Are all energy resources created equal?

A comparative analysis of the dynamics of resources for the energy system

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Declaration of own work

I declare that this thesis:

“Are all energy resources created equal? A comparative analysis of the dynamics of resources for the energy system”

is entirely my work and that where any material originates from the work of others, this is fully cited and referenced, and/or acknowledged as appropriate.

Signed:

Jamie Speirs

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This thesis was conducted alongside my employment at Imperial College as a Research Associate in the Centre for Environmental Policy.

A number of academic publications have arisen from research related to this thesis and are listed below. I thank all my co-authors for their collaboration and contribution to my research.

Peer reviewed journal articles

Candelise, C., J. F. Speirs and R. J. K. Gross (2011). "Materials availability for thin film (TF) PV technologies development: A real concern?" Renewable and Sustainable Energy Reviews **15**(9): 4972-4981.

Houari, Y., J. Speirs, C. Candelise and R. Gross (2014). "A system dynamics model of tellurium availability for CdTe PV." Progress in Photovoltaics: Research and Applications **22**(1): 129-146.

Sorrell, S. and J. Speirs (2014). "Using growth curves to forecast regional resource recovery: approaches, analytics and consistency tests." Phil. Trans. R. Soc. A **372**(2006): 1-36.

Sorrell, S., J. Speirs, R. Bentley, R. Miller and E. Thompson (2012). "Shaping the global oil peak: A review of the evidence on field sizes, reserve growth, decline rates and depletion rates." Energy **37**(1): 709-724.

Sorrell, S., J. Speirs, R. Bentley, A. Brandt and R. Miller (2010). "Global oil depletion: A review of the evidence." Energy Policy **38**(9): 5290-5295.

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Sorrell, S., R. Miller, R. Bentley and J. Speirs (2010). "Oil futures: A comparison of global supply forecasts." Energy Policy **38**(9): 4990-5003.

Speirs, J., M. Contestabile, Y. Houari and R. Gross (2014). "The future of lithium availability for electric vehicle batteries." Renewable & Sustainable Energy Reviews **In Press**.

Academic Reports

Sorrell, S., J. Speirs, R. Bentley, A. Brandt and R. Miller (2009). Global Oil Depletion: An assessment of the evidence for a near-term peak in global oil production. London, UKERC.

Speirs, J., R. Gross, C. Candelise and W. Gross (2011). Materials Availability: Potential constraints to the future low-carbon economy. Working Paper I: A thin film PV case study. London, UK Energy Research Centre.

Speirs, J., Y. Houari, M. Contestabile, R. Gross and B. Gross (2013). Materials Availability: Potential constraints to the future low-carbon economy. Working Paper II: Batteries, Magnets and Materials. London, UK Energy Research Centre.

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Abstract

There is a longstanding debate about the future availability of energy resources, and a significant literature has developed around the issues of oil availability in particular. More recently, the availability of lesser-known critical metals, such as lithium and indium, has been called into question. These metals are key components in low-carbon energy technologies and a new evidence base that questions their future availability is emerging. Much of this research applies methods and techniques also applied to the analysis of oil resources, with the implicit assumption that these resources are in some way analogous. However, although there are similarities, there are also structural differences and the appropriateness of the assumed analogy has not been sufficiently tested. This thesis explores the similarities and differences in the structure of the oil, lithium and indium resource systems, examining the likely response of these systems to availability constraints and testing the appropriateness of this assumed analogy.

The systems that define the market for resources are dynamically complex and involve a number of different interlinked variables. The way in which these resource systems respond to changes in surrounding conditions arises from the structure of these variables and their linkages. However, much of the existing analysis of critical metals relies on simplistic assumptions regarding the structure and function of these systems. To address this knowledge gap, this thesis first presents case studies of the three resource systems. The case studies are then used to develop three system dynamics models.

This thesis finds that, while there are many similarities in the structure of the three resource systems modelled, the differences between them have a significant impact on their dynamic system behaviour. Analysis which overlooks these differences is likely to draw inaccurate conclusions. In particular, the resilience of metals to periods of constrained availability is potentially greater than that of oil if metal recycling is taken into account. However, metals recovered as by-products are potentially limited in their ability to resist constrained availability.

Table of Contents

Table of Figures

Table of Tables

Chapter 1: Introduction

> *"The power of population is so superior to the power in the earth to produce subsistence for man that premature death must, in some shape or other, visit the human race".*

Thomas Robert Malthus, (1798)

> *"Because we can expect future generations to be richer than we are, no matter what we do about resources, asking us to refrain from using resources now so that future generations can have them later is like asking the poor to make gifts to the rich."*

Julian Simon, (1983)

This thesis is concerned with the future availability of energy resources and the robustness of dynamic resource systems to constraints in resource production capacity. It is reasonable to assume that the condition of future society is dependent on the availability of resources. However, there is considerable disagreement on whether useful resources will be scarce or abundant in the future. The polarity of opinion on this issue is significant, with some predicting chronic resource unavailability and societal collapse whilst others predict virtually infinite resource availability, economic growth and development. The debate has been contentious since the earliest authors of the discourse (Malthus 1798; Hazlitt 1807) and though the resources at the centre of the debate may have changed over time, the contention of the discourse has remained. In more recent history the pivotal role played by fossil fuels in the advancement of society has led the debate in the direction of energy, with resources like oil taking centre stage and with a whole spectrum of opinion as to the future availability of energy resources (Sorrell *et al.* 2009).

In the last decade a host of lesser known metals have become the new focus of the resource availability debate due to their role in the manufacturing of technologies, which may be used to decarbonise the energy sector. Technologies such as solar photovoltaics (PV), which may be used to decarbonise electricity generation, and electric vehicles (EV), which may be used to decarbonise transportation, use a host of metals such as indium and lithium with relatively low abundance and relatively low historical demand. However, global trends in the adoption of decarbonisation targets have led some to forecast dramatic increases in the manufacturing of low-carbon technologies (Angerer *et al.* 2009b; DCM 2009; McKinsey 2009; IEA 2010a; Marcus 2010) leading to concern over the availability of the less abundant metals used in their manufacture. Metals such as these may be referred to in the literature as ‘low-carbon technology metals’, a subset within the wider ‘critical materials’.

The debate surrounding the availability of critical materials is contentious in a similar way to previous incarnations of the resource availability debate. Those with the most pessimistic outlook dismiss more optimistic positions (Ehrlich 1968; Tahil 2008) while the optimists similarly dismiss pessimists (Simon 1998); both using logic common to the wider resource availability debate to defend their positions. This common logic implies that, at a fundamental level, resources are the same and that if an argument is sufficient to conclude the relative availability of one resource then it is also sufficient to conclude the relative availability of another. However, resources have fundamental differences, and these differences may have significant bearing on whether it is appropriate to use one as an analogue for another. For example, fossil fuels are destroyed during most of their end uses, while metals such as indium are not, and can be recycled (Speirs *et al.* 2011). Fossil fuels are produced for their own economic worth , while indium is typically produced as a by-product of the production process of the base metal Zinc (Candelise *et al.* 2011). Finally, production of indium is growing exponentially in response to new applications and end uses (Candelise *et al.* 2011), while fossil fuel markets are more mature, and production rates growing less rapidly (IEA 2012).

This thesis presents three case study chapters. The first describes many of the dynamics affecting exhaustible, non-recyclable resources, and oil as an example being an incumbent resource which has received significant research effort. The second and third case study chapters examine two metals, lithium and indium, representing resources only recently of concern to the energy system and about which much less is known. These case studies are then used to inform the development of three system dynamic models used to test and evaluate these resource systems to examine whether these resources are similar enough to be considered analogous when drawing conclusions about their future availability.

1.1 Motivation for research and novelty

There are three key motivations for the research described in this thesis which respond to gaps in the current evidence base:

- The incomplete nature of the current and evolving debate around the assessment of critical materials;
- The lack of explicit recognition of the complex and dynamic structure of resource systems; and
- The lack of evidence for the assumed analogy between historically important exhaustible, non-recyclable resources and metals receiving more recent commercial attention.

Aspects of these motivations are discussed below.

1.1.1 The critical materials debate

In the past decade a discourse has emerged around the availability of the 'critical materials', so-called for their perceived criticality to the particular economy of focus (Speirs *et al.* 2013b). This debate is often discussed in similar terms to previous resource availability topics such as oil availability (Sorrell *et al.* 2009). The critical materials are often assessed using high level comparative metrics, which can then be used to rank materials in order of their perceived criticality (Speirs *et al.* 2013b). These are referred to as 'criticality assessments.' Several of the materials that appear in these assessments are exotic metals perceived to be critical to the manufacture of low-carbon energy technologies. These metals are referred to here as the 'low-carbon technology metals.' Figure 1.1 presents the results of several material criticality assessments, highlighting those materials that appear most often. Most of these materials are used in low-carbon energy technologies, including all of the most regularly recurring metals.

Figure 1.1: Comparison of the critical materials identified in five different studies

Metal	NRC	EC	JRC	AEA	Fraunhofer
Indium	✔	✔	✔	✔	✔
Gallium	✔	✔	✔		✔
Rare Earth Elements	✔	✔	✔		✔
Cobalt		✔		✔	✔
Niobium	✔	✔			✔
Platinum Group	✔	✔			✔
Tantalum	✔	✔			✔
Copper	✔			✔	✔
Germanium		✔			✔
Antimony		✔			✔
Lithium	✔			✔	
Titanium	✔				✔
Tin				✔	✔
Phosphorus				✔	
Lead				✔	
Silver					✔
Selenium					✔
Tellurium			✔		
Magnesium		✔			
Tungsten		✔			
Manganese	✔				
Vanadium	✔				

Source: NRC (2008) EC (2010) Moss et al. (2011) AEA Technology (2010) Angerer *et al.* (2009b)

Notes: Materials ranked by number of studies they appear in, with materials appearing in all five studies ranked first.

The idea that energy technologies are particularly exposed to the availability of critical materials has led to a number of further studies which perform similar assessments, but focus only on energy technologies and the more scarce metals used in their manufacture (DOE 2011; Moss *et al.* 2011).

One difficulty with the use of high level comparative metrics is the need to base them on simple data available for all materials being considered (Speirs *et al.* 2013b). This can lead to overly simplistic methodologies which fail to capture all the nuance of the respective resource systems, highlighting the need for more 'narrow and deep' analysis of individual cases to allow for the specific characteristics of each metal to be sufficiently examined.

In criticality assessments there is an inherent assumption that the low-carbon technology metals are fundamentally comparable and that any differences in their respective resource systems are small enough to be adequately captured in a single criticality assessment methodology. There is also an implication that these metals are comparable with other types of resources discussed in the resource availability debate, such as coal and oil (Beauchemin 2008). Neither of these apparent assumptions have been examined or tested in the existing evidence base.

This thesis is designed to respond to both knowledge gaps described above: to examine low-carbon technology metals in sufficient detail to capture their subtleties and characteristics; and to conceptually and quantitatively examine the extent to which there is comparability within the critical materials, and between them and other resources.

1.1.2 The dynamics of resource systems

A range of different techniques have been used to assess the future availability of energy resources. When looking at extensively researched resources such as oil, the list of techniques applied to their assessment is wide and varied, from the earliest types of Hubbert curve analysis, to the scenarios work of Shell, to the 'megaprojects' databases of Chris Skrebowski (ITPOES 2008). System dynamics has also been applied to the oil resource system, allowing for the complex dynamics of the economic and geological aspects of resource use to be characterised and examined (Sterman *et al.* 1988; Sterman 2000).

The critical materials, however, have not received the same level of analysis. Reports which examine these resources tend to exclude key variables and often take a static view of the relationship between variables (Candelise *et al.* 2011; Speirs *et al.* 2011). In addition, the variables selected in these studies are rarely selected systematically, with the result that studies using broadly similar methodologies have arrived at entirely different conclusions (Candelise *et al.* 2011; Speirs *et al.* 2011). Very recent published work begins to apply system dynamics methodologies to the assessment of low-carbon technology metals, though this approach has not yet been extensively applied (Houari *et al.* 2013).

This thesis examines the availability of resources for the energy sector, and assesses the extent to which resources are comparable, the extent to which they are different, and what can be learned through making comparisons about the underlying nature of resource availability. This approach arises from the fact that there is an assumed analogy between resources that are well researched, such as oil, and resources which are less well known, such as metals (Beauchemin 2008; Rustad 2012; Vikström *et al.* 2013). This analogy is manifest in the literature, where resource modelling techniques originally developed for oil resource analysis are applied to other resources, including metals (Bardi 2005; Cordell *et al.* 2009; May *et al.* 2011; Mohr *et al.* 2011; Vikström *et al.* 2013). However, the appropriateness of this analogy has not been sufficiently tested, and differences in the structure of different resource systems may be as important for their 'dynamic behaviour' as their similarities. These resources exist within dynamic systems, where many interdependent variables and feedback loops define the way in which these systems respond to changes in the surrounding conditions. This dynamic behaviour and the underlying structure of the system which defines that behaviour are central to understanding the likely responses of these systems to availability constraints in the future.

1.2 Research question and objectives

The purpose of this research is to examine the conceptual and methodological issues surrounding the assessment of resource availability, in particular as it pertains to the future energy system and its technologies. The new resource availability concerns highlighted above may have a commonality with each other, and the assessment experience of one resource may have implications, or 'shed light,' on another. Alternatively, the differences between resources may be more influential, making the behaviour of one resource significantly different from the behaviour of another.

With this potential commonality in mind the purpose of this research can be summarised by the following research question:

How do the resource systems surrounding exhaustible non-recyclable resources and metal resources critical to the future energy system behave in response to constrained availability in the future and are these responses similar?

In this research question the phrase 'constrained availability' can be defined as an unforeseen curtailment of a source of supply for a limited defined period of time.

This question can be further disaggregated into the following **component questions:**

- How are the resource systems surrounding energy resources constructed and how do they differ?
- What tools are appropriate to assess and compare these different systems?
- How similar are the responses of these different systems to future availability constraints and what drives those responses?

To address both the conceptual and quantitative components of the research question seven **research objectives** are pursued through the course of this thesis.

Objective 1: Create an analytical framework through which the availability of different resources can be assessed and compared

Objective 2: Identify a modelling methodology to both conceptually and quantitatively test and compare different resource systems

Objective 3: Define the key characteristics of exhaustible, non-recyclable resources

Objective 4: Define and characterise low-carbon technology metals to make useful comparison

Objective 5: Create conceptual representations of the dynamic structure of these systems for conceptual comparison

Objective 6: Define the mathematical relationships underlying the conceptual structures of these systems and test their behaviours to provide quantitative comparison

Objective 7: Test the response of different energy resource systems to constraints in future availability and examine these responses for their similarities and differences

Objective 8: Conclude on the extent to which these resources systems behave similarly or differently, their responses to constrained availability, and the effectiveness of potential policy responses.

1.3 Definitions/nomenclature

Throughout this thesis several terms are used that warrant definition in order to provide clarity. This section presents these terms and provides brief explanations of their intended meaning.

The term 'resource system' is used to describe the dynamic system surrounding the supply of and demand for a resource such as oil, lithium or indium. This includes market variables such as price. The term 'system behaviour' refers to the response of the resource system to changes in its defining parameters. For example, if supply of a resource becomes suddenly scarce, the nature of the price response to that scarcity, and any subsequent responses are referred to as 'system behaviour'.

There are a host of terms used in the literature to refer to the list of metals and other materials that are currently part of the debate around non fossil fuel resources that might play a critical role in future economic prosperity. These terms are used inconsistently, and do not refer to a consistent group of materials. The terms 'critical materials', 'strategic minerals' and 'strategic metals' are all found in the literature. In this thesis the term 'critical materials' is used, and refers to any metal or non-metal resource perceived to be potentially critical to future economic development globally, from either a global national or commercial/industrial perspective. The term 'low-carbon technology metal' is used here to distinguish from the critical materials those metals that are of most concern to the future manufacturing of low-carbon energy technologies.

The term 'resource availability' is used in preference to the often used 'resource scarcity', referring to the extent to which the quantity of a resource produced in the future is commensurate with the demand for that resource.

This thesis uses the example of oil to inform the development of a generic resource system model, and considers oil to include all liquids currently traded as oil and included in commonly gathered statistics. This typically includes crude oil, natural gas liquids and syncrude. However, the modelling discussed in Chapter 7 and 8 is constructed at a high generic level and doesn't differentiate between the different marginal production costs of these different oil sources.

Electric Vehicles (EV) is used her to refer to all vehicles that have a reliance on advanced battery technologies, dominated currently by lithium ion chemistries. This therefore includes battery electric vehicles, plugin hybrid vehicles, and to a lesser extent other hybrids and hydrogen fuel cell vehicles.

Photovoltaics (PV) are technologies utilising photons from solar radiation to generate electricity. In critical metals analysis thin-film PV technologies are of most interest as they use materials that are potentially scarce. Copper indium gallium diselenide (CIGS) and cadmium telluride (CdTe) are the two thin film technologies most often discussed in critical metals literature. Other PV technologies, including first generation crystalline silicon, second generation amorphous silicon, and a host emerging PV technologies may all play a role in the future PV market.

1.4 Thesis structure

The structure of this thesis is described here, along with a diagram depicting the chapter structure and the relationship between chapters and objectives (Figure 1.2). The relevance of these chapters to the conceptual or qualitative aspects of the research is also indicated.

Chapter 2 sets the context within which this thesis sits. This takes the form of a literature review, covering aspects of the historical perspectives around resource availability, from the work of Malthus (1798) to the Club of Rome report 'Limits to Growth' (1972). The chapter then examines the growing concerns around resources and energy, from early concerns over fossil fuel energy resources to modern concerns over the availability of low-carbon energy technology metals. Finally, Chapter 2 examines some of the conceptual issues surrounding the resource availability debate.

Chapter 3 presents an analytical framework through which the components of the research question can be assessed. This includes diagrammatic representation of the proposed approach and discussion of the use and purpose of case studies to examine in detail the pertinent factors that characterise a resource system. It also discusses the use of system dynamics as a tool to investigate and compare both the conceptual aspects of resource system structure and the functional relationships behind those structures which define their behaviour.

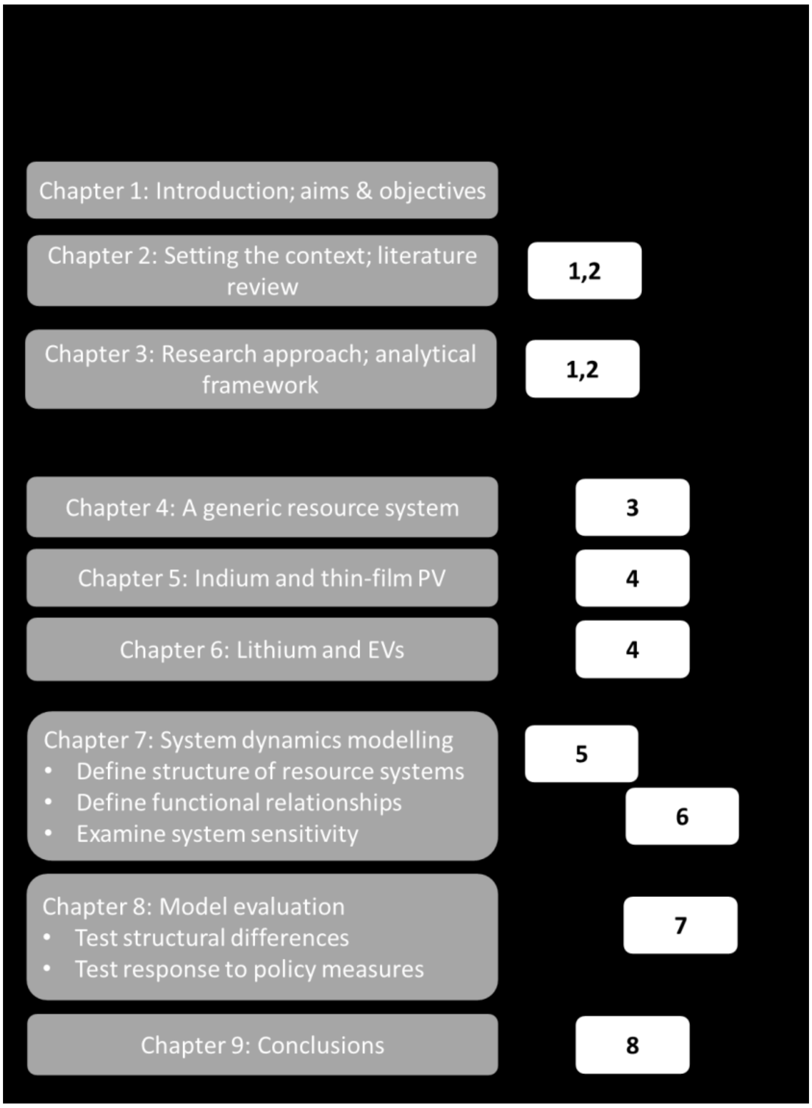
Chapters 4, 5 and 6 present three case studies which examine three different resource systems. Chapter 4 examines the dynamics of exhaustible, non-recyclable resources to inform the design of a generic resource system. Chapter 5 examines the case of lithium, focusing on the issues affecting its production, and its use in the batteries of EVs. Chapter 6 examines the case of the indium resource system, again focussing particularly on the issues of its production, and its use in the manufacturing of thin-film PV modules.

Chapter 7 presents the process of creating and testing three system dynamics models which represent each of the three resources systems covered in the case study chapters. This chapter includes the development of causal loop diagrams to represent the structure of each system, the definition of the functional relationships underpinning the structure, and the various tests and model validation performed to defend the models.

Chapter 8 then tests these models to examine the dynamic behaviour they exhibit when subjected to a range of different conditions. This examines the impacts of the different model structures on the resultant model dynamic behaviours, the responses of these models to constraints in the availability of resources and the response of these models to different potential policy measures.

Finally Chapter 9 concludes the thesis, examining the results of the analysis, drawing conclusions on those results in light of the research question, highlighting the limitations of the research and presenting recommendations for future work.

Figure 1.2: Diagram of the thesis chapter structure, illustrating each chapter's objectives and contribution to conceptual and quantitative insights



Chapter 2: Setting the context

"Our ignorance is not so vast as our failure to use what we know"

Hubbert, year unknown

This chapter presents the context surrounding the central research question outlined in Chapter 1. The chapter reviews the relevant existing literature and forms the evidence base upon which the research approach is premised (Chapter 3).

The historical context in Section 2.1 describes the development of the debate around resource availability and its transition from arguments of subsistence, to include fossil fuels and mineral resources. The chapter then focuses on the energy-specific arguments and the modern development of the debate to include issues of critical materials and the low-carbon technology metals. This debate is less well developed and this is a key motivation for the research described in this thesis, as outlined in Chapter 1. The chapter then visits some of the key concepts underpinning the arguments common in the resource availability debate. A common characterisation of the debate is that of a polarised argument, with one side represented by geological arguments and the other side represented by economic arguments (Sorrell *et al.* 2009). This is undoubtedly an oversimplification, though it provides a useful structure with which to investigate the issues surrounding the principal disagreements in the debate.

2.1 A history of scarcity

Before considering the contemporary aspects of resource availability research this section examines the long-term historical context within which the modern debate is framed.

2.1.1 Malthus

In 1798 Thomas Robert Malthus published his first "Essay on the Principles of Population" (Malthus 1798). Concern over unconstrained population growth was not unprecedented at this time and several works are likely to have informed Malthus' interest and opinion on the topic (Wallace 1753; Godwin 1793; De Condorcet 1955; Hume 1977). However, the considerable contribution Malthus provided was to begin quantifying the factors thought to shape the future improvement of society.

Malthus central contention was that the tendency of unchecked population growth (driven, as Malthus romantically describes it, by "the passion of the sexes") is always to grow faster than human ability to subsist from the earth's natural resources. This point is presented as follows:

> *"Population, when unchecked, increases in a geometrical ratio. Subsistence increases only in an arithmetical ratio."*

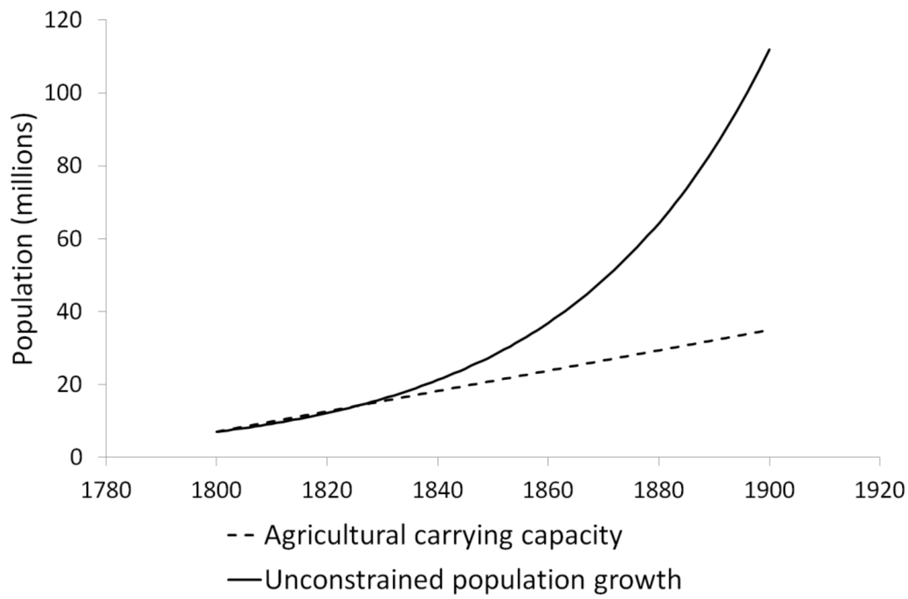
Malthus (1798)

Malthus' calculation was simple. He began by estimating man's unconstrained population growth rate. In most societies of the time, population growth was constrained by a number of factors including: disease; famine and starvation; and conflict. Malthus therefore used the population growth rate of the United States of America as an analogue. The United States had significant population growth at the end of the eighteenth century and, in Malthus' opinion, represented the closest to an unconstrained population growth rate available. Malthus stated that the US population appeared to double every 25 years. This exponential rate of growth was, Malthus believed, a result of the ample means of subsistence arising from the abundance of arable land and the prevalence of early marriages.

Malthus then estimated the maximum speed of growth in agricultural carrying capacity in the UK. Malthus assumed that the UK could double the agricultural carrying capacity over a 25 year period, but that over the next 25 years it would only be able to increase its agricultural carrying capacity by the same absolute amount as in the first 25 years, and so on. Malthus was describing linear or arithmetic growth in contrast to the exponential growth assumed for unchecked population growth.

The immediate outcome of these assumptions is that population growth, if unchecked, tends to grow significantly faster than growth in agricultural productivity (Figure 2.1). Malthus postulated that this was the single biggest obstacle to the 'perfection of society' and that this obstacle was, in his opinion, insurmountable. The result would be that some members of society would inevitably fall into famine and starvation, disease through overcrowding and malnourishment, or death through war of conquest, factors Malthus classed as 'misery'. This misery would be the undesirable result of overpopulation and would place a fundamental check on future population growth.

Figure 2.1: Illustration of Malthus' assumptions regarding unconstrained population growth and agricultural carrying capacity



Source: Malthus (1798)

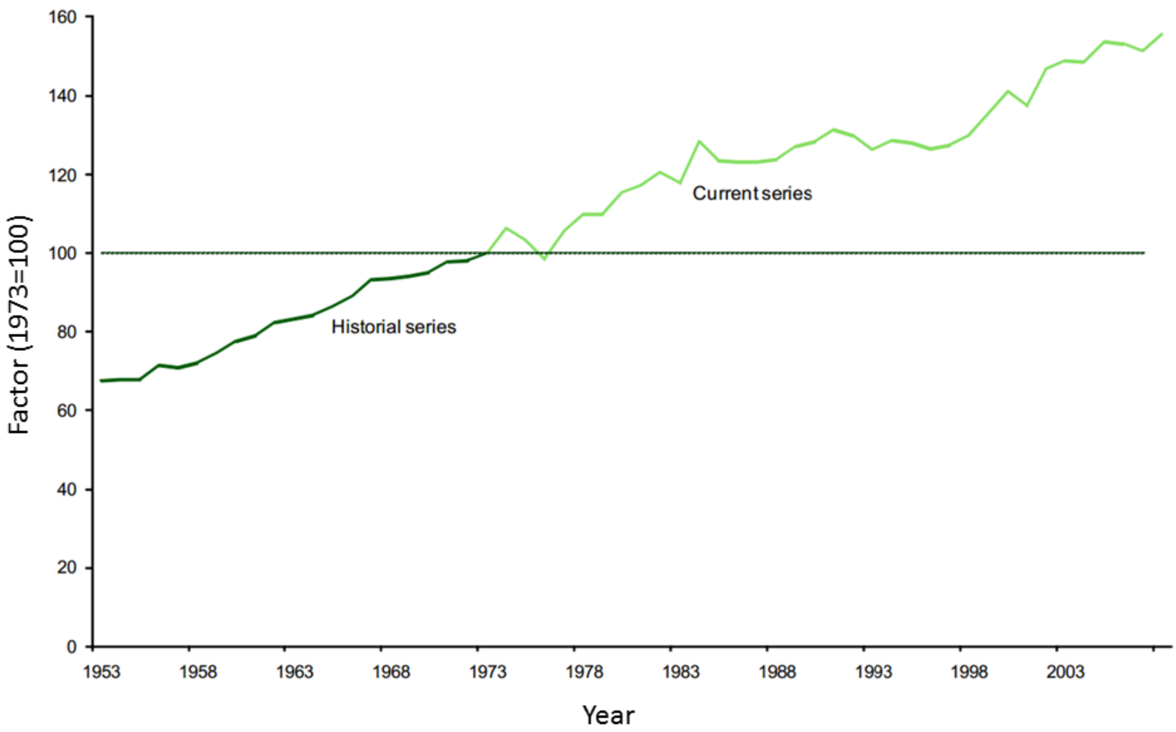
Malthus' views were almost immediately contested (Hazlitt 1807), beginning the contentious debate between the Malthusians (or Neo-Malthusians), those with a pessimistic view of future resource availability, and so called Cornucopians[1], those with an optimistic view of future resource availability.

The simple assumptions of Malthus, while an important phase in the evolution of the debate, are subject to valid criticism. For instance, Malthus assumes that an unchecked population will grow exponentially without some form of 'misery' that influences the rate of death. However, birth rates have decreased in many countries in the last century (Woolston 1924), and modern forecasts of global population dynamics typically form asymptotic s-shaped curves without any increased death rates in their scenarios. The UN Population

[1] From the Greek myth of the 'Horn of Plenty' or 'Cornucopia'.

Division publishes reports forecasting the growth in global populations and in recent publications has estimated a reference case which stabilises towards the end of this century (UN 2013). This scenario assumes a global average fertility rate that converges towards the replacement level, which for low mortality countries is approximately 2.1 children per woman. This assumption is based on data which are currently tending in this direction, though individual country cases vary markedly. After this criticism it is interesting to note that the UK agricultural productivity has grown arithmetically over the last 50 years (Figure 2.2), and UK population appears to have grown only as rapidly as Malthus' carrying capacity assumptions would allow[2], though it is likely that this trend has been governed by trends in fertility as much as it has been by those factors Malthus labelled 'misery'.

Figure 2.2: Historical agricultural productivity in the UK since 1953



Source: Keep (2009)

Malthus' assumptions could be considered crude by modern standards; there is no acknowledgment of the wider range of variables affecting human subsistence and their

[2] Extension of the agricultural carrying capacity trend in Figure 2.2 gives a population of 66 million in 2011 while the 2011 census estimated a UK population of 63 million

variation over time. This lack of dynamic assumptions has, to a certain extent, been evident in many resource availability estimates since the work of Malthus. Though simple metrics can be powerful tools, the lack of dynamic and comprehensive inclusion of assumptions is a limitation on much of the resource assessment work to date.

2.1.2 Jevons

Another significant event in the resource availability discourse was the publishing of William Stanley Jevons book entitled "The Coal Question". Published in 1865, the book marks the transition of the resource availability debate into the era of industrialisation, energy, and towards the assessment of non-renewable resources. In "The Coal Question" Jevons makes many observations still central to the debate on non-renewable resource supply, including energy return on energy invested (EROEI), energy taxation and peak supply, a topic at the heart of the oil supply debate (see Chapter 4). Interestingly, Jevons also foresaw the phenomenon known as the 'rebound effect' (Sorrell 2007c), also referred to as the 'Jevons paradox' in the context of coal demand.

Jevons noted that coal was highly important to the UK economy. Coal created the steam which drove industry and locomotion. Coal also provided the heat to smelt iron and produce steel, the fundamental building block of the industrial age. In his words:

> *"Coal in truth stands not beside but entirely above all other commodities. It is the material energy of the country—the universal aid—the factor in everything we do. With coal almost any feat is possible or easy; without it we are thrown back into the laborious poverty of early times."*

Jevons (1865)

Jevons also noted the rate at which coal was being consumed, and on comparison with the known coal resource in the UK, became concerned.

> *"But it is at the same time impossible that men of foresight should not turn to compare with some anxiety the masses yearly drawn with the quantities known or supposed to lie within these islands."*

Jevons (1865)

For Jevons, a man who popularised the quantitative method within economics, the problem could be examined by looking at the numbers. In striking similarity to Malthus, Jevons developed a simple model, and based its structure on two simple premises:

1. that coal consumption in the UK would continue to grow at the rate of 3.5% which had been observed over the preceding decades; and
2. that the price of coal would increase as a function of the depletion of the coal resource and that those high prices would place some limit on the height of prosperity.

These assumptions lead Jevons to forecast a peak in prosperity, which he defines in this way:

> *"the absolute amount of coal in the country rather affects the height to which we shall rise than the time for which we shall enjoy the happy prosperity of progress."*

Jevons (1865)

On the basis of this analysis Jevons predicted that production of coal would begin to decline within a century, and that, as a result of the high prices and reduced availability of coal, the UK economy with coal as its 'material of energy' would begin to suffer. Jevons predicted that this would lead to the succession of the UK as the leading global economic power, a position taken by the oil rich United States.

Like Malthus before him, Jevons conclusions were criticised (Brown 1931; Wood 1988a; Wood 1988b) and did little to extinguish the wider resource availability debate.

Jevons' work brought the resource availability discourse to energy and fossil fuels have remained amongst the most debated resources to date. While Jevons work lacks a complete acknowledgement of the pertinent variables, it does begin to recognise some of the dynamic aspects of the issue, including the concept of peak production, and the economic consequences of such an event. However, the key feedback loops between coal price, coal production and coal demand are not considered in Jevons' work.

2.1.3 Hubbert

Given that the United States experienced similar economic fortunes to the coal-fired Britain of the 19th century, it is unsurprising that a new phase in the debate was fostered there. In 1956 Marrion King Hubbert presented his paper "Nuclear energy and the fossil fuels" to an audience comfortable in the ever increasing US domestic production of oil, the fuel powering the first modern superpower economy. In the paper, Hubbert noted that US oil production had been following an exponential trend. As he states:

> *"...petroleum has been produced in the United States since 1859, and by the end of 1955 the cumulative production amounted to about 53 billion barrels. The first half of this required from 1859 to 1939, or 80 years, to be produced; whereas, the second half has been produced during the last 16 years".*

Hubbert (1956)

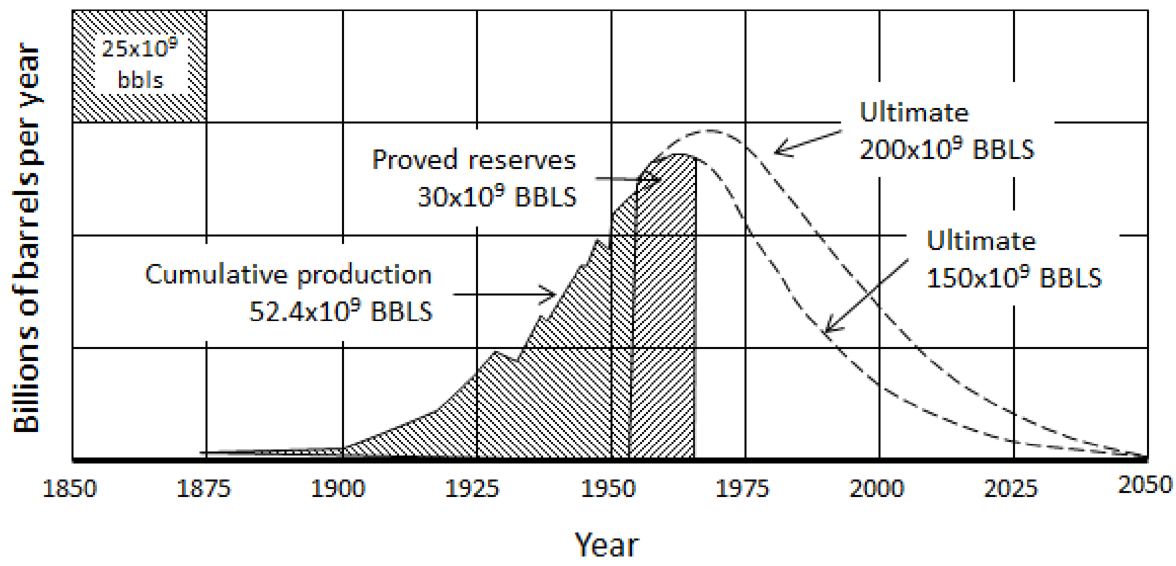
Hubbert questioned the sustainability of such growth for a non-renewable and finite resource such as oil, and conducted the analysis that would give rise to the phrase 'Hubbert Curve'. Hubbert first stated that a non-renewable resource must ultimately decline in production after its initial period of growth.

