. Secondly, we show the impact of soft-linking on model results, particularly energy demand drivers and GDP. Lastly, we quantify the relevance of each soft-linking feedback parameter on the modeling results.

2. Methodology

The different underlying methodology of CGEMs and ESMs results in specific advantages and disadvantages for each model. CGEMs describe the whole economy (i.e., general equilibrium) and emphasize the possibility of substituting different production factors in order to maximize the profits of economic agents (e.g., firms, households, and government). However, they considerably lack BU details as they simplify the substitution possibilities between energy and other factors (e.g., capital, labor, and material) using merely the CES production function. Instead, ESMs provide high BU details consisting of many technologies, related costs, physical constraints, potentials, and load profiles, all described in hourly temporal resolution across long-term time horizon and for several regions. However, a weakness of ESMs is that they do not account for general equilibrium effects.

Soft-linking aims to take advantage of both modeling methodologies: the whole economy equilibrium of CGEMs and high BU details of ESMs.

For the soft-linking, we choose ThreeME and IESA-Opt due to their high granularity and state-of-the-art capabilities. ThreeME follows a neoKeynesian formulation based on a highly disaggregated (65 sectors) economy description. Moreover, its recursive dynamic formulation allows for analyzing the short, mid, and long-term economic shocks as opposed to other CGEMs (e.g., EMEC (Östblom and Berg, 2006)) that only calculate the initial and last periods. IESA-Opt is a highly detailed energy system model (Sánchez Diéguez et al., 2022) with >860 technologies and the corresponding cost and technical data. As opposed to other ESMs (such as TIMES), IESA-Opt features an hourly temporal resolution (in chronological order), which is crucial in modeling scenarios with high shares of VRES.

In the following, we describe further the methodology and level of details of both models. Then, we explain the soft-linking steps and underlying assumptions.

Moreover, in this section, we use specific terms that might have a different definition in each model. In order to increase the clarity, we provide the definition here:

- **Sector** (*s*) is defined in both the energy and macroeconomic models. It refers to a group of activities that share the same or related business activity, product, or service. In Section 2.3.2, we modify the sectoral definition of the macroeconomic model to be consistent with the energy model. Each sector is composed of several energy activities.
- **Activity** (***a***) (or activity demand driver) is defined in the energy model. It refers to the energy demand driver, which is an exogenous input to the energy system model. For instance, the steel production industry is considered an activity, which is part of the Basic Metal sector.
- **Commodity** (***c***) is defined in the macroeconomic model. It refers to a basic good that can be interchangeable with other goods in the macroeconomic model. Each commodity can be produced by one or several sectors or be imported. Examples: basic metal, paper, electricity, and oil.
- **Energy carrier** (***e***) is defined in both the energy system and macroeconomic models. It refers to different substances or commodities that are used to carry the energy across the supply-demand chain.

2.1. A brief introduction to the ThreeME model

Reynès et al. describe the ThreeME model, including all underlying formulations (Reynès et al., 2021). In short, this CGEM is specifically developed to analyze the impacts of the energy transition on the economy. ThreeME is an open-source country model specially designed to evaluate the medium- and long-term impact of environmental and energy policies at the macroeconomic and sector levels. To do so, ThreeME combines two essential features. Firstly, it has the main characteristics of neoKeynesian models by assuming a slow adjustment of effective quantities and prices to their notional level, the Taylor rule, and the Phillips curve. Notional level refers to the optimal values that maximize the utility function of each agent (i.e., sectors, household, and government). The Taylor rule is an equation relating the interest rate value to inflation and economic growth levels. The Phillips curve refers to the economic relationship between the rate of unemployment and the rate of change in money wages. Therefore, compared to standard multi-sector CGEMs, ThreeME has the advantage of allowing for under-optimum equilibria, such as the presence of involuntary unemployment. Secondly, ThreeME combines the top-down CGE approach with bottom-up energy models by including several electricity generation technologies.

Fig. 1 demonstrates the methodological framework of ThreeME. This model maximizes the utility of each agent in period t subject to several constraints, such as market clearing (e.g., demand is equal to supply). The model is recursive dynamic (i.e., myopic), which means it first optimizes period t and then uses the endogenous results (e.g., prices, wages, and production levels) for optimizing the next period (i.e., $t+1$). After the model optimizes the last period (determined by the user), it provides the projection of the endogenous parameters, such as prices, household income, GDP, and employment rate, over the whole horizon. Moreover, ThreeME requires several exogenous parameters: the social accounting matrix (SAM) of the base year, population growth forecast, economic growth forecast, and substitution elasticities. SAM is a comprehensive and economy-wide database recording data about all transactions between economic agents in a specific economy for a specific period (Ferrari et al., 2023). The population and economic growth forecasts determine labor availability and productivity projection. Elasticities define the substitution proportion of production factors in production functions.

In a CES function, the substitution between production factors can either follow the linear, fixed-proportion (i.e., Leontief) or Cobb-Douglas production functions. The linear production function represents a production process in which the inputs are perfect substitutes (e.g., labor can be substituted completely with capital). The fixed-proportion production function reflects a production process in which the inputs are required in fixed proportions. In the Cobb-Douglas production function, the inputs can be substituted, if not perfectly. ThreeME assumes a nested CES function (Reynès, 2019) to describe the substitution between production factors (Fig. 2). This CES production function requires four inputs, KLEM, capital (K), labor (L), energy (E), and material (M). The production factors (KLEM) can be substituted with each other. The Elasticity of Substitution (ES) parameters determines the substitution level between each input. Each pair (i.e., K-E, KE-L, KEL-M) has its own ES, which is explained further in the description of the model (Reynès et al., 2021).

An essential characteristic of a standard neoKeynesian macroeconomic AS-AD (aggregated supply and demand) model is that demand determines supply. The demand comprises (intermediate and final) consumption, investment and export whereas the supply comes from imports and domestic production (see Fig. 3). As feedback with eventually some lags, supply affects demand through several mechanisms. The level of production determines the quantity of inputs used by the firms and thus the quantity of their intermediate consumption and investment which are two components of the demand. It determines the level of employment as well and consequently the household final consumption. Another effect of employment on demand goes through the wage setting via the unemployment rate which is also determined by the active population. The active population is mainly determined by

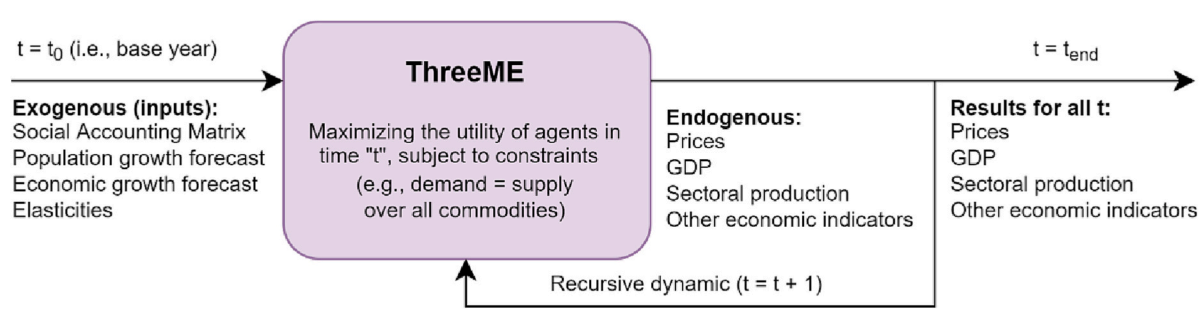

Fig. 1. The basic representation of ThreeME and the corresponding inputs and outputs.

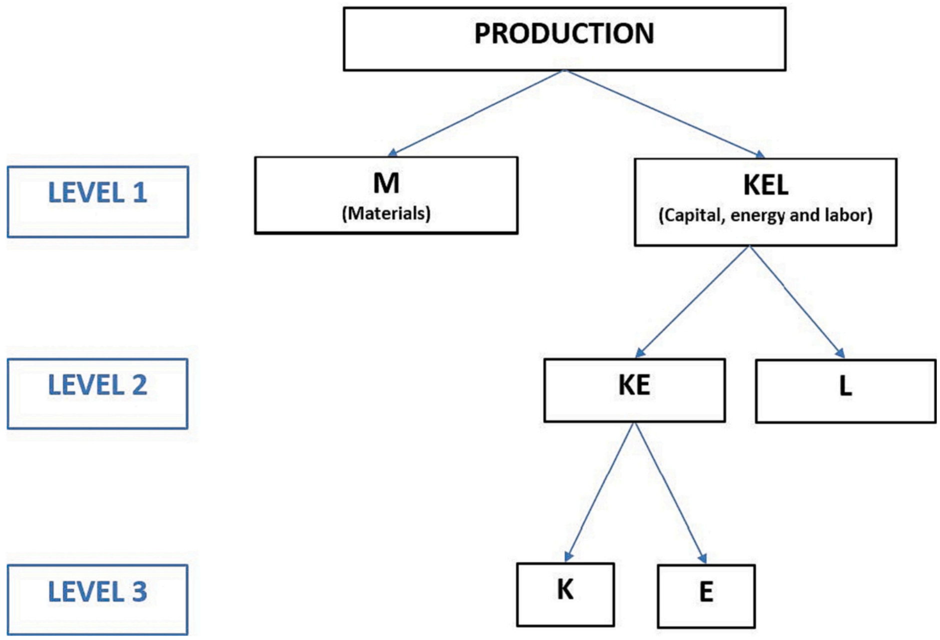

Fig. 2. Nested CES production function in ThreeME.

