Annual Decarbonization Perspective 2024

Technical Documentation

EVOLVED ENERGY RESEARCH

ABOUT THIS REPORT

This report provides supporting material to the 2024 Annual Decarbonization Perspective, an annual report investigating options for long-term deep decarbonization pathways for Europe. Supporting materials include documentation of modeling methodologies, scenario assumptions, and underlying databases.

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EVOLVED ENERGY RESEARCH

ABOUT EVOLVED ENERGY RESEARCH

Evolved Energy Research (EER) is a research and consulting firm focused on questions posed by transformation of the energy economy. Their consulting work and insight, supported by complex technical analyses of energy systems, are designed to support strategic decision-making for policymakers, stakeholders, utilities, investors, and technology companies.

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This documentation adopts a nested structure, which begins with a discussion of the specific analysis conducted (which includes specific scenario assumptions); a discussion of the underlying databases (which may be used across a variety of analyses that utilize the same underlying geographic representation); and a discussion of the models (RIO and EnergyPATHWAYS) which can be used across a variety of databases with different geographic representations.

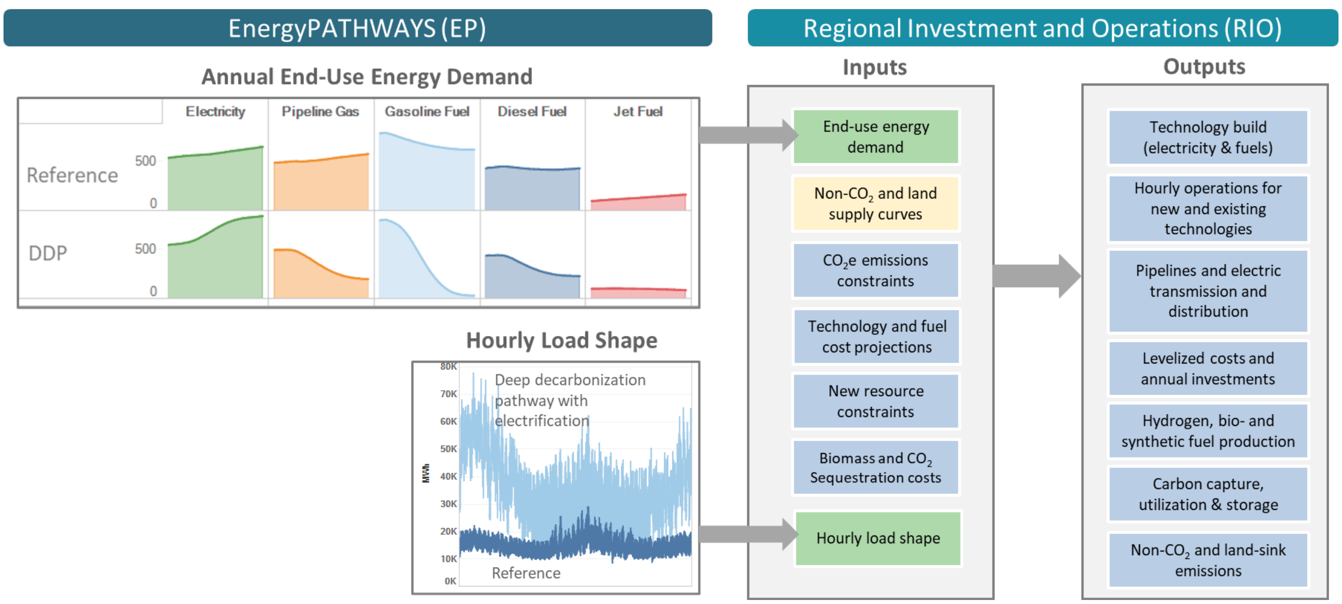
S1. Analysis

1.1. Description

This study employs a scenario modeling approach demonstrated in previous work (1,2,3,4,5). In this work, we develop low-carbon scenarios for the European economy. The scenarios are a detailed representation of infrastructure as it changes over time, under both static basline conditions as well as under the constraint of reaching significantly reduced emissions leve.s. The low-carbon scenarios include only technologies that are commercial or have been demonstrated at pilot scale, with performance and cost characteristics taken from well-vetted public sources (Section S2). This study expands the framework beyond the E&I system to include an assessment of emissions and mitigation opportunities in non-energy, non-CO_2 sectors and land sectors of the economy. This allows for a comprehensive accounting of all greenhouse gas emissions and the opportunity to compare tradeoffs between emissions reduction opportunities in different sectors under different scenarios.

The modeling work was performed using RIO (section 3.1) and EnergyPATHWAYS (EP) (section 3.3), numerical models with high temporal, sectoral, and spatial resolution developed by the authors for this purpose. Final-energy demand scenarios were developed in EP, a bottom-up stock accounting model with fifty-seven demand subsectors for the European economy (EU+UK) in four sectors: residential, tertiary, transport, and industry. EP outputs, including time-varying electricity and fuel demand, were input into RIO, a linear programming model that combines capacity expansion and sequential hourly operations to find least-cost supply-side pathways. RIO has unique capabilities for this energy systems analysis: it models in detail interactions among electricity generation, fuel production, and CCUS, allowing accurate evaluation of the economics of coupling between these sectors; it tracks storage state of charge over an entire year, allowing accurate assessment of balancing requirements in electricity systems with very high levels of VRE; and it solves for all infrastructure decisions on a five year time-step to optimize the entire energy system transition, not only the endpoint. RIO finds technology configurations that minimize the net present value of the sum of all energy system costs over the 30-year modeling period, 2021 – 2050. The steps of the modeling analysis are framed at a high level by the flow chart in Figure 1.

Figure 1. Scenario stock-accounting tool (EP) paired with economy-wide partial equilibrium model (RIO)



1.1.1. EnergyPATHWAYS (EP)

On the energy demand side, we developed a model of US energy demand by sector across the economy**.** For this purpose, we created EnergyPATHWAYS (EP)—a bottom-up stock-rollover model of all energy-using technologies in the economy—to represent how energy is used today and in the future. The EP model is a comprehensive energy accounting and analysis framework designed specifically to examine large-scale energy system transformations.

1.1.2. Land Sink Baseline

Baseline land sink at a EU member-state level with were taken from the European Commission guidance [1]. This source represents both baseline land sector emissions reductions as well as the potential for mitigation through 2030. We do not anticipate additional mitigation activities after 2030 in this analysis.

1.1.3. Non – Energy, Non- CO_2

Non-Energy, Non-CO2 baseline emissions projections are taken from the report "Global Non-CO2 Greenhouse Gas Emissions Projections and Mitigation" by the U.S. Environmental Protection Agency (50). This includes baseline forecast of non-energy non-co2 emissions as well as detailed mitigation supply curves that allow for tradeoffs between non-energy reductions and other sectors in the RIO optimization.

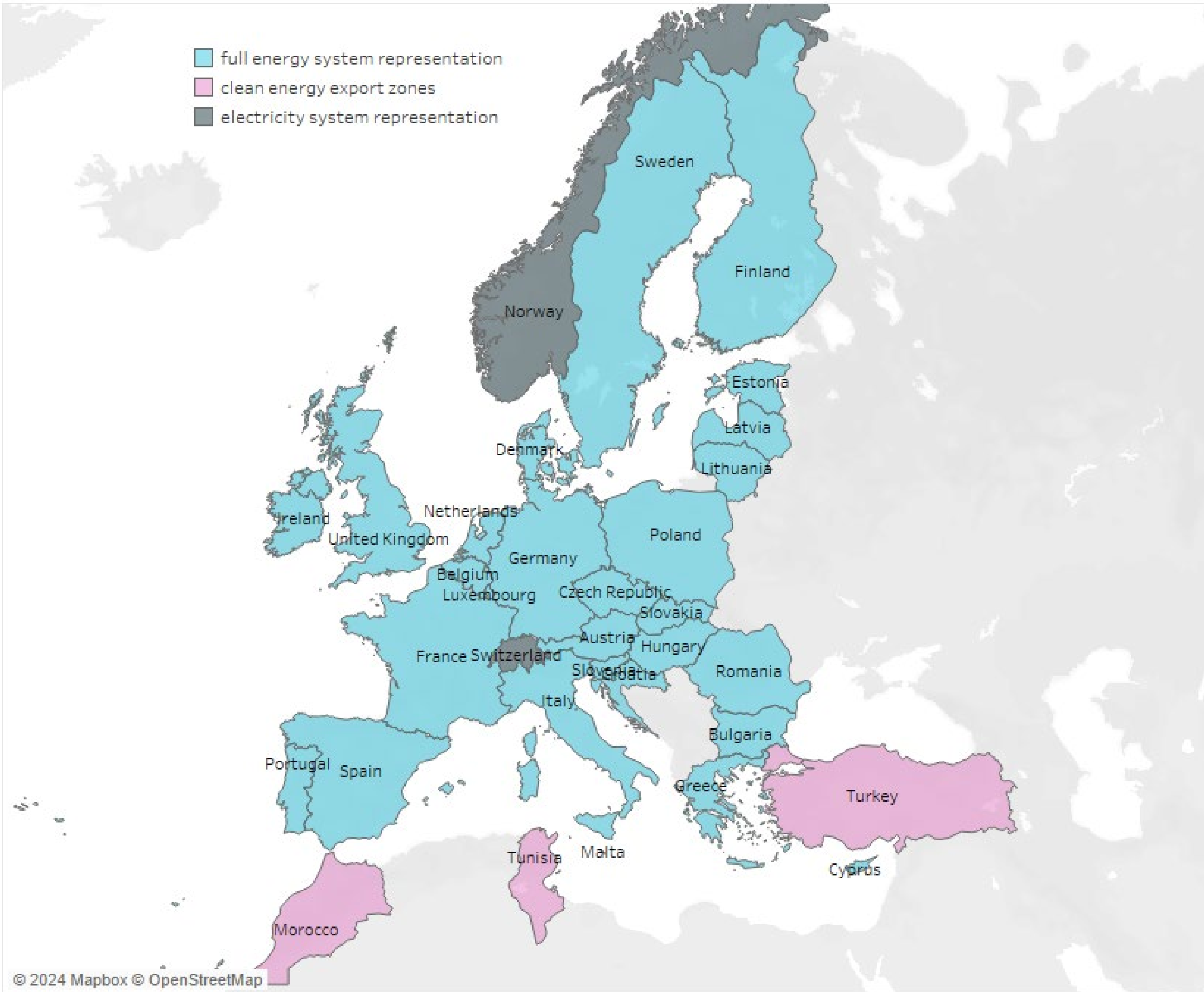
1.2. Database

EnergyPATHWAYS and RIO are numerical modeling platforms that can operate with flexible configurations of underlying data. As of 2024, EER has developed databases for the U.S., Europe, Australia, and Mexico that have been used to develop long-term low-carbon pathways. This analysis employs EER's European database, which includes full supply and demand data for EU27+UK countries; electricity supply and demand data for Norway and Switzerland; and exportable clean energy potential for Turkey; Morocco; and Tunisia.

1.3. Geography

In addition to being flexible in terms of underlying data, the models are flexible in the spatial granularity with which they can represent a geographic area. This is called our model topology and is used as the unit of differentiation for supply/demand balances (electricity and other blends), policy constraints, transmission constraints, resource availability (e.g. biomass), and technology availability. This analysis includes the EU 27 and the UK with full energy system representations. Switzerland and Norway are modeled as electricity only zones. Turkey, Tunisia, and Morocco can provide clean electricity and fuels to the other modeled zones.

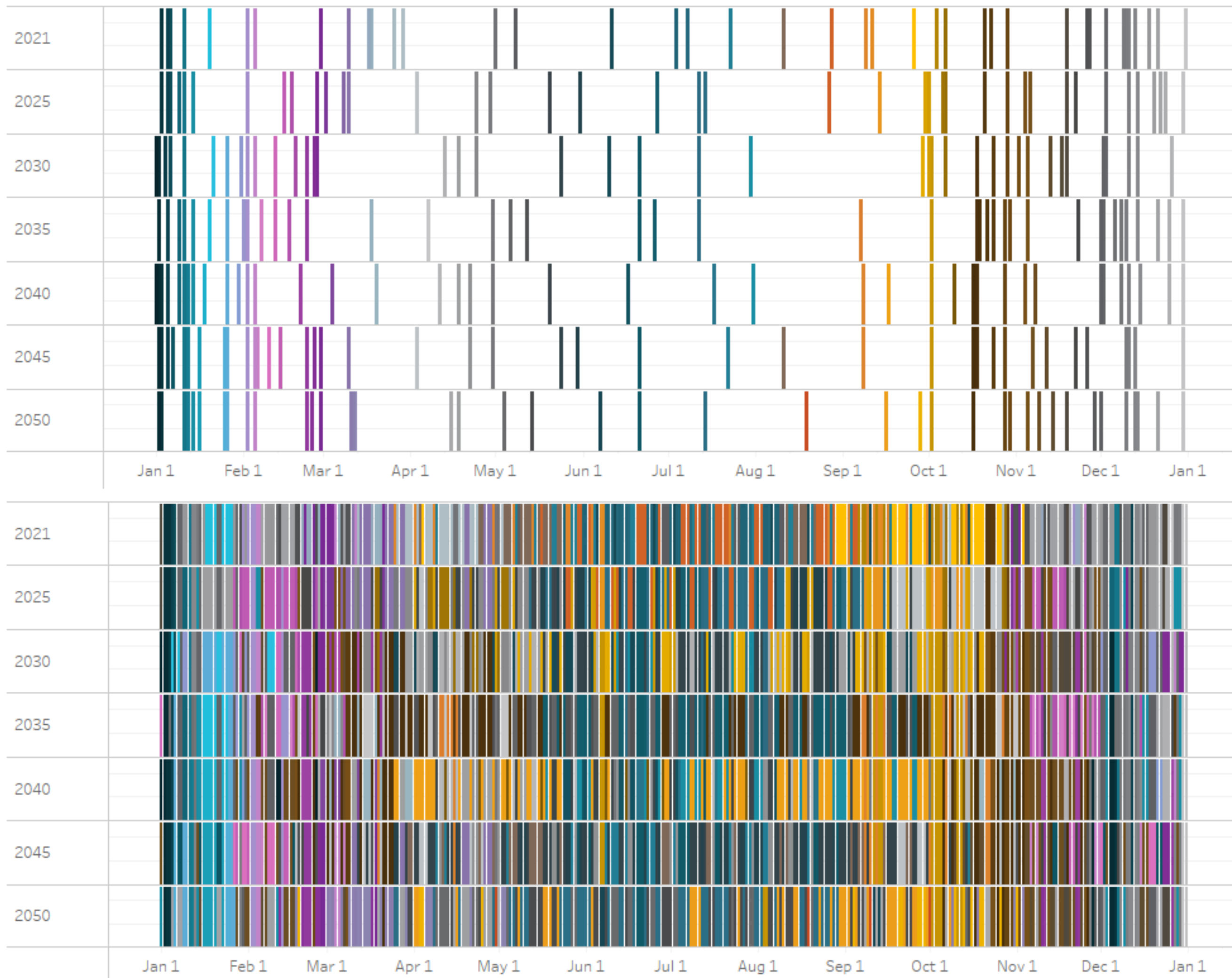
Figure 2 Zonal representation in EnergyPATHWAYS and RIO.



1.4. Temporal Representation

RIO is an optimization model that can be flexibly configured for different levels of temporal detail. A broader discussion of the approach EER uses for temporal representation can be referenced here (3.1.3). There are two principal components to this temporal representation: first, how many years are represented in the optimization; second, how many days are sampled in each modeled year. The 2024 ADP uses seven years to represent the thirty years between 2021 and 2050. In each modeled year, forty days are sampled based on load and renewable shapes from a 2017 historical weather year. As is explained further in section 3.1.3, different days are selected for different future years because increasing electrification and wind and solar development result in a different mix of 40 days providing the best approximation of a full year (365 days) of operations.

Table 1. Modeled days from the 2017 weather year used when modeling future operations for snapshot years.



1.5. General assumptions

The inputs below are configurable model inputs that were employed across all scenarios.