> *"in the production of any resource of fixed magnitude, the production rate must begin at zero, and then after passing through one or several maxima, it must decline again to zero."*

Hubbert (1956)

Hubbert recognised that the area under this curve must represent the total volume of resource produced over all time, the Ultimately Recoverable Resource (URR). Hubbert estimated initial US oil reserves by analysis of the available estimates of regional reserves and arrived at a range of estimates from 150 to 200 billion barrels (Gb) of oil, Hubbert's estimate of URR. He then plotted historical data for US production and by what he described as an iterative graphical process, fit a bell shaped curve to the data (Figure 2.3).

Figure 2.3: Hubbert's analysis of historical US oil production and forecast production based on two separate estimates of URR



Source: Hubbert (1982)

Hubbert's choice of curve is contentious, and has given rise to serious debate (Sorrell *et al.* 2009). The s-shaped logistic curve, and its first differential, a bell shaped curve, are symmetrical, and while the US data fit this curve well, Hubbert did recognise the simplicity of his assumption.

> *"There is no necessity that the curve…as a function of [time] have a single maximum or that it be symmetrical".*

Though his conclusions incited derision at the time, US oil production did actually reach a peak in 1969, surprising many and lending a level of credence to Hubbert's work, which was already being applied in a global context. The debate over the timing of a global peak in oil production has since become one of the most active areas of the resource availability discourse, reaching new levels of contention (Sorrell *et al.* 2009).

In addition to concerns over Hubbert's choice of curve, a host of other criticisms have been raised in the literature. Disagreements over the classification of oil are common, with some using a very restrictive classification of crude oil and others including a host of unconventional sources of oil (Brandt 2007). This raises the question of substitutability of resources, with some clearly considering many conventional and unconventional sources entirely substitutable (P.W. Huber 2005). The question of substitution can be extended past liquid fossil fuels to alternative liquid fuels and transport technologies, though some analysis indicates the need to begin crash programs significantly in advance of a peak in oil production to develop and deliver substitutes in time (Hirsch 2008).

Other concerns echo Jevons' work regarding the economic feedbacks, with some authors critical of the lack of economic foundation in Hubbert's analysis (Ryan 1965) (for more recent views see (Rehrl & Friedrich 2006) or (Watkins 2006)) though more recently efforts have been made to address these gaps (Reynes *et al.* 2010).

Through his analysis Hubbert moved the discussion surrounding resource availability forward, developing much more sophisticated techniques for resource availability estimation than previously applied. However, Hubbert's analysis still lacked a full account of all pertinent variables and their dynamic interactions.

2.1.4 Limits to growth

In 1972, Meadows *et al.* published their book, "The limits to growth", a report commissioned by the global think tank The Club of Rome (Meadows 1972). This report brought together the previous resource concerns of population growth and non-renewable resources, to study the interlinked issues associated with growth. The report listed five world growth trends with which it was concerned:

- accelerating industrialisation;
- rapid population growth;
- widespread malnutrition;
- depletion of non-renewable resources; and
- environmental degradation.

The report then employed a relatively new modelling discipline, system dynamics, in order to capture the relationship between each of these issues, and project a likely scenario for their temporal development. The resulting model was called 'World 3'.

The tools of system dynamics and its conceptual underpinning, systems thinking, provide a method by which the interdependence of variables, so-called 'feedback loops,' can be characterised and examined. Most dynamic systems contain these loops, and for even very basic systems with few loops, unintuitive system behaviour can often arise. Interpreting these systems intuitively can therefore lead to significant misinterpretation and one value of the formalism of system dynamics is in guiding the modeller past mental biases and misinterpretations. Chapter 3 contains a more detailed discussion of system dynamics.

The 'World3' model was developed to capture the system feedback loops surrounding the five world growth trends listed above. The full model, dealing with such a wide range of variables and global systems in one framework, is necessarily complex and a conceptual representation is presented in the causal-loop diagram in Figure 2.4. In the 'Limits to Growth' report, the model was used to test various assumptions regarding availability of resources and the interrelationship between resources, population growth and industrial growth. From these model runs, the authors drew some striking conclusions:

> "...under the assumption of no major change in the present system, population and industrial growth will certainly stop within the next century, at the latest."
>
> Meadows (1972)

In the tradition of historical resource scarcity debate, this conclusion, and the work supporting it, received much criticism. However, several limitations of the work are also recognised by the authors. In the book 'groping in the dark', Donella Meadows lists three aspects of the model that were considered by the authors to be lacking (Meadows *et al.* 1982). These are:

- the constant capital-output ratio (which assumes no diminishing returns to capital);
- the residual nature of the investment function; and
- the generally ineffective labour contribution to output.

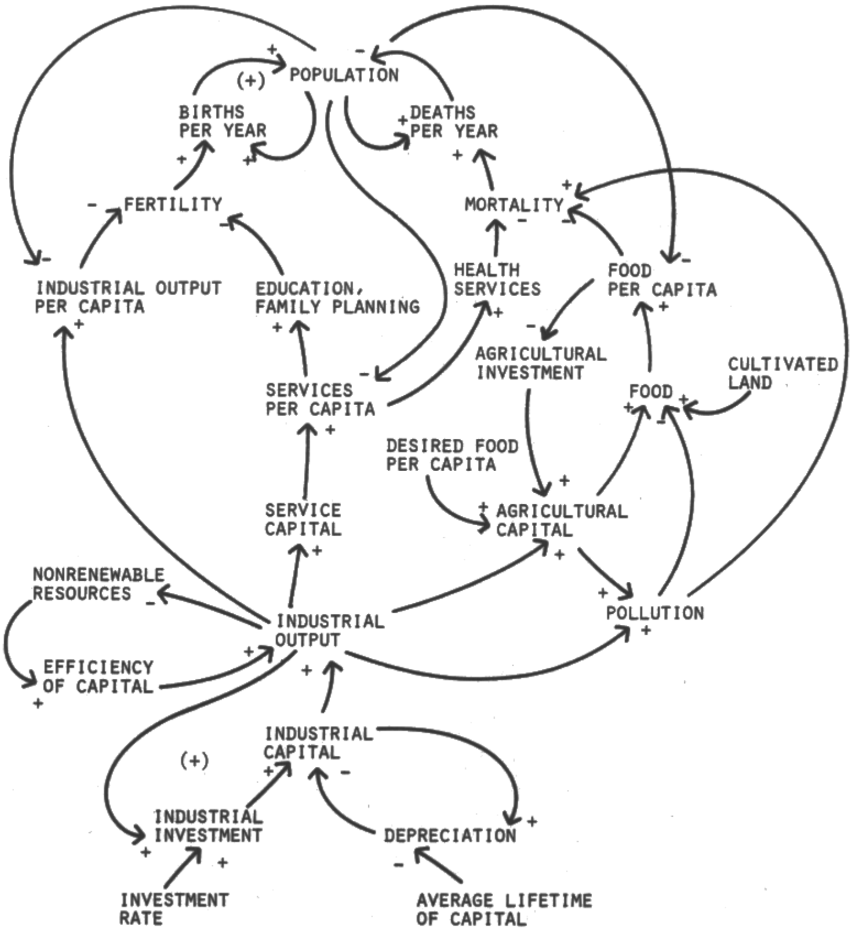
Other significant criticisms exist and the work has been scrutinised by commentators over the last four decades. In the book 'Models of doom', Cole (1973) discusses various limitations to the work. For instance, the historical data upon which the model is based are described as "extremely poor" (Cole 1973) and numerical relationships within the model were often estimated indirectly by comparison, particularly where appropriate primary data were not available. A fundamental criticism of the model is highlighted by Freeman (1973), who cites the underestimation of the impact of 'technical progress'. Freeman defines this as the economic concept of achievement of greater output for the same input (technical efficiency), or the introduction of new products or processes (substitution). This is a similar criticism to that levelled at Malthus and has the capacity to dramatically change the outcomes of models such as this one. Critics with cornucopian outlooks have even criticised the premise that any resource should be considered finite (Aligica 2009; Lomborg 2013). This follows the premise that technological progress will deliver substitutes and material efficiencies that will overcome rising demand, and population growth can continue unhindered long into the future.

Other critics focussed more on the methodological shortcomings of the modelling approach. Smil (2005), for example, criticises the combination of dissimilar physical processes into compound variables, something he describes as "particularly meaningless".

Development of the model and reporting of its findings has continued with at least two books published since the first release of Limits to Growth (Meadows *et al.* 1992; Meadows *et al.* 2004).

The Limits to Growth report and its continuing work moved the resource scarcity debate forward to consider the interrelated issues arising from resource demand and its links to population growth. This included non-fossil fuel mineral resources, something largely neglected in the discourse previously. The work also included a comprehensive and dynamic methodology, acknowledging the interdependence of variables and the associated feedbacks, though criticisms remain regarding aspects of the model's application. Limits to growth can therefore be seen as a step forward in the estimation of future resource availability and its impacts.

Figure 2.4: Causal-loop diagram of important feedback loops in the World3 system dynamics model



Source: Meadows (1972)

2.1.5 Ehrlich and Simon

Finally, the Ehrlich-Simon wager focussed the resource scarcity debate on metal resources and their economics (Wikipedia 2014b). In 1968 Paul Ehrlich, an ecologist and demographer, published a book entitled 'The population bomb' (Ehrlich 1968). Ehrlich's thesis was as follows. Global population was forecast to increase dramatically in the coming century. Given the link between population and demand for resources, the forecast population growth would surely lead to a significant increase in demand for finite commodities such as fossil fuels and metals. That resource demand growth would be so significant that supply would not be able to keep pace, leading to constrained availability. If resource availability was 'tight' then the price of these resources would surely rise to historically high levels as a consequence and historically high prices would cause difficulty for a global economy built on cheap energy and goods.

Julian L. Simon, a professor of business administration and noted cornucopian, disagreed with the neo-Malthusian nature of Ehrlich's claims regarding overpopulation. Simon's argument was that population growth would most likely lead to technological development, creating substitutes, and efficiencies that would overcome availability constraints, and facilitate continued reduction in commodity prices. On this basis Simon challenged Ehrlich with a wager which he believed would settle the argument. Simon asked Ehrlich to choose any commodity and any date more than a year in the future. Simon would then bet that the price of the commodity would be lower on that future date than at the time the bet was placed. Ehrlich and some of his colleagues picked five metals: chromium, copper, nickel, tin, and tungsten. They proposed that these five metals would increase in price over the decade between 1980 and 1990 and they bought, on paper, $200 of each.

The price of the five metals decreased over the next ten years and Ehrlich lost the bet.

The value of commodities prices as indicators of scarcity is debated, particularly over short time periods, and the result of the wager did not go any way to modifying the positions of Ehrlich or likeminded neo-Malthusians. Indeed Simon entered other, similar bets with less cornucopian outcomes[3], and the same bet over a longer timeframe would have returned a different outcome (Grantham 2011).

2.1.6 Summary of historical debate

The debate surrounding the future availability of resources has proved contentious for many years, and has spread from its beginnings in population and agricultural carrying capacity to include energy resources amounts others. The brief history recounted above simplifies the discourse and pays particular attention to the more polar aspects of the debate. Nevertheless, while much of the existing research examines these polar aspects, the debate continues. This thesis aims to step away from the contentious aspects of the scarcity debate

[3] In 1995 Simon entered a bet with David South, a professor in the School of Forestry, Auburn University. Simon bet that the inflation adjusted price of pine sawtimber between 1995 and 2000 would decrease. David South bet it would increase. Over that period the price per 1000 board feet increased from $224 to $336, a 50% increase.

by examining the response of systems to constrained availability, rather than asking whether scarcity is likely, or whether future availability will constrain society's future goals.

2.2 Concepts of the scarcity debate

The debate around the availability of resources is often characterised as an argument between geologists, who are assumed pessimists or neo-Malthusian, versus economist who are presumed optimists or cornucopians. This is likely a function of the polarity of some views in the debate, with geologists such as Hubbert (1982) and Campbell (1997) presenting pessimistic views while economists such as Adelman and Lynch (Adelman & Lynch 1997; Lynch 1999) present optimistic views. However this is only a characterisation and other views exist representing a spectrum of research and debate (Gately 2004). The reality is that the dynamics of these resource systems respond to a range of influence including economics, geology, physical principles, and politics and government policies (Fantazzini *et al.* 2011)

For the purposes of this thesis the characterisation of geological and economic arguments is helpful to frame some of the key drivers of the dynamics of resource systems. The following sections provide exposition of the geological principles and economic theory which define resource systems, drawing principally from the literature on oil and highlighting the commonalities found in critical metal resource systems.

2.2.1 Geological perspectives and diminishing return

> *"The intrinsic limitations of these laws eventually affect all human activities because neither economic incentives nor political will can bend or break these laws of nature"*

(Fantazzini *et al.* 2011)

The geological concepts, or natural physical laws of resource production, are commonly cited by those who take a pessimistic view of the future of resource availability (Campbell 1997; Laherrère 1999). The central premise is that mineral resources are for all practical purposes finite (Hubbert 1982). Though the processes that create and concentrate these resources in the earth's crust are natural, they occur over geological time scales, and their exploitation is likely to be several orders of magnitude shorter[4]. This fact is often presented as self-evident, given that the planet is of a finite volume, the planet's constituents include these resources and therefore these resources must also be finite (Kaufman 2009; Valero *et al.* 2011). The physical implications of this are summarised in the following three paragraphs.

The physical limits of individual deposits

In an individual well or mine, there is an increasing marginal effort to production i.e. the difficulty in producing a unit of the resource increases as the resource is depleted (IEA 2008; Yaksic & Tilton 2009; IEA 2013). A common analogy used to explain this is the squeezing of a wet sponge. When the sponge is first squeezed water is easily liberated. However, after a while it is increasingly difficult to expel water, until such point as the sponge no longer gives up any water, though water undoubtedly remains (Fantazzini *et al.* 2011). In the life of an oil well the early period of production, the primary recovery phase, oil flows freely under the inherent pressure of the well (Sorrell *et al.* 2009). After a period this inherent pressure is relieved and further production must be encouraged through the application of extra pressure, often through pumping water into the reservoir. This is referred to as secondary recovery (Sorrell *et al.* 2009). Finally, the application of water pressure leads to increased water percentage in the produced oil (water cut) at which point enhanced oil recovery techniques (tertiary recovery) must be applied to increase production, though at an ever increasing cost (Babadagli 2007). Similar can be said of metal ore resources, which must be extracted at increasing depth or under the increasing top burden, leading to similar diminishing returns to effort (Barbier 2013).

The physical limits of additional deposits

The producer of a resource, when faced with the challenges of diminishing returns to effort in his existing deposits, may look to maintain or increase his production through the addition of new deposits. However, there are also physical limits here, and again, increasing effort in exploration is rewarded with diminishing returns (Hall & Cleveland 1981). This can

[4] There is some debate as to the exact oil formation mechanism (Höök *et al.* 2010). However, the rate at which oil is created is measured over thousands of years. In contrast, the global oil market is less than 200 years old, and over that period a third of estimated recoverable resources have been produced. At current depletion rates the next third will be produced in the next 40 years.

be demonstrated by examining the quantity of oil discovered against a proxy for exploratory effort, often the number of exploratory wells drilled (Meisner & Demirmen 1981; Laherrère 2003; Inoue 2006). In the early phase of exploration there are many undiscovered fields and the probability of finding a deposit is high. In addition, the probability of discovering a large deposit is also high, given that large deposits are more conspicuous to most exploration techniques (Sorrell *et al.* 2009). An analogy of this issue is strawberry picking. When a picker first enters the field, there are many strawberries and finding the next strawberry is relatively easy. The large strawberries are also easier to find than smaller ones, and since they are more attractive for several reasons, these tend to be picked first. Once a large number of strawberries have been picked, finding the next strawberry is relatively difficult, and finding a large strawberry increasingly unlikely. In oil it is recognised that discovery peaked in the 1960s and the issues of field size distribution have been well documented (Sorrell *et al.* 2009). The metals lithium and indium are likely to experience similar physical limits in terms of the discovery of new deposits, though this is complicated by issues such as the difference between brine and mineral deposits of lithium and the by-product nature of indium production (see Chapter 5 and Chapter 6).

The physical limits of marginal resources

A third physical limit is that the marginal resource tends to be of decreasing quality, i.e. as exploration continues and an increasing number of deposits are found, the ease with which resources can be extracted from new deposits decreases (Skinner 1976; Cleveland 1991). In the early phase of production many high quality deposits exist, and producers choose to produce the high quality resources first as they tend to provide the best returns. However, once these high quality or high concentration resources have been produced then producers are left with lower quality or lower concentration resources, which yield less for a given unit of effort (IEA 2008; Wykes & Stockman 2011). These marginal resources are often unconventional resources in the fossil fuel markets where new discoveries are often either more viscous (heavy), more contaminated (sour), in deeper water, in less porous geology (shale oil or gas), or in hard to access geographical locations (polar oil) (Lindholt & Glomsrod 2012; Chew 2014). In the case of metal resources, where once copper was produced from ore containing 12.17% of the metal, it is now produced from ores with an average of close to 0.8% metal at significantly increased effort to the producer (Crowson 2012).

The implication of these three physical principles is that for any **fixed definition** of a finite resource, production is likely to take the form of a bell-shaped curve, with growth in the early part of the production cycle as easy, abundant resources are exploited, followed by decline in production as these physical principles begin to bear on production rates (Sorrell *et al.* 2009).

2.2.2 Economic concepts

The economic arguments surrounding resource availability come to some different conclusions to their geological counterparts (Adelman & Lynch 1997; Lynch 1999; Adelman 2003; Mills 2008), basing these conclusions largely around the market and its response to price signals, i.e. when demand increases, so too does price and when demand decreases price also follows (Stiglitz & Walsh 2006). The concepts of equilibrium price are explored again in the context of resource price formation in Section 4.2.4.

As price changes several responses are incentivised, all of which serve to bring supply into equilibrium with demand. These responses are summarised in the four paragraphs below.

Price incentives to production and discovery

When resource prices increase the producers of those resources are incentivised to either increase production if there is spare capacity to do so, invest in new production capacity or to explore in an attempt to discover more resources to be exploited (Sterman 2000; Ten Cate & Mulder 2007; Mohn 2008). In doing so the producer hopes to take advantage of the high price by discovering and producing new resources that are economic to produce at this new price level. As discussed above, there are physical factors that may influence the costs of exploration and production.

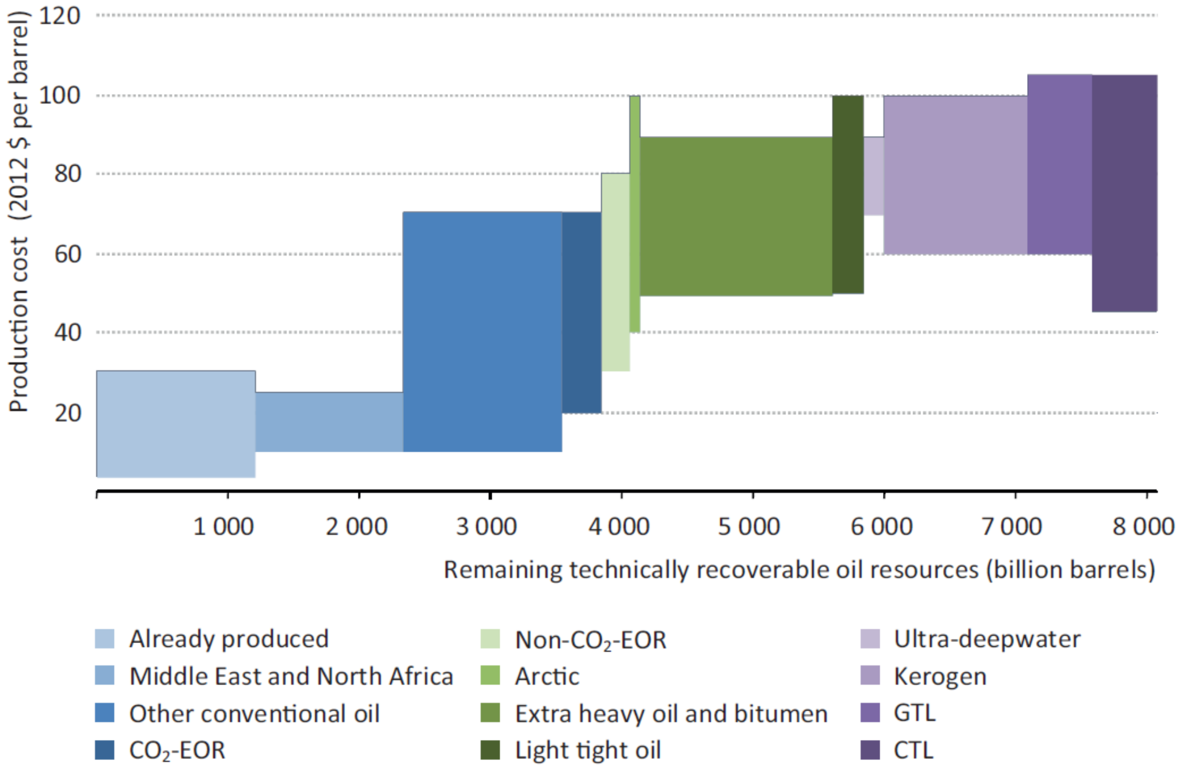
A branch of economic research dating back 50 years examines the process of exploration and production of oil resources under these neoclassical economic assumptions of producer behaviour (Mohn 2008). This research examines a number of oil regions including the United States (Fisher 1964), and the UK Continental Shelf (Pesaran 1990). These studies apply econometric modelling techniques to capture a range of factors that underlie exploration behaviour, including oil price changes, historical exploration success licencing policies, seismic surveys, depletion and technological progress, with modern studies finding a relationship between oil price and exploration behaviour (Mohn 2008).

Exploration for critical metals deposits also increases in responds to price signals. For example, anecdotal evidence suggests that recent high price for rare earth elements (REE) has encouraged producers to explore potential deposits in Greenland, the United States, and Australia with a view to producing in the near future (Reuters 2009). The general neoclassical principles on which this response is based are likely the same as for oil exploration, though the specific conditions of licencing policies, exploration techniques, historical success and other dependant factors are likely to vary.

Price incentives to produce unconventional resources

If a producer is not able to produce or discover more conventional resources in response to high prices, he may be incentivised to seek additional production from unconventional deposits (Chew 2014). For these marginal deposits, the cost of production is likely higher than for conventional resources (Yaksic & Tilton 2009; IEA 2013), and without a sufficiently high price it is unlikely that producer would pursue such resources. This concept of a 'marginal cost curve' is common in resource economics (Figure 2.5) and is used to help characterise the supply curve for extracted resources, or as an indicator of depletion-threatened commodities (Tilton 2003). It is also possible that new techniques and technologies are needed to produce these marginal resources (Stevens 2010; Weijermars & Watson 2011). High prices will typically incentivise the development of such technologies, though often policy support is also needed to drive this technological innovation where long-term strategic goals are an additional driver (Stevens 2010).

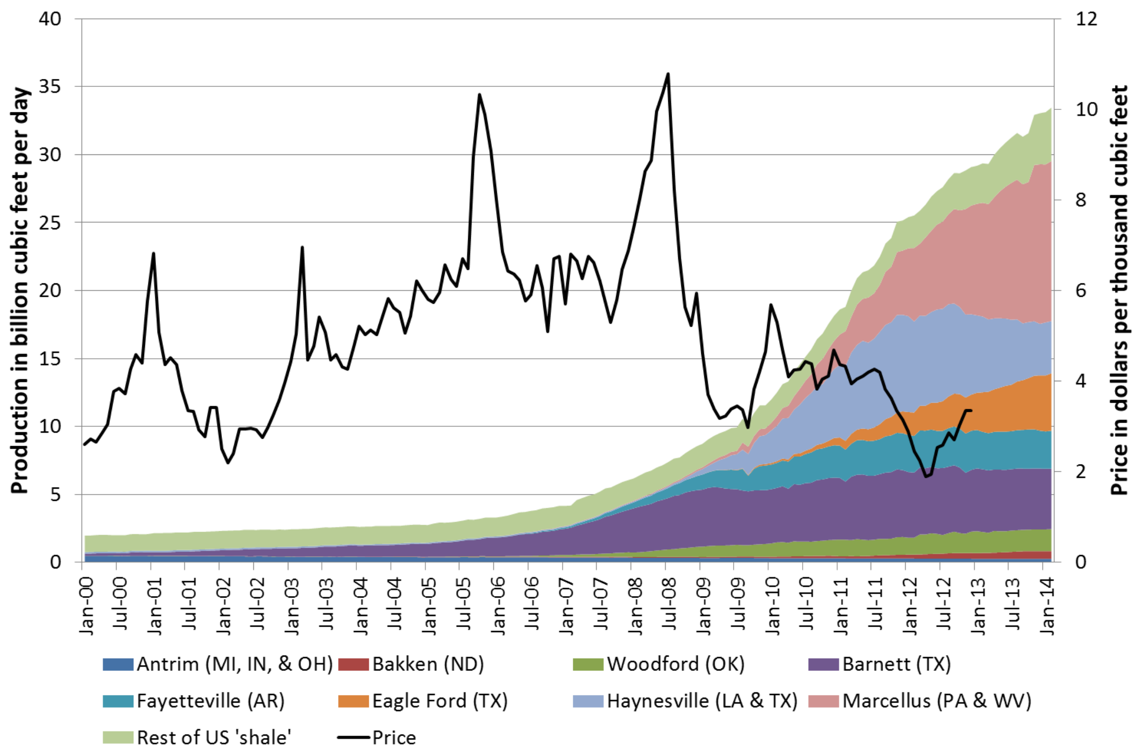
Figure 2.5: Marginal resources cost curve for liquid fuels



Source: IEA (2013)

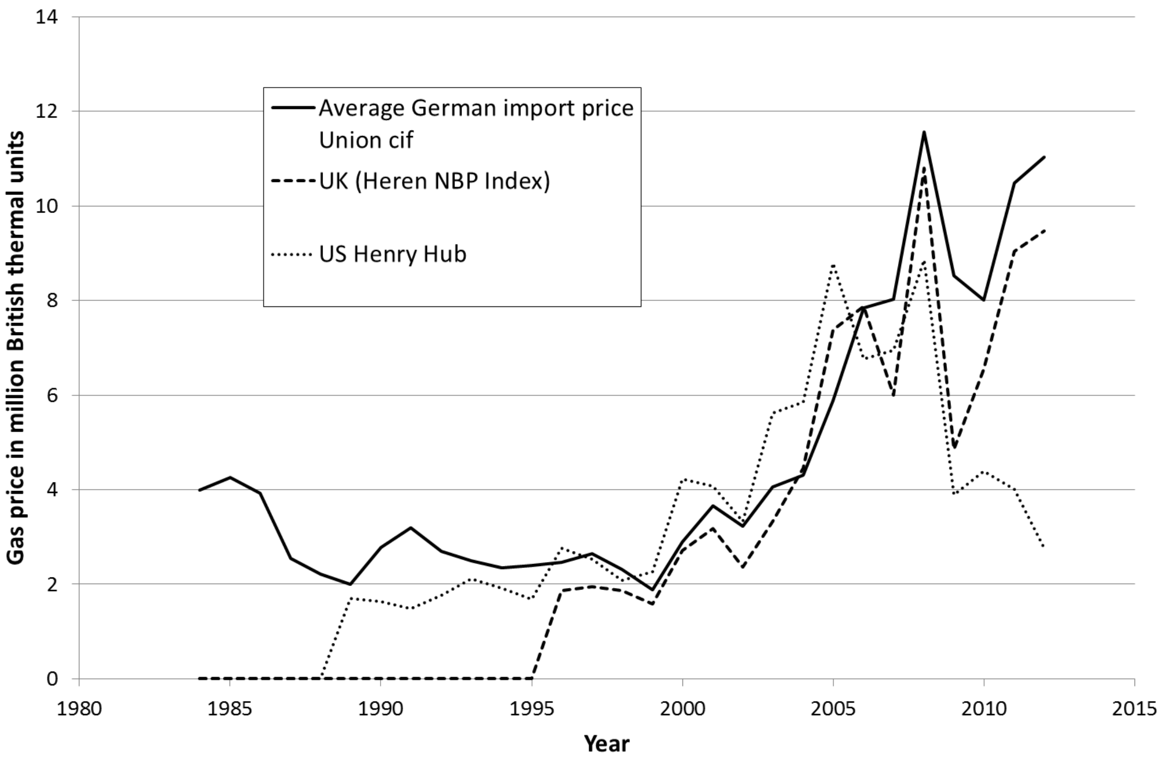
The development of shale gas and shale oil provide an example of this response. Until the 2000s there were many known shale gas and shale oil deposits in the United States but little incentive to exploit them. In 1980 government support through the Crude Oil Windfall Profit Tax Act gave unconventional fuel producers a tax credit, incentivising the development of unconventional production technologies (Stevens 2010). However, until the mid-2000s a low gas price diminished the profitability of unconventional gas production and supply rates grew only slowly (Figure 2.6). In the mid-2000s high spikes in the US wellhead price of natural gas coincided with significant increases in US shale gas production, suggesting that, while a number of factors lead to the development in shale gas, the profitability brought about by high gas prices was a significant driver. Ongoing high prices may also be a driver in increased interest in unconventional gas production in Europe (Pearson *et al.* 2012). The current gas price in Europe has diverged from the US price in recent years (Figure 2.7) leading some to suggest that shale gas production in Europe will now be profitable, and could help to reduce gas prices from their current level (Gosden 2014). However, this is contested with some suggesting that the US analogy is not appropriate for Europe given the differing geology, regulatory framework and market conditions (Rathbone & Bass 2013; Rogers 2013).

Figure 2.6: US shale gas production in billion cubic feet per day against monthly wellhead price of natural gas in dollars per thousand cubic feet



Source: EIA (2014c), EIA (2014d)

Figure 2.7: US and European gas price history, highlighting the recent divergence.



Source: BP (2013)

Price incentives to efficiency

A third response to increasing resource price is to decrease demand through efficiency. Often, technologies or practices exist that can increase the efficiency of natural resource use. However, these technologies and practices often have an associated cost, and they may not be economic under existing price conditions. When prices increase the incentive is apparent and these technologies and practices are adopted, decreasing demand (Stiglitz & Walsh 2006). This relationship between price and efficient use of resources is one of the motivations behind resource taxation (Söderholm 2011), which hopes to incentivise the efficient use of resources, amongst other goals (Eckermann *et al.* 2012).

Klier and Linn (2010) demonstrate this relationship between gasoline price and demand for vehicle fuel efficiency. The US vehicle market changed significantly between 2002 and 2007, with US manufacturers, and SUVs in particular, selling significantly less. By examining vehicle sales data between 1978 and 2007 they, found that nearly half of the decline in sales of these less efficient vehicles was due to the impact of the gasoline price, which is significantly influenced by the crude oil price.

Price incentives to substitution

A fourth response to high resource price is substitution, where a proportion of a resource's demand is reduced by using a substitute that can provide the same utility (Stiglitz & Walsh 2006). Many end-uses of resources have substitutes that can displace incumbent end-uses. However, these substitutes often come at an increased cost, a sacrifice in performance (often translating into cost), or require further costly research to make them viable (Bretschger & Smulders 2012). Substitution is usually driven by the relative cost-effectiveness of adopting substitutes (Cleveland 2003). As the price of a resource increases existing substitutes will become more cost effective, or the research needed to develop substitute technologies is incentivised (Bretschger & Smulders 2012). The result is a decrease in demand for the original resource, and the stabilisation of price.

An example of this is the battery electric vehicle (BEV). The price of fuel for internal combustion engine (ICE) vehicles has increased significantly in recent years. While the concept of BEVs have existed for over a century, the development of an BEV to replace the ICE vehicle has been hampered by the historically low price of ICE vehicles and the cost associated with developing BEVs with comparable utility (Weiss *et al.* 2012). In recent years, with a historically high oil price many manufacturers have been pursuing BEV designs, with several already for sale, and other alternative technologies for sale or in development, such as hybrid electric vehicles (HEVs), plug in hybrids (PHEVs) and fuel cell vehicles (FCVs). The point at which these technologies become economically competitive is a function of a number of factors, most notably the price of fuel, and the learning and resulting cost reduction of technological development. While technologies such as HEVs already have relatively short payback periods, BEV are likely to take much longer to close the price gap to ICEs (Weiss *et al.* 2012). As a result, substitution from ICEs to BEVs is likely to require policy support.

One key feature of these responses is that they make up a system which is subject to time delays, resulting in oscillating cycles (Sterman 2000). As demand increases, price follows quickly. However, the price responses highlighted above are slower to appear. To use the example of the 1970's oil shocks (See Chapter 4), by the time price responses and policy measures were impacting on the demand for oil, many of the original pressures on supply from the Middle East had relaxed. The result was an oil glut, with prices crashing to historical lows (Garvin Jr. 1981). The implications of delays in dynamic systems are discussed in Chapter 3.

2.3 Energy and the low-carbon transition

Energy is critical to the global economy, providing an input to almost all goods and services and fuelling economic growth (Stern 2010). However, the energy system faces mounting pressure to remain affordable in the face of depleting resources and to decarbonise in response to rising atmospheric greenhouse gas concentrations and associated impacts of climate change (Stern 2007; Hoggett 2014). While a transition to low-carbon energy technologies will relieve the resource pressure on traditional fossil fuels, it is likely to place other pressure on the resources needed to deliver this new energy system (Moss *et al.* 2011). Understanding the scale of change needed to decarbonise and what resources will come under supply pressure as a result, is an important part of planning this transition and managing it effectively.

This section first presents the scale of the future challenge of transitioning to a low-carbon energy system and the technologies that will deliver that transition. The section concludes by linking these technologies to the metals used in their manufacture, which have been described by some as relatively scarce (Andersson 2000; Tahil 2007; Tahil 2008; Angerer *et al.* 2009b). Some fear that this scarcity may leave them potentially incapable of maintaining adequate supply, as demand for low-carbon technologies increases dramatically through the course of the low-carbon transition (Andersson 2000; Tahil 2007; Tahil 2008). However, this narrative is contingent on policy successfully delivering a low carbon transition. The scenarios explored in this thesis assume that this is the case but it should be noted that there is significant uncertainty around the deployment of low carbon technologies. This uncertainty is not explored in this thesis.

2.3.1 Energy system change: demand growth and the low-carbon transition

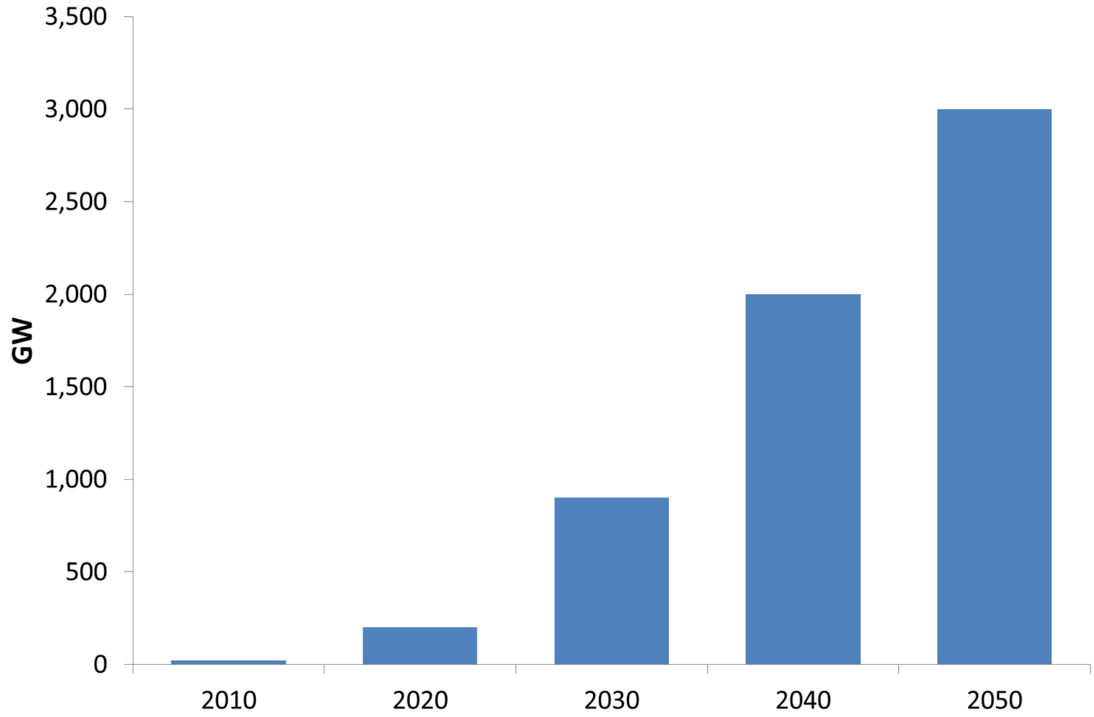
The existing global energy system is clearly both dependent on specific resources and indispensable to the global economy. However, that system is predicted to undergo radical transformation in the coming decades, as it grows and transitions to low-carbon generation. It is important to understand the associated changes to the energy system expected in the coming decades as these significantly impact on the quantities and types of resources needed to make this transition.