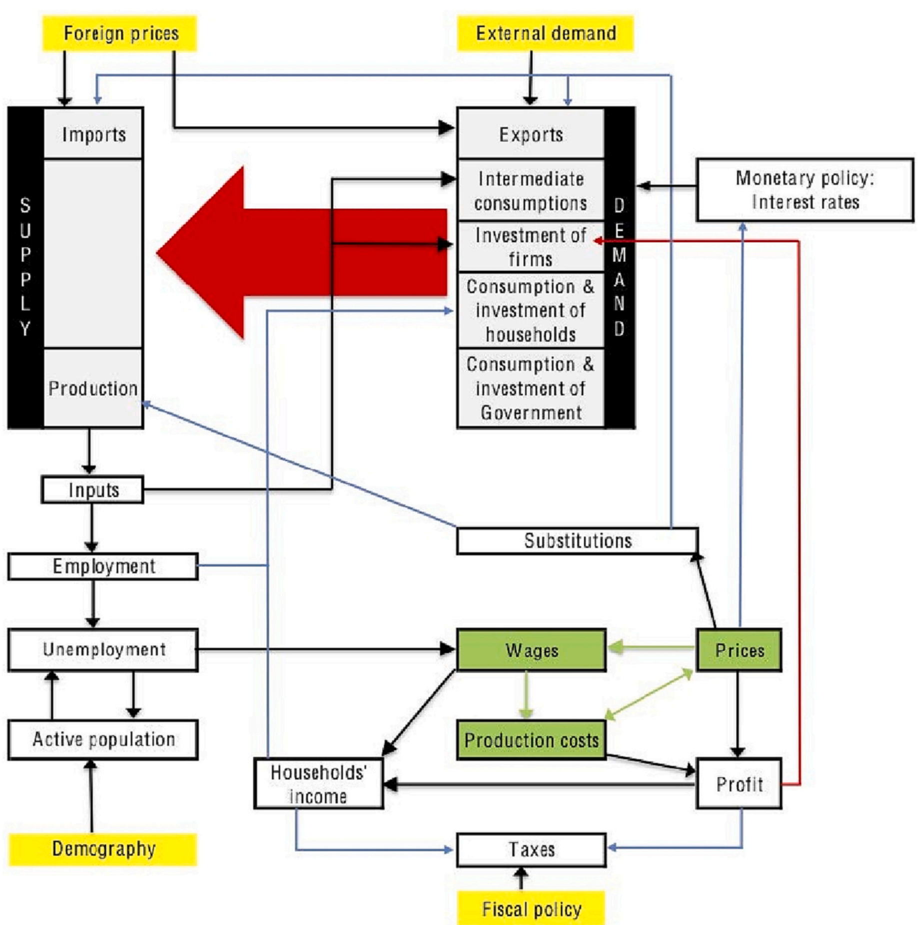

Fig. 3. Schematic of the ThreeME model.

exogenous factors such as demography but also by endogenous factors: because of discouraged worker effects, the unemployment rate may affect the labor participation rate and thus the active population.

2.2. A brief introduction to the IESA-Opt model

IESA-Opt is a detailed open-source optimization ESM at the national level (Sánchez Diéguez et al., 2022). It optimizes energy system investments over the horizon from 2020 to 2060 in 5-year time steps while simultaneously accounting for hourly and daily operational constraints (Sánchez Diéguez et al., 2021) (see Fig. 4). The objective function of the model minimizes the net present value of energy system costs to achieve total energy needs under certain techno-economic and policy constraints (e.g., a specific GHG reduction target in a particular year) (Fattahi et al., 2021).

The IESA-Opt model includes a complete sectoral representation of the energy system technologies and infrastructure that account for all greenhouse gas emissions considered in the targets. In addition, it takes into consideration a detailed description of the cross-sectoral flexibility, namely, flexible heat and power cogeneration, demand shedding from power-to-X and electrified industrial processes, short- and long-term storage of diverse energy carriers, smart charging and vehicle-to-grid for electric vehicles, and passive storage of ambiance heat for the built environment. Overall, the model includes >860 technologies, with the corresponding capital, variable, and fixed operational cost projections, operational constraints (e.g., availability profile and ramping rate), flexibility constraints (e.g., CHP parameters, demand shedding capacity, pumping loss, demand shifting range), and minimum and maximum deployment potential. Moreover, the energy infrastructure is modeled in nine networks: three different voltage levels of electricity, two different pressures of natural gas, two different pressures of hydrogen, one carbon capture, utilization, and storage (CCUS), and one heat network. While the electricity and heat networks are balanced hourly, the gaseous networks are balanced daily due to their relatively low intraday variation.

Furthermore, the IESA-Opt model reflects the emission constraints in the EU Emissions Trading System (ETS), the non-ETS sectors, and the international navigation and aviation sectors (Martínez-Gordón et al., 2022). Since ETS sector emissions are traded in the EU ETS market, we assume an exogenous ETS emission price projection as a scenario parameter. Because the national emission reduction policy targets both ETS and non-ETS sectors, we set the aggregate national emission constraint on both sectors. If the constraint is binding, the model generates an aggregated national emission shadow price, equal to the marginal increase in the system cost if the aggregated emission constraint gets one unit tighter, e.g., by 1 t of CO_2.

The model simultaneously solves multi-year planning of investments, retrofitting, and economical decommissioning with intra-year operational, flexible, and dispatch decisions at hourly temporal resolution. In the present study, the model is applied to the case study of the Netherlands under the current climate policy (which is explained in Section 3.1) and conservative projections for the economy and availability of resources.

2.3. Soft-linking the IESA-Opt and ThreeME models

In this section, we describe the soft-linking procedure in three steps. First, we identify the connection points between two models, i.e., which parameters should be linked between two models. Then, we modify the ThreeME model by aligning its sectoral definitions with IESA-Opt definitions and demonstrating the challenges regarding specific connection points of IESA-Opt and ThreeME. Finally, we demonstrate the soft-linking steps and underlying assumptions on feedback parameters between the two models.

2.3.1. Identifying connection points

Connection points refer to the shared parameters between two models that can get linked. To identify these points, we review each model's input and output parameters. Fig. 1 demonstrates the exogenous inputs of ThreeME as SAM, population and economic growth forecast, and elasticities. Subsequently, ThreeME can provide outputs such as the projection of prices, sectoral production, GDP, and other derived economic indicators (e.g., trade and employment rate). Moreover, the exogenous input of IESA-Opt is described in Fig. 4 as the demand drivers for energy consumption (e.g., number of houses, km of transport, tons of steel, and other sectorial activities), technological data, (i.e., costs, potentials, and energy balance), resource potentials and prices, demand and VRES profiles, electricity trade potential, and energy policy landscape. Consequently, IESA-Opt can provide the technological mix, energy mix, energy prices, cross-border energy trade, and other derived energy system parameters.

Linking the outputs and inputs of two models directly can be challenging as the outputs of ThreeME do not exactly match the inputs of IESA-Opt (and vice versa). Moreover, the endogenous parameters of ThreeME are frequently described in monetary units, while IESA-Opt

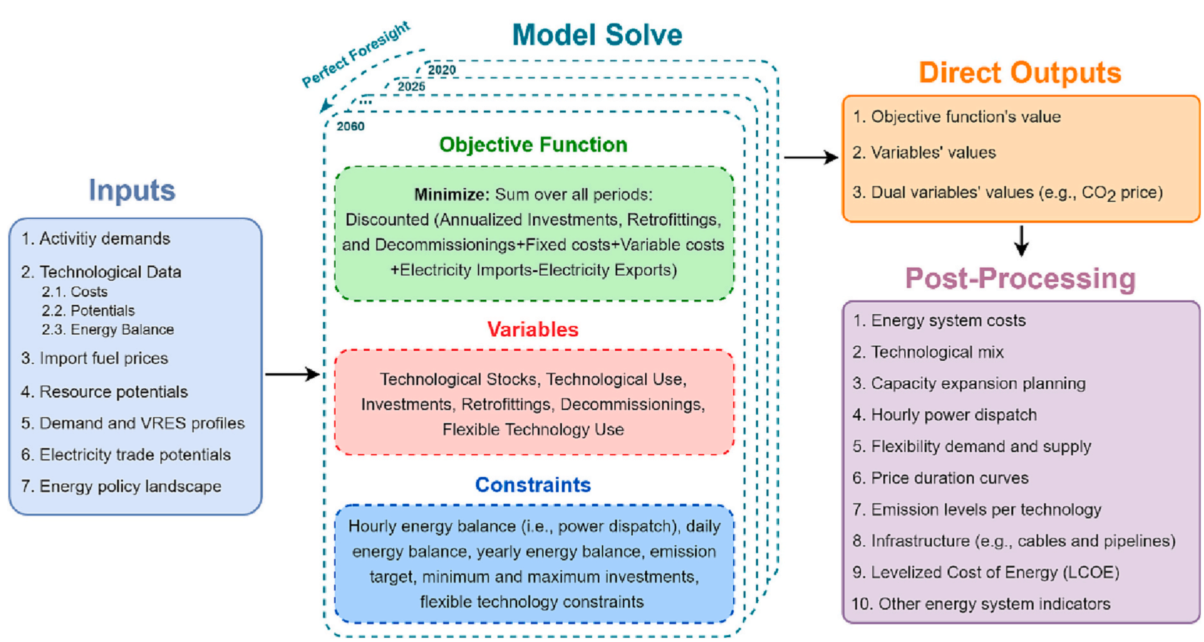

Fig. 4. The methodological framework of the IESA-Opt model.
Source: (Fattahi et al., 2022).

uses both physical and monetary units. Therefore, we need 'translation' models to convert the parameters from one model to the other.

Moreover, all the converted parameters are defined over the period 2020 to 2050. IESA-Opt provides a perfect foresight cost optimized solution over the period 2020 to 2050 with 5-years increments. In contrast, ThreeME myopically simulates the economic general equilibrium with yearly increments from the base year (e.g., 2020) to 2050. Therefore, the exchanged parameters are inherently defined from 2020 to 2050. For instance, by exchanging imported gas prices between two models, we refer to the evolution of the yearly gas price from 2020 until 2050. Since the IESA-Opt model operates in 5-year intervals, we use linear interpolation to estimate the yearly value of parameters.

The proposed method and connection points for soft-linking ThreeME and IESA-Opt are demonstrated in Fig. 5. First, we modify the sectoral aggregation level of ThreeME to match IESA-Opt (described further in Section 2.3.2), since both models have different levels of detail and aggregation. For instance, ThreeME describes more than thirty different service sectors, while IESA-Opt assumes merely four technologies to satisfy the aggregated energy demand of the service sector. Then, a demand conversion model links the exogenous energy demand driver parameter of IESA-Opt to the endogenous sectoral production parameter of ThreeME (explained further in Section 2.3.3). Linking ThreeME to IESA-Opt parameters is more challenging as both models endogenously calculate the energy related parameters. Therefore, we need to modify ThreeME by making the energy related parameters exogenous (i.e., energy and capital productivity, energy mix, energy prices, and cross-border energy trade). Afterwards, an energy mix conversion model links the endogenous energy related parameters of IESA-Opt (i.e., technological mix, energy mix, energy prices, and cross-border energy trade) to corresponding parameters of ThreeME (explained further in Section 2.3.4). Furthermore, the conversion models should take care of the unit conversion as some of the exchanged parameters have different units.

The exchange of parameters can continue until their values reach the convergence criteria (described in Section 2.4). In the case of convergence, the outcome of both models consistently describes both the energy system and economy.

The activity demand projections used in energy models generally come from energy outlooks or statistical projections (e.g., Dutch energy outlook (Overveld et al., 2021)). However, the conversion procedure of economic assumptions to energy activities is often not transparent (the gray box in Fig. 5). By soft-linking we can improve the consistency of the energy and economic scenarios by aligning the shared input parameters of both models.

