École polytechnique de Louvain

Assessment of an energy-economy model based on the Energy Return On Investment (EROI) metric

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Abstract

This master thesis discusses an energy-economy model which was developed by researcher Michael Dale during his PhD thesis. The field of energy analysis is briefly presented. An adaptation of Dale's model is then developed. Our approach differs from Dale's one regarding to several assumptions, regarding to the model's scope and to some parameters and equations. We present and analyse the results of our adapted model. The differences with Dale's original model are underlined and new conclusions are drawn.

Concepts central to this master thesis are biophysical economics, the energy transition, Energy Return On Investment (EROI) and capital intensity of energy production.

Contents

Chapter 1

Introduction

1.1 Context

Energy and economy are very closely related. Every economic activity requires energy in order to be carried out. Admittedly, the abundance of cheap energy in the form of fossil fuels has been powering economic growth since the industrial revolution. Nonetheless, in the last few decades, the idea that this abundance of cheap energy might come to an end has been growing [1]. On one hand, reserves of fossil fuels are finite hence they will someday become depleted. On the other hand, the intensive use of fossil fuels, via the emission of greenhouse gases, causes dangerous climatic change. Hence, a shift to renewable energy sources is primordial. Such a shift causes numerous questions, because of the fundamental differences which separate renewable energies from fossil fuels.

Availability

Fossil fuels are stock resources, while renewable energies are flow resources. For fossil fuels, it means that they are limited in total amount. Only a fixed quantity is available, without restriction on the speed at which it is consumed. Even if renewables have no limits in total amount, they have a strict constraint on the total energy flux available at any particular time. Since the annual world energy demand is currently following a steady increase, the question is whether the available energy flux from renewables will be able to fulfill this demand in the future.

Accessibility

Any energy producing device itself requires energy in order to operate. This leads to the concept of net energy yield and to the Energy Return On Investment (EROI) metric. The EROI of a facility is defined as the ratio between the energy produced throughout its lifetime and the energy needed for its construction, operation, maintenance, and dismantling. An energy resource is called accessible when it presents a high EROI value. A major issue with renewable energy sources is that their EROIs are notoriously lower than the ones of fossil fuels.

Capital intensity

Due to the diffuse nature of renewable sources, renewable energy installations require more capital investment than fossil fuels ones. Hence, when transitioning towards renewables, the size of the energy sector is expected to increase manyfold. This is susceptible of profoundly affecting the structure of the global economy.

1.2 Previous research

In order to study the shift from fossil fuels to renewable energies, the researcher Michael Dale developed an energy-economy model. He named it GEMBA, standing for "Global Energy Modeling: a Biophysical Approach". As indicated by its name, this model falls in the category of biophysical models, which consider that economic activity is constrained by physical factors, in particular energy. Energy is treated by Dale as a non-substitutable factor of production. Besides, his model uses energy instead of price to measure economic stocks and flows. This goes opposite to standard economic practice.

One of the major innovations of Dale is the use of a global EROI curve for each energy resource. According to his model, the transition towards renewable energies happens mainly because of the falling EROIs of fossil energies. Unfortunately, Dale's conclusions about the success of this transition are very pessimistic.

1.3 Our contribution

Dale's results were published in 2011. Since then, more detailed studies about EROI dynamics have been produced, both for fossil fuels [2][3] and renewable energies [4][5]. In this thesis, we adapt Dale's model thanks to these new data. We also make changes to the model equations in order to incorporate other key elements of the energy transition. First, while Dale considers that the transition occurs because of the depletion of non-renewable resources, we are convinced that the climatic constraint will be its main driver. Hence, unlike Dale, we consider that the transition must take place very rapidly i.e. before 2050. Second, we clearly distinguish the part of economic production which goes to consumption and the part which is reinvested back into the economy. This allows us to assess if changes in consumption and investment rates can ease the energy transition.

The present report is organised as follows.

To begin with, the field of energy analysis is presented in chapter 2 and its main concepts are defined: net energy yield, Energy Return On Investment (EROI), Ultimately Recoverable Resource (URR), Technical Potential (TP) and capital intensity. Most importantly, we describe how the EROI curves used in our model were built.

In chapter 3, we first present how biophysical economics shape our view of the global economy, and how this contrasts with standard economic theory. Then, we present our adaptation of Dale's model and the main assumptions on which it is based. We explicitly stress the differences with Dale's original version in terms of goal, scope and equations.

Chapter 4 presents the model's results. We also discuss how these results are affected by changes in parameters' values.

Finally, in chapter 5 we reflect on the model's results and on the discussion on parameters' values. The content of the master thesis is summarised and future perspectives are presented for research.

Chapter 2

Energy analysis

According to M. Dale, energy analysis is the operation of measuring the energy flows through a process or system under investigation. Energy analysis draws a lot of its importance from assessing the multiple input and output flows of energy transformation devices. Firstly, it enables us to evaluate the environmental impacts linked to the transformation of energy, and particularly the emissions of greenhouse gases. Secondly, since energy resources are available in limited quantities, it is meaningful to allocate them to processes with good energy returns. Thirdly, energy analysis enables us to detect current trends in energy systems which might deeply affect our modern, industrial societies.[6] These trends will be extensively discussed in the current and following sections.

When considering an energy production device, the energy output of the device can only be regarded in light of the different energy inputs which were required in order to produce that energy. These energy inputs can take two forms: either energy consumed by the device, or energy used to extract and deliver the material inputs for building the device. We denote these two types of energy by *process energy* and *embodied energy*, respectively. Furthermore, energy inputs can also be classified as direct or indirect. Let us take the example of a drilling rig from Murphy et al. The direct process energy consists of the natural gas consumed on the drilling platform, while the direct embodied energy is the energy which was necessary to construct the drilling rig. Then, the indirect process energy includes the fuel used to fly the workers out of the platform, and the indirect embodied energy includes the energy required to produce the helicopter.[7]

We can now define two fundamental concepts: the net energy yield and the EROI. The net energy yield of an energy system is defined as the output of this system minus all its energy inputs:

$$\text{Net energy yield} = \text{Energy output} - \sum \text{Energy inputs}$$

The Energy Return On Investment (EROI) is then defined by taking the quotient of these quantities, instead of the difference:

$$\text{EROI} = \frac{\text{Energy output}}{\sum \text{Energy inputs}} \tag{2.1}$$

Unlike net energy yield, the EROI is dimensionless. This property makes the EROI extremely useful, since it enables EROI comparisons for energy production devices of different sizes.

Let us consider a standard energy conversion facility. This facility produces a total amount of energy E_g during its lifetime. The yearly production is called $\dot{E}_g$. On the other hand, the total energy input required during the life cycle of the facility can be expressed as $E_c + E_{op} + E_d$. These quantities are the inputs needed during the construction, the operation and maintenance and the decommissioning, respectively. The rates at which the inputs are used are denoted by $\dot{E}_c$, $\dot{E}_{op}$ and $\dot{E}_d$. All these quantities are represented on Figure 2.1 . One should note that this figure considers the particular case when all energy flows are constant through time.

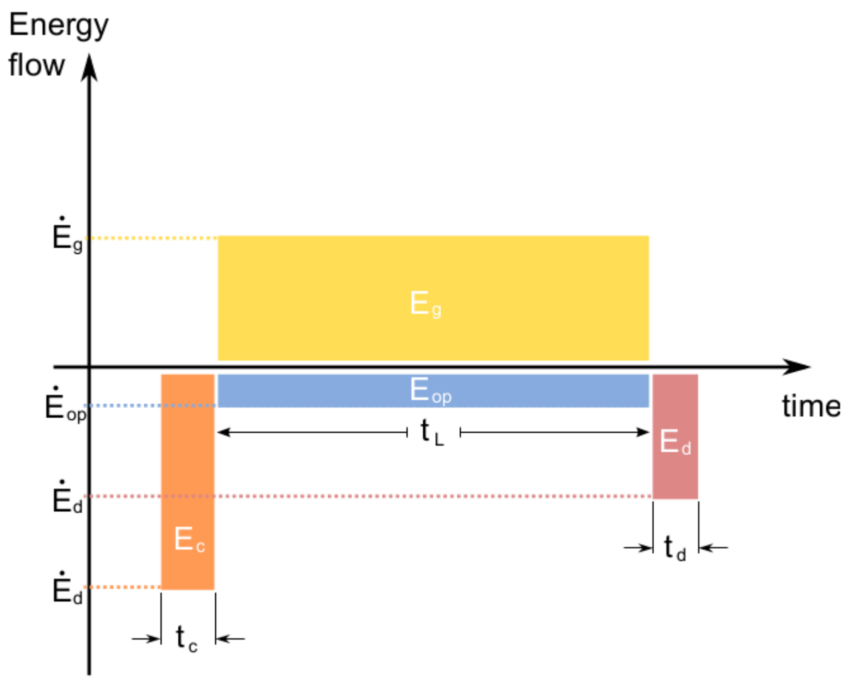


Figure 2.1: Energy inputs and outputs throughout the life cycle of an energy conversion facility, from [7]

The EROI of the facility can be defined as

$$\text{EROI} = \frac{E_g}{E_c + E_{op} + E_d} \tag{2.2}$$

However, in many cases, we only know the energy flows during a particular period, not during the whole lifetime of the facility. We then define the yearly EROI as

$$\text{EROI}_{\text{year}} = \frac{\dot{E}_g}{\dot{E}_c + \dot{E}_{op} + \dot{E}_d} \tag{2.3}$$

In this thesis, we will always make the assumption that both EROIs are equal. This is of course not true in general. The energy expenses and their returns rarely take place at the same moment, hence the yearly EROI varies a lot during the life cycle of the facility. [7]

Besides, when dealing with energy analysis, it is fundamental to precise the boundaries of the system under consideration: what do we count as inputs ? What do we count as outputs ? Indeed, such clarification is often absent from EROI computation studies, making it impossible to compare different results [8]. Figure 2.2 categorises the different types of EROI in function of the boundaries used for energy inputs and outputs.

Boundary for Energy Inputs		Boundary for Energy Outputs		
		1. Extraction	2. Processing	3. End-Use
1	Direct energy and material inputs	$EROI_{1,d}$	$EROI_{2,d}$	$EROI_{3,d}$
2	Indirect energy and material inputs	$EROI_{stnd}$	$EROI_{2,i}$	$EROI_{3,i}$
3	Indirect labor consumption	$EROI_{1,lab}$	$EROI_{2,lab}$	$EROI_{3,lab}$
4	Auxiliary services consumption	$EROI_{1,aux}$	$EROI_{2,aux}$	$EROI_{3,aux}$
5	Environmental	$EROI_{1,env}$	$EROI_{2,env}$	$EROI_{3,env}$

Figure 2.2: Possible choices of boundaries for EROI computation, from [7]

In this thesis, when we discuss the EROI of an energy source, it will always be $EROI_{stnd}$ ("stnd" meaning "standard"). That is, we consider only the direct and indirect energy inputs, but not the energy consumed by the workers when spending their paycheck or the energy consumed by ancillary devices (this latter would be the energy embodied in the machines used to build the machines involved in the energy production process). The energy output is computed as the energy available at the extraction point or production facility (well-head, mine mouth, etc.). In the case of oil, it means that we consider as output the quantity of energy contained in the crude oil leaving the well. We do not consider the subsequent loss when refining the oil or the potential conversion loss when transforming the refined oil into electricity. The energy cost of transporting the oil to end-users is not considered either in $EROI_{stnd}$.[7][9]

The reason why we chose to use $EROI_{stnd}$ is that this type of EROI is the most documented in the literature.

2.1 Global aggregated EROI curves

Energy analysis can be applied to a wide range of systems. In our case, we are interested in analysing the world energy production. Hence, we need to use EROI values for the global production from different energy resources. We break up these resources into the following categories:

1. Coal
2. Oil, both conventional and non-conventional
3. Gas, both conventional and non-conventional
4. solar
5. wind
6. other renewables (biomass, hydropower, geothermal energy, tidal energy, wave energy, Ocean Thermal Energy Conversion (OTEC)) + nuclear

Let us consider the case of oil. Equations 2.2 and 2.3 are appropriate to compute the EROI of one oil well. However, two wells can have very different EROI values, for example due to the difference of depth at which the oil is located [6]. In this case, we can compute the aggregated EROI of the two wells. If we denote the wells by 1 and 2, we have by equation 2.1:

$$\text{EROI}_1 = \frac{\text{Outputs}_1}{\text{Inputs}_1} \quad \text{and} \quad \text{EROI}_2 = \frac{\text{Outputs}_2}{\text{Inputs}_2}$$

$$\text{EROI}_{1+2} = \frac{\text{Outputs}_1 + \text{Outputs}_2}{\text{Inputs}_1 + \text{Inputs}_2} \tag{2.4}$$

$$= \frac{\text{Inputs}_1}{\text{Inputs}_1 + \text{Inputs}_2}\,\text{EROI}_1 + \frac{\text{Inputs}_2}{\text{Inputs}_1 + \text{Inputs}_2}\,\text{EROI}_2 \tag{2.5}$$

We can generalise this statement to any number of wells. It implies that the aggregated EROI of a set of energy production facilities is the mean of their respective EROIs weighted by their energy inputs. This way, the global aggregated EROI of oil production worldwide at one point in time can be obtained on the basis of the EROIs of all oil wells in activity at this point. Such aggregated EROI is said to be "static". However, what interests us is to obtain a dynamic estimate of the aggregated EROI of world oil production as a function of time t. More precisely, instead of having an EROI function of t, we prefer to have an EROI function of the global cumulated production of oil, denoted by C. C is itself a function of t, which gives us for each year the total amount of crude oil which has been produced worldwide since the first industrial use of oil in 1860. Obviously, $C(t)$ is a monotonously increasing function.[6]

Like Dale, we assume that the dynamic EROI function for oil is of the following form:

$$\text{EROI}(C) = \epsilon\, G(C)\, H(C) \tag{2.6}$$

In this expression, ϵ is a scaling factor, G is an increasing function of C and H is decreasing with C. The shape of EROI(C) is described on Figure 2.3.[6]

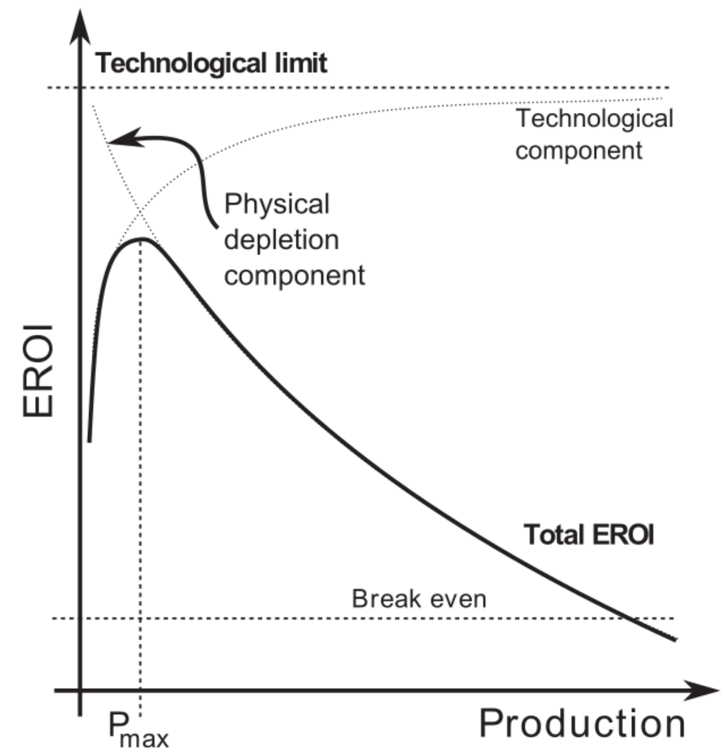


Figure 2.3: Dynamic aggregated EROI function for an energy source, from [10]

G is called the technological component. It represents technological learning with experience. As technology matures, the oil wells gain in efficiency. In other words, the oil wells of one generation consume less energy and require less material inputs than the oil wells of the previous generation. This contributes to increasing the global EROI of oil with experience i.e. with C. However, there are fundamental theoretical limits to efficiency. We will always need a minimum level of embodied energy in the well infrastructure in order to deliver a given energy output. This is why G is represented with an asymptotic upper bound.[6]

H is the physical depletion component. It reflects the fact that oil wells are drilled first at sites which offer the best returns, both financial and energetic. The first oil wells correspond to better types of oil, located near the surface. These wells are located in less hostile environments, and in places necessitating less serious safety or environmental measures. This is less true for the second generation of oil wells, and even less true for the third generation. Thus, depletion of oil wells contributes to increase the energy inputs, hence the EROI, with C.[6]

By combining components G and H, we obtain a bell shaped curve as depicted on Figure 2.3: the global EROI of oil initially increases up to a point C_{max}, before declining (C_{max} is noted P_{max} on Figure 2.3). When the oil EROI drops below one, this resource is no more of economic use. Indeed, an EROI below one means that you need to invest more energy in extracting the oil than the energy you obtain from the oil itself. In practice, the minimum EROI value for a resource to be economically useful is strictly above one. Indeed, there are subsequent losses in the energy production process, which are not accounted for in the EROI (e.g. energy cost of refining, cost of transporting the oil to end users, conversion losses if the oil is used to generate electricity).[6]

In fact, the description of the global aggregated EROI curve which we gave for oil is applicable to any energy resource i.e. coal, gas, and even renewables. However, in the case of a renewable energy source, the x-axis of Figure 2.3 is not C anymore, but P. P is the total yearly production from the energy source. For renewables, equation 2.6 then becomes:

$$\text{EROI}(P) = \epsilon\, G(P)\, H(P)$$

The decrease of H with P reflects the fact that the first wind turbines or solar panels will be placed at the most favourable sites. When expanding the installed capacity, devices will have to be placed at sites which offer lower returns, hence they will make the total aggregated EROI decrease.[6]

We define the Ultimately Recoverable Resource (URR) of a non-renewable energy source as the total amount of that resource which can be harvested with an EROI superior to one. In other words, it is the value of C when the EROI curve crosses the horizontal line EROI$= 1$. However, the cumulated production C will never reach URR in practice since our definition of the EROI does not take all energetic costs into account: the resource will loose its economic interest before its EROI falls to one. Typically, the URR is broken into three parts: the historical cumulated production, the discovered reserves and the undiscovered resource. Hence, the estimations of URR evolve with knowledge i.e. the evaluation of the undiscovered resource must be regularly revised. Nonetheless, there are large discrepancies in the literature concerning the definition of URR. The definition of URR which we use is the same as Court and Fizaine, but differs namely from Dale's one.[2]

The equivalent of URR for a renewable energy resource is the technical potential (TP). It is the maximal amount of energy which can be extracted from that source with an EROI superior to one.[6]

URR and TP define the *availability* of energy resources: they tell us how much energy is available at most from these resources. The EROI of these resources on the other hand, defines their *accessibility*. As explained by Dale, "the EROI ratio defines the usefulness of an energy source by determining how accessible it is in producing energy for human purposes".[6]

2.1.1 EROI curves for global wind and solar potentials

This subsection describes work which has been produced at the UCLouvain previous to this master thesis, mostly by the PhD student Elise Dupont.

Research has been performed at the UCLouvain to determine global EROI curves for wind and solar resources, together with their technical potential [4][5]. The obtained curves are plotted on Figure 2.4:

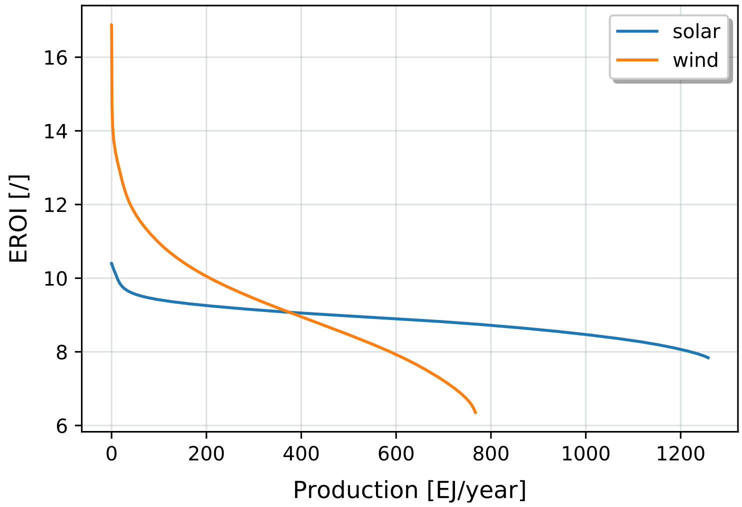


Figure 2.4: Global EROI curves for wind and solar

One immediately observes that unlike on Figure 2.3, these curves are monotonously decreasing functions. In other words, the technological improvement component G has been omitted. Indeed, the EROIs of next-generation wind and solar technologies were anticipated. With these next-generation technologies, it is assumed that wind and solar energy production devices will have reached physical limits in efficiency. Further technological improvements will not be able to significantly improve their EROI anymore. Moreover, the currently installed capacities of wind and solar power are extremely small compared to the global potentials of these resources. According to [11], the world energy production from wind and solar sources were respectively 4 and 1.6 EJ/year in 2017. The installed capacity of wind and solar facilities which do not correspond to next-generation technologies is therefore negligible.

