Concepts, Data Sources, and Techniques

Handbook of Energy Modeling Methods

World Energy Projection System (WEPS): Industrial Demand Module

Independent Statistics & Analysis

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1. Introduction

The WEPS Industrial Demand Module (World Industrial Model, or WIM) projects the amount of energy that is directly consumed as a fuel or as a feedstock by industrial processes and activities. The projection includes consumption by energy-intensive manufacturing industries, non-energy intensive manufacturing industries, and nomanufacturing industries.

WIM projects energy consumption for 16 industry categories for all WEPS regions and fuels over the projection period. Table 1 lists each covered industry category, some representative industries for each, and their respective Nomenclature of Economic Activities (NACE2) codes which are the European statistical classification of economic activities. By clearly defining the boundaries for each industry category using NACE2, we ensure that the energy demand and macroeconomic activity are matched and represented as accurately as possible.

We assume that the following factors determine industry energy consumption changes over time:

- Changes in industrial gross output, defined as the total dollar value of services provided by a given industrial sector, adjusted to reflect purchasing power parity
- Changes in energy intensity (EI), defined as thousands of British thermal units (Btu) of energy consumed per U.S. dollar of gross output
- Sustained changes in industrial energy prices

Increased industry category gross output generally leads to higher consumption, and sustained fuel price increases will encourage some fuel switching and efficiency improvements. Energy intensities are generally expected to have a downward slope as manufacturers replace older capital stock with newer, more efficient technology; however, this assumption has limits because many mature industries in advanced economies will already employ the most efficient means of production currently available. This logic does not apply to fuels consumed as feedstocks, such as several petroleum-based fuels and natural gas plant liquids in the basic chemicals industry, which are not subject to efficiency improvements.

WIM uses an array of energy intensity (EI) models to find the best fit for each region-industry based on historical trends, statistical measures, and analyst judgement. The WIM EI models use historical energy intensity data to estimate coefficients, which they then apply to compute projections for the projection period. WIM then ranks the EI model results using several statistical indicators; selects the top ranked energy intensity model result, subject to analyst override; and calculates the energy consumption for each region-industry as gross output multiplied by the projected energy intensity. Finally, WIM shares out the total region-industry consumption to individual fuels.

Table 1: Industrial Sector Industry Categories for the World Energy Projection System (WEPS)

NACE 2	Industry Category	Representative Industries
C10	Food	Food, beverage, and tobacco product manufacturing
C17-18	Paper	Paper manufacturing, printing and related support activities
C20.1	Basic chemicals	Inorganic chemicals, organic chemicals (for example, ethylene, propylene), resins, and agricultural chemicals. Includes chemical feedstocks
C19	Refining	Petroleum refineries and coal products manufacturing to include coal and natural gas used as feedstock
C24.1-3	Iron and steel	Iron and steel manufacturing, including coke ovens
C24.4	Non-Ferrous metals	Primarily aluminum and other non-ferrous metals such as copper, zinc, and tin, including carbon anode production for primary aluminum smelting
C23	Non-Metallic minerals	Primarily cement and other non-metallic minerals such as glass, lime, gypsum, and clay products
C11-16, 22,31-33	Other industrial	All other manufacturing
C20.2-6,21	Other chemicals	Pharmaceuticals, medicinal and botanical, paint and coatings, adhesives, detergents, and other miscellaneous chemical products. Includes chemical feedstocks
A01-03	Agriculture	Agriculture, forestry, and fishing
B05	Oil extraction	Oil and natural gas extraction
B06	Coal extraction	Coal extraction
B07-09	Other extraction	Metallic and non-metallic minerals mining such as bauxite, iron, lithium, sand, or gold
C29-30	Motor vehicles	Transportation equipment— motor vehicles and aircraft - manufacturing
C24.5-28	Other metal-based durables	Other metal based durables (OMBD) manufacturing, computer and electronic products, machinery, and electrical equipment appliances and components
F41-43	Construction	Buildings (residential and commercial) construction, heavy and civil engineering construction, industrial construction, and specialty trade contractors