An increase in global energy demand is the first significant system change expected in the near to medium term future. This is independent of any transition to low-carbon generation, but is an important determinant of the demand that will be placed on low-carbon technologies in the future. Some estimates predict that global primary energy demand will grow by 16% - 47% between 2010 and 2035 (IEA 2012).

The second significant global energy system change is decarbonisation. Though there is still no ratified global framework towards mitigating the worst effects of climate change, many countries are continuing with their own decarbonisation targets and the world's energy mix is likely to develop on a much more low-carbon trajectory than previously. The IEA Energy Technology Perspectives (ETP) report presents a global energy system scenario consistent with a 50% reduction in GHG emissions by 2050. This is the decarbonisation thought necessary to limit global warming to 2°C and avoid the worst effects of global climate change in the consensus of scientific evidence (IEA 2010a). In order to achieve such a radical decarbonisation, the growth in renewable and low-carbon technologies is likely to be significant.

Given the drive to decarbonise, the proportion of primary energy coming from renewable energy sources is expected to rise. Some estimates suggest that renewable energy will grow, from 13% of primary energy in 2010, to between 14% and 26% of primary energy in 2035 (IEA 2012). A number of technologies make up this share of renewable energy. PV currently accounts for a small share of global electricity - around 0.6% of global installed capacity (IEA 2007; EPIA 2010). Nevertheless, cumulative installed capacity is in excess of 39 GW (EPIA 2011), representing a 27 fold expansion relative to the year 2000 (EPIA 2010). This growth is forecast to continue and the IEA scenario estimates cumulative installed capacity to reach 3000GW by 2050, providing up to 11% of global electricity (Figure 2.8).

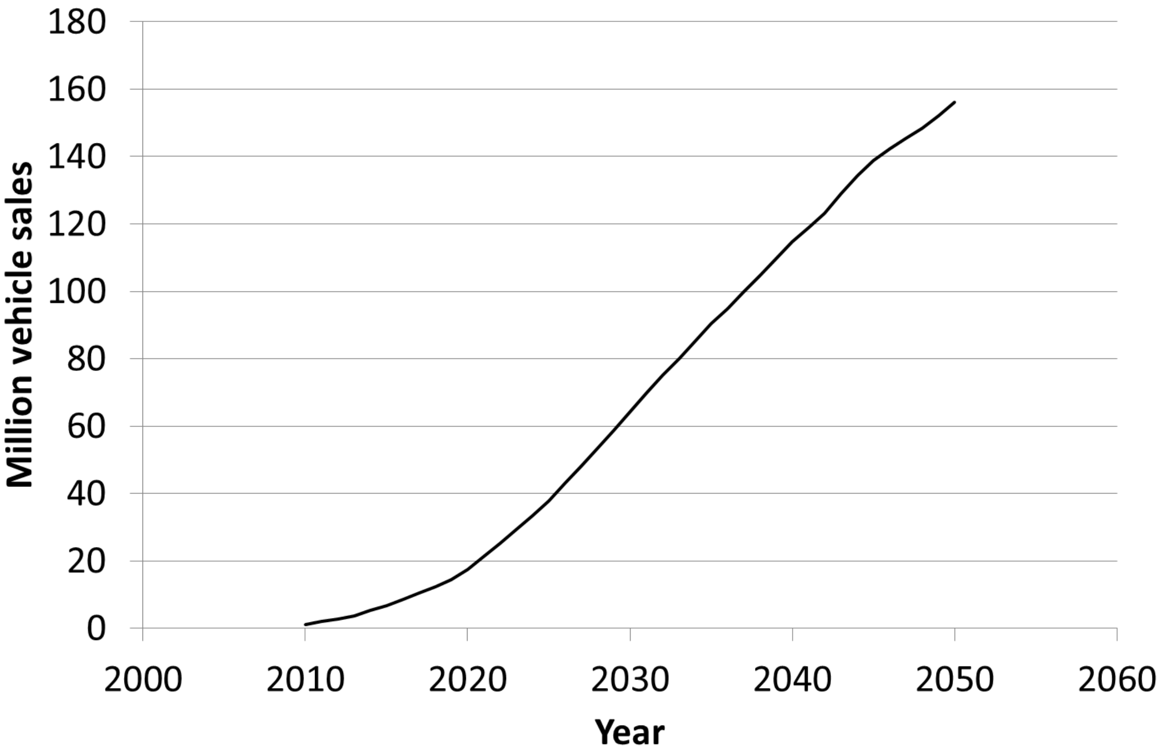
Figure 2.8: Forecast of cumulative installed capacity of PV to 2050



Source: IEA (2010a)

EVs are also expected to play a significant role in decarbonising the economy. Growing from a low base EV sales are expected to grow significantly, selling hundreds of millions of units annually in the coming decades (Speirs *et al.* 2013a). The IEA 'BLUE Map' scenario presents a future EV sales trajectory based on a global decarbonisation scenario commensurate with maintaining global temperature increases to within 2°C. This scenario estimates EV sales of over 150 million units by 2050 (IEA 2010a) (Figure 2.9).

Figure 2.9: IEA Bluemap scenario of electric vehicle uptake to 2050



Source: IEA (2010a)

Note: This includes hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), battery electric vehicles (BEV) and fuel cell vehicles (FCV).

While these low-carbon technologies do not require fossil fuel resources as a primary energy input, they do require resources for their manufacture. The significant growth in the demand for these technologies has raised concern for the availability of their constituent resources, with some resources in particular rising to the top of the debate.

There are several different PV technologies, including crystalline silicon (xSi), thin-film technologies such as cadmium telluride (CdTe) and copper indium gallium (di)selanide (CIGS), as well as a range of other technologies, including dye sensitised and organic cells (Speirs *et al.* 2011). While the resources used in the manufacturing of xSi cells are thought to be relatively abundant, several metals used in the manufacture of thin-film cells are cited as relatively scarce and potentially constraining to the development of large scale manufacturing. These include tellurium used in the manufacture of CdTe cells and indium, gallium and selenium used in the manufacture of CIGS cells. These metals are produced in small quantities, are subject to tariffs or are only found in low concentrations and are therefore raising concern as to their availability.

EV designs also incorporate critical metals. Neodymium magnets are used in the electric motors powering EVs, while lithium-ion (Li-ion) batteries are typically used for electricity storage (Speirs *et al.* 2013a; Speirs *et al.* 2014a). Both neodymium and lithium are discussed in the academic literature as potentially constraining future demand (Tahil 2008; Yaksic & Tilton 2009; Vikström *et al.* 2013). Both are reasonably abundant metals, though the scale of demand implied by the growth in EV demand has caused some concern.

2.3.2 Critical materials debate

In response to the concerns over the availability of non-fossil fuel resources, a literature has recently emerged in an attempt to assess these materials and the likelihood and impact of a shortage in their supply (i.e. their criticality) (Angerer *et al.* 2009b; Erdmann & Graedel 2011; Speirs *et al.* 2013b). The critical materials debate, as it is sometimes referred to, has attempted to codify the assessment of these materials in a structured methodology and then compare these materials to compile lists of materials in order of their criticality (Speirs *et al.* 2013b). Many methodologies exist and, depending on perspective the outcomes of these assessments can be very different (Speirs *et al.* 2013b). Three criticality assessments are compared in Table 2.1, demonstrating the variation in results.

Table 2.1: Summary findings of three material criticality assessments

Angerer[1]	EC[2]	Morley & Eatherly[3]
Gallium	Antimony	Gold
Neodymium	Beryllium	Rhodium
Indium	Cobalt	Mercury
Germanium	Fluorspar	Platinum
Scandium	Gallium	Strontium
Platinum	Germanium	Silver
Tantalum	Graphite	Antimony
Silver	Indium	Tin
Tin	Magnesium	Magnesium
Cobalt	Niobium	Tungsten
Palladium	PGMs (Platinum Group Metals)	Baryte
Titanium	Rare earths	Talc
Copper	Tantalum	Bismuth
Selenium	Tungsten	Palladium
Niobium		Nickel
Ruthenium		Boron
Yttrium		Andalusite
Antimony		
Chromium		

Source: Angerer *et al.* (2009b) EC (2010) Morley and Eatherley (2008)

Notes:

[1]In order of scarcity, based on projected demand from 'emerging technologies' over production of material in 2006. Based on assessment of 15 materials and 32 emerging technologies.

[2]In alphabetical order, chosen based on minimum score for both economic and supply risk.

[3]Materials scoring >17 in assessment of criticality. Based on 8 risk criteria.

To understand this variation, several papers have investigated and compared different critical materials assessments. Erdmann and Graedel (2011) examine 10 criticality studies, including German and Japanese sources. The review highlights the impact on results of metric choice, weighting, scope, study focus or perspective (i.e. metals critical to the globe, an individual country or an industry etc.) and the number of materials analysed. In addition to this paper, recent criticality assessments (DOE 2011; Moss *et al.* 2011) and discussion papers (Schüler *et al.* 2011; Peiro *et al.* 2012) review previous methodologies, listing the methods used and the materials designated critical. Finally, Speirs *et al.* (2013b) normalise the criticality assessments of 15 studies to examine and compare the variation between studies and to investigate its causes. Some of the findings of these works are discussed below.

In the assessment of material criticality, authors typically gather together a range of metrics or 'factors' representing important variables determining materials future availability. A range of metals or other materials are then scored against these factors before aggregating scores (with weighting in some cases) to provide a relative measure of criticality. While methodologies developed to assess metal criticality vary widely, there are some commonly assessed factors.

Supply factors incorporate measure such as: geological availability (a measure of what is physically present); economic availability (a measure of what can be economically accessed); and recycling (a measure of the availability of metal recovery from end-of-life products).

Geopolitical factors are used to capture the risks to supply posed by political decisions within and across country borders. This includes measures of the impacts of domestic policy, measures of the impacts of trade policies such as export quotas and tariffs and measures that account for the amount of global production originating in countries with adverse political situations.

Demand factors capture the estimates of future demand and account for the potential of substitution to relieve future demand.

Finally, several other factors are often incorporated into criticality methodologies capturing effects such as cost reductions impact on demand, environmental policies and their influences on legislation and production and the economic importance of a particular material. A more complete review of methodologies is provided by Speirs *et al.* (2013b).

Despite the variation in results of critical materials studies materials critical to the energy industry frequently feature in the critical lists of materials criticality assessments. Reflecting this fact, studies assessing only those materials critical to the energy sector have emerged. A report published by the Joint Research Council (JRC) of the European Commission (EC) assesses the risk of supply shortages of critical metals to the low-carbon technologies of the SET-plan (Moss *et al.* 2011)[5] The report identifies 14 metals which will be required in quantities greater than 1% of current world supply per year in order to deliver the SET-plan. These metals are tellurium, indium, tin, hafnium, silver, dysprosium, gallium, neodymium, cadmium, nickel, molybdenum, vanadium, niobium and selenium. Though the report concludes that the SET-plan is unlikely to be significantly affected by metals availability, it does highlight potential concerns if the uptake of thin film PV technologies such as CdTe and CIGS increases more than is estimated.

The US Department of Energy published its Critical Materials Strategy in 2010, with an update in 2011 (DOE 2010; DOE 2011). This report highlights EVs, PV, Wind turbines and fluorescent lighting as the key low-carbon energy technologies potentially affected by interruptions to the supply of low-carbon technology metals. The report highlights the rare earth elements in particular, stating that their supply “may affect clean energy technology deployment in the years ahead” (DOE 2011). The report also highlights key actions required to mitigate critical materials supply disruptions, including funding for strategic research, development of a critical materials research plan, international engagement with experts and coordination amongst US federal agencies (DOE 2011).

However, the limitations of high level comparative studies addressing critical materials issues means that insights and understanding of these issues are necessarily limited. In order to facilitate the consistent use of metrics across all metals covered in criticality assessment, only relatively simple metrics may be applied (Speirs *et al.* 2013b). To assess

[5] The SET-plan is a guidance plan to help European energy policy makers with the goal of: Accelerating knowledge development, technology transfer and up-take; Maintaining EU industrial leadership on low-carbon energy technologies; Fostering science for transforming energy technologies to achieve the 2020 Energy and Climate Change goals; and Contributing to the worldwide transition to a low-carbon economy by 2050 (EC 2014)

the full range and complexity of the issues surrounding these metals, closer study on a case by case basis is warranted.

2.4 Summary

The concepts of scarcity and the availability of resources have continually developed since their early beginnings. The modern debate encompasses a wide range of dynamic factors from physical and geological concepts to the economic theory of responses to scarcity. The critical metal resources raising availability concern most recently are significantly less well understood than resources such as oil that have experienced a sustained period of global economic importance, and thus research attention. The assessment of critical metal availability, and particularly how their supply and demand might respond to constraints in availability, is insufficiently understood given the current level of analysis. The following chapter describes the research approach used in this thesis to more fully explore the dynamic and interlinked nature of resource systems, and explore the similarities and differences in the structure and dynamic behaviour of different resource systems.

Chapter 3: Research approach

If we knew what it was we were doing, it would not be called research, would it?

Albert Einstein, date unknown

Research is what I'm doing when I don't know what I'm doing.

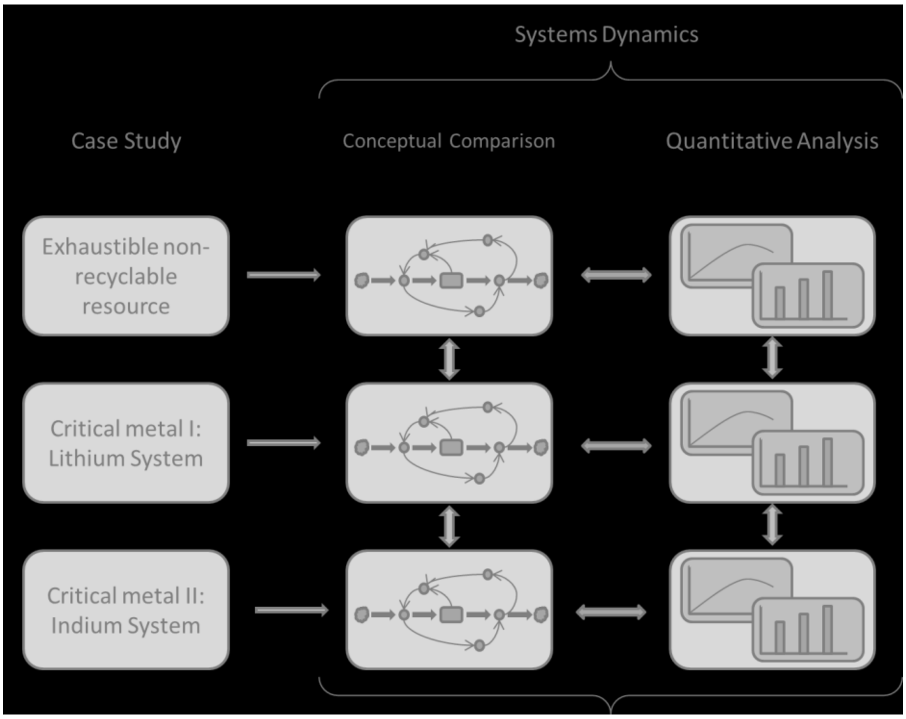
Wernher von Braun, 1957

The purpose of this chapter is to describe an approach which addresses the objectives laid out in Chapter 1 and ultimately answers the central research question. The chapter begins by describing the analytical framework which encompasses all the components of the research approach and their relationship to each other. The chapter then describes the two separate methodological approaches that make up the analytical framework. First it proposes the use of case study to examine the specific cases of three separate resources: an exhaustible, non-recyclable resource; and two low-carbon technology metals lithium and indium. The chapter then goes on to explore system dynamics and its use here; first as a way of describing and comparing the conceptual relationships between the key system variables and second as a quantitative methodology that can be used to simulate these systems to compare their dynamic behaviours under certain system conditions.

3.1 Analytical framework

Many important questions and knowledge gaps arise while researching a topic such as resource availability. The key issues arising during this research are captured in Chapter 2. The analytical framework described here has been designed to respond to the key knowledge gaps and guide the research towards results that address all aspects of the research question. A diagram summarising the analytical framework is presented in Figure 3.1. Justification for the construction of the analytical framework is presented in this section. The three phases of the analytical framework are dealt with in turn below.

Figure 3.1: Analytical framework for assessing comparability of energy resource systems



3.2 The need for case study

The need for specific case study arises for two main reasons. First, existing comparative methodologies applied to the availability aspects of low-carbon technology metals are typically simplistic and broad in order to manufacture sufficient comparability between metals (Speirs *et al.* 2013b). The purpose of this study is to compare the systemic differences between resources as much as their similarities. In order to fully capture the nuances associated with each resource compared in this research a more 'narrow and deep' methodology is applied.

Second, having identified the use of system dynamics within this analytical framework, case study provides a way to investigate the nature of systems and their construction. This includes examining the system as it currently appears, interpreting this observation into causal structure, identifying the initial conditions that might be appropriately applied to modelling these systems and identifying the experienced behaviours (reference modes) which these models are expected to replicate. Case study is broad enough in its approach to capture these issues and provide a basis on which the chosen resource systems can be modelled.

3.2.1 Case study approach

The method of case study research is not universally defined. Stake (1998), for example, states:

> *"As a form of research, case study is defined by interest in individual cases, not by the methods of inquiry used"*

Case studies therefore draw on a number of different techniques, with the precise approach being defined by the author. The general steps towards case study have been summarised by Soy (1997) as:

1. Determine and define the research questions
2. Select the cases and determine data gathering and analysis techniques
3. Prepare to collect the data
4. Collect data
5. Evaluate and analyse the data

The case studies in this thesis follow these steps. The first step is addressed in earlier chapters of this thesis, while the fourth and fifth steps are addressed in the case study chapters (4, 5 and 6) and the final chapters (7 and 8) respectively. Steps two and three are dealt with in Section 3.2.3 and Section 3.2.4.

3.2.2 Limitations of case study

Hodkinson and Hodkinson (2001) present eight potential limitations of case study methods. These are dealt with in turn below.

1. Too much data

Case study approaches can be used to gather large quantities of data, and these quantities can become difficult to manage and analyse. However, the case studies in this thesis aim to gather pertinent information with which to build system dynamics models. This focus help avoid issues of too much data

2. Too expensive

Given the quantities of data case studies deal with the cost of case study projects can become problematic. However, the research conducted here builds from existing funded research projects, and the nature of doctoral research is necessarily constrained by costs from the beginning, meaning that cost problems are unlikely to arise in this instance.

3. The difficulty of representing complexity

Case study methods can be used to delve deep into very complex research questions. These can often be difficult to represent and communicate effectively since case studies often rely on narrative to present results. However, in this thesis case study is followed by quantitative modelling and, though representing complexity in models is also challenging, the diversity of approaches is designed to improve capacity to represent complex systems.

4. Difficult to represent numerically

Hodkinson and Hodkinson (2001) note that some case study research has difficulty in maintaining comparability over longditudinal data. This arrises due to the inconsistency of the data sets gathered. Energy resource datasets suffer similar issues of data quality and while this limitation is acknowledged, efforts have been made to represent these data issues and focus on the trends and issues that are least impacted by this limitation.

5. Not generalisable

Case studies, which by their nature deal exclusively with specific cases, are difficult to generalise. The ability to generalise is a central theme of the research question studied in this thesis: do different resources used in the energy system behave similarly to constrained availability? As such the three case studies are compared specifically to identify the extent to which they can be generalised.

6. Difficult to maintain objectivity

Given the inherent case-by-case nature of case study methods, and the lack of a universally defined approach as highlighted in Section 1.2.1, it may be difficult for researchers to discard biases and remain objective. The original research on which these case studies build was conducted using a systematic review methodology, mitigating this issue to an extent. Systematic review is a method emerging from Evidence Based Policy and Practice (EBPP) that provides a rigorous and repeatable method of evidence gathering designed to avoid biases such as ‘cherry-picking’ and confirmation bias (Sorrell 2007a) (See Section 3.2.3 for more discussion of systematic review).

7. Easy to dismiss

Hodkinson and Hodkinson (2001) suggest that findings of case study research are easy to dismiss if they are unpopular. The reasons given centre around the lack of percieved sistematic rigour, e.g. the potential biases of researchers is used as a reason to dismiss findings. Again the use of system dynamics in addition to case study is designed to reinforce the systematic rigor of the research approach.

3.2.3 Selection of cases and data collection

The selection of cases can be based on a number of factors. Cases may be chosen because they are of intrinsic interest, or a specific part of the research question. Other cases may be selected for desired characteristics and may provide results that can be generalised. Desired characteristics of a case may be information richness or uniqueness. They may provide extreme examples, or they may provide generic or typical characteristics. Cases may also be chosen because they provide easy access to data, or facilitate in some practical way the analysis needed to answer the research question (Johansson 2003).

The first case study addressed in this research is that of a generic, exhaustible, non-recyclable resource system. One of the central concepts motivating the research question is to test the implied hypothesis within the literature that there is comparability between low-carbon technology metals and more traditional energy resources with a longer history and richer literature and discourse. The examination of the dynamics that are common to many commodities traditionally considered as energy resources under the heading of a generic resource helps to gather the evidence needed to inform a generic resource system model that can be tested against other resources. Oil is used often in this thesis to help inform the development of the generic resource model and the choice of oil as an example is supported by the following facts.

Oil is historically one of the most important energy resources. The modern oil market is at least 150 years old, representing 41% of global primary energy and at a price of $100 per barrel, representing $5.4 trillion (BP 2013). Oil also has a rich literature and oil data are widely available, providing evidence with which to inform the case study. As discussed in the previous chapter, the availability of oil has been discussed in the academic literature at least as early as the 1950s (Hubbert 1956). This discourse has continued and is as prolific now as it has ever been (Sorrell *et al.* 2009). Data on historical production, historical reserves and historical price are freely available. Finally, oil has been modelled extensively and therefore has an evidence base on which to build a system dynamics model. From the earliest simple extrapolative models (Hubbert 1956) to more recent and complex models (Sterman 2000; IEA 2008) modelling of the oil resource system has been conducted extensively, using a range of techniques and for a range of purposes. Though many of these methods have not been fully documented and published (IEA 2008), several models have been published in full and enough is known about these techniques to learn from and build on them (Sorrell *et al.* 2009).

Two critical metals are chosen as the second and third case studies. Lithium and indium as resource systems are significantly less researched, largely as a function of the relative economic importance of these metals compared to oil and the burgeoning nature of their low-carbon applications. There are enough data on these metals to inform the construction of system dynamics models representing their market systems. However, the main purpose for including these metals is to provide examples of critical metals that can be critically compared to oil. These two metals are used in two key low-carbon technologies central to low-carbon transition scenarios: lithium used in electric vehicles and indium used in thin-film photovoltaics (Candelise *et al.* 2011; Speirs *et al.* 2011). They are also diverse, in that the nature of their extraction and therefore the structure of their dynamic market systems, are different. Lithium is produced for its own value while indium is produced mostly as a by-product of zinc mining. These two metals therefore allow the comparison of different types of critical metals, as well as the comparison of critical metals to oil.

Systematic review

The case studies selected draw from research conducted by the author and colleagues for the UK Energy Research Centre (UKERC) Technology and Policy Assessment (TPA) theme and acknowledged at the beginning of this thesis. The central method of that research is systematic review, a form of evidence gathering designed to be exhaustive, robust and nonbiased. Due to the divergence in focus between the original TPA research and this thesis the case studies are augmented with data collected outwith the TPA systematic reviews. For this reason systematic review is not presented as a central research method of this thesis. It is however worth discussing the TPA process briefly, which has informed the evidence-gathering and assessment in this thesis greatly.

The TPA approach is informed by a range of techniques referred to as 'evidence-based policy and practice' (EBPP), including the practice of systematic review (UKERC 2014). This aspires to provide more robust evidence for policymakers and practitioners, avoid duplication of research, encourage higher research standards and identify research gaps. Core features of this approach include exhaustive searching of the available literature and greater reliance upon high quality studies when drawing conclusions (Sorrell 2007a). Petticrew (2001) sets out a detailed comparison of systematic review and traditional narrative reviews, highlighting the areas of improvement that good-quality systematic reviews can bring to the process of evidence assessment at each stage of the process. The improvements cited include the clear definition of a research question or testable hypothesis, the use of defined protocols to allow reviews to be replicable and the assessment of study quality in the process of evidence selection (Petticrew 2001).

Energy policy presents a number of challenges for the application of systematic review and the approach has been criticised for excessive methodological rigidity in some policy areas (Sorrell 2007a). UKERC has therefore set up a process that is inspired by this approach, but is not bound to any narrowly defined method or technique. The process carried out for each assessment includes the following components:

- Publication of Scoping Note and Assessment Protocol.
- Establishment of a project team with a diversity of expertise.
- Convening an Expert Group with a diversity of opinions and perspectives.
- Stakeholder consultation.
- Systematic searches of clearly defined evidence base using keywords.
- Categorisation and assessment of evidence.
- Review and drafting of technical reports.
- Expert feedback on technical reports.
- Drafting of synthesis report.

- Peer review

The process of systematic review, which forms the core of this process, is a rigorous method for evidence gathering. This process begins with setting out a search strategy in the assessment protocol, which is reviewed by experts. This protocol sets out: a) the sources of evidence to be searched; and b) the key words and Boolean search logic to be used in those searches. Once evidence is collected its inclusion in the analysis is subject to selection criteria, also defined in the assessment protocol. These selection criteria can include:

- The quality of review process the evidence has been subject to (e.g. peer review);
- The methodological rigour and experiment design;
- The comparability of evidence; and
- The applicability of evidence to the specifics of the research question.

Selection criteria can be highly rigorous, excluding a very large number of studies that do not meet the quality threshold. For example Wallace *et al.* (2004) conducted a systematic review into financial support for defaulting homeowners. The final review excluded 97% of the evidence uncovered in the initial review, based on their failure to meet the selection criteria.

The influence of systematic review on the evidence included in the case study chapters of this thesis improves the robustness of evidence inclusion above that likely through traditional narrative analysis.

3.2.4 Form of the case study chapters

Each case study chapter is structured in the following way. The first section presents a brief history of the resource system in question, covering the history of its discovery and early uses, and presenting the available historical data on production and price. The second section reviews the evidence on the structure of the resource system, beginning with the formation of demand, examining the aspects of production and supply and finally examining the formation of the resource price. The final section reviews the efforts to estimate future supply and demand of the resource through various techniques. This structure captures the full range of information needed to construct and simulate working models of these resource systems, providing an outline around which the three resource models can be structured.

3.3 The need for conceptual comparison

The objectives of this research identify the need to conceptually compare the resource systems studied here. Comparison is at the centre of the research question and by first comparing these systems at a conceptual level, focus can be placed on the broad structures of the systems. This stage of model development also allows time to be taken over the definition of system boundaries and the degree to which aspects of the system are aggregated, procedures identified by the founder of system dynamics, Forrester, as "two of the most difficult steps in successful modelling." (Sterman 2000).

The procedure of creating and comparing causal structure is referred to by Sterman as "mapping the system structure" and like any map these causal structures provide a means to navigate the research problem. Once these structures have been mapped, the process of comparison will highlight the key similarities and differences and provide insight into the most interesting things to test when performing quantitative analysis.

3.4 The need for quantitative analysis

Ultimately, to answer the research question and, in particular, the need to identify 'to what extent' these systems are similar, the causal structures must be interpreted into full system dynamics models and simulated to test the behaviours of the systems under certain conditions in order establish quantitative results. Causal loop diagrams and conceptual structures are usually too complex to predict intuitively and even simple structures produce unintuitive behaviours (Sterman 2000). Human mental biases and overconfidence in human judgment contribute to this error and many of these judgemental errors have been documented and examined (Kahneman *et al.* 1982; Hogarth 1987).

Quantitative simulation also allows for the identification of mistakes in the causal structure and conceptual models. Sterman (2000) stresses the importance of creating a full quantitative version of any model as soon as possible to iteratively develop the causal structure of models and test the implications of new and adapted structure as the modelling proceeds. This allows for the identification of error at the earliest possible stage.

Finally, quantitative simulation also allows for the testing of sensitivities in a systematic way. The results of such an analysis can be used to help test the model and improve it iteratively. Sensitivity analysis can also be used to highlight key assumptions in the model that are important to test, helping to target the process of model analysis.

Previous quantitative approaches

Resource demand is commonly modelled in resource availability analyses (Sterman 2000; IEA 2012). This can be as specific as demand in response to the growth of a particular end use (Andersson 2000; Tahil 2007; Tahil 2008) or range of end uses, demand as a function of population or macroeconomic factors such as global GDP, or demand as a combination of these. However, dealing with demand in isolation from supply is a significant simplification of the real world conditions, and models that resolve both supply and demand endogenously are likely to be more robust (Sterman 2000).

Resource supply is a commonly modelled aspect of the resource availability system (Fthenakis 2009; Sorrell *et al.* 2009; Yaksic & Tilton 2009; Houari *et al.* 2013). It is principally concerned with the rate at which resources are produced, but can also incorporate aspects of the resource estimates and their change over time, and aspects of the available production capacity.

Resource price is a less commonly modelled aspect of resource systems as it significantly increases the dynamic complexity of system models. There are, however, examples of price being incorporated into resource system models (Sterman 2000). In fact, depending on the purpose of the model, excluding price may render the model and its findings not fit for purpose. Sterman (2000) discusses a US energy policy model as an example of the pitfalls of placing economics variables such as price outside the boundaries of models. The Project Independence Evaluation System model (PIES). The PIES model was designed in the 1970s to evaluate US policy measures against a number of criteria, including: their impact on alternative energy sources; their impact on economic growth, inflation and unemployment; their regional and social impacts; their vulnerability to import disruption; and their environmental effects. However, as a result of leaving the economy outside the model boundaries the model was inherently contradictory. If the model made investments in one part of the economy, there would be no reciprocal impacts anywhere else. As a result, the model proved to be overly optimistic and was abandoned in favour of alternatives.

Supply, demand and price are all dependent on each other in resources systems, creating feedback loops that entirely dictate the behaviours of their systems. If supply becomes 'tight' producers are able to command a higher price. The increase in price signals a demand response, to either work with less (efficiency) or work with something else (substitution). The high price also encourages other producers to enter the market, or makes marginal resources cost effective, and both supply and demand responses serve to bring the price to its new equilibrium. Because of these feedbacks the system dynamics modelling methodology is well placed to simulate and interrogate these types of system.

3.5 System dynamics

Dynamically complex systems are inherently difficult to understand and system dynamics has been developed as a tool to aid the process of understanding them. System dynamics was developed by Jay Forrester in the 1950s at MIT and is linked to the concepts of systems thinking (Richardson 1991; Richmond 1994). The system dynamics approach uses stocks, flows, feedback loops and time delays to represent, simulate and study dynamically complex systems (see 3.5.2). Reviews of the historical development of system dynamics can be found in Lane (1994) and Richardson (1991).

System dynamics has been applied to a number of different dynamic problems. Initially Forrester called the discipline 'industrial dynamics', and many of the early applications focussed on the dynamics of management and decision-making in engineering businesses (Forrester 1961; Lane 1994). Since then the system dynamics approach has been applied widely, from medical research including human metabolism and obesity (Giabbanelli *et al.* 2011) to, to the nonlinear armament strategies in military arms races between nations (Behrens *et al.* 1997). Two high profile and notable applications of system dynamics are the Urban Dynamics model (Forrester 1969), designed to model and test city management policies, and the World 3 model, used in the 'Limits to growth' report (Meadows 1972). System dynamics has also been applied frequently to issues of energy policy, including oil resources (Sterman *et al.* 1988), the decarbonisation of road transport (Contestabile 2010) and the availability of critical metal resources for PV manufacture (Houari *et al.* 2013).

It has long been acknowledged that intervention in a system will often have unintended consequences, and that policy interventions will often be resisted by the system. Sterman (2000) provides a number of examples of 'the law of unintended consequences.' In this vein Lewis Thomas noted:

> *"When you are confronted by any complex social system, such as an urban centre or a hamster, with things about it that you're dissatisfied with and anxious to fix, you cannot just step in and set about fixing with much hope of helping. This realization is one of the sore discouragements of our century….You cannot meddle with one part of a complex system from the outside without the almost certain risk of setting off disastrous events that you hadn't counted on in other, remote parts. If you want to fix something you are first obliged to understand…… the whole system….Intervening is a way of causing trouble."*

Thomas (1974)

The goal of learning about the complete nature of dynamic systems is one of the core purposes of system dynamics.

There are manifold reasons behind our inability to understand dynamically complex systems intuitively. The human thought process tends to interpret the world as linear, ignoring the circularity of feedback loops in favour of a linear concept of action and reaction. This is exemplified by commonly used language such as 'cause and effect' or 'side effect'. In reality there is no such thing as a linear cause and effect and, as a result, there are no side effects. All effects are a direct result of their preceding actions, though they may be classified as 'side effects' depending on whether they were anticipated. Mental models are also used to interpret the world around us. These mental models can be very difficult to break, and our natural thinking processes provide significant barriers to learning (Kahneman *et al.* 1982; Hogarth 1987). Sterman (2000) lists and discusses a range of these barriers in Chapter 1 of his book 'Business Dynamics' In the face of these barriers, system dynamics provides a structured and formalised process through which these tendencies in thought process can be isolated, the fundamental components of a complex system and the underlying relationships pieced together, and the system simulated independently of our mental models (Sterman 2000).

The following sections describe the formal process of system dynamics modelling, including the construction of conceptual 'causal loop diagrams' and the formulation of stock and flow models, representing the second and third stages of the analytical framework. Finally it briefly addresses some of the perceived weaknesses of system dynamics.

3.5.1 Systems thinking: structure and behaviour

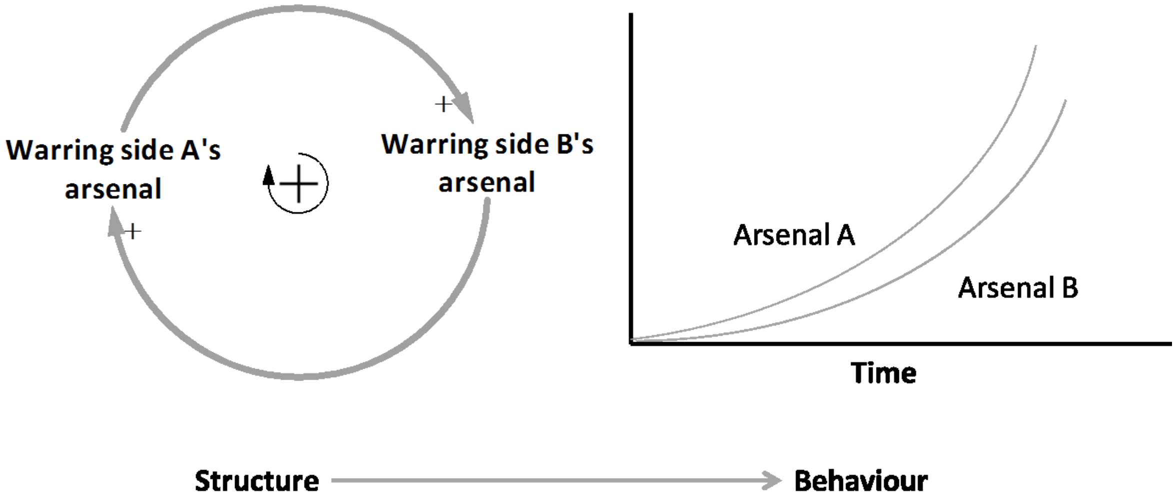
Feedback, the iterative interaction of components of a system, is at the heart of system dynamics. The system structure, or the combination of components and their feedback, dictates the systems behaviour, meaning the way in which a system reacts to changing conditions (see 1.3). All behaviour arises from three basic structures: positive feedback; negative feedback; and negative feedback with time delay. Illustrative examples of these three basic structures are presented with explanation in the following sections. They are illustrative only and do not necessarily represent working models.