2.3.2. Modifying ThreeME to IESA-Opt sectoral definition

Often, CGEMs and ESMs represent different definitions of sectors. A CGEM is typically framed around economic sectors. It is calibrated on a Supply Use Table (SUT) as this contains the economic transactions between agents, including firms (i.e., sectors), government, and household. The ThreeME model is calibrated using Eurostat's NACE system of economic activity classifications with 65 economic sectors. Moreover, the energy sector is further disaggregated into 17 energy sectors using the energy balance data. NACE is the acronym[2] used to designate the various statistical classifications of economic activities developed since 1970 in the European Union. NACE provides the framework for collecting and presenting an extensive range of statistical data according to economic activity in the fields of economic statistics (e.g., production, employment, national accounts) and in other statistical domains (Eurostat, 2008).

Instead, an ESM is usually framed around energy supply and demand sources, and it is calibrated on energy balance statistics. For example, the IESA-Opt model divides the national energy use into five main sectors: built environment (i.e., residential and services), agriculture, industry, transport, and energy conversion sectors. The Dutch database of this model is calibrated using the Dutch 2020 CBS (Central Bureau of Statistics) energy balance reports.

We start the soft-linking procedure by aligning the sectoral definition of two models. In this regard, we aggregate the sectoral definition of ThreeME to match with IESA-Opt. We group the 65 macroeconomic activity sectors into 32 sectors, as shown in Table 1. The left column demonstrates IESA-Opt sectors, while the right column lists modified ThreeME sectors based on the NACE standard.

We were able to connect agriculture, industry, and transport to one another by either directly assigning NACE codes to IESA-Opt sectors or by grouping multiple NACE codes under one sector. For energy conversion, however, we had to use the additional 17 energy sectors in ThreeME, which do not have NACE codes but can still be associated with a NACE sector (e.g. Manufactured gas by C19 relates to C19 - Manufacture of coke and refined petroleum products). Furthermore, the residential and commercial sectors are not compatible as their definitions differ greatly between the two models. Additionally, as ThreeME offers more detailed descriptions of service sectors that are not applicable to IESA-Opt (e.g. J61 - Telecommunications), most of these service sectors have been grouped as the rest of the economy sector.

2.3.3. Demand conversion (from ThreeME to IESA-Opt)

Soft-linking practices often skip explaining their demand conversion procedure in detail. However, studies such as Krook-Riekkola et al. (Krook-Riekkola et al., 2017a) demonstrate their sectoral demand conversion parameters and corresponding units. Inspired by their study, we demonstrate our method to convert ThreeME variables into IESA-Opt energy demand drivers.

The sectoral demand conversion parameters for soft-linking IESA-Opt and ThreeME are demonstrated in Table 2. For most sectors, since we already aligned both models' sectoral definitions, we can directly connect the required energy demand drivers of IESA-Opt to the sectoral production growth out of ThreeME:

$$D_{a,t^*,n+1} = D_{a,t_b} \cdot \left(\prod_{t_b}^{t^*} \alpha_s . PrG_{s,t,n} \right)$$

where $D_{a,\ t^*,\ n+1}$ is the demand of activity a, in time t^*, iteration $n+1$, exogenous input to IESA-Opt; $D_{a,\ t}$ is the demand of activity a, in the base year t_b, in IESA-Opt calibration; α_s is the demand conversion factor of sector s; and $PrG_{s,\ t,\ n}$ is the gross production growth of sector s, in time t, iteration n, and endogenous output from ThreeME. The demand conversion factor (β_s) determines the correlation between physical production growth (used in the energy model) and the monetary sectoral growth (used in the economy model). The value of this parameter, which can be obtained by correlating historic data, hardly deviates from one in the case of Sweden (Krook-Riekkola et al., 2017a). Therefore, in this study we assume this factor to be equal to one to increase the clarity of the linking procedure.

Not all activity demand drivers of IESA-Opt can be linked to ThreeME through the mentioned formula, namely, the number of houses and the amount of vehicle kilometers of passenger cars and motorcycles. For instance, the number of houses (exogenous input to IESA-Opt) depends more on the demography and housing policies of the country rather than economic growth or governmental income (output of ThreeME).

The residential heat demand is determined endogenously in IESA-Opt. This model requires the number of houses and heat degree days as inputs to optimize the cost-effective insulation level of houses and corresponding heat supply technologies. For the number of houses, we assume the projection forecasts of CBS (Netherlands Statistics (CBS), 2023), which is in line with the assumed demography projections of ThreeME. Similarly, the services heat demand is determined

[2] NACE is derived from the French title "Nomenclature générale des Activités économiques dans les Communautés Européennes" (Statistical classification of economic activities in the European Communities).

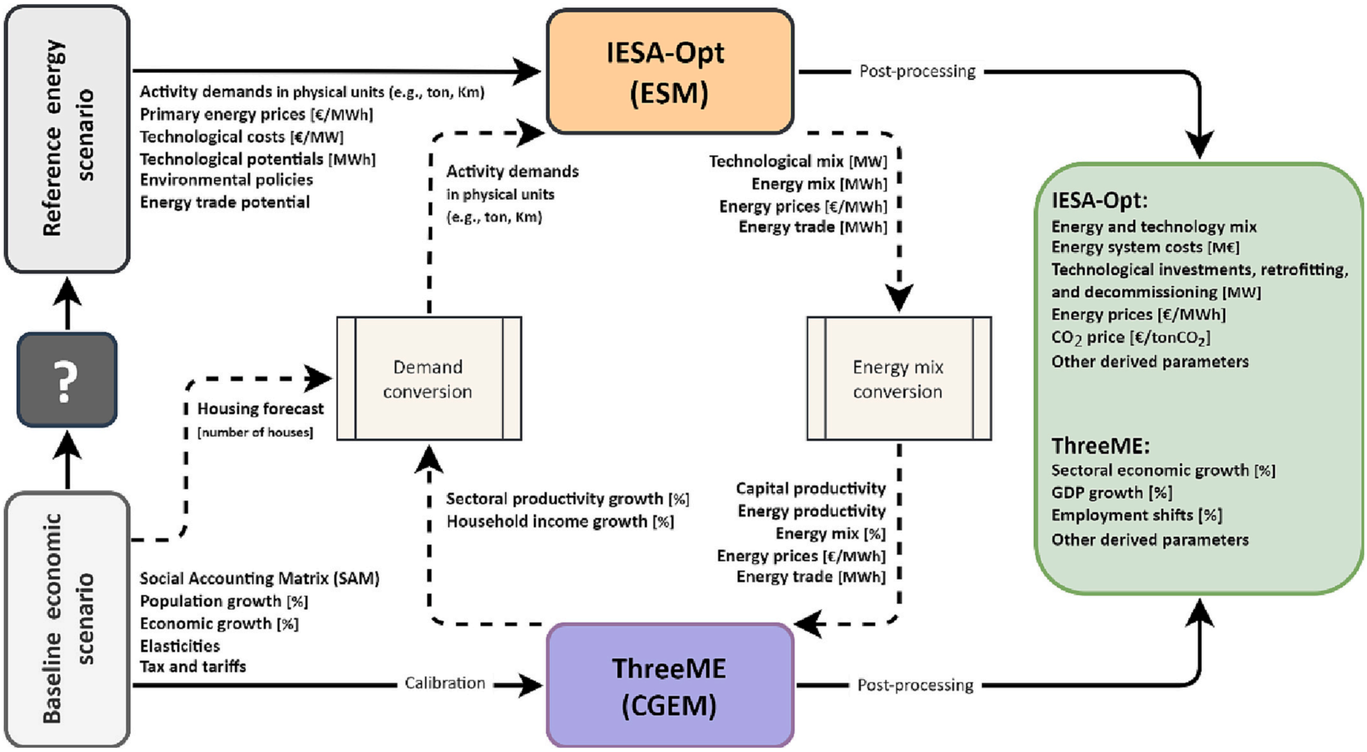

Fig. 5. Schematic of soft-linking ThreeME and IESA-Opt.
Soft-linking aims to remove the black box between economic and energy scenarios.
Dashed lines refer to the required data exchange for the soft-linking process.
Solid lines refer to the required data exchange for stand-alone model runs.

endogenously. IESA-Opt requires the amount of square meter service space and heat degree days as inputs to calculate the cost-effective insulation level and heat supply technologies. However, unlike the residential sector, we can assume that the office space demand follows the economic growth of the services sector.

Moreover, IESA-Opt requires the vehicle km demand as an exogenous input. Estimating the transport demand projections is rather a complex task that depends on several factors such as household income, fuel price, population densities, public transport availability, and roads congestion levels (Breugem et al., 2002). However, transport projection can be estimated by the variations in income and fuel price (Ajanovic et al., 2012):

$$TD_{t^*,n+1} = TD_{t_b}\cdot\left(\prod_{t_b}^{t^*} HIG_{t,n}\right)^{\varepsilon_{HI}}\cdot\left(\prod_{t_b}^{t^*} FPG_{t,n}\right)^{\varepsilon_{FP}}$$

where $TD_{t^*,n}$ is the transport demand in time t^*, iteration $n+1$, and exogenous input to IESA-Opt; $HIG_{t,n}$ is the households' income growth in time t, iteration n, and endogenous output of ThreeME; ε_{HI} is the elasticity of transport demand to households' income; $FPG_{t,n}$ is the fuel price growth in time t, iteration n, and endogenous output of ThreeME; and ε_{FP} is the elasticity of transport demand to fuel price. The choices of long-term ε_{HI} and ε_{FP} elasticities usually come from historic econometrics analyses that can vary significantly: $0.65 \le \varepsilon_{HI} \le 1.25$ and $-0.55 \le \varepsilon_{FP} \le -0.05$ (Litman, 2021). We choose the subjective values of $\varepsilon_{HI} = 1.2$ and $\varepsilon_{FP} = -0.3$ for the elasticities. Moreover, since passenger car fuel mix changes to electricity over time, we use a weighted average fuel cost based on the endogenous gasoline and electricity prices of IESA-Opt. For the aviation, we use the endogenous kerosene price calculated by IESA-Opt.

2.3.4. *Energy conversion (from IESA-Opt to ThreeME)*

This section describes the underlying assumptions of reflecting IESA-Opt outputs on the ThreeME model. Here we link four parameters, namely, technological mix, energy efficiency, energy mix, and energy prices. Moreover, in each subsection, we explain the required modification in ThreeME to take the mentioned energy-related parameters as exogenous parameters.

2.3.4.1. *Technological mix.*

The optimal technological mix (from a cost perspective) to satisfy a specific energy activity might differ significantly under different scenarios. For instance, to satisfy a particular demand for electricity, the energy model optimally invests in, e.g., coal power plants or wind turbines. Since the cost of these technological options can vary greatly, it can greatly affect the monetary flow of the economy. Under tight environmental policies, some monetary flows (e.g., coal power plants) might disappear, and new substitutes (e.g., wind turbines) appear. This variation can affect the rest of the economy, such as employment and trade levels. We can trace this effect on different parts of the economy (e.g., sectoral employment and trade levels) by converting the technological mix into an appropriate input for the CGEM.