Data source: U.S. Energy Information Administration

2. Description of the Projection Method

For each WEPS region-industry combination (for example, Japan-Paper), we project an energy intensity (EI) curve that forms the basis for energy demand over the projection period. The interaction between a given region-industry's projected energy intensity and projected gross output (provided by the WEPS Global Activity Module) largely determines its energy demand:

$$EI=\frac{\text{Consumption}}{\text{Gross Output}}.$$

Calculation of alternative energy intenensity (EI) curves

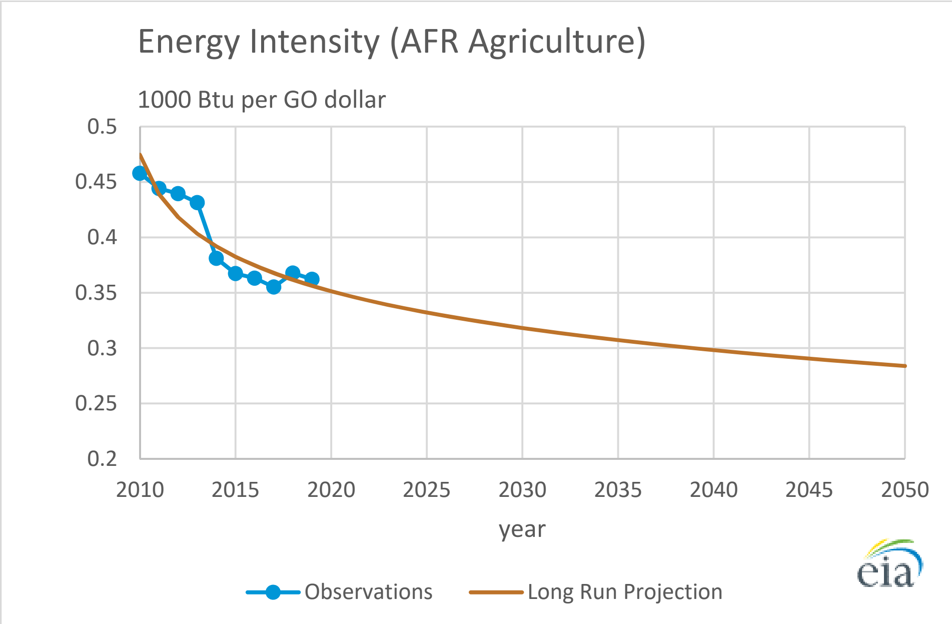
For each region-industry combination, the model uses historical data going back to 2010 and a two-step estimation process to project alternative EI curves. The first stage is to estimate the underlying trend by three methods:

1. An exponential decay model, if the historical EI slope is negative, or an inverted exponential decay model if the slope is positive (Figure 1)
2. A logarithmic growth model (Figure 2)
3. A zero-slope model equal to the mean if the model uses ordinary least squares (OLS) or median if the model uses least absolute deviations (LAD) (Figure 3)

The first and second specifications listed above are competing theories of the way in which energy intensity changes over time. Logarithmic growth or decline assumes that EI will grow or decline at a continually diminishing rate into the foreseeable future according to the trend established by history, subject to any upper bounds of reasonable intensity, unless acted upon by an exogenous force. Exponential and inverted exponential decay assume older production methods and technologies are replaced with newer at a continuous percentage rate,approaching an asymptote that represents complete adoption of a newer technology. The third specification—no change in EI—assumes that WEPS does not have enough information to expect that a meaningful trend in the data is discernable (that is, slope equals 0), and therefore, energy intensity reverts to the mean (the OLS intercept) or median (the LAD intercept).

The second stage in the estimation process is to use an autoregressive model with a one-period lag (AR(1)) on the residuals of the first estimation stage. Currently, the model assigns a coefficient of 0.9 to the autoregressive term, a choice that represents the assumption that the data will slowly converge back to the trend.