The curves were generated using a bottom-up approach, as opposed to a top-down approach which would be based on input-output tables. More specifically, a grid-cell approach was followed. For every geographical location on Earth, the EROI of wind and solar technologies was assessed. In the case of wind, the EROI was computed according to an optimal array placement. In the case of solar energy, several technologies were competing against each other: photovoltaic solar panels (poly-crystalline or mono-crystalline silicon) and concentrated solar power (parabolic through, power tower, etc.). For each cell, the solar technology which offered the best EROI was selected. It was further assumed that wind and solar facilities did not hinder each other: the maximum capacities of wind and solar power can both be installed at the same time in one location. [4][5]

All locations on Earth were considered. First, areas such as Antarctica, Greenland and small isolated islands were put aside because they were too remote. Second, it was assumed that no solar facility could be installed in seas and oceans. It was considered that floating offshore wind turbines could be installed up to 200 nautical miles i.e. 370 km from the coast. Third, geographical constraints were taken into account. Land cover (urban area, forest, crop land, etc.) determined what portion of the area was available to install energy production facilities. Terrain slope also put a constraint on which technologies could be used. [4][5]

Concerning the energy inputs which came into account in EROI calculation, the methodology from [12] was used. All calculations were performed on a bottom-up physical basis, instead of using financial values to estimate physical inputs. Indeed, converting financial values to energy flows could introduce important bias in computations. For each technology, inputs were computed for the following twelve life-cycle phases:

1. Raw material extraction and beneficiation to concentrates
2. Concentrate material transport
3. Processing of concentrates into facility components
4. Transport of facility components from factory to installation site
5. Facility construction
6. Fuel extraction and processing
7. Fuel transport
8. Facility operation to generate electricity
9. Facility maintenance
10. Maintenance material transport
11. Facility decommissioning
12. Decommissioned materials transport

Both process energy and embodied energy were considered in the inputs. The twelve life-cycle phases are represented on Figure 2.5.

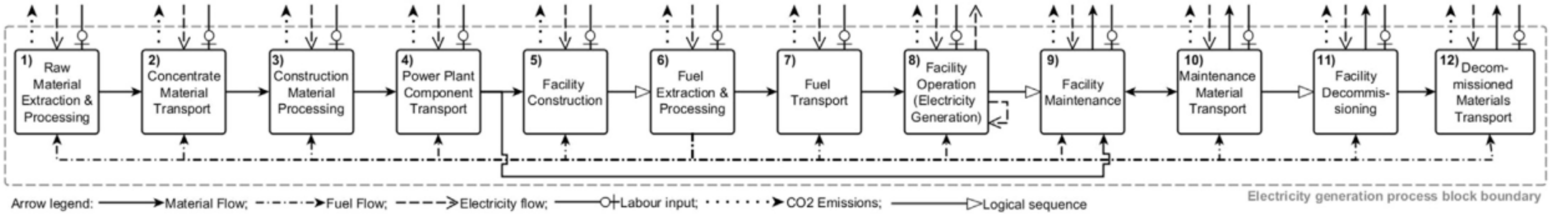


Figure 2.5: Life-cycle phases taken into account for computing the energy inputs of wind and solar technologies, from [12]

Some of the process energy inputs are in the form of electricity. Moreover, the current electricity mix is in great part supplied by fossil-based sources. When transforming fuels into electricity, typically two thirds of the energy from the fuels is lost. In other words, one needs 3 Joule of fuel to produce 1 Joule of electricity. To reflect this, the electricity energy inputs were multiplied by a factor 2.24. This factor was calculated based on the 2015 global electricity grid mix [12]. However, when the energy system transitions towards renewables, the fraction of the electricity mix supplied by fossil-based sources diminishes. In a 100% renewable energy system, there are no conversion losses, hence the electricity energy inputs do not need anymore to be multiplied by any factor. The consequence is a modification of the EROI curves of wind and solar, which will be discussed in chapter 4.

The energy inputs of wind turbines were adapted according to geographical locations, for example by taking into account the water depth which determines the required height of the monopile supporting offshore non-floating wind turbines. The energy outputs of wind and solar facilities were determined for each geographical location, depending on mean wind speed or solar irradiance. Once the EROI had been computed for each cell, the total amount of gross energy which could be produced for this cell was computed. By summing up the amounts of gross energy from all cells, the technical potential of wind and solar potentials was obtained. Their values are 767 and 1258 EJ/year, respectively.

Based on the above calculations, the global marginal EROI curves for wind and solar have been computed. It is considered that the first energy production facilities are built at locations which deliver the best EROI. Once the first locations are occupied, locations corresponding to the second-best EROI are chosen, and so on. The marginal EROI curves tell us for a given yearly production corresponding to a given installed capacity, what is the EROI of the last device which was installed. The global marginal EROI curves are plotted on Figure 2.6. [4][5]

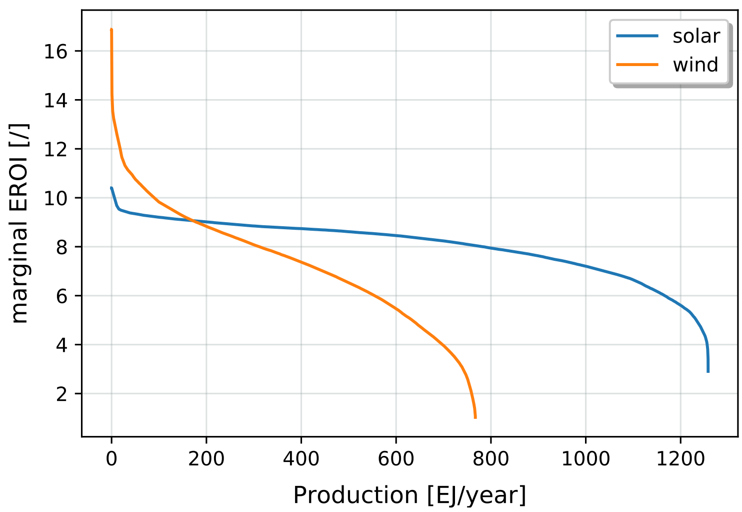


Figure 2.6: Global marginal EROI curves for wind and solar

The solar curve is rather flat, which indicates that the EROI values of solar resources tend to be more or less evenly distributed around the globe. We observe that the EROI of solar facilities ranges from 10.4 to 2.3. On the other hand, the marginal EROI curve for wind follows a sharp decrease. The best EROI is 16.9, but corresponds only to a few locations. The potential of locations with an EROI greater than 10 is 89 EJ/year, out of a total of 767 EJ/year. The worst EROI is 1. 50% of the global technical potential corresponds to locations with an EROI between 8.0 and 4.2.

Once the global marginal EROI curves have been produced, the global EROI curves from figure 2.4 can be computed. For each level of yearly production, the mean EROI of the energy producing facilities is computed according to equation 2.5. Since we take averages of EROI values, the resulting curves are flatter than the curves from figure 2.6. Logically, the mean EROI and marginal EROI of the first sites are the same. On figure 2.4, the best mean EROI values are also 10.4 for solar and 16.9 for wind. However, the mean EROI value when we occupy the last site, which is the worst one, is very different from the marginal EROI value of this site. The minimum mean EROI is around 7.8 for solar and 6.4 for wind.

As noted by Court and Fizaine, Dale does not mention this crucial difference between the EROI curve and the marginal EROI curve in his PhD thesis. He does not precise to which type correspond his renewable EROI curves. [2][6]

Finally, Figure 2.7 provides as an illustration the world map of EROI values for wind energy technologies, as well as the corresponding suitability factors. The suitability factor is the percentage of local area that can be devoted to wind turbine installation.

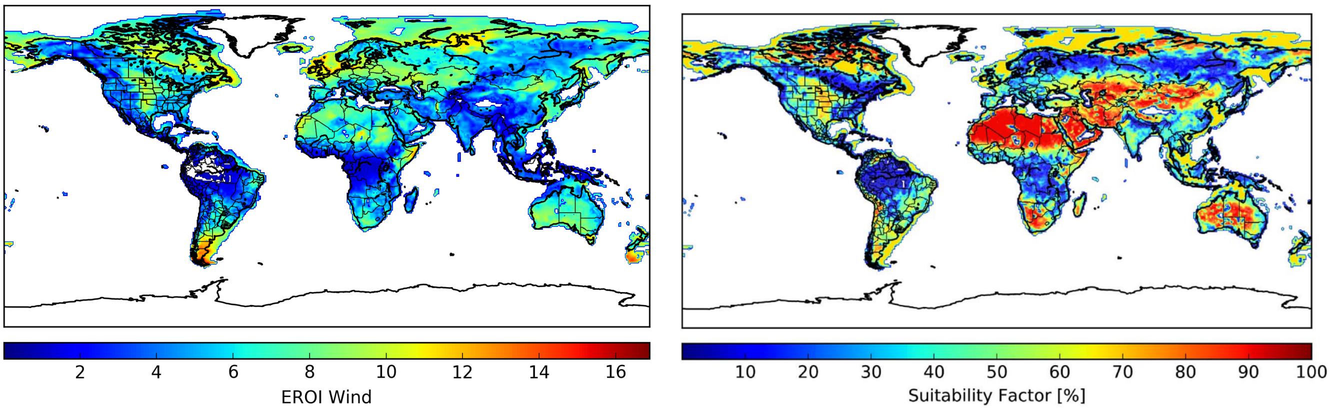


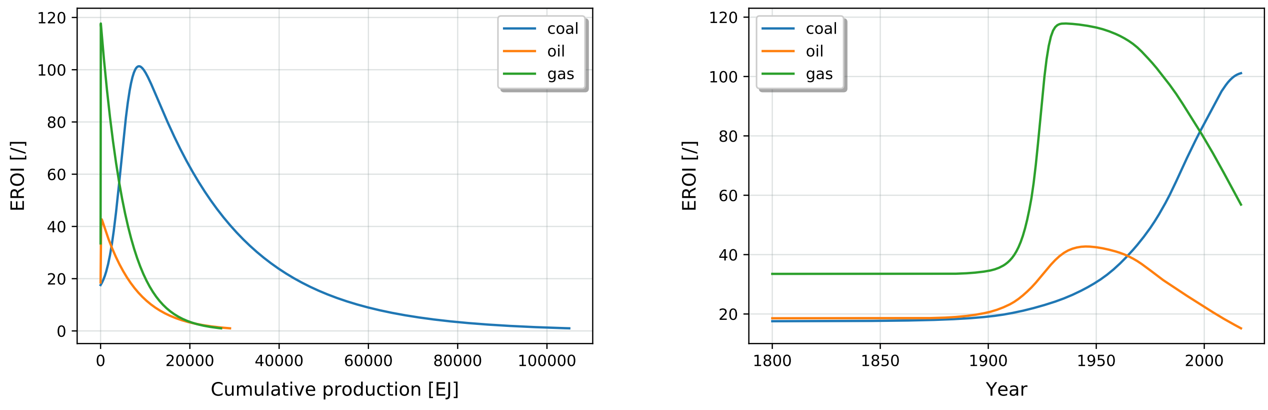
Figure 2.7: World maps of EROI and suitability factor for wind technologies

One should note that the spots in the North Sea which are already used in 2019 offer among the best EROI values.

2.1.2 Global EROI curves for fossil fuels

Contrary to wind and solar energy, we do not dispose of reliable global EROI curves for fossil fuels. Their extraction is performed in many countries by national companies, which do not make their data public. Moreover, most of the data available consist in costs and revenues from oil fields. Converting these economic data into energy flows introduces an important bias in EROI estimations [3][13].

Court and Fizaine produced the global EROI curves for coal, oil and gas which are drawn on Figure 2.8 (a). When combining these curves with historical energy production data from [11], we obtain the curves drawn on Figure 2.8 (b) for the evolution of the EROI of fossil fuels in function of time.



(a) Global EROI curves

(b) Corresponding historical evolution of EROI

Figure 2.8: Global EROI curves for fossil fuels, according to [2]

Unfortunately, these curves disagree with many estimations from the EROI literature. In particular, the important difference between the EROI of oil and gas seems difficult to justify. [3][9][13][14]

We prefer to reconstruct global EROI curves for fossil fuels. We keep the approach of Court and Fizaine to determine the components ϵ, G and H of the EROI function. [2]

So, we consider that the technological component of the EROI of coal, oil and gas has the following form:

$$G(\rho) = \Xi + \frac{1 - \Xi}{1 + exp(-\xi\,(\rho - \tilde{\rho}))}$$

where the variable ρ is given by $\rho = \frac{C}{URR}$ and is called the *exploited resource*. It indicates what fraction of the total available resource has already been used. The profile of $G(\rho)$ is depicted on Figure 2.9.

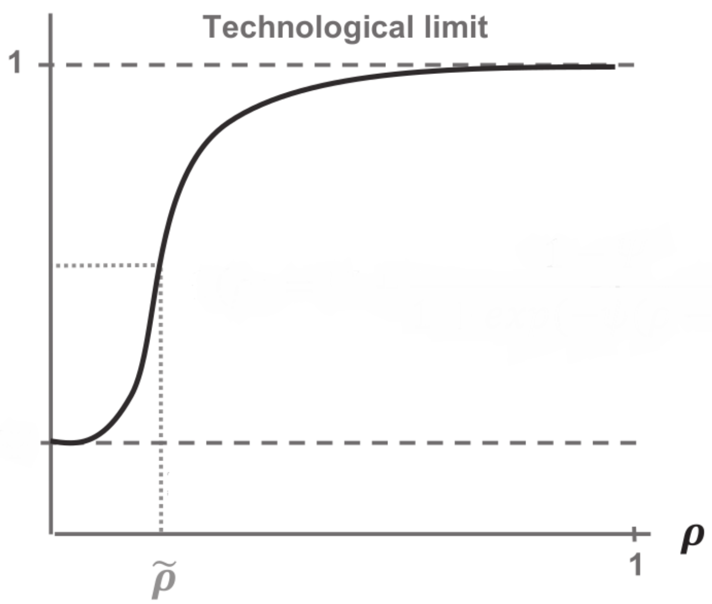


Figure 2.9: Profile for the technological component of the EROI, from [2]

The function $G(\rho)$ is strictly increasing. It has an upper asymptote, which represents the fundamental theoretical limit in efficiency. Its derivative decreases to zero when approaching this limit. However, the derivative first increases from the origin up to a point $\tilde{\rho}$. As explained by Court and Fizaine, in this formulation "technological learning is slow at first and must endure a minimum learning time effort before taking off". [2]

The physical depletion component is simply modeled as a decreasing exponential:

$$H(\rho) = e^{-\phi\,\rho}$$

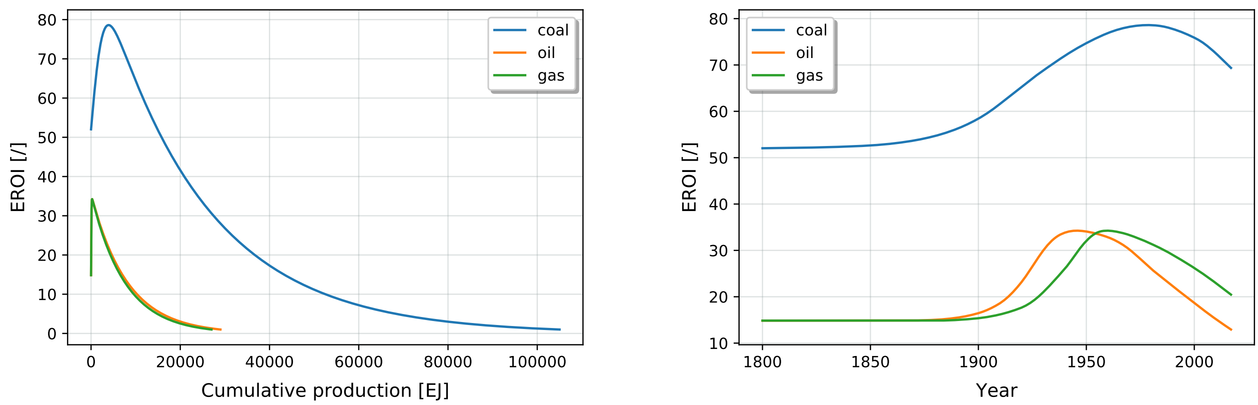
where the parameter ϕ is taken to be $log(\epsilon)$, such that EROI$(\rho) = 1$ when $\rho = 1$. [2]

Table 2.1 displays the values we chose for the different parameters.

Table 2.1: Values of the parameters used for the global EROI curves of fossil fuels

Resource	URR [EJ]	ϵ	Ξ	ξ	$\tilde{\rho}$
Coal	105000	100	0.07	70.5	0.001
Oil	29000	35.5	0.0	658.3	0.0005
Gas	27000	35.5	0.0	658.3	0.0005

Figure 2.10 plots the corresponding EROI curves.



(a) Global EROI curves

(b) Corresponding historical evolution of EROI

Figure 2.10: Global fossil EROI curves used for baseline run

In order to choose the values of the parameters ϵ, Ξ, ξ and $\tilde{\rho}$, we started from the values proposed by Court and Fizaine, then made adaptations such that the EROI curves roughly agreed with the estimates from [3]. For URR, we kept the values used by Court and Fizaine. Indeed, as will become clear in the following sections, the exact value of URR for fossil fuels has no impact on the model results, given the time horizon of the simulation.

We chose very similar values for the parameters of oil and gas. Indeed, oil and gas are often studied together with a common EROI curve, since these resources are extracted from the same fields, with overlapping production operations [3]. Moreover, oil and gas are substitutable to each other in many industrial applications.

Like Court and Fizaine, we consider that our EROI curve for oil covers all types of oil, including non-conventional oil. The same applies for gas. The coal EROI curve includes all types of coal (bituminous, sub-bituminous, lignite), even if they differ in quality. Indeed, creating a separate EROI curve for each type of oil or coal would unnecessarily complexify the model. It would not enable to gain accuracy either, because of the lack of EROI data for fossil fuels.

2.1.3 Global EROI curves for other renewables and nuclear

Research to produce global EROI curves has been mainly focused on wind and solar energies, as well as fossil fuels. We dispose of less data regarding the EROI of the remaining energy sources. These sources include:

- biomass: solid biomass, bio-ethanol, bio-diesel, etc.
- hydropower: dam systems, run-of-river systems, etc.
- geothermal energy
- tidal energy
- wave energy
- ocean thermal energy conversion (OTEC)
- nuclear fission

The above mentioned sources are all renewable energies, except nuclear fission. To our knowledge, the technical potentials of these renewable sources are by far smaller than the technical potentials of wind and solar energies. On the other hand, as will become clear in next chapter, the aim of our model is to study a transition towards a nearly 100% renewable energy mix, in which nuclear power would only play a marginal role.

So, the global EROIs of the resources considered in this section are less well known, and these resources play a much smaller role in the model we will investigate. We therefore regroup all these resources together and model their global EROI curve very simply as a horizontal line. More precisely, we consider that the aggregated technical potential of all these resources is in total 200 [EJ/year], and that they have a constant mean EROI of 6, whatever the yearly level of energy production.

The chosen values for EROI and TP are based on [6] and [3]. Of course, we are aware that modelling the global EROI as a constant value is rather simplistic and that our values for EROI and TP are subject to large uncertainties. For this reason, we will investigate the effects of different values for EROI and TP in chapter 4, respectively within the ranges [4,20] [/] and [100,800] [EJ/year].

2.2 Capital intensity of energy sources

So far, we have analysed the availability (URR or TP) and accessibility (EROI curve) of energy sources. Another important characteristic which differentiates these sources from one another is their capital intensity.

Given an energy production facility, we define χ, its capital intensity, as the proportion of energy inputs which consist of embodied energy, as opposed to process energy. We generalise this definition to each global energy resource, by taking the mean capital intensity of all production facilities for this resource.

As explained by Dale, renewable energy sources have a far smaller power density than fossil fuels. Indeed, fossil fuels can be seen as flows of solar energy which accumulated during millions of years and then were "concentrated through time by compression and heat from geological activity" [6]. In other words, even if the technical potential of renewable energies is huge, they are extremely *diffuse* compared to non-renewable energies. For this reason, renewables require a more important infrastructure than fossil fuels. This infrastructure aims at concentrating renewable flows of energy into electricity or work. In the case of fossil fuels, the concentration process has already been done for us by nature.