Table 2 General assumptions common to all scenarios

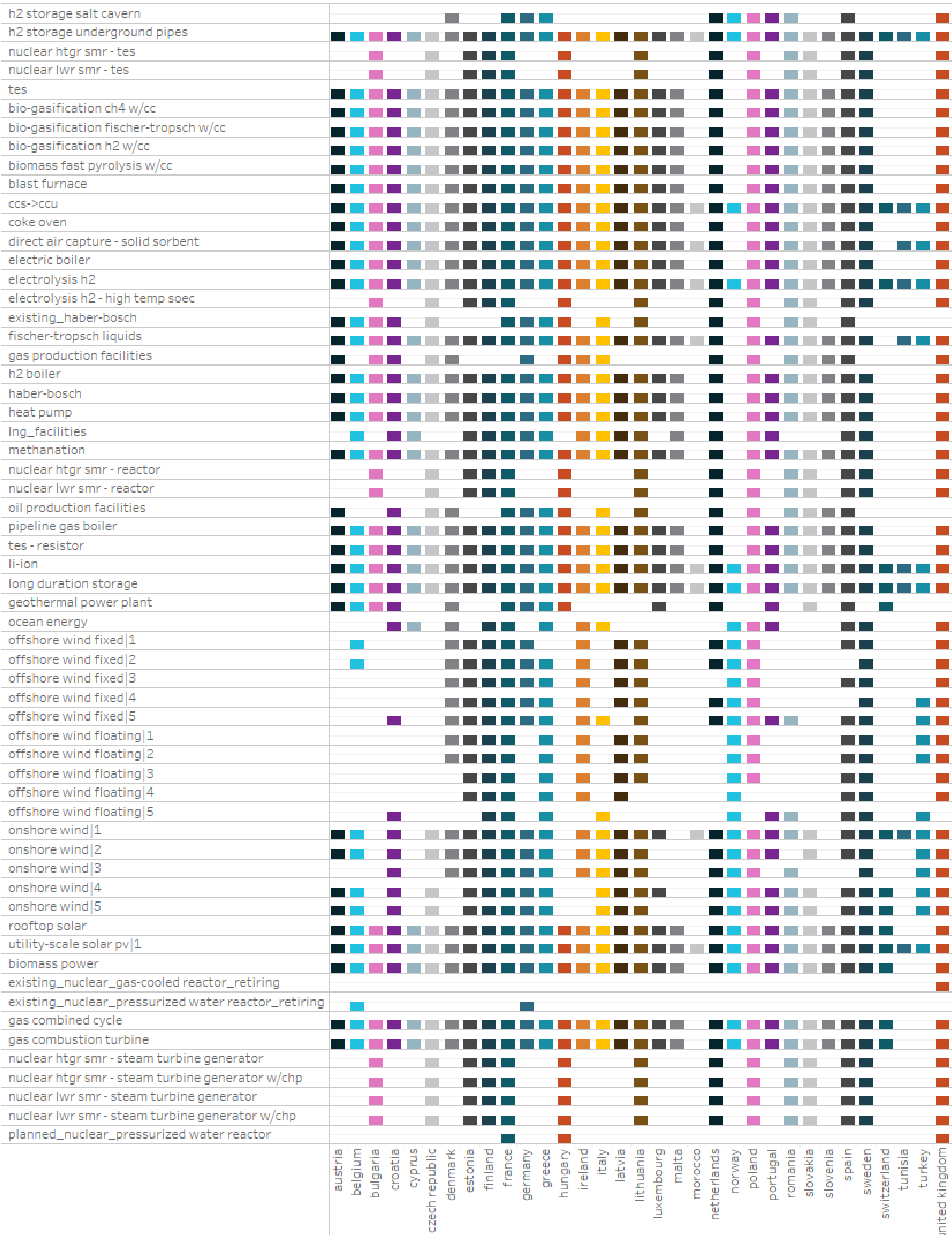
ASSUMPTION	VALUE	NOTES

SOCIETAL DISCOUNT RATE	3%	PURE TIME PREFERENCE USED IN THE OPTIMIZATION
DEMAND SIDE COST OF CAPITAL	3-8% REAL	REAL COST OF CAPITAL, DEPENDING ON SUBSECTOR AND ASSUMED FINANCING SOURCE
COST OF CAPITAL FOR ELECTRICITY TECHNOLOGIES	4-8% REAL	REAL COST OF CAPITAL, BASED ON UTILITY WEIGHTED AVERAGE COST OF CAPITAL
COST OF CAPITAL FOR FUEL CONVERSION TECHNOLOGIES	8% REAL	REAL COST OF CAPITAL WITH ADDITIONAL RISK DUE TO MARKET EXPOSURE
COST OF CAPITAL FOR NON-ENERGY INDUSTRIAL TECHNOLOGIES	15% REAL	REAL COST OF CAPITAL WITH ADDITIONAL RISK DUE TO MARKET EXPOSURE
HYDRO YEAR	AVERAGE	BASED ON LONG-RUN AVERAGE OF HYDRO GENERATION (83)
HYDRO ENERGY CONSTRAINT	FIXED DAILY ENERGY BUDGETS	DOESN'T ALLOW DEVIATION FOR DAILY ENERGY FROM HISTORICAL RECORD. CONSERVATIVE ASSUMPTION.
NUMBER OF ELECTRICITY DAY SAMPLES	40	ELECTRICITY OPERATIONS SAMPLED WITH 40 DAYS IN EACH YEAR (960 HOURS). THE 40 DAYS WERE CHOSEN INDEPENDENTLY FOR FUTURE YEARS BASED ON CLUSTERING AROUND GROSS LOAD AND RENEWABLE PRODUCTION FEATURES.
GENERATOR RETIREMENTS	ECONOMIC	GENERATORS ARE ASSUMED TO RETIRE AT THE END OF A SPECIFIED PHYSICAL LIFETIME BUT CAN RETIRE SOONER TO AVOID FIXED O&M COST IN ORDER TO MINIMIZE TOTAL SYSTEM COST.
CURRENCY	EUR	
CURRENCY YEAR	2022	
ENERGY UNIT	GWH	
MASS UNIT	HECTOTONNE	
VOLUME UNIT	LITER	
DISTANCE UNIT	KILOMETER	

1.6. RIO Technologies

RIO provides comprehensive representations of infrastructure for producing, converting, storing, and delivering energy. The figure below shows the energy technologies made available for deployment in each zone in the **Core** scenario.

Figure 3 RIO Technology Availability


h2 storage salt cavern
h2 storage underground pipes
nuclear htgr smr - tes
nuclear lwr smr - tes
tes
bio-gasification ch4 w/cc
bio-gasification fischer-tropsch w/cc
bio-gasification h2 w/cc
biomass fast pyrolysis w/cc
blast furnace
ccs->ccu
coke oven
direct air capture - solid sorbent
electric boiler
electrolysis h2
electrolysis h2 - high temp soec
existing_haber-bosch
fischer-tropsch liquids
gas production facilities
h2 boiler
haber-bosch
heat pump
lng_facilities
methanation
nuclear htgr smr - reactor
nuclear lwr smr - reactor
oil production facilities
pipeline gas boiler
tes - resistor
li-ion
long duration storage
geothermal power plant
ocean energy
offshore wind fixed|1
offshore wind fixed|2
offshore wind fixed|3
offshore wind fixed|4
offshore wind fixed|5
offshore wind floating|1
offshore wind floating|2
offshore wind floating|3
offshore wind floating|4
offshore wind floating|5
onshore wind|1
onshore wind|2
onshore wind|3
onshore wind|4
onshore wind|5
rooftop solar
utility-scale solar pv|1
biomass power
existing_nuclear_gas-cooled reactor_retiring
existing_nuclear_pressurized water reactor_retiring
gas combined cycle
gas combustion turbine
nuclear htgr smr - steam turbine generator
nuclear htgr smr - steam turbine generator w/chp
nuclear lwr smr - steam turbine generator
nuclear lwr smr - steam turbine generator w/chp
planned_nuclear_pressurized water reactor
austria
belgium
bulgaria
croatia
cyprus
czech republic
denmark
estonia
finland
france
germany
greece
hungary
ireland
italy
latvia
lithuania
luxembourg
malta
morocco
netherlands
norway
poland
portugal
romania
slovakia
slovenia
spain
sweden
switzerland
tunisia
turkey
united kingdom

1.7. Scenarios

Scenarios are created from a set of assumptions that specify the demand side of the energy system, including service demand, end-use technology adoption rates, and energy efficiency, plus constraints on the economy-wide RIO optimization, including available resources and emissions targets. For this study we developed a total of nine different scenarios. The key attributes of each are described in this section, first for the EnergyPATHWAYS demand side cases, and then scenario inputs to the RIO model.

1.7.1. EnergyPATHWAYS Demand-Side Cases

Three dimensions form the basis for differences in the demand-side across the runs: energy service demand; energy efficiency; fuel-switching; and technology cost and performance.

Providing the same level of energy services across scenarios makes meaningful comparisons possible. All scenarios except for Low Demand operate against the same projections of energy service, which are projected using regression analysis from historical data. In the Low Demand scenario, we posited large reductions in energy services that are plausibly consistent with new patterns of development and cultural, with the goal of understanding the impact such changes could have on decarbonization outcomes.

High efficiency trajectories were defined for many technologies and were adopted in all the low-carbon scenarios. In the Baseline scenario, we freeze both technology adoption (i.e. EV sales) as well as technology cost and performance at a 2021 vintage.

In aviation and industrial subsectors for which individual technologies were not tracked, percent-per-year efficiency improvements were used.

In most cases, fuel switching means switching from fossil combustion to electricity, but the broader term also encompasses the use of hydrogen and ammonia in end-uses and shifts in industrial processes, such as switching to direct reduced iron (DRI) in iron-and-steel production.

The Table below summarizes the demand-side assumptions used in the scenarios. Four different demand-side cases were created to represent variations in service demand, efficiency, and fuel-switching:

- **Baseline** – Baseline projected service demand with frozen 2021 efficiency levels and technology cost and performance
- **Core**– Baseline projected service demand with high energy efficiency and rapid electrification of end-uses.
- **Low Demand** – Lower trajectories of long-term service demand with high energy efficiency and rapid electrification of end-uses.
- **Slow Electrification** Baseline projected service demand with high energy efficiency and delayed fuel switching. (Fuel switching adoption slows by 20 years relative to the **Core** scenario)

In the next section, detailed assumptions for each demand case are provided, referencing the demand case names above.

Table 3 Mapping from scenario names to demand-side cases

	SCENARIO NAME	DEMAND CASE NAME	SERVICE DEMAND	ENERGY EFFICIENCY	ELECTRIFICATION
1	CORE	CORE	BASELINE	CORE	CORE
2	BASELINE	BASELINE	BASELINE	BASELINE	BASELINE
3	LOW DEMAND	LOW DEMAND	LOW TRAJECTORY	CORE	CORE
4	SLOW ELECTRIFICATION	SLOW ELECTRIFICATION	BASELINE	CORE	SLOW ELECTRIFICATION
5	CONSTRAINED RENEWABLES	CORE	BASELINE	CORE	CORE
7	LOW FOSSIL FUEL PRICES	CORE	BASELINE	CORE	CORE
8	NO SEQUESTRATION	CORE	BASELINE	CORE	CORE
9	NO NEW NUCLEAR	CORE	BASELINE	CORE	CORE

1.7.1.1. Stock Rollover

The tables below show the sales shares and stock shares for four demand technology groups: Electrified Technologies (**Electric**), High Efficiency Technologies (**HE**), Hydrogen Technologies (**H2**), and Reference Technologies (**Reference**) today, in 2030, and in 2050. The sales shares are inputs to EnergyPATHWAYS while the stock shares are a result determined by the stock rollover. The full demand-side representation consists of more than 200 technology types across all subsectors and end-uses, but we aggregated some of them here to show broader trends in the input values. The stock shares shown are determined by the stock rollover assumptions specified in the measure for each technology, the lifetimes of the infrastructure, and the methodology described in section 3.3.3.

Table 4 Sales shares by scenario and technology group

Subsector	Year	Demand Technology	baseline	core	IRA	low demand	slow consumer uptake
buses	2023	Baseline	98%	94%	95%	94%	97%

Table 5 Stock shares by scenario and technology group

Subsector	Year	Demand Technology	baseline	core	IRA	low demand	slow electrification
buses	2023	Baseline	98%	97%	98%	97%	98%

1.7.1.2. Subsector Energy Efficiency and Fuel Switching

The outputs of the stock rollover, when combined with the projected service demand that the technology stocks must supply, provide the majority of final energy demand projections in our model. In subsectors where we did not have technology-level detail, we employed subsector-level estimates of energy efficiency and fuel switching. Energy efficiency here means measures that increase the same-fuel efficiency of providing an energy service. Fuel switching, which can also contribute to end-use efficiency, means measures that change the share of a delivered energy service that is satisfied by a specific energy carrier. All final energy demand is modeled and presented with higher heating values (HHV). For that reason, HHV conversion efficiencies are used for all technologies in the study. Because only the lower heating value (LHV) of fuels are usable in most applications, adjustments were made when applying fuel switching measures where the ratio of LHV/HHV decreased (e.g. switching from natural gas to hydrogen in industrial process heating applications).

Table 6 Energy efficiency measures included in all net-zeros scenarios

SECTOR	SUBSECTOR	CITATION	DESCRIPTION
INDUSTRY	VARIOUS	[1]	MEASURES WERE DERIVED FROM DEMAND-TECHNOLOGY ASSUMPTIONS IN THE UNDERLYING EUCO DATASET WHICH INCLUDED COST AND PERFORMANCE IMPROVEMENTS AT THE END-USE LEVEL BY INDUSTRY
RESIDENTIAL	RES LIGHTING		2% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS
TERTIARY	BUILDING LIGHTING		2% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS
TERTIARY	COMMERCIAL REFRIGERATION		.5% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS
TERTIARY	ICT AND MULTIMEDIA		.5% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS
TERTIARY	MISCELLANEOUS BUILDING TECHNOLOGIES		.5% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS
TERTIARY	STREET LIGHTING		2% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS
TERTIARY	VENTILATION AND OTHERS		.5% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS
TRANSPORTATION	AVIATION		2% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS

TRANSPORTATION	BUNKERS		1% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS
TRANSPORTATION	PASSENGER RAIL		.5% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS
TRANSPORTATION	POWERED 2-WHEELERS		.5% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS
TRANSPORTATION	COASTAL SHIPPING AND INLAND WATERWAYS		1% YEAR OVER YEAR EFFICIENCY IMPROVEMENTS

Table 7 Fuel switching measures (% of Baseline Energy Switched to 'Energy-To')

Subsector	Energy -To	End-Use	Target Year	baseline	core	IRA	slow electrification	low demand
agriculture-crops	electricity	hvac	2050		90			90

1.7.1.3. Service Reductions in Low Demand Scenario

Table 9 shows energy service reductions in the Low Demand scenario. Reductions were assumed to increase linearly to 2050.

Table 8 Service demand reductions to 2050 for the Low Demand scenario

SECTOR	SUBSECTOR	2050 SERVICE REDUCTION
INDUSTRY	FOOD, BEVERAGES AND TOBACCO	20%
INDUSTRY	MACHINERY EQUIPMENT	20%
INDUSTRY	OTHER NON-FERROUS METALS	20%
INDUSTRY	OTHER INDUSTRIAL SECTORS	20%
INDUSTRY	PULP, PAPER AND PRINTING	20%
INDUSTRY	TEXTILES AND LEATHER	20%
INDUSTRY	TRANSPORT EQUIPMENT	20%
INDUSTRY	WOOD AND WOOD PRODUCTS	20%
INDUSTRY	CEMENT	20%
INDUSTRY	CERAMICS & OTHER NMM	20%

INDUSTRY	GLASS PRODUCTION	20%
INDUSTRY	OTHER CHEMICALS	20%
INDUSTRY	PHARMACEUTICAL PRODUCTS ETC.	20%
INDUSTRY	IRON AND STEEL - EAF	20%
INDUSTRY	BASIC CHEMICALS	20%
INDUSTRY	ALUMINIUM	20%
INDUSTRY	IRON AND STEEL - INTEGRATED STEELWORKS	20%
INDUSTRY	BASIC CHEMICALS - NON-ENERGY	20%
RESIDENTIAL	REFRIGERATORS AND FREEZERS	5%
RESIDENTIAL	WASHING MACHINES	5%
RESIDENTIAL	CLOTHES DRYERS	5%
RESIDENTIAL	DISHWASHERS	5%
RESIDENTIAL	TV AND MULTIMEDIA	20%
RESIDENTIAL	ICT EQUIPMENT	20%
RESIDENTIAL	RES LIGHTING	20%
RESIDENTIAL	OTHER APPLIANCES	20%
RESIDENTIAL	RES SPACE HEATING	20%
RESIDENTIAL	RES WATER HEATING	20%
RESIDENTIAL	RES COOKING	5%
RESIDENTIAL	RES SPACE COOLING	20%
TERTIARY	SER SPACE HEATING	20%
TERTIARY	SER WATER HEATING	20%
TERTIARY	SER SPACE COOLING	20%
TERTIARY	BUILDING LIGHTING	20%
TERTIARY	COMMERCIAL REFRIGERATION	5%
TERTIARY	ICT AND MULTIMEDIA	20%
TERTIARY	MISCELLANEOUS BUILDING TECHNOLOGIES	20%
TERTIARY	STREET LIGHTING	20%
TERTIARY	VENTILATION AND OTHERS	20%
TRANSPORT	AVIATION - FREIGHT: INTRA-EU	30%
TRANSPORT	AVIATION - PASSENGER: INTRA-EU	30%
TRANSPORT	BUNKERS: INTRA-EU	20%
TRANSPORT	AVIATION - FREIGHT: EXTRA-EU	30%
TRANSPORT	AVIATION - PASSENGER: EXTRA-EU	30%
TRANSPORT	BUNKERS: EXTRA-EU	20%
TRANSPORT	COASTAL SHIPPING AND INLAND WATERWAYS	20%
TRANSPORT	FREIGHT RAIL	20%
TRANSPORT	MOTOR COACHES, BUSES AND TROLLEY BUSES	0%
TRANSPORT	PASSENGER CARS	30%
TRANSPORT	POWERED 2-WHEELERS	30%

TRANSPORT	HEAVY GOODS VEHICLES - DOMESTIC	20%
TRANSPORT	HEAVY GOODS VEHICLES - INTERNATIONAL	20%
TRANSPORT	LIGHT COMMERCIAL VEHICLES	20%

S2. Data

The database used in this analysis to represent the European energy economy has high geographical resolution for technology stocks; technology cost and performance; built infrastructure and resource potential, and high temporal resolution for electricity loads by end-use and for renewable (wind and solar) generation profiles.