The variation in the technological mix required to satisfy a specific sectoral activity affects the capital productivity of the corresponding sector. An increase in the technological cost of a specific sector can be interpreted as a decrease in the capital (K) productivity in the corresponding sector. Therefore, compared to the base year, variations in technological costs in IESA-Opt translate into variations in sectoral capital productivity in the ThreeME model:

$$Prod^K_{s,t,n+1} = Prod^K_{s,t_b}\cdot\beta_s\cdot\left(\frac{WAC_{a,t_b}}{WAC_{a,t,n}}\right)$$

where $Prod^K_{s,\,t,\,n+1}$ is the capital (K) productivity of sector s, in time t, iteration $n+1$, and exogenous input to ThreeME; $Prod_{s,\,t_b}{}^K$ is the capital productivity of sector s, in the base year t_b, and exogenous input to ThreeME; β_s is the ratio of energy capital costs over sectoral capital costs

Table 1
Modified ThreeME sectors based on IESA-Opt sectoral definition row colors refer to the IESA-Opt energy sector definition: agriculture, industry, transport, energy conversion sectors.

IESA-Opt sectors	Modified ThreeME sectors
Agriculture	A01 - Crop and animal production, hunting and related service activities; A02 - Forestry and logging; A03 - Fishing and aquaculture
Basic metal	C24 - Manufacture of basic metals
Chemical products	C20 - Manufacture of chemicals and chemical products
Rubber and plastic	C22 - Manufacture of rubber and plastic products
Non-metallic minerals	C23 - Manufacture of other non-metallic mineral products
Paper and board	C17 - Manufacture of paper and paper products
Food products	C10-12 - Manufacture of food products; beverages and tobacco products
Land transport	H49 - Land transport and transport via pipelines; H52 - Warehousing and support activities for transportation; H53 - Postal and courier activities
Navigation	H50 - Water transport
Aviation	H51 - Air transport
Coal production	Solid fossil fuels
Natural gas production	Manufactured gas by C19 (refineries byproduct); Manufactured gas by C24 (basic metal byproduct); extracted natural gas
Natural gas import	Imported natural gas
Biogas production	Manufactured gas by sector D
Crude oil production	Crude oil
Petroleum refining for energy use	C19 - Manufacture of coke and refined petroleum products; Oil and petroleum products (energy)
Petroleum refining for chemical use	Oil and petroleum products (chemical)
Biomass production	Biomass by A02; Biomass by C16 (wood byproduct); Biomass by C20 (chemicals byproduct);
Biofuel production	Manufactured biofuels
Electricity by solid fossil fuels	Electricity production by solid fossil fuels
Electricity by gas	Electricity production by gas
Electricity by petroleum	Electricity production by petroleum
Electricity by hydro	Electricity production by hydro
Electricity by tide, wave, and ocean	Electricity production by tide, wave, and ocean
Electricity by wind	Electricity production by wind
Electricity by solar	Electricity production by solar
Electricity by geothermal	Electricity production by geothermal
Electricity by biomass and biofuels	Electricity production by biomass and biofuels
Electricity by waste	Electricity production by waste
Electricity by nuclear	Electricity production by nuclear
-	Rest of the economic sectors

of sector s, and exogenous from historic data; $WAC_{a,\ t,\ n}$ is the weighted average cost of activity a, in time t, iteration n, and endogenous output of IESA-Opt; and $WAC_{a,\ t_b}$ is the weighted average cost of activity a, in the base year t_b, in IESA-Opt calibration. In ThreeME, $Prod^{K}_{s,\ t,\ n}$ is an exogenous value, which usually is assumed equal to its value in the base year (i.e., $Prod_{s,\ t_b}{}^{K}$). However, we modify ThreeME to take this parameter as an exogenous value with the mentioned formulation. Moreover, in this study we assume $\beta_s = 1$; thus, any variation in energy capital costs implies changes in the sectoral capital costs.

2.3.4.2. Energy efficiency. The change in the technological mix and energy efficiency from IESA-Opt affects the sectoral energy productivity factor in ThreeME. From the energy model perspective, energy efficiency occurs in two ways: (1) exogenous increased efficiency of single technology due to technological development, and (2) endogenous substitution of technologies resulting in lower energy demand to satisfy the same activity. Similarly, in ThreeME, (1) the exogenous energy productivity factors determine the production levels based on consumed energy, and (2) the exogenous substitution elasticities together with endogenous prices determine the substitutions in the energy mix. In this section, we suggest a link for the first measure of efficiency, while in the next sub-section (i.e., energy mix) we connect the second energy efficiency measure.

With an increase in energy efficiency, the energy productivity should increase, meaning that less energy is required to reach the same amount of production. The variations in energy efficiency can translate into energy productivity by:

$$Prod^{E}_{s,t,n+1} = Prod^{E}_{s,t_b} \cdot \left(\frac{EU_{a,t_b}}{AL_{a,t_b}} \bigg/ \frac{EU_{a,t,n}}{AL_{a,t,n}} \right)$$

where $Prod^{E}_{s,\ t,\ n+1}$ is the energy (E) productivity of sector s, in time t, iteration $n + 1$, and exogenous input to ThreeME; $Prod_{s,\ t_b}{}^{E}$ is the energy productivity of sector s, in the base year t_b, and exogenous input of ThreeME; $EU_{a,\ t,\ n}$ is the energy use of activity a, in time t, iteration n, and endogenous output of IESA-Opt; $AL_{a,\ t,\ n}$ is the activity level of activity a, in time t, iteration n, and exogenous input to IESA-Opt (which is based on an endogenous output of ThreeME in iteration n); $EU_{a,\ t_b}$ is the energy use of activity a, in the base year t, and endogenous output of IESA-Opt calibration; and $AL_{a,\ t_b}$ is the activity level of activity a, in the base year t, and exogenous input to IESA-Opt. Similar to $Prod^{K}_{s,\ t,\ n+1}$ parameter, in ThreeME, $Prod^{E}_{s,\ t,\ n+1}$ is an exogenous value, which is usually equal to $Prod_{s,\ t_b}{}^{E}$. However, we modify ThreeME to take this parameter as an exogenous value with the mentioned formulation.

2.3.4.3. Energy mix. ThreeME assumes exogenous elasticities of import, export, and energy use to endogenously determine the share of import, export, and energy mix based on the price difference. However, these shares can be replaced by the energy trade and energy mix outcomes

Table 2
Sectoral demand conversion between CGEM and ESM row colors refer to the IESA-Opt energy sector definition: the built environment, agriculture, industry, transport, energy conversion sectors.

ThreeME parameters and variables (Outputs)	IESA-Opt demand parameters (Inputs)
Exogenous CBS housing forecast	Number of houses [Khouses]
	Electricity demand – residential [PJ]
Rest of the economy production growth	Square meter of service space [Mm2]
	Electricity demand – services [PJ]
Agriculture production growth	Electricity demand – Agriculture [PJ]
	Heat demand – Agriculture [PJ]
	Machinery demand – Agriculture [PJ]
Basic metal production growth	Steel production [Mton]
	Aluminum production [Mton]
	Zinc production [Mton]
Chemical production growth	Nitric Acid production [Mton]
	Urea production [Mton]
	Chlorine production [Mton]
	Other Ammonia-based fertilizers [Mton]
	Other ETS chemicals [Idx_2020]
Rubber and plastic production growth	Ethylene production [Mton]
	Propylene production [Mton]
	Other HVC products [Mton]
Non-metallic production growth	Glass production [Mton]
	Ceramics production [Mton]
Paper and board production growth	Paper and board production [Mton]
Food production growth	Food production [Idx_2020]
Refined products exports growth	Naphtha [PJ]
	Road fuel [PJ]
	Kerosene [PJ]
	Fuel oil [PJ]
	Other oil products [PJ]
Other industry production growth	Other ETS industry [Idx_2020]
	Other non-ETS industry [Idx_2020]
Households' income growth, fuel price growth	Motorcycles [Gvkm]
	Passenger cars [Gvkm]
Land transport production growth	Light-duty vehicles [Gvkm]
	Heavy-duty vehicles [Gvkm]
	Buses [Mvkm]
	Rail [Mvkm]
Water transport production growth	Domestic navigation [Mvkm]
	International navigation [Mvkm]
Households' income growth, fuel price growth	Intra-EU aviation [Mvkm]
	Extra-EU aviation [Mvkm]
Production in energy commodities	Endogenous

from the IESA-Opt model. Therefore, we modify the energy production factor of ThreeME by assuming substitution elasticity of zero (i.e., the so-called Leontief production function). Thus, modified ThreeME takes energy shares exogenously:

$$\varphi_{e,c,s,t,n+1} = EU_{e,a,t,n} \Big/ \sum_{e} EU_{e,a,t,n}$$

where $\varphi_{e,\ c,\ s,\ t,\ n+1}$ is the share ($\sum_e \varphi_{e,\ c,\ s,\ t,\ n} = 1$) of energy carrier e in producing commodity c, in sector s, in time t, iteration n, in the ThreeME model; $EU_{e,\ a,\ t,\ n}$ is the energy use of activity a, from energy carrier e, in time t, iteration n, from IESA-Opt; and $\sum_e EU_{e,\ a,\ t,\ n}$ is the summation of all energy use of activity a, in time t, iteration n, from IESA-Opt.

2.3.4.4. Energy prices. Except for the price of imported energy carriers (that is exogenously equal for both models), other energy prices are endogenously determined in both models. However, IESA-Opt provides more accurate energy prices (i.e., shadow prices) as it includes rich details of the energy system's interactions and constraints. For example, the hourly shadow prices of electricity network are used to determine the average yearly price, which is then imposed into ThreeME.

Originally, ThreeME calculates the price mark-up based on the price elasticity of demand, which is an exogenous parameter. Since the prices in ThreeME are endogenous variables, we modify them to be equal to energy price values from IESA-Opt. Therefore, we alter the energy commodity price formula by removing the mark-up:

$$P_{e,t,n+1} = P_{GDP,t,n}.YAP_{e,t,n}$$

where $P_{e,\ t,\ n+1}$ is the energy price of energy carrier e, in time t, iteration $n+1$, and exogenous input to ThreeME; $P_{GDP,\ t,\ n}$ is the GDP price (i.e., inflation correction factor), in time t, iteration n, and endogenous output of ThreeME; and $YAP_{e,\ t,\ n}$ is the yearly average price of energy carrier e, in time t, iteration n, and endogenous output of IESA-Opt.