This quick guide to the structural elements of system dynamics is drawn from Sterman (2000) but similar expositions of these concepts can be found in Radzicki and Taylor (2008), Wolstenholme (1990) and Morecroft (2007).

Positive/reinforcing feedback and exponential growth

The positive or reinforcing feedback loop is the first fundamental structure used to define a dynamic system. These feedback loops tend to amplify the behaviour in the system. For example, in an arms race, the more weapons built by one side of the conflict, the more the other side will build in retaliation. The arsenals of the two warring sides will therefore grow, and weapons manufacturing in the system will tend to increase exponentially. The loop is therefore built of two components (the two warring sides) and their feedback (the effects of one side's behaviour on the other's). This can be represented by the causal loop diagram in Figure 3.2. In this diagram the '+' sign in the centre denotes the 'positive' feedback loop. This can also be represented by 'R' which stands for 'reinforcing'. The circular arrow at the centre denotes the direction of causality, and the '+' sign next to the feedback arrows denotes the positive impact of that feedback.

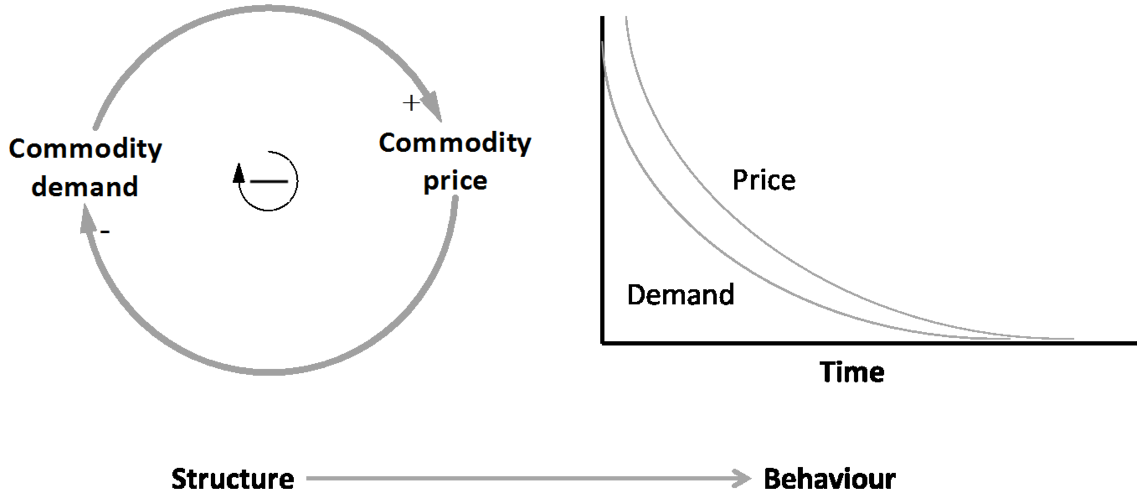
Figure 3.2: Positive feedback loop of two warring sides and the resulting behaviour of the system



Negative/balancing feedback and goal seeking

The second fundamental structure in dynamic systems is the negative or balancing feedback loop. Negative feedback loops tend to oppose change, seek equilibrium and tend to be self-limiting. For example, if the price of a commodity increases, one of the responses is that demand tends to decrease, though as demand decreases, so too does the price, until demand and price stabilise. This loop is therefore made of two components (price and demand) and their feedback (the negative influence on price on demand and the positive influence of demand on price). This structure and its behaviour can be represented by the causal loop diagram in Figure 3.3. The notation in this feedback is similar to Figure 3.2, only the '-' sign denotes the negative feedback, which can also be represented by a 'B', for 'balancing'.

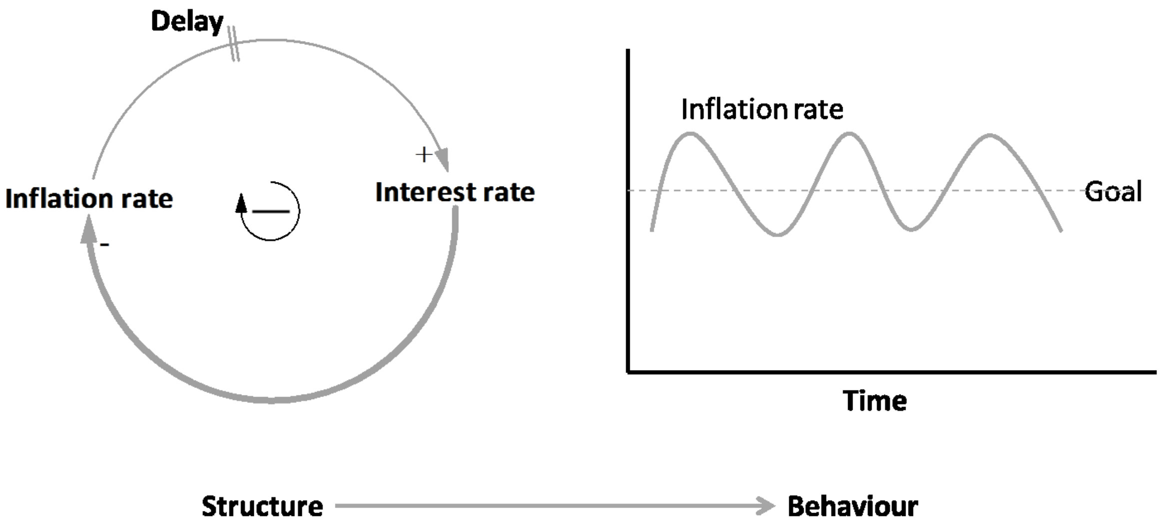
Figure 3.3: Negative feedback loop of commodity price, demand and the resulting behaviour of the system



Negative feedback with delays and oscillation

The third basic feedback structure in system dynamics is the negative feedback loop with delay. In any negative feedback loop, the system tends towards a goal. In the example in Figure 3.3 the goal is the price at which demand is stable. The system compares its conditions to the goal iteratively, and while there is a large discrepancy between condition and goal, there is a large response. As the condition tends towards the goal and the discrepancy is reduced, the response is also reduced, and the condition tends towards its goal asymptotically. If delay is introduced anywhere in that system then the system no longer responds to current discrepancy, but to the discrepancy between some previous condition and the goal. This leads a system to oscillate. For example, a government may want to control its inflation to a specific rate by manipulating interest rates. Unfortunately, measuring inflation is a slow process, with data published infrequently. This causes delay, which complicates the system. If inflation is below the goal, then the goal seeking policy may try to increase it by reducing interest rates. However, by the time policy makers are aware of the impact of that interest rate shift, inflation rates may already have met the goal and increased above it. Now policy makers will want to increase interest rates to help reduce inflation, and again with the delay in inflation rate measurement, the goal may be surpassed before policy makers are aware. If this continues then the rate of inflation will fluctuate above and below the system goal indefinitely. This system is therefore made up of two components (the inflation rate and interest rate), the feedbacks (the effect of inflation rate on interest rate policy and the effect of policy decisions on the interest rate) and a time delay (the time it takes for interest rate to be measured and reported back to the policy makers). This structure and its behaviour can be represented by the causal loop diagram in Figure 3.4.

Figure 3.4: Negative feedback loop with delay of interest rate and inflation rate, and the resulting behaviour of the system



Other behaviours: products of the three structures

All other behaviour in dynamic systems is derived through a combination of these three basic structures. S-shaped or sigmoid growth, for example, is much more common in natural systems than the unlimited exponential growth arising from positive feedback loops. At some point, natural systems reach limits, which restrict growth. By combining positive and negative feedback loops, sigmoid growth can be simulated. Sigmoid growth may be experienced in resource discovery. The cumulative discovered resource is likely to grow exponentially in the early years, as discovery techniques improve and effort increases. However, at some point, discovery begins to get harder and harder as the number of undiscovered wells decreases and the exploratory effort needed to add the next discovery increases. This leads to goal seeking behaviour which moderates the growth phase, creating the sigmoid pattern.

If delays are introduced to the negative feedback loop in the structure, sigmoid growth with overshoot and oscillation is generated. This might be the case in a population system where the goal is the carrying capacity of the habitat, and delay is introduced given the time taken for new-born members of the population to grow to adulthood. As the population increases more of the habitats resources are used, and population growth slows as resources are used up. However, as the population nears the goal there are new-borns who have yet to grow to adulthood, at which point they will require more resources to survive. By the time they have reached adulthood, the resource demands of the population might have exceeded the carrying capacity, and the population will die back. At which point consumed resources may have grown back, incentivising population to rise again.

If a second negative feedback is added, then overshoot and collapse can be generated. The fixed goals implied in the previous two examples are replaced in this structure with a goal dependent on the components of the system. This produces a bell shaped curve akin to the Hubbert curves discussed in Chapter 2.

Other modes of behaviour include stasis/equilibrium, randomness and chaos. These are described in more detail, along with fuller explanations of all the types of structure and behaviour, in 'Business Dynamics' (Sterman 2000).

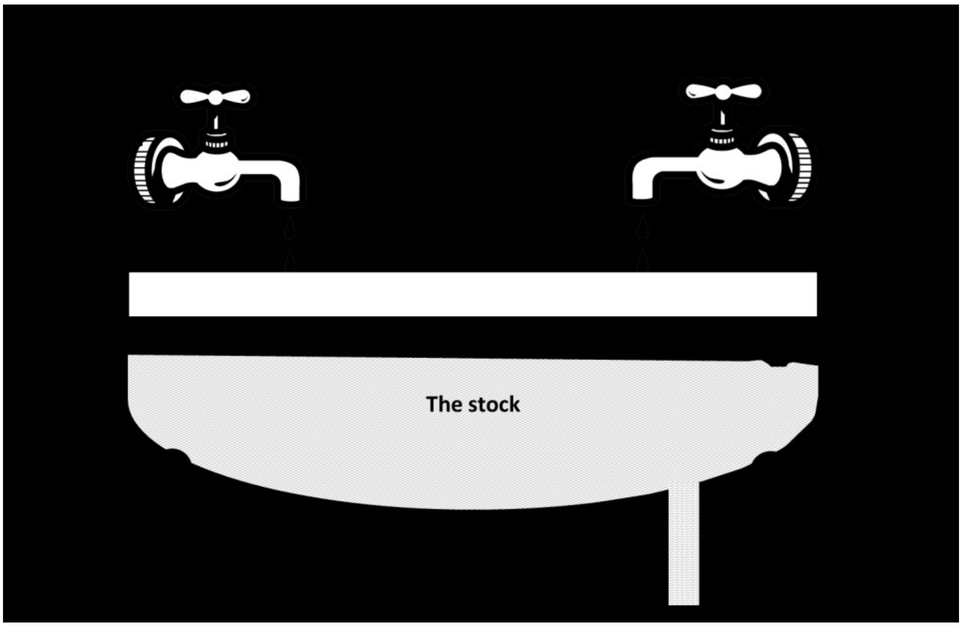
3.5.2 The elements of system dynamics

Causal loop diagrams are useful tools in communicating the structure of feedback loop structures in a clear way. However, causal loop diagrams lack the ability to distinguish between stocks and flows, which along with feedback are the centre of dynamic system theory. Dynamic behaviour is thought to arise from the *Principle of Accumulation*, which states that all dynamic behaviour occurs when flows accumulate in stocks (Radzicki & Taylor 2008). In essence, dynamic systems are governed by rates of change, and system dynamics models calculate those various rates of change when simulated. The calculation of rates of change is in other words, calculus (Sterman 2000), and stock and flow diagrams help us separate and simplify the complex equations at the route of dynamic systems. The following describes the use of stocks and flows in system dynamics, and their combination to create the structure and behaviours discussed above.

Stocks and flows: building blocks of system dynamics

Stocks can be described as accumulations, which characterise the state or condition of the system and inform the decisions and actions taken (Forrester 1961). Flows are the rates of change of a stock, with inflows accumulating in stocks and outflows depleting them (Forrester 1961). A commonly used analogy is the hydraulic metaphor (Sterman 2000; Radzicki & Taylor 2008). If the stock was a bathtub, the quantity of water in the bathtub is the sum of the accumulation of water flowing in over time, minus the water flowing out through the plughole over time.

Figure 3.5: The bath tub analogy of stocks and flows in system dynamics



Source: Adapted from Sterman (2000)

In mathematical terms, the stock, or bathtub, *integrates* inflow and outflow, and can be represented as:

$$Stock(t) = \int_{t_0}^{t} [Inflows(s) - Outflow(s)]ds + Stock(t_0)$$

3.1

Stocks critical contribution to dynamic systems can be summarised as follows (adapted from (Mass 1980)):

1. **Stocks represent the state of the system and provide the basis for action:** in systems, stocks tell the decision makers of the system what the current conditions are, upon which the decision makers may act.
2. **Stocks provide inertia and memory:** stocks only change if there is an inflow or outflow. As such, the past events of a system are recorded in stocks, and their inertia means that they can only be changed through changes in the flows.
3. **Stocks form delay:** delays are processes whose outflow lags their inflow and, as such, they always involve stocks, which are needed to accumulate the difference between these temporally separated inflows and outflows.
4. **Disequilibrium is dependent on stocks:** most inflow and outflow processes are dependent on different factors and rarely equilibrate. Stocks provide for the accumulation of the difference between these flows.

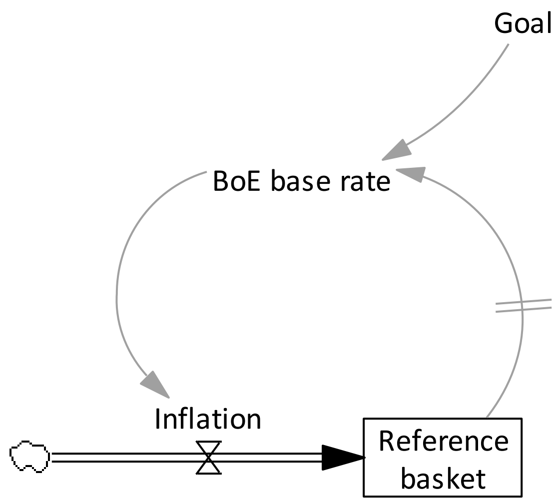
Creating structure through stocks and flows

Ultimately, stocks and flows are used in system dynamics modelling to capture and simulate the structures identified in causal loop diagrams. Since causal loop diagrams do not differentiate between stocks and flows, the first challenge is to identify which components should be interpreted as stocks and which should be interpreted as flows. Sterman (2000) suggests some ways to distinguish. Units of measurement are useful in determining which variables should be stocks and which should be flows. Absolute quantity units, such as monetary units ($, £ etc), volumes (litres, m^3 etc) and weights (tonnes, kilos) are usually associated with stocks, while rates are measured in the same unit as the stock per time period, such as $ per hour, litre per second or tonnes per year. Another way to distinguish between stocks and flows is the 'snapshot' method. As previously discussed, stocks record the condition of a system. If time could be frozen in a 'snapshot', the stocks would be those things that had some memory or record of the state of the system. Stocks would therefore be the things that could be counted or measured in the snapshot. To return to the hydraulic metaphor, a picture of a bath with the tap running would allow you to estimate the volume of water in the bath, but would yield no information as to the rate at which it is filling up.

Once the stocks and flow have been identified, the stock and flow diagram of the system can be created. Returning to a previous example, Figure 3.4 represents the stock and flow diagram interpretation of the negative feedback with delay causal loop diagram describing the relationship between inflation rate and interest rate. First, the stocks and flows are identified. Using the units method of identification, both sides of the causal loop diagram are percentage rates, suggesting that both are flows. In this system, the stock would be the element of the system that inflation rate flows into. This is also the part of the system measured which provides the information on inflation rate to the decision makers who set interest rates. Using the UK as an example, the stock would be a 'reference basket' of products[6] and the interest rate would be the Bank of England (BoE) base rate of interest, set by the monetary policy committee of the BoE.

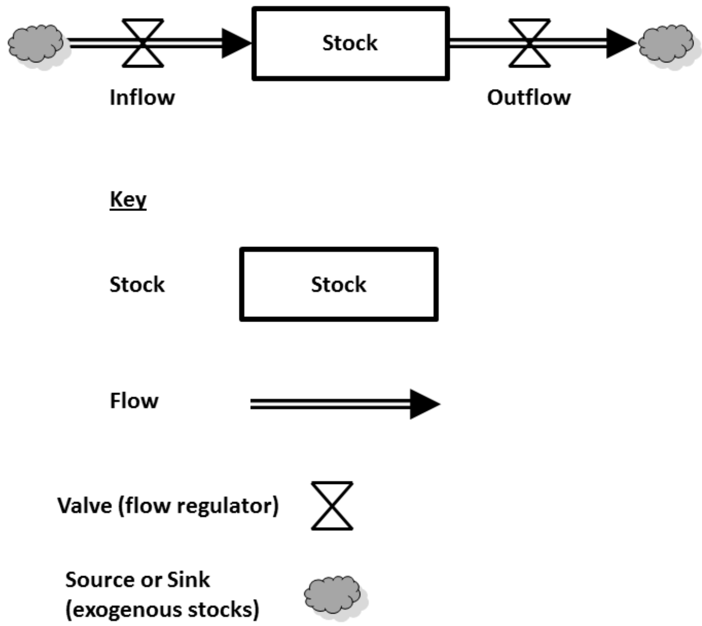
The standard notation in stock and flow diagrams was proposed by Forrester (1961) and is presented in Figure 3.7. Stocks are typically drawn as boxes, while flows are drawn as straight double lined arrows with an hourglass like 'tap' symbol. It is another important contribution of the stock and flow diagram that flows of material (in this case inflation) and flows of information or effect (in this case the measurement of reference basket, the knowledge of the intended goal and the impact of interest rate on inflation) are differentiated. Information and effect are drawn as curved arrows. Delay notation in this case is the same as causal loop diagrams, though other types of delay notation, such as conveyor belt stocks, exist in stock and flow diagrams (Houari *et al.* 2013).

Figure 3.6: Stock and flow diagram of the relationship between interest rate and inflation



[6] The Consumer Price Index (CPI) and Retail Price Index (RPI) are measures of the changing price of a range products, used to calculate the inflation rate of an economy.

Figure 3.7: Stock and flow notation key



Source: Forrester (1961)

In addition to stocks and flows, auxiliary variables are also useful when modelling dynamic systems. In Figure 3.6, the goal and the BoE base rate are represented by auxiliary variables. These can be used to represent constants (such as the goal), simplifications of stock and flow elements (such as the BoE base rate) and exogenous variables. Auxiliary variables can be eliminated by creating only stock and flow representations, though the benefit of auxiliaries is that simplifications of exogenous parts of models can be made and explicit statement of variables such as goals can make stock and flow diagrams more easily navigated.

Finally, the underlying mathematical relationship between these stock and flow units must be defined. This is done through the software platform used to generate stock and flow diagrams. Chapter 7 describes the functional relationships used in the models in this research.

3.5.3 The choice of modelling platform

Very early in the history of system dynamics, it was recognised that to simulate the system dynamics models efficiently, the computational power of computers would be required.

Early programming languages, such as SIMPLE, gave way over time to graphical user interface programs such as Vensim and Stella. There is also the possibility to recreate system dynamics modelling in other modelling software such as Matlab. Modern system dynamics programs facilitate the creation of complex systems and allow the user to focus on the dynamics and underlying functional relationships without spending undue time on the operation and interrogation of complex programming languages.

Three criteria were considered when choosing modelling software used in the analysis in this thesis:

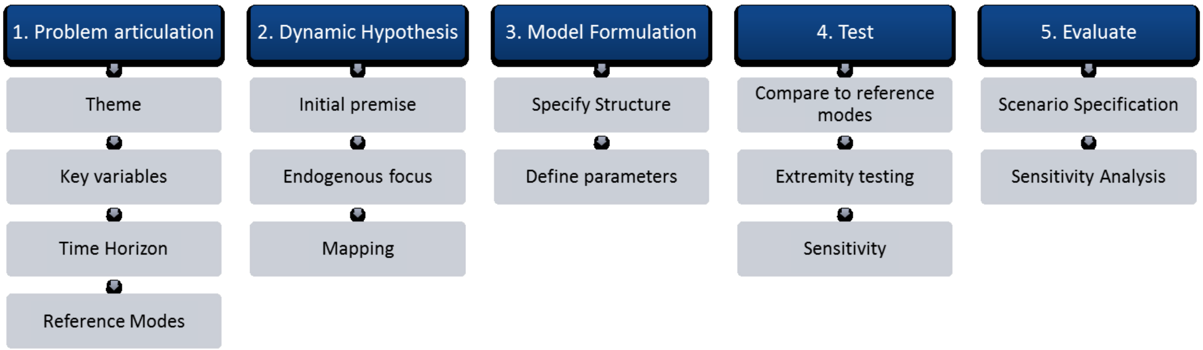
1. Access and cost: is the software available from and did they have affordable licencing agreements;
2. Ease of use: is the software accessible, intuitive, and practical; and
3. Functionality: does the software contain useful functions that will be helpful for the intended analysis?

An extensive list of available software can be found online (Wikipedia 2014a) and using the criteria above, Vensim PLE plus was chosen as the optimal software for the purposes of this research.

3.5.4 The modelling process

There are several guides to the system dynamics modelling process, giving detailed step-by-step instruction (Morecroft 2007; Pejic-Bach & Ceric 2007; Radzicki & Taylor 2008). This thesis follows the conventional modelling steps laid out by Sterman (2000), summarised in Figure 3.8. Following these steps first provides causal loop diagrams and other system mapping tools used for the conceptual comparison, which is the second stage of the analytical framework. The final product of these steps is the creation and testing of full simulation models of the chosen resource systems, which will provide the quantitative analysis defined in the third stage of the analytical framework.

Figure 3.8: Steps of the systems dynamics modelling process



Source: Adapted from Sterman (2000)

Problem articulation and boundary definition

> *"A clear purpose is the single most important ingredient for a successful modelling study"*
>
> Sterman (2000)

Problem articulation is the first step in developing and using a system dynamics model. This involves defining specifically what the problem is and what is interesting about it. It is important to be specific and explicit so a testable hypothesis can be derived. In Chapter 1, an explicit research question is proposed and its component questions and necessary objectives discussed. This is developed into an analytical framework and thesis structure designed to respond to the research question.

Other considerations at this stage include listing the key variables and defining which are endogenous and which exogenous to the model. At this stage, it is important to make sure all the important variables are included endogenously. There are examples of models with key variables dealt with exogenously, limiting the usefulness of the model for its intended purpose. Boundary charts are a typical method of defining exogenous and endogenous variables and these will be derived in the case study chapters that follow.

It is also important to define a sensible time horizon that meets the requirements of the research question. Reference modes, i.e. examples of the types of behaviour the model should be able to replicate, should also be identified and considered. Reference modes are identified in the case study chapters and validation against reference modes and time horizon settings are discussed in Chapter 7.

Formulation of dynamic hypothesis

In this step, the current knowledge and analysis of a particular problem is examined. This is said to represent the 'initial hypothesis'. The dynamic hypothesis is formed by explaining the initial hypothesis using feedback structures.

System dynamics practitioners often use a host of 'mapping' techniques to begin to set out the structure of the dynamic system formally. Using these techniques, the modeller can work towards a full dynamic explanation of the system to be modelled. Mapping techniques include boundary diagrams, subsystem diagrams, causal loop diagrams and stock and flow charts. This mapping process should be done iteratively with simulation of a fully working model in order to identify mistakes in structure as early as possible. To achieve this Sterman recommends creating a fully operational model as soon as possible (Sterman 2000).

Whilst many elements of the mapping of a dynamic hypothesis appear throughout this thesis, the key stages of mapping and dynamic structure development are dealt with in Chapter 7.

Formulation of a simulation model

Formulating a full working simulation model as a stage of system dynamics modelling can be split into two stages. *Specification* involves the final creating of a stock and flow diagram defining the structural aspects of the model. The underlying functional relationships between the elements of the structure are then defined.

Estimation is the process by which the initial conditions of the system are set. This is achieved by examining the literature and evidence base surrounding these systems and defining appropriate initial values for all variables based on that evidence base.

Specification and estimation are documented in Chapter 7, with evidence used to derive the initial conditions drawn from the case study chapters.

Testing

There are a host of model tests and validation techniques used in system dynamics to support and defend system dynamics models. Many of these are discussed in the literature

(Sterman 2000). Four key tests are utilised in this research (see Chapter 7) and these are discussed briefly below.

Integration error tests or '*Dt* error' tests are used to eliminate spurious dynamics which arise due to integration settings in a model[7]. System dynamics models are usually solved using numerical integration. This is necessary since system dynamics models are based on nonlinear ordinary differential equations solved simultaneously in each model time step (Sterman 2000)[8]. For example, a stock in system dynamics is calculated as the integral of all the flows connected to it. Numerical integration yields an approximation of the underlying continuous dynamics of systems and modellers usually have the choice over both what type of numerical integration to use and what time steps the model should be solved in. If the time step is too large or the integration method not suitable, then the continuous dynamics of the system may change more swiftly than the frequency of calculation (time steps) can cope with, resulting in spurious error. This can be tested for by examining the impact of reducing the time step on the model solution. If there is a significant difference between the results using different time steps, the period of calculation is too long. By continually reducing the time step until results are consistent, *Dt* error can be avoided. Type of integration method can also be tested by examining the impact of different methods on the model solution.

The behaviour of the model can also be tested against the behaviour witnessed in **reference modes**. A model of a real world system should be able to approximately replicate the behaviour of historical data for that system given the correct input variables. The 'reference mode' is the name used in system dynamics to refer to this type of data. Reference modes can also include widely accepted forecasts of potential future dynamic behaviour in a system. By examining the output of system dynamics against these reference modes, the model values and structure can be refined and revised in light of any model behaviour which obviously conflicts with the reasonable expectations of that system in the real world.

[7] Dt stands for Delta time, and means 'change over time'

[8] More detail on the use of numerical integration in system dynamics models can be found in Annex A of Sterman (2000)

Models should behave in a realistic fashion under **extreme conditions** and testing for this conformity is a useful way to examine the validity of model structure. For example, if the bath tap is off and the plug removed the volume of the bath can only drop to zero and not below. If the price of a product increases, at some point demand for the product will reach zero. This can be carried out by either inspecting the functions underlying the model individually, or by applying extreme input parameters and simulating the model. In this thesis, the model was simulated under extreme conditions and results examined.

Finally, **sensitivity analysis** can be used to test the models reactions to uncertainty in assumptions. Models can be: sensitive numerically, where numerical values of output change as assumptions change; behaviourally, were the behaviour of the system changes to changes in assumptions; and to policy, where the impacts of policy decisions change the functioning structure of the system. Models should be tested across the range of sensible assumption uncertainty.

Details of these tests and their results are set out in Chapter 7.

Evaluation

The evaluation of the model is the final analytical stage in the modelling process. From the values derived in this stage, it should be possible to address the extent to which the research question can be addressed, and useful insights and discussion should arise. The first stage in evaluation in this thesis is to examine the behaviour of the models under different plausible conditions, or groups of assumptions coherent with a particular narrative view of system conditions. This allows the development of a story, or narrative, around the choice of assumptions, which can then be explored in terms of its outcomes for model behaviour. Packaging up assumptions in this way can help navigate the uncertainty in assumptions and allow for useful conclusions to be drawn.

3.5.5 Criticisms of system dynamics

System dynamics has received criticism in the past, and its use in high profile research such as the Limits to Growth report (Meadows 1972), has attracted particularly detailed critical analysis (Cole 1973). Featherston and Doolan (2012) refer to five areas of criticism that system dynamists should address when developing and using system dynamics models. These criticisms are discussed in brief below.

The application of system dynamics

Some system dynamics models attract criticism for their application of the modelling methodology. These criticisms are either that the question addressed by the model is not suitable, that the application of system dynamics was in some way flawed, that the conceptual definition of system dynamics is wrong, or that it encourages unnecessarily large models (Barlas 2007; Forrester 2007). These criticisms are not that system dynamics is inherently flawed, but that it has not been effectively applied. The criticism of the World 3 model by Cole (1973) falls under this category.

These criticisms are put down to a poor level of system dynamics understanding and training, leaving some unequipped to apply the methodology correctly (Featherston & Doolan 2012). In this thesis, efforts have been made to understand and apply correctly the system dynamics method in order to avoid criticism of poor application.

Mimicry of historical data and validation

The inability of system dynamics models to replicate real systems accurately is a criticism that has been levelled at the discipline historically (Simon 1981; Keys 1990; Hayden 2006). When models are evaluated ex-post against historical data and found not to have replicated the development of a system accurately this is often seen as a shortcoming. However, system dynamics practitioners would argue that the central purpose of the methodology is not to forecast the future accurately, but to use models to understand why certain behaviour occurs (Forrester 2007; Radzicki & 2007; Featherston & Doolan 2012).

The focus of this thesis is around the study of dynamic system behaviour and its drivers, and not on the forecasting of future states of dynamic resource systems.

Complexity

The tendency of system dynamics to oversimplify complex systems is a criticism that has been levelled by some authors (Keys 1990; Hayden 2006). Critics suggest that this oversimplification takes the form of: *reductionism*, or describing a system only by its parts (Keys 1990); lack of *pluralism*, or the inability of system dynamics to represent different system perspectives, or the diverse responses of different actors within the system (Keys 1990); and the inability of system dynamics to deal with the *openness* of social systems (Hayden 2006).

The criticism of over-simplification in computational modelling is not unique to system dynamics (Rossis 1986; Grosholz 2011). However, several attempts have been made to improve the application of system dynamics in the light of these criticisms (Newell *et al.* 2011), or to defend system dynamics where there are differences of opinion (Radzicki & 2007).

This thesis makes every attempt to capture the important aspects of the dynamic systems modelled. However, models are necessarily simplifications of real systems (Sterman 2000). Where this thesis makes simplifications that are potentially critical to the outcome of the thesis conclusions this is highlighted and discussed in the final chapter.

Determinism

Determinism is the criticism that system dynamics is deterministic in terms of its disregard for human free will, its representation of humans in systems as components (cogs in a machine) or its proposition of all-encompassing 'grand theories' (Jackson 1991; Lane 2000).

The system dynamics modelling conducted in this thesis makes no pretence at providing a grand theory, and uses system models to examine responses under specific conditions. Again, where simplification of human behavioural elements of the model is deemed influential to results this is discussed in the final chapter.

Hierarchy

Hierarchy in systems modelling is the relationship between subsystems that defines the rules, obligations, controls, regulations and limitations in the system (Checkland 1981). Some criticise system dynamics for not dealing with the hierarchy of systems explicitly, and many of the tools for representing system dynamics models, such as causal loop diagrams, have no way to express this hierarchy. This is only reflected in system dynamics models once the numerical relationship between sub-systems is defined, which for some is too late in the process (Hayden 2006). However, this definition of hierarch seems 'fuzzy' and inadequate, and the proposals to deal with this problem are, in result, relatively unconvincing. This is reflected in a statement in Featherston and Doolan (2012):

> *"Perhaps hierarchy, and maybe Checkland's (1981) other 'basic' system ideas, need to be discussed application by application to ensure their consideration in modelling, or perhaps system dynamics needs to crystallise its thinking in this area and construct formal theories around system hierarchy"*

Based on this exposition it is difficult to ascertain whether the models in this thesis are sensitive to issues of hierarchy, though the numerical relationship between important aspects of model subsystems is exposed for the reader in Chapter 7.

3.6 Summary

This chapter sets out the research approach followed in this thesis, which uses case study to inform the creation of three system dynamics models used to conceptually and quantitatively compare three different dynamic resource systems. The process of gathering evidence in the case studies is exposed, and the system dynamics modelling process is laid out in steps.

The strengths and weaknesses of the approach are discussed. In particular the common criticisms of system dynamics are dealt with. The exposure of the models in this thesis to the common themes of criticism is presented, and any areas where these criticisms have significant bearing will be discussed in the final chapter.

The following three chapters present the oil, lithium and indium case studies. These chapters are followed by Chapter 7 and Chapter 8, which develop the concepts discussed in the case study chapters into fully simulating system dynamics models and tests and evaluates these models against the objectives set out in Chapter 1.

Chapter 4: Case study – A generic, exhaustible, non-recyclable resource

Precious treasure and oil are in a wise man's dwelling, but a foolish man devours it.

Proverbs 21:20

This chapter describes the range of issues commonly experienced in the demand, discovery, production and price formation of exhaustible, non-recyclable resources. This information is used to inform the construction of a generic, exhaustible, non-recyclable resource model (from this point referred to as the generic resource system model) (See Chapter 7). The generic resource is one that is recovered for its own economic value, destroyed in its main end-uses and its price discovery process follows the marginal cost of production as predicted in neoclassical economic theory (Stiglitz & Walsh 2006). The availability of oil and interaction between supply, demand and political factors has been extensively studied. This chapter therefore reviews the literature on oil in order to inform the development of the generic resource system model. However, this generic, non-recyclable resource is not subject to the political factors, market distortions and cartel influences experienced in the global oil market (EIA 2014f).

Oil has historically been one of the most economically important commodities, influencing the shape of the energy system, the development of society, and the foreign policy of nations (Yergin 1991). As a function of its importance, the oil resource system has been examined in more detail than most, and an extensive evidence base exists upon which this thesis draws (Sorrell *et al.* 2009). Oil is therefore an ideal case with which to inform the generic resource system model.

This chapter describes the host of variables that influence the development of resource systems, and examines the extent to which these variables have been expressed in the existing literature on resource availability modelling. The chapter examines the oil resource system as an example, beginning with a brief review of the history of the oil market. This is followed by a discussion of the issues surrounding oil demand. This topic is further disaggregated into issues surrounding: the uses of oil; the extent to which it can be substituted for alternatives; the use of demand side factors in oil resource modelling; and the problems associated with aspects of the demand side. The discovery process and issues of reserves and resources are then discussed. Issues surrounding the production of oil are then considered before examining the formation of the oil price. The chapter then analyses the approaches to modelling the oil resource system.

The structure of this chapter is replicated in the subsequent two case study chapters, in order to provide comparability to the assessment of the three case study resources and to provide a systematic framework with which to examine the important variables defining these resource systems.

4.1 The origins of a resource system: the history of oil

The 'age of oil', or the beginnings of the modern oil resource system, is often said to have its origins in the 1850s (Yergin 1991). Small levels of petroleum recovery have been recorded for over 4000 years, but the commercialisation of the oil market in North America in the middle of the 19th century set the foundations of today's multi-trillion dollar oil industry. The main market for this oil was initially for one of its distillates, paraffin, which was used as a lamp oil, but a range of new uses for oil quickly proliferated as the understanding of crude oil chemistry improved, and distillation techniques created an increasing number of oil derived products (Yergin 1991). Kerosene was developed first and demand quickly increased through its use in street lighting throughout North America. However, at this time the main source of oil for processing into paraffin and kerosene products was from shale rock, bitumen and coal. Supply of these sources of hydrocarbon could not keep pace with the increasing demand for its products, and discoveries of oil reservoirs that could be drilled to produce oil quickly became the dominant source of oil (Yergin 1991).

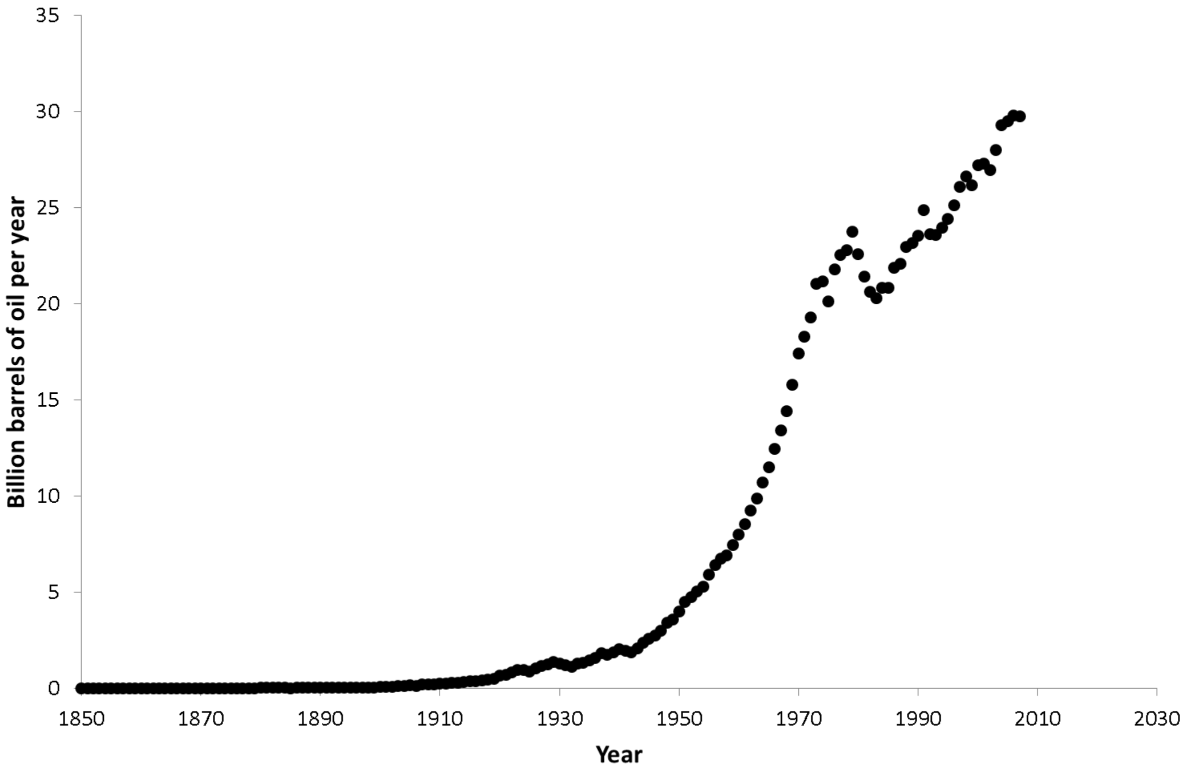
The literature is vague on what site should be considered the first modern oil well but small projects in North America, Azerbaijan, Poland and Romania are all early contenders (Cleveland & Morris 2014a). Some of these wells were hand-dug but some used drilling techniques powered by hand or even by steam engine. These early projects began a boom in oil discovery and production, helping keep pace with the rising demand for oil products.