The model of the European energy economy is separated into 58 energy-using demand subsectors. *Subsectors*, such as residential space heating, refer to energy use associated with the delivery of an energy service. A detailed description of the methods EnergyPATHWAYS uses to project energy-service demand, energy demand, and ultimately cost and emissions associated with the performance of that service is found below in section S3. The general approach is described above in sections 1.1.1 and 3.3.3.

2.1. Demand–Side Data Description

Table 10 lists all the subsectors in the European database, grouped by demand sector. It also specifies the methods (A, B, C, D) used to calculate energy demand in each subsector. These methods are described in detail in section 3.3.3.

Table 9 Sectors, subsectors, and methods of energy demand projection

SECTOR	SUBSECTOR	METHOD
FOOD, BEVERAGES AND TOBACCO	INDUSTRY	C
MACHINERY EQUIPMENT	INDUSTRY	C
OTHER NON-FERROUS METALS	INDUSTRY	C
OTHER INDUSTRIAL SECTORS	INDUSTRY	C
PULP, PAPER AND PRINTING	INDUSTRY	C
TEXTILES AND LEATHER	INDUSTRY	C
TRANSPORT EQUIPMENT	INDUSTRY	C
WOOD AND WOOD PRODUCTS	INDUSTRY	C
CEMENT	INDUSTRY	C
CERAMICS & OTHER NMM	INDUSTRY	C

SECTOR	SUBSECTOR	METHOD
GLASS PRODUCTION	INDUSTRY	C
OTHER CHEMICALS	INDUSTRY	C
PHARMACEUTICAL PRODUCTS ETC.	INDUSTRY	C
IRON AND STEEL - EAF	INDUSTRY	C
BASIC CHEMICALS	INDUSTRY	C
ALUMINIUM	INDUSTRY	C
IRON AND STEEL - INTEGRATED STEELWORKS	INDUSTRY	C
CEMENT CO2 CAPTURE	INDUSTRY	C
BASIC CHEMICALS - NON-ENERGY	INDUSTRY	C
REFRIGERATORS AND FREEZERS	RESIDENTIAL	A
WASHING MACHINES	RESIDENTIAL	A
CLOTHES DRYERS	RESIDENTIAL	A
DISHWASHERS	RESIDENTIAL	A
TV AND MULTIMEDIA	RESIDENTIAL	A
ICT EQUIPMENT	RESIDENTIAL	A
RES LIGHTING	RESIDENTIAL	C
OTHER APPLIANCES	RESIDENTIAL	A
RES SPACE HEATING	RESIDENTIAL	A
RES WATER HEATING	RESIDENTIAL	A
RES COOKING	RESIDENTIAL	A
RES SPACE COOLING	RESIDENTIAL	A
SER SPACE HEATING	TERTIARY	A
SER WATER HEATING	TERTIARY	A
SER CATERING	TERTIARY	D
SER SPACE COOLING	TERTIARY	A
VENTILATION AND OTHERS	TERTIARY	D
STREET LIGHTING	TERTIARY	D
BUILDING LIGHTING	TERTIARY	D
COMMERCIAL REFRIGERATION	TERTIARY	D
MISCELLANEOUS BUILDING TECHNOLOGIES	TERTIARY	D
ICT AND MULTIMEDIA	TERTIARY	D
AGRICULTURE, FORESTRY, AND FISHING	TERTIARY	D
AVIATION - FREIGHT: INTRA-EU	TRANSPORT	C
AVIATION - PASSENGER: INTRA-EU	TRANSPORT	C
BUNKERS: INTRA-EU	TRANSPORT	C
AVIATION - FREIGHT: EXTRA-EU	TRANSPORT	C
AVIATION - PASSENGER: EXTRA-EU	TRANSPORT	C
BUNKERS: EXTRA-EU	TRANSPORT	C
COASTAL SHIPPING AND INLAND WATERWAYS	TRANSPORT	C
FREIGHT RAIL	TRANSPORT	C
PASSENGER RAIL	TRANSPORT	D

SECTOR	SUBSECTOR	METHOD
MOTOR COACHES, BUSES AND TROLLEY BUSES	TRANSPORT	C
PASSENGER CARS	TRANSPORT	C
POWERED 2-WHEELERS	TRANSPORT	C
HEAVY GOODS VEHICLES - DOMESTIC	TRANSPORT	A
HEAVY GOODS VEHICLES - INTERNATIONAL	TRANSPORT	A
LIGHT COMMERCIAL VEHICLES	TRANSPORT	A

The methods for representing demand-side subsectors are described in section S3. Table 11 describes the input data used to populate stock representations in the subsectors that employ Method A and Method B (3.3.3.1, 3.3.3.2), and Table 12 describes the energy service demand inputs for these subsectors.

Table 10 Demand stock data for Method A/B Subsectors

SUBSECTOR	INPUT UNIT	STOCK UNIT	SERVICE DEMAND DEPENDENT	DRIVER	INPUT DATA: GEOGRAPHY	INPUT DATA: YEAR(S)	ADDITIONAL DETAIL	SOURCE
CLOTHES DRYERS	CLOTHES DRYERS	CLOTHES DRYERS	NO	HOUSEHOLDS	COUNTRY	2000-2021		[1,2]
DISHWASHERS	DISHWASHERS	DISHWASHERS	NO	HOUSEHOLDS	COUNTRY	2000-2021		[1,2]
ICT EQUIPMENT	ICT EQUIPMENT	ICT EQUIPMENT	NO	HOUSEHOLDS	COUNTRY	2000-2021		[1,2]
OTHER APPLIANCES	OTHER APPLIANCES	OTHER APPLIANCES	NO	HOUSEHOLDS	COUNTRY	2000-2021		[1,2]
REFRIGERATORS AND FREEZERS	REFRIGERATORS AND FREEZERS	REFRIGERATORS AND FREEZERS	NO	HOUSEHOLDS	COUNTRY	2000-2021		[1,2]
TV AND MULTIMEDIA	TV AND MULTIMEDIA	TV AND MULTIMEDIA	NO	HOUSEHOLDS	COUNTRY	2000-2021		[1,2]
WASHING MACHINES	WASHING MACHINES	WASHING MACHINES	NO	HOUSEHOLDS	COUNTRY	2000-2021		[1,2]
RES SPACE HEATING	CAPACITY FACTOR	KWH/HOUR	YES		COUNTRY	2001-2021		[1,2]
RES WATER HEATING	CAPACITY FACTOR	KWH/HOUR	YES		ALL	2021		[1,2]
RES SPACE COOLING	CAPACITY FACTOR	KWH/HOUR	YES		COUNTRY	2001-2021		[1,2]
RES COOKING	CAPACITY FACTOR	KWH/HOUR	YES		ALL			BY ASSUMPTION
SER SPACE HEATING	CAPACITY FACTOR	KTOE/HOUR	YES		COUNTRY	2001-2021		[1,2]
SER WATER HEATING	CAPACITY FACTOR	KTOE/HOUR	YES		ALL	2021		[1,2]
SER SPACE COOLING	CAPACITY FACTOR	KTOE/HOUR	YES		COUNTRY	2001-2021		[1,2]
HEAVY GOODS VEHICLES - DOMESTIC	VEHICLE	VEHICLE	NO		COUNTRY	2000-2021		[1,2]

SUBSECTOR	INPUT UNIT	STOCK UNIT	SERVICE DEMAND DEPENDENT	DRIVER	INPUT DATA: GEOGRAPHY	INPUT DATA: YEAR(S)	ADDITIONAL DETAIL	SOURCE
HEAVY GOODS VEHICLES - INTERNATIONAL	VEHICLE	VEHICLE	NO		COUNTRY	2000-2021		[1,2]
LIGHT COMMERCIAL VEHICLES	VEHICLE	VEHICLE	NO		COUNTRY	2000-2021		[1,2]
MOTOR COACHES, BUSES AND TROLLEY BUSES	VEHICLE	VEHICLE	NO		COUNTRY	2000-2021		[1,2]
PASSENGER CARS	VEHICLE	VEHICLE	NO		COUNTRY	2000-2021		[1,2]
HEAVY GOODS VEHICLES - DOMESTIC	VEHICLE	VEHICLE	NO		COUNTRY	2000-2021		[1,2]

Table 11 Energy/Service demand inputs for Method A/B Subsectors

SUBSECTOR	INPUT UNIT	SERVICE DEMAND UNIT	STOCK DEPENDENT	DRIVER	INPUT DATA: GEOGRAPHY	INPUT DATA: YEAR(S)	ADDITIONAL DETAIL	SOURCE
CLOTHES DRYERS	HOURS	HOURS	TRUE		COUNTRY	2001-2021		[1,2]
DISHWASHERS	HOURS	HOURS	TRUE		COUNTRY	2001-2021		[1,2]
ICT EQUIPMENT	HOURS	HOURS	TRUE		COUNTRY	2001-2021		[1,2]
OTHER APPLIANCES	HOURS	HOURS	TRUE		COUNTRY	2001-2021		[1,2]
REFRIGERATORS AND FREEZERS	HOURS	HOURS	TRUE		COUNTRY	2001-2021		[1,2]
TV AND MULTIMEDIA	HOURS	HOURS	TRUE		COUNTRY	2001-2021		[1,2]
WASHING MACHINES	HOURS	HOURS	TRUE		COUNTRY	2001-2021		[1,2]
RES SPACE HEATING	KWH	KWH	NO	HOUSEHOLD USEFUL SURFACE AREA	COUNTRY	2001-2021	TECHNOLOGY	[1,2]
RES WATER HEATING	KWH	KWH	NO	HOUSEHOLDS	COUNTRY	2001-2021	TECHNOLOGY	[1,2]
RES SPACE COOLING	KWH	KWH	NO	HOUSEHOLD USEFUL SURFACE AREA	COUNTRY	2001-2021	TECHNOLOGY	[1,2]
RES COOKING	KWH	KWH	NO	HOUSEHOLDS	COUNTRY	2001-2021	TECHNOLOGY	[1,2]
SER SPACE HEATING	KTOE	KTOE	NO	TOTAL SERVICES USEFUL SURFACE AREA	COUNTRY	2001-2021	TECHNOLOGY	[1,2]
SER WATER HEATING	KTOE	KTOE	NO	TOTAL SERVICES USEFUL SURFACE AREA	COUNTRY	2001-2021	TECHNOLOGY	[1,2]

SUBSECTOR	INPUT UNIT	SERVICE DEMAND UNIT	STOCK DEPENDENT	DRIVER	INPUT DATA: GEOGRAPHY	INPUT DATA: YEAR(S)	ADDITIONAL DETAIL	SOURCE
SER SPACE COOLING	KTOE	KTOE	NO	TOTAL SERVICES USEFUL SURFACE AREA	COUNTRY	2001-2021	TECHNOLOGY	[1,2]
HEAVY GOODS VEHICLES - DOMESTIC	KM	KM	NO	GDP	COUNTRY	2001-2021		[1,2]
HEAVY GOODS VEHICLES - INTERNATIONAL	KM	KM	NO	GDP	COUNTRY	2001-2021		[1,2]
LIGHT COMMERCIAL VEHICLES	KM	KM	NO	GDP	COUNTRY	2001-2021		[1,2]
MOTOR COACHES, BUSES AND TROLLEY BUSES	KM	KM	NO	POPULATION	COUNTRY	2001-2021		[1,2]
PASSENGER CARS	KM	KM	NO	POPULATION	COUNTRY	2001-2021		[1,2]

Demand subsectors with technology stocks also require technology-specific parameters for cost and performance. These input sources by subsector and technology-type are shown in Table 13.

Table 12 Demand technology inputs for Method A/B subsectors

SUBSECTOR	TECHNOLOGIES	SOURCE
RES SPACE HEATING	ALL	COST:[3] EFFICIENCY: [4]
RES SPACE COOLING	ALL	COST:[3] EFFICIENCY: [3]
RES WATER HEATING	ALL	COST:[3] EFFICIENCY: [4]
RES COOKING		COST:[3] EFFICIENCY: [4]
CLOTHES DRYERS	ALL	COST:[4] EFFICIENCY: [1]
DISHWASHERS	ALL	COST:[4] EFFICIENCY: [1]
ICT EQUIPMENT	ALL	COST:[4] EFFICIENCY: [1]
OTHER APPLIANCES	ALL	COST:[4] EFFICIENCY: [1]
REFRIGERATORS AND FREEZERS	ALL	COST:[4] EFFICIENCY: [1]
TV AND MULTIMEDIA	ALL	COST:[4]

SUBSECTOR	TECHNOLOGIES	SOURCE
		EFFICIENCY: [1]
WASHING MACHINES	ALL	COST:[4] EFFICIENCY: [1]
SER SPACE HEATING	ALL	COST:[3] EFFICIENCY: [4]
SER SPACE COOLING	ALL	COST:[3] EFFICIENCY: [3]
SER WATER HEATING	ALL	COST:[3] EFFICIENCY: [4]
HEAVY GOODS VEHICLES - DOMESTIC	ALL	COST: [5] EFFICIENCY: [1,2]
HEAVY GOODS VEHICLES - INTERNATIONAL		COST: [5] EFFICIENCY: [1,2]
LIGHT COMMERCIAL VEHICLES		COST: [5] EFFICIENCY: [1,2]
MOTOR COACHES, BUSES AND TROLLEY BUSES		COST: [5] EFFICIENCY: [1,2]
PASSENGER CARS		COST: [6] EFFICIENCY: [1,2]

Table 13 the data sources for service demand projections for subsectors represented with Method C (3.3.3.3), and Table 14 shows the data sources for service efficiency for these subsectors.