So, Dale takes the constant values $\chi = 0.1$ for fossil fuels and $\chi = 0.9$ for renewables. We keep $\chi = 0.1$ for fossil fuels. Moreover, the value $\chi = 0.9$ is confirmed for solar by the data from Elise Dupont which were used to generate the wind and solar EROI curves. However, these data also indicate that $\chi = 0.8$ for wind. We use this value instead of Dale's one. Finally, our last resource, "other renewables and nuclear" is a mix of renewable and non-renewable energies (Dale considers uranium as non-renewable). We therefore take $\chi_k = 0.5$ for this last resource, as a compromise between $\chi = 0.1$ and $\chi = 0.9$. This value will be further discussed in chapter 4. [4][5][6]

Chapter 3

The GEMBA model

3.1 Context

In most standard economic textbooks, the economy is represented using the following diagram:

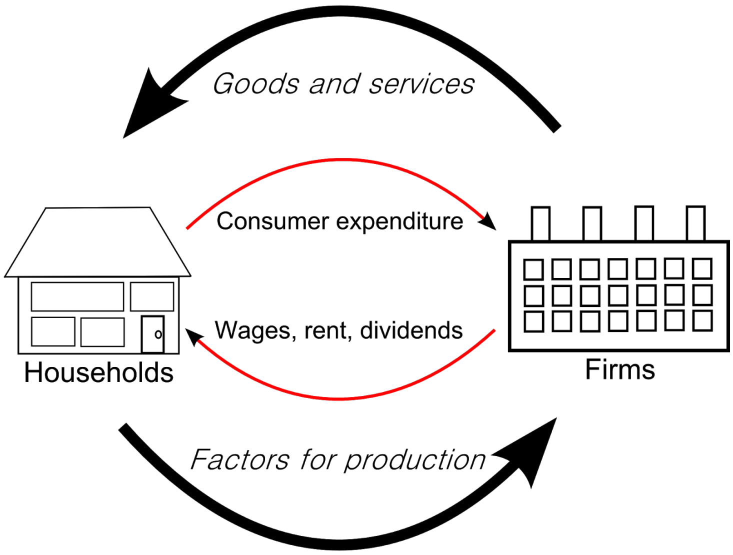


Figure 3.1: Standard schematic view of the economy, from [15]

The focus is on the circular flow of capital, labour, goods and services. Behaviour within the economy is considered to be determined solely by processes internal to it. According to this view, "the economy may be categorised as closed-loop feedback system, which is presumably also physically open to the flow of energy and materials, although it is unclear from the model" [6].

Such view of the economy does not consider explicitly the throughput of materials and energy, on which the system relies for its functioning. Indeed, on one hand the economy needs a source of energy and materials. On the other hand, the economy needs a sink to absorb all the waste which it produces. Neither the source, nor the sink can be considered to be infinite. The limited capacity of the sink translates into the problem of global warming: simply said, human societies produce more CO_2 every year than what the Earth can absorb. Furthermore, the energy resources on which the system relies are constrained by their EROI. As indicated by Hall, the EROI of fossil fuels on which the economy currently relies has undergone a steady decline in previous years [16]. The urgency of global warming may translate into a massive shift towards renewable energy sources. Since these energy sources have a notoriously lower EROI than fossil fuels, this will further constrain the source on which the economy relies. These considerations can difficultly be dealt with using standard economic theory.

In response to these claims, economists generally put forward two main points:

1. Energy scarcity will inspire technological change or promote a more efficient use of the resource, therefore making available new sources of energy or enabling the economy to function with less energy inputs. [6]
2. Production factors are substitutable. If energy sources become constrained, energy inputs can be compensated for by increasing investments in labour and capital.

Our responses to these points are the following:

1. The global warming constraint requires a very rapid shift towards renewable energies. Indeed, most of the world energy production will have to come from renewable sources by 2050, if the Paris agreement is to be respected. This shift will have to carried out using current and next-generation technologies, which EROIs are known and relatively low. It is very unlikely that on such short time horizon, a new technology would be discovered, which would radically transform the energy landscape. Even the breakthrough of nuclear fusion, which has been under development since decades, is not expected before 2070.
   As for improvements in energy efficiency, these must be taken into account, but bearing in mind that the potential gains are limited. Indeed, there exists theoretical limits to energy efficiency, from which our current technologies are already very close.
2. We believe that the substitutability of energy as an input for production is limited too. Any industrial process needs a minimum amount of energy in order to be carried out. Neglecting this would amount to violating the laws of thermodynamics. [6]

Moreover, the metrics which are traditionally used to measure economic activity, such as GDP, are based on price calculations. Despite all the obvious advantages of basing these metrics on prices, we believe that this approach faces some weaknesses:

1. Prices are very volatile and difficult to predict. Oil analysts and macroeconomists have failed to forecast the prices of oil over the past twenty-five years. It therefore seems unlikely that we could produce reliable predictions for energy prices up to the year 2050.
2. Money is adapted to deal with human-to-human interactions. However, human-to-nature interactions do not consist in monetary transactions, ruled by market mechanisms. For this reason, the use of money i.e. price is not suited to analyse human-to-nature interactions.
3. The costs of many technologies are indirectly influenced by the price of energy. Thus, in order to project the future costs of these technologies, one needs to estimate the future energy prices. These projected technological costs then cannot be used to forecast energy prices, otherwise the reasoning is circular. [6]

Based on these considerations, Dale decided to construct a *biophysical* economic model of the energy-economy system, which he named the GEMBA model. This acronym stands for "Global Energy Modeling: a Biophysical Approach". Biophysical economics is a branch of economics which stems back to the eighteenth century, and which has been gaining increasing attention since the second half of the twentieth century [10]. "The biophysical economist believes that, the laws of the physical sciences must constrain the choices available to an economic agent and hence use “basic ecological and thermodynamic principles to analyze the economic process" [10]. As further explained by Dale, "from the biophysical systems perspective, a social system such as an economy is seen in terms of the physical activities that take place in it. This is clearly different from the social ways in which the activities of society are seen from the political-economic perspective." [6]

Thus, the numeraire used in Dale's model is energy (expressed in Joule) instead of price. By doing so, he avoids the traps into which can fall price-based analyses:

1. Energy flows and inputs are much less volatile than prices and can be more confidently used when designing predictions.
2. Energy flows are a very convenient way to analyse human-to-nature interactions. This can be done namely using bottom-up engineering analysis.
3. Global available energy resources and their EROI curves can be estimated with our present knowledge. Based on these and on an adequate model of the economy, we can project future energy demand, and evaluate how the energy sources will fulfill this demand. This does not imply any circular reasoning.

Furthermore, by expressing economic flows in terms of energy units, Dale can assure himself that his GEMBA model respects the laws of thermodynamics, and in particular the principle of energy conservation. [6]

Finally, in a biophysical economic model such as GEMBA, economic growth is not self-evident. Growth is considered to be constrained by the availability and accessibility of energy resources. Such consideration generally cannot be taken into account in traditional economic models. Indeed, long-term economic growth is generally assumed, "either explicitly or implicitly through the use of a discounted value on future investments". [6]

3.2 Presentation of the model

In this section, we present the adaptation of Dale's GEMBA model which we implemented. First, we state the scope and boundary of Dale's model, and explain to what extent we deviate from these. Then, the model is described and its equations explained. A summary of the model equations follows, which indicates how they combine so that they can be used for computer simulation. After that, the parameter values used for baseline simulation are detailed. Finally, the model assumptions are summarised and the main differences with Dale's initial model are stated.

3.2.1 Scope and boundary

Before entering any description of a system model, one should specify the scope and boundary of this system. To describe scope, Dale explains that his aim is to study the following questions:

- "Are the technical potentials of renewable energy sources enough to supply the current demand for energy or is energy descent inevitable ?"
- "What would be the effect on the physical resource economy of a transition to an energy supply system run entirely on renewable energy sources ?" [10]

In order to answer these questions, Dale only needs to consider the global aggregated energy demand, not the size of the population. In standard economic modelling, energy demand is often determined by the product of population and per capita consumption. However, using per capita (i.e. average) energy demand does not show the inequalities in energy consumption over the population. A good model should at least take the regional inequalities into account. These inequalities are particularly pronounced when considering the global economy. Their evolution over time depends upon a number of interacting social factors, which fall outside the scope of the GEMBA model. For this reason, Dale models energy consumption without making use of population size. [6]

Furthermore, flows of food are maintained simply to support the population, whatever the level of economic activity. Since population is not considered within the GEMBA model, flows of food are not taken into account either. Agriculture is outside the scope of the model. [6]

When addressing his research questions, Dale focuses on the concept of peak oil and resource scarcity: he thinks that given the limited availability and accessibility of fossil resources, society will have to transition towards renewable energy sources. Hence, in Dale's model, the transition to renewable energies occurs solely because of the depletion of fossil fuels. However, we believe that the problem of fossil fuels scarcity is much less pressing than global warming. Hence, we think that the main driver of the energy transition will be instead the capping of CO_2 emissions, set in line with climatic goals. Expressed in terms of source and sink like in the previous section, Dale considers that the constraints on economic activity will come from the depletion of the source. We rather think that the major problem is a problem of sink: human societies produce more CO_2 than what can be absorbed by the Earth, and through this dangerously destabilise climate. In order to remedy to this, the economy is forced to adapt its functioning and to use the source differently i.e. to shift from fossil to renewable energies. This in turn affects the economy, since the EROI values and capital intensities of these two types of energy are very different.

Because of this difference, the energy transition predicted by Dale's model takes place very progressively, from 2015 up to 2100 and beyond. In our adaptation of the model however, we impose that the energy transition must occur very rapidly: most of the global energy demand must be fulfilled by renewable sources already by 2050.

So, our adapted GEMBA model also aims at answering Dale's research questions. We prefer to formulate our own research question though, in order to mark the difference between Dale's approach and ours. Our question is the following:

- In what measure is an energy transition towards nearly 100% renewable production in 2050 feasible at global scale, without provoking a collapse of the global economy ?

We allow ourselves to envision the possibility of a collapse, since it is the conclusion Dale draws from his model. We aim to find under which conditions we can obtain conclusions less pessimistic than him.

Dale uses his model to examine the long-term future (up to 2200), while we stick to short-term and medium-term. Indeed, we think that the evolution of technology can difficultly be predicted on longer time scales.

We further point out that as stated in our research question, we aim to investigate a transition towards nearly 100% renewable production. In this scenario, nuclear power only plays a marginal role. Like in Dale's initial model, we do not consider population size and agriculture.

We can now define the boundaries of our model, which are exactly the same as Dale's ones. When modelling energy use at a country level, it is easy to meet the energy demand: the lack of energy is compensated explicitly, thanks to energy import, or implicitly, thanks to the import of capital goods with high embodied energy. So, constraints on energy production should be studied at global scale. For this reason, our energy-economy model is a global one. We further specify its boundary by stating the inputs and outputs of the system. The essential output of the system is human-made capital, such as cars, buildings, etc. This output is produced thanks to the processing of energy resources. Thus, the necessary inputs to the system are the energy resources, characterized by their EROI curve and capital intensity. Other inputs, like materials, water, etc. are not modelled [6].

3.2.2 Model description and equations

We now describe our adaptation of the GEMBA model. Some of the equations and notations are different from Dale's ones. However, the global dynamics are very similar.

Like the initial version, our model consists in a discrete-time system. Indeed, this allows us to include complex and non-linear elements, such as the EROI curves. No analytical solution can be found for such non-linear discrete-time system.

We consider that the global economy is divided in two sectors: the industrial sector and the energy sector. The industrial sector is also called the main economy. We characterize the main economy by the total amount of industrial capital stock present in it. This quantity is captured by the variable K_{ind}. Its units are [capital goods]. Moreover, the main economy relies on the energy sector for its functioning. This energy sector is composed of a number of energy sources, together with all the infrastructure (in [capital goods]) devoted to energy production. This infrastructure is not explicitly represented by a model variable.

In order to operate, the economy requires the energy sector to generate a primary energy production P [EJ/year]. We assume that P is a function of K_{ind}:

$$P = \epsilon\, K_{ind} \tag{3.1}$$

where ϵ, called the energy requirement factor of the economy, is in [EJ/(years $\cdot$ capital goods)].

The energy sector is divided into non-renewable and renewable energy sources. As described in section 2, we consider the following energy sources:

Non-renewable:

- coal
- oil
- gas

Renewable:

- wind
- solar
- other renewables and nuclear

In our model, each energy source, indexed by k, is fully defined by the following characteristics:

- Incept date$_k$: the first year the energy source is used under its modern form.[1]
- URR_k or TP_k, as defined in section 2.
- The EROI function of the resource, described in section 2.
- χ_k, the capital intensity of the energy source, already defined in section 2.

Furthermore, the variable P_k [EJ/year] designates the primary energy production from each energy source. For non-renewable sources, the variable C_k [EJ] designates the total cumulated energy production since the incept date. The variable ρ_k is called the exploited resource. For non-renewables, $\rho_k = \frac{C_k}{\mathsf{URR}_k}$ and for renewables, $\rho_k = \frac{P_k}{\mathsf{TP}_k}$.

Given the value of P, we can find the value of each P_k thanks to the parameter γ_k and the equation

$$P_k = \gamma_k \, P$$

γ_k is called the fraction of supply. $\sum_k P_k = P$ hence logically, $\sum \gamma_k = 1$.

As explained in section 2, the EROI of resource k is the ratio between its gross energy output and its energy inputs. Hence, we have the formula

$$\mathsf{EROI}_k = \frac{P_k}{S_{1,k} + S_{2,k}}$$

where $S_{1,k}$ designates the energy inputs in the form of process energy, and $S_{2,k}$ the energy inputs in the form of embodied energy. Both $S_{1,k}$ and $S_{2,k}$ are in [EJ/year]. Besides, the definition of χ_k implies the equation

$$\chi_k = \frac{S_{2,k}}{S_{1,k} + S_{2,k}}$$

By combining these two equations, we can obtain the values of the energy inputs as a function of P_k:

$$S_{1,k} = (1 - \chi_k) \, \frac{P_k}{\mathsf{EROI}_k}$$
$$S_{2,k} = \chi_k \, \frac{P_k}{\mathsf{EROI}_k}$$

$S_{1,k}$ represents energy which is directly consumed by the energy sector for its functioning. The energy which reaches the main economy is therefore

$$E = P - \sum_k S_{1,k}$$

Thanks to this energy, the main economy generates the industrial output Y, measured in [Capital goods/year]:

$$Y = \frac{E}{q}$$

In the equation, the factor q is the energy intensity of industrial production, in [EJ/capital good].

[1] For example, we consider that wind has only been used since the year 2000. This is false, since before that wind energy had already been used for long to power mills. However, we neglect such archaic form of wind use.

Part of the industrial output must return to the energy sector in order to maintain and expand its infrastructure: this feedback of capital to the energy sector is represented by the variable F (in [capital goods/year]). Besides, we already know $S_{2,k}$, the quantity of energy embodied in this capital feedback as well as q, the energy intensity of industrial production. We therefore have

$$F = \frac{\sum_k S_{2,k}}{q}$$

Let us now define s, the saving rate of the economy. It means that a fraction $(1-s)$ of the industrial output is directly consumed by the economy. The rest is invested in industrial capital and energy sector capital. The investment in energy sector capital has already been defined as F. We call Acc_{ind} the investment in industrial capital. We have

$$s\,Y = \mathsf{Acc}_{ind} + F$$

which we rearrange as

$$\mathsf{Acc}_{ind} = s\,Y - F \tag{3.2}$$

We call Acc_{ind} the accumulation of industrial capital stock. We must also take into account the depreciation of industrial capital stock, given by

$$\mathsf{Dep}_{ind} = \delta\,K_{ind}$$

In this equation, δ stands for the depreciation rate of industrial capital stock.

Thanks to Acc_{ind} and Dep_{ind}, we can write the equation for the evolution of industrial capital stock:

$$K_{ind}(t+1) = K_{ind}(t) + \mathsf{Acc}_{ind}(t) - \mathsf{Dep}_{ind}(t)$$

As made clear by the previous equation, our model is a discrete-time model. The starting date of the model simulation is the year 1800. We take a time step of 1 year, and run the simulation up to 2050. The initial condition for K_{ind} must be a strictly positive value in 1800. $C_k = 0$ for all fossil fuels in 1800.

The diagram on next page depicts the structure of our adapted GEMBA model. All stages of energy production are aggregated into a single process, since the EROI definition already takes all these stages into account [6]. A summary of the model's variables and parameters is also presented. The different energy sources are indexed by k.

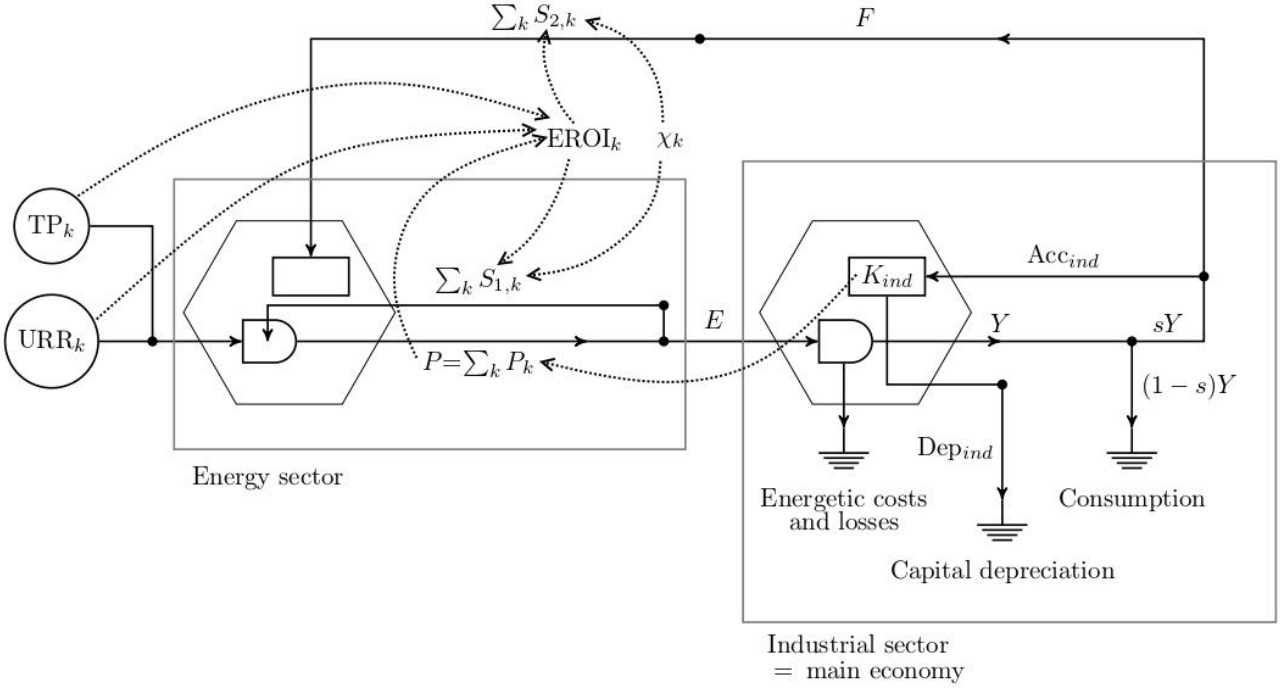


Figure 3.2: Diagram of the adapted GEMBA model. The economy is divided into two main parts: the energy sector and the industrial sector, also called the main economy.

Variables	
K_{ind} = capital stock of industrial sector	[Capital goods]
P = total primary energy production	[EJ/year]
P_k = primary energy production of resource k	[EJ/year]
E = energy flow which reaches the main economy	[EJ/year]
Y = industrial output of the economy	[Capital goods/year]
F = capital feedback to the energy sector	[Capital goods/year]
$\sum_k S_{1,k}$ = process energy consumed by the energy sector	[EJ/year]
$\sum_k S_{2,k}$ = energy embodied as capital consumed by the energy sector	[EJ/year]
C_k = total cumulated production of fossil resource k	[EJ]
ρ_k = exploited resource	[/]
Acc_{ind} = accumulation of industrial capital stock	[Capital goods/year]
Dep_{ind} = depreciation of industrial capital stock	[Capital goods/year]

Parameters	
URR_k = Ultimately Recoverable Resource (fossil fuels only)	[EJ]
TP_k = technical potential (renewables only)	[EJ/year]
γ_k = fraction of supply	[/]
EROI_k = Energy Return On Investment	[/]
χ_k = capital intensity	[/]
Incept date_k = incept date	[year]
ϵ = energy requirement factor of the economy	[EJ/(year·capital good)]
q = energy intensity of industrial production	[EJ/capital good]
s saving rate of the economy	[/]
δ = depreciation rate of industrial capital stock	[/]

The diagram represents the stocks and flows of the model. The only stocks are the capital stocks of the industrial and energy sectors, as well as URR_k. The other variables represent flows of capital or energy. The solid lines represent physical flows, while the dotted ones stand for transfer of information.

Moreover, each hexagon on the diagram encompasses capital stock (in the rectangular box) as well as its productive action, both for the energy and industrial sectors. Capital stock from the energy sector is represented, even if the adapted model's equations do not include a variable for it.

Besides, there are three sinks in the model. The first one, "energetic costs and losses", represents costs and losses in the energy transformation chain, which are not included in the EROI definition (e.g. transport losses, cost of storage for renewables, etc.). The second one, capital depreciation, represents the fact that any capital stock has a limited lifetime and depreciates over time. Finally, the consumption sink represents all capital stock which is used in the economy for non-productive activities (e.g. material goods of households).

One should further note that F and $\sum_k S_{2,k}$ represent the same physical flow, respectively from the capital and embodied energy perspectives.

In addition, we observe that according to the GEMBA model, "the economy is seen as a physically open system, dependent on flows from its environment in order to sustain itself" [6]. A key difference compared to standard economic models is that not only capital (or money), but also energy which is embodied in this capital, must flow back from the main economy to the energy sector.

3.2.3 Summary of model equations

We now summarise how the equations described above combine to form a discrete-time model.