2.4. Execution

The applied steps of the soft-linking process are summarized in Fig. 6. Since the activity demands are the required inputs of IESA-Opt, we choose ThreeME as the starting point. First, the sectoral production output of ThreeME is converted into energy demand drivers through the demand conversion model (explained in Section 2.3.3). Then, we run IESA-Opt based on the acquired energy demand drivers. Next, the energy-related outputs of IESA-Opt are converted into required inputs of ThreeME through the energy conversion model (explained in Section 2.3.4). At this point, we increase the iteration index by one and repeat the iteration. Finally, the process stops when the energy demand drivers are converged according to the convergence criterion. Once the process is converged, we can report the outcomes of both models with the highest iteration index as the final results.

Depending on the linking level and iteration index, we define several stages: First, the stand-alone (SA) stage, which refers to the activity values obtained exogenously as described in the reference scenario Section 3.1. At this stage, there is no link between the two models. Second, the no-feedback (NF) stage is the one-way linking of ThreeME outputs into IESA-Opt. In this stage, the energy activity demands are reported at iteration 0 just before the red diamond in Fig. 6. Third, the feedback loop (FL) stage in which the soft-linked ThreeME and IESA-Opt exchange data in iterations (*i*) until reaching the convergence criterion. Table 3 summarizes the soft-linking stages.

Moreover, there is a need to determine convergence or stop criteria that determine when the iterations should stop. Some studies set predefined convergence criteria (e.g., the differences in energy consumption per energy carrier and calibrated sector are <10% (Fortes et al., 2013)), and some others set no convergence criteria and decide when to stop after analyzing the outcome of each iteration (Krook-Riekkola et al., 2017a). Since the only impact of ThreeME on IESA-Opt in this soft-linking process is through the variation in energy demand drivers, we set the convergence criterion as:

Table 3
The soft-linking stages and the corresponding execution steps.

Stages	n-value	Description
SA	NA	Exogenous input to the stand-alone IESA-Opt model
NF	0	ThreeME → Demand conversion
FL-1	1	ThreeME → Demand conversion → IESA-Opt → Energy conversion → ThreeME → Demand conversion
FL- *i*	*i*	Repeating the iterations *i* times

$$\left|\frac{D_{a,t^*,n} - D_{a,t^*,n-1}}{D_{a,t^*,n-1}}\right| \leq 1\% \forall s, t \; and \; n > 1$$

where the absolute variations in demand drivers for all sectors and times between two iterations are <1%.

3. Applying the soft-linking procedure

This section primarily has two goals: First, analyzing the impact of soft-linking on the modeling results, and second, quantifying the relevance of feedback parameters between two models. Therefore, the choice of the scenario parameters is of secondary importance. However, we summarize the main characteristics of this scenario.

3.1. Reference scenario

For the IESA-Opt model, except the number of houses that is obtained from CBS, the projected development of other activities and part of the resource costs are extracted from the Dutch national energy outlook (KEV) (Overveld et al., 2021) and JRC's POTEnCIA central scenario for the Netherlands (Mantzos et al., 2019), which is based on GDP growth rates presented in the 2018 aging report (European Commission Directorate-General for Economic and Financial Affairs, 2018). s scenario leans towards business-as-usual economic development, which

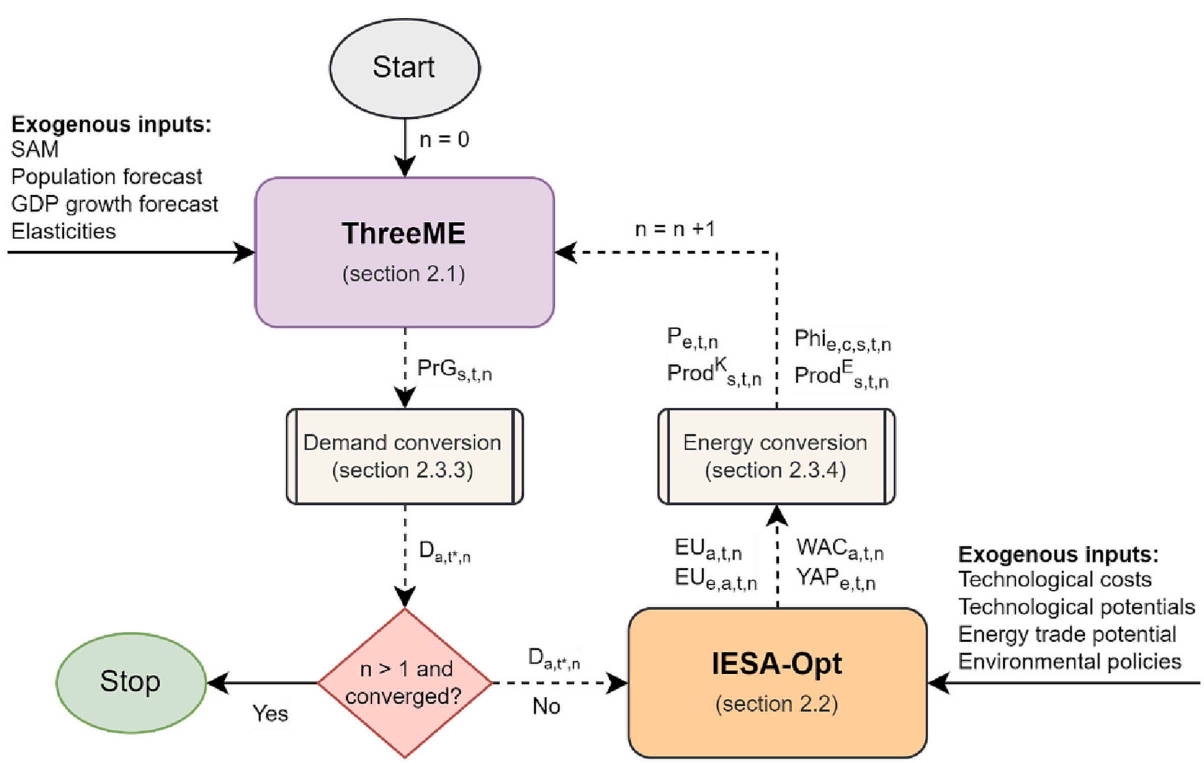

Fig. 6. The execution flowchart of the iterative soft-linking process. Dashed lines refer to the iterative soft-linking process.

would fall within the second shared socioeconomic pathway (SSP2) (Riahi et al., 2017). Moreover, the environmental policy landscape of the Netherlands follows the EU Green Deal (European Commission, 2019), where the Netherlands steps up its ambition to reduce its greenhouse gas (GHG) emissions by 55% compared to 1990 levels in 2030, and becomes GHG neutral in 2050.

For the ThreeME model, the SAM of the Netherlands in 2015 is obtained from the National Accounts datasets of Eurostat (Eurostat, 2015). Moreover, the population and GDP growth forecasts are obtained from the Dutch statistical agency (CBS).

Although both models use a separate source of GDP and population forecasts, the assumed values are not considerably different (see Table 4). IESA-Opt data sources assume a GDP growth of 1.45% (from 2020 to 2050), while ThreeME assumes a constant 1.5% growth.

3.2. Impact of soft-linking on the outcomes

3.2.1. Sectoral development

Fig. 7 demonstrates the activity demand levels of main Dutch industrial sectors in 2050 during different linking stages. The soft-linking approach increases the activity demand levels by 30.4% on average compared to the stand-alone IESA-Opt assumptions. The first increase in the NF stage is primarily due to the economic growth assumptions of ThreeME. Thus, it does not reflect any feedback from IESA-Opt. However, considering the first feedback from IESA-Opt (i.e., FL1), the activity demand levels reduce by 10.8% on average compared to the NF stage. The reason for this decrease is described further in Section 3.3. After FL1, the average reduction in activity demand levels is negligible (2.7% from FL1 to FL2 and 0.03% from FL2 to FL3). In total, compared to the SA stage (i.e., stand-alone IESA-Opt without linking), soft-linking increases the activity demand levels by 19.5% on average.

The presence of a significant gap demonstrates the discrepancy between exogenous sources and the ThreeME outcome, due to the varying assumptions made. Utilizing exogenous demand levels makes the results heavily reliant on a number of assumptions that are challenging to evaluate. Soft-linking enhances the transparency and traceability of demand side assumptions, guaranteeing a general economic equilibrium that is in line with the energy-climate policy.

The increase in activity demand levels varies across different sectors: from approximately 40% in basic metals to roughly 5% in food products. Due to the lack of information on the assumptions of exogenous sources, we can hardly trace the reasoning behind this variation.

In this case study, the soft-linking procedure meets the convergence criterion after three iterations. However, the activity demands of 2050 already reach significant convergence in the first iteration (i.e., FL1 stage). In a similar study, the soft-linking procedure reached significant convergence after the first iteration (Krook-Riekkola et al., 2017a). Moreover, other sectors behave similarly through the iterations except for the passenger car and aviation sectors. The reason is that these sectors follow a different energy demand conversion formulation dependent on household income and fuel prices.

The projection of activities in the last iteration (i.e., the FL3 step) does not grow linearly as assumed in the reference economic scenario (see the NF stage in Fig. 8). Compared to the assumed linear production growth in ThreeME, the soft-linked production growth hampers in 2030, mainly due to lower export levels that can be explained by higher energy costs. In the reference scenario, ThreeME assumes a constant 2% increase in prices (both domestic and international commodities) to account for the inflation. However, the energy prices of IESA-Opt (i.e., shadow prices) are calculated as the marginal cost of the technologies that satisfy the energy demand in each period. Therefore, enforcing ThreeME to use IESA-Opt energy prices causes considerable price disparity between energy-intensive products and the rest of the products.

Table 4
The assumed GDP growth and population forecasts of the reference scenario in both models.

		2020	2030	2040	2050
GDP growth [%]	IESA-Opt	1.4	1.1	1.5	1.8
	ThreeME	1.5	1.5	1.5	1.5
Population [million]	IESA-Opt	17.5	18.4	19.1	19.2
	ThreeME	17.4	18.5	19.0	19.3

For instance, for the steel production sector in 2030, IESA-Opt decommissions the current blast furnace technology and instead invests in the direct reduction from hydrogen technology. While blast furnace technology mainly requires coal, the latter primarily relies on hydrogen and electricity. Moreover, as the output of IESA-Opt, the price of electricity and hydrogen should increase considerably in 2030 to reach the 55% GHG emission reduction policy. As a result, the weighted average energy price for steel production increases by 270% from 2020 (coal-based) to 2030 (hydrogen and electricity-based). This price upsurge increases the price of steel commodity by 44% from 2020 to 2030. In contrast, in the same period, the international price of steel increases merely by 22% (i.e., 2% growth per year). Fig. 9 demonstrates that the steel price surges from 2030 to 2035, resulting in the lower competitiveness of domestic steel compared to the international market. Accordingly, ThreeME lowers the growth of exported steel between 2030 and 2035 (see Fig. 10), consequently decreasing the need for domestic steel production.