Table 13

SUBSECTOR	UNIT	DRIVER	INPUT DATA: GEOGRAPHY	OTHER DOWNSCALING METHOD	INPUT DATA: YEAR(S)	ADDITIONAL DETAIL	SOURCE
AVIATION - FREIGHT: EXTRA-EU	TONNE KILOMETERS	GDP	COUNTRY		2000-2021		[1,2]
AVIATION - FREIGHT: INTRA-EU	TONNE KILOMETERS	GDP	COUNTRY		2000-2021		[1,2]
AVIATION - PASSENGER: EXTRA-EU	KILOMETERS	POPULATION	COUNTRY		2000-2021		[1,2]
AVIATION - PASSENGER: INTRA-EU	KILOMETERS	POPULATION	COUNTRY		2000-2021		[1,2]
BUNKERS: EXTRA-EU	TONNE KILOMETERS	GDP	COUNTRY		2000-2021		[1,2]
COASTAL SHIPPING AND INLAND WATERWAYS	TONNE KILOMETERS	GDP	COUNTRY		2000-2021		[1,2]
FREIGHT RAIL	TONNE KILOMETERS	GDP	COUNTRY		2000-2021		[1,2]
POWERED 2-WHEELERS	KILOMETERS	POPULATION	COUNTRY		2000-2021		[1,2]
RES LIGHTING	LUMEN_HOUR	HOUSEHOLD USEFUL SURFACE AREA	COUNTRY		2000-2021		[1,2]
BUNKERS: INTRA-EU	TONNE KILOMETERS	GDP	COUNTRY		2000-2021		[1,2]
IRON AND STEEL - EAF	TONNE		COUNTRY		2000-2021	END-USE	[1,2]

SUBSECTOR	UNIT	DRIVER	INPUT DATA: GEOGRAPHY	OTHER DOWNSCALING METHOD	INPUT DATA: YEAR(S)	ADDITIONAL DETAIL	SOURCE
IRON AND STEEL - INTEGRATED STEELWORKS	TONNE		COUNTRY		2000-2021	END-USE	[1,2]
CERAMICS & OTHER NMM	TONNE		COUNTRY		2000-2021	END-USE	[1,2]
BASIC CHEMICALS	TONNE		COUNTRY		2000-2021	END-USE	[1,2]
OTHER CHEMICALS	TONNE		COUNTRY		2000-2021	END-USE	[1,2]
ALUMINIUM	TONNE		COUNTRY		2000-2021	END-USE	[1,2]
OTHER NON-FERROUS METALS	TONNE		COUNTRY		2000-2021	END-USE	[1,2]
MACHINERY EQUIPMENT	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]
OTHER INDUSTRIAL SECTORS	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]
PULP, PAPER AND PRINTING	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]
PHARMACEUTICAL PRODUCTS ETC.	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]
TEXTILES AND LEATHER	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]
TRANSPORT EQUIPMENT	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]
WOOD AND WOOD PRODUCTS	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]
CEMENT	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]
BASIC CHEMICALS - NON-ENERGY	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]
FOOD, BEVERAGES AND TOBACCO	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]
GLASS PRODUCTION	2015 EUROS (VALUE ADDED)		COUNTRY		2000-2021	END-USE	[1,2]

Table 14

SUBSECTOR	INPUT DATA: GEOGRAPHY	OTHER DOWNSCALING METHOD	INPUT DATA: YEAR(S)	ADDITIONAL DETAIL	SOURCE
AVIATION - FREIGHT: EXTRA-EU	COUNTRY		2000-2021		[1,2]
AVIATION - FREIGHT: INTRA-EU	COUNTRY		2000-2021		[1,2]
AVIATION - PASSENGER: EXTRA-EU	COUNTRY		2000-2021		[1,2]
AVIATION - PASSENGER: INTRA-EU	COUNTRY		2000-2021		[1,2]
BUNKERS: EXTRA-EU	COUNTRY		2000-2021		[1,2]
COASTAL SHIPPING AND INLAND WATERWAYS	COUNTRY		2000-2021		[1,2]
FREIGHT RAIL	COUNTRY		2000-2021		[1,2]
POWERED 2-WHEELERS	COUNTRY		2000-2021		[1,2]
RES LIGHTING	COUNTRY		2000-2021		[1,2]
BUNKERS: INTRA-EU	COUNTRY		2000-2021		[1,2]
IRON AND STEEL - EAF	COUNTRY		2000-2021		[1,2]

SUBSECTOR	INPUT DATA: GEOGRAPHY	OTHER DOWNSCALING METHOD	INPUT DATA: YEAR(S)	ADDITIONAL DETAIL	SOURCE
IRON AND STEEL - INTEGRATED STEELWORKS	COUNTRY		2000-2021		[1,2]
CERAMICS & OTHER NMM	COUNTRY		2000-2021		[1,2]
BASIC CHEMICALS	COUNTRY		2000-2021		[1,2]
OTHER CHEMICALS	COUNTRY		2000-2021		[1,2]
ALUMINIUM	COUNTRY		2000-2021		[1,2]
OTHER NON-FERROUS METALS	COUNTRY		2000-2021		[1,2]
MACHINERY EQUIPMENT	COUNTRY		2000-2021		[1,2]
OTHER INDUSTRIAL SECTORS	COUNTRY		2000-2021		[1,2]
PULP, PAPER AND PRINTING	COUNTRY		2000-2021		[1,2]
PHARMACEUTICAL PRODUCTS ETC.	COUNTRY		2000-2021		[1,2]
TEXTILES AND LEATHER	COUNTRY		2000-2021		[1,2]
TRANSPORT EQUIPMENT	COUNTRY		2000-2021		[1,2]
WOOD AND WOOD PRODUCTS	COUNTRY		2000-2021		[1,2]
CEMENT	COUNTRY		2000-2021		[1,2]
BASIC CHEMICALS - NON-ENERGY	COUNTRY		2000-2021		[1,2]
FOOD, BEVERAGES AND TOBACCO	COUNTRY		2000-2021		[1,2]
GLASS PRODUCTION	COUNTRY		2000-2021		[1,2]

Table 16 shows baseline energy demand projection input data sources for subsectors employing Method D (3.3.3.4).

Table 15 Energy demand data sources for Method D subsectors

SUBSECTOR	UNIT	DRIVER	INPUT DATA: GEOGRAPHY	OTHER DOWNSCALING METHOD	INPUT DATA: YEAR(S)	ADDITIONAL DETAIL	SOURCE
SER CATERING	KTOE	TOTAL SERVICES USEFUL SURFACE AREA	COUNTRY		2000-2021		[1,2]
VENTILATION AND OTHERS	KTOE	TOTAL SERVICES USEFUL SURFACE AREA	COUNTRY		2000-2021		[1,2]
STREET LIGHTING	KTOE	TOTAL SERVICES USEFUL SURFACE AREA	COUNTRY		2000-2021		[1,2]
BUILDING LIGHTING	KTOE	TOTAL SERVICES USEFUL SURFACE AREA	COUNTRY		2000-2021		[1,2]
COMMERCIAL REFRIGERATION	KTOE	TOTAL SERVICES USEFUL SURFACE AREA	COUNTRY		2000-2021		[1,2]
MISCELLANEOUS BUILDING TECHNOLOGIES	KTOE	TOTAL SERVICES USEFUL SURFACE AREA	COUNTRY		2000-2021		[1,2]
ICT AND MULTIMEDIA	KTOE	TOTAL SERVICES USEFUL SURFACE AREA	COUNTRY		2000-2021		[1,2]

SUBSECTOR	UNIT	DRIVER	INPUT DATA: GEOGRAPHY	OTHER DOWNSCALING METHOD	INPUT DATA: YEAR(S)	ADDITIONAL DETAIL	SOURCE
AGRICULTURE, FORESTRY, AND FISHING	KTOE		COUNTRY		2000-2021	END-USE DETAIL	[1,2]
PASSENGER RAIL	KTOE		COUNTRY		2000-2021	RAIL TYPE	[1,2]

Energy service demand in the model in general is taken from the AEO. In cases where additional granularity is needed for downscaling or to show an underlying trend, *demand drivers* are used (listed as 'driver' in the tables above and below). Table 17 describes the data used for this purpose including the original level of geographical granularity. This data is then mapped to the model's selected geographies as required.

Table 16 Demand Drivers

Driver	Geographic Granularity	Data Year (s)	Additional Detail	Source
Total services useful surface area	Country	2000-2021		[1,2]
Heating degree days	Country	2000-2021		[1,2]
households	Country	2000-2021		[1,2]
Household useful surface area	Country	2000-2021		[1,2]
Gdp	Country	2000 – 2050		[7]
population	Country	2000 – 2050		[8]

Table 18 shows the data sources for energy service demand load shapes by subsector, which are used to build system-level load shapes bottom-up.

Table 17 Load shape sources

Shape Name	Used By	Input Data Geography	Input Temporal Resolution	Source
Bulk Electricity System Load	Initial electricity reconciliation, all subsectors not otherwise given a shape	Country	Hourly	ENTSO-E
Flat shape	heavy goods vehicles	n/a	n/a	n/a
residential_electricity	Residential subsectors not otherwise given a shape	Country	Hourly	Evolved Energy Research decomposition of ENTSO-E system load data using assumed load factors by sector

Shape Name	Used By	Input Data Geography	Input Temporal Resolution	Source
commercial_electricity	Commercial subsectors not otherwise given a shape			
industry_electricity	Industrial subsectors not otherwise given a shape			
EV	Passenger vehicles	Europe	Month, hour, workday/non-workday	Evolved Energy Research analysis of 2016 National Household Travel Survey in the United States
water_heating	Water heating subsectors	Country	Month, hour, workday/non-workday	Marlon Schlemminger (2021). ML_Household_End-use_Load-profiles [Data set]. LUIS.
electric_furnace_res	Residential HVAC technologies	NUTS1	Hourly	Evolved Energy Research Regressions trained on NREL building simulations in select U.S. cities for a typical meteorological year and then run on NUTS1 level HDD and CDD.
high_efficiency_central_ac_res				
reference_central_ac_res				
high_efficiency_heat_pump_cooling_res				
high_efficiency_heat_pump_heating_res				
reference_room_ac_res				
high_efficiency_room_ac_res				
low-tech_heat_pump_heating_res_hybrid50				
commercial_heat_pump_hybrid50	Commercial HVAC technologies			
boiler_com_hybrid50				
dx_ac_com				
chiller_com				
boiler_com				
furnace_com				
commercial_heat_pump				

2.2. Supply–Side Data Description

The supply-side data used in RIO has a high-level of geographic granularity in terms of resource availability for biomass, renewable energy, geologic sequestration, etc. It also has very detailed technology representations for both electricity technologies as well non-electricity technologies like fuel conversion, direct air capture, and hydrogen production.

Table 18 Supply-side technology data sources

SECTOR	TECHNOLOGY	CAPITAL COSTS	FIXED OM	VARIABLE OM	EFFICIENCY/CAPACITY FACTOR	RESOURCE POTENTIAL
ENERGY	BIO-GASIFICATION CH4 W/CC	[9]	[9]	[9]	[9]	
ENERGY	BIO-GASIFICATION FISCHER-TROPSCH W/CC	[9]	[9]	[9]	[9]	

SECTOR	TECHNOLOGY	CAPITAL COSTS	FIXED OM	VARIABLE OM	EFFICIENCY/CAPACITY FACTOR	RESOURCE POTENTIAL
ENERGY	BIO-GASIFICATION H2 W/CC	[9,10]	[9,10]	[9,10]	[9,10]	
ENERGY	BIOMASS FAST PYROLYSIS W/CC	[11]	[11]	[11]	[11]	
ENERGY	BIOMASS POWER	[12]	[12]	[12]	[12]	
ENERGY	DIRECT AIR CAPTURE – SOLID SORBENT	[13]	[13]	[13]	EER ANALYSIS; [13]	
ENERGY	ELECTRIC BOILER	[14]	[14]	[14]	BY ASSUMPTION	
ENERGY	ELECTROLYSIS H2	[15]	[15]	[15]	[16]	
ENERGY	FISCHER-TROPSCH LIQUIDS	[17]	[17]	[17]	[18]	
ENERGY	GAS COMBINED CYCLE	[12]	[12]	[12]	[12]	
ENERGY	GAS COMBINED CYCLE W/CC	[12]	[12]	[12]	[12]	
ENERGY	GAS COMBUSTION TURBINE	[12]	[12]	[12]	[12]	
ENERGY	GAS W/CC - RETROFIT	[12]	[12]	[12]	[12]	
ENERGY	H2 BOILER	[14] BY ASSUMPTION	[14] BY ASSUMPTION	[14] BY ASSUMPTION	BY ASSUMPTION	
ENERGY	H2 STORAGE SALT CAVERN	[19]	[19]	[19]	BY ASSUMPTION	[20]
ENERGY	H2 STORAGE UNDERGROUND PIPES	[19]	[19]	[19]	BY ASSUMPTION	
ENERGY	HABER-BOSCH	[21]	[21]	[21]	[22]	
ENERGY	HEAT PUMP	[14]	[14]	[14]	[14]	
ENERGY	LI-ION	[12]	[12]	[12]	[12]	
ENERGY	LNG_FACILITIES	[23]	[23]	[23]	BY ASSUMPTION	
ENERGY	LONG DURATION STORAGE	[24]	[24]	[24]	[24]	
ENERGY	METHANATION	[17]	[17]	[17]	[18]	
ENERGY	NUCLEAR HTGR SMR – REACTOR	[25]	[25]	[25]	[25]	
ENERGY	NUCLEAR HTGR SMR - STEAM TURBINE GENERATOR	[25]	[25]	[25]	[25]	
ENERGY	NUCLEAR HTGR SMR - STEAM TURBINE GENERATOR W/CHP	BY ASSUMPTION	BY ASSUMPTION	[25]	[25]	
ENERGY	NUCLEAR HTGR SMR - TES	[26]	[26]	[26]	[26]	
ENERGY	NUCLEAR LWR SMR – REACTOR	[25]	[25]	[25]	[25]	
ENERGY	NUCLEAR LWR SMR - STEAM TURBINE GENERATOR	[25]	[25]	[25]	[25]	
ENERGY	NUCLEAR LWR SMR - STEAM TURBINE GENERATOR W/CHP	BY ASSUMPTION	BY ASSUMPTION	[25]	[25]	
ENERGY	NUCLEAR LWR SMR - TES	[26]	[26]	[26]	[26]	

SECTOR	TECHNOLOGY	CAPITAL COSTS	FIXED OM	VARIABLE OM	EFFICIENCY/CAPACITY FACTOR	RESOURCE POTENTIAL
ENERGY	OFFSHORE WIND	[12]	[12]	[12]	[12]	INTERNAL ANALYSIS
ENERGY	ONSHORE WIND	[12]	[12]	[12]	[12]	INTERNAL ANALYSIS
ENERGY	PIPELINE GAS BOILER	[14]	[14]	[14]	BY ASSUMPTION	
ENERGY	ROOFTOP SOLAR	[12]	[12]	[12]	[12]	[27]
ENERGY	STEAM REFORMING	[16]	[16]	[16]	[16]	
ENERGY	STEAM REFORMING W/CC	[16]	[16]	[16]	[16]	
ENERGY	TES	[26]	[26]	[26]	[26]	
ENERGY	TES - RESISTOR	[26]	[26]	[26]	[26]	
ENERGY	UTILITY-SCALE SOLAR	[12]	[12]	[12]	[12]	INTERNAL ANALYSIS

Table 19 RIO Commodity Inputs

CATEGORY	COMMODITY	POTENTIAL	COST
ENERGY SYSTEM	AGRICULTURAL WASTE	[28]	[28]
ENERGY SYSTEM	BIOETHANOL BARLEY, WHEAT, GRAIN MAIZE, OATS, OTHER CEREALS AND RYE	[28]	[28]
ENERGY SYSTEM	SUGAR FROM SUGAR BEET	[28]	[28]
ENERGY SYSTEM	MISCANTHUS, SWITCHGRASS, RCG	[28]	[28]
ENERGY SYSTEM	WILLOW	[28]	[28]
ENERGY SYSTEM	POPLAR	[28]	[28]
ENERGY SYSTEM	FUELWOOD RESIDUES	[28]	[28]
ENERGY SYSTEM	RESIDUES FROM LANDSCAPE CARE	[28]	[28]
ENERGY SYSTEM	MANURE SOLID, LIQUID	[28]	[28]
ENERGY SYSTEM	SUNFLOWER, SOYA SEED	[28]	[28]
ENERGY SYSTEM	MUNICIPAL WASTE	[28]	[28]
ENERGY SYSTEM	RAPE SEED	[28]	[28]
ENERGY SYSTEM	SLUDGE	[28]	[28]
ENERGY SYSTEM	FUELWOODRW	[28]	[28]
ENERGY SYSTEM	C&P_RW	[28]	[28]
ENERGY SYSTEM	SECONDARY FORESTRY RESIDUES - WOODCHIPS	[28]	[28]
ENERGY SYSTEM	WOOD PELLET IMPORTS	[29]	[29,30]
ENERGY SYSTEM	NATURAL GAS	[31]	[32]
ENERGY SYSTEM	LNG	[31]	[32]
ENERGY SYSTEM	COAL	[31]	
ENERGY SYSTEM	OIL	[31]	
ENERGY SYSTEM	LIGNITE	[33]	
ENERGY SYSTEM	GEOLOGIC SEQUESTRATION	[34]	
ENERGY SYSTEM	HYDROGEN IMPORT	[35]	[35]

CATEGORY	COMMODITY	POTENTIAL	COST
LAND SECTOR	LAND SINK - BASELINE	[36]	
LAND SECTOR	LAND SINK - MITIGATION	[36]	
NON-CO2	AEROSOLS/METERD DOSE INHALERS: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	ALUMINUM PRODUCTION: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	COAL MINING: CH4 REDUCTIONS	[37]	[37]
NON-CO2	CROPLANDS: N2O REDUCTIONS	[37]	[37]
NON-CO2	ELECTRIC POWER SYSTEMS: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	FIRE EXTINGUISHERS: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	FOAM BLOWING: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	HCFC-22 PRODUCTION: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	LANDFILLS: CH4 REDUCTIONS	[37]	[37]
NON-CO2	LIVESTOCK: CH4 REDUCTIONS	[37]	[37]
NON-CO2	LIVESTOCK: N2O REDUCTIONS	[37]	[37]
NON-CO2	MAGNESIUM PRODUCTION: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	NITRIC AND ADIPIC ACID PRODUCTION: N2O REDUCTIONS	[37]	[37]
NON-CO2	PV CELL MANUFACTURING: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	REFRIGERATION AND AIR CONDITIONING EQUIPMENT: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	RICE CULTIVATION: CH4 REDUCTIONS	[37]	[37]
NON-CO2	SEMICONDUCTOR MANUFACTURING: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	SOLVENTS: F-GASES REDUCTIONS	[37]	[37]
NON-CO2	WASTEWATER: CH4 REDUCTIONS	[37]	[37]
NON-CO2	WASTEWATER: N2O REDUCTIONS	[37]	[37]

Table 20 RIO blend delivery cost sources

BLEND	DELIVERY COSTS
HYDROGEN BLEND	[38]
PIPELINE GAS BLEND	[39]
ELECTRICITY	[39]

S3. Models

3.1. RIO

3.1.1. Overview

RIO is a highly temporally-resolved capacity expansion model that is designed to faithfully represent energy systems from today to any imagined future. It does so with an emphasis on flexibility of resource and technology configurations. RIO also includes a parameterization of the land-use and non-energy, non-CO_2 sectors, allowing for the representation of truly economy-wide emissions reduction pathways.