Initialisation:

$$K_{ind}(0) = K_0$$
$$C_k(0) = 0 \quad \forall k$$
$$\rho_k(0) = 0 \quad \forall k$$

for $t = 0 : t_{end}$

$$P(t) = \epsilon(t)\, K_{ind}(t)$$
$$P_k(t) = \gamma_k(t)\, P(t)$$
$$S_{1,k}(t) = (1-\chi_k)\, \frac{P_k(t)}{\mathrm{EROI}_k(\rho_k(t))}$$
$$S_{2,k}(t) = \chi_k\, \frac{P_k(t)}{\mathrm{EROI}_k(\rho_k(t))}$$
$$C_k(t+1) = C_k(t) + P_k(t) \qquad \text{for non-renewables}$$
$$\rho_k(t+1) = \frac{C_k(t+1)}{\mathrm{URR}_k} \qquad \text{for non-renewables}$$
$$\rho_k(t+1) = \frac{P_k(t)}{\mathrm{TP}_k} \qquad \text{for renewables}$$
$$E(t) = P(t) - \textstyle\sum_k S_{1,k}(t)$$
$$Y(t) = \frac{E(t)}{q(t)}$$
$$F(t) = \frac{\sum_k S_{2,k}(t)}{q(t)}$$
$$\mathrm{Acc}_{ind}(t) = s(t)\, Y(t) - F(t)$$
$$\mathrm{Dep}_{ind}(t) = \delta\, K_{ind}(t)$$
$$K_{ind}(t+1) = K_{ind}(t) + \mathrm{Acc}_{ind}(t) - \mathrm{Dep}_{ind}(t)$$

end

In the above for loop, the index k of the variables and parameters designates all energy sources k such that Incept date$_k > t$.

The reader should note that in the model equations, not only the variables, but also a number of parameters are allowed to vary with time.

The discrete-time model is implemented in Python. Our code is in appendix A. We chose to use Python, unlike Dale who uses VenSim, in order to have full transparency in our model equations and in the calibration of parameters' values.

3.2.4 Parameter values used for baseline simulation

To begin with, we choose the following incept dates for the energy sources:

Table 3.1: Values used in our model for the incept dates

coal	oil	gas	wind	solar	others
1800	1860	1880	2000	2000	1800

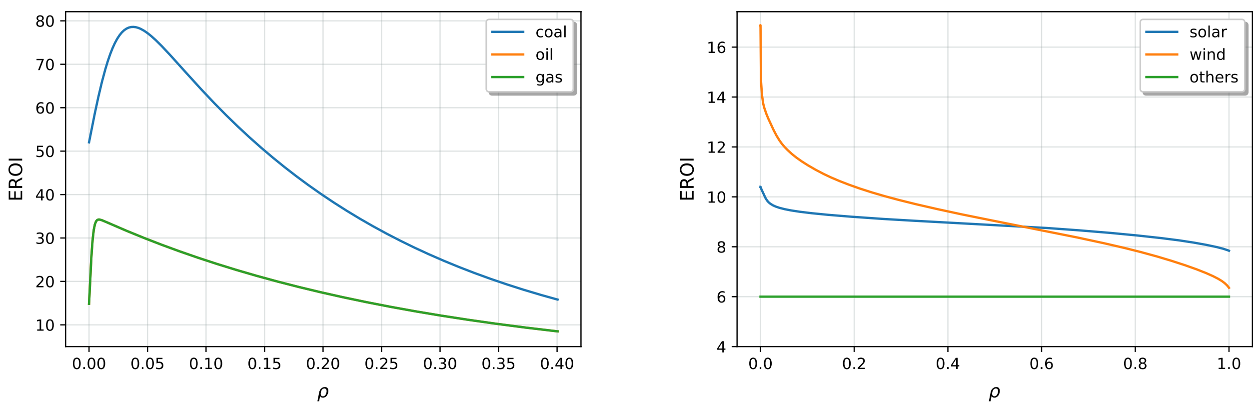
These values are chosen based on [6], [2] and [11]. They are slightly different from Dale's ones.

For baseline run, we use the values of URR$_k$, TP$_k$ and χ_k from section 2:

Table 3.2: Values of URR$_k$, TP$_k$ and χ_k used for baseline run

	coal	oil	gas	wind	solar	others
URR [EJ]	105000	29000	27000	-	-	-
TP [EJ/year]	-	-	-	767	1258	200
χ [/]	0.9	0.9	0.9	0.8	0.9	0.5

The functions EROI$_k(\rho_k)$ are also the ones from section 2. They are summarised on Figure 3.3.



(a) Non-renewables (b) Renewables

Figure 3.3: Functions EROI$_k(\rho_k)$ used for baseline run

The EROI curves for oil and gas are superposed. We only plot the EROIs of fossil fuels up to $\rho_k = 0.4$, in order to obtain a clearer plot. This is not problematic since in baseline simulation, ρ_k never exceeds 0.4 for fossil fuels.

Moreover, we choose constant exogenous values for δ and $s(t)$. $\delta = 0.05$, $s(t) = 0.1\ \forall t$.

Besides, we dispose of historical data for global primary energy production between 1800 and 2017, from [11]:

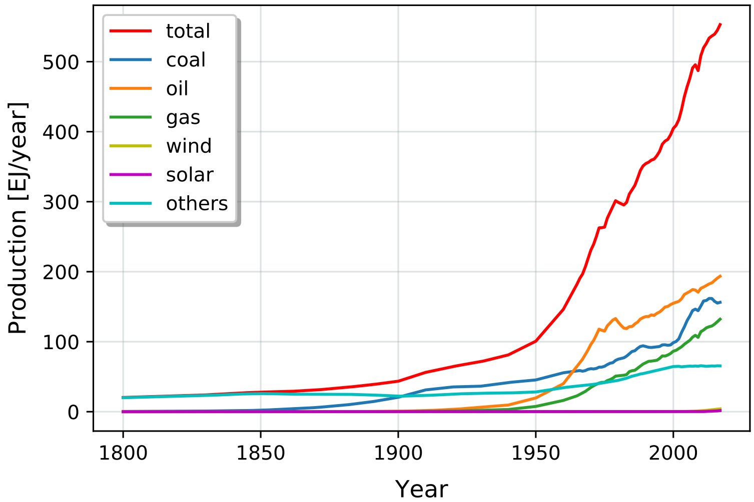


Figure 3.4: Historical primary energy production by energy source, from [11]

These data give us $P_k(t)$ for all energy sources between 1800 and 2017. Based on these, we can compute the historical values of $\gamma_k(t)$ thanks to the formula

$$\gamma_k(t) = \frac{P_k(t)}{\sum_k P_k(t)}$$

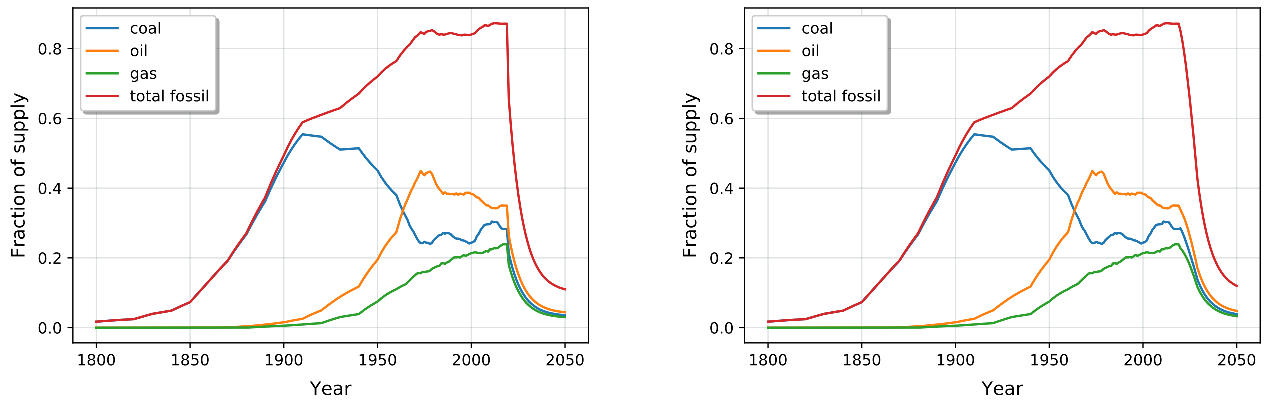
Then, we wish to impose values for $\gamma_k(t)$ between 2019 and 2050 which are compatible with the respect of the Paris agreement. To this end, we take example on EU's climatic goals [17]:

- In 2020, achieve a 20% cut in greenhouse gas emissions compared with 1990
- In 2030, achieve a 40% cut in emissions compared with 1990
- in 2050, achieve between 80% and 95% of emissions cut compared with 1990

We believe that one major contributor to this cut in greenhouse gas emissions must be a cut in the use of fossil fuels. Hence, we impose that $\gamma_k(t)$ for fossil resources must follow an exponential decrease between 2019 and 2050, such that

- $\sum_k \gamma_{k,\text{fossil}} = 0.7$ in 2020
- $\sum_k \gamma_{k,\text{fossil}} = 0.5$ in 2030
- $\sum_k \gamma_{k,\text{fossil}} = 0.15$ in 2050

So in our model, we impose the profiles from Figure 3.5(a) for $\gamma_k(t)$ of fossil resources. In these profiles, we assume that $\gamma_k(2018) = \gamma_k(2017)\ \forall k$.



(a) Before smoothing

(b) After smoothing

Figure 3.5: Value of γ_k imposed for fossil fuels in baseline run

Nonetheless, the discontinuity in 2019 is too brutal hence unrealistic, even with ambitious climatic targets. For this reason, we smooth the γ_k profiles thanks to the following formula:

$$\gamma_{k,\text{smoothed}}(t) = \frac{\sum_{\tau=t-9}^{t} \gamma_k(\tau)}{10} \quad \forall t > 2019 \tag{3.3}$$

Thus, the γ_k profiles which we finally impose in our Python simulation are the ones from Figure 3.5(b).

Regarding the value of $\gamma_k(t)$ for non-fossil energies, they are fixed between 1800 and 2017 by historical production data. Between 2019 and 2050, we have

$$\gamma_{\text{wind}} + \gamma_{\text{solar}} + \gamma_{\text{others}} = 1 - \sum_k \gamma_{k,\text{fossil}}$$

where we omitted the variable (t) for the sake of brevity.

We further add the following equations in order to fix the values of γ_{wind}, γ_{solar} and γ_{others} between 2019 and 2050:

$$\gamma_{\text{wind}} = (\gamma_{\text{wind}} + \gamma_{\text{solar}} + \gamma_{\text{others}}) \cdot \frac{\text{EROI}_{\text{wind}}}{\text{EROI}_{\text{wind}} + \text{EROI}_{\text{solar}} + \text{EROI}_{\text{others}}} \tag{3.4}$$

$$\gamma_{\text{solar}} = (\gamma_{\text{wind}} + \gamma_{\text{solar}} + \gamma_{\text{others}}) \cdot \frac{\text{EROI}_{\text{solar}}}{\text{EROI}_{\text{wind}} + \text{EROI}_{\text{solar}} + \text{EROI}_{\text{others}}} \tag{3.5}$$

$$\gamma_{\text{others}} = (\gamma_{\text{wind}} + \gamma_{\text{solar}} + \gamma_{\text{others}}) \cdot \frac{\text{EROI}_{\text{others}}}{\text{EROI}_{\text{wind}} + \text{EROI}_{\text{solar}} + \text{EROI}_{\text{others}}} \tag{3.6}$$

These equations reflect the fact that renewable energies with higher EROIs will be favoured compared to the ones with lower EROIs.

The obtained γ_k profiles are then smoothed thanks to equation (3.3).

We still have to choose profiles for the exogenous parameters $\epsilon(t)$ and $q(t)$. We assume that thanks to technological progress, the amounts of energy required by one unit of industrial capital stock and by one unit of industrial output decrease with time. We therefore impose decreasing exponential profiles for $\epsilon(t)$ and $q(t)$. The exact curves for $\epsilon(t)$ and $q(t)$, together with the value of $K_{ind}(0)$, are computed such that energy production $P(t)$ from the model simulation fits in the least-squares sense with historical data from [11]. The curves for $\epsilon(t)$ and $q(t)$ are plotted on Figure 3.6. The value for $K_{ind}(0)$ is 5 [Capital goods].

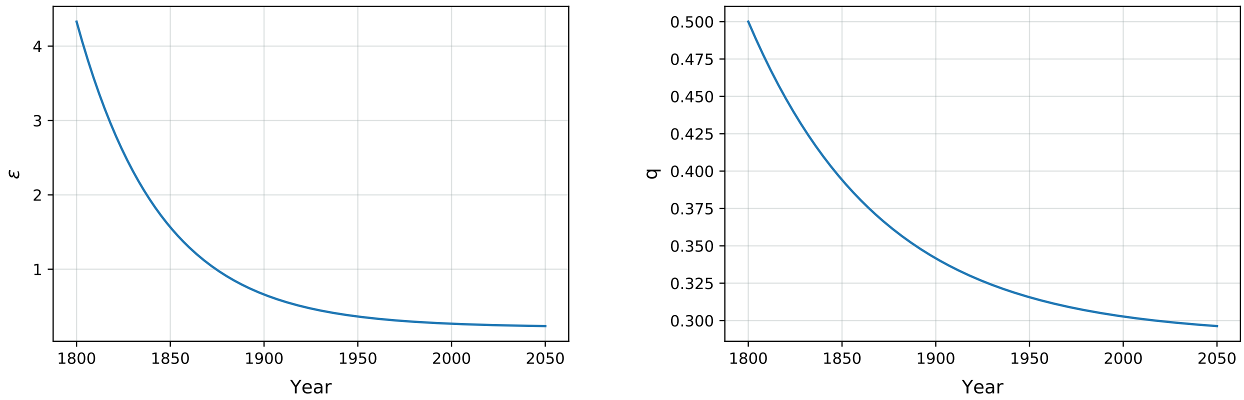


Figure 3.6: Curves for the exogenous parameters $\epsilon(t)$ and $q(t)$ in baseline run

Furthermore, we explained in chapter 2 that in the definition we use for the EROI of fossil fuels, energy losses which occur after the leaving of the mine or well are not taken into account. Thus, our global fossil EROI curves do not include, among others:

- energy lost during refining of crude oil
- energy lost when converting coal to electricity
- energy cost of transporting fuel to end-users
- energy lost when converting heat to work in vehicle engines
- in future years, potential energy costs associated to carbon capture and sequestration when burning fossil fuels

On the other hand, most renewable energies directly produce energy as electricity, which can be seen as the energy form of the highest quality. Therefore, we do not need to consider conversion losses for energy generated by renewable sources. Nonetheless, there are other losses for renewables, which are not taken into account in our EROI curves. For example:

- energy cost of building and operating the electricity grid infrastructure
- transmission losses on the electricity grid
- energy cost and losses associated to energy storage (such storage is crucial in an energy system based on renewables, because of the intermittency in production)

All the above mentioned costs are difficult to assess at global scale. In our model, they are simply captured by the parameters $\epsilon(t)$ and $q(t)$.

When looking at these costs and losses, we notice that one Joule of energy produced by fossil fuels and one Joule produced by renewable sources cannot be directly compared with precision [18]. In other words, the EROI curves of fossil fuels and renewable energies are not completely on an equal footing. Thus, electrification of the energy system, induced by the transition towards renewables, might cause the parameters $\epsilon(t)$ and $q(t)$ to vary a lot. This will be discussed in next chapter.

The Python code for baseline simulation based on the above parameter values lies in appendix A. The results of the simulation are described in chapter 4.

3.2.5 Recapitulation of the model's assumptions

We identify hereunder the main assumptions of the model. Many of these assumptions directly come from Dale's PhD thesis [6]. Then, some of the listed assumptions are further explained.

1. The energy-economy system is thermodynamically open, exchanging both energy and materials with its environment. Those exchanges are subject to the laws of thermodynamics.
2. The behaviour of the global socioeconomic system is defined primarily in terms of physical activities (biophysical systems assumption)
3. Growth of the system is a result of the creation of human-made capital, thereby increasing the capacity of the system to exploit energy resources.
4. All physical and economic activity is ultimately constrained by the availability and accessibility of energy supply.
5. The human-made capital (economic infrastructure) generates both demand for energy, as well as providing the factors of production.
6. The demand for primary energy is aggregated and dependent only on the size of the industrial capital stock.
7. The energy sources are totally substitutable.
8. The global socioeconomic system is simplified to the interaction of just two interdependent, but separable components (or sectors): the industrial sector and the energy sector.
9. The energy sector is composed of 6 energy sources: 3 non-renewable and 3 renewable. These energy sources are characterized by four parameters: their incept date, their availability (URR or TP), their accessibility (EROI curve) and their capital intensity.
10. The EROI curve characterizing an energy source can be computed beforehand for the time scope of the model, by anticipating technological progress.
11. The capital needs of the energy sector take priority over the needs of the main economy.

The energy demand cited in assumption 6 is equivalent to the primary energy production $P(t)$. Indeed, we assume that the energy demand is always exactly met by production.

Assumption 7 has not been explained yet in the above sections. Normally, certain energy carriers are only fit for certain end uses. For example, electricity is not suited for obtaining high temperatures in certain industrial processes. In this case, combustion of a fuel is much better suited. This constraint on the link between energy carriers and end uses is not considered within the GEMBA model. The primary energy production required in equation 3.1 is for homogeneous energy, regardless of source, carrier or quality. In other words, energy sources are assumed to be perfectly substitutable [6]. The main reason behind this assumption is that disaggregating energy demand into different energy carriers would considerably complexify the GEMBA model. It would also require a substantial amount of work and research.

This being said, we will still investigate the potential impacts of an electrification of the energy system in next chapter, via changing values for the parameters $\epsilon(t)$ and $q(t)$.

Moreover, assumption 11 underlines the fact that in equation 3.2, the capital subsidies for the energy sector are subtracted first from industrial output. Only the rest is available for the accumulation of industrial capital stock. The justification for such assumption is that energy is vital for the functioning of the main economy; hence, the needs of the energy sector must be fulfilled prior to those of the industrial sector.

3.2.6 Main differences with Dale's initial model

The main differences between our adaptation of GEMBA and the initial version from Dale are the following:

1. Dale simulates the long-term future (up to the year 2200), while we stick to the 2050 horizon.
2. Dale takes the allocation of energy production between resources, γ_k, to be an endogenous variable. However, we model it as a parameter, which is fixed first by historical production up to 2017, then by climatic goals between 2019 and 2050. We take $\gamma_k(2018) = \gamma_k(2017)\ \forall k$.
3. Dale considers 14 different energy resources. We diminish this number to 6 by aggregating several of these resources.
4. Our values for technical potentials of wind and solar are very different from Dale's ones
5. Our EROI curves and Dale's ones are very different.
6. In order to fit with historical production data, Dale modifies his EROI curves via a calibration procedure. We do not modify our EROI curves. In our adaptation of GEMBA, the only parameters which are adjusted in order to fit with historical data are $\epsilon(t)$, $q(t)$ and $K_{ind}(0)$.
7. In Dale's version, all flows and stocks are expressed in Joules. In our adaptation however, we consider two different units: [Joules] and [Capital goods].
8. Dale considers explicitly the energy sector capital stock in his equations. We do not.
9. In our model, $\epsilon(t)$, $q(t)$ and $s(t)$ are allowed to vary with time. This is not the case with Dale.

Points 1 and 2 are reflected by the difference between our research question and Dale's ones, as explained in subsection 3.2.1.

Moreover, Dale uses the following formula for γ_k:

$$\gamma_k = \frac{\rho_k \,\mathsf{EROI}_k}{\sum_k \rho_k \,\mathsf{EROI}_k}$$

He does not really justify the reason for such choice, though. We are critical regarding to this formula. Indeed, we think that the allocation of energy production between resources is dependent on many factors, such as price, technology, political decisions, etc. These factors are outside the scope of the GEMBA model. Therefore, we do not think that given the limited number of variables in the model, we can find an accurate formula for γ_k. This is why we choose to model γ_k exogenously between 1800 and 2017. Between 2018 and 2050, γ_k for fossil fuels is also modeled exogenously. Once γ_k is known for fossil fuels, we have $\sum_k \gamma_{k,\mathsf{renewable}} = 1 - \sum_k \gamma_{k,\mathsf{fossil}}$. The exact subdivision of $\sum_k \gamma_{k,\mathsf{renewable}}$ between wind, solar and other renewables is then determined endogenously thanks to equations 3.4 - 3.6. These equations are based on the assumption that among renewable energies, the ones with higher EROI will be preferred.