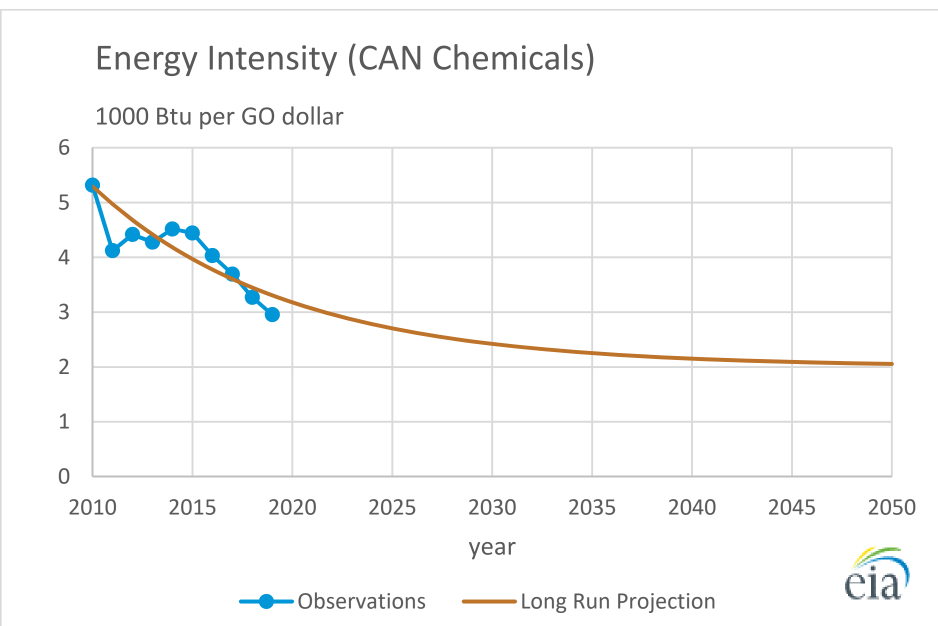
Figure 1: Log Trend Example



Data source: U.S. Energy Information Administration

The logarithmic trend example in Figure 1 shows a downward trend in the energy intensity of African (AFR) agriculture. Rather than just projecting a straight line, we project a line whose slope diminishes over time and that is not bound by an explicit asymptote.

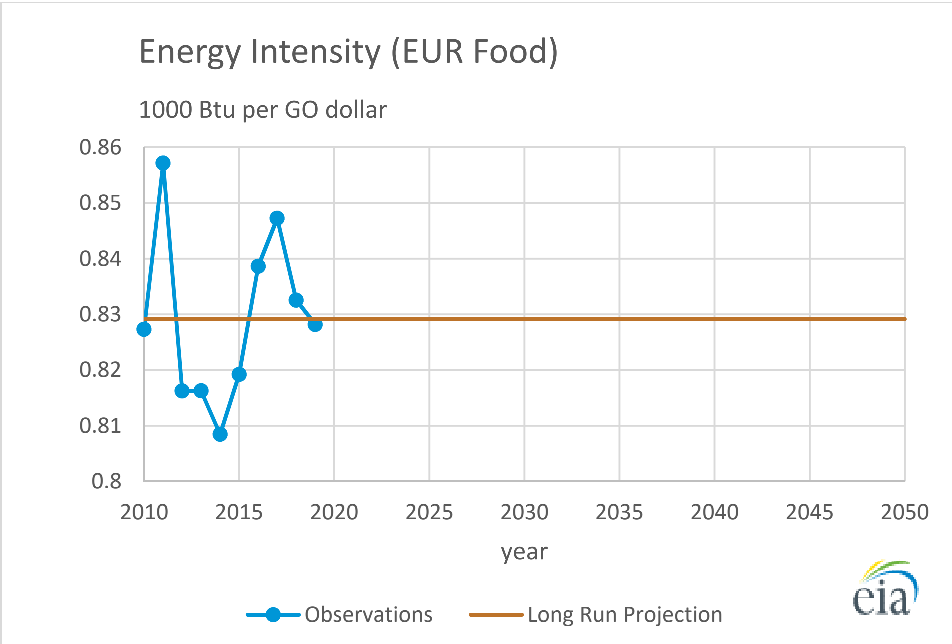
Figure 2: Exponential Decline Example



Data source: U.S. Energy Information Administration

Figure 2. This exponential decline example shows a decline in the energy intensity of Canada's (CAN) basic chemical manufacturing. Unlike the similar-looking logarithmic decline, the exponential decline approaches a horizontal asymptote close to 2.0.

Figure 3: Mean/Median Reverting Example



Data source: U.S. Energy Information Administration

Figure 3. In this mean/median reverting example, the energy intensity of Europe's food production oscillates with no discernable trend. We can reasonably expect that, in the long run, the EI will tend to revert to the mean.