Capacity expansion modeling typically refers to a linear optimization modeling framework that optimizes *investments in* and *operations of* electricity systems; These are forward-looking models that effectively trade off costs in building (i.e. generator investments) and running (i.e. generator fuel costs) the system subject to a variety of constraints including electricity policy and emissions targets. These modeling frameworks have been used in the past for a variety of purposes. Some of the main historical applications of capacity expansion models include:

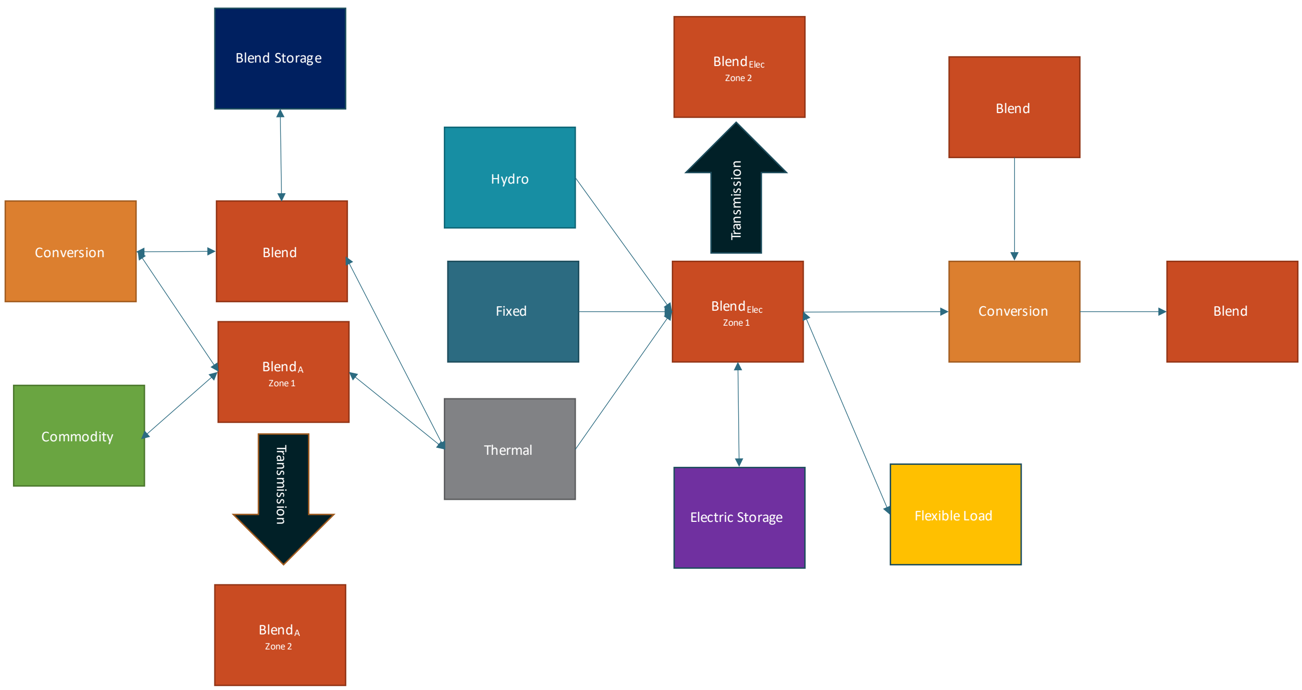
1. Narrow resource-selection decisions
    - Principally an investigation of the cost-effectiveness of individual thermal resources. Highly temporally resolved, but limited in terms of investment decisions. It doesn't ask the question of universal resource selection, but operates as a screening curve for an individual resource.
2. Criteria pollutant analyses.
    - Emphasis on individual plant detail, pollution control equipment, pollution permitting costs, and thermal power plant operations necessary to faithfully represent criteria pollutant emissions.
3. Near-term policy targets.
    - Principally for analysis of RPS policies with up to 50% renewable penetration. These analyses often don't cross thresholds wherein higher temporal resolution becomes critical; the emphasis is on spatially and technologically resolved resource locations, performance, and transmission costs.

The historical applications of capacity expansion matter because the initially intended context and objectives of modeling platforms significantly affect their emphasis and structural design. Capacity expansion modeling is, in principle, simple. Given infinite computing power, all capacity expansion models would be the same. However, in developing real capacity expansion models in a world with computational limits, simplifications have to be made to make a problem tractable without significant deviations from the answer that woud be provided by a theoretically perfect model.

Capacity expansion models designed to answer one set of questions are generally inappropriate for analyzing others. RIO was designed from the ground-up to answer the questions posed by deep decarbonization. In addition to the core elements of any capacity expansion framework (e.g. system reliability), the deep decarbonization emphasis is reflected in the design and features of the RIO model. These include its ability to balance temporal and spatial representations; and economy-wide approach that reduces analytical boundary conditions and identifies unique sector coupling opportunities; and a unique flexibility in technologies. The sections below provide a high-level overview of the analytical framework in RIO.

3.1.2. Model Components

Figure 4 RIO model component schematic



3.1.2.1. Blend

Blends represent aggregation points in the model. The fundamental characteristic of blends is fungibility with regards to inputs. So, for example, pipeline gas (blend) may be decarbonized with a reduction in natural gas being displaced with biogas. This is an altered composition of the inputs to the blend, but the users of that blend are still demanding the same product of pipeline gas, so there is substitutability for inputs while maintaining the same output. These blends are where end-use demands calculated by EnergyPATHWAYS are seen by the model and where intraregional transmission and distribution costs and infrastructure are determined.

- Key Input Characteristics: Costs, Losses, Inputs, Operational Timestep, Physical/Non-Physical
- Ex. Pipeline Gas, Diesel Fuel, CO_2 Utilization, Hydrogen

3.1.2.2. Conversion

Conversions are supply technologies that *convert* blends to other blends. They can be specified with multiple input blends and can themselves be inputs to other blends.

- Key Input Characteristics: Efficiency (input blends), Capital Cost, Fixed OM, Variable OM, Output Blends, Electricity Reliability Required, Operational Timestep, Tradability (between zones)
- Ex. Bio – Fuels, Direct Air Capture, Electrolysis

3.1.2.3. Commodity

Commodities are a model component that can be used in a variety of different ways but are unique in that they are not represented with capacity build decisions. They are instead viewed as discrete products by the model.

- Key Input Characteristics: Potential, Cost, Emissions, Tradability (between zones)
- Ex. Biomass feedstocks, Natural gas primary energy, Geologic sequestration potential

3.1.2.4. Blend Storage

Blend storage technologies allow for the storing of blend throughput where the model is tracking the balance of supply and demand on a sub-annual basis.

- Key Inputs: Capital Cost, Fixed O&M, Variable O&M, Efficiency, Operational Timestep
- Ex. Salt Cavern H2 Storage, Thermal Energy Storage

3.1.2.5. Thermal Power Plant

Thermal powerplants are technologies that take an input of a blend (other than electricity) and produce electricity. They can also have coproducts that are blends. For example, a CHP plant may produce electricity with steam as a coproduct.

- Key Inputs: Capital Cost, Fixed O&M, Variable O&M, Efficiency, Dual Fuel (T/F), Ramp Rate, Min. Annual Capacity Factor, Maximum Annual Capacity Factor, Eligible to Provide Ancillary Services (T/F), Dependability
- Ex. Combined-Cycle Gas Power Plants, Coal Power Plants

3.1.2.6. Fixed Power Plant

Fixed powerplants are technologies that have "fixed" output potential, like wind and solar that dictate their generation of electricity on an hourly basis.

- Key Inputs: Capital Cost, Fixed O&M, Variable O&M, Hourly Capacity Factors, Eligibe to Provide Ancillary Services (T/F)
- Ex. Onshore Wind, Utility-Scale Solar PV

3.1.2.7. Hydro

Hydro powerplants are technologies that can generate electricity between an envelope of minimum and maximum hourly capacity factors with the additional constraint of energy budgets (i.e. cumulative capacity factors) applied over longer timescales.

- Key Inputs: Capital Cost, Fixed O&M, Variable O&M, Hourly Capacity Factors (Min/Max), Energy Budgets, Eligible to Provide Ancillary Services (T/F), Dependability,
- Ex. Dispatchable Hydro

3.1.2.8. Electricity Storage

Electricity storage technologies are those that can charge or discharge electricity hourly.

- Key Inputs: Capital Cost, Fixed O&M, Variable O&M, Efficiency, Self-Discharge Rate, Minimum Duration, Maximum Duration, Eligible to Provide Ancillary Services (T/F)
- Ex. Li-Ion, Vanadium Flow, Long Duration Storage

3.1.2.9. Flexible Load

Flexible loads are able to increment or decrement energy from a base electricity load. They are constrained by maximum hourly increment or decrement amounts and the maximum timescale of the energy shift. For example, if a load (ex. Residential water heating) has a maximum shift of four hours, load decremented in hr_0 would have to be offset by a load increment by hr_4.

- Key Inputs: % of Load Flexible, Maximum Advance (hours), Maximum Delay (hours), Variable Cost (cost of energy deviated from load setpoint).
- Ex. Water Heating, Air Conditioning, Space Heating, Light-Duty Autos, Light-Duty Trucks

3.1.2.10. Transmission

Transmission allows for the transfer of blend throughput from a blend in one zone to a blend in another zone. In practice, transmission functionality is used principally to represent electricity transmission or pipelines.

- Key Inputs: Capital Cost, Fixed O&M, Losses, Operational Timestep, Hurdle Rates, Dependability (Electric Transmission-Only), Deemed Emissions Rates (Electric Transmission-Only)
- Ex. Electricity Transmission, H2 Pipelines, Ammonia Pipelines, CO_2 Pipelines

3.1.3. Temporal Representation

RIO's representation of time is unique in that it can represent both short-term and long-term system operations simultaneously while maintaining problem tractability. This requires compressing the theoretical maximum number of represented time-slices to a more tractable number.

Table 21 Time parameterization examples

TEMPORAL REPRESENTATION	DESCRIPTION	TIME SLICES
THEORETICAL MAXIMUM TIME SLICES	(60S/M*60M/H*8760H/Y*30Y)	9.46E8
PARAMETERIZED SUB-HOURLY RESOURCE PERFORMANCE	RIO PARAMETERIZES RESOURCE RAMP RATES AND PRODUCTION RELIABILITY (WIND/SOLAR) TO CHARACTERIZE RESOURCE PERFORMANCE WITHOUT EXPLICITLY MODELING SUB-HOURLY OPERATIONS	2.63E5

YEAR SLICES	INSTEAD OF REPRESENTING EVERY YEAR, WHERE CHANGES BETWEEN SYSTEM CONDITIONS AND POLICY MIGHT BE MARGINAL, RIO ESTABLISHES A SCHEDULE OF THE MOST CRITICAL YEARS AND MODEL THESE SPECIFICALLY.	6.13E4
DAY SAMPLING/DAY LINKAGES	INSTEAD OF REPRESENTING EVERY HOUR OF THE YEAR, WE DAY SAMPLE AND CREATE A SYNTHETIC YEAR OF FULLY-REPRESENT DAYS (REFERRED TO AS SAMPLES) AND MAPPED ENERGY BALANCES (REFERRED TO AS PERIODS) IN ORDER TO ASSESS LONG-DURATION STORAGE	8995

3.1.3.1. Day Sampling

RIO utilizes the 8760 hourly profiles for electricity demand EnergyPATHWAYS, technology-specific generation profiles for wind and solar, and optimizes operations for a subset of representative days (sample days) and maps them to the rest of the year. Operations are performed over sequential hourly timesteps. To ensure that the sample days can reasonably represent the full set of days over the year, RIO uses clustering algorithms on the initial 8760 data sets.

The challenge of day sampling in any modeling platform is faithfully representing both extreme conditions, which drive investment for system reliability, while also accurately representing annual averages for things like renewable resource capacity factors. The clustering process is designed to identify days that represent a diverse set of potential system conditions, including different fixed generation profiles and load shapes. The number of sample days impacts the total runtime of the model. A balance is struck in the day selection process between representation of system conditions through number of sample days, and model runtime. Clustering and sample day selection occurs for each model year in the time horizon.

RIO automates the day sampling for every model year based on inputs supplied in the model setup process. The parameters used for day binning are shown in Table 22.

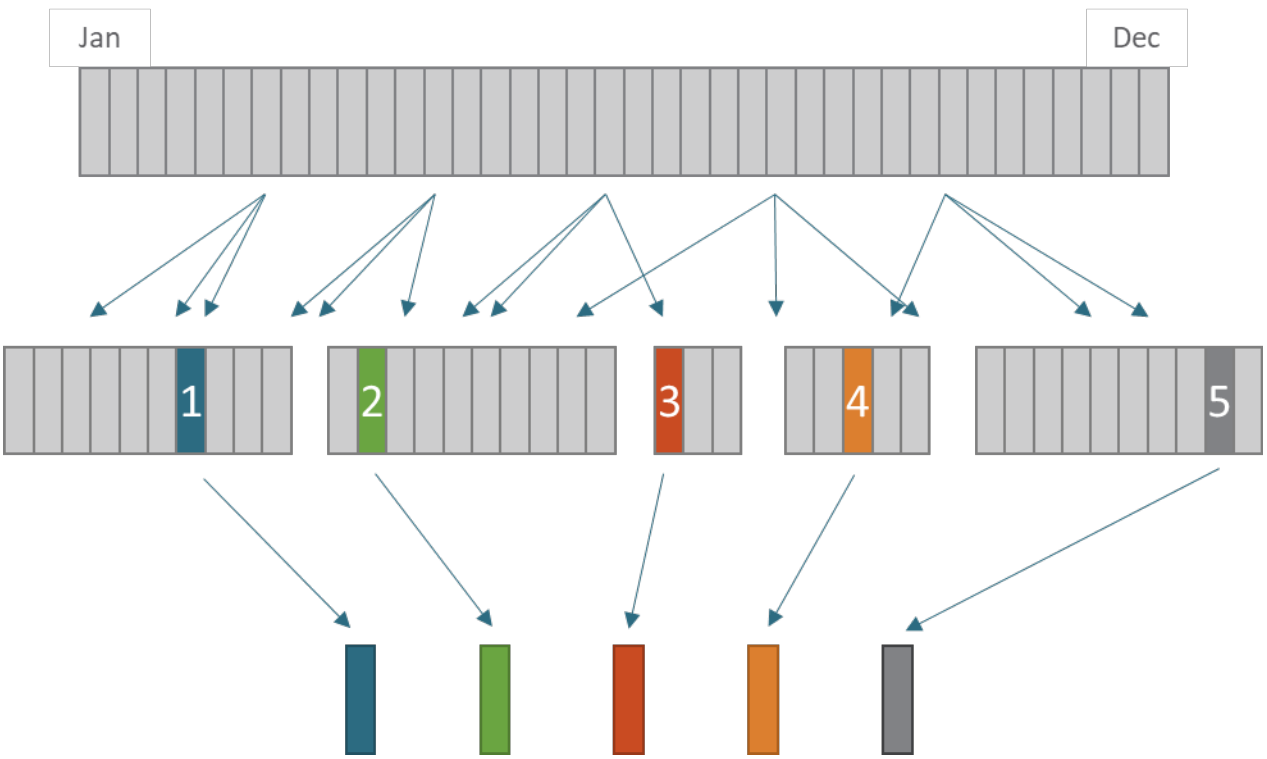
Table 22 Day sampling characteristics

BINNING CHARACTERISTIC	DESCRIPTION
HOURLY NET LOAD	DAILY NET LOAD BASED ON A FIRST-ORDER ESTIMATION OF RENEWABLE DEPLOYMENT.
MAXIMUM NET LOAD	MAXIMUM NET LOAD OVER THE DAY.
SUM OF NET LOAD ENERGY	SUM OF DAILY NET LOAD
SUM OF GROSS LOAD ENERGY	SUM OF DAILY END-USE LOAD.
DAY OF YEAR	VARIABLE REPRESENTING WHEN DURING THE YEAR THE DAY OCCURS