This boom also led to the development of commercial refineries that utilised recent discoveries in petroleum chemistry to produce a number oil derived products (Frank 2005).

While the oil industry was in its early years of development, internal combustion engines were also a burgeoning industry. Many of these early designs ran on fuels derived from coal. However, from the 1880s, internal combustion engines designed to run on distillates of oil began to emerge. By the beginning of the 20th century, automotive fuels had become the major demand for oil products, a position that remains today, more than a century later (Yergin 1991).

The rise of the oil fuelled automotive industry lead to significant increases in oil demand incentivising oil producers and prospectors, creating 'oil booms' across North America. During this period, oil production grew exponentially and despite small interruptions resulting from World War I and World War II, this trend continued until 1970s (Figure 4.1).

Figure 4.1: Historical global oil production since 1850

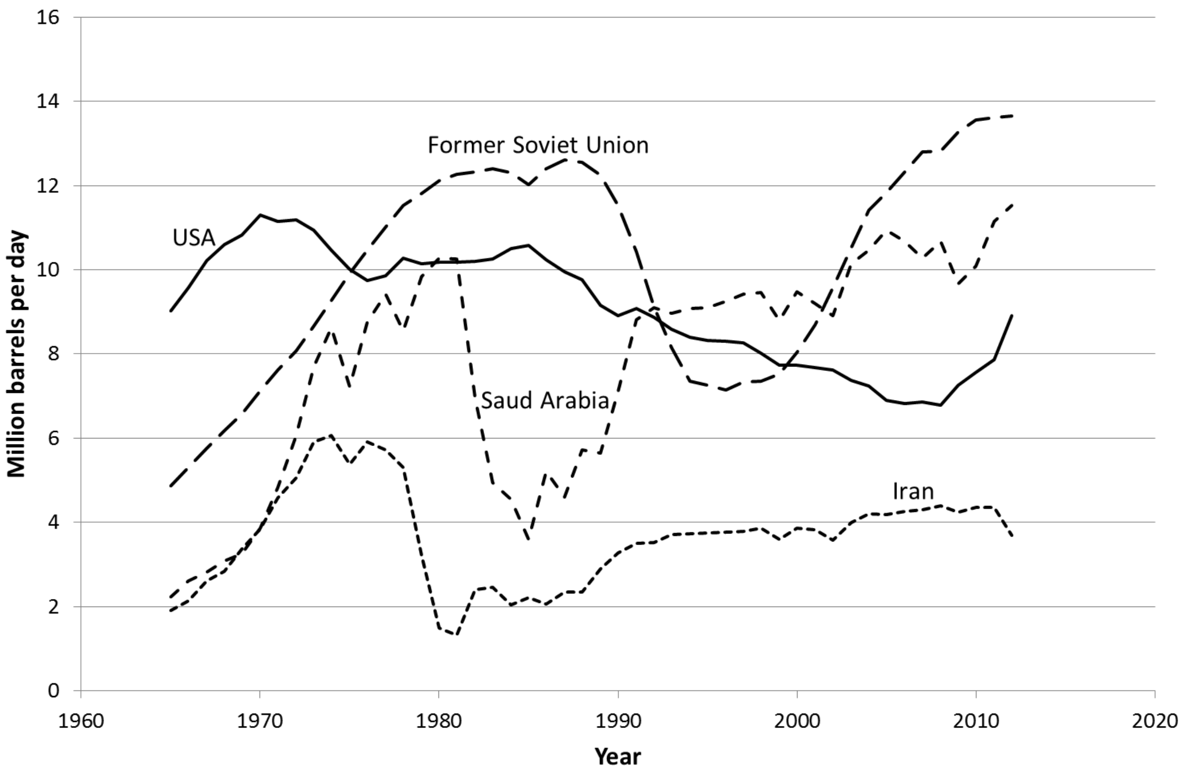


Source: Sorrell *et al.* (2009)

Notes: Oil in this figure includes crude oil, condensate, natural gas liquids, liquid petroleum gas, heavy oil, and synthetic crude oil from oil sands.

North America, and particularly the United States, dominated global oil production for most of the first half of the 20th century (Figure 4.2). However, some saw the exponential growth in US oil production as unsustainable trend and Hubbert (1956) developed techniques to estimate the point at which US oil production growth might cease, leading to peak production and subsequent decline. Though many refuted Hubbert's argument, US production did in fact peak in 1970, very close to his estimated date (see section 2.1.3). This decline in US oil production led to the Soviet Union becoming the largest global producer in 1976, until its own oil production decline under the centrally planned Soviet economy (Reynolds & Kolodziej 2008). Significant oil finds were made in the Middle East, and in Saudi Arabia particularly, during the late 1940s and early 1950s (Simmons 2005). During the period between 1970 and 1990, these finds and the subsequent discovery and development of Middle Eastern oil, led to Saudi Arabia becoming the largest global producer of oil through the 1990s (Yergin 1991; Simmons 2005). The renewed political stability of the Former Soviet Union region improved production rates significantly and, were it still unified, it would be the largest oil producer today (Reynolds & Kolodziej 2008; BP 2013) . Saudi Arabia may have the capacity to produce more than the Former Soviet Union, but its position as 'swing producer' means it maintains an element of unutilised spare capacity (EIA 2014f). As swing producer Saudi Arabia manage their oil production, increasing or decreasing it to maintain a desired oil price on global markets. The role of OPEC countries, and Saudi Arabia specifically in the management of capacity to stabilise price is discussed in more detail in Section 4.2.2.

Figure 4.2: Top four oil producing countries since 1965



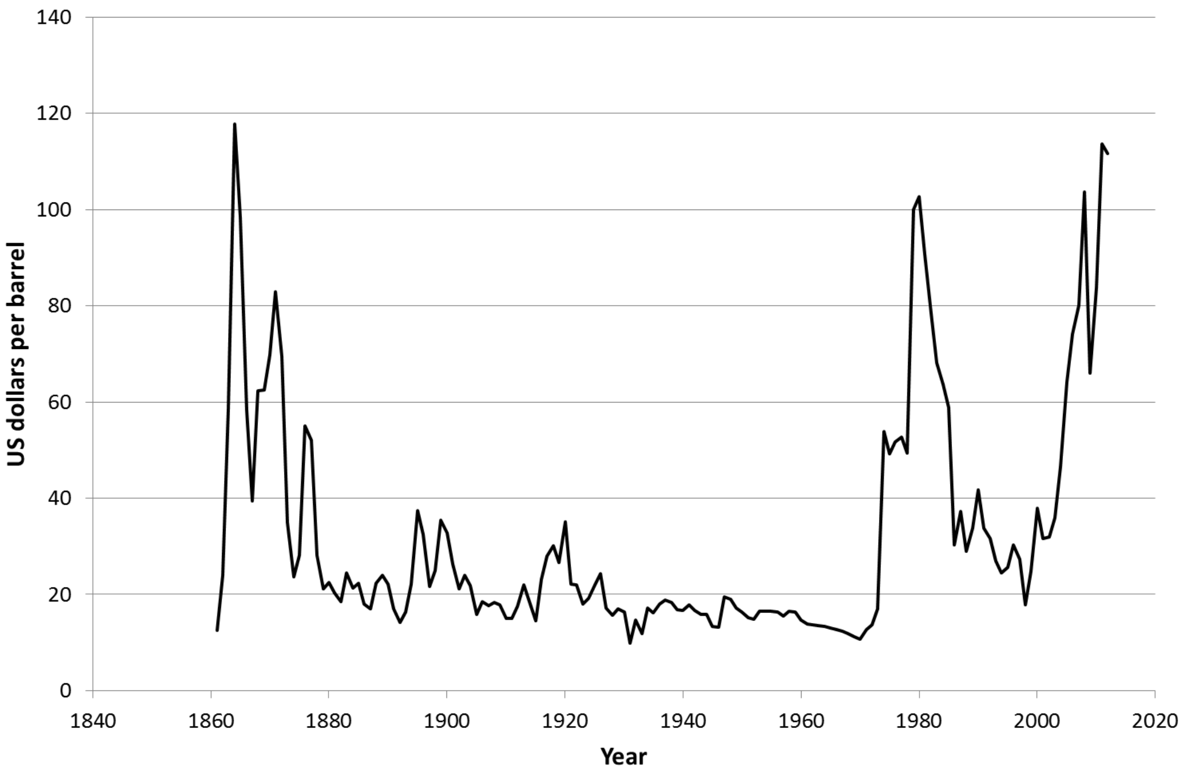
Source: BP (2013)

Notes: Oil price based on three separate price indicators: 1861-1944 US average; 1945-1983 Arabian Light posted at Ras Tanura; and 1984-2012 Brent dated.

In the 1970s, two events disrupted the previous trends in oil production, collectively referred to as the 1970s oil crises or oil shocks (Yergin 1991). The first of these occurred in 1973, when the Arab members of the Organisation of Petroleum Exporting Countries (OPEC) proclaimed an oil embargo in response to the Western countries support for Israel during the Yom Kippur War (Cleveland & Morris 2014b). OPEC was created by exporting countries in 1960 to help support the global price of oil by strategically limiting global supply (OPEC 2014). However, in this instance the organisation attempted to use its control of global production to punish supporters of its enemy. The second oil crisis occurred in 1979 as a result of the Iranian Revolution (Cleveland & Morris 2014b). The revolutionary protests hampered oil production in Iran, and given Iran was a significant exporter, the global oil market was affected. The reducing production from Iran can be seen in Figure 4.2.

These events are reflected in both historical production (Figure 4.1) and the historical oil price (Figure 4.3). The oil price has undergone four broad phases throughout the history of the modern oil market. The first and largest phase, from the mid-1800s to the mid-1900s, was a period of price reduction and stabilisation. The high and volatile oil price at the beginning of this phase is largely a function of the relatively small oil market responding to the rapidly increasing demand for oil derived products (Yergin 1991). By the end of the 1960s the global oil price was near its 100 year low and was significantly less volatile than at any other period throughout the previous century. The impact of the 1970s oil crises on price was significant, upturning the trend of the previous century and forming the second phase in global oil price. However, the high prices of the late 1970s subsided during the 1980s as countries responded to constrained global production (Goldstein 1985). These responses included the utilisation of spare capacity by OPEC countries and the application of efficiency incentives to reduce oil demand in oil importing countries. The third phase in historical oil price stretches from the late 1990s to the present day. A combination of international conflicts such as the Gulf War, the Iraq War and the Arab spring, economic growth in the BRICS countries and the increasingly difficult to produce marginal oil resource led to rapid and significant price rises to historically high levels (BBC 2008). This is the fourth phase of oil price and despite a global economic recession during that period, the global oil price is still at a level that can be considered historically high.

Figure 4.3: Historical global oil price in 2012 US dollars per barrel since 1860



Source: BP (2013)

Notes: Oil price based on three separate price indicators: 1861-1944 US average; 1945-1983 Arabian Light posted at Ras Tanura; and 1984-2012 Brent dated.

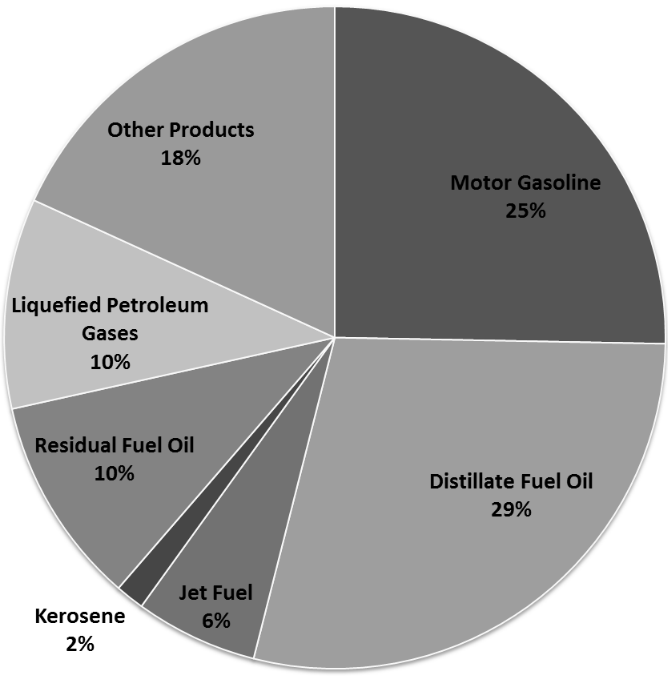
4.2 The dynamics of resource systems

4.2.1 Demand

The development of a resource begins with its demand. A number of factors can drive the demand of a resource, including the economic conditions, policy incentives, and technological transition. The oil market provides a useful example.

Transport fuels make up the majority of oil demand, including motor gasoline, distillate fuel oil (which includes diesel) and jet fuel (Figure 4.4). Developments in transport markets are therefore among the most influential factors in oil demand. Oil consumption has increased significantly in the last three decades, largely due economic growth in BRICS countries, particularly the Asian markets (Enerdata 2013). In contrast, Europe and North America have seen relatively little demand growth over the same period. This is a function of the impact of economic recession in these regions in recent years, coupled with efficiency improvements in vehicles (EIA 2014g).

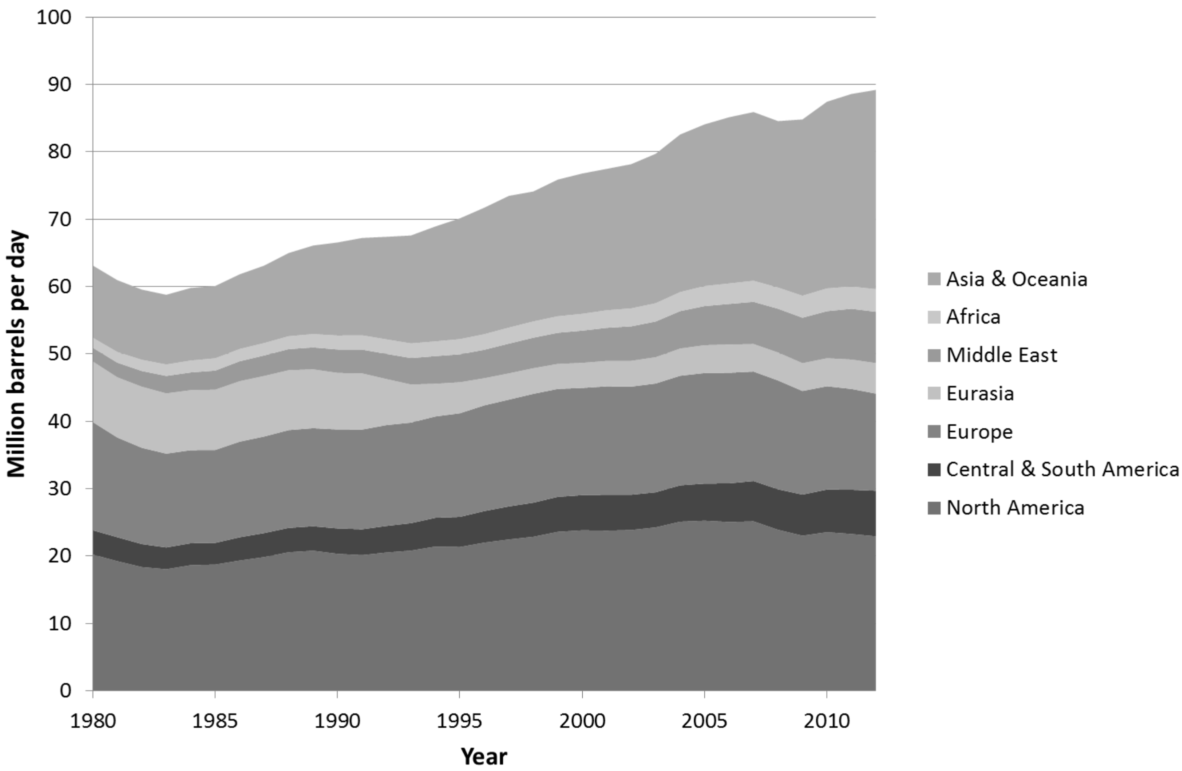
Figure 4.4: Global oil consumption by end product in 2010



Source: EIA

Note: Distillate fuel oil includes diesel

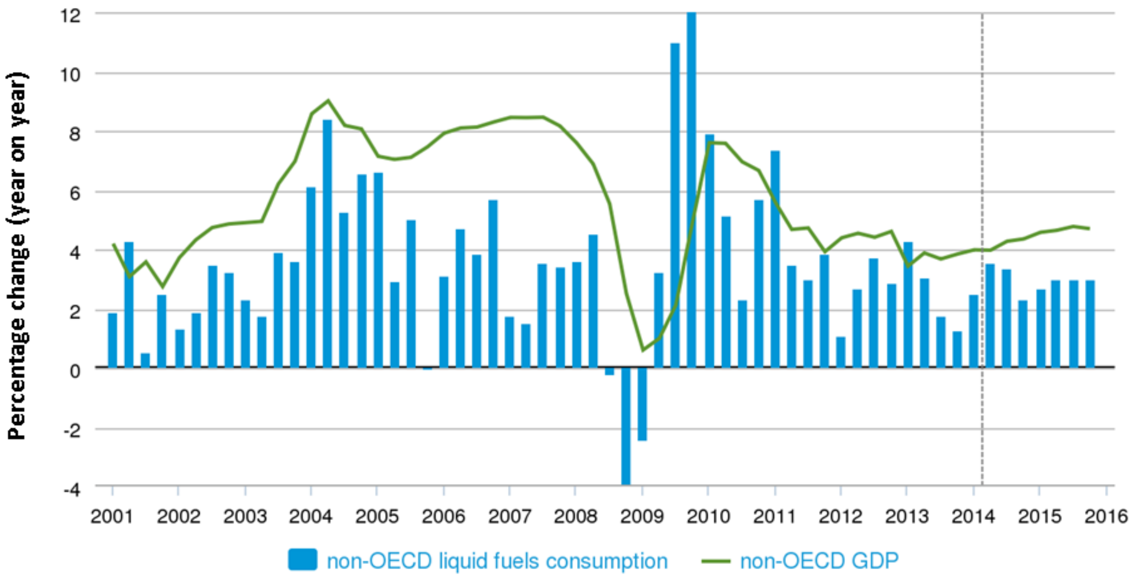
Figure 4.5: Global oil consumption by region from 1980 to 2012



Source: (EIA 2014b)

There is a long-recognised relationship between economic growth and oil demand. This relationship is demonstrated for non-OECD countries in Figure 4.6. Strong links between these two variables can clearly be demonstrated empirically, though the direction of causality is still contested (Kaufmann 1992; Narayan & Popp 2012). It is likely that the relationship between GDP and oil demand is overly simplistic to explain oil consumption trends, with changes in the aggregate activity levels in each major end-use sector; and by changes in the structure of activity within each sector likely to provide a more accurate predictor of oil consumption (Schipper *et al.* 1990). However, accounting for these factors will necessarily increase the complexity of oil demand estimation.

Figure 4.6: Non-OECD liquid fuels consumption and GDP



Source: EIA (2014a)

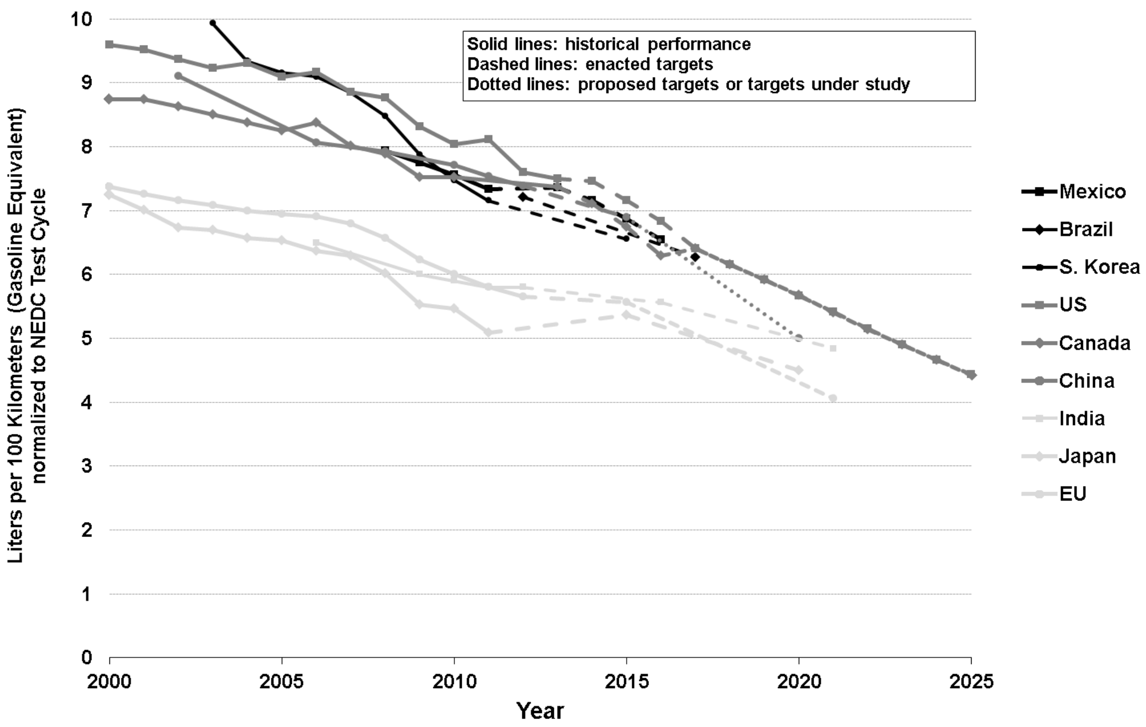
Efficiency

Due to the large role that transport plays in oil demand, the efficiency of motor vehicles is a significant factor affecting future demand. However, driving behaviour also impacts demand, and should also be considered (see rebound discussion below) (NRC 2002; Gallagher *et al.* 2007). If the oil price is high for an extended period of time, then consumers may favour more efficient vehicles, and manufacturers are likely to respond to this consumer preference by manufacturing more efficient vehicles. Alternatively, if a government thinks there are advantages in increasing the efficiency of its country's vehicle fleet it may introduce policy to incentivise manufacturers to improve efficiency. Examples of this kind of policy can be seen in the US Corporate Average Fuel Economy (CAFE) standards (NRC 2002; Gallagher *et al.* 2007; NHTSC 2010). Vehicle efficiency policies may also arise as measures to mitigate greenhouse gas (GHG) emissions, as higher fuel efficiency and lower CO_2 emissions are linked. Vehicle taxation in the UK is an example of a policy aimed at incentivising the purchase of vehicles with lower CO_2 emissions, resulting in improved vehicle efficiency (Brand *et al.* 2013).

The progress in vehicle efficiency has a weakening effect on the link between GDP and oil demand. Over time it is expected that this might lead to a peak in oil demand (The

Electricity Journal 2013), through a process known as 'absolute decoupling' and related to the economic concept of the Kuznets curve (Bithas & Kalimeris 2013).

Figure 4.7: Historical progress in vehicle efficiency and forecast impact of future targets by country from 2000 to 2025



Source: ICCT (2011)

Note:

1. China's target reflects gasoline vehicles only. The target may be higher after new energy vehicles are considered.
2. The U.S. standards are fuel economy standards set by NHTSA, which is slightly different from GHG standards due to A/C credits.
3. Gasoline in Brazil contains 22% of ethanol (E22), all data in the chart have been converted to gasoline (E00) equivalent
4. Supporting data can be found at: http://www.theicct.org/info-tools/global-passenger-vehicle-standards.

In response to efficiency measures an energy system can experience what is known as the rebound effect (Sorrell 2007b). Though this effect is not addressed in this thesis it is worth exploring briefly its implications. Some of the energy demand reductions associated with an efficiency measure can be eroded as reduced demand is likely to make energy cheaper. At a lower price consumers may be willing to use more energy, or a firm may become more profitable and increase its output, using more energy as a result. This is known as the direct rebound effect. Even if direct energy consumption does not rebound, the energy economy as a whole may not experience all the expected benefits of efficiency measures due to indirect rebound effects. These occur when energy consumers take the additional income resulting from cheaper energy prices and spend that income on other goods and services that use energy. The overall impact of rebound effects is debated, but a systematic review of the evidence concluded that at least 10% of energy efficiency improvements might be lost in efficiency measures focussed on transport energy efficiency (Sorrell 2007b).

Substitution

Substitution of a resource can also lead to reduction in demand. For oil, substitutions in vehicle technologies are likely to have the greatest impact given the role of transport in oil demand. As an energy vector, oil can be substituted with coal-to-liquids and gas-to-liquids processes, which can synthesise liquid fuels from these non-liquid fossil resources (Hirsch *et al.* 2005). However, this is likely to have an impact only at the margins due to the costs involved. Countries with significant coal and gas resources but no oil resources may pursue this route (Rong & Victor 2011). These technologies may also have an increased CO_2 intensity and therefore conflict with future climate change policies. Biofuels may also substitute for oil, with a significantly decreased CO_2 impact. This is a technology being pursued in many countries, which is particularly successful in Brazil, where sugarcane is abundant and the process to convert it to liquid fuel relatively cheap (De Carvalho Macedo 1992). At the technology level, electric and hydrogen vehicles remove the need for oil derived fuels, and the development of these types of technologies is expected to play an increasing role in the future (see Chapter 5). As an intermediate technology, compressed natural gas can be used as a transport fuel in suitably modified internal combustion engines. The prospect of such a substitution has been boosted in recent years with the increases in shale gas production in the United States. The low US gas price has prompted calls to develop this type of transport fuel as a way to reduce transport costs and reliance on foreign oil and potentially emissions (Mallapragada *et al.* 2014). However, the progress of these substitute energy vectors or substitute technologies is in its infancy, and the evidence is uncertain as to the rate oil can be substituted in the future.

Another route to oil demand reduction that is additional to efficiency and substitution is the encouragement of transport mode shifting. Encouraging passengers to change from private transport to public transport options, or to walking or cycling may have a significant impact on emissions (Aamaas *et al.* 2013), and may also reduce oil demand (Noland *et al.* 2006). In addition, switching from vehicular transport to active modes of transport such as walking and cycling may have significant physical health benefits (Rabl & de Nazelle 2012), providing a potential win-win for policy makers and encouraging this type of oil demand reduction policy.

4.2.2 Resource discovery, reserves and capacity

Discovery

Non-renewable resources such as fossil fuels or minerals are discovered before they can be produced. The recoverable quantities of those discoveries are often referred to as reserves and the production of those reserves is dependent on, amongst other things, the available production capacity, which is a capital input into the production process. The dynamics of resource discovery, and the capacity to produce discovered reserves, are fundamental to the resource availability system. For example, oil discovery begins with exploration and production (E&P) companies, who employ surface geological assessment, seismic survey techniques and wild cat drilling to identify new oil fields (Sorrell *et al.* 2009).

The first trend in this process is seen in the *field size distribution* of discovered fields where the word ‘size’ refers to the Ultimately Recoverable Resource (URR). It is widely assumed that the majority of resources are found in a small number of large fields and that these fields are typically discovered early in the exploration of an oil producing region. The precise distribution varies with region, and is highly disputed (Drew 1997; Kaufman 2005). Ivanhoe and Leckie (1993) conducted one of the first studies of field size distribution, which demonstrated the relative importance of larger oil fields to the global resource (Table 4.1). Fields were divided into 10 size categories based on their estimated URR. The 370 fields with URR larger than 500 million barrels (giant fields or larger) represented only 1% of discovered fields, but 75% of the volume of all global oil discoveries. This assessment was replicated by

Simmons (2002), Robelius (2007), and most recently by the IEA (2008) who estimated that of 70,000 fields producing in 2007, the 110 largest produced half of global production, the 20 largest fields produced 25% and the 10 largest produced 20%.

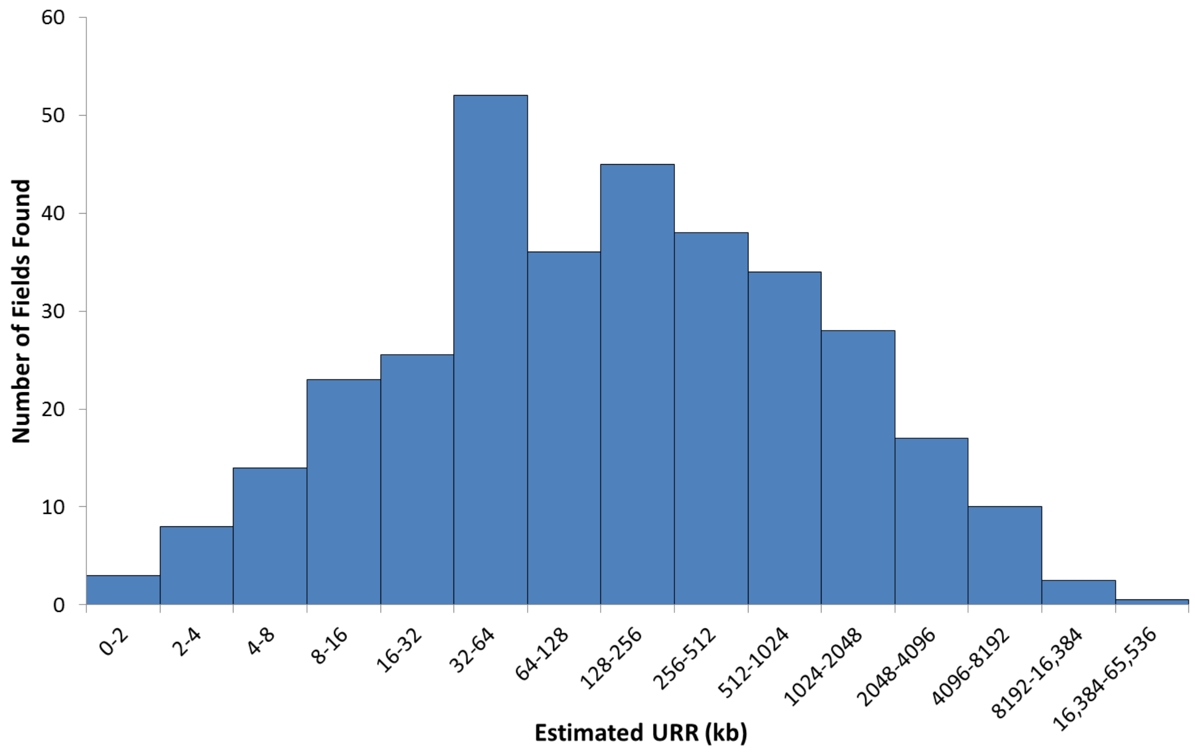
Table 4.1: Ivanhoe and Leckie's estimates of the size distribution of the world's oilfields

Category	Estimated URR (million barrels)	Number globally
Megagiant	>50,000	2
Supergiant	5,000-50,000	40
Giant	500-5,000	328
Major	100-500	961
Large	50-100	895
Medium	25-50	1109
Small	10-25	2128
Very small	1-10	7112
Tiny	0.1-1	10,849
Insignificant	<0.1	17,740
Total		41,164

Source: Ivanhoe and Leckie (1993)

To understand the distribution of field sizes in a region analysts typically infer the underlying distribution from the distribution of known fields. Arps and Roberts (1958) were among the first to observe that the frequency distribution of the logarithm of known field sizes resembled a normal distribution Figure 4.8. This observation was repeated subsequently in several studies (Kaufman 1963; Drew & Griffiths 1965). The understanding of field size distribution lead to the development of sophisticated discovery process models, designed to improve the estimation of YTF (Kaufman 1975; Lee & Wang 1983; Forman & Hinde 1985).

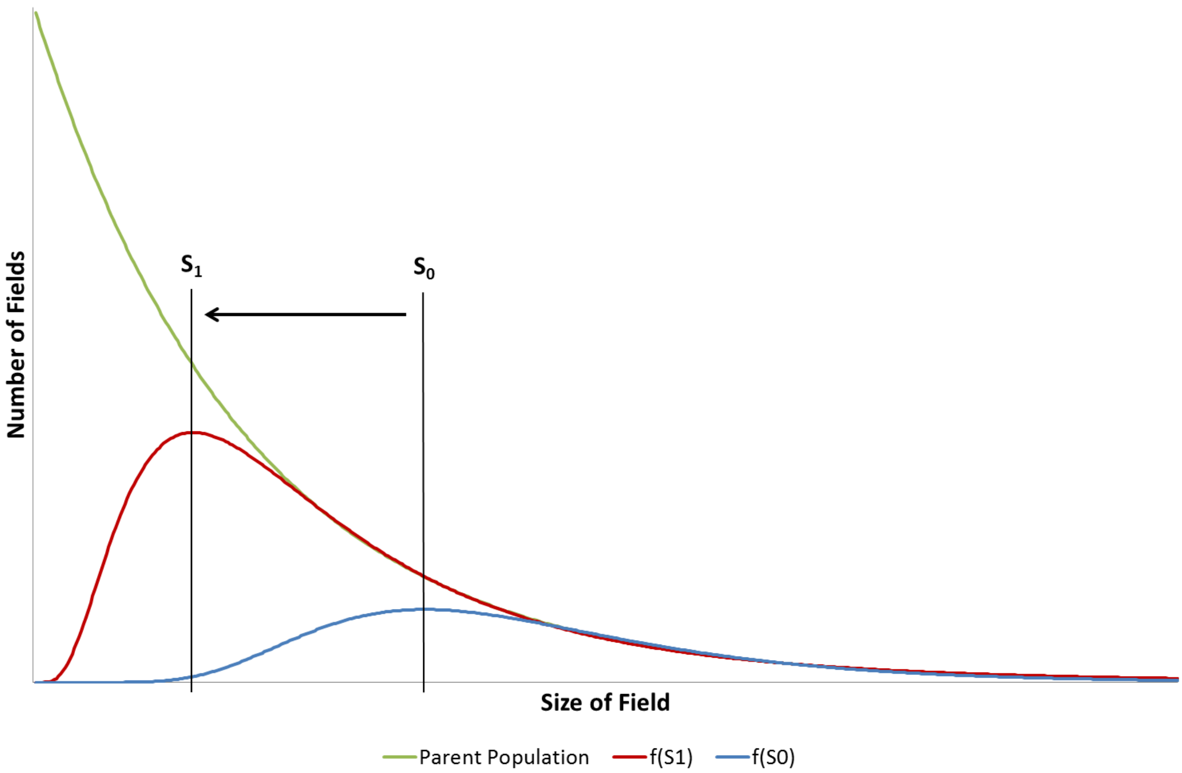
Figure 4.8: Oil and gas field size distribution for the Denver basin in 1958



Source: Adapted from Arps and Roberts (1958) and Drew (1997)

The observed distribution likely under represents small fields that are relatively less economic to develop, referred to as economic truncation (Arps & Roberts 1958; Schuenemeyer & Drew 1983; Attanasi & Drew 1984; Drew *et al.* 1988). The underlying distribution is thus expected to take a 'power-law' form, with the modal size of the observed fields decreasing over time as these smaller fields become economic to produce, and the observed distribution slowly transitions to the underlying distribution (Figure 4.9)(Drew 1997). The result of this is that the size of discovered fields is expected to be large in the initial years and diminishing over time.

Figure 4.9: How the undersampling of small fields may lead to a lognormal frequency distribution of the size of discovered field size



Source: Drew (1997)

Note: Green line indicates 'power-law' size distribution of the population of fields. Blue line indicates the approximately lognormal size distribution of the sample of discovered fields at time t0. Red line indicates size distribution of the sample of discovered fields at t1>t0 when changes in economics and technology have lowered the size threshold for economically viable fields.