Not all sectors experience a production reduction in the energy transition. For example, Fig. 11 demonstrates the projections of passenger car and aviation sectors before and after soft-linking (i.e., in the NF and FL3 stages). As we assumed in Section 2.3.3, the passenger car and aviation transport demands are correlated positively with household income and negatively with fuel prices. Thus, both sectors grow steadily in the NF stage as part of the reference economic scenario. However, after soft-linking, the demand of each sector follows a different pathway.

The passenger car demand curve follows an s-curve that decreases in 2025 and increases considerably after 2035 compared to the NF line. The main driver for this behavior is the variation in household income (see Fig. 12) that follows an s-curve. Additionally, the passenger car fuel price (i.e., electricity) stays almost steady from 2030 to 2045. In 2050, the electricity price reduces by 9% compared to 2045, which further boosts the 2050 passenger car demand (see Fig. 11).

The aviation demand follows a similar pattern until 2035 but falls considerably until 2050. From 2035 onwards, household income continues to increase; however, as shown in Fig. 12, the kerosene price increases at a noticeably faster rate (e.g., 80% increase from 2040 to 2050) due to the stringent net-zero climate policy in 2050. Therefore, the projected aviation demand reduces by 11% from 2040 to 2050 (see Fig. 11).

3.2.2. The economy

Fig. 13 shows the variations in GDP during the different stages of the soft-linking. GDP is an aggregate measure of production equal to the sum of the gross added values of all resident institutional units engaged in production (plus any taxes and minus any subsidies) (Lequiller and Blades, 2014).

In the FL3 stage, considering the feedback of IESA-Opt (i.e., capital and energy productivity, energy mix, energy prices, and cross-border energy trade), the GDP decreases by an average of 5.5% compared to the NF stage (i.e., baseline economic scenario). Since the assumed GDP growth of both models are similar (see Section 3.1), the main part of this decrease is due to the considerable impact of the IESA-Opt feedback parameters in the first iteration. After the FL1 stage, the variation in the GDP trend is hardly affected by the number of iterations between the two models.

The decrease in economic activity is mainly driven by the decrease in exports (−12.3% in 2050, see Fig. 14), whereas the decreases in

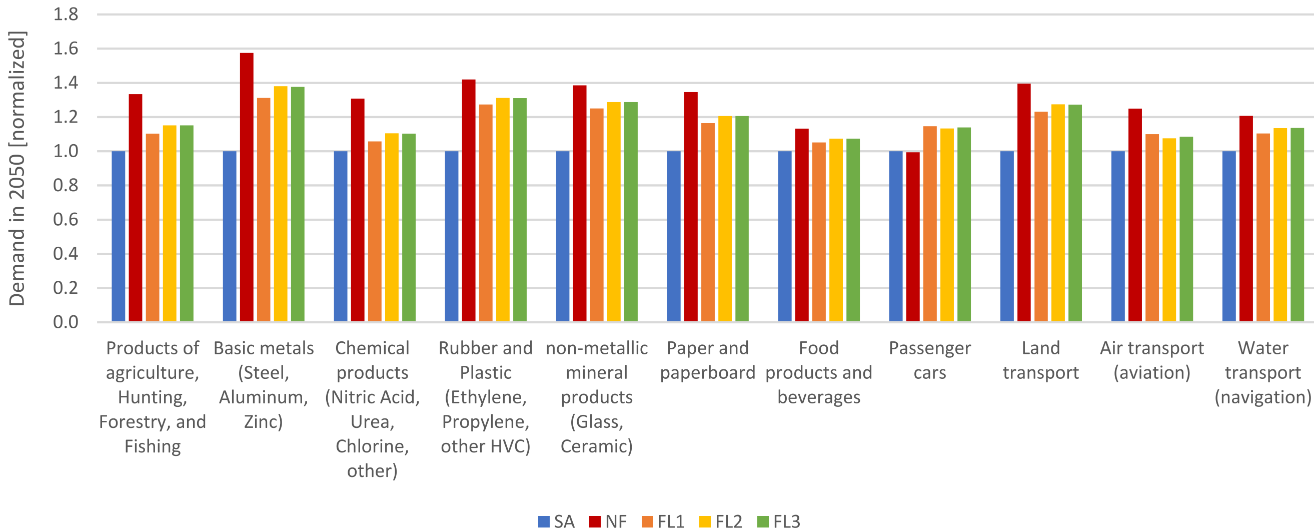

Fig. 7. Energy demand activities of IESA-Opt normalized to the SA stage. SA: Stand-Alone IESA-Opt, NF: No Feedback from IESA-Opt to ThreeME, FLi: Feedback Loop between two models (i.e., two-way soft-linking) at the iteration i.

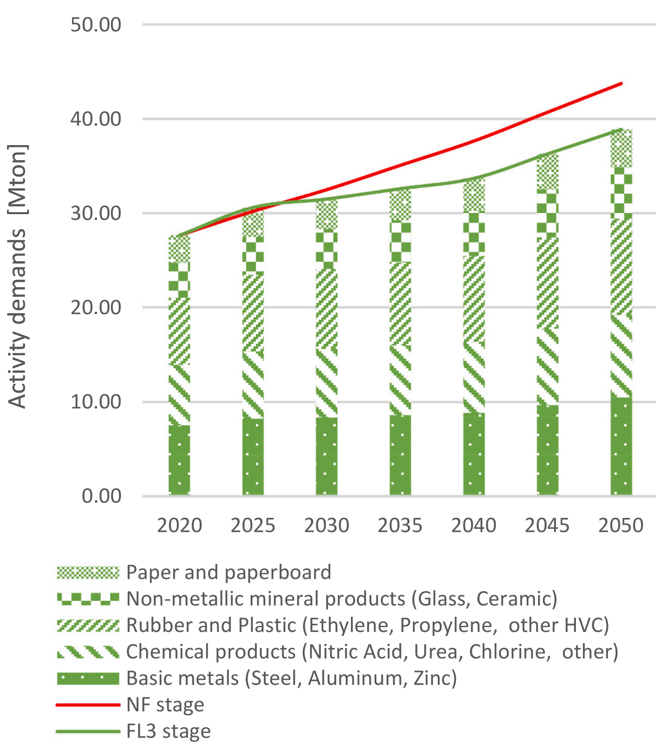

Fig. 8. Energy activity demand projections of the primary industrial sectors of the Netherlands in the third iteration (i.e., the FL3 step).

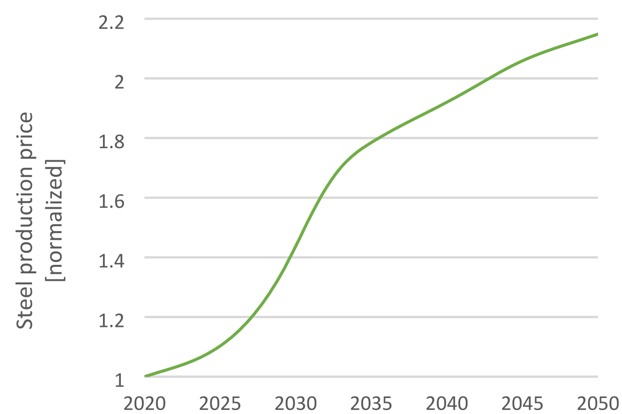

Fig. 9. Steel commodity price normalized to 2020. This price is endogenously calculated in ThreeME based on the imported energy prices from IESA-Opt.

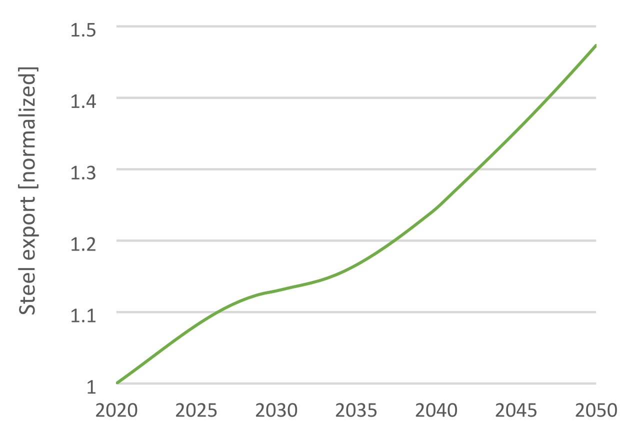

Fig. 10. The export projection of the steel commodity according to ThreeME and normalized to 2020.

investment and consumption are relatively small compared to the NF stage. This trade balance deterioration is driven by the increase in the domestic price of energy commodities and thus sectoral commodities (as explained in Section 3.2.1). The increase in prices leads to the lower international competitiveness of domestic products starting from 2030 to 2040 (assuming a business-as-usual scenario in the rest of the world). After 2040, the IESA-Opt energy prices do not change considerably, and international commodity prices continue to increase at the constant rate of 2% (as assumed in the reference scenario). Therefore, the reduction in exports remains and starts to decrease slightly as the difference between domestic and international prices decreases.

3.3. The relevance of feedback parameters

The presented soft-linking approach consists of two directions: demand conversion and energy mix conversion. While the demand

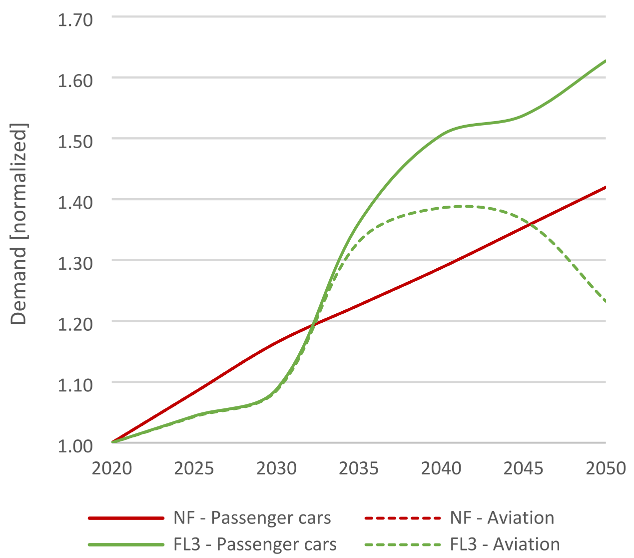

Fig. 11. Passenger car and aviation demand projections in the NF and FL3 stages. The values are normalized to 2020 levels.