RENEWABLE CAPACITY FACTOR	DAILY CAPACITY FACTORS OF SPECIFIED RENEWABLE GENERATION TYPES (ONSHORE WIND, OFFSHORE WIND, SOLAR)

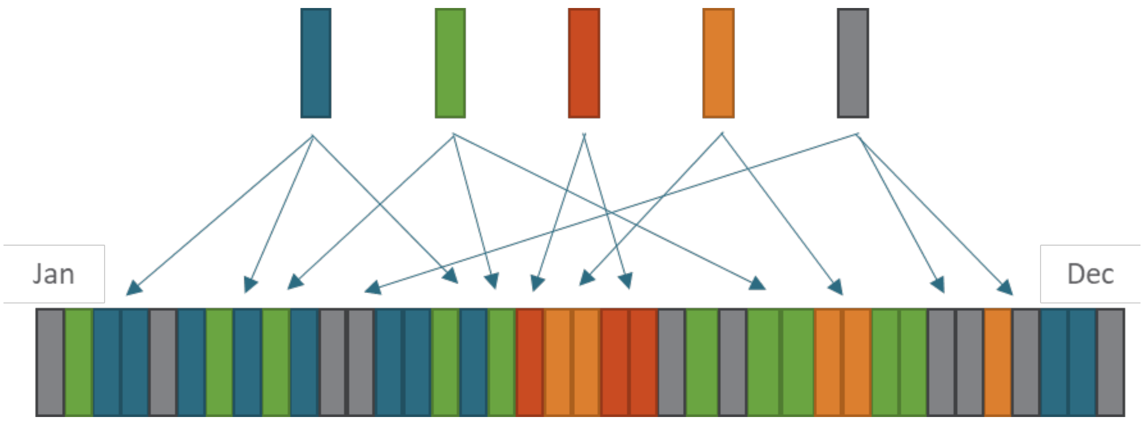
Once sampling characteristics have been selected, RIO uses clustering algorithms to bin representative days in each modeled year. This process is shown graphically in Figure 5. Each cluster in the second row represents days that were found to be statistically similar based on the supplied characteristics. The archetypal day within the cluster is then extracted and used as the representative day in the rest of the modeling process.

Figure 5 Day clustering to create day samples



After the representative days are selected, the model synthesizes the year based on the cluster associations developed in the day sampling process. This creates a full 365-day representation composed of a reduced set of daily operations, shown in Figure 6.

Figure 6 Full year synthesis based on day samples



RIO provides an assessment of day sampling performance to allow for tuning of day selection weights and characteristics in order to best represent the system being modeled.

3.1.4. Spatial Representation

RIO represents discrete demand/supply regions flexibly based on model run configurations. This zonal representation becomes the basic unit of constraint enforcement in the model formulation in terms of energy balances and electricity reliability provision. These zones can have unique enforced policy regimes, resource availability, hourly load and resource shapes, existing generators, etc. They can be linked to other zones with policy regimes and physical transmission ties.

3.1.5. Other Model Features

3.1.5.1. Operations

Time sequential operations are an important component of determining the value of a portfolio of energy system resources. These model components work in complimentary fashion to serve the needs of the system. Whether a portfolio of resources is optimal or not depends on whether it can maintain system reliability (supply the needs of the system in every zone at every modeled timescale) and whether it is cheaper than other portfolios. RIO determines the least-cost system constrained by the operational realities of the portfolio technologies.

This is a division between those resources that do not have any multiday constraints on their operations, i.e. they can operate in the same way regardless of system conditions, and those resources that will operate differently depending on system condition trends that last longer than a day. An example of the former is a gas generator that can produce the same output regardless of system conditions over time, and an example of the latter is a long-duration storage system whose state of charge is drawn down over time when there is not enough energy to charge it. The long-term category includes all long-term storage mediums.

Operational decisions determine the value of one investment over another, so it is important to capture the detailed contributions and interactions of the many different types of resource that RIO can build.

Thermal

Thermal resources are resources that convert the thermal energy embodied in fuel (e.g. coal, gas, uranium) into electricity. Because the production of electricity is only dependent on fuel inputs, many of these resources are dispatchable (i.e. they can adjust their electricity output based on grid conditions). This dispatchability is limited by additional constraints. For example, if they make steam as a co-product for industrial uses, they are often limited in dispatchability given the need to satisfy multiple demands. Additionally, ramp rates and startup and shutdown operations limit their ability to respond to grid conditions over a certain timeframe.

Fixed

Fixed resources refer to resources that have a "fixed" or endogenously determined hourly output shape. This resource categorization is generally reserved for renewable resources like solar and wind. Unlike thermal resources, the dispatchability of such resources is limited to the ability to "turn off" or curtail their anticipated output.

Hydro

The hydro resource characterization is used for reservoir hydro resources that can change their output profiles subject to water availability, reservoir characteristics, and minimum and maximum operating capacities. Hydro systems (combinations of pumps, turbines, and reservoirs oftentimes existing in series with one another) are complex and are generally represented in the model as a fleet, where systemwide operational constraints can be parameterized from historical data. We generally use historical minimum and maximum output levels monthly, parameterized from historical hydro years. We have two methodologies for enforcing energy budgets in our sample days.

Fixed daily energy budgets

This represents the most conservative approach for representing hydro availability because it presupposes no day-to-day flexibility in the allocation of hydro energy budgets. We sample historical hydro output and the hydro fleet has to allocate that energy budget across the day subject to p_{min} and p_{max} constraints.

Daily cumulative energy constraints

This methodology takes advantage of RIO's unique linking of sample days across the year into a cumulative energy balance representation. In this methodology, analogous to the one used for long-duration electricity storage, we track cumulative hydro output that results from optimized sample output. This hydro output schedule (across the entire year) is constrained by input parameters which establish a temporal envelope in which hydro output can deviate from historical conditions. If we establish a long temporal envelope (i.e. by using an input parameter that establishes an envelope where hydro generation can lead or lag by>30 days) then the hydro has a large amount of temporal flexibility in how it can allocate its energy budget. This can be helpful in addressing seasonal energy balances that arise with the penetration of large amounts of renewable energy.

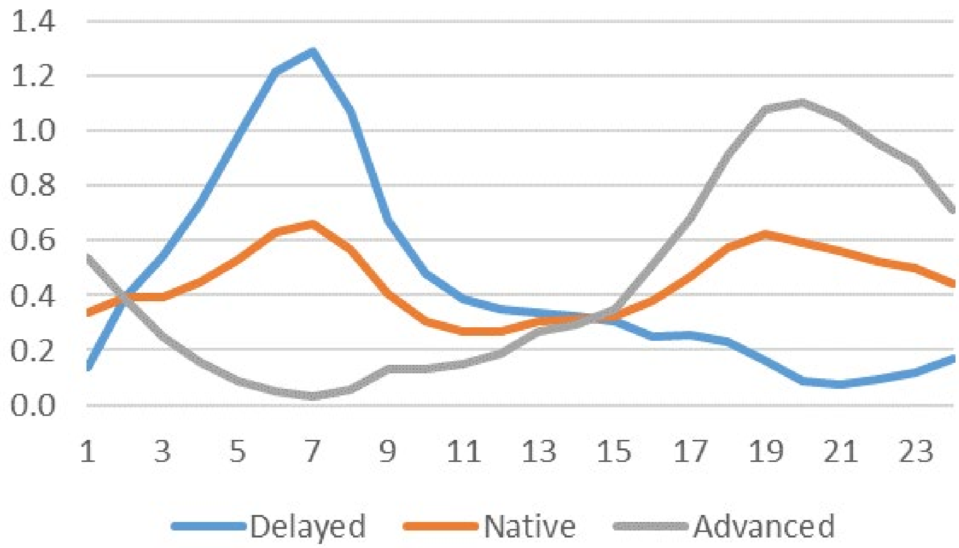
Electricity Storage

Electricity storage is subject to constraints on its input and output power (enforced by limiting such charging and discharging to less than the installed capacity of the resource) as well as state of charge constraints. We assess the necessary investment in storage reservoir capacity as the maximum of short-term state-of-charge (SOC) (assessed within the sample day and assessed hourly) and long-term SOC (assessed with the persistence of storage input/output energy balances across periods). We calculate an availability of short-term SOC based on temporal envelope input parameters that enforce conservatism in daily operations based on the need to reserve SOC to address longer-term imbalances. An input of "annual" completely bifurcates the battery SOC between short and long-term imbalances. An input of “monthly” allows for a monthly reallocation of battery SOC based on system conditions. For example, this would reflect a scenario where it is predictable to system planners on a monthly basis how much SOC needs to be maintained to address longer-term imbalances.

Flexible Load

Flexible loads are end-use loads (electric vehicles, space heating, water heating, etc.) where there can be a delay in the delivery of electricity to a customer without incurring significant costs in terms of customer utility. This is referred to as “latent flexibility”, though there may be necessary investments needed to unlock this flexibility (e.g. controls, smart meters, etc.). RIO models these flexible loads using flexibility envelopes parameterized with the share of end-use energy that is deemed flexible (analogous to customer participation rates) along with the number of hours this energy can be advanced (moved ahead in time from when demand would otherwise occur) or delayed (moved back in time). We parameterize end-use loads differently based on the inherent characteristics of the shape of the native service demand. EVs, for example, have a service demand shape based on a statistical assessment of the arrival time of uncharged batteries to chargers (i.e. the shape peaks when vehicles are likely to be arriving home with less than fully charged batteries). Given this definition, charging can’t be advanced from the native shape (i.e. moved ahead to a time before vehicles arrive home) but it can be delayed. For thermal end-uses, there can be advances or delays, reflecting the ability to pre-heat or pre-cool as well as the ability to delay demand for electricity by taking advantage of lags in temperature changes.

Figure 7 Flexible Load Example Shape



The realized end-use load has to stay within the delayed/advanced energy envelopes. That can be accomplished with deviations above and below the native load shapes. Tighter advance/delay windows and smaller shares of eligible load that is flexible establish more narrow opportunities for load flexibility.

Conversion

Conversion technologies maintain operational flexibility based on user input. Flexibility can be maintained on an hourly basis (similar to electricity generation technologies); sample-day basis (i.e. output has to be the same across all hours on a sample day but can vary between sample days); or annual basis (output has to be flat across all hours of the year). This framework is used to represent the operational realities of non-electricity technologies (e.g. a petroleum refinery doesn't ramp its output on an hourly basis) and to reduce the computational requirements of the model where hourly operational representations are superfluous.

Blend Storage

Flexibility for blend storage technologies can be maintained on an hourly or sample-day basis. This allows regimes for short-term and long-term operations as well as regimes for only long-term operations (with no ability to balance on an hourly basis) for blend storage technologies.

Transmission

RIO uses a pipe-flow constraint formulation[1]. Transmission flows are constrained by the capacity of the line in every hour. When transmission is built by the model, additions are assumed to be symmetrical, meaning the capability of flow on the line is equal in both directions. However, not all existing transmission has equally sized paths in each direction.

Blends

Blend supply and demand balances can be enforced on either an hourly, sample-day, or annual basis depending on user input. For blends with potentially significant storage costs, hourly supply/demand balances should be enforced. Electricity is a unique blend where supply/demand must be maintained hourly and is also subject to additional reliability constraints discuss in 3.1.5.2.

3.1.5.2. Electricity Reliability

Electricity is a unique energy product that requires not just an operational representation of meeting supply/demand balances based on the model conditions, but a representation of the likelihood that the modeled conditions are not exhaustive of all potential conditions that the electricity system may face that would threaten this supply and demand balance. This is necessitated due to the possibility that renewable generation conditions may be worse than forecasted and represented in the sample-days; generators and transmission lines may experience unexpected outages; and climactic conditions may create hourly (or sub-hourly) load peaks that exceed represented conditions.

Planning reserves are used to ensure a system has adequate capacity to meet load in all anticipated conditions (assessed on a statistical basis). This includes meeting load during extreme weather events, significant droughts of renewable production, and unforced outages of thermal capacity. Historically, reserves have been assessed in a probabilistic manner. Each hour's loss of load probability (a measure of the likelihood of the inability for the system's supply to meet its demand obligations) could be

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[1] See this NREL presentation for more information and contrast against DC power-flow constraint formulations: https://www.nrel.gov/docs/fy17osti/68929.pdf

assessed independently of other hours. That made the problem tractable from a system planning perspective. Resource capacities and their expected contribution to meeting loads in each hour could be determined exogenously and run through Monte Carlo simulations. In capacity expansion modeling, such statistical techniques are not computationally tractable. There have been attempts to apply this statistical approach to capacity expansion modeling, with all generators getting a reliability value with a pre-calculated statistical methodology. However, this misunderstands the reliability economics of deeply decarbonized energy systems by those attempting it because:

- At high levels of renewable penetration, the most critical reliability times are only somewhat correlated with end-use load levels. For example, an extremely low-wind day in the Northeast with average load levels is much more critical from a reliability standpoint than an average wind day with elevated load levels. This endogeneity means that it's impossible to determine a-priori when the "reliability events" will occur, which is implicit in models that pre-select super peak periods.

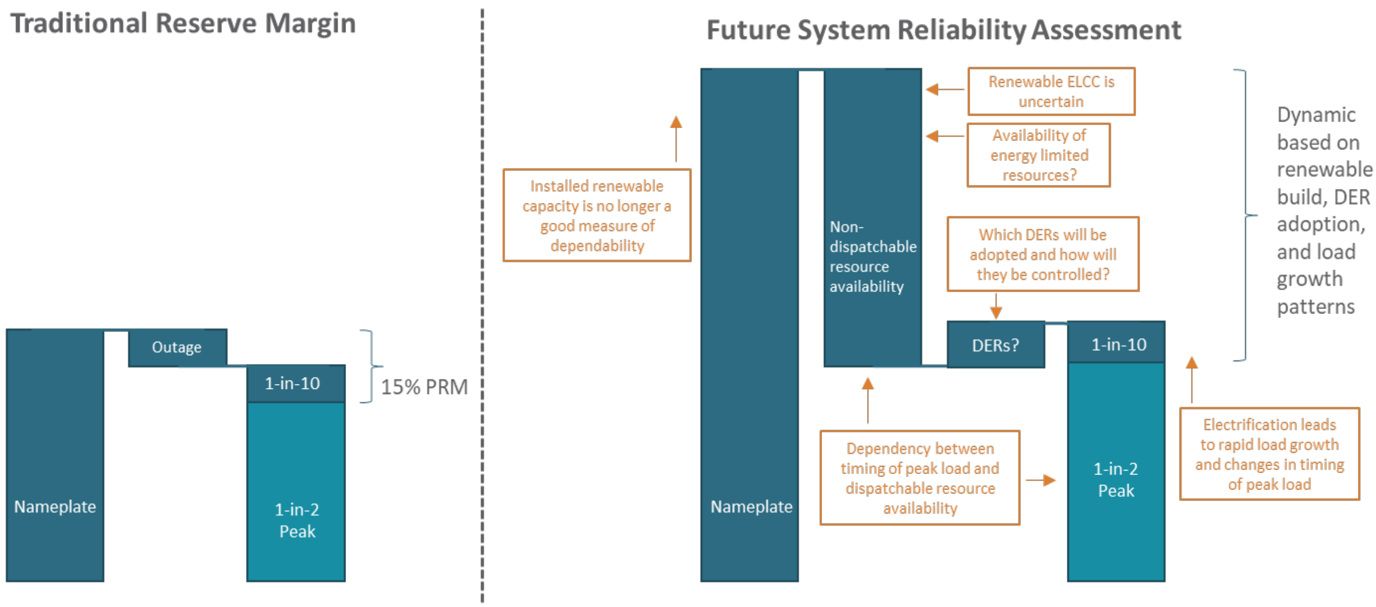
- Reliability events in the future with large amounts of duration-limited resources (i.e. energy storage) are persistence events and the "state-of-charge" of these resources during reliability events is determined by the portfolio of resources that have been built during the capacity expansion and so can't be pre-calculated.