Reserves and resources

Once discovered, resources must be assessed, with those proportions that are economically recoverable designated reserves. The definition and classification of reserves and resources is one of the most difficult aspects of the resource systems. Confusing and misleading statements commonly arise through the misinterpretation of reserve and resource estimates or a lack of transparency in reporting them (Bentley *et al.* 2007; Sorrell *et al.* 2009).

First, reserves must be distinguished from resources. In the example of oil, reserves can be defined as:

"quantities of oil in known fields which are considered to be technically …. And economically feasible to extract under defined conditions"

Sorrell *et al.* (2009)

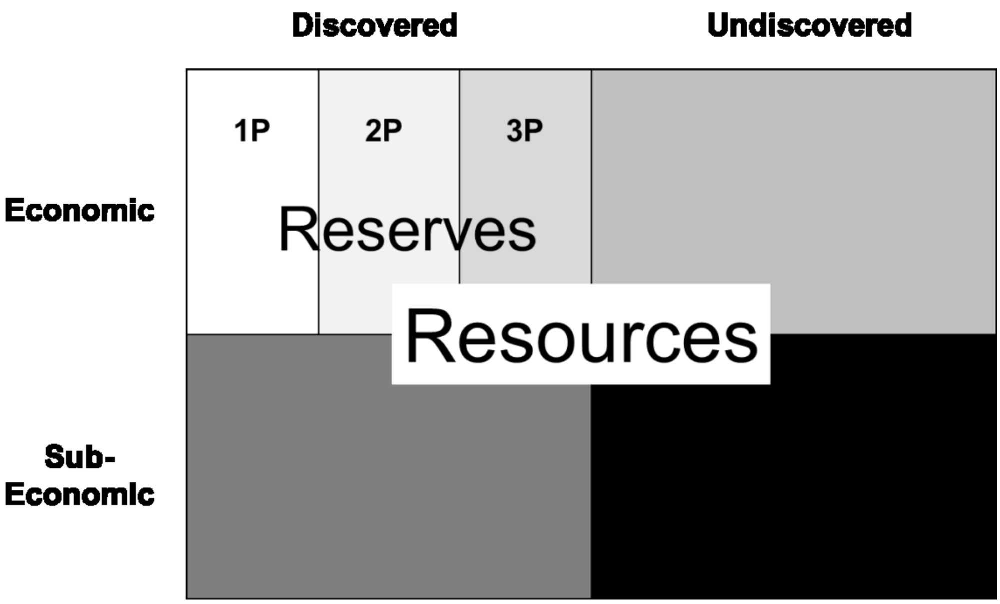
Resources on the other hand can be defined as:

"the total quantities estimated to exist, including those in known fields which are not considered economically feasible to extract as well as those in undiscovered fields"

Sorrell *et al.* (2009)

The relationship between reserves and resources, and other resource classifications, is commonly illustrated by the diagram in Figure 4.10, known as a McKelvey Box.

Figure 4.10: The McKelvey Box, illustrating the relationship between oil reserves and resources



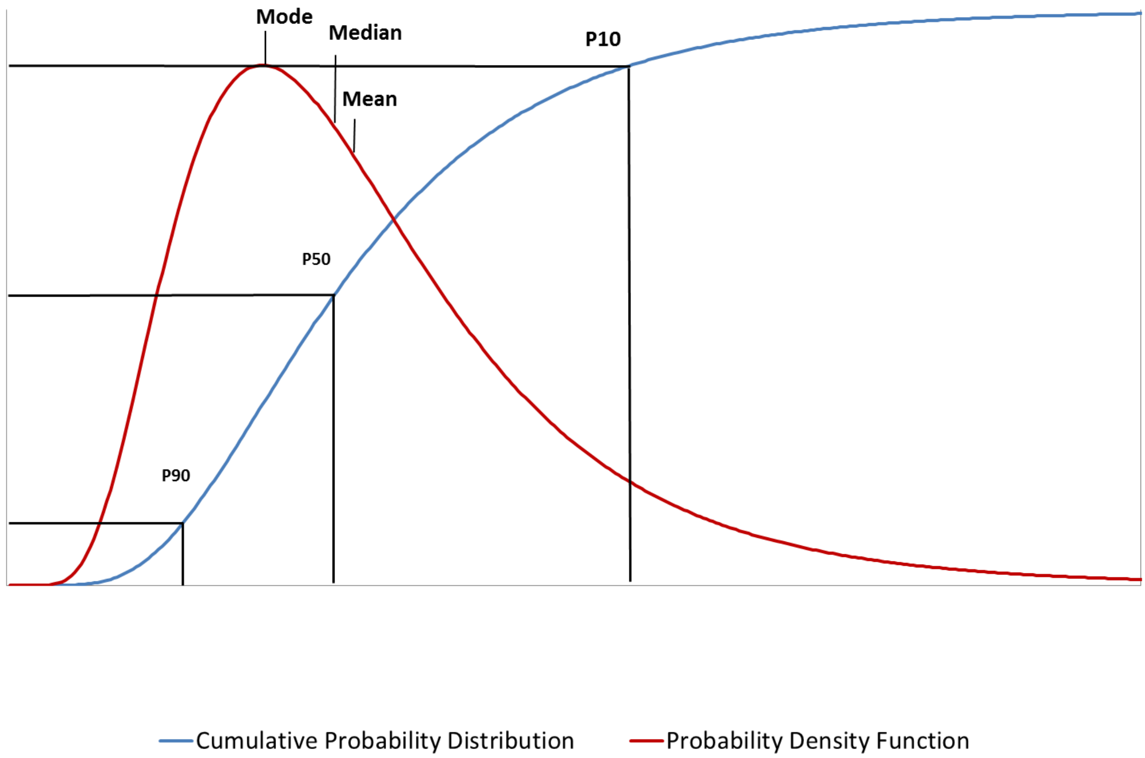
Source:McKelvey (1972)

Reserve estimates are inherently uncertain, relying on assumptions about oilfield geology, extraction technology, economics of production, and the variation of these factors over time. To reflect this reserve estimates are often quoted to three levels of uncertainty. Proved reserves, also known as 1P, refers to reserve estimates with a high probability of being produced. 1P reserve estimates are often equated to P90 estimates, which state a 90% probability that the reservoir will produce more oil than stated in the reserve estimate. This is therefore a very conservative estimate and is often the preferred approach in the investment community to prevent the overstatement of reserves by companies seeking investment (SEC 2009). Proved and probable reserves, also known as 2P, refers to reserves estimates with a medium probability of being produced. 2P estimates are often equated to P50 estimates, which state a 50% probability that the reservoir will produce more oil than stated in the reserve estimate; i.e. the median estimate. Proved, probable and possible reserves, also known as 3P, refers to reserve estimates with a low probability of being produced. 3P reserve estimates are often equated to P10 estimates, which state a 10% probability that the reservoir will produce more oil than stated in the reserve estimate. Though often equated to 1P, 2P and 3P, probabilistic estimates (P90, P50 and P10) must be estimated through the development of probability distributions of the possible outcomes of reserve estimates (Schulyer 1999) (Figure 4.11).

Table 4.2: Deterministic and probabilistic terminologies associated with oil reserves estimation.

Qualitative estimates		Probabilistic estimates	Definition
Proved	1P	P90	High or 90% probability
Proved and probable	2P	P50	Medium or 50% probability
Proved, probable and possible	3P	P10	Low or 10% probability

Figure 4.11: Probability and cumulative probability distribution of recoverable reserves



Source: Sorrell *et al.* (2009)

Note: The probability density function (red line) represents a statistical distribution which in this example is skewed to the left. In the context of reserve estimates, there is no probability of there being a negative volume of oil, but there is a high probability of reserves being somewhere between 0.5 and 2 units, and a small probability of there being a much large amount. The P90, P50 (median) and P10 estimates all represent points on the cumulative distribution function (blue), which is the integral of the probability density function. The vertical scale refers solely to the cumulative distribution.

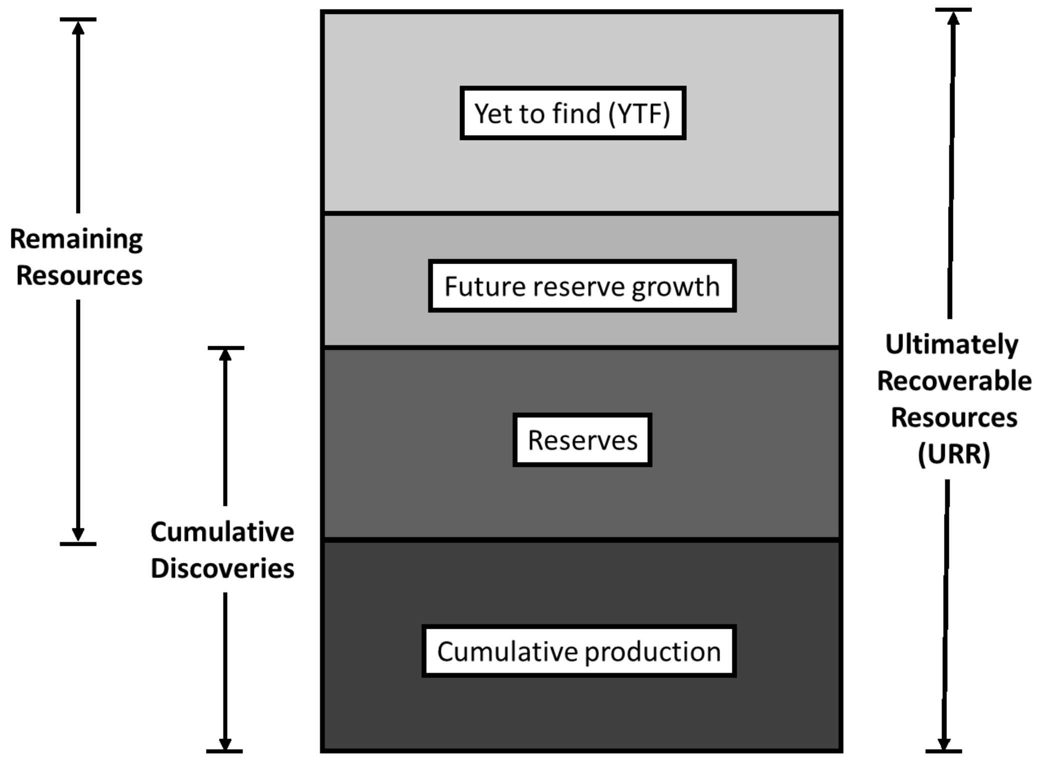
Reserve estimates may be changed over time in a number of ways. Production of a resource reduces reserves for a region or corporation, while new discoveries increase them. Reserves may also be revised as geological knowledge improves, extraction technologies develop, or other changes occur in economic conditions or reporting practices (Sorrell *et al.* 2009). Another measure of resources, known as Ultimately Recoverable Resources (URR) and commonly used in oil resource assessment, attempts to account for these variations. URR is defined as:

> *"the amount of [a non-renewable commodity]] that is estimated to be economically extractable […] over all time"*

Sorrell *et al.* (2009)

In the oil example, to capture the range of variables influencing future recovery, URR estimates consist of four components (Figure 4.12). Cumulative production represents the total volume of oil produced from a field or region. Reserves, as discussed above, are those resources estimated to be recoverable both technically and economically. Together these can be referred to as 'cumulative discoveries', and their time series can be used in the estimation of URR as discussed below.

Figure 4.12: The components of ultimately recoverable resources (URR)



Source: Sorrell *et al.* (2009)

Reserve growth can be defined as:

> *"...the commonly observed increase in recoverable resources in previously discovered fields through time."*

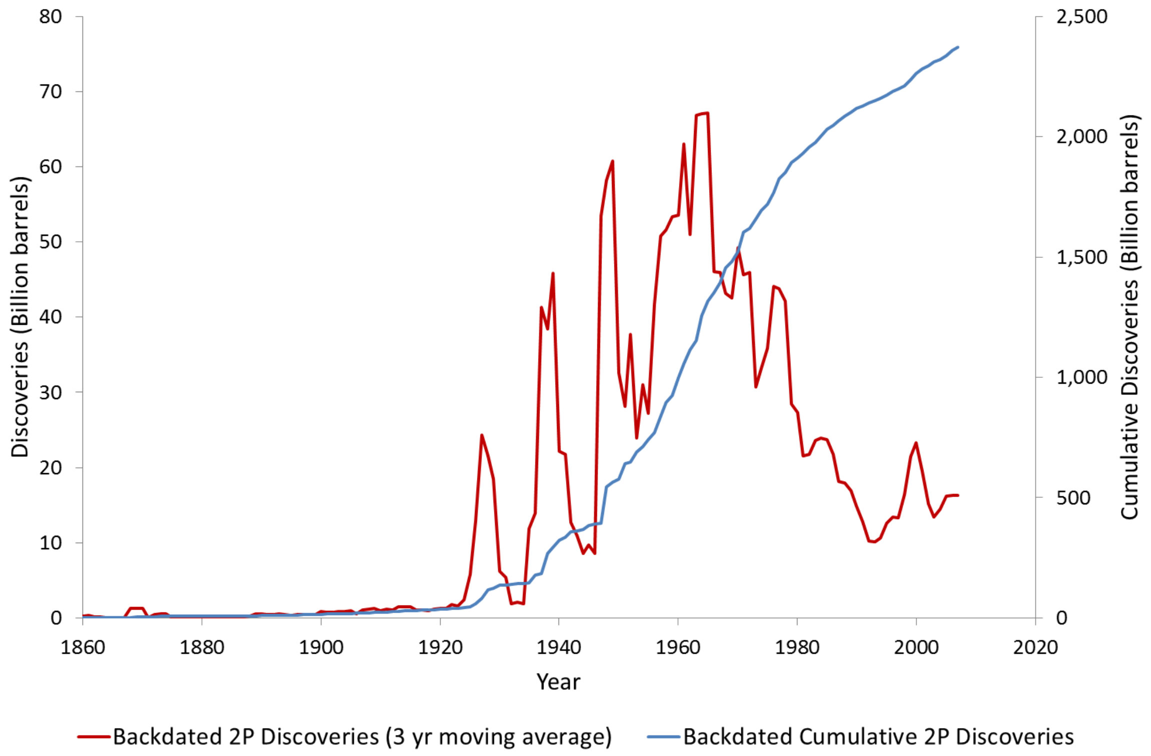
Klett and Schmoker (2003)

Reserve growth accounts for the majority of reserve additions and is expected to do so in the future, though it has historically been a controversial and misunderstood topic (Sorrell *et al.* 2009).

There are several sources of reserve growth. *Geological factors* include any additions to reserves arising through improved geological knowledge of reservoirs. This might include improved knowledge of the shape, volume and characteristics of reservoirs, or the merging of smaller fields initially thought to be separate (Drew 1997). *Technological factors* include any additions to reserves arising from improved technology that increases the proportion of oil recoverable from a reservoir (the recovery factor). It is typical to distinguish between: Primary recovery, where oil is recovered under its own pressure; secondary recovery, where oil pressure is raised artificially using pumps or injection of gas or fluid; and tertiary recovery or enhanced oil recovery (EOR) where thermal or chemical techniques are employed to change the behaviour of oil in the reservoir and improve recovery. *Definitional factors* that may create reserve additions include the change in reserve classification schemes, changes in reporting practices, and variations in economic conditions such as production costs and oil price.

Future discoveries are the final component of URR estimates, and are often referred to as Yet To Find (YTF). As shown in Figure 4.13 global discoveries of oil have followed an approximate bell shaped trend, and though discoveries appear to have peaked sometime in the early 1960s, there appears to be scope for future discoveries following the apparent trend. Any estimate of URR will change depending on the total volume of oil discovered over all time and therefore these estimates must make some account of future discoveries.

Figure 4.13: Global trends in backdated discoveries and cumulative discoveries



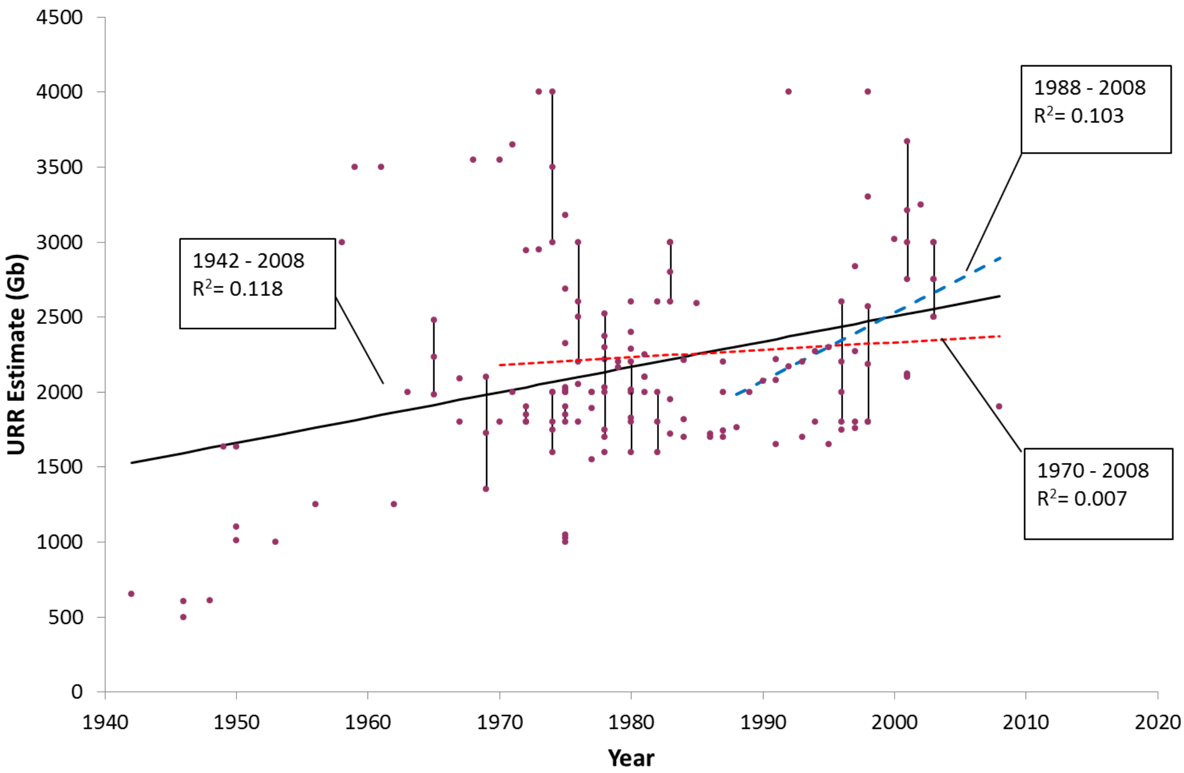
Source: IHS Energy

Note: Includes crude oil, condensate, NGL, LPG, heavy oil and syncrude. Based upon backdated 2P reserve estimates.

Estimates of URR are influential in the forecasting of future oil production, with large URR estimates used to support the more optimistic forecasts of future production. However, the wide range of different classifications of oil (conventional, biofuels, oil sands, shale oil), the range of different data used, and the range of different techniques all contribute to the wide range of URR estimates, and the on-going lack of consensus.

Since the earliest estimates of global oil URR (White 1920), URR estimates have tended to increase. At least 100 estimates have been published since then and the general trend in these is demonstrated in Figure 4.14.

Figure 4.14: Global URR estimates over the last 70 years



Source: Sorrell *et al.* (2009)

Most of the recent estimates are in the range of 2000 Gb to 3000 billion barrels, which compares to cumulative production to 2011 of over 1200 Gb (IEA 2008; BP 2013). Two influential contemporary estimates are the United States Geological Survey (USGS) World Petroleum Assessment (WPA) (USGS 2000) and the IEA World Energy Outlook (WEO) (IEA 2008).

The USGS WPA (USGS 2000), held as the most comprehensive assessment of global oil URR, uses a combination of methods, taking a bottom-up approach, and is the product of 100 person years of effort by 41 geoscientists over a period of five years (USGS 2000; Ahlbrandt 2002). The resulting estimate is bigger than previous estimates conducted by the USGS and has attracted criticism over its validity (Laherrère 2001), though it underpins several authoritative estimates of future oil production (EIA 2008; IEA 2008). The assessment estimated resources with the potential to be added to reserves between 1996 and 2025 using existing technology. The study examined seven regions further disaggregated to 937 'petroleum provinces', though 528 of these were not assessed, presumably because they were unlikely to contribute to global oil supply during the timeframe. Reserve growth was estimated by estimating a reserve growth function for US fields and applying that to all fields considered in the assessment. This obviously only includes fields discovered before 1996 and no estimate of reserve growth was applied to undiscovered fields. Undiscovered resources were estimated through a combination of geological assessment and discovery process modelling, the results of which informed a Monte Carlo analysis used to generate probability distributions of the likely volume of undiscovered resource. The mean estimate for the global conventional URR was **3345 Gb,** of which 3021 Gb were conventional oil and the remainder natural gas liquids (NGLs). This was 47% greater than previous USGS estimates, the result in part of the inclusion of reserve growth and the increase in the estimated NGL resource. The full breakdown of mean results is presented in Table 4.3.

Table 4.3: USGS 2000: mean estimates of global URR for conventional oil (billion barrels)

	US conventional oil	**World (non-US) crude oil**	**World (non-US) NGLs**	**World total conventional oil**
Cumulative production	171	539	7	**717**
Remaining 2P reserves	32	859	68	**959**
Reserve growth	76	612	42	**730**
Undiscovered resources	83	649	207	**939**
URR	**362**	**2659**	**324**	**3345**
Remaining recoverable reserves	191	2120	317	**2628**

Source: USGS (2000)

Note: All figures refer to January 1996.

The USGS evaluated the on-going 'accuracy' of their assessment through to December 2003 (Klett 2005) and found that, assuming a linear rate of discovery, less than half the oil expected had actually been discovered. Reasons for this may include the lack of access to promising regions including Iraq, Iran and Libya, the low oil price in the 1990s (Klett 2005), and the lack of adjustment to undiscovered resources for reserve growth (Sorrell *et al.* 2009). The evaluation found that reserve growth additions appear to be meeting the estimates of the USGS WPA (USGS 2000).

In 2008, the IEA published its latest edition of the WEO, which included an update to the USGS WPA (USGS 2000) work, examining the timeframe from 2007 to 2030. Using data from IHS Energy, an updated evaluation of the USGS WPA assessment (Klett *et al.* 2007), and additional analysis from USGS and IEA databases a new collection of global URR estimates was generated (Table 4.4). The result of this assessment is a global conventional oil URR estimate of **3577 Gb,** 6.9% greater than the USGS estimate (USGS 2000). However, the IEA WEO (2008) also provides a 'long-term oil-supply cost curve' which provides slightly more optimistic figures, and if added to cumulative production, implies a URR of **4276 Gb**.

Table 4.4: IEA WEO (2008): mean estimates of global URR for petroleum liquids (Billion barrels)

	OECD	Non-OECD	World	% diff from USGS (2000)	OECD as % of total
Cumulative production	363	765	1128	32.20%	57.30%
Remaining 2P reserves	95	1147	1241	7.70%	29.40%
Reserve growth	27	375	402	6.70%	-44.90%
Undiscovered resources	185	620	805	23.00%	-14.30%
URR	670	2907	3577	18.70%	6.90%
Remaining recoverable reserves	307	2142	2448	24.70%	-52.80%

Source: IEA (2008)

In 2013 the IEA WEO presented new oil resources estimates, focusing on sources of unconventional oil (IEA 2013). This work built on the original estimates of conventional oil established by the USGS, and shows a modest increase from the 2008 estimate from 2,448 billion barrels to 2,668 billion barrels in 2013. However, the unconventional contribution to global resources in this new estimate is significant. Approximately 3,300 billion barrels of oil are estimated to be recoverable, more than doubling the estimate of remaining recoverable resources.

Table 4.5: Remaining recoverable oil resources and proven reserves, 2012 (billion barrels)

	Conventional resources		Unconventional resources			Totals	
	Crude oil	NGLs	EHOB	Kerogen oil	Light tight oil	Resources	Proven reserves
OECD	**315**	**102**	**811**	**1 016**	**115**	**2 359**	**240**
Americas	250	59	808	1 000	81	2 197	221
Europe	59	33	3	4	17	116	14
Asia Oceania	6	11	0	12	18	47	4
Non-OECD	**1 888**	**363**	**1 069**	**57**	**230**	**3 606**	**1 462**
E.Europe/Eurasia	347	82	552	20	78	1 078	150
Asia	96	27	3	4	56	187	46
Middle East	971	168	14	30	0	1 184	813
Africa	254	54	2	0	38	348	130
Latin America	219	32	498	3	57	809	323
World	**2 203**	**465**	**1 879**	**1 073**	**345**	**5 965**	**1 702**

Source: IEA (2013)

Notes: Proven reserves (which are typically not broken down by conventional/unconventional) are usually defined as discovered volumes having a 90% probability that they can be extracted profitably. EHOB is extra-heavy oil and bitumen. The IEA databases do not include NGLs from unconventional reservoirs (*i.e*. Associated with shale gas) outside the United States, because of the lack of comprehensive assessment: unconventional NGLs resources in the United States are included in conventional NGLs for simplicity.

Capacity and strategic reserves

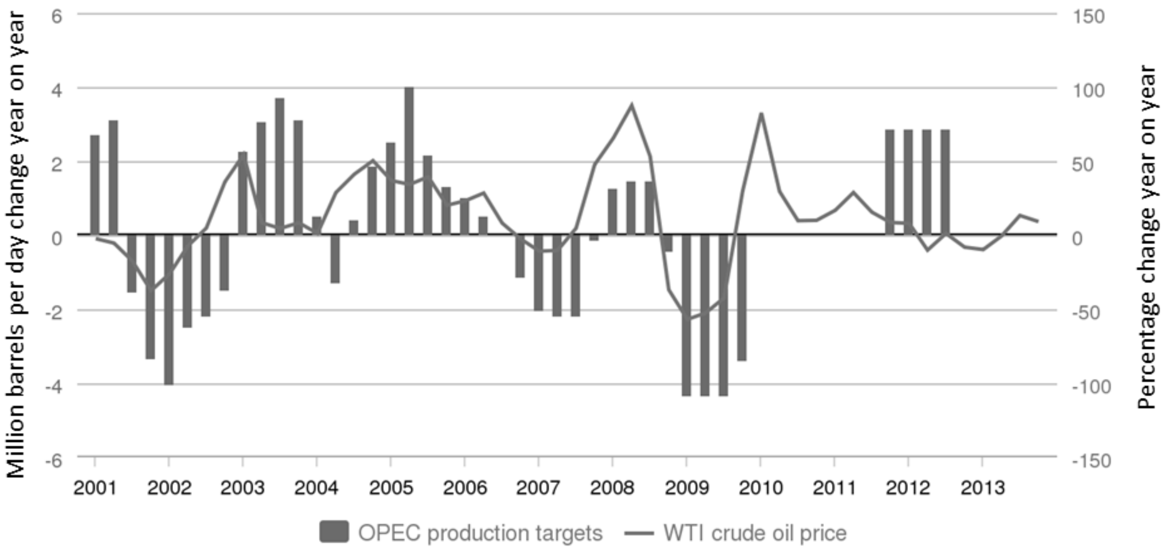
To produce a resource there must be an investment in capital equipment capable of extraction. For exhaustible resources this extraction equipment has a maximum rate at which it can produce the resource, termed the production capacity. To increase this more investment is needed. The dynamics governing the rate at which capacity can be built and the rate at which it decreases through age and wear determine the responsiveness of resource production to its drivers (See Section 4.2.3).

Often the rate at which production capacity can be increased is limited due to capacity build rates and other planning, building, financing and commissioning issues. Strategic reserves of several different commodities are therefore held by countries or economic regions in order to buffer the impacts of potential constraints in building additional capacity. The issues of capacity building and strategic reserves are highlighted below in the case of oil.

Global oil production capacity is greater that global production, the balance termed 'spare capacity[9]. Currently spare capacity is almost exclusively held by OPEC countries, and the level of this spare capacity is often used as a measure of the tightness of global oil supply (EIA 2014f). OPEC's ongoing mission is to maintain the oil price at a level to support the industry, and this is achieved by maintaining and exercising spare capacity. If the global oil price is seen as too high and damaging to the global economy, then spare capacity will be utilised. If the oil price is judged too low to support the industry, then production will be constrained. Some have argued that the OPEC countries are limited in the modern day in terms of their capacity to play 'swing producer'. However, analysis of the historical data presents compelling evidence that until very recently the impact of OPEC production quotas on the global oil price was significant (Figure 4.15).

[9] EIA defines spare capacity as "the volume of production that can be brought on within 30 days and sustained for at least 90 days" (EIA 2014f)

Figure 4.15: Changes in OPEC production targets and the West Texas Intermediate (WTI) oil price

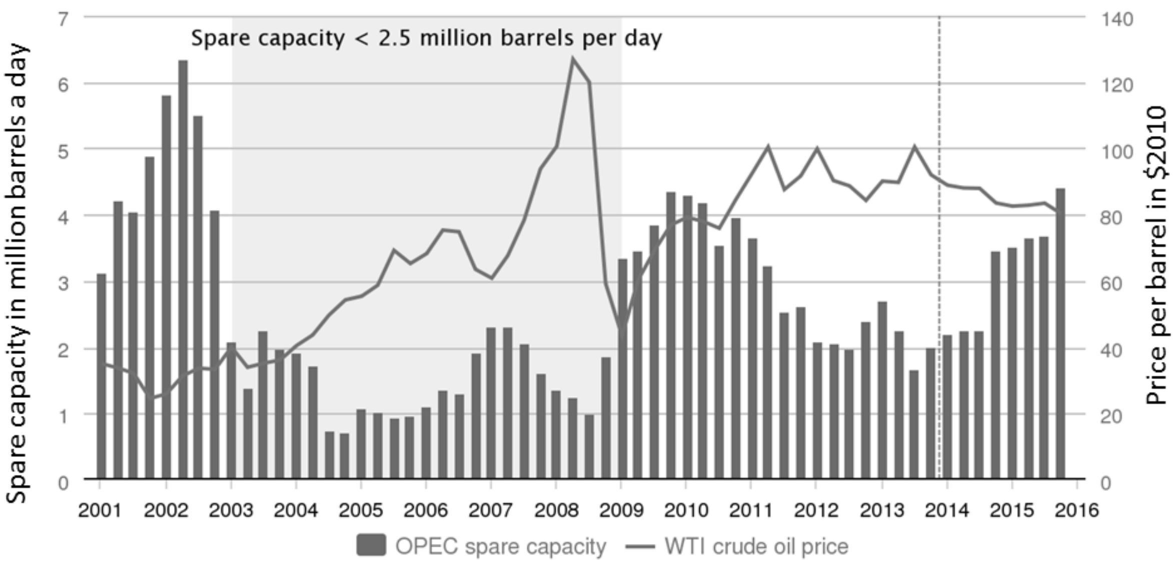


Source: EIA, Thompson Reuters

Note: Updated quarterly with last update 31st December 2013

In recent years, OPEC has maintained in the order of 2 to 4 million barrel per day of spare production capacity. However, between 2003 and 2009, spare capacity was below 2.5 million barrels, an event which has been linked to the oil price spike experienced in 2008 (Figure 4.16). Under a Hotelling view of exhaustible resource economics (Hotelling 1931; Hotelling 1991), privately owned oil companies prevalent in the western world are unlikely to be incentivised to keep spare capacity. OPEC's production capacity is largely owned by the national oil companies of its members and is therefore more susceptible to incentives than purely profit taking.

Figure 4.16: OPEC spare production capacity and WTI crude oil price



Source: EIA, Thompson Reuters

Note: Updated quarterly with last update 11th February 2014

Building new production capacity is a difficult process given the physical and financial scale of these operations and the environments in which they are often installed. A typical offshore oil rig can take 18 to 36 months to construct. However, the time taken from the financial commitment to rig delivery can be significantly longer than this due to shipyard backlogs (Kaiser & Snyder 2012). As production moves into marginal resources in deeper waters or Polar Regions, the first of a kind nature of many of these projects is likely to extend rig delivery times further. This can have a significant effect on the oil resource system's ability to respond to extended periods of tight supply.

Given the economic implications of tight oil supply, many countries and regional political organisations store quantities of oil as a 'strategic reserve'. These reserves can be strategically released onto the global oil market in response to capacity constraints which affect global oil supply, such as weather events that force rig closures, or civil or international conflicts which affect oil producing regions. Approximately 4.1 billion barrels is held globally, with the majority organised and operated the US Strategic Petroleum Reserve and the 28 members of the International Energy Agency (IEA 2007; Reuters 2011). This volume is equivalent to ~45 days of supply at consumption of 90 million barrels per day.

4.2.3 Resource production

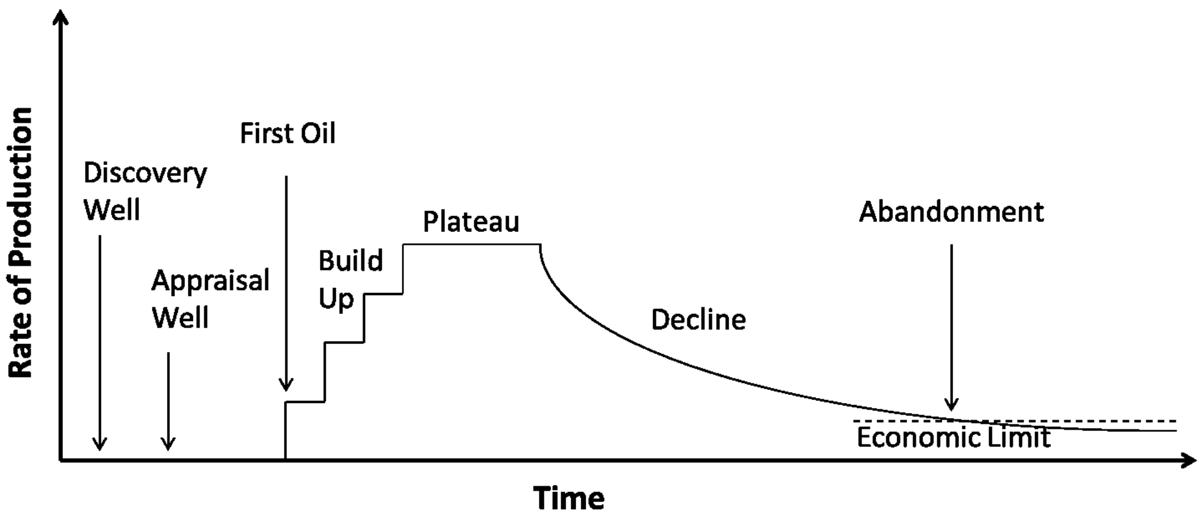
During the production of a resource physical and economic forces have some influence on the rate of production. Often the marginal resource is more difficult to produce and economically rational producers are likely to produce the 'easiest' resources first. This has an impact on the production profile of discrete areas of production (say a mine or well) and knock-on impacts on the production of wider geographical regions of production. Many of these issues are well illustrated in the example of global oil production, and these are discussed below.

The Oil Production Cycle

The production cycle of an oil field has a characteristic shape and while this shape varies between individual fields, the fundamental characteristics are consistent. At the aggregated global level, the shape of field production cycles influences the shape of the global production cycle, as well as future production volumes.

The first phase of oil production is known as 'build-up'. During this phase investment is made in the expansion of production capacity. This typically involves drilling wells, fabricating and installing capital equipment, and training and installing labour. Once production capacity has been increased to a maximum, production will be maintained at 'plateau' until the reservoir pressure has decreased and production begins to 'decline'. The decline phase is typically the longest phase of the production cycle and the rate of decline is an important determinant of the URR for that well. Once the field production rate has declined below economic feasibility, the well is abandoned, sometimes referred to as economic truncation.