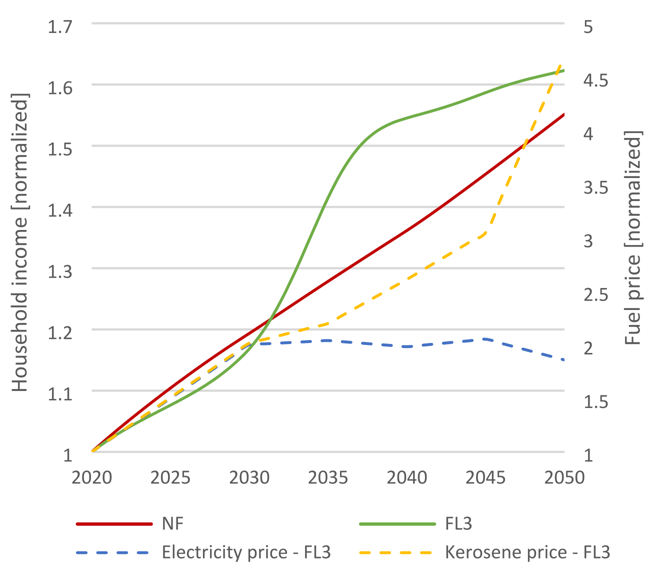

Fig. 12. The household income and fuel price projections in the NF and FL3 stages. The values are normalized to 2020 levels.

conversion contains only the energy demand parameter, the energy mix conversion involves four parameters: productivity factors, energy mix, energy prices, and energy trade.

This section demonstrates the impact of soft-linking these parameters on the energy demand drivers. This impact is compared at six levels: no feedback from IESA-Opt to ThreeME, feeding back only productivity factors, only energy mix, only energy prices, only energy trade, and complete feedback (i.e., soft-linked).

The impact of feedback parameters on the primary Dutch industrial demands in 2050 is presented in Fig. 15. First, the energy mix feedback increases the demand levels by 1% on average in all sectors compared to the no-feedback stage. The higher endogenous electrification rate (the output of IESA-Opt) stimulates sectoral production as there will be less demand for fossil energy commodity imports.

Second, feeding back the capital and energy productivity factors reduces energy demand drivers by merely 0.4% compared to the NF stage. While the energy productivity increases in all sectors (due to

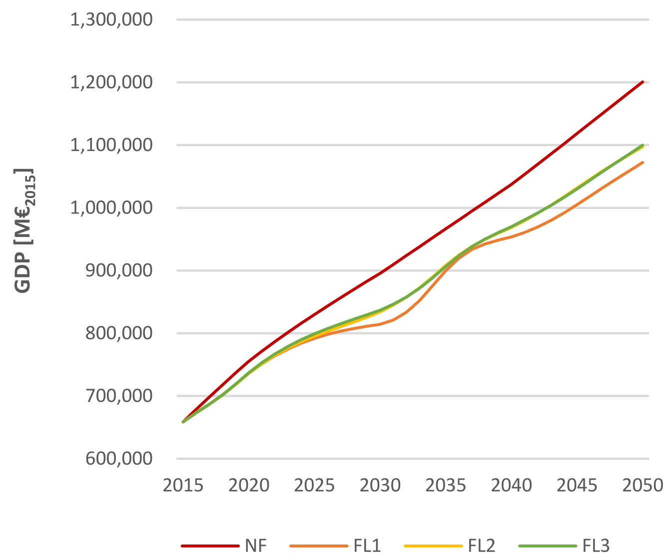

Fig. 13. Variations in the GDP during different steps of soft-linking. NF: No Feedback from IESA-Opt to ThreeME, FL*i*: Feedback Loop between two models (i.e., two-way soft-linking) at iteration *i*.

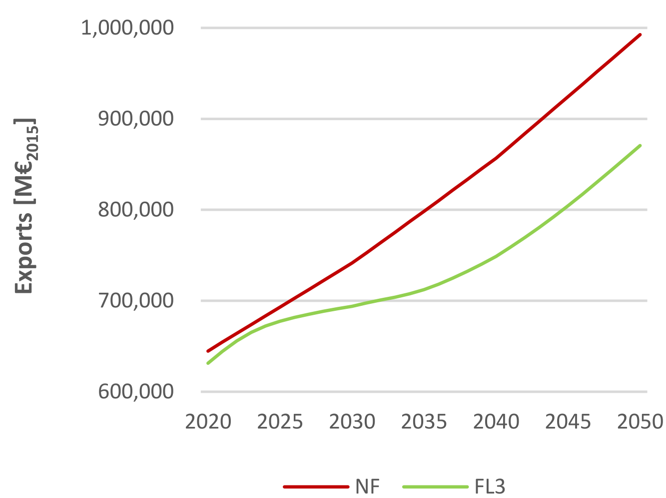

Fig. 14. The projection of exports in the NF and FL3 stages (i.e., before and after soft-linking).

higher efficiency), the capital productivity increases in some sectors (e.g., basic metals) and reduces in others (e.g., paper and paperboard). For instance, in the basic metals sector, IESA-Opt invests in the hydrogen direct reduction process, which is assumed to be slightly cheaper and more efficient than blast furnaces. This leads to an increase in capital and energy productivity, resulting in lower demand for capital and energy - consequently, 0.8% higher steel production.

Third, the energy trade feedback reduces the sectoral demand by 0.9% compared to the NF stage. The primary reason for this minimal impact is the assumption of constant energy commodity exports (except electricity) from 2020 onwards. Consequently, the energy import volumes that IESA-Opt determines endogenously do not change considerably compared to the base year. Therefore, by assuming drastic changes in energy trade volumes in the long term, we expect that the impact of this feedback parameter will become more prominent.

Fourth, the energy commodity prices are the primary feedback parameter with a 15% average decrease in the energy activity drivers compared to the NF stage. The higher energy prices increase the production costs and thus domestic commodity prices (as explained in Section 3.2.1). Since domestic commodities become more expensive

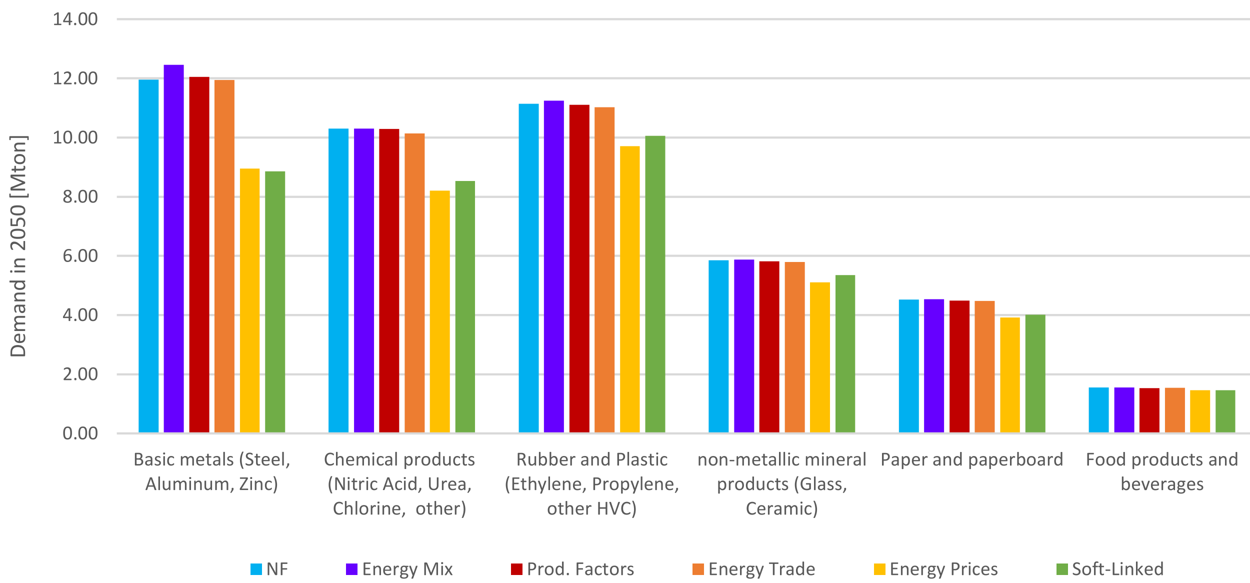

Fig. 15. The variations of primary Dutch industrial demands in 2050 with respect to soft-linking feedback stages. NF: No feedback from IESA-Opt to ThreeME, feeding back only energy mix, only productivity factors, only energy prices, only energy trade, and full feedback (i.e., soft-linked).

compared to the NF stage, and ThreeME assumes a constant growth of international prices from the base year, the competitiveness of domestic products reduces (depending on the assumed export elasticity). As a result of reduced exports, the production levels reduce drastically. Therefore, the impact of this parameter on the final results depends primarily on the IESA-Opt energy prices and assumed growth of international prices and trade elasticity.

In summary, the energy commodity price feedback has the highest impact on the final results compared to other feedback parameters. However, the magnitude of this feedback depends on specific modeling assumptions both in the economy and energy models.

4. Discussion

Although the demonstrated soft-linking approach ensures the economic equilibrium of the energy system, it comes with several assumptions that can affect the results (summarized in Table 5). Here we briefly discuss the key assumptions and their potential impact on the outcomes.

Table 5
The list of main soft-linking assumptions and issues to be resolved.

Assumption/issue	Resolution
Sectoral definition matching	Is challenging. A more detailed CGEM is required
Novel value chains	Need for forward-looking CGEM
Linking investment costs	Soft-link capital costs where necessary
Differences between the energy and economic capital costs	The impact on results is not considerable
Perfect foresight as opposed to the myopic methodology	Proposing a modification in ThreeME
Convergence criterion	We should monitor the process, not only the criterion
Demand-elasticity in ESMs	Can be used when soft-linking is out of reach
Importance of elasticities and the base year choice	Sensitivity analyses are required
Relevance of international trade	Global CGEM or sensitivity analyses are required
Price linking method	Further investigation is required
Assumed energy price projections	Alternative scenario analysis is required
Further analyzing the economic results	In-depth economic analysis is required

4.1. Sectoral definition matching

Tables 1 and 2 clearly show how the sectoral definition matching between the two models is established. However, this is can be highly critical and difficult to carry out since it either may interrupt the logic of one of the models or disturb the relation between data sources and models sectors. In this study, we used energy and economy models with high sectoral resolution and with the ability of grouping sectors. For example, sectors can get merged in ThreeME to match IESA-Opt sectors. Therefore, matching their sectoral definitions raised minimal challenges.

In the proposed soft-linking process, the IESA-Opt energy demand drivers are calculated based on endogenous ThreeME sectoral growth. Although we aligned the sectoral definition of ThreeME to IESA-Opt, still the linking can be improved. For instance, the growth in the land transport sector determines the growth in the light and heavy-duty vehicles, busses, and trains in IESA-Opt. However, the demand for busses and trains is not necessarily determined by the land transport sector growth. Increasing the sectoral disaggregation of ThreeME could resolve this issue. For instance, EMEC (Krook-Riekkola et al., 2017a) provides greater sectoral detail by distinguishing between public transport, road freight, and rail transport sectors.

4.2. Novel value chains

In this study, a CGE model based on historic data, such as SAM and elasticities, was utilized. However, due to its reliance on existing data, it is unable to accurately reflect novel production value chains like green hydrogen, synthetic fuels, DAC, and BECCS that do not yet have a significant impact on the economy. One approach would be assuming these value chains behave similar to current economic commodities (e.g., green hydrogen can be treated as natural gas). However, in order to be more accurate, these production value chains and their associated elasticities must be added to the CGE model.