- The must-serve requirement of electricity loads is heterogeneous on an hourly basis. Flexible-loads (end-use loads and things like electrolyzers) don't require reliable provision even on an hourly basis, and the importance of load participation means that they have to be included in the reliability calculation in a dynamic way.

All of this is to emphasize that the conditions that will stress electricity systems in the future and define reliability needs will shift in nature compared to today, shown in Figure 8. Capacity is the principal need for reliable system operations when the dominant sources of energy are thermal. Peak load conditions set the requirement for capacity because generation can be controlled to meet the load and fuel supplies are not constrained. As the system transitions to high renewable output, the defining metric of reliability need is not peak load but net load (load net of renewables). Periods with the lowest renewable output may drive the most need for other types of reliable energy even if they do not align with peak gross load periods. In addition to that, resources will become increasingly energy constrained. Storage can only inject the energy it has in charge into the system. Reliability is therefore increasingly driven by energy need as well as capacity need.

In the future, the defining reliability periods may be when renewables have unusually low output, and when that low output is sustained for unusually long periods. To model a reliable system in the future, both capacity and energy needs driven by the impact of weather events and seasonal changes on renewable output and load need to be captured.

Figure 8 Reliability framework in high renewable systems



To ensure we capture the impacts of these changing conditions on reliability, we enforce a planning reserve requirement on load in every modeled hour. This "planning demand" is found by scaling load up to account for the possibility that demand in each hour could be greater than expected. At the same time, we determine a dependable contribution of each resource to meeting the planning demand. Dependability is defined as the output of each resource that can be relied upon during reliability events. The planning demand must be met or exceeded by the summed dependable contributions of available resources in each hour.

Thermal

Thermal resources are the only resources that RIO credits entirely with their latent potential to deliver energy. Thermal resources are considered fuel-secure within the framework of the RIO model. That means that, even when not generating, they could do so in the event of contingency conditions. We derate this potential by each resource's forced outage rate, which represents the share of time that the resource may be unavailable over the year on an unplanned basis. For a fleet of generators, this represents the share of nameplate capacity that can be expected to be available in any single hour.

Fixed

Fixed resources contribute to reliability based on the combination of hourly energy output and curtailment. Hourly energy output is the actual contribution to providing energy, and curtailment represents the ability to do so under contingency conditions. We derate this hourly energy output to represent potential underproduction (from forecast error) and to represent a broader set of expectations for renewable production not represented in the weather years we are using within the optimization.

Hydro

Hydro resources, due to their energy budgets, are duration-limited. This necessitates that we credit their capacity contribution only when realized in energy output. If we credited their nameplate capacity (or P_{max} values in each hour) we would overstate their potential to maintain this sustained peaking capability. Increasing the assumed flexibility of hydro generators—by increasing the window of Daily cumulative energy constraints—we can increase the potential capacity contributions of hydro resources. This contribution is additionally derated by a value that represents the unforced outage rate of hydro resources.

Electricity Storage

Similar to hydro resources, storage resources must maintain states of charge to support their reliable discharge. We therefore credit storage for capacity contributions only when generating (and add a capacity obligation to their charge schedule). This contribution is derated by a forced outage rate on the storage resource, as well as a derate associated with the reliability of the energy in the storage reservoir.

When the discharge is supported by long-term charge/discharge behaviors, we additionally derate capacity contributions by residual state of charge, parameterizing the uncertainty that the reservoir will be full when called upon to provide reliability.

Flexible Load

Flexible load capacity contributions are realized when load is shifted away from critical capacity hours. This is therefore a "realized" dynamic capacity contribution, not an exogenous, deemed value.

Transmission

We also assess the contribution of transmission imports and their reliability contributions. Instead of using deemed import reliability, we assess the reliability of transmission corridors as a combination of corridor characteristics (i.e. do they represent system n-1 conditions; forced outage rates, etc.) as well as their ability to support their physical transfer capacity with energy. This is determined within the optimization, and, for a single zone, represents the capacity for other zones to provide energy when necessary to support the reliability contributions of the line. This is a combination of available capacity in other zones, load and resource diversity between zones, and policy considerations around the types of energy allowed for import.

For zones who are exporting, this supported export flow becomes a reliability obligation within the zone. This approach symmetrically credits and obligates zones so that capacity can be assessed in the entire system concurrently.

Conversion

The electricity demanded by conversion technologies also received a dependability factor. For technologies that are not deemed must-serve load, this electricity demand is not included in the planning reserve calculation. The supply/demand balance for this load must still be maintained, however.

3.1.5.3. Investment Decisions

Concurrently with optimal operational decisions, the model makes resource build decisions that together produce the lowest total system cost. RIO allows for four types of capacity decisions for each of its supply technology types (thermal, fixed, hydro, electricity storage, conversion, blend storage):

1. New Build
2. Extensions
3. Repowers
4. Retirements
5. Retrofits

Details about these decision types are included below.

3.1.5.4. New Builds

New construction decisions are based on an assessment of the cost share of a resource installed in any model year. This cost share represents the realized levelized cost streams based on the selected modeled years. The example below shows how this is calculated for an example resource installed in 2022. We assess the costs of that resource *in* the years that we model (i.e. vintaged new build decisions) *for* the years which we model (i.e. the payments made in the modeled years for resources installed).

Table 23 New resource cost schedule

	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036
NPV	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$1,000	$96	$96	$96	$96	$96	$96	$96	$96	$96	$96	$96	$96	$96	$96	$96
$262	$96					$96					$96				

3.1.5.5. Extensions

Extensions are decisions to maintain capacity at the end of its useful life. The model includes specified extension costs that are generally lower than the cost of newly built resources. The lifetimes of such extensions are also model inputs. The costs are implemented with the same structure used in New Builds.

3.1.5.6. Repowers

Repowers are decisions to bring capacity back online after a period of defined dormancy. This repower represents "mothballing" a plant before bringing it back for further use. The costs are implemented with the same structure used in New Builds.

3.1.5.7. Retirements

Retirements are a decision made during the duration of a plant's life. When changing economic and policy conditions creates an environment where the plant's value to the system is less than its ongoing costs (i.e. fixed O&M), the model will retire the plant in order to realize the ongoing cost savings.

3.1.5.8. Retrofits

Retirements are a decision made upon retirement of the retrofittable technology. We associate technology builds with the technologies they are able to retrofit and upon retirement, the model can choose to retrofit the retiring technology.

3.1.5.9. Transmission Investment

In addition to investing in new generation, the model can invest in the expansion of transmission corridors to deliver additional energy between zones. The cost of this transmission investment is assessed in a similar manner to that of newly built supply technologies, though the model doesn't maintain the ability to retire new transmission assets.

3.2. EnergyPATHWAYS/RIO Integration

EnergyPATHWAYS is used to define energy demand scenarios that provide input parameters for RIO optimizations. These input parameters include hourly demand shapes for energy carriers like electricity, hydrogen, and pipeline gas. They also include total end-use demand for all energy carriers as well as total demand-side equipment costs, which are used to calculate total energy system costs in RIO.

3.3. EnergyPATHWAYS

3.3.1. Overview

The EnergyPATHWAYS model is a comprehensive energy accounting and analysis framework specifically designed to examine large-scale energy system transformations. It accounts for the costs and emissions associated with producing, transforming, delivering, and consuming energy in an economy. It has strengths in infrastructure accounting and electricity operations that separate it from models of similar types. It is used, as it has been in this analysis, to calculate the effects of energy system decisions on future infrastructure, emissions, and costs to energy consumers and the economy more broadly.

The model works using decision-making "stasis" as a baseline. This means, for example, that when projecting energy demand for residential space heating, EnergyPATHWAYS implicitly assumes that consumers will replace their water heater with a water heater of a similar type. This baseline does, however, include efficiency gains and technology development required by codes and standards or reasonably anticipated based on techno-economic projections. If there are deviations from the current system in terms of technology deployment, these are made explicit in our scenario with the application of measures, which represent explicit user-defined changes to the baseline. These can take the form of adjustments of sales shares measures (changes in the relative penetration of technology adoption in a defined year) or of stock measures (changes to the amount of technology deployment by a defined year).

EnergyPATHWAYS projects energy demand and costs in subsectors based on explicit user-decisions about technology adoption (e.g. electric vehicle adoption) and activity levels (e.g. reduced VMTs). These projections of energy demand across energy carriers are then sent to the supply-side of the model. In combination with RIO, the supply-side of the model calculates upstream energy flows, primary energy usage, infrastructure requirements, emissions, and costs of supplying energy. These supply-side outputs are then combined with the demand-side outputs to calculate the total energy flows, emissions, and costs of the modeled energy system.

The sections below describe the EnergyPATHWAYS demand-calculation methods in detail.

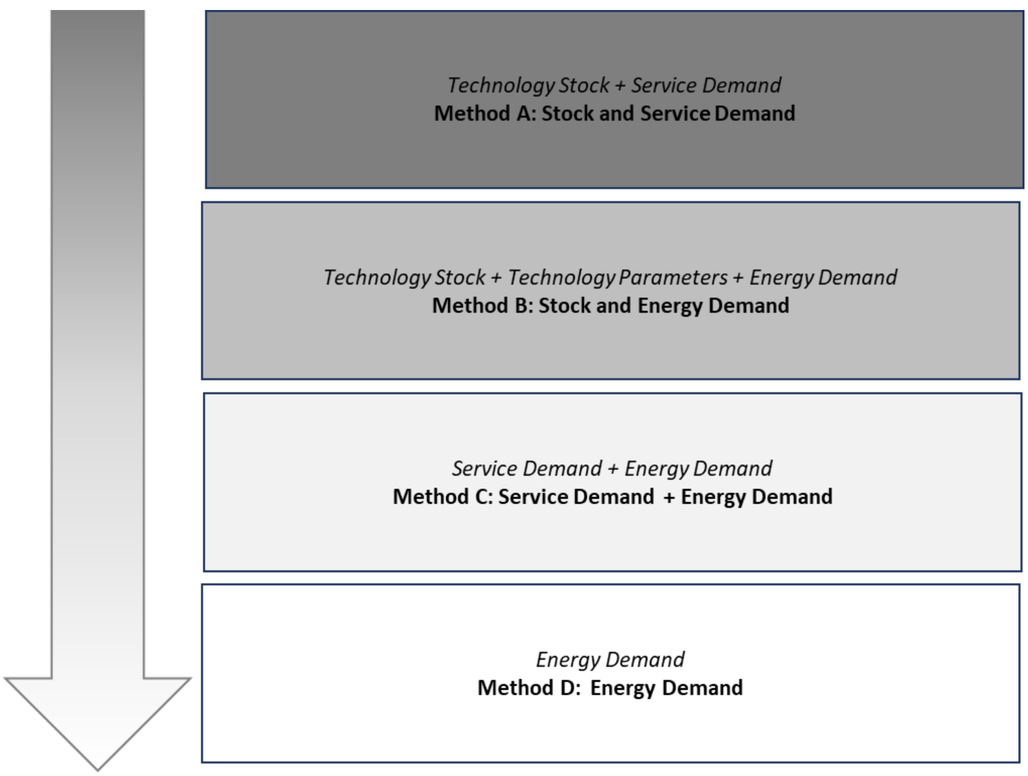
3.3.2. Subsectors

Subsectors represent separately modeled units of demand for energy services. These are often referred to as end-uses in other modeling frameworks. EnergyPATHWAYS is flexible in the configuration of subsectors, and methods used in each subsector depend on data availability. The high level of detail in subsectors in the EnergyPATHWAYS U.S. database is enabled by the availability of numerous high-quality data sources for the U.S. energy economy. Below we describe the calculations used for individual subsectors on the demand-side. Total demand is simply the summation of these calculations for all subsectors.

3.3.3. Energy Demand Projection

Data availability determines subsector granularity and informs the methods used in each subsector. The flow diagram below represents the decision matrix used to determine the methods—named A, B, C, D—used to model an individual energy demand subsector (Figure 9). The arrow downward indicates a progression from most-preferred (A) to least-preferred (D) methodology for modeling a subsector. The preferred methods allow for more explicit measures and better accounting of costs and energy impacts. Each method for projecting energy demand is described below.

Figure 9 Methods for projecting energy demand



3.3.3.1. Method A: Stock and Service Demand

This method is the most explicit representation of energy demand possible in the EnergyPATHWAYS framework. It has a high data requirement; many end-uses are not homogenous enough to represent with technology stocks and others do not have measurements of energy service demand. When the data requirements are met, EnergyPATHWAYS uses the following formula to calculate energy demand from a subsector.

Equation 1

$$E_{ycr} = \sum_{v \in V} \sum_{t=T} U_{yvtcr} * f_{vtc} * d_{yr} * (1 - R_{yrc})$$

Where

E = Energy demand in year y of energy carrier c in region r

U_{yvtcr} = Normalized share of service demand in year y of vintage v of technology t for energy carrier c in region r

f_{vtc} = Efficiency (energy/service) of vintage v of technology t using energy carrier c

d_{yr} = Total service demand input aggregated for year y in region r

R_{yrc} = Unitized service demand reductions for year y in region r for energy carrier c. Service demand reductions are calculated from input service demand measures, which change the baseline energy service demand levels.

Service Demand Share (U)

The normalized share of service demand (U) is calculated as a function of the technology stock (S), service demand modifiers (M), and energy carrier utility factors (C). Below is the decomposition of *U* into its component parts of *S* and *M and C.*

Equation 2

$$U_{yvtr} = \frac{S_{yvtr} * M_{yvtr} * C_{tc}}{\sum_{v \in V} \sum_{t \in T} S_{yvtr} * M_{yvtr}}$$

Where

S_{yvtr} = Technology stock in year y of vintage v of technology t in region r

M_{yvtr} = Service demand modifier in year y for vintage v for vintage t in region r

C_{tc} = Utility factor for energy carrier c for technology t

The calculation of these factors is detailed in the sections below

Technology Stock (S)

The composition of the technology stock is governed by stock-rollover mechanics in the model, technology inputs (lifetime parameters, technology decay parameters), initial technology stock states, and the application of sales share or stock measures. The section below describes the ways in which these model variables can affect the eventual calculation of technology share.

Initial Stock

The model uses an initial representation of the technology stock to project forward. This usually represents a single-year stock representation based on customer survey data (e.g. the U.S. Commercial Building Energy Consumption Survey data informs 2012 technology stock estimates) but can also be "specified" into the future, where the composition of the stock is determined exogenously. At the end of this initial stock specification, the model uses technology parameters and rollover mechanics to determine stock compositions by year.

Stock Decay and Replacement

EnergyPATHWAYS allows for technology stocks to decay using linear representations or Weibull distributions, which are typical functions used to represent technology reliability and failure rates. These parameters are governed by a combination of technology lifetime parameters. Technology lifetimes can be entered as minimum and maximum lifetimes or as an average lifetime with a variance.

After the conclusion of the initial stock specification period, the model decays existing stock based on the age of the stock, technology lifetimes, and specified decay functions. This stock decay in a year (y) must be replaced with technologies of vintage (v) $v = y$. The share of replacements in vintage v is equal to the share of replacements unless this default is overridden with exogenously specified sales share or stock measures. This share of sales is also used to inform the share of technologies deployed to meet any stock growth.

Sales Share Measures

Sales share measures override the pattern of technologies replacing themselves in the stock rollover.

An example of a sales share measure is shown below for two technologies—A and B—that are represented equally in the initial stock and have the same decay parameters. EnergyPATHWAYS applies a sales share measure in the year 2020 that requires 80% of new sales in 2020 to be technology A and 20% to be technology B. The first equation shows the calculation in the absence of this sales share measure. The second shows the stock rollover governed with the new sales share measure.