Concerning points 4 and 5, we consider that our EROI curves for wind and solar are more reliable than Dale's ones. Indeed, Dale creates his EROI curves by fitting a function to a range of static EROI values found in the literature. The curves we use however, were produced using a careful bottom-up engineering approach. We also think that our EROI curves for fossil fuels, even if they are much more approximate than our wind and solar curves, are still more reliable than Dale's ones. Indeed, we generate these curves based on [2] and [3] and we directly use them. On the other hand, Dale modifies his initial EROI curves afterwards for calibration purposes. The differences between Dale's EROI curves before and after calibration can be huge. This is illustrated by Figure 3.7 for the case of coal:

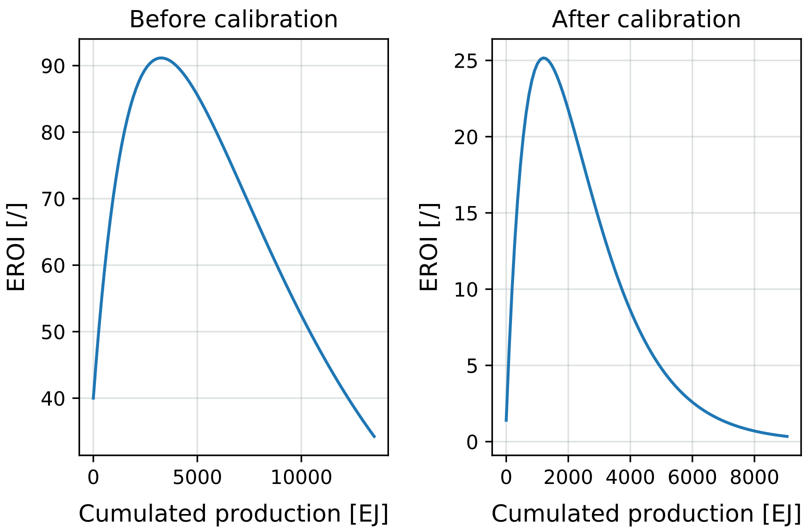


Figure 3.7: Dale's EROI curves for coal before and after calibration

None of the papers thanks to which we built our EROI curves for wind, solar and fossil fuels had yet been published when Dale was writing his PhD thesis.

Nevertheless, our aggregated EROI curve for other renewables and nuclear is not accurate at all. We do not see it as a main issue, since these resources are not meant to play an important role in our model.

As already mentioned above, point 6 implies that Dale's EROI curves are much less reliable: his initial EROI curves are based on data from the literature, but after calibration they are completely modified and become biased.

Moreover, Dale represents capital goods only through the energy they consume when they are produced. We find this approach very unintuitive, this is why we choose to introduce the unit [Capital goods] in our model, as stated in point 7. The conversion between [Joules] and [Capital goods] is made thanks to parameters $\epsilon(t)$ and $q(t)$.

In point 8, we state that unlike Dale, we do not consider explicitly the energy sector capital stock in our equations. Indeed, in Dale's model, this capital stock is only an intermediate variable, which complexifies the model. Furthermore, Dale defines the energy production $P(t)$ as well as the energy demand $D(t)$, but it is unclear whether production exactly meets demand at any time or not. When skipping the variable "energy sector capital stock", we impose that $P(t) = D(t)\ \forall t$ and make the model equations more transparent. Moreover, we implemented a discrete-time simulation according to Dale's equations. It systematically produced parasitic oscillations. We are convinced that these oscillations are inherent to Dale's equations. We do not encounter such a problem with our modified set of equations.

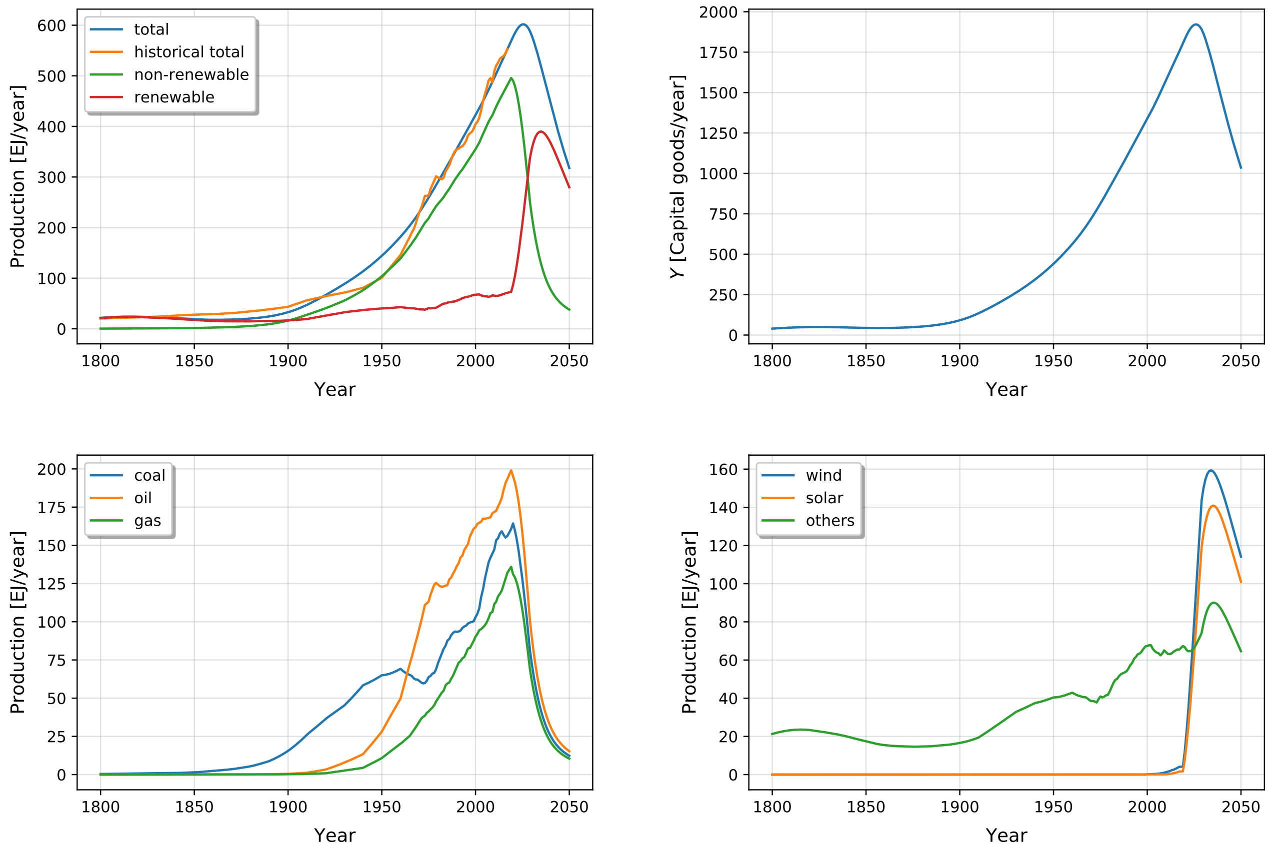
Finally, point 9 allows us to gain in flexibility compared to Dale. We will make use of this flexibility in next chapter.

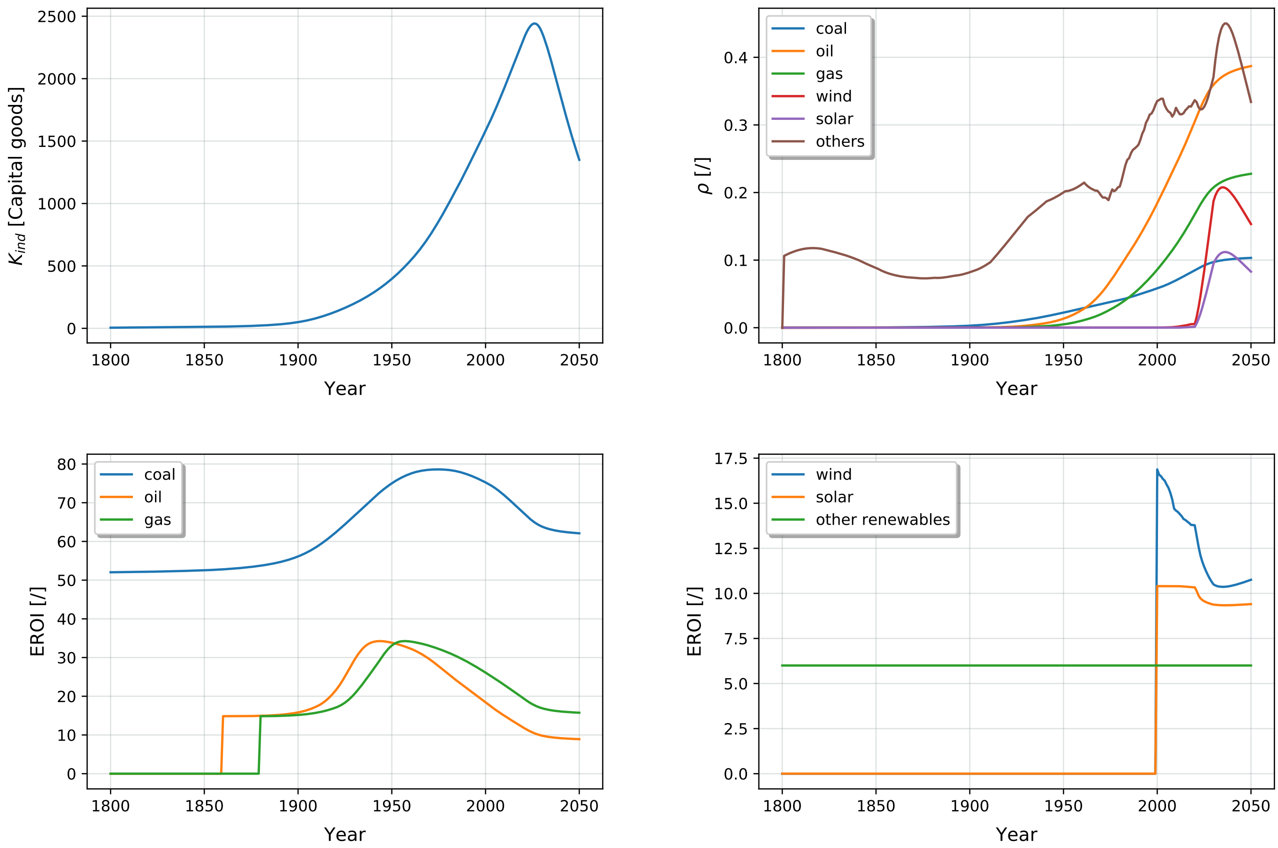
Chapter 4

Model's results and discussion

4.1 Results from baseline simulation

The results from baseline simulation are plotted hereunder.





First, we observe that $P(t)$ closely follows historical production up to 2017. Then, $P(t)$ continues to grow during a short time. It peaks to 598 [EJ/year] in 2025 and strongly declines afterwards.

The energy production from non-renewable sources decreases exponentially starting from 2017. This was anticipated, given the γ_k profiles described in previous chapter. On the other hand, the energy production from renewable sources grows sharply after 2017. It peaks to 386 [EJ/year] in 2034, then follows a steady decline.

$Y(t)$ behaves exactly like $P(t)$, with a peak in 2025. $K_{ind}(t)$ too.

Furthermore, $\rho_k(t) < 0.5 \ \forall t$ for all energy resources. We are far from using the full potential of any energy resource.

Finally, the EROIs of coal, oil and gas peak in 1974, 1943 and 1956 respectively, at values 78.6, 34.3 and 34.3. The EROIs of wind and solar start respectively at values 16.9 and 10.4. The greater the energy production from wind and solar, the lower their EROI. The EROI of resource k is set to zero when $t <$ Incept date$_k$.

So, we see that the results of our adaptation of GEMBA are globally similar to Dale's ones: massive transition towards renewable energies produces a collapse of the global economy. The energy production curves obtained by Dale with his GEMBA model are plotted on Figure 4.1. The collapse comes sooner and is more brutal in our version of the model, because we impose a very rapid shift to renewables via γ_k.

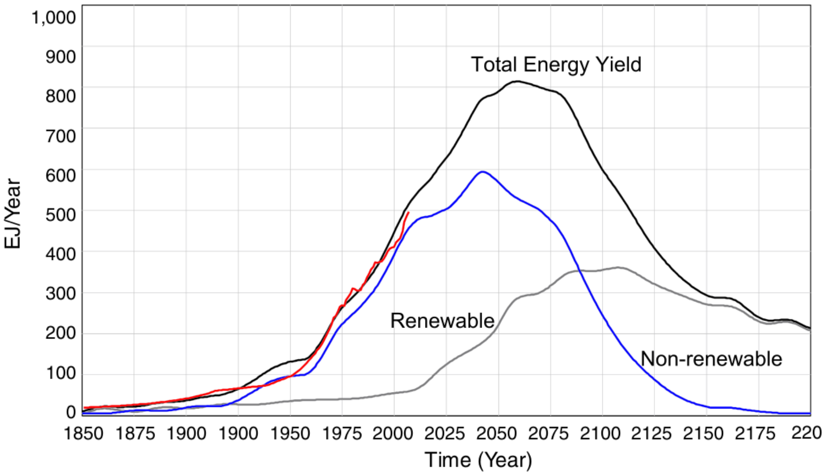


Figure 4.1: Energy production curves obtained by Dale with baseline simulation of his model, from [19]

4.2 Cause of the collapse

We will now investigate the cause of the collapse. As explained above, this collapse is caused by the transition to renewable energies, rather than by a decrease in the EROI of fossil fuels. To convince us about it, we run a simulation where the EROIs of coal, oil and gas take the constant values 65, 22 and 22, respectively i.e. their EROI curves are horizontal lines. All the other parameters are the same as in baseline simulation. The results are plotted on Figure 4.2 and we see that they are practically the same as before. With constant EROI curves, the global economy collapses all the same.

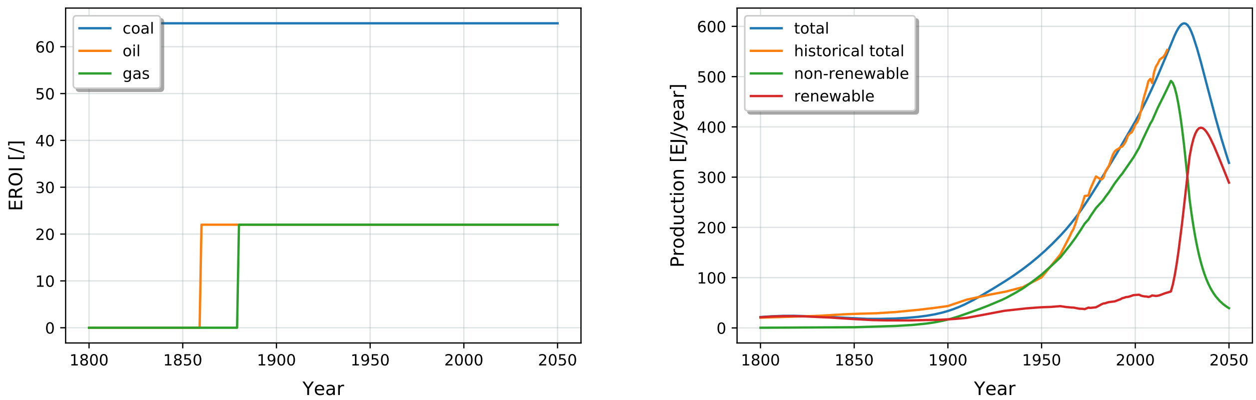


Figure 4.2: Simulation results with constant EROI values for fossil fuels

Renewable resources differ from non-renewable resources by two main characteristics: their lower EROI values and their higher capital intensity. Thus, it must be one of these two aspects which causes the collapse.

Let us first test whether the difference of EROI is the cause of the collapse. As explained in the previous chapters, we view our EROI curves for wind and solar as reliable. However, we are not so sure about our fossil fuels EROI curves. Thus, we run a new simulation where the EROI of coal has been divided by 5, the EROIs of oil and gas have been divided by 2 compared to baseline run.

This way, the EROIs of renewables fall in the same range of values as the EROIs of fossil fuels. All parameters are the same as in baseline simulation, except $\epsilon(t)$ which is adjusted such that $P(t)$ fits with historical production data. Figure 4.3 plots the simulation results. We can observe that the profile of $P(t)$ does not change a lot compared to baseline run. The collapse still happens. Therefore, the difference of EROI between renewables and fossil fuels is not the cause for it.

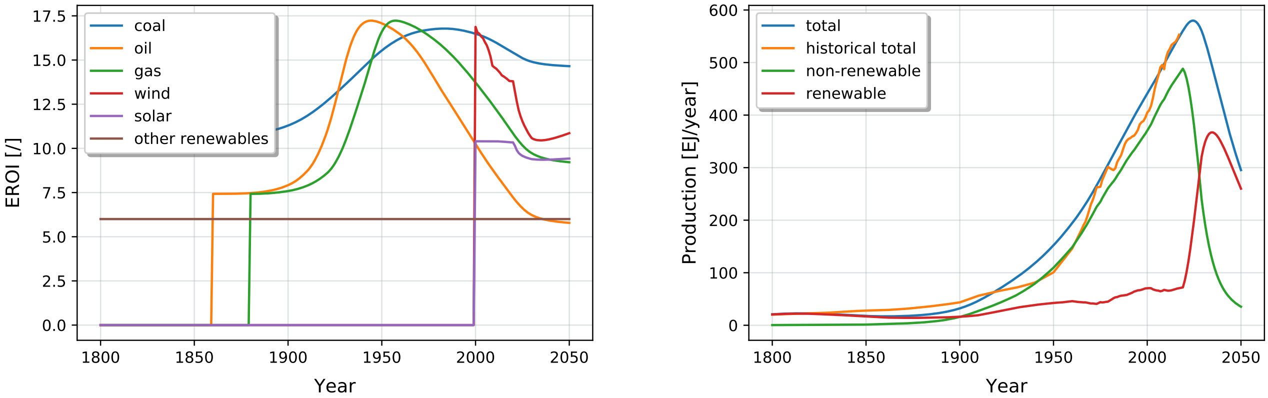


Figure 4.3: Simulation results with lower EROI values for fossil fuels

We now test whether the difference of capital intensity is the cause of the collapse. To this end, we run a new simulation where $\chi_k = 1$ for all energy sources, fossil and renewable alike. All parameters are the same as in baseline simulation, except $\epsilon(t)$. This time, we define $\epsilon(t)$ as a rational function, whose coefficients are computed such that $P(t)$ fits historical production data in the least-squares sense. Using a rational function gives us a better fit in this case than a decreasing exponential. Figure 4.4 plots the simulation results. We observe that there is no collapse. The massive shift to renewables is not even noticeable when looking at $P(t)$. Thus, we conclude that the difference of χ_k between fossil fuels and renewables is the sole cause of the collapse in baseline run.

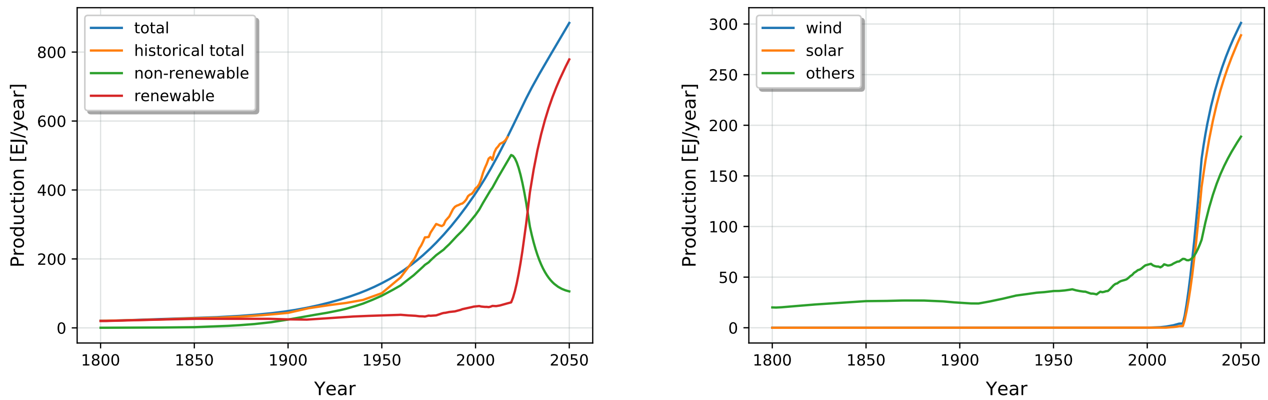


Figure 4.4: Simulation results with $\chi_k = 1$ for all resources

Let us now explain why this difference in χ_k is so problematic.

According to our model diagram 3.2, industrial output $Y(t)$ is divided into three distinct flows:

- First, a fraction $(1-s)$ of Y disappears into a sink. This corresponds to consumption in the economy.
- Then, a part F of Y is sent back to the energy sector in order to fulfill its capital needs.
- Finally, what is left of Y is reinvested back into industrial capital stock. This third flow is named Acc$_{ind}$.

If χ_k becomes higher, it does not mean that the energy sector needs more energy inputs, but it means that these inputs are distributed differently: $S_{1,k}$ diminishes while $S_{2,k}$ gains in importance. The problem is that the inputs $S_{2,k}$ come from a physical flow from which a significant part first goes into a sink. On the other hand, the flow from which comes $S_{1,k}$ does not meet any sink. This implies that energy inputs $S_{2,k}$ are comparatively much more "expensive" to the economy than the inputs $S_{1,k}$.

So when the economy transitions to resources with higher χ_k, $\sum_k S_{1,k}$ decrease. Consequently, E and Y increase. It implies that consumption $(1-s)Y$ also increases, as well as $F = \frac{\sum_k S_{2,k}}{q}$. Not much is left for Acc$_{ind}$, which becomes lower than Dep$_{ind}$. K_{ind} therefore falls, followed by P, which means that E and Y both fall. Despite this, χ_k stays invariant, hence Acc$_{ind}$ stays below Dep$_{ind}$, K_{ind} continues to fall and the economy collapses.

4.3 Change in the saving rate

We saw in previous section that the transition to renewables causes the collapse of the global economy because of their high capital intensity. This collapse behaviour is very robust: changing the values of most parameters does not enable us to avoid it. Nevertheless, this is not the case for parameter $s(t)$. Indeed, the model is extremely sensitive regarding to the value of the saving rate.