Selecting the best EI curve

We use the Akaike Information Criterion (AIC) to rank the EI curves by goodness-of-fit and select the best EI curve. *We also employ* diagnostic flags to ensure that the EI models are reasonable at each stage in the estimation process:

- When modelling growth using the inverted exponential decay method, we flag inconsistency from the expected direction of the trend (up or down).
- We flag significant correlations between residuals and time in the first stage estimation.
- We flag increases in variance after first stage estimation.
- We flag decreases in log likelihood after the first stage estimation.

3. Fuel Switching and Efficiency Improvement

To consider fuel-switching, we categorize consumption into six broad fuel categories:

- Petroleum (liquid fuels)
- Natural gas

- Coal
- Electricity
- District heat
- Renewables

The model accounts for fuel switching between four fuel categories: Petroleum, Natural Gas, Coal, and Electricity. We do not consider fuel switching between specific fuels within a category (for example, diesel and gasoline, which are both in the Petroleum category). Switching one petroleum fuel for another (say, diesel for gasoline) would, in most cases, not make sense given that a) their prices are positively correlated, limiting possible cost savings; and b) any savings on fuel costs would not justify the investment cost of switching, for example, from a diesel generator to one that runs on gasoline.

Fuel switching in response to year-to-year changes in relative prices affects fuel shares. The model represents the effect through a fuel-switching algorithm that uses industrial sector cross-price elasticities for coal, natural gas, liquid fuels, and electricity. For example, for consecutive years y-1 and y, the incremental change in coal use due to natural gas price changes is calculated as:

$$\text{Coal Use}_{y} - \text{Coal Use}_{y\text{-}1} = \text{constant} \times \frac{\text{Natural Gas Price}_{y} - \text{Natural Gas Price}_{y\text{-}1}}{\text{Natural Gas Price}_{y\text{-}1}} \times \text{Cross Price Elasticity.}$$

The model performs a similar calculation for other pairs of fuels, such as coal-electricity. In addition, we introduced an algorithm in the *International Energy Outlook 2021* (IEO2021) to project fuel-efficiency improvements based on longer-term price trends, rather than simple changes across consecutive years. Currently, this algorithm considers only petroleum products used for fuel (distillate, residual fuel oil, liquid petroleum gas (LPG)). If, as in the IEO High Oil Price case, WIM encounters sustained fuel price increases in petroleum products, the new algorithm will simulate efficiency improvements that decrease energy intensity, on the assumption that manufacturers will upgrade to more fuel efficient equipment.

4. Steel Industry

We model steel industry energy consumption differently than other industries (described above). We develop projections for steel (virgin and recycled) based on a combination of historical production trends, government and industry policies, and analyst judgment.

The model uses historical data available from the World Steel Association for producing steel, using oxygen blown converters (OBC) and electric arc furnaces (EAF), and producing direct-reduced iron (DRI).

The model currently estimates total crude oil steel production as a power function of the real gross output, in dollars of value, of the iron and steel industry. For most regions, the model assigns a coefficient of 1 to the gross output term, indicating that a 1% increase in gross output corresponds to a 1% increase in total steel production.

We project quantities of steel produced in OBCs and EAFs by dissagregating the projected total steel produced, based on projected proportions for OBC and EAF. We use logarithmic trend models to estimate the proportions. The logarithmic trend represents an assumed continuously diminishing absolute change in the proportions over the projection period. Based on expert judgment, EIA analysts may overwrite the model-projected proportions for OBC and EAF.

Electric arc furnaces primarily take two types of material inputs: scrap and direct-reduced iron. So, the model estimates the proportion of DRI in total EAF production, assuming that the complement is substantially scrap. As for OBC and EAF, the model uses a logarithmic trend to project the proportion of DRI produced, and we can overwrite the model-estimated proportions.

Unlike EAFs, oxygen-blown converters typically don't use a lot of scrap; instead EAFs primarily use iron produced in a blast furnace, usually within the same integrated steel mill. The model, therefore, doesn't disaggregate scrap, pig iron, and less common iron inputs.

With the projections from these three products (OBC steel, EAF steel, and DRI), we use a three-factor linear model to estimate the marginal consumption by each production process on each fuel type. OBC production is generally coal-intensive but may also use natural gas enrichment. EAF steel production is electricity-intensive, and DRI production is natural gas-intensive, due to the role of syngas in removing oxygen from iron ore.

We initially calibrate the steel model to the energy-intensity-based model described above. We use the EI model across industrial sectors, and it can accommodate judgment-based adjustments to specific factors.