S = Stock

D = Stock decay

G = Year on year stock growth

R = Stock decay replacement

H = User specified share of sales for each technology

N = New Sales

a = Technology A

b = Technology B

<u>Before Measure (i.e. Baseline)</u>

S_{2019} = 100

S_{a2019} = 50

S_{b2019} = 50

D_{2020} = 10

D_{a2020} = 5

D_{b2020} = 5

S_{2020} = 110

$G_{2020} = S_{2020} - S_{2019} = 110 - 100 = 10$

R_{a2020} = D_{a2020} = 5

R_{b2020} = D_{b2020} = 5

G_{a2020} = $\frac{D_{a2020}}{D_{2020}} * \ G_{2020}$ = 5/10 * 10 =5

G_{b2020} = $\frac{D_{b2020}}{D_{2020}} * \ G_{2020}$ = 5/10 * 10 = 5

N_{a2020} = $R_{a2020} + \ G_{a2020}$ = 5 + 5 = 10

N_{b2020} = $R_{b2020} + \ G_{b2020}$ = 5 + 5 = 10

S_{a2020} = $S_{a2019} + \ D_{a2020} + \ N_{a2020}$ = 50 – 5 + 10 = 55

S_{b2020} = $S_{b2019} + \ D_{b2020} + \ N_{b2020}$ = 50 – 5 + 10 = 55

After Sales Share Measure

S_{2019} = 100

S_{a2019} = 50

S_{b2019} = 50

D_{2020} = 10

D_{a2020} = 5

D_{b2020} = 5

S_{2020} = 110

$G_{2020} = \ S_{2020} - S_{2019} = 110 - 100 = 10$

R_{a2020} = $D_{2020} * H_{a2020}$ = 10 * .8 = 8

R_{b2020} = $D_{2020} * H_{b2020}$ = 10 * .2 = 2

G_{a2020} = $G_{2020} * H_{a2020}$ = 10 * .8 = 8

G_{b2020} = $G_{2020} * H_{b2020}$ = 10 * .2 = 2

N_{a2020} = $R_{a2020} + \ G_{a2020}$ = 8 + 8 = 16

N_{b2020} = $R_{b2020} + \ G_{b2020}$ = 2 + 2 = 4

S_{a2020} = $S_{a2019} + \ D_{a2020} + \ N_{a2020}$ = 50 – 5 + 16 = 61

S_{b2020} = $S_{b2019} +\ D_{b2020} +\ N_{b2020}$ = 50 – 5 + 4 = 49

This shows a very basic example of the role that sales share measures play in influencing the stock of technology. In the context of energy demand, these technologies can use different energy carriers (i.e. gasoline internal combustion engine vehicles to electric vehicles) and/or have different efficiency characteristics.

Though not shown in the above example, the stock is tracked on a vintaged basis, so decay of technology A in 2020 in the above example would be decay in 2020 of all vintages before 2020. In the years immediately following the deployment of vintage cohort, there is very little technology retirement given the shape of the decay functions. As a vintage approaches the end of its anticipated useful life, however, retirement accelerates.

Stock Specification Measures

EnergyPATHWAYS also allows for stock specification measures, which create exogenous specification of technology stocks along the year index (i.e. existing stock in a year), as opposed to sales share measures which operate along the vintage index (i.e. sales in a year). They both interact with the same basic stock rollover mechanics in the model but are interpreted differently by the model.

In the example below, EnergyPATHWAYS replicates the stock in 2020 of our previous sales share example where Technology A is 61 units in 2020 and Technology B is 49 Units.

After Stock Specification Measure

S_{2019} = 100

S_{a2019} = 50

S_{b2019} = 50

D_{2020} = 10

D_{a2020} = 5

D_{b2020} = 5

S_{2020} = 110

$G_{2020} = S_{2020} - S_{2019} = 110 - 100 = 10$

N_{a2020} = $S_{a2020} - S_{a2019} + D_{a2020}$ = 61 – 50 + 5 = 16

S_{b2020} = $S_{2020} - S_{a2020}$ = 110 – 61 = 49

N_{b2020} = $S_{b2020} - S_{b2019} + D_{b2020}$ = 49 – 50 + 5 = 4

$H_{a2020} = \frac{N_{a2020}}{N_{2020}}$ = .8

$H_{b2020} = \frac{N_{b2020}}{N_{2020}}$ = .2

R_{a2020} = $D_{2020} * H_{a2020}$ = 10 * .8 = 8

R_{b2020} = $D_{2020} * H_{b2020}$ = 10 * .2 = 2

G_{a2020} = $G_{2020} * H_{a2020}$ = 10 * .8 = 8

G_{b2020} = $G_{2020} * H_{b2020}$ = 10 * .2 = 2

The model uses the stock specifications to produce sales shares that result in the specified stock. Where a stock specification measure requires more new sales than are available through natural rollover decay and stock growth, the model early-retires infrastructure to increase the pool of available sales based on the probability of retirement for given combination of vintage and technology. The model separately tracks physical and financial lifetimes, so even though technologies may be taken out of service, they are still paid for. Further discussion of this accounting can be found in 3.3.4.1.

Service Demand Modifier (M)

Many energy models use stock technology share as a proxy for service demand share. This makes the implicit assumption that all technologies of all vintage in a stock are used equally. This assumption obfuscates some key dynamics that influence the pace and nature of energy system transformation. For example, new heavy-duty vehicles are used heavily at the beginning of their useful life but are sold to owners who operate them for reduced-duty cycles later in their lifecycles. This means that electrification of this fleet would accelerate the rollover of electrified miles faster than it would accelerate the rollover of the trucks themselves. Similar dynamics are at play in other vehicle subsectors. In subsectors like residential space heating, the distribution of current technology stock is correlated with its utilization. Even within the same region, with the same climactic conditions, the choice of heating technology informs its usage. Homes that have baseboard electric heating, for example, are often seasonal homes with limited heating loads.

EnergyPATHWAYS has two methods for determining the discrepancy between stock shares and service demand shares. First, technologies can have the input of a *service demand modifier*. This is used as an adjustment between stock share and service demand share.

Using the example stock of Technology, A and B, the formula below shows the impact of service demand modifier on the service demand share.[2]

S = Stock

x = Stock ratio

M = service demand modifier

U = service demand allocator

$S_{2019} = 100$

$S_{a2019} = 50$

$S_{a2020} = 50$

$x_{a2019} = \frac{S_{a2019}}{S_{2019}} = \frac{50}{100} = .5$

$x_{b2019} = \frac{S_{b2019}}{S_{2019}} = \frac{50}{100} = .5$

$M_{a2019} = 2$

$M_{b2019} = 1$

[2] EnergyPATHWAYS again ignores the index of vintage (v) for simplicity, but this is an important index to reflect technology utilization determined by age.

$U_{a2019} = \frac{S_{a2019} * M_{a2019}}{\sum_{t=a..b} S_{t2019} * M_{t2019}} = \frac{50*2}{150}$ = .667

$U_{b2019} = \frac{S_{b2019} * M_{b2019}}{\sum_{t=T} S_{t2019} * M_{t2019}} = \frac{50*1}{150}$ = .333

When service demand modifiers aren't entered for individual technologies, they can potentially still be calculated using input data. For example, if the service demand input data is entered with the index of t, the model calculates service demand modifiers by dividing stock and service demand inputs.

Equation 3

$M_{tyr} = \frac{s_{tyr}}{d_{tyr}}$

Where

M_{ty} = Service demand modifier for technology t in year y in region r

s_{tyr} = Stock input data for technology t in year y in region r

d_{tyr} = Energy demand input data for technology t in year y in region r

Energy Carrier Utility Factors (C)

Energy carrier utility factors are technology inputs that allocate a share of the technology's service demand to energy carriers. The model currently supports up to two energy carriers per technology. This allows EnergyPATHWAYS to support analysis of dual-fuel technologies, like plug-in-hybrid electric vehicles. The input structure is defined as a primary energy carrier with a utility factor (0 – 1) and a secondary energy carrier that has a utility factor of 1 – the primary utility factor.

3.3.3.2. Method B: Stock and Energy Demand

Method B is like Method A in almost all its components except for the calculation of service demand. In Method A, service demand is an input. In Method B, the energy demand of a subsector is used as a substitute input for service demand. From this input, EnergyPATHWAYS takes the additional step of deriving service demand, based on stock and technology inputs.

Equation 4

$$E_{ycr} = \sum_{v \in V} \sum_{t=T} U_{yvtcr} * f_{vtc} * D_{yr} * (1 - R_{yrc})$$

Where

E = Energy demand in year y of energy carrier c in region r

U = Normalized share of service demand in year y of vintage v of technology t for energy carrier c in region r

f = Efficiency (energy/service) of vintage v of technology t using energy carrier c

D = Total service demand calculated for year y in region r

R_{yrc} = Unitized service demand reductions for year y in region r for energy carrier c

Total Service Demand (D)

Total service demand is calculated using stock shares, technology efficiency inputs, and energy demand inputs. The intent of this step is to derive a service demand term (D) that allows us to use the same calculation framework as Method A.

Equation 5

$$D_{yr} = \sum_{v \in V} \sum_{c \in C} \sum_{t=T} U_{yvtcr} * f_{vtc} * e_{ycr}$$

Where

D_{yr} = Total service demand in year y in region r

f_{vtc} = Efficiency (energy/service) of vintage v of technology t using energy carrier c

e_{ycr} = Input energy data in year y of carrier c in region r

3.3.3.3. Method C: Service and Service Efficiency

Method C is used when EnergyPATHWAYS does not have sufficient input data, either at the technology level or the stock level, to parameterize a stock rollover. Instead EnergyPATHWAYS replaces the stock terms in the energy demand calculation with a service efficiency term (j). This is an exogenous input that substitutes for the stock rollover dynamics and outputs in the model.

Equation 6

$$E_{ycr} = j_{ycr} * d_{yr} * R_{yrc} - O_{yrc}$$

where

E_{ycr} = Energy demand in year y for energy carrier c in region r

j_{ycr} = Service efficiency (energy/service) of subsector in year y for energy carrier c in region r

d_{yr} = Input service demand for year y in region r

R_{yrc} = Unitized service demand multiplier for year y in region r for energy carrier c

O_{yrc} = Energy efficiency savings in year y in region r for energy carrier c

Energy Efficiency Savings (O)

Energy efficiency savings are a result of exogenously specified energy efficiency measures in the model. These take the form of prescribed levels of energy savings that are netted off the baseline projection of energy usage.

3.3.3.4. Method D: Energy Demand

The final method is simply the use of an exogenous specification of energy demand. This is used for subsectors where there is neither the data necessary to populate a stock rollover nor any data available to decompose energy use from its underlying service demand.

Equation 7

$$E_{ycr} = e_{ycr} - O_{yrc}$$

Where

E_{ycr} = Energy demand in year y for energy carrier c in region r

e_{ycr} = Input baseline energy demand in year y for energy carrier c in region r

O_{yrc} = Energy efficiency savings in year y in region r for energy carrier c

3.3.4. Demand-Side Costs

Cost calculations for the demand-side are separable into technology stock costs and measure costs (energy efficiency and service demand measures).

3.3.4.1. Technology Stock Costs

EnergyPATHWAYS uses vintaged technology cost characteristics as well as the calculated stock rollover to calculate the total costs associated with technology used to provide energy services.[3]

$$C_{yr}^{stk} = C_{yr}^{cap} + C_{yr}^{ins} + C_{yr}^{fs} + C_{yr}^{fom}$$

Where

C_{yr}^{stk} = Total levelized stock costs in year y in region r

C_{yr}^{cap} = Total levelized capital costs in year y in region r

C_{yr}^{ins} = Total levelized installation costs in year y in region r

C_{yr}^{fs} = Total levelized fuel switching costs in year y in region r

C_{yr}^{fom} = Total fixed operations and maintenance costs in year y in region r

Technology Stock Capital Costs

The model uses information from the physical stock rollover used to project energy demand, with a few modifications. First, the model uses a different estimate of technology life. The financial equivalent of the physical "decay" of the technology stock is the depreciation of the asset. The asset is depreciated over the "book life," which doesn't change, regardless of whether the physical asset has retired.

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[3] Levelized costs are the principal cost metric reported, but the model also calculates annual costs (i.e. the cost in 2020 of all technology sold).

To provide a concrete example of this, a 2020 technology vintage with a book life of 15 years is maintained in the financial stock in its entirety for the 15 years before it is financially "retired" in 2035. This financial stock estimate, in addition to being used in the capital costs calculation, is used for calculating installation costs and fuel switching costs.

Equation 8

$$C_{yr}^{cap} = \sum_{v \in V} \sum_{t \in T} S_{tvyr}^{fin} * W_{tvr}^{cap}$$

Where

C_{yr}^{cap} = Total levelized technology costs in year y in region r

W_{tvr}^{cap} = Levelized capital costs for technology t for vintage v in region r

S_{tvyr}^{fin} = Financial stock of technology t and vintage v in year y in region r

EnergyPATHWAYS primarily uses this separate financial accounting so that EnergyPATHWAYS accurately accounts for the costs of early-retirement of technology. There is no way to financially early-retire an asset, so physical early retirement increases overall costs (by increasing the overall financial stock).

Levelized Capital Costs (W)

EnergyPATHWAYS levelizes technology costs over the mean of their projected useful lives (referred to as book life). This is either the input mean lifetime parameter or the arithmetic mean of the technology's max and min lifetimes. EnergyPATHWAYS additionally assesses a cost of capital on this levelization of the technology's upfront costs. While this may seem an unsuitable assumption for technologies that could be considered "out-of-pocket" purchases, EnergyPATHWAYS assumes that all consumer purchases are made using backstop financing options. This is the implicit assumption that if "out-of-pocket" purchases were reduced, the amount needed to be financed on larger purchases like vehicles and homes could be reduced in-kind.

$$W_{tvr}^{cap} = \frac{d_t * z_{tvr}^{cap} * (1 + d_t)^{l_t^{book}}}{(1 + d_t)^{l^{book}} - 1}$$

Where

W_{tvr}^{cap} = Levelized capital costs for technology t for vintage v in region r

d_t = Discount rate of technology t

z_{tvr}^{cap} = Capital costs of technology t in vintage v in region r

l_t^{book}= Book life of technology t

Technology Stock Installation Costs

Installation costs represent costs incurred when putting a technology into service. The methodology for calculating these is the same as that used to calculate capital costs. These are levelized in a similar manner.

Technology Stock Fuel Switching Costs

Fuel switching costs represent costs incurred for a technology only when switching from a technology with a different primary energy carrier. This input is used for technologies like gas furnaces that may need additional gas piping if they are being placed in service in a household that had a diesel furnace. Calculating these costs requires the additional step of determining the number of equipment sales in a given year associated with switching fuels.

$$C_{yr}^{fs} = \sum_{v \in V} \sum_{t \in T} S_{tvyr}^{fs} * W_{tvr}^{fs}$$

Where

S_{tvyr}^{fs} = Financial stock associated with fuel-switched equipment installations

W_{tvr}^{fs} = Levelized fuel-switching costs for technology t for vintage v in region r

d_t = Discount rate of technology t

z_{tvr}^{fs} = Fuel switching costs for technology t in vintage v in region r

Technology Stock Fixed Operations and Maintenance Costs

Fixed operations and maintenance (O&M) costs are the only stock costs that utilize physical and not financial representations of technology stock. This is because O&M costs are assessed annually and are only incurred on technologies that remain in service. If equipment has been retired, then it no longer has ongoing O&M costs.

$$C_{yr}^{fom} = \sum_{v \in V} \sum_{t \in T} S_{tyvr} * W_{tvr}^{fom}$$

Where

S_{tyvr}= Technology stock of technology t in year y of vintage v in region r

W_{tvr}^{fom} = Fixed O&M costs for technology t for vintage v in region r

3.3.4.2. Measure Costs

Measure costs are assessed for interventions either at the service demand (service demand measures) or energy demand levels (energy efficiency measures). While these measures are abstracted from technology-level inputs, EnergyPATHWAYS uses a similar methodology for these measures as EnergyPATHWAYS does for technology stock costs. EnergyPATHWAYS uses measure savings to create "stocks" of energy efficiency or service demand savings. These measure stocks are vintaged like technology stocks and EnergyPATHWAYS uses analogous inputs like capital costs and useful lives to calculate measure costs.

Service Demand Measure Costs

Service demand measure costs are costs associated with achieving service demand reductions. In many cases, no costs are assessed for these activities as they represent conservation or improved land-use planning that occurs at zero or negative-costs.

Equation 9

$$C_{yr}^{sd} = \sum_{v \in V} \sum_{m \in M} S_{mvyr}^{sd} * W_{mvr}^{sd}$$

Where

C_{yr}^{sd} = Total service demand measure costs

S_{mvyr}^{sd} = Financial stock of service demand reductions from measure m of vintage v in year y in region r

W_{mvr}^{sd} = Levelized per-unit service demand reduction costs

Energy Efficiency Measure Costs

Energy efficiency costs are costs associated with the reduction of energy demand. These are representative of incremental equipment costs or costs associated with non-technology interventions like behavioral energy efficiency.

Equation 10

$$C_{yr}^{ee} = \sum_{v \in V} \sum_{m \in M} S_{mvyr}^{ee} * W_{mvr}^{ee}$$

Where

C_{yr}^{ee} = Total energy efficiency measure costs

S_{mvyr}^{sd} = Financial stock of energy demand reductions from measure m of vintage v in year y in region r

W_{mvr}^{ee} = Levelized per-unit energy efficiency costs

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