In baseline run, the saving rate is chosen to be constant for simplicity and its value is set at 0.1. This choice is not arbitrary. On one hand, taking a smaller value for s i.e. $s = 0.08$ produces Acc$_{ind}(t) < 0$ in $t = 1800$, which is not acceptable. On the other hand, taking a higher value i.e. $s = 0.2$ or larger does not enable us to fit accurately $P(t)$ to historical production data, even after adjusting $\epsilon(t)$.

But what if the economy anticipates the collapse and adapts its behaviour in order to prevent it ? In our adaptation of Dale's model, we already considered that the profile of $\gamma_k(t)$ after 2018 was deliberately chosen by the economy in order to mitigate climate change. Why not consider that the economy also deliberately modifies its saving rate in order to avoid collapse ?

To this end, we consider the profile for $s(t)$ plotted on Figure 4.5.

The saving rate is constant up to 2018, then increases between 2019 and 2050, at the same rate as $\sum_k \gamma_{k,\text{renewable}}$. This corresponds to a scenario where the energy transition is accompanied by a reduction in consumption rate: a smaller fraction of Y is consumed so that after the capital feedback to the energy sector, enough capital remains for investment in the industrial sector.

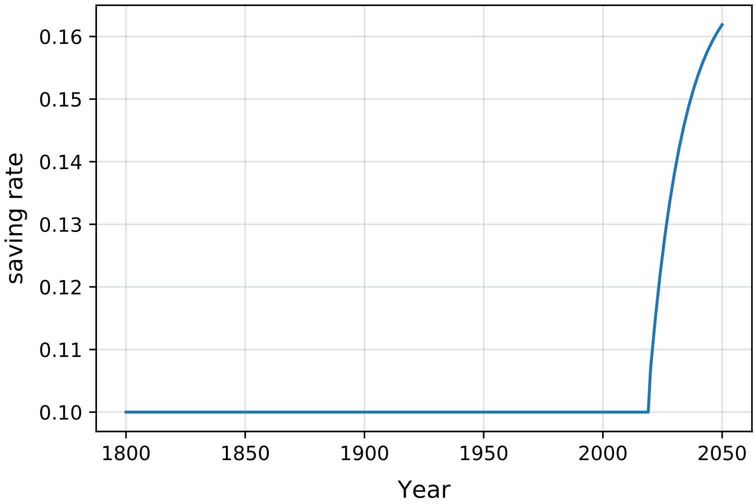
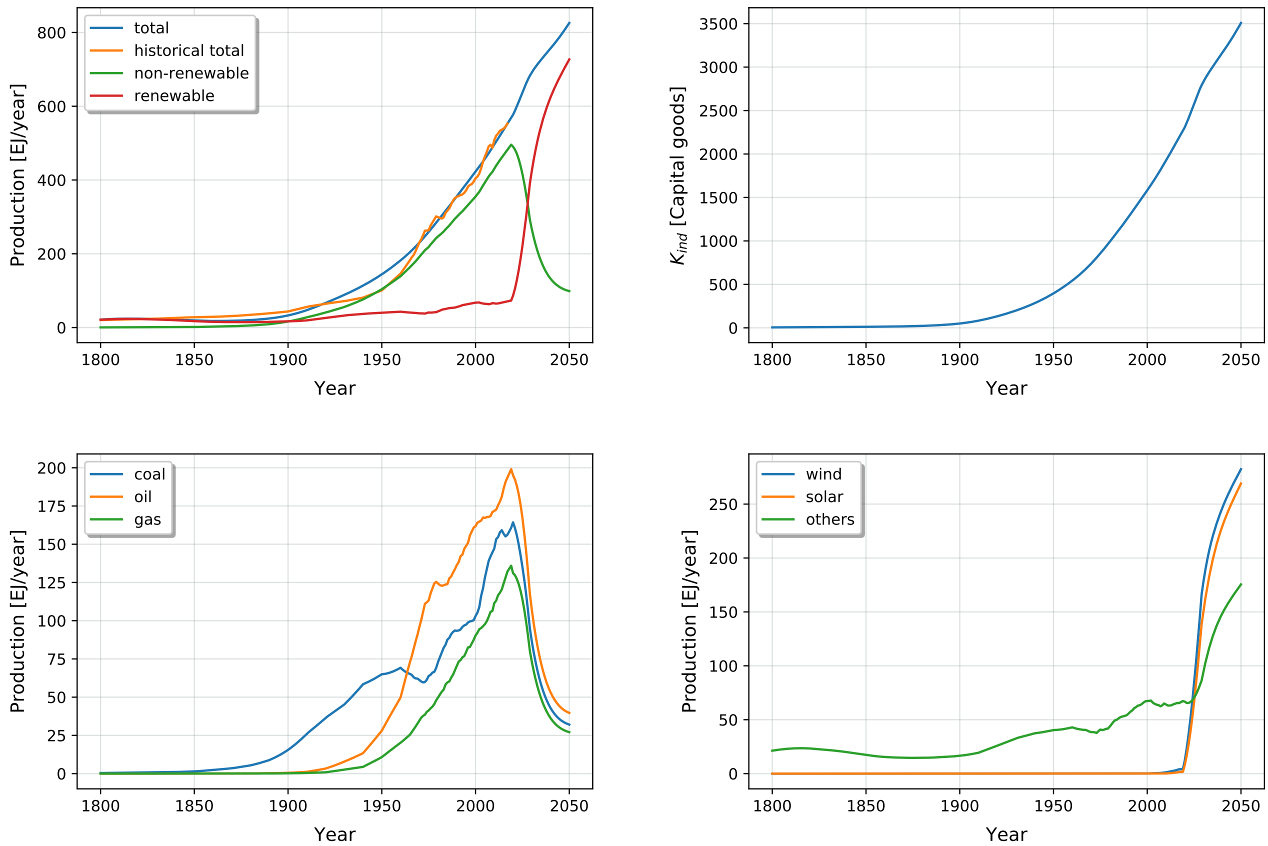
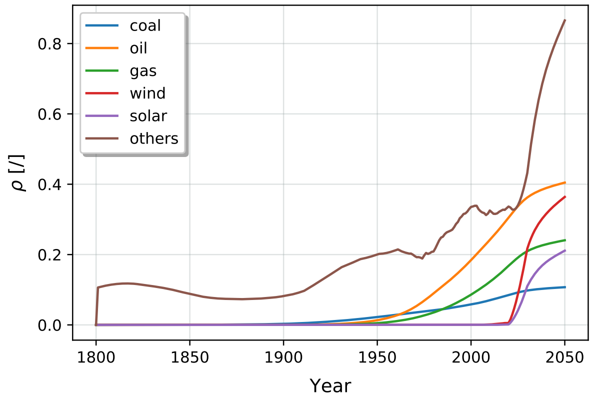
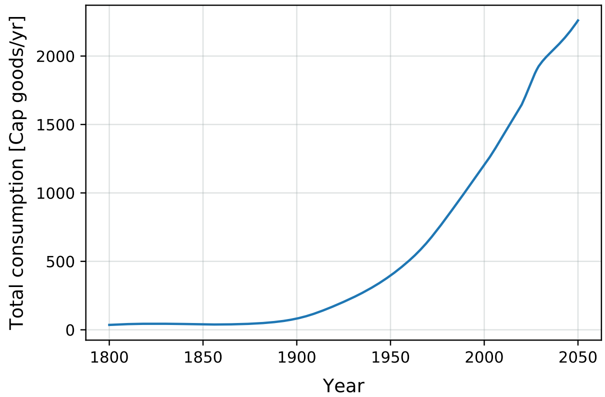


Figure 4.5: Imposed profile for $s(t)$

We run a new simulation, which incorporates this increasing profile for $s(t)$. All parameters are the same as in baseline simulation except $s(t)$. The simulation results are plotted hereunder.







We observe that with this new profile for $s(t)$, the collapse is completely avoided. $P(t)$ and $Y(t)$ follow a monotonous increase up to 2050. Moreover, this pattern could be extended beyond 2050. Indeed, in 2050, $\rho_k(t) \ll 1$ for all resources except "other renewables and nuclear". This is no problem, since this resource is substitutable with wind and solar. Besides, the last figure in the lower right-hand corner plots the total consumption of the economy, $(1-s)Y(t)$. We observe that even if $(1-s)$ diminishes between 2019 and 2050, total consumption follows its increase.

4.4 Sensitivity to parameters

When $s(t)$ is kept constant at all times, the collapse behaviour of the system is very robust to changes in parameter values. However, once we consider the outcome with increasing $s(t)$ for $t > 2019$, collapse vanishes. In this case, the resulting long-term growth path is sensitive to changes in parameter values.

In this section, we consider only the case with increasing $s(t)$ for $t > 2019$. We discuss the sensitivity of the simulation results to several model parameters.

Technical potential of other renewables and nuclear

We stated in chapter 2 that we chose TP $= 200$ [EJ/year] for the resource "other renewables and nuclear". We now discuss other values for this TP.

When we take an increasing $s(t)$ after 2019, we observe that energy production from the resource "other renewables and nuclear" comes close to its technical potential. So, if we take a higher value for TP, nothing changes (since with TP $= 200$, the value of TP is already not limiting). If we take a lower value for TP on the other hand, the model behaves differently. Figure 4.6 shows the model's results when TP=100. The corresponding Python code lies in appendix B: it required some adaptations compared to baseline simulation.

We notice that the production of "other renewables and nuclear" reaches its upper limit in 2032. Starting from this date, more production is allocated to wind and solar in order to compensate for the saturation of other renewables and nuclear. Nonetheless, energy production from wind and solar stays well below their technical potential.

Besides, we see that when more energy production becomes allocated to wind and solar in 2032, the growth of $P(t)$ slows down. This slow-down comes from the fact that wind and solar are more capital intensive than other renewables and nuclear.

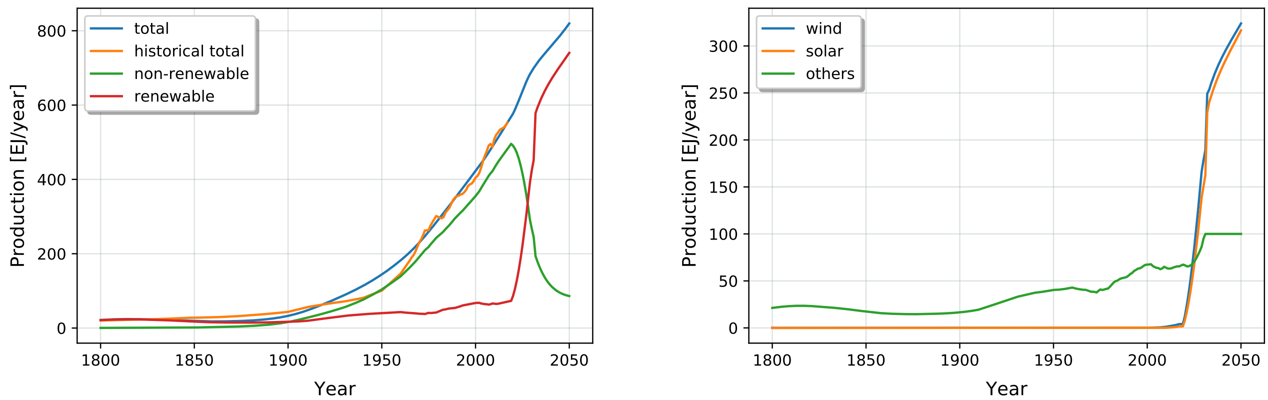


Figure 4.6: Simulation results when TP=100 for other renewables and nuclear

Capital intensity of other renewables and nuclear

In chapter 2, we explained that we chose $\chi_k = 0.5$ for the resource "other renewables and nuclear", as a compromise between the values used by Dale for nuclear and for renewables, which were respectively 0.1 and 0.9. We now discuss different values for this χ_k.

Figure 4.7 plots the $P(t)$ curves obtained with $\chi_k = 0.4$ and $\chi_k = 0.55$. Each time, $\epsilon(t)$, which is a monotonously decreasing function, is adjusted such that $P(t)$ best fits to historical production data in the least-squares sense.

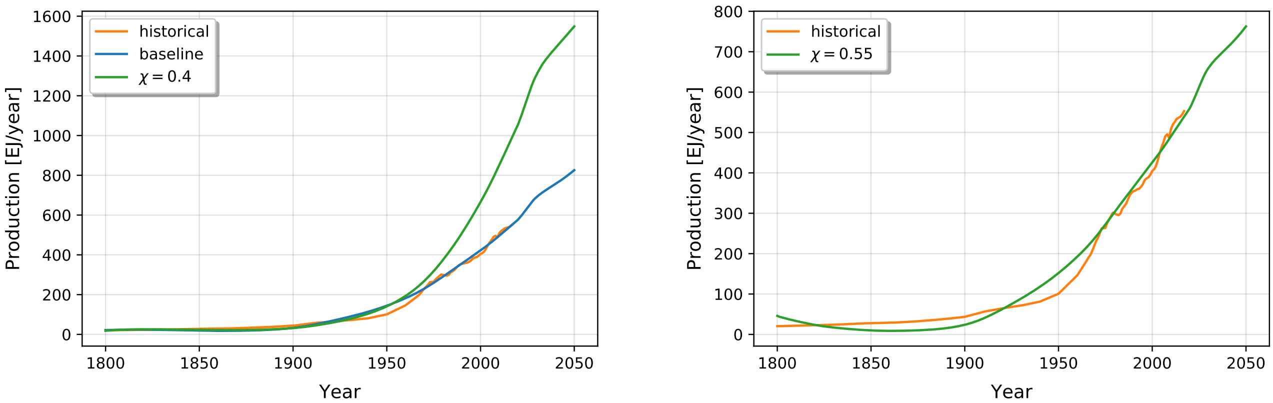


Figure 4.7: $P(t)$ obtained with different capital intensities for other renewables and nuclear

We observe that the model is very sensitive to the value of the capital intensity, even with calibration of $\epsilon(t)$. When $\chi_k = 0.4$, $P(t)$ does not fit anymore with historical production after 1970. Wen $\chi_k = 0.55$, $P(t)$ decreases in the first years of the simulation, which is not acceptable. Moreover, we also tried $\chi_k = 0.6$, but then we automatically obtained negative values for Acc$_{ind}$, which is not acceptable either.

EROI of other renewables and nuclear

In chapter 2, we stated that we chose a constant EROI of 6 for the resource "other renewables and nuclear". The following figure plots the results obtained when the EROI of this resource is kept constant, but now at values 13 and 20, respectively. In each case, $\epsilon(t)$ is adjusted such that $P(t)$ fits at best with historical production data.

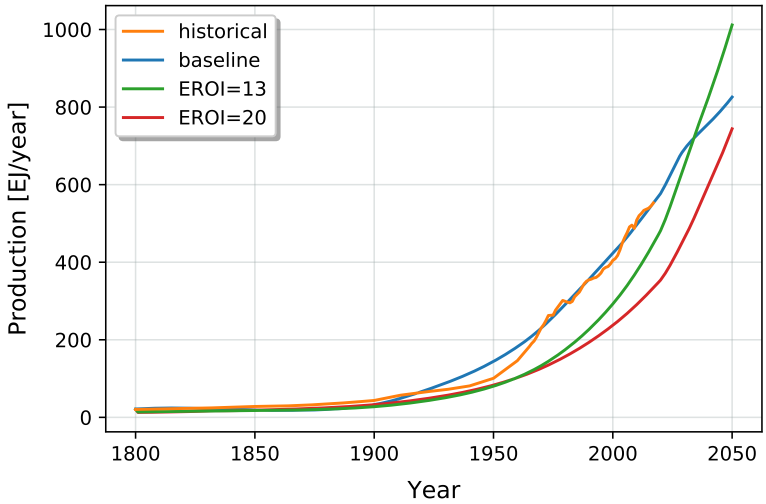


Figure 4.8: $P(t)$ obtained with different EROI values for other renewables and nuclear

We notice that despite the adjustment of $\epsilon(t)$, $P(t)$ cannot fit with historical data for $t > 1950$. Besides, one will notice that $P(t)$ gets higher when EROI=13 than when EROI=20. This is counter-intuitive and has to do with the calibration of $\epsilon(t)$, which is different in both cases.

Furthermore, taking a lower EROI value i.e. EROI=5 gives us negative values for Acc$_{ind}$, even after calibration of $\epsilon(t)$.

EROI curves for wind and solar

In chapter 2, we explained that the EROI curves for wind and solar used in baseline simulation were computed based on the 2015 electricity grid mix. However, during the energy transition, this mix will evolve until we reach a nearly 100% renewable system. Thus, we run a new simulation by taking the extreme case when the EROI curves for wind and solar are directly computed based on a 100% electricity grid mix. This is equivalent to multiplying the wind EROI curve by 1.25 and the solar EROI curve by 1.18. The results are plotted on Figure 4.9.

Without surprise, the economy benefits from this increase in EROI values, and higher levels of primary energy production are attained.

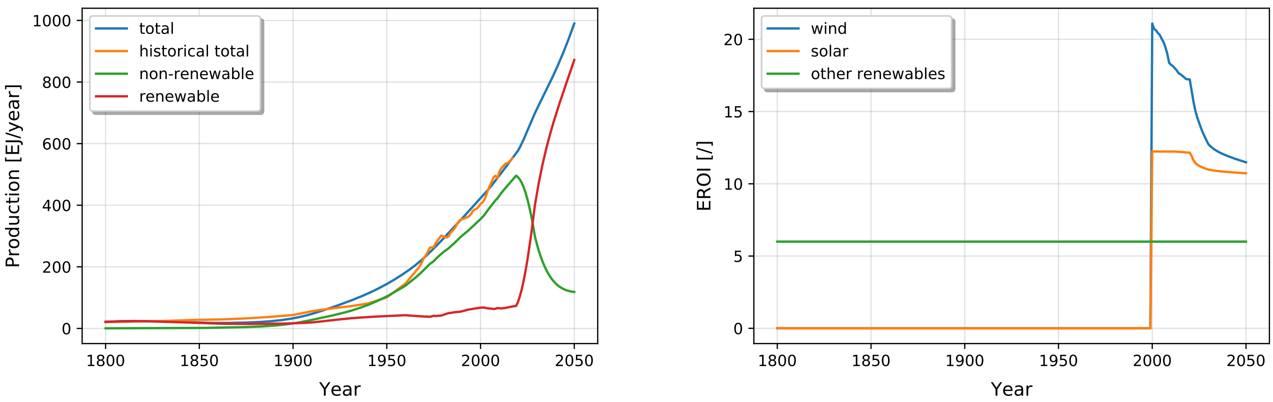


Figure 4.9: Simulation results with modified EROI curves for wind and solar

Other parameters

We can also change other parameters of the model. Indeed, we performed simulations where:

- the EROI curves of oil and gas were multiplied by two, the EROI curve of coal was kept alike.
- the EROI curves of all fossil fuels were divided by two.
- the capital intensity of wind and solar was modified by ± 0.1.

The outcomes of all these simulations were not very different from the results with standard parameter values, and the differences were no surprise. Hence, we do not detail them here.

Moreover, we already explained that the model is extremely sensitive to changes in the value of $s(t)$. Decreasing s produces negative values for Acc$_{ind}$, while with larger s we cannot fit accurately our $P(t)$ curve to historical production data. So, we prefer to keep the value $s(t) = 0.1 \; \forall t < 2019$.

4.5 Exogenous function for energy production

Up until now, we have considered that $P(t)$ was a function of K_{ind}. But what if this was not the case ? To address this question, we run a new simulation where $P(t)$ is fixed exogenously. Like Dale, we take a sigmoid profile for exogenous $P(t)$:

$$P(t) = \frac{P_0 \, P_\infty \, e^{r\,(t-1800)}}{P_\infty + P_0 \, (e^{r\,(t-1800)} - 1)} \tag{4.1}$$

The values of P_0, P_∞ and r are chosen such that $P(t)$ fits with historical production data. All equations are the same as in baseline simulation, except $P(t) = \epsilon(t) \, K_{ind}(t)$ which is replaced by equation 4.1. Figure 4.10 plots the simulation results when all parameters are kept the same as in baseline simulation, except parameter $\epsilon(t)$ which is removed. We observe that $P(t)$ does not collapse, since it is fixed exogenously. However, $K_{ind}(t)$ collapses exactly like in baseline simulation.

Moreover, Figure 4.11 plots the simulation results when this time $s(t)$ increases after 2019. The results are similar to the ones with endogenous $P(t)$. $K_{ind}(t)$ reaches a slightly higher value with exogenous $P(t)$ since the imposed profile for $P(t)$ is a bit steeper than the one obtained endogenously.

In conclusion, imposing an exogenous profile for $P(t)$ does not modify a lot the behaviour of the energy-economy system.