Figure 4.17: Stylised production cycle of an oil field



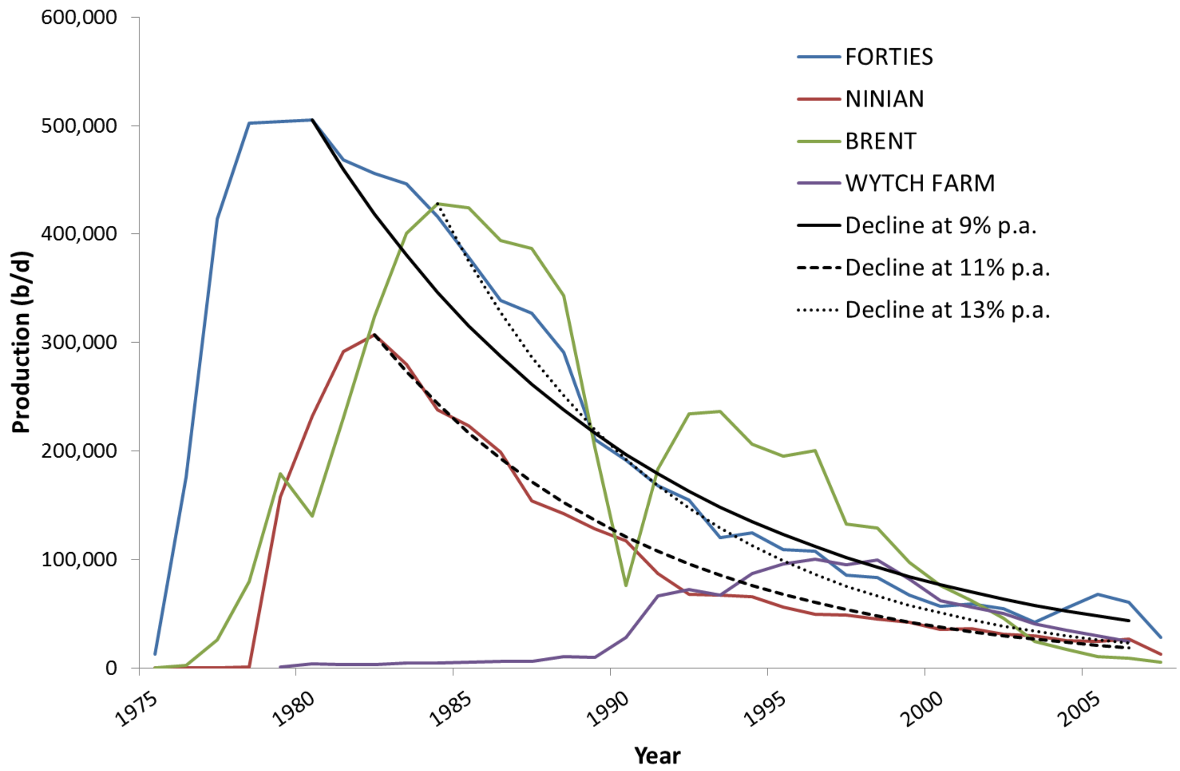
Source: Sorrell *et al.* (2009)

Since build-up is typically faster than decline, many fields exhibit a left skewed shape. Brandt (2007) examines the shape of oil production curves by attempting to fit different curve functional forms to historical oil production data for 74 post-peak regions. First Brandt tested the assumption that regional oil production data typically follows a bell shaped curve by applying a Gaussian curve, and two more simple, non-bell shaped models: an exponential model and a linear model. Brand then applied Asymmetric versions of each of these models to test the symmetry of these data sets. Brandt's (2007) results suggest that, while the goodness of fit is marginal between different models, the asymmetric models tend to fit better than their symmetrical counterparts, and that median rate of decline is 5% less than the median rate of increase, supporting the fact that oil production tends to be left skewed.

Decline rate

The rate of decline may impact significantly on the future production of a group of fields. Estimating the aggregate decline rate for a group of fields is often a key component of oil production forecasts, with decline rates varying significantly depending on location, geology and development (Sorrell *et al.* 2009) (Figure 4.18). However, despite significant work in recent years to consolidate understanding of oil field decline rates (CERA 2008; IEA 2008; Höök *et al.* 2009a) confusion is still evident in some of the emerging literature (Maugeri 2012).

Figure 4.18: Production from four UK oil fields fitted by three exponential decline models



Source: Department of Energy and Climate change (DECC)

The term 'decline' can be applied to various levels of aggregation. When applied to a regional level, it is important to distinguish between the *overall* decline rate, which includes all fields, including those yet to pass their peak, and the *post-peak* decline rate, which refers to the subset of fields of a region that are in decline. A third category, the 'natural' decline rate, is sometimes used; it excludes the effects of capital investment.

The decline rate of a field or region may be modelled using either exponential or harmonic decline in a technique known as decline curve analysis (DCA) (Figure 4.19).

Modelling of decline rates began in the early 20th century (Sorrell *et al.* 2009), though modern DCA is built on the work of Arps (1945) who defined three variables through which decline curves could be expressed: (i) the initial rate of production ($Q(t_0)$); (ii) the decline rate (λ); and (iii) the curvature of decline (β). These are combined the in hyperbolic equation:

$$Q'(t) = \frac{Q'(t_0)}{(1 + \lambda\beta(\mathrm{t} - t_0))^{1/\beta}}$$

4.1

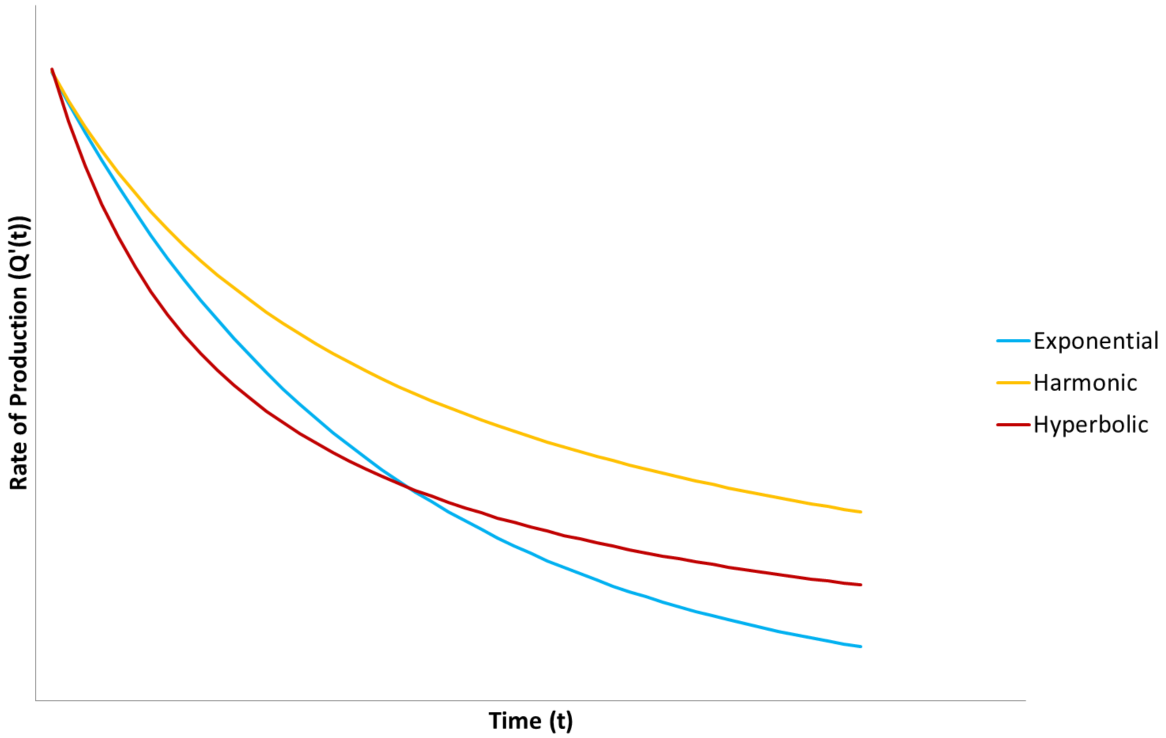
In the case where *b=0* this can be simplified to the exponential equation:

$$Q'(t) = (t_0)e^{-\lambda(t-t_0)}$$

4.2

More recently decline models have developed to include linearised curves(Li & Horne ; Spivey ; Luther 1985) and econometrics (Chen 1991). Decline curve models are often used to estimate URR of a field.

Figure 4.19: Three types of curve used in Decline Curve Analysis (DCA)



Source: Sorrell *et al.* (2009)

Towards the end of the last decade, three studies examined decline rates in a sample of individual fields in order to estimate global aggregate decline rates (CERA 2008; IEA 2008; Höök *et al.* 2009a). These studies use different field samples (though all include giant fields which constitute half of global oil production), different definitions, and different methods of production weighting (Sorrell *et al.* 2009). Nevertheless, their estimates of the aggregate decline rate of post peak fields are reasonably consistent: 5.1%/year (IEA); 5.5%/year (Hook *et al*.); and 5.8%/year (CERA) (Table 4.6). The three studies also agree on three points:

- The average decline rate is greater than the production-weighted decline rate, since larger fields decline more slowly than smaller fields (Table 4.7). This is particularly the case in the large fields in the Middle East.
- OPEC fields decline more slowly than other fields, partly reflecting the large field size in OPEC countries and partly through quota restrictions and disruptions to production due to political conflict
- Offshore fields tend to decline more quickly than other fields, reflecting the higher rate of production demanded at these fields in order to recover the higher fixed costs. This tends to lead to higher production peaks, and steeper resulting decline

Table 4.6: Estimates of production-weighted aggregate decline rates for samples of large post-peak fields (%/year)

Parameter	IEA	Höök, et al.	CERA
Onshore	4.3	3.9	-
Offshore	7.3	9.7	-
Non-OPEC	7.1	7.1	-
OPEC	3.1	3.4	-
Total	5.1	5.5	5.8

Source: IEA(2008), CERA (2008) and Höök, *et al*.(2009).

Note: Studies use different data sets, definitions and methods of production weighting. Details missing for CERA since access to the full study is not available.

Table 4.7: IEA estimates of aggregate production-weighted decline rates for different sizes of post-peak field (%/year)

	Total	Supergiant	Giant	Other
Onshore	4.3	3.4	5.6	8.8
Offshore	7.3	3.4	8.6	11.6
Non-OPEC	7.1	5.7	6.9	10.5
OPEC	3.1	2.3	5.4	9.1
All Fields	5.1	3.4	6.5	10.4

Source: IEA (2008)

Note: The production-weighted decline rate is 1.4% in decline phase 1, 3.6% in decline phase 2 and 6.7% in decline phase 3. The production-weighted average for phase 1 is strongly influenced by Ghawar. The production-weighted sample average for post-plateau fields is 5.8%.

Importantly, two of these decline rate studies find that decline rates appear to be increasing over time or, rather, newer fields tend to have steeper decline rates (IEA 2008; Höök *et al.* 2009a). This aligns with the findings of all three studies in that newer fields tend to be smaller (see 4.2.2) and/or offshore. The results of these studies are also likely to be underestimates given that the average size of fields in their samples is likely to be greater than the average size of all fields globally[10]. Given this, the IEA estimate the global decline rate for post peak fields at 6.7%/year, optimistically assuming that smaller fields are not in their sample decline at the same rate as 'large' fields (10.4%/year). Since some fields currently producing are in 'build-up', the decline rate of all fields is less than the decline rate of post-peak fields, possibly between 4.1 and 4.5%/year (CERA 2008; Sorrell *et al.* 2009).

Depletion Rate

Not to be confused with decline rate, depletion rate is a measure of the rate at which the recoverable resources of a field or region are being produced. The depletion rate of a field is defined as the ratio of annual production to an estimate of resources. When the resource estimate is proved reserves, the depletion rate is simply the inverse of the more common reserve production (R/P) ratio. However, depletion rates can also be calculated using more

[10] Data sets of field sizes are likely to be biased towards larger fields since smaller fields are impractical to record, often impractical to produce, and difficult to detect.

inclusive resource estimates such as proved and probable reserves or URR. In contrast to decline rate estimates, depletion rate estimates rely on inherently uncertain and variable estimates of resources, and with higher estimates of resource comes lower estimates of the depletion rate.

The depletion rate typically follows the profile of production increasing rapidly during the build-up phase, reaching a maximum rate near peak production, and slowly decreasing as production declines. Höök *et al.* (2009b) demonstrate that the maximum depletion rate for giant oil fields (defined as those producing more than 100,000 barrels of oil per day) falls within a relatively narrow range, with a production weighted average of 7.2% per year. The concepts of depletion and decline rates are linked. For fields that are depleted very quickly, very high peak production may be achievable, but this will create steeper decline rates. This has been used in the past as a way to confine the range of possible assumptions in oil production forecasts (Sorrell *et al.* 2009). It is therefore possible to use these measures to critique the plausibility of oil production models, though care must be taken to make fair comparison (McGlade 2014).

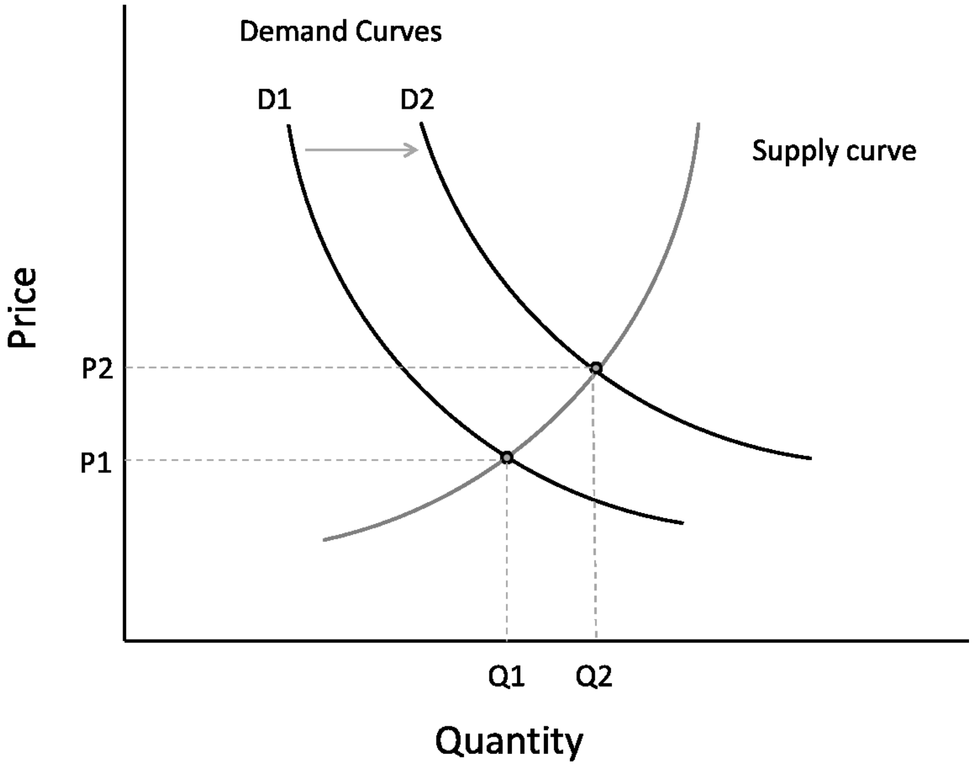
4.2.4 Formation of the resource price

The price of a resource or commodity is commonly taken to be one of two things: the price paid for immediate delivery, known as the 'spot price'; or, the price paid on the commodities trading exchanges for the commodity to be delivered at a predetermined point in the future, known as the 'futures price'. Other types of trading products exist, such as options or spreads, but these are not considered further in this analysis (Newell 2011). Futures price data is more commonly referenced since this information is published by the commodities exchanges that they are traded on while the spot price is harder to obtain as it is an aggregate of all the prices paid by refiners, who do not collate this data.

Economics of resource price formation

Price formation is typically a function of the supply/demand balance. As previously mentioned, supply of a resource is a function of price, among other related variables, and as price rises, so too does the quantity of supply. The price at which supply and demand are balanced is known as the equilibrium price. Figure 4.20 demonstrates this as understood in microeconomic theory (Stiglitz & Walsh 2006). As demand increases, shown as the shift in demand curves from D1 to D2, then the price at which supply and demand are in equilibrium also increases. The quantity of output will also increase under these conditions, as shown on the x axis in Figure 4.20.

Figure 4.20: Supply and demand curves indicating the changing equilibrium price with changing demand



Source: Adapted from Stiglitz and Walsh (2006)

Notes: Demand and supply curves indicate the level of demand or supply for any given price. The equilibrium price (where supply and demand are in balance) occurs at the intersection between supply and demand curves (P1). As demand increases, indicated by the shift from demand curve D1 to D2, then the equilibrium price also shifts, moving from P1 to P2. This shift also increases the quantity of commodity supplied, moving from Q1 to Q2.

A number of issues in the resources markets are likely to interfere with the functioning of price formation as described above. Traders are unlikely to know the equilibrium price exactly. In practice, traders in commodities first form an *expectation* about the price level needed to clear the market[11], and base their trades on that expectation (Sterman 2000).

[11] The 'market clearing price' is the price at which the quantity supplied equals the quantity demanded. This is synonymous with the equilibrium price.

That expectation is likely to be wrong and is adjusted in subsequent transactions, as traders examine the market responses, particularly the actual price (Sterman 2000). This process of anchoring a price and then adjusting it iteratively is known as 'price discovery'(Garbade & Silber 1983). Traders' expected price will respond to changes in the apparent supply/demand balance (inventories), changes in the apparent cost associated with producing a resource and any other information that may lead traders to expect price to be changing, such as news of developments in oil extraction technologies, or geopolitical issues in oil producing countries(Newell 2011). The time it takes traders to discover the actual equilibrium price creates a delay in the price discovery feedback loop, which can create some lag in the response to a changing equilibrium price (Sterman 2000). These, and other system delays, create the conditions for price volatility and oscillation, a common feature of historical commodities price. This volatility is particularly apparent when examining the historical oil price on a daily frequency (Figure 4.21).

Figure 4.21: Daily oil price from 1995 to 2014

Source: EIA (2014e)

The availability of spare capacity is another factor influencing the functioning of price discovery (Carollo 2012). A simple supply and demand price formation model, as presented in Figure 4.20, assumes that:

1. There is always spare producing capacity; and
2. There is always spare refining capacity.

Since neither of these is necessarily true the impact of these assumptions is worth considering in the example of oil. First, spare producing capacity has fluctuated significantly in recent years, and the oil price has responded to that spare capacity, particularly when spare capacity is very low (see Figure 4.16). This response reflects the markets' fear that low spare capacity leads to unserved demand. Second, the refinery business traditionally has very tight profit margins (CME Group 2013). Refinery operators are therefore reluctant to build significant quantities of spare capacity. In addition, shifts in the types of crude available to the spot market mean that refiners have to upgrade their plant periodically to accommodate changes in viscosity and sulphur content (Cross *et al.*). This means that it is very difficult for refinery capacity to keep pace with changing market conditions, impacting on the availability of capacity (CME Group 2013). Literature on the implication of these production and refinery capacity issues suggests that as much as $27 of the price increases seen between 2004 and 2006 can be attributed to tight production and refining capacity (Kaufmann *et al.* 2008).

In the wake of the oil price peak of 2008, research began to examine the extent to which traders could influence the spot price through its trading in the futures market (Kaufmann & Ullman 2009; Silvério & Szklo 2012). The concern expressed by several commentators was that traders sought to profit by increasing their trading in futures contracts, which the market would perceive as increased demand, resulting in increased price. It has often been argued that traders have little influence on the price of commodities, and that the market fundamentals of supply and demand are the only important factor. Research suggests that recent price increases in the oil market may have been based on these fundamentals, but exacerbated by oil trading (Kaufmann & Ullman 2009). Further, it has been suggested that the influence of traders on the spot market has been increasing over time (Silvério & Szklo 2012).

Regional prices

Until now this section has been referring to 'price', implying the global market price. However, many resources are subject to regional variations in price. For example, while oil is traded globally, there are some regional characteristics to the oil market, and this is reflected in price. Oil around the world is produced in different qualities, usually measured in terms of the viscosity (light crudes are low viscosity and heavy crudes are high viscosity) or the level of sulphur (sweet crudes have low sulphur content while sour crudes have high sulphur content). These different crude oils have different prices since the light sweet crudes are traditionally easier to refine and therefore in higher demand. Benchmark crude oils are used to provide reference price information for buyers and sellers. West Texas Intermediate (WTI) a North American benchmark, and Brent Blend in the UK, are two examples of benchmarks, useful as reference as they are both light and sweet, though Brent Blend is slightly heavier and sourer (Fattouh 2010). Dubai and OPEC reference basket are two other another oil price benchmarks, representing prices more relevant to the heavier and sourer crudes coming from the middle east (OPEC 2005; Fattouh 2010). Given the differences in these benchmarks, WTI historically traded at a premium to these other crudes. However, WTI has been discounted significantly against Brent Blend in recent years, conflicting with the expected market response to oil quality (Kao & Wan 2012). A number of factors may influence these changing regional price differences. US refiners have upgraded their capacity for refining sour crudes in response to the increased production and trading in these types of oil. As a result, the sweet WTI crude is in less demand. This has also led to increasing inventories of WTI, further impacting on price (Kao & Wan 2012).

Figure 4.22: The monthly WTI and Brent oil price history in dollars per barrel between 1995 and 2014

Source: EIA (2014e)

Note: This time series shows the slight premium commanded by WTI from 1995 until 2010, at which point WTI is discounted against Brent significantly for the remainder of the time series.

Price elasticity of supply and demand

For most goods or services, demand decreases as the price increases. The relationship between a change in price and the resulting change in demand is referred to as the *price elasticity of demand* (Stiglitz & Walsh 2006). Understanding the percentage change in demand given a one percent change in price is a difficult task and price elasticity is a function of a number of variables (Hamilton 2008). First, the availability of substitutes significantly affects demand elasticity. If there are easily available and close substitutes, then demand is likely to decrease significantly as price increases and consumers switch to these substitute goods. For oil, substitutes, while available, are not close substitutes, are more expensive and are not widely available. The proportion of average income spent on a good or service also impacts on its demand elasticity (Stiglitz & Walsh 2006). If the proportion is low, then consumers can accept large price rises without experiencing significant changes in their personal finances. For oil, this is a regionally specific variable, as the proportion of income spent on oil derived products varies significantly by region. Countries have varying taxes on oil and its derived products, varying trends in the usage of important oil products such as transport fuel and, above all, varying incomes. Countries such as the US pay much less for their oil than Western Europe, though much of the difference is a result of tax in European countries. While the lower price in the US might suggest that demand should be less elastic there, the high taxes in Europe mean that large changes in oil price result in much smaller changes in the pump price of petrol or diesel. It is therefore difficult to unpick the various factors influencing elasticity of demand. Price elasticity of demand is also difficult to measure directly and aggregating to the global level is therefore also problematic.

Historically, oil demand was thought to be relatively inelastic, as its utility and lack of substitutes meant that consumers were willing to experience significant price rises before reducing demand through switching modes of transport, or car journeys. However, the price of oil has increased significantly in recent years, at a much faster rate than wages. This has prompted some revaluation of the relationship between oil demand and oil price.

Price also has an impact on supply, which is referred to as the *price elasticity of supply*, again determined by a number of factors. First, the time delay between price change and the industry's ability to respond is critical. Given the long time-delays associated with bringing on new capacity, oil demand can be very inelastic in the short-run where responsiveness is a function of the spare capacity. In the long run, new capacity can be built, but this relies on long term price certainty. In recent years, where oil price has become more volatile, the response of producers has been more muted than would be expected given the very large rise in average price in the last decade.

4.2.5 The distorting impacts of Cartel on resource systems.

This chapter begins to build evidence to inform the generic resource system model and is largely informed by the experience of the oil market. However, to simplify this model and provide a robust base-case resource model with which to compere to other resources it is not subject to the cartel influences experienced in the global oil market. The Organisation of Petroleum Exporting Countries (OPEC) provides the cartel influence in the global oil market and OPEC's impact is to distort many of the aspects of the resource system from the expected behaviour under perfect market conditions (Gately 2004; Hamilton 2008; Carollo 2012; EIA 2014f).

OPEC members, in particular Saudi Arabia, act as swing producer, increasing or decreasing production through a centrally coordinated quota system in order to manipulate global oil prices (EIA 2014f; OPEC 2014). The aim of this is to maintain prices within a band which provides sufficient profit to support producers while limiting higher prices which might erode demand (EIA 2014f; OPEC 2014).

The impact of this market distortion is that marginal production costs do not necessarily correspond to price. OPEC spare capacity is low price and does not respond to market conditions directly, but through the quota system, which is controlled within the organisation. The generic resource system does not seek to replicate this mechanism and therefore is distinguished from the oil resource system by this significant market dynamic.

4.3 Modelling resource systems

The modelling of resource systems is an active area of resources research, with a range of different approaches and modelling techniques used to capture these systems. The oil resource system has proved a particularly attractive subject matter, with many different models focusing on different aspects of the system. This section examines some modelling efforts in order to shed some light on the important aspects of resource system modelling.

The approaches used to model commodity production can be grouped in four categories:

- **simple models,** such as reserve-to-production ratios and curve fitting;
- **system simulation models**, which simulate the underlying economic or physical processes governing discovery and extraction;
- **bottom-up models**, which build up regional supply forecasts from well or field level; and

- **economic models**, which tend to ignore physical processes and focus on the effects of oil price and the impacts of investment[12] (Sorrell *et al.* 2009).

The relative merits of these approaches are contested and the results based on one type of model often differ from the results of another. These model types and the issues surrounding them are discussed below.

4.3.1 Simple models

Simple models include reserve to production or R/P ratios and curve fitting techniques akin to Hubbert's (1982) forecasting methods. R/P ratios simply take the known reserves of a given company, region or for the world, and divides by the current production rate for the same region. The result is an estimate of the number of years of remaining production before reserves are depleted. This may be useful for measuring the future prospects of one company against another, but is less reliable when used to predict the number of years a region can continue to produce.

First, the R/P ratio assumes that reserves are fixed. However, as noted in Section 4.2.2 reserves are traditionally a conservative estimate and likely to grow over time. Second, R/P ratios assume that production rates are fixed and maintainable until the last unit is produced. As Section 4.2.3 notes, production is subject to exponential increases in the early phase of production, entering a phase of decline towards the end of production. This decline can be slowed through investment in enhanced recovery techniques, but these techniques are unlikely to provide the kind of production profile assumed in an R/P ratio.

If trying to estimate the future production profile of a resource producing region, the R/P ratio is likely to be unreliable for the reasons laid out above. Figure 4.23 presents the R/P ratio for oil from 2000 to 2007 calculated for three oil producing regions: The United States, Norway and the UK. Each of these regions has experienced a peak in oil production, with a subsequent period of decline[13]. The R/P ratios provide no indication of this historical

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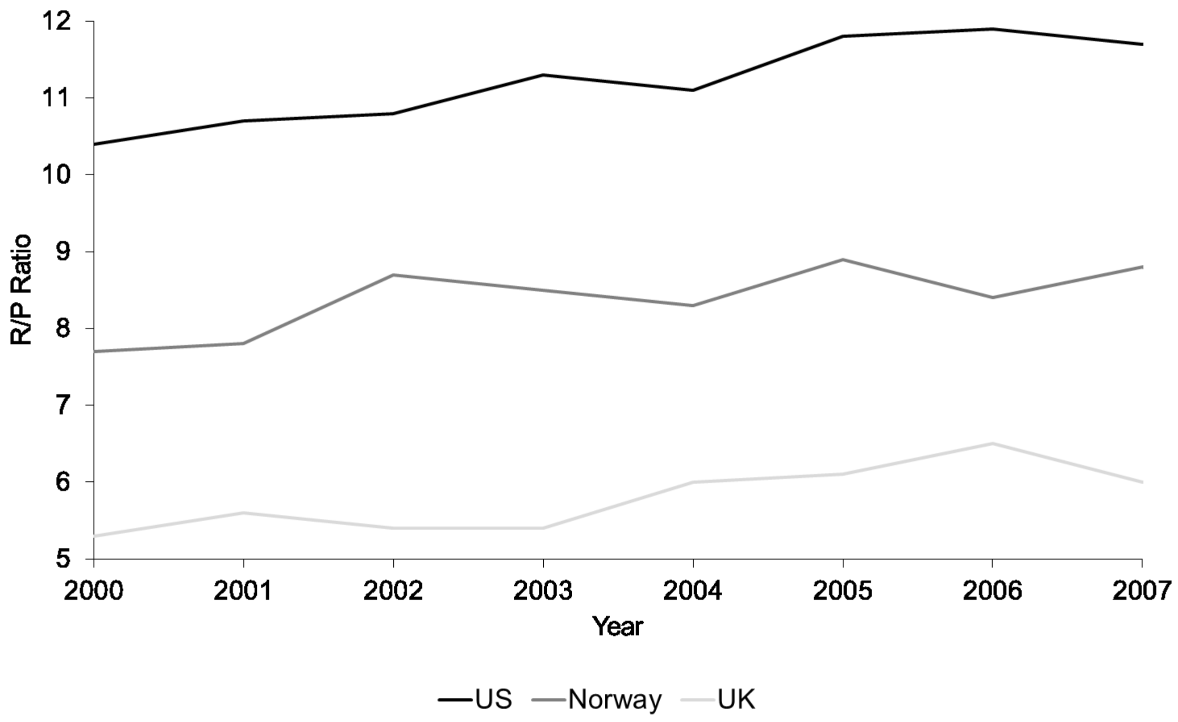
[12] A Technical Report (Bentley *et al.* 2009) and annex to Chapter 7 of the Global Oil Depletion report (Sorrell *et. al.* 2009) provide more detail on oil supply models.

[13] US oil production has rebounded significantly in recent years in response to unconventional oil production. This is not reflected in R/P ratio behaviour.

production trend. A more legitimate application of the R/P ratio is to invert it and present it as a ‘depletion rate’, as discussed in Section 4.2.3 (Sorrell *et al.* 2009).

Figure 4.23: R/P ratios - example of proved reserve to production ratios for the United States, Norway and the UK



Source: Sorrell *et al.* (2009)

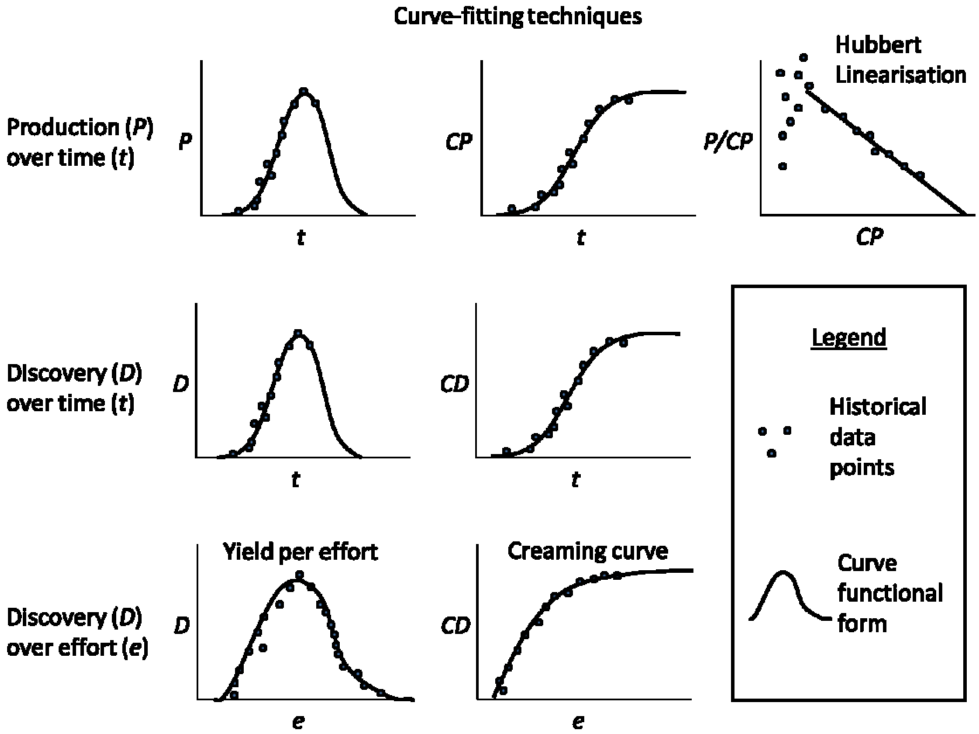
Note: Oil production in the United States peaked in 1970, Norway in 2001 and in the UK in 1999

Curve fitting models provide a slightly more sophisticated approach to modelling future resource production (Figure 4.24). These techniques vary but a general methodology can be summarised as follows:

1. Decide on the shape of the future production cycle, defined as a mathematical function;
2. Include constraints such as URR to improve the model fit; and
3. Fit the constrained mathematical function to the historical production data and project into the future.

These methods build on the work of Hubbert (1956), as discussed in Section 2.1.3. While these techniques provide relatively accessible and transparent supply forecast methodologies, they are subject to a number of difficulties.

Figure 4.24: Types of curve-fitting technique



Curve-fitting models are constrained by assumed URR estimates. However, URR has traditionally been underestimated through a combination of inadequate techniques and exclusion or underestimation of future reserve growth. This results in an underestimate of future supply, though the magnitude of this effect is disputed (Sorrell *et al.* 2009).

Another problem is the assumption of curve functional form. No robust theoretical mechanism exists to select the curve function that most accurately predicts the future performance of particular resource production. The sensitivity of curve-fitting techniques to assumptions of functional form have been demonstrated to be significant (Sorrell *et al.* 2009). The most commonly assumed function, the logistic function, is symmetrical. However, there is no strong evidence to suggest that oil production, for example, follows a symmetrical path, and separate analyses by Sorrell *et al.* (2009) and Brandt (2007) suggest that oil production is more likely to be positively skewed.

Simple models of future resource production, while accessible and transparent, are subject to a number of limitations which limit their usefulness for many supply modelling purposes.

4.3.2 System simulation models

System simulation models seek to represent the physical and/or economic mechanisms that govern the process of discovery and extraction. The rate of production is then a function of the discovery process, rather than an assumed production profile over time as seen in curve fitting. These models range from simple models akin to curve-fitting to complex system dynamics models which fully incorporate economics of investment and the resulting economic influence on URR. An early example of a simulation approach predicted a peak in US oil production between 1964 and 1973 (Davis 1958). Later oil simulation models incorporate the modelling of substitutes and therefore predict the smooth transition between substitutes as price of depleting oil increases (Greene *et al.* 2004).

Two problems are encountered in simulation models. First, the many relationships and correlations between variables in a system simulation model are hard to quantify in the face of limited, conflicting or non-existent data. For example Davidsen *et al.* (1990) includes a function representing the quantity of undiscovered oil that will be discovered in the future. This is considered a function of the cumulative investment in exploration technology. Ideally this relationship would be derived from empirical evidence, though in reality the data on which to base such a relationship is unlikely to be available.

Second, these models are often so sensitive to their variables that they become unstable, with small variations in the input parameters creating significant differences in results. The fine balance between negative and positive feedback in these models makes it difficult to set initial values, creating uncertainty in their results.

4.3.3 Bottom-up models

Bottom-up models start with project, field or regional production and build up production forecasts for larger regions. This approach has become more prominent in recent years, but relies on detailed field-by-field data, often proprietary and confidential (Bentley & Boyle 2008).

Bottom-up approaches can be divided into three categories. Regional models such as Campbell's (Campbell 1995; Campbell 1996; Campbell 2004) build up oil production forecasts for separate regions and aggregate them, often to a global level. Campbell's approach involves curve fitting techniques and has produced several very pessimistic estimates of a date of peak global oil supply. Simple mid-point peaking assumptions, a narrow definition of crude oil and the tendency of curve fitting techniques to underestimate URR all contribute to this pessimistic bias (Sorrell *et al.* 2009).

Field level oil models such as Smith's (2008) disaggregate this process further to provide more robust results (Sorrell *et al.* 2009). Smith's model includes decline rates, forecasts of enhanced oil recovery impacts and estimates of reserve growth. However, as the granularity of these models increases, so too does the data requirement. These models work well over short timeframes, but the increasing quantities of data and number of assumptions needed compromise their ability to forecast over longer timeframes.

Skrebowski provides a third approach in the 'megaprojects' database (Skrebowski 2004; Skrebowski 2005; Skrebowski 2006; Skrebowski 2007). This model aggregates the future production of very large oil extraction projects. Since these have long lead times and produce the majority of new oil supply they can provide significant insight into future supply trends. These megaprojects' oil production rates are combined with estimates of the decline in existing fields to give a forecast of total production. While this is insightful over the 3 to 5 year period due to lead times, medium to long term forecasts are difficult with this type of modelling.