4.3. Linking investment costs

In the present study we linked the investment costs of two models because an investment in a capital-intensive technology resulting from ESM can affect the capital intensity of the corresponding sector in CGEM, and hence, the economic equilibrium. Although some other studies such as Krook-Riekkola et al. (Krook-Riekkola et al., 2017a) did not include linking investment costs in their soft-linking approach, they mentioned this issue as a shortcoming of their approach.

Even though we showed that the impact of this linking parameter is not considerable on the results, we advise including this linking parameter for sectors in which the ratio of capital over variable costs can shift considerably during the course of energy transition. An example is the transport sector where the ratio of capital over variable costs for electric cars is noticeably higher than conventional cars.

4.4. Differences between the energy and economic capital costs

We are assuming the energy model capital costs represent the whole capital costs of the sector ($\beta_s = 1$). However, this is not the case in reality, as an energy-related capital cost of a specific sector only represents a share of its total investment costs. We can analyze the historical data to identify the energy-related capital cost-share of each sector. This share can be used as a sectoral elasticity in Section 2.3.4 to calculate the $Prod_{s,t,n}^K$ more accurately. Although we have demonstrated that the impact of linking the capital factor on the results is not significant, we suggest calibrating the β_s values from the base year. Moreover, in a similar study (Krook-Riekkola et al., 2017a), β_s values for the Swedish economy are extracted; however, the reported values do not differ considerably from 1, which was used in this study. Therefore, we do not expect considerable change in the results if real β_s values are used.

4.5. Perfect foresight as opposed to the myopic methodology

Although the underlying methodologies of both models are different, there is one major difference that can cause inconsistency between two models. On the one hand, in the IESA-Opt model, the objective function (i.e., energy system costs) is minimized with perfect foresight to provide a socially optimal energy transition pathway. On the other hand, the ThreeME model simulates a general equilibrium between several economic agents (e.g., households and government) with myopic foresight. Thus, these economic agents only apply adaptive expectations with backward-looking under bounded rationality. As a result, the investment decisions in IESA-Opt look ahead, while their effect in ThreeME has a myopic impact. Similarly, this inconsistency between the two models is briefly recognized by Fortes et al. (Fortes et al., 2013) as GEM-E3 (Capros et al., 2013) is a recursive dynamic model while TIMES (Loulou et al., 2016) has perfect foresight.

To diminish this inconsistency, we propose defining a social objective function in ThreeME that optimizes a specific variable over the trajectory. In this way, the model can employ future information to reach a perfect foresight equilibrium iteratively.

4.6. Convergence criterion

There are other candidates for the convergence criteria. Fortes et al. (Fortes et al., 2013) use the criterion that the variation in energy consumption per energy carrier between iterations should be lower than 10% or 1 PJ. Another criterion is used by Labriet et al. (Labriet et al., 2010) in which the average relative difference between the energy demand driver values obtained at two successive iterations should be smaller than a sufficiently small threshold. The present paper uses the energy demand driver as the primary convergence criterion because it is essential for the IESA-Opt results. However, we should not merely rely on a convergence criterion; besides, we need to administer the linked parameters at each stage to ensure meaningful linking as Krook-Riekkola et al. (Krook-Riekkola et al., 2017a) suggested.

4.7. Demand-elasticity in ESMs

ESMs such as the TIMES model family have the capability of implementing demand-elasticities, which allow for changes in demand due to endogenous commodity prices or substitution elasticities. This approach can help with demand adjustments in response to changes in prices, but is not an adequate substitution for soft-linking. Soft-linking ensures that economic equilibrium is kept in line with the energy policy set by the ESM, which demand-elasticities are not capable of doing. On the other hand, demand-elasticities have the advantage of not requiring the time and effort that soft-linking does, thus the choice between the two depends on the objectives and capabilities of the research team.

4.8. Importance of elasticities and the base year choice

CGEM results highly depend on the assumed elasticities. The variation in economic behavior can lead to variations in elasticities, which can highly affect the results. For instance, a robust national willingness to reduce energy imports can lower substitution elasticity between domestic and imported energy commodities. In this study, we merely used default elasticities. However, there is room to investigate the role of variations in elasticities in the final results. For instance, as was shown in the results section, trade elasticity plays a crucial role in determining the competitiveness of domestic products and thus economic growth. Moreover, the energy system transition can considerably impact these elasticities in long-term (e.g., 2050).

Moreover, the choice of the base year determines the starting point of the economy. Therefore, we suggest choosing a "good" starting year that represents the economy the best. For instance, choosing 2020 as the base year might underestimate the economic growth as it was under the temporary impact of the covid-19 pandemic. Moreover, the chosen base year should be near enough to represent the most recent state of the economy. Therefore, we choose 2015 as the base year in the present study. However, we suggest using the more recent "good" base year given the corresponding SAM is available.

4.9. Relevance of international trade

ThreeME assumes a steady-state increase in international energy and commodity prices. However, this assumption is far from reality as the international price of commodities can change considerably based on different national policies, notably climate policies. For instance, domestic climate policies increase energy prices and, consequently, sectoral commodity prices. Thus, domestic commodities become less competitive in the international market, which results in lower exports and consequently lower domestic GDP growth. Therefore, the assumed growth of international commodity prices can drastically affect the impact of energy policies on economic growth.

This issue can be addressed in two ways: first, performing a sensitivity analysis of the results by assuming several exogenous international commodity price projections. Second, use a global CGEM to account for international trade. The second method, however, comes at the cost of reduced domestic modeling details as global CGEMs are considerably more aggregated than national ones.

4.10. Price linking method

In ThreeME, the commodity price is endogenously defined as a mark-up over costs. In the present paper, we assumed that the IESA-Opt energy commodity prices (i.e., shadow prices) are passed directly to ThreeME. Therefore, a higher energy price simulated by IESA-Opt corresponds implicitly to a higher mark-up. However, it could also have been modeled through an increase in input cost, in particular the one of capital. Similarly, Krook-Riekkola et al. (Krook-Riekkola et al., 2017a) faced challenges in linking prices.

The price linking assumption impacts the generated incomes, their beneficiaries, and thus, the overall economic impact. Therefore, different methods of price linking and their impact on the results need further investigation.

4.11. Assumed energy price projections

The reference scenario used in the present study does not consider the recent high levels of fossil fuel prices, particularly in Europe, which are caused by the disrupted supply of natural gas and oil. However, the assumed energy price projections play an essential role in the results, as it was shown in the results.

With higher fossil fuel prices, low-carbon energy sources become more cost-effective. Therefore, the commodities made using low-carbon energy become cheaper than fossil fuel-based commodities. Therefore, with higher international fossil fuel prices, we expect the relative competitiveness of domestic commodities to increase since the share of low-carbon energy is expected to increase considerably in the Netherlands. This effect can be quantified with the proposed method in the present paper; however, it falls out of the scope of this study.

4.12. Further analyzing the economic results

The present study merely analyzes the aggregated economic indicators such as the export and GDP levels. However, the relevance of soft-linking on more detailed economic indicators was not discussed. Therefore, there is a need for an in-depth analysis of the results that would require looking at additional economic indicators, decomposing economic impacts (in particular between substitution effects and income effects), and sensitivity analysis of critical parameters (e.g., elasticities) of the model. Since these in-depth economic analyses falls out of the scope of this study, we keep that for further research.

5. Conclusion

The present study aims at providing a transparent soft-linking approach for highly disaggregated computable general equilibrium model (CGEM) and energy system model (ESM) at the national scale; and subsequently analyze and demonstrate the relevance of various linking parameters on results, such as energy demand drivers and GDP.

Compared to the stand-alone IESA-Opt (without linking), the soft-linking increases the activity demand levels of 2050 by 19.5% on average. This outcome is particularly significant for ESM modelers, as they often use the exogenous energy demand drivers from external sources. Furthermore, this outcome shows that the assumed exogenous energy demand drivers of ESMs are not necessarily consistent with the expected economic growth. Therefore, soft-linking can bridge this gap by ensuring general economic equilibrium instead of partial equilibrium in ESMs. However, we should ensure that novel production value chains (resulting from ESMs) are captured properly in CGEs. For instance, green hydrogen is expected to play a major role in achieving net-zero emission targets; however, its production value chain is not properly modeled in CGE models that rely on historic SAM and elasticities.

Moreover, in the first soft-linking iteration, the energy demand drivers in 2050 reduced by 10.8% on average compared to the no-feedback (NF) stage, in which IESA-Opt outputs are not fed into ThreeME. We showed that this reduction in energy demand drivers led to a 5.5% reduction in GDP. This outcome is particularly relevant to CGE modelers as they often oversimplify the energy system and its impact on the economy. Therefore, soft-linking can improve the CGEM results by accounting for ESM feedbacks that emerge from analyzing climate policies with rich bottom-up details.

Furthermore, we demonstrated that in this case study, the energy prices parameter is the primary feedback among four feedback parameters: productivity factors, energy mix, energy prices, and energy trade. The energy prices parameter reduces the energy activity drivers in 2050 by 15% on average compared to the NF stage. We illustrated that the energy prices of IESA-Opt increase the production cost of ThreeME commodities and consequently reduce the international competitiveness of domestic products. Therefore, high energy prices (resulting from IESA-Opt) decrease the exports, and thus, GDP and energy demand drivers. This outcome elevates the significance of international trade assumptions or the need for a global economy model while modeling a national energy-economy linked system.

In addition, as explained in the discussion section, the proposed soft-linking method and analyses can be improved in several ways, such as performing sensitivity analyses on primary scenario parameters (e.g., elasticities), using a global CGEM or an international scenario framework, increasing the sectoral detail of ThreeME, improving the price linking between models, providing in-depth economic analyses, and analyze the results considering high fossil fuel price projections.

Although there exist other studies that provide a transparent soft-linking methods for national models, the present study improves the literature by increasing the transparency level and quantifying the relevance of the feedback parameters in the utilized approach. Each soft-linking effort requires making particular assumptions depending on the underlying methodology and resolution of the used models. Therefore, comparing the results of soft-linking approaches would be challenging. However, readers can benefit from the higher transparency and diversity of approaches, and employ a mixed approach that is best suited for their study.

CRediT authorship contribution statement

Amirhossein Fattahi: Writing – original draft, Conceptualization, Methodology, Software, Data curation, Formal analysis, Visualization. **Frédéric Reynès:** Writing – review & editing, Conceptualization, Software. **Bob van der Zwaan:** Writing – review & editing, Conceptualization. **Jos Sijm:** Writing – review & editing, Conceptualization, Resources. **André Faaij:** Writing – review & editing, Conceptualization, Supervision, Resources, Formal analysis.

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