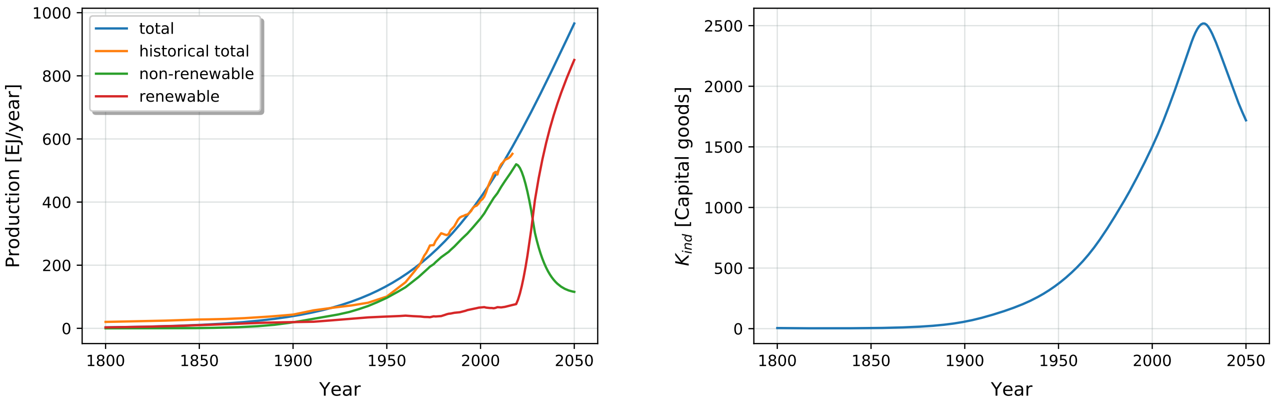


Figure 4.10: Simulation results with $P(t)$ fixed exogenously, $s(t)$ constant

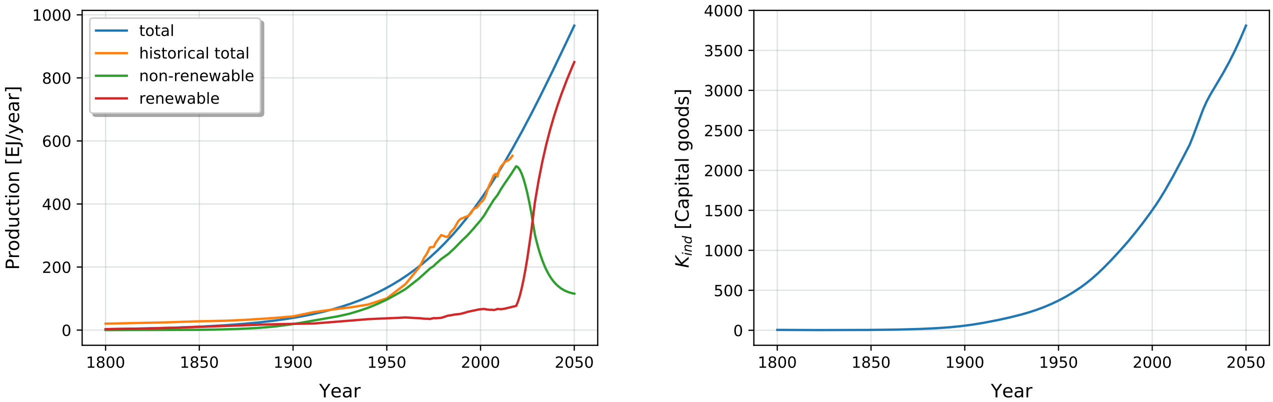


Figure 4.11: Simulation results with $P(t)$ fixed exogenously, $s(t)$ increasing after 2019

4.6 Issues with the model's equations

In chapter 3, we explained that one Joule of energy produced by fossil fuels and one Joule produced by renewable sources could not be directly compared with precision. We know that the electrification of the energy system will thoroughly modify the way energy is used in the economy, suppressing some energy losses but also adding new costs. There are two possible scenarios: after electrification, an equal level of economic activity will either require less primary energy than before, or it will require more of it.

The first scenario corresponds to a decrease in $\epsilon(t)$ and $q(t)$ when the transition towards renewables takes place. The second scenario corresponds to an increase in $\epsilon(t)$ and $q(t)$. We test both these scenarios with our model, by taking the profiles from Figure 4.12 for $\epsilon(t)$ and $q(t)$.

The profile for $\epsilon(t)$ goes from 1800 to 2050, but part of the graph is cut for clarity. The changes in $\epsilon(t)$ and $q(t)$ after 2019 go at the same pace as the change in $\sum_k \gamma_{k,\text{fossil}}$.

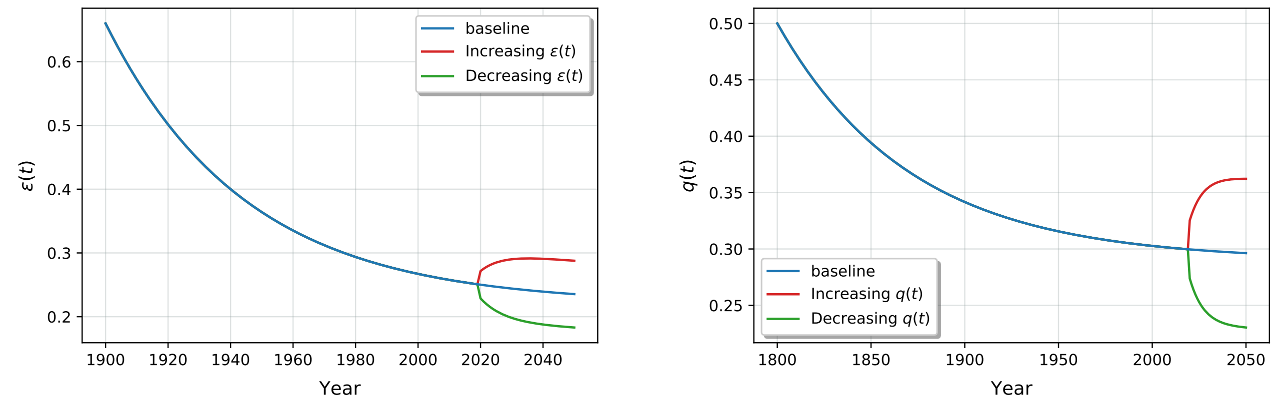


Figure 4.12: Imposed profiles for $\epsilon(t)$ and $q(t)$

We test separately the variations of $\epsilon(t)$ and $q(t)$. Figure 4.13 plots the results obtained when increasing and decreasing $\epsilon(t)$, while $q(t)$ is kept the same as in baseline simulation. On the other hand, Figure 4.14 plots the results obtained when increasing and decreasing $q(t)$, while $\epsilon(t)$ is the same as in baseline.

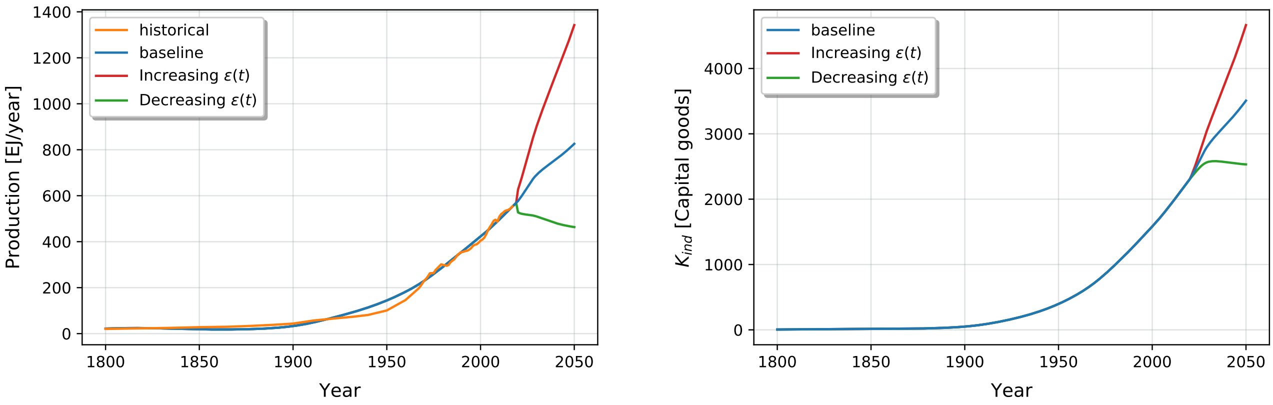


Figure 4.13: Results obtained with increasing and decreasing profiles for $\epsilon(t)$

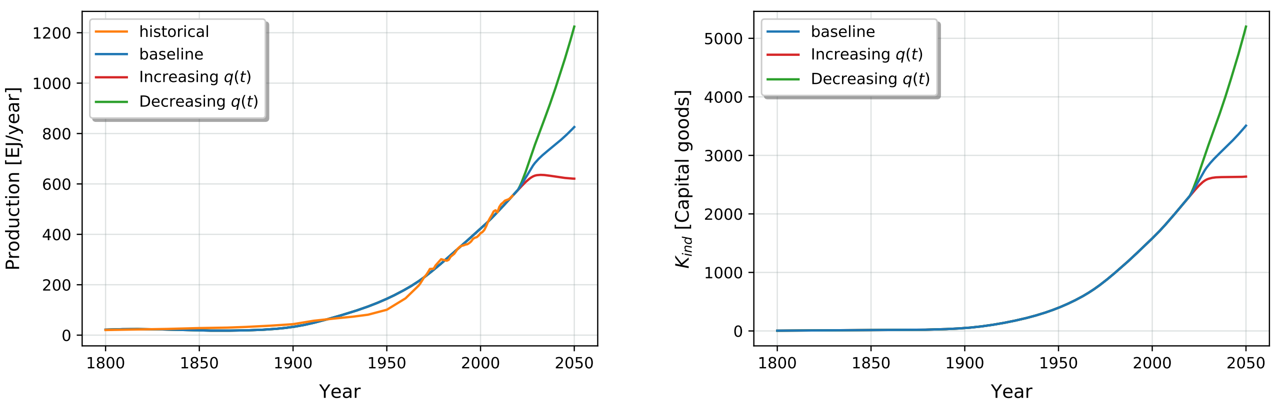


Figure 4.14: Results obtained with increasing and decreasing profiles for $q(t)$

The obtained results are dissonant. Increasing $\epsilon(t)$ or $q(t)$ has an opposite effect, although these two actions are supposed to represent the same phenomenon of electrification. Idem for decreasing them.

This is due namely to two flaws in the model equations. First, decreasing $\epsilon(t)$ corresponds to a gain in efficiency; more economic activity can be performed with the same production of primary energy. However, our model equations are defined in such a way that a decrease in $\epsilon(t)$ penalises economic activity. Second, an increase or decrease in $q(t)$ also corresponds to a change in efficiency: it implies that each capital good has more or less embodied energy in it. Thus, given a level of industrial output $Y(t)$, a change in $q(t)$ should not directly affect $F(t)$, whose units are [Capital goods/year]. A change in $q(t)$ should only directly affect the flow of energy $\sum_k S_{2,k}(t)$ corresponding to $F(t)$. Our model equations tell the contrary.

The two flaws cited above come from two main defaults in our model equations:

1. $K_{ind}(t)$ produces an energy demand in the form of $P(t)$. Logically, this energy demand from the main economy should be instead $E(t)$. Indeed, the main economy should only be concerned by $E(t)$, the energy flow which effectively reaches it, and not by $P(t)$, which includes direct energy feedback to the energy sector.
2. $Y(t)$ is only indirectly related to $K_{ind}(t)$. It would be more logical that the output of the industrial sector would be directly related to the size of its capital stock.

So we see that our model equations, even if they are already modified compared to Dale's ones, face some weaknesses. We therefore suggest further modifications.

Instead of having $P(t)$ proportional to $K_{ind}(t)$, we can set $Y(t) = \kappa(t)\, K_{ind}(t)$, where $\kappa(t)$ is called the capital effectiveness (units: [1/year]). Then, the energy flow required by the industrial sector is $E(t) = q(t)\, Y(t)$. We also have the identities:

$$\begin{aligned}
E &= P - \sum_k S_{1,k} \\
&= P - \sum_k P_k \frac{(1-\chi_k)}{\mathsf{EROI}_k} \\
&= P - \sum_k \gamma_k\, P \frac{(1-\chi_k)}{\mathsf{EROI}_k} \\
&= P(1 - \sum_k \gamma_k \frac{(1-\chi_k)}{\mathsf{EROI}_k})
\end{aligned}$$

So based on $E(t)$, we can find $P(t)$ thanks to the formula

$$P = \frac{E}{1 - \sum_k \gamma_k \frac{(1-\chi_k)}{\mathsf{EROI}_k}}$$

We therefore suggest the following new version of GEMBA.

Initialisation:

$$K_{ind}(0) = K_0$$
$$C_k(0) = 0 \quad \forall k$$
$$\rho_k(0) = 0 \quad \forall k$$

for $t = 0 : t_{end}$

$$Y(t) = \kappa(t)\, K_{ind}(t)$$
$$E(t) = q(t)\, Y(t)$$
$$P(t) = \frac{E(t)}{1-\sum_k (1-\chi_k) \frac{\gamma_k(t)}{\mathsf{EROI}_k(\rho_k(t))}}$$
$$P_k(t) = \gamma_k(t)\, P(t)$$
$$S_{2,k}(t) = \chi_k \frac{P_k(t)}{\mathsf{EROI}_k(\rho_k(t))}$$
$$C_k(t+1) = C_k(t) + P_k(t) \qquad \text{for non-renewables}$$
$$\rho_k(t+1) = \frac{C_k(t+1)}{\mathsf{URR}_k} \qquad \text{for non-renewables}$$
$$\rho_k(t+1) = \frac{P_k(t)}{\mathsf{TP}_k} \qquad \text{for renewables}$$
$$F(t) = \frac{\sum_k S_{2,k}(t)}{q(t)}$$
$$\mathsf{Acc}_{ind}(t) = s(t)\, Y(t) - F(t)$$
$$\mathsf{Dep}_{ind}(t) = \delta\, K_{ind}(t)$$
$$K_{ind}(t+1) = K_{ind}(t) + \mathsf{Acc}_{ind}(t) - \mathsf{Dep}_{ind}(t)$$

end

where k designates all energy sources k such that Incept date$_k > t$.

We notice that these new equations do not face the two flaws mentioned above.

First, we see that if we increase $\kappa(t)$, $Y(t)$ directly increases. If we decrease it, $Y(t)$ directly decreases. So a gain in efficiency cannot penalise economic activity (or at least not directly).

Second, let us imagine that for a given level of $Y(t)$, we multiply $q(t)$ by factor A. Then $E(t)$ is multiplied by A, therefore $P(t)$ is multiplied by A and $S_{2,k}(t)$ too. Hence, $F(t)$ keeps unchanged since $F(t) = \frac{\sum_k S_{2,k}(t)}{q(t)}$. In other words, gaining in efficiency through $q(t)$ does not affect the level of capital feedback to the energy sector (in [Capital goods/year]), even if it affects the amount of energy embodied in this capital.

Our new equations therefore seem to have better properties than the previous ones. Unfortunately, with these equations, we cannot obtain a reasonable fit to historical production data, even after calibration of $\epsilon(t)$, $\kappa(t)$ and $K_{ind}(0)$. Thus, these equations do not give us any valuable simulation results.

Chapter 5

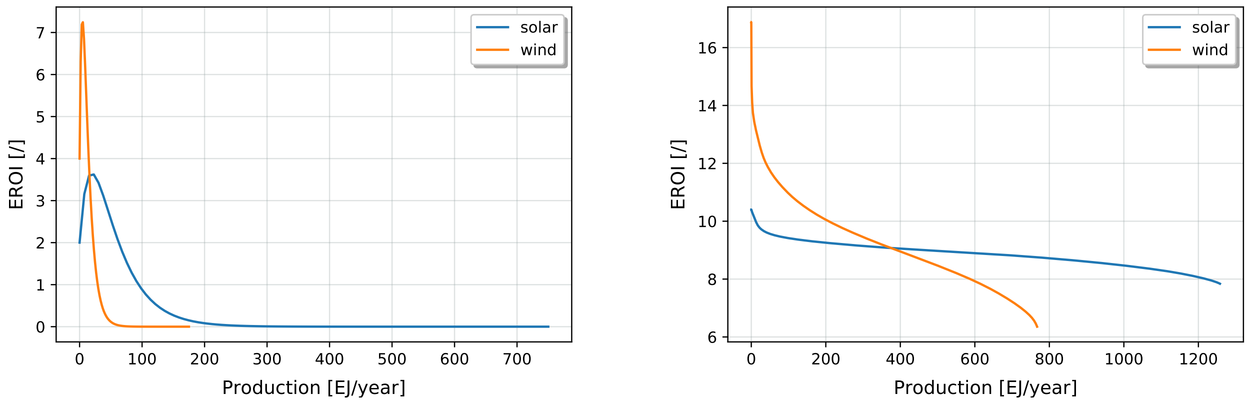
Conclusion

5.1 Reflections

In the previous chapter, we saw that baseline simulation of our model produced the same results as Dale: the massive shift from fossil fuels to renewable energies causes a collapse of the global economy. This collapse happens despite the fact that compared to Dale, we use much more optimistic EROI curves for renewable energies. In fact, the collapse does not come from a change in EROI of energy sources. It appears that EROI values only influence the growth rate of the economy, when it is growing. The collapse is simply due to the higher capital intensity of renewable energies. When the system transitions to renewables, the capital feedback to the energy sector increases manyfold. This is equivalent to saying that the energy sector expands significantly within the economy. An important part of the economy therefore becomes unproductive in a sense, since the production from the energy sector is generally taken for granted in economic analysis. While a significant part of industrial production gets directed towards the energy sector, the consumption from households associated with this production of capital must still be fulfilled. Because of this, there is not enough capital left for re-investment in the industrial sector, and the global economy collapses.

This collapse behaviour of the economy is very robust. Variations in most parameters of the model are not able to alter it. The only way to avoid it is to change the saving rate of the economy while the transition takes place. In other words, the energy transition can only be successful if it is accompanied by changes in consumption habits, which translate into a decreasing consumption rate of the global economy. The model with decreasing consumption rate predicts that the total amount of goods consumed will continue its exponential increase, even if this increase happens at a reduced rate.

Surprisingly, we observe that both the cause of the collapse and the "solution" to fix it consist in changes in the structure of the economy, not in purely physical factors. The global potentials of wind and solar are well sufficient to supply the projected energy demand in 2050 and beyond, and this despite their decreasing EROI values with spatial expansion. Dale drew the opposite conclusion, that renewable potentials would not be enough to meet the projected energy demand. This is because Dale is much more pessimistic about the EROI curves of renewables, and because he considers a much longer time scale than us (up to 2200). Figure 5.1 compares the wind and solar EROI curves used by Dale and by us. We believe that our EROI curves, which have been produced recently, are more realistic. Furthermore, we think that it is extremely difficult to make predictions about the long-term future, namely because of technological progress.



(a) used by Dale

(b) used by us

Figure 5.1: Difference in EROI curves used by Dale and by us. Dale's curves are much more pessimistic.

Limitations of the model

We observe that the results from our adaptation of Dale's model are in fact optimistic. Renewable energy sources can sustainably support the global economy, provided that the energy transition is accompanied by a decrease in consumption rate. However, we must stay critical of these results. Our model faces a number of limitations:

1. Our description of the global economy is very simplistic. Hence, our observations about the effect of different capital intensities may be inaccurate.
2. We impose a shift in production towards renewables through exogenous profiles for γ_k, but nothing tells us that such a brutal shift is feasible in practice.
3. Many issues associated to renewable energy production are overlooked in our model, such as intermittency and storage. In particular, our assumption that all energy sources are substitutable is too optimistic.
4. Our model does not take the constraints on other natural resources such as minerals into account.
5. Our adapted GEMBA model is extremely sensitive to changes in the value of the saving rate s. Thanks to this, a slight increase in s allows the global economy to easily avoid collapse. Such conclusion is maybe too naive. According to some economic models such as the Solow-Swan model, the value of s has in fact no major impact on the long-term growth of the economy.
6. Discussion on the values of the model's parameters produces unsatisfactory results.

Regarding to point 6, we have observed in chapter 4 that with increasing saving rate and no collapse, the model is very sensitive to changes in some parameters' values. This sensitivity obliges us to recalibrate $\epsilon(t)$ each time we modify one of these parameters, such that we do not exactly know if the observed effect is due to the change in parameter value or to the new calibration of $\epsilon(t)$. This is particularly the case for Figure 4.8.

Furthermore, many changes in parameters' values either lead to problems in the simulation (e.g. negative Acc$_{ind}$) or to energy production curves which cannot be fitted to historical production data via calibration of $\epsilon(t)$. This is for example the case on Figures 4.7 and 4.8. Thus, the model is not extremely robust.

Besides, a crucial issue is the effect that the electrification of the energy system will have: some energetic costs and losses will be suppressed while new ones will appear. In our model, this should reflect itself in changing values for parameters $\epsilon(t)$ and $q(t)$ after 2019. However, our model's results when changing $\epsilon(t)$ and $q(t)$ are not coherent, due to imperfections in the model's equations. Hence, we are not able to draw any conclusion about the potential effects of electrification of the energy system. We suggested new equations to correct the imperfections. Unfortunately, these new equations did not lead us anywhere because we were not able to reasonably fit the obtained $P(t)$ to historical production data.

5.2 Summary

In this report, we studied an adapted version of Dale's GEMBA model.

First, concepts from the field of energy analysis were presented. In particular, the construction of the EROI curves used in the model was explained. The EROI curves for wind and solar were produced at the UCLouvain, following a careful bottom-up engineering approach. The EROI curves for fossil fuels were adapted from [2], while all other resources were aggregated together and were given a constant EROI value. Moreover, the difference in capital intensity between fossil and renewable energy sources was underlined.

In the following chapter, the adapted GEMBA model was presented. The field of biophysical economics, to which belongs the model, was introduced, stating its major differences with conventional economic approach. The main point is that biophysical economists consider that the economy is constrained by physical laws from the natural sciences. In the case of GEMBA, a particular focus is put on energy, which is the numeraire of the model instead of price. The research question behind our adapted GEMBA model was also presented: in what measure is an energy transition towards nearly 100% renewable production in 2050 feasible at global scale, without provoking a collapse of the global economy ?
The model's equations, structure and parameter values were then described. After that, we stated explicitly the main assumptions of the model and we stressed our differences with Dale's original version. These include the fact that Dale simulates the long-term future, while we stick to the 2050 horizon. For Dale, the economy transitions naturally from fossil fuels to renewables when the EROIs of fossil fuels become too low. In our adapted model, the transition is forced and rapid, in response to the climatic emergency.

Then, the results of our model were presented and discussed. Like Dale, we obtained a collapse of the economy. This collapse was not due to the lower EROI values of renewables, but due to their higher capital intensity. Nevertheless, this collapse could be avoided by increasing the saving rate of the economy as it transitions towards renewable energy sources.

Finally, we reflected on the model's results and on its limitations. Dale's recommendation at the end of his PhD dissertation was that more research should be directed towards energy efficiency. Our conclusion is that the major challenge induced by the energy transition is rather to adapt the structure of the economy, in response to the increasing size of the energy sector. According to our simulations, the output of the global economy can continue to grow beyond 2050 without being limited by the technical potentials of renewable energies, which are high. Consumption of the global economy can continue to grow too. However, we cannot say if the consumption *per capita* must decrease or not as a result of the increasing saving rate of the economy. Indeed, the GEMBA model does not take population into consideration. It is also important to note that with our adapted GEMBA model, we were not able to assess the effect of the electrification of the global energy system. The model does not take into account the limited substitutability between different forms of energy either.

5.3 Research perspectives

We believe that further research could be carried out in four main directions.

To begin with, research could be conducted about the implications of the growing size of the energy sector during the transition. In our model, these implications were essential. But would another modeling approach of the global economy lead to the same conclusions ? Such research would not need to be in the field of biophysical economics. No availability or accessibility considerations for energy sources would need to be taken into account.
In fact, extensive research has already been carried through to assess the effects of decreasing EROI of the energy sector, but we are not so sure that similar attention has been drawn to the changing capital intensity of this sector. This should be compensated for, since according to our model, capital intensity plays a much more crucial role in the transition than EROI.

Another avenue for research would be to take the evolution of World's population into account. Inserting population considerations into the GEMBA model would enable us among others to see if the decrease in consumption rate also implies a decrease in per capita consumption or not. On the other hand, it would require us to divide our global economy into distinct regions, in order to take into account the significant regional variations in per capita quantities.

Furthermore, we think that the energy-economy model could be improved, such that different energy carriers would explicitly be taken into account and energy sources could not simply be assumed to be substitutable. Different end-uses of energy such as transport, agriculture, heating, etc. would also need to be distinguished. It would give us a more detailed picture of the energy flows within the economy. This research path, just like the previous one, was already suggested by Dale at the end of his PhD dissertation.

Finally, if the GEMBA model focuses on the energy constraint, it would be valuable to also incorporate a constraint on materials into it. Indeed, renewable sources rely on an important infrastructure, which requires various metals. The massive deployment of renewables and the subsequent intensive use of these metals might induce an increase in their energy costs of extraction over time, since the most accessible metals are mined first [20]. This could have substantial impact on the energy system.

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Chapter A

Python code used for baseline simulation

```
'''
2019-05-25
Pierre JACQUES, student at the UCLouvain
Baseline simulation for the adpated GEMBA model
'''

from numpy import*
import matplotlib.pyplot as plt
from scipy import interpolate

'''
Fossil resources
0: coal
1: oil
2: gas

Renewable resources
0: wind
1: solar
2: other renewables + nuclear
'''

URR = array([105000, 29000, 27000]) # [EJ]
TP = array([767.14, 1258.04, 200]) # [EJ/year]

Incept_date1 = array([1800, 1860, 1880]) # [year]
Incept_date2 = array([2000, 2000, 1800]) # [year]

# Parameters for the EROI curves of fossil fuels [/]
Peak_EROI = array([100, 35.49, 35.49])
XI = array([0.0733, 0.0, 0.0])
xi = array([70.4688, 658.31543, 658.32543])
rho_tilde = array([0.001, 0.0005, 0.0005])
phi = log(Peak_EROI)

rho_wind_val = array
    ([0,0.014354004,0.779510291,2.348970242,4.337767459,6.170257886,7.969057091,9.601384078,11.0
     / TP[0]
```

```
EROI_wind_val = array
    ([16.876,16.87591626,14.66916159,14.09969255,13.74728877,13.5691905,13.43367259,13.32586785,

EROI_wind = interpolate.interp1d(rho_wind_val , EROI_wind_val)

rho_solar_val = array
    ([0 ,0.098794334 ,2.35377704 ,4.528466061 ,6.756971863 ,8.805953542 ,10.8359135
     / TP[1]
EROI_solar_val = array
    ([10.4021 ,10.40209256 ,10.30838649 ,10.24227141 ,10.16769621 ,10.10220673 ,10.

EROI_solar = interpolate.interp1d(rho_solar_val , EROI_solar_val)

EROI_others = 6

# Capital intensities of the energy resources [/]
chi1 = 0.1 * ones(3)
chi2 = 0.8 * ones(3)
chi2[1] = 0.9
chi2[2] = 0.5

delta = 1/20 # Depreciation rate of industrial capital stock [1/year]
s = 0.1 # saving rate [/]


def simulate(t0, nYears):

    # Pre-allocation of vectors and matrices ----- START -----

    # Industrial capital stock [EJ].
    # We make the assumption that the global economy begins with 5 [EJ]
      of
    # industrial capital stock at the year 1800.
    K_ind = 5 * ones(nYears)

    # Annual primary energy production of the two energy sectors [EJ/
      year]
    P1 = zeros((3,nYears))
    P2 = zeros((3,nYears))

    # Total primary annual energy production [EJ/year]
    P = zeros(nYears)

    # Primary energy production minus process energy inputs [EJ/year]
    E1 = zeros((3,nYears))
    E2 = zeros((3,nYears))

    # Energy flow which reaches the industrial sector [EJ/year]
    E = zeros(nYears)

    # Capital feedback to the energy sector [Cap goods/year]
    F = zeros(nYears)

    # Total industrial output [Cap goods/year]
    Y = zeros(nYears)

    # Exploited resource for each energy source [/]
    rho1 = zeros((3,nYears))
```

```
    rho2 = zeros((3,nYears))

    # EROI of each energy source [/]
    EROI1 = zeros((3,nYears))
    EROI2 = zeros((3,nYears))

    # Fraction of supply of the energy sources [/]
    gamma1 = zeros((3,nYears))
    gamma2 = zeros((3,nYears))

    # Pre-allocation of vectors and matrices ----- END -----


    # We load the data giving historical values for fraction of supply of each energy source
    data = load('/tmp/outfile1.npz')

    gamma1_long = data['gamma1']
    gamma2_long = data['gamma2']
    gamma3_long = data['gamma3']

    gamma_intraFossil = gamma1_long[:,-1] / sum(gamma1_long[:,-1])

    gamma1[:, 0:218] = gamma1_long
    gamma2[0, 0:218] = gamma2_long[3,:]
    gamma2[1, 0:218] = gamma2_long[2,:]
    gamma2[2, 0:218] = gamma2_long[0,:] + gamma2_long[1,:] + gamma2_long[4,:] + gamma3_long[:]

    gamma1[:,218] = gamma1[:,217]
    gamma1[:,219] = gamma1[:,217]
    gamma2[:,218] = gamma2[:,217]
    gamma2[:,219] = gamma2[:,217]

    gamma1_smoothed = copy(gamma1)
    gamma2_smoothed = copy(gamma2)

    # Imposed profile for the fraction of supply of fossil fuels after 2019
    b0 = -1.33958976e-01
    b1 = 2.70010730e+02
    b2 = 0.1
    X = arange(nYears - 218) + 2018
    gamma_imposed = exp(b0 * X + b1) + b2

    # Profile for the energy requirement factor of the economy [EJ / (year[U+FFFD]capital goods)]
    a0 = -2.23417874e-02
    a1 = 4.16284628e+01
    a2 = 0.22
    XX = t0 + arange(nYears)
    eps = exp(a0 * XX + a1) + a2

    # Profile for the energy intensity of industrial production [EJ/capital good]
    c0 = -1.40300573e-02
    c1 = 2.36934554e+01
    c2 = 0.29
```

```
    q = exp(c0 * XX + c1) + c2

    t = t0

    for iYear in arange(nYears):
        i1 = Incept_date1 <= t
        i2 = Incept_date2 <= t

        # Technological component of the EROI [/]
        G1 = XI[i1] + (1 - XI[i1]) / (1 + exp(- xi[i1] * (rho1[i1, iYear
            ] - rho_tilde[i1])))

        # Resource quality component of the EROI [/]
        H1 = exp(- phi[i1] * rho1[i1, iYear])

        EROI1[i1, iYear] = Peak_EROI[i1] * G1 * H1

        EROI2[2, iYear] = EROI_others
        if(iYear >= 200):
            EROI2[0, iYear] = EROI_wind(rho2[0, iYear])
            EROI2[1, iYear] = EROI_solar(rho2[1, iYear])

        P[iYear] = eps[iYear] * K_ind[iYear]

        if(iYear >= 220):
            gamma1[i1, iYear] = gamma_imposed[iYear - 218] *
                gamma_intraFossil
            gamma2[i2, iYear] = (1 - gamma_imposed[iYear - 218]) * EROI2
                [i2, iYear] / sum(EROI2[i2, iYear])
            gamma1_smoothed[i1, iYear] = sum(gamma1[i1, iYear-9:iYear
                +1], axis=1) / 10
            gamma2_smoothed[i2, iYear] = sum(gamma2[i2, iYear-9:iYear
                +1], axis=1) / 10

        P1[i1, iYear] = gamma1_smoothed[i1, iYear] * P[iYear]
        P2[i2, iYear] = gamma2_smoothed[i2, iYear] * P[iYear]

        if(iYear != nYears-1):
            rho1[i1, iYear+1] = rho1[i1, iYear] + P1[i1, iYear] / URR[i1
                ]
            rho2[i2, iYear+1] = P2[i2, iYear] / TP[i2]

        # Fuel subsidy for the two energy sectors [EJ/year]
        S11 = (1 - chi1[i1]) * P1[i1, iYear] / EROI1[i1, iYear]
        S12 = (1 - chi2[i2]) * P2[i2, iYear] / EROI2[i2, iYear]

        # Capital subsidy for the two energy sectors [EJ/year]
        S21 = chi1[i1] * P1[i1, iYear] / EROI1[i1, iYear]
        S22 = chi2[i2] * P2[i2, iYear] / EROI2[i2, iYear]

        E1[i1, iYear] = P1[i1, iYear] - S11
        E2[i2, iYear] = P2[i2, iYear] - S12

        E[iYear] = sum(E1[:,iYear]) + sum(E2[:,iYear])

        Y[iYear] = E[iYear] / q[iYear]
        F[iYear] = (sum(S21) + sum(S22)) / q[iYear]
        Acc = s * Y[iYear] - F[iYear]
```

```
        if(Acc<0):
            print("No energy available for industrial capital stock at year %d - the economy collapses" %(iYear+t0))
            break

        Dep = delta * K_ind[iYear]

        if(iYear != nYears-1):
            K_ind[iYear+1] = K_ind[iYear] + Acc - Dep

        t = t + 1


t0 = 1800
nYears = 251
simulate(t0, nYears)
print("End Simulation")
```

Chapter B

Python code with increasing s and TP_{others}=100

```
'''
2019-05-25
Pierre JACQUES, student at the UCLouvain
Simulation of the adapted GEMBA model with increasing s and TP_others
    =100
'''

from numpy import*
import matplotlib.pyplot as plt
from scipy import interpolate

'''
Fossil resources
0: coal
1: oil
2: gas

Renewable resources
0: wind
1: solar
2: other renewables + nuclear
'''

URR = array([105000, 29000, 27000]) # [EJ]
TP = array([767.14, 1258.04, 100]) # [EJ/year]

Incept_date1 = array([1800, 1860, 1880]) # [year]
Incept_date2 = array([2000, 2000, 1800]) # [year]

# Parameters for the EROI curves of fossil fuels [/]
Peak_EROI = array([100, 35.49, 35.49])
XI = array([0.0733, 0.0, 0.0])
xi = array([70.4688, 658.31543, 658.32543])
rho_tilde = array([0.001, 0.0005, 0.0005])
phi = log(Peak_EROI)

rho_wind_val = array
    ([0,0.014354004,0.779510291,2.348970242,4.337767459,6.170257886,7.969057091,9.601384078,11.0
     / TP[0]
```

```
EROI_wind_val = array
    ([16.876,16.87591626,14.66916159,14.09969255,13.74728877,13.5691905,13.43367259,13.32586785,

EROI_wind = interpolate.interp1d(rho_wind_val, EROI_wind_val)

rho_solar_val = array
    ([0,0.098794334,2.35377704,4.528466061,6.756971863,8.805953542,10.8359135
     / TP[1]
EROI_solar_val = array
    ([10.4021,10.40209256,10.30838649,10.24227141,10.16769621,10.10220673,10.

EROI_solar = interpolate.interp1d(rho_solar_val, EROI_solar_val)

EROI_others = 6

# Capital intensities of the energy resources [/]
chi1 = 0.1 * ones(3)
chi2 = 0.8 * ones(3)
chi2[1] = 0.9
chi2[2] = 0.5

delta = 1/20 # Depreciation rate of industrial capital stock [1/year]


def simulate(t0, nYears):

    # Pre-allocation of vectors and matrices ----- START -----

    # Industrial capital stock [EJ].
    # We make the assumption that the global economy begins with 5 [EJ] of
    # industrial capital stock at the year 1800.
    K_ind = 5 * ones(nYears)

    # Annual primary energy production of the two energy sectors [EJ/year]
    P1 = zeros((3,nYears))
    P2 = zeros((3,nYears))

    # Total primary annual energy production [EJ/year]
    P = zeros(nYears)
    P_ = zeros(nYears)

    # Primary energy production minus process energy inputs [EJ/year]
    E1 = zeros((3,nYears))
    E2 = zeros((3,nYears))

    # Energy flow which reaches the industrial sector [EJ/year]
    E = zeros(nYears)

    # Capital feedback to the energy sector [Cap goods/year]
    F = zeros(nYears)

    # Total industrial output [Cap goods/year]
    Y = zeros(nYears)

    # Exploited resource for each energy source [/]
    rho1 = zeros((3,nYears))
```

```
    rho2 = zeros((3,nYears))

    # EROI of each energy source [/]
    EROI1 = zeros((3,nYears))
    EROI2 = zeros((3,nYears))

    # Fraction of supply of the energy sources [/]
    gamma1 = zeros((3,nYears))
    gamma2 = zeros((3,nYears))

    # saving rate of the economy [/]
    s = 0.1 * ones(nYears)
    s_smoothed = copy(s)

    # Pre-allocation of vectors and matrices ----- END -----


    # We load the data giving historical values for fraction of supply of each energy source
    data = load('/tmp/outfile1.npz')

    gamma1_long = data['gamma1']
    gamma2_long = data['gamma2']
    gamma3_long = data['gamma3']

    gamma_intraFossil = gamma1_long[:,-1] / sum(gamma1_long[:,-1])

    gamma1[:, 0:218] = gamma1_long
    gamma2[0, 0:218] = gamma2_long[3,:]
    gamma2[1, 0:218] = gamma2_long[2,:]
    gamma2[2, 0:218] = gamma2_long[0,:] + gamma2_long[1,:] + gamma2_long[4,:] + gamma3_long[:]

    gamma1[:,218] = gamma1[:,217]
    gamma1[:,219] = gamma1[:,217]
    gamma2[:,218] = gamma2[:,217]
    gamma2[:,219] = gamma2[:,217]

    gamma1_smoothed = copy(gamma1)
    gamma2_smoothed = copy(gamma2)

    # Imposed profile for the fraction of supply of fossil fuels after 2019
    b0 = -1.33958976e-01
    b1 = 2.70010730e+02
    b2 = 0.1
    X = arange(nYears - 218) + 2018
    gamma_imposed = exp(b0 * X + b1) + b2

    # Profile for the energy requirement factor of the economy [EJ / (year�capital goods)]
    a0 = -2.23417874e-02
    a1 = 4.16284628e+01
    a2 = 0.22
    XX = t0 + arange(nYears)
    eps = exp(a0 * XX + a1) + a2

```

```
    # Profile for the energy intensity of industrial production [EJ/
        capital good]
    c0 = -1.40300573e-02
    c1 = 2.36934554e+01
    c2 = 0.29
    q = exp(c0 * XX + c1) + c2

    # function used to generate the profile for saving rate after 2019
    d0 = -6.83429745e-02
    d1 = 1.37642211e+02
    XXX = arange(nYears - 218) + 2018
    frac = exp(d0 * XXX + d1)

    # indices of renewable resources producing at full potential
    i2_full = zeros(3)

    t = t0

    for iYear in arange(nYears):
        i1 = Incept_date1 <= t
        i2 = Incept_date2 <= t

        # indices of renewable resources not producing at full potential
        i2_nonFull = logical_and(i2, logical_not(i2_full.tolist()))

        # Technological component of the EROI [/]
        G1 = XI[i1] + (1 - XI[i1]) / (1 + exp(- xi[i1] * (rho1[i1, iYear
            ] - rho_tilde[i1])))

        # Resource quality component of the EROI [/]
        H1 = exp(- phi[i1] * rho1[i1, iYear])

        EROI1[i1, iYear] = Peak_EROI[i1] * G1 * H1

        EROI2[2, iYear] = EROI_others
        if(iYear >= 200):
            EROI2[0, iYear] = EROI_wind(rho2[0, iYear])
            EROI2[1, iYear] = EROI_solar(rho2[1, iYear])

        P[iYear] = eps[iYear] * K_ind[iYear]
        P_[iYear] = P[iYear] - sum(TP[i2_full>0])

        if(iYear >= 220):
            gamma1[i1, iYear] = gamma_imposed[iYear - 218] *
                gamma_intraFossil
            gamma2[i2_nonFull, iYear] = (1 - gamma_imposed[iYear - 218])
                 * EROI2[i2_nonFull, iYear] / sum(EROI2[i2_nonFull, iYear
                ])
            gamma1_smoothed[i1, iYear] = sum(gamma1[i1, iYear-9:iYear
                +1], axis=1) / 10
            if(any(i2_full.tolist())):
                gamma2_smoothed[i2_nonFull, iYear] = gamma2[i2_nonFull,
                    iYear]
            else:
                gamma2_smoothed[i2_nonFull, iYear] = sum(gamma2[
                    i2_nonFull, iYear-9:iYear+1], axis=1) / 10
            s[iYear] = 0.075 * frac[iYear-218] + 0.17 * (1-frac [iYear
                -218])
```

```
            s_smoothed[iYear] = sum(s[iYear-9:iYear+1]) / 10

        P1[i1, iYear] = gamma1_smoothed[i1, iYear] * P_[iYear]
        P2[i2_nonFull, iYear] = gamma2_smoothed[i2_nonFull, iYear] * P_[iYear]
        P2[i2_full>0, iYear] = TP[i2_full>0]

        if(iYear != nYears-1):
            rho1[i1, iYear+1] = rho1[i1, iYear] + P1[i1, iYear] / URR[i1]
            rho2[i2, iYear+1] = P2[i2, iYear] / TP[i2]

            # We handel the case when the exploited resources of renewables go over 1
            i2_full = rho2[:, iYear+1] > 0.999
            P2[i2_full, iYear] = TP[i2_full]
            rho2[i2_full, iYear+1] = 0.9999

        # Fuel subsidy for the two energy sectors [EJ/year]
        S11 = (1 - chi1[i1]) * P1[i1, iYear] / EROI1[i1, iYear]
        S12 = (1 - chi2[i2]) * P2[i2, iYear] / EROI2[i2, iYear]

        # Capital subsidy for the two energy sectors [EJ/year]
        S21 = chi1[i1] * P1[i1, iYear] / EROI1[i1, iYear]
        S22 = chi2[i2] * P2[i2, iYear] / EROI2[i2, iYear]

        E1[i1, iYear] = P1[i1, iYear] - S11
        E2[i2, iYear] = P2[i2, iYear] - S12

        E[iYear] = sum(E1[:,iYear]) + sum(E2[:,iYear])

        Y[iYear] = E[iYear] / q[iYear]
        F[iYear] = (sum(S21) + sum(S22)) / q[iYear]
        Acc = s[iYear] * Y[iYear] - F[iYear]
        if(Acc<0):
            print("No␣energy␣available␣for␣industrial␣capital␣stock␣at␣year␣%d␣-␣the␣economy␣collapses" %(iYear+t0))
            break

        Dep = delta * K_ind[iYear]

        if(iYear != nYears-1):
            K_ind[iYear+1] = K_ind[iYear] + Acc - Dep

        t = t + 1


t0 = 1800
nYears = 251
simulate(t0, nYears)
print("End␣Simulation")
```

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