4.3.4 Economic models

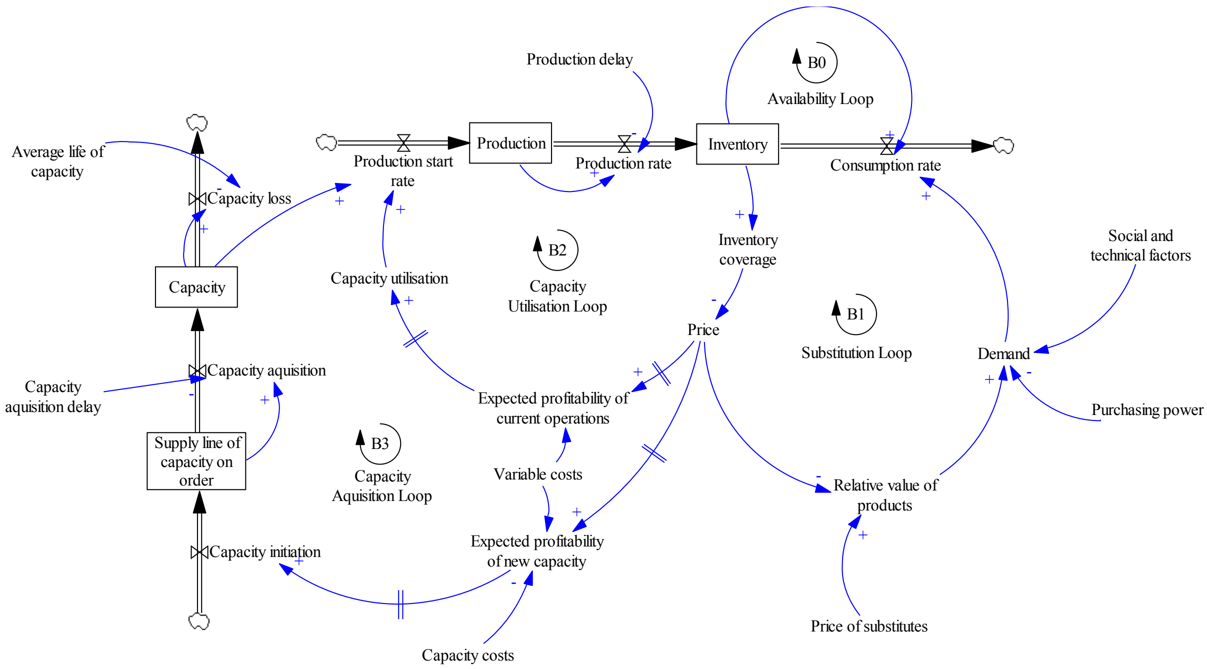
Economists approach resource supply modelling differently, focusing on investment pathways and price effects rather than the physical phenomena discussed above. Optimal depletion theory (ODT) models and econometric models represent two types of economics approaches, which are expanded on below.

ODT builds on Hotelling's (1931, 1991) insight that rational resource producers should equate the value of their resource in the ground to the profit of a produced resource invested. This suggests that the value of a resource minus extraction costs should rise at the rate of interest. In their simplest form, ODT models predict that extraction begins at its maximum, and reduces over time due to the declining present value of future production. This produces a production curve very different from the empirically observed one (Figure 4.17). ODT methods have been extended in various ways, improving the comparability between the model forecasts and measured production rates in practice (Holland 2008). ODT models are, however, limited by the lack of empirical grounding and the assumption that resource producers have full knowledge about the extent and distribution of undiscovered resources (Sorrell *et al.* 2009).

Econometric models are data rich statistical models that forecast future production largely through economic variables (Sorrell *et al.* 2009). There are numerous variants and the technique has improved over time. Early econometric models did not include any geological parameters and often produced unrealistic magnitudes or signs (Walls 1992). Later 'hybrid' models improved this by including a small number of noneconomic factors (Moroney & Berg 1999), or augmenting curve fitting models with economic variables (Kaufmann & Cleveland 2001). Econometric models are better empirically grounded than ODT methods. However, they have a poor record in predicting future production over anything other than very short time periods (Lynch 2002).

Sterman (2000) presents a third type of economic model, built using system dynamics and entitled the Generic Commodity Market Model. A simple causal loop diagram of this model is shown in Figure 4.25. This model, like other economics models, excludes many of the geological principles found in the other model types, focusing more on the feedbacks between supply, demand, price and the capacity investments needed to deliver production. If adapted to represent the oil market for example, the omission of geological variables is likely to limit the usefulness of this model to forecast long run supply trends. However, due to the detailed nature of the feedback loops representing investment behaviour in response to price and the inherent delays, the model provides a good way to test market responses to changes in market conditions in the short to medium term. In order for the model to represent the kinds of peak behaviour expected, whether driven by supply or demand, it requires adaptation, particularly to the model subsystems concerned with demand, which as it stands has no geological constraint on future production.

Figure 4.25: Sterman's generic structure of commodity markets



Source: Adapted from Sterman (2000)

Note: Feedbacks with double strikethrough indicate delay

4.4 Summary

This chapter covers a range of the issues governing commodity resource systems, which are summarised in the following points:

- Since its early beginnings oil has become one of the most important resources in the global economy. The dynamic system that governs its dynamic responses to system change has many elements, and provides a good example with which to explore the important aspects of generic resource system dynamics.
- Demand is a function of end uses. For oil the most important of these is transport fuel. Many have linked the demand for oil products to GDP, with raising affluence leading to increased consumption. Opportunities for increasing efficiency and to develop substitutes can reduce resource demand, and these measures are

increasingly sought in recent years, leading to a decoupling of the relationship between GDP and demand.

- Resource supply is a function of the available resource, the capacity to use that resource, and the utilisation of that capacity. There are also physical factors that are thought to govern the rate at which a resource can be produced, and the rate at which production declines.
- The formation of resource price is a function of traders' expectations about the market, including the availability of inventory to cover demand. Inventory is defined as oil produced but as yet not supplied to the market. It can be contained in tanks, pipelines, tankers or other types of oil storage. While inventory is stable, supply is sufficient to meet demand, and the price is unaffected. However, if supply is not sufficient to meet demand, inventories will decrease, and traders will increase their price expectations in the face of the increased potential for availability constraints. Increased price feeds back to demand through the price elasticity function, creating one of the significant feedback loops in resource systems.
- Resource system modelling as an active area of research. A great deal of research is undertaken to develop models of various aspects of the oil resource system. However, these models use a range of different modelling approaches, and their results often disagree.

This chapter has highlighted some important aspects of resource systems including the links between demand and economic growth, the potential impact of marginal costs on resource extraction and price, and nature of the price formation process. The concepts refered to in this chapter are used in Chapter 7 to inform the construction of a generic resource model.The following chapters present case studies of two metals: lithium in Chapter 5, followed by indium in Chapter 6, which are also used to contribute to the modelling in Chapter 7.

Chapter 5: Case study – Lithium and electric vehicles

> *"I think that cars today are almost the exact equivalent of the great Gothic cathedrals: I mean the supreme creation of an era, conceived with passion by unknown artists, and consumed in image if not in usage by a whole population which appropriates them as purely magical objects"*
>
> Roland Barthes, 1972

Lithium is a metal found in both rock ore and dissolved in brine deposits. Lithium is one of the most abundant elements on earth though economic accumulations of lithium in the lithosphere are less common and lithium has historically had relatively few uses. However, lithium's use as a component of li-ion battery chemistries has the potential to significantly increase its demand, particularly given the low-carbon uses of these batteries in electric vehicles (EVs).

This chapter describes the host of variables that influence the development of lithium resources and examines the extent to which these variables have been expressed in the existing literature. Unlike fossil fuels such as oil, the future production of lithium has not been modelled extensively in the literature. First, a brief history of lithium and its exploitation is presented. The chapter then examines the lithium resource system, beginning with issues of demand, then exploring the lithium resource, the production of that resource and the formation of the lithium price. Finally, the chapter examines the existing estimates of future lithium production. The evidence base surrounding future lithium availability is limited, reflecting the relatively recent development of the lithium battery market and the resulting concern over future supply.

5.1 A brief history of lithium

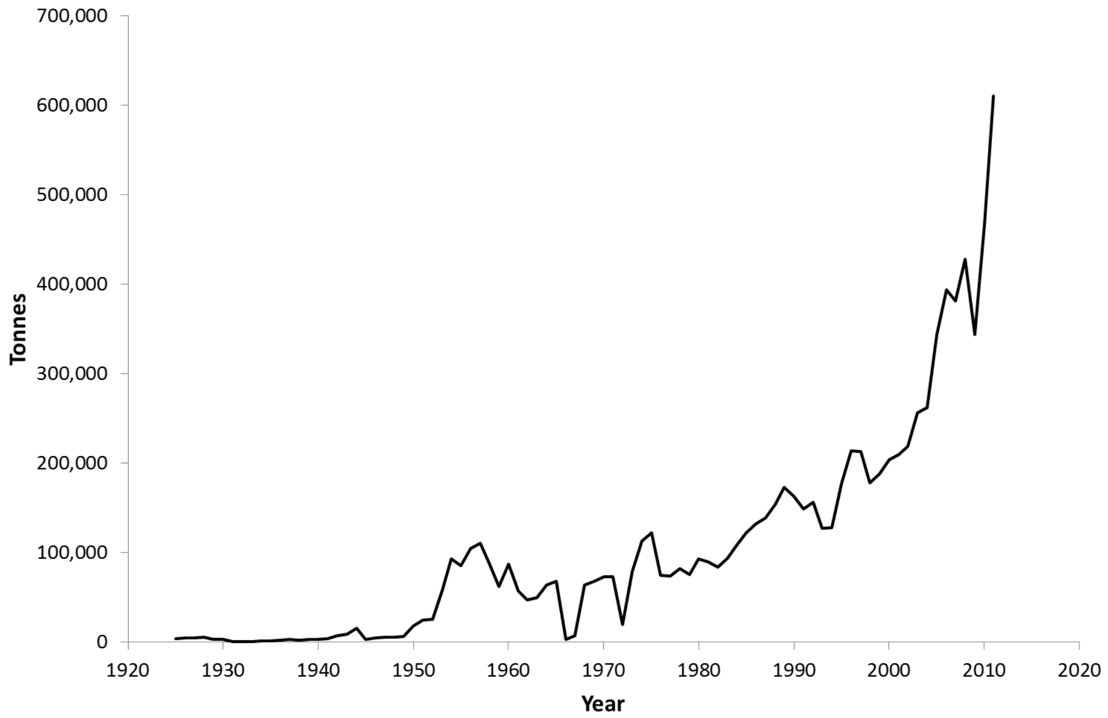
In 1817 Johan August Arfwedson discovered a new element in the ore petalite. The new metal was named lithium after the Greek word *lithos* meaning stone, to reflect its discovery in a solid mineral. The commercial production of lithium did not begin until the 1920s, and lithium's fist significant use came shortly after, as a component of greases used in aircraft in the Second World War. Lithium has subsequently had a host of other uses including in the production of nuclear fusion weapons during the cold war and as an additive in glass to decrease the melting temperature.

At the end of the cold war lithium demand began to decrease, a trend reversed by the development of Li-ion batteries for the consumer electronics industry. Now batteries are the dominant use for lithium, a trend set to continue as the consumer electronics industry grows and as new uses are developed for lithium based batteries. This growth in demand is reflected in the historical production of lithium, which presents some volatility, but largely follows an exponential growth over the past century (Figure 5.1).

One potentially significant new use of lithium batteries is in electric vehicles (EVs). The high energy densities achievable make these battery chemistries the most promising technology for electricity storage onboard EVs, and the majority of new EV designs incorporate lithium-based batteries. However, the increasing debate on the availability of critical metals raises questions regarding the feasibility of manufacturing Li-ion batteries at scale (DOE 2010; Kara *et al.* 2010; DOE 2011). Large quantities of lithium will be needed to manufacture enough automotive Li-ion batteries to meet 2050 decarbonisation scenarios (CCC 2008; IEA 2009; IEA 2010a) and some doubt has been cast over the mining sector's ability to satisfy this demand.

The lithium price has tended to decrease over the past 60 years (Figure 5.2). However, if recent demand increases are sustained and decarbonisation targets drive the uptake of electric vehicles, the lithium price is likely to experience inflationary pressure. Whether future production can offset this high demand to maintain price is dependent on a number of supply and demand side factors, each with a significant element of future uncertainty.

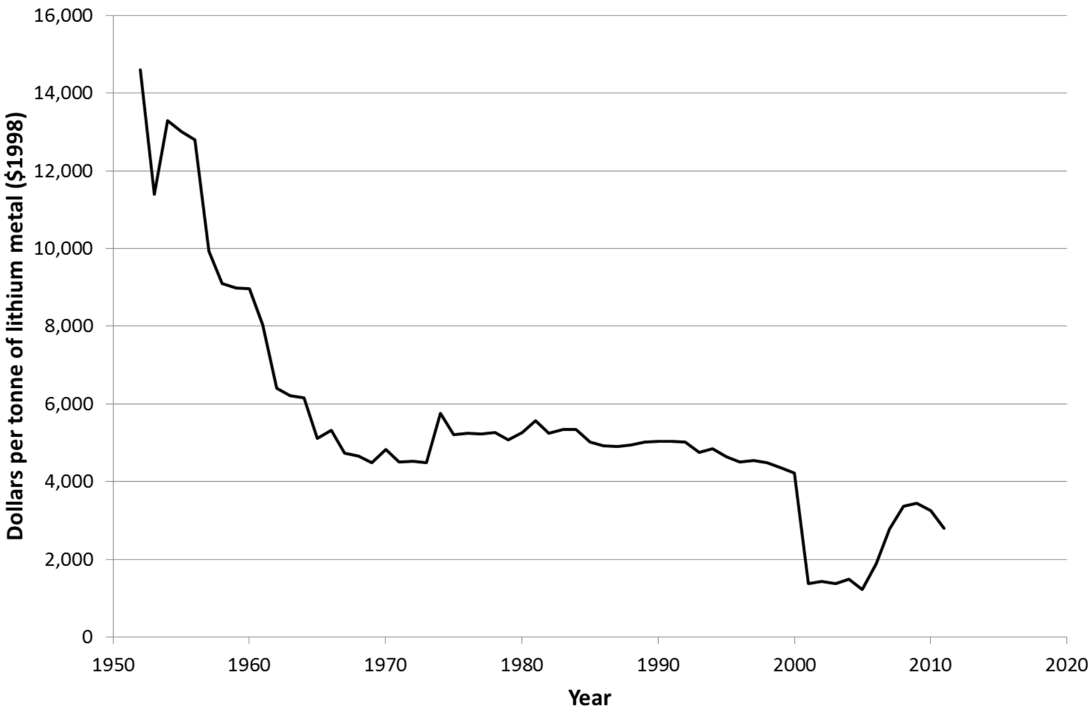
Figure 5.1: World annual lithium ore and carbonate production, 1925-2011



Source: USGS

Notes**:** No US data after 1954. No data for Rhodesia (Zimbabwe) and other African countries between 1966 and 1967

Figure 5.2: Lithium price between 2950 and 2011, presented in 1998 dollars



Source: USGS

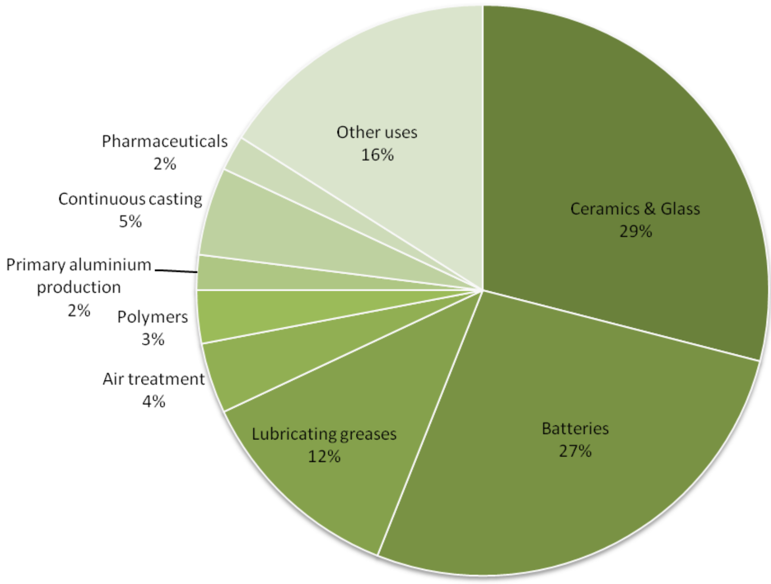
Notes: The Consumer Price Index conversion factor, with 1998 as the base year, was used to adjust the unit value in current U.S. dollars to unit value in constant 1998 U.S. dollars.

5.2 The lithium resource system

5.2.1 Demand

The lithium resource system has very different demand drivers to traditional energy resources. Demand for Li-ion batteries is a major and increasing end-use demand for lithium currently and, whilst this demand is currently driven largely by consumer electronics, electric vehicles are likely to become the largest end-use demand in the future (Figure 5.3). The electric vehicle market will largely be driven by decarbonisation targets for some time, making lithium demand policy-driven, rather than market driven. The issues arising from electric vehicle demand and its implications for lithium are discussed below.

Figure 5.3: Distribution of end-uses for lithium in 2011.



Source: USGS (2012)

Lithium in electric vehicle batteries

The calculation of future lithium demand from EVs involves several factors and is subject to significant uncertainty. However, the common elements typically considered are:

- the number of EVs forecast to be manufactured in the future;
- the size of EV batteries in kWh; and
- the lithium intensity per KWh of battery.

There are several scenario studies, presenting a range of different outlooks of the future EV market. To illustrate the range of scenarios found in the literature, Speirs *et al.* (2013a) compare several studies (DCM 2009; McKinsey 2009; Angerer et al. 2009b; IEA 2010; Marcus et al. 2010), disaggregated by vehicle type and over a range of time horizons, the earliest beginning in 2008 and the longest projecting to 2050. For example, in scenarios to 2050, global Plug-in Hybrid Electric Vehicle (PHEV) sales estimates range from 10 to 79 million vehicles per year and Battery Electric Vehicle (BEV) sales estimates range from 12 to 84 million vehicles per year in 2050. However, of those studies, the International Energy Agency (IEA) scenarios (IEA 2010a) are of specific interest, because they:

- provide estimates of vehicle sales in 2050, a key year in terms of climate goals; and

- are based on an internally consistent scenario to half global CO_2 emissions by 2050 compared with 2005 levels[14].

Implications for the EV market in 2050 based on the IEA scenarios are summarised in Table 5.1.

Table 5.1: Annual vehicle sales (millions) in 2050 under the IEA 'Blue Map' and 'Blue EV shifts' scenarios

	HEV	PHEV	BEV	FCV
Blue Map	14	62	47	34
Blue EV shifts	6	20	104	0

Source: *(IEA 2010a)*

Current EV designs commonly use Li-ion batteries (Rosenberg and Garcia 2010). As discussed below, a number of Li-ion and Li-metal chemistries are currently being developed and it is likely that Li-based batteries will continue to dominate the EV market for the foreseeable future. The lithium intensity (i.e. the weight of lithium per vehicle) must be estimated before any estimates of future EV lithium demand can be made based on the EV uptake scenarios.

Deriving lithium intensity for Li-ion batteries ideally requires knowledge of:

- the nominal voltage of the battery (volts, V);
- the specific capacity of the battery chemistry (Ampère-hours per gram, Ah/g); and
- the concentration of lithium in the active materials of the battery when this is assembled (weight percent, wt%).

While large Li-ion batteries are required for BEV and PHEV designs, smaller batteries of the order of 1 to 1.5 kWh are generally sufficient for Hybrid Electric Vehicles (HEVs) and Fuel Cell Vehicles (FCVs), where they allow storing of energy generated on board via regenerative braking and shaving the peaks and troughs of fuel cell duty cycles. Since the capacity of PHEV and BEV batteries is likely to be 10 to 20 times that of HEV and FCV batteries, and

[14] According to the Intergovernmental Panel on Climate Change (IPCC 2007) this is the minimum necessary to maintain temperature rises to within 2°C to 3°C

since HEVs and FCVs make up a relatively small proportion of the total vehicle market in 2050 based on the IEA scenarios presented in Table 3.1 above, the total lithium demand from HEVs and FCVs is likely to be negligible.

The amount of lithium contained in an EV battery is a function of the size and chemistry of the battery, its construction and its rated performance. However, it is very difficult to define with certainty the amount of lithium that each individual EV battery will require.

The calculation of the global lithium demand for EVs in year *y* ($D_{Li,y}$) can be summarised by the following equation:

$$D_{Li,y} = (M \times S \times I)_{BEV} + (M \times S \times I)_{PHEV} \qquad \textbf{5.1}$$

Where *M* is the market size (annual vehicle sales) of BEVs/PHEVs in year *y*, *S* is the average size (kWh) of a BEV/PHEV battery in year *y*, and *I* is the average intensity (amount of lithium per unit energy capacity (kWh) of a BEV/PHEV battery in year *y*.).

A similar approach has been taken implicitly or explicitly in a number of relevant studies (Speirs *et al.* 2013a).

The rated energy of the battery, expressed in kWh, is one of the main parameters determining the all-electric range (AER) of a BEV or PHEV. It is often declared by the manufacturer and as such its relationship with the lithium content is not transparent. The actual energy stored in an EV battery (and hence its true lithium content) is usually significantly higher than its rated energy would suggest, for reasons discussed below. Here the average rated energy of EV batteries is referred to as battery size for simplicity.

In principle there is no standard battery size for BEVs and PHEVs. Automotive Original Equipment Manufacturers (OEMs) may decide to manufacture different types of BEV or PHEV with very different AER capabilities and therefore different battery sizes. In reality, trade-offs exist between AER on the one hand and cost, weight and volume of the battery on the other. This constrains the extent to which battery size can vary across different models of BEVs and PHEVs. In particular for PHEVs, research carried out at Imperial College London reinforces this point by demonstrating that from a pure economic perspective the optimum battery size is to be found in a relatively narrow range (5-15 kWh), independently of the size of the car (Contestabile et al. 2011).

BEV models currently being commercialised generally use Li-ion batteries capable of storing in the region of 16-35 kWh, depending on the size of the car, delivering maximum ranges in the order of 120-160 km (Table 5.2).

Table 5.2. Key technical specifications of BEV models on the market in the UK as of July 2013

BEV model	Battery energy (kWh)	Range (km)	Max Speed (km/h)
Smart fortwo electric drive	16.5	140	100
Citroen C-Zero	16	130-160	130
Puegeot iOn	16	150	130
Mitsubishi i-MiEV 2012	16	150	130
Nissan Leaf	24	160	140
Renault Fluence Z.E.	22	160	135
Renault Zoe	22	160	135
Mia electric	12	120	100

Source: DECC (2013), OEM websites, Car Magazine website.

Today's plug-in hybrid vehicles (PHEVs) also use Li-ion batteries; however, compared to BEVs, their size varies significantly across vehicle models. This is due to the fact that different powertrain architectures are possible, which are suited to using different modes of operation and to achieving different all-electric ranges. In particular, the Toyota Prius plug-in has been designed to have limited all-electric operation capabilities and hence has a small battery pack (in the order of 4.3 kWh). On the other hand, range-extended electric vehicles such as the Chevrolet Volt are capable of delivering high performance while operating in EV mode and hence have a significantly larger battery pack (16 kWh, see Table 5.3)

Table 5.3. Key technical specifications of PHEV models on the market in the UK as of July 2013

Vehicle model	Battery energy (kWh)	EV range (km)	Max EV speed (km/h)
Toyota Prius Plug-in Hybrid	4.3	20	100
Chevrolet Volt	16	60	190
Vauxhall Ampera	16	60	N/A
Volvo V60	11.2	50	120

Sources: DECC (2013), OEM websites, Green Car Congress website.

The amount of lithium required per kWh of battery is an important determinant of total demand for lithium in electric vehicles. However, its estimation is far from straightforward, contributing to the wide range of figures reported in the literature. There are different methods used to derive these estimates, each with its own limitations, discussed below (Rade & Andersson 2001; Angerer *et al.* 2009b; Tahil 2010; Gruber *et al.* 2011; Kushnir & Sandén 2012).

Estimating material intensity in batteries requires knowledge of the voltage that the battery is capable of delivering while in operation, its specific capacity[15] and the chemical composition of its active materials. However, this information is only readily available to the battery manufacturers. One method of estimating material intensity (labelled method 'A' in Table 5.4) is to quote industry data where available. This is done in several of the studies cited in Table 5.4. Alternatively, in principle, it is possible to measure voltage and specific capacity of a battery, then disassemble it and analyse its composition in a laboratory. This process (labelled 'B'), sometimes referred to as "reverse engineering", is often not practical as it is expensive and results obtained for one particular type of cell would not be of general validity. The two remaining options are: (i) to use published data for battery voltage and specific capacity and then make assumptions on its composition (labelled 'C'); or (ii) to estimate the amount of Li required by starting from the theoretical value required under ideal conditions and then adding to it in order to take into account real operation conditions

[15] The total current that the battery can deliver when discharged per unit weight of the battery.

(labelled ‘D’). The following discussion takes the latter approach and enables the ‘sense checking’ of the figures found in the literature.

There are three key factors which vary and must be accounted for in an assessment of lithium intensity in Li-Ion batteries:

- Variation in lithium intensity between different battery chemistries
- Impact of losses on lithium intensity
- Impact of over-specification on lithium intensity

First, the amount of lithium used per kWh depends on the stoichiometry of the electrochemical reaction for the battery considered[16] and on its corresponding electromotive force (E_0)[17]. Based on Faraday’s laws, the theoretical Li demand per kWh can be calculated as:

$$I = \frac{m.10^3}{E_0 ac} \qquad \textbf{5.2}$$

where *I* is the lithium intensity in g/kWh, *m* is the molar mass of lithium in g/mol, E_0 is the electromotive force in volts, a is the fraction of lithium available and *c* is the charge of 1 mol of lithium ions in Ah/mol.

Using the appropriate values:

$$I = \frac{6941}{E_0 a.\frac{96{,}485}{3{,}600}} \qquad \textbf{5.3}$$

For example, the conventional Li-ion chemistry (originally commercialised by Sony) is based on the following redox process:

[16] The degree to which specific anode and cathode materials can make available the Li that they contain is a factor which should be accounted for, as this varies significantly across Li-ion battery electrode materials and depends on their ability to release the Li contained without their microscopic structure being affected.

[17] For more detail on these and other electrochemistry concepts, refer to relevant textbooks (Hamann et al. 2007; Atkins 2009).

$$6C + LiCoO_2 \leftrightarrow Li_{0.5}C_6 + Li_{0.5}CoO_2 \qquad E_0 \approx 4\ V \qquad \textbf{5.4}$$

Where the cathode material $LiCoO_2$ can only exchange roughly half of its lithium content, hence the fraction of lithium available (a) would be 50%. Entering these values in the formula the theoretical amount of Li needed per kWh of a conventional Li-ion battery would be 129.5g[18].

Another relevant Li-ion chemistry uses lithium iron phosphate ($LiFePO_4$) cathodes and lithium titanium oxide ($Li_4Ti_5O_{12}$) anodes; this chemistry is inherently safer than the one previously discussed and hence potentially more suited to EVs. The electromotive force (E_0) of this system is ≈ 2V. Assuming that 100% of the Li contained in $LiFePO_4$ and 75% of the Li contained in $Li_4Ti_5O_{12}$ can be made available[19], the theoretical amount of Li needed per kWh will be 172.6g. The two examples provided clearly illustrate that Li intensity is not the same for different chemistries.

Calculating g(Li)/kWh in this way provides a theoretical minimum and not the actual Li intensity of real EV batteries. However, starting from the theoretical value is useful, not least because it shows that lithium intensity changes from one battery chemistry to another simply as a result of the different electrochemical processes involved. Actual lithium intensity will be higher than the theoretical value for two main reasons, discussed below.

Impact of losses on lithium intensity

The voltage of a Li-ion battery when operating is significantly lower than its electromotive force E_0, the difference being a result of resistance within the battery. When the cell is operating, its actual voltage, ΔV (the difference in potential between the electrodes), can be expressed as:

$$\Delta V = E_0 - (iR_I) \qquad \textbf{5.5}$$

Where i is the current being drawn from the cell and R_I is the internal resistance of the cell. R_I is the result of the ohmic resistance of the electrolyte and electrodes as well as the

[18] Or 689g of lithium carbonate using a conversion factor of 5.33.

[19] These are commonly made assumptions based on the structure of the materials.

resistance due to the kinetics of charge transfer at the interface between electrodes and electrolyte. In summary the difference between E_0 and ΔV, usually referred to as overpotential, is a function of both how the cell is operated (i.e. how fast the cell is discharged) and how it is constructed (i.e. chemical composition of the electrodes, their density, thickness and size of the particles of active material; the concentration of the lithium salt used as electrolyte and the chemical composition of the solvents used). Hence substituting E_0 with ΔV in equation 5.2), Li demand per kWh will be higher than the theoretical value because ΔV is always smaller than E_0. The difference between E_0 and ΔV is too complicated to be estimated theoretically from first principles for any battery chemistry; its experimental measurement on the other hand is straightforward. However the values obtained for a specific battery model cannot be generalised, not even to batteries using the same chemistry.

Impact of over-specification on lithium intensity

Manufacturers often 'over-specify'[20] batteries, typically for two reasons: (i) to offset the expected degradation through use; and (ii) to improve the rated cycle life, which is typically calculated as the number of charge-discharge cycles achievable before energy capacity falls below 80% of the rated value. In many cases the over-specification of the battery is quite substantial, and the depth of charge-discharge cycles is constrained to avoid full discharge and resulting degradation[21]. The extent to which the battery is over-specified and the level to which discharge depth is constrained can vary greatly across manufacturers, chemistry and intended use of the battery. As a consequence the actual amount of Li present in the battery can increase by as much as a factor of two[22].

[20] i.e. to manufacture batteries that can perform significantly better than the rated values.

[21] Fully discharging the battery mechanically stresses the electrode materials and generally results in faster degradation.

[22] See for example Eberle and von Helmolt (2010), where the authors report that despite the 16kWh nominal energy of the battery of the new Chevrolet Volt PHEV,it is operated at 50% maximum depth of discharge and hence the actual usable energy is only 8kWh.

Table 5.4. Estimates of Lithium Carbonate (Li_2CO_3) usage per kWh found in the literature.

Source	Vehicle Application	Material intensity (kg Li/ kWh)	*Methodology* [a]
Chemetall GmbH (Engel-Bader 2010)	BEV (25 kWh)	0.165	A
	PHEV (16 kWh)	0.176	
	HEV (1 kWh)	0.375	
Meridian International Research (Tahil 2007)		0.300	A
Meridian International Research (Tahil 2010)		0.563	D
Kushnir and Sanden (2012)	Average for four chemistries	0.160	D
Rade and Andersson (2001)	Li-ion (Mn)	0.140	D
	Li-ion (Ni)		
	Li-ion (Co)		
Argonne National Laboratory (Gaines & Nelson 2009)	HEV4 (1.2 kWh)	0.308	C
	PHEV20 (6 kWh)	0.244	
	PHEV40 (12 kWh)	0.246	
	EV100 (30 kWh)	0.246	
Gruber et al (2011)	Li-ion (Co, Mn, Ni)	0.114	D
Evans (2009)		0.113	A
Evans cited by Reuters (Rosenberg & Garcia 2010)	Chevrolet Volt (16 kWh)	0.158	A
Engel (2007)		0.050	A
Fraunhofer ISI (Angerer *et al.* 2009a)	$LiCoO_2$	0.180	D
	$LiFePO_4$	0.120	
Dundee Capital Markets (DCM 2009)		0.080	A
National Renewable Energy Laboratory (Neubauer 2011)	HEV (1.7 kWh)	0.100	Internal modelling study (C or D)
	PHEV12 (5.6 kWh)	0.108	
	PHEV35 (17.5 kWh)	0.110	

BEV75 (29.5 kWh)	0.112
BEV150 (67kWh)	0.112

Potential for lithium weight shedding

The focus of research and development in li-ion batteries is currently aimed at increasing safety, lowering cost, increasing energy density and improving cycle life, with a long-term view towards low environmental impact (Ritchie 2004; Armand & Tarascon 2008). Raw lithium contributes only 1-2% of final battery cost (Kushnir & Sandén 2012)[23]. Accordingly, little discussion about reductions in lithium content can be found in the literature. Rade and Andersson (2001) provide one of the few estimates of future lithium intensity of Li-ion batteries based on the improvement of active material utilisation (the amount of lithium content in the anode and cathode that can be made available in the reaction) from a current 50% to 60-80% depending on chemistry, leading to intensity reductions of 21-34%. Whether or not these developments can be realised is uncertain.

Given that lithium has historically contributed only a small percentage of total battery costs it may seem unintuitive that lithium availability has received so much attention in the literature. However, if lithium costs increase significantly they may become a greater proportion of costs. Given the significant potential for lithium demand growth in electric vehicle manufacturing future lithium price could increase in the future.

The cost of lithium batteries is currently one of the barriers to the wider adoption of EVs and reducing battery costs is a priority for many EV manufacturers (Gallagher & Nelson 2014). Trends that may interfere with cost reductions, such as escalating lithium costs, are therefore of concern. Given the significant volumes of lithium needed to supply forecast electric vehicle demand, and the limitations in substitution options, electric vehicle manufactures will have limited potential to insulate themselves from the impacts of increasing lithium price.

[23] Though this is a relatively low proportion of vehicle cost it is a larger share of battery costs and will rise as a proportion if lithium price increases in response to tight supply conditions. Given this apparently low cost it is conceivable that vehicle manufacturers may try to protect themselves from future supply constraints by stockpiling lithium. However, vehicle manufacturers may not be as concerned as some in the discourse over the future availability of lithium.

Two alternative lithium-based chemistries currently being developed are lithium-air (Armand & Tarascon 2008) and lithium-sulphur (Hassoun et al. 2012). Both of these technologies have higher energy density and thus ability to dramatically improve the driving range of electric vehicles compared to Li-ion batteries currently on the market. Improvements associated with these technologies may increase both the market share of lithium batteries as well as the average size (kWh) of EV batteries, resulting in an overall increase in annual demand for lithium as per Equation 5.3. In order to reduce lithium demand in EV applications it may therefore be necessary to substitute lithium completely from EV batteries.

Potential for substitution

Early BEVs such as the General Motors EV1 used lead acid batteries and more recently the Think City used Sodium/Nickel Chloride (also known as ZEBRA) batteries. However, lithium based batteries have significant advantages over these two battery types and it is unlikely that they will be used in future BEVs and PHEVs. Since lithium is the lightest metal and has an extremely negative electrode potential, lithium-based batteries have much higher gravimetric energy density than lead-acid batteries, allowing EVs to achieve acceptable ranges without imposing a high weight penalty. Unlike ZEBRA batteries which use molten Sodium at 300-350˚C, lithium batteries operate at room temperature and because they don't need preheating they are always available for use, which is a very desirable characteristic for vehicles with no fixed usage patterns, such as passenger cars. These favourable characteristics, together with the high power density and long cycle life, explain why Li-ion batteries are the current technology of choice for BEVs and PHEVs. Moreover, lithium batteries are a much younger technology than lead acid batteries, and as such it is expected that they still have significant margin for improvement.

Other non-lithium chemistries are being researched at present which may compete with lithium-based batteries. However, alternatives to lithium are limited, because prospective systems need to have high energy density and achieving this requires using light metals such as Sodium, Magnesium and Aluminium.

Battery systems currently under investigation include Magnesium/Sulphur and Aluminium/ Graphite Fluoride. However, the practical viability of these systems has not been demonstrated and their future use in electric vehicles depends on the occurrence of significant technological improvement (Armand & Tarascon 2008). Metal air chemistries such as sodium air and zinc air are also possible alternatives to lithium air. Sodium air batteries in particular have the potential to mitigate some of the problems of Li/air technology but significant technological improvement is still needed before this technology may be considered for practical applications (Peled et al. 2011).

To summarise, alternatives to lithium-based batteries exist. However in the short to medium term, lithium-based chemistries seem favoured, while in the long term other options may become competitive, giving rise to potential substitution. However, alternative technologies are currently far from mature and technological improvement is still needed. It is also possible that the current research focus on Li-ion may constrain the funding for research and development in non-lithium alternatives, further slowing their technological development.

Lithium in other end-uses

Lithium is used in many applications other than EV batteries (Figure 5.3). The most important of these are ceramics and glass, and consumer electronics batteries, making up approximately 55% of demand in 2011. A number of other end-uses make up the rest of demand, although these are unlikely to increase significantly in the future. These include nuclear fusion control rods, lubricants, polymers and pharmaceuticals.

The development of consumer electronics demand is likely to play an ongoing role in determining future lithium demand, and it is uncertain to what extent this demand might grow in the future or whether suitable substitutes or opportunities for material efficiency might offset any growth in future consumer electronics demand.

Future lithium demand

Speirs *et al.* (2013a) present estimates of future lithium demand based on assumptions in the literature around three demand influencing variables:

- The battery capacity used in PHEV and BEVs;
- The lithium intensity per kWh of battery; and
- The annual vehicle sales in 2050.

The result of this analysis is a range of demand in 2050 of between 180,000 and 1,000,000 tonnes of lithium per year. This is a very wide range and appears very challenging in comparison to recent production estimates, which were only 35,000 tonnes in 2013 (USGS 2014a). However, the maximum of this range assumes large battery sizes and high lithium intensity in these batteries Table 5.5. In addition the estimate is a simple calculation and is not dynamic in terms of changing variables over time, the impact of rising price on demand, and the resulting incentives to reduce or substitute lithium under high price scenarios. The maximum estimate for lithium demand in 2050 can therefore be seen as a worst case, which is unlikely to be realised.

Table 5.5: Estimates of future lithium demand from electric vehicles in 2050

Variable	**Value**			
	Low case		**High case**	
Vehicle type	**PHEV**	**BEV**	**PHEV**	**BEV**
Battery capacity (kWh)	9		16	35
Lithium intensity (g/kWh)	190		380	
Annual vehicle sales	62	47	62	47
Total lithium demand	**184,000**		**989,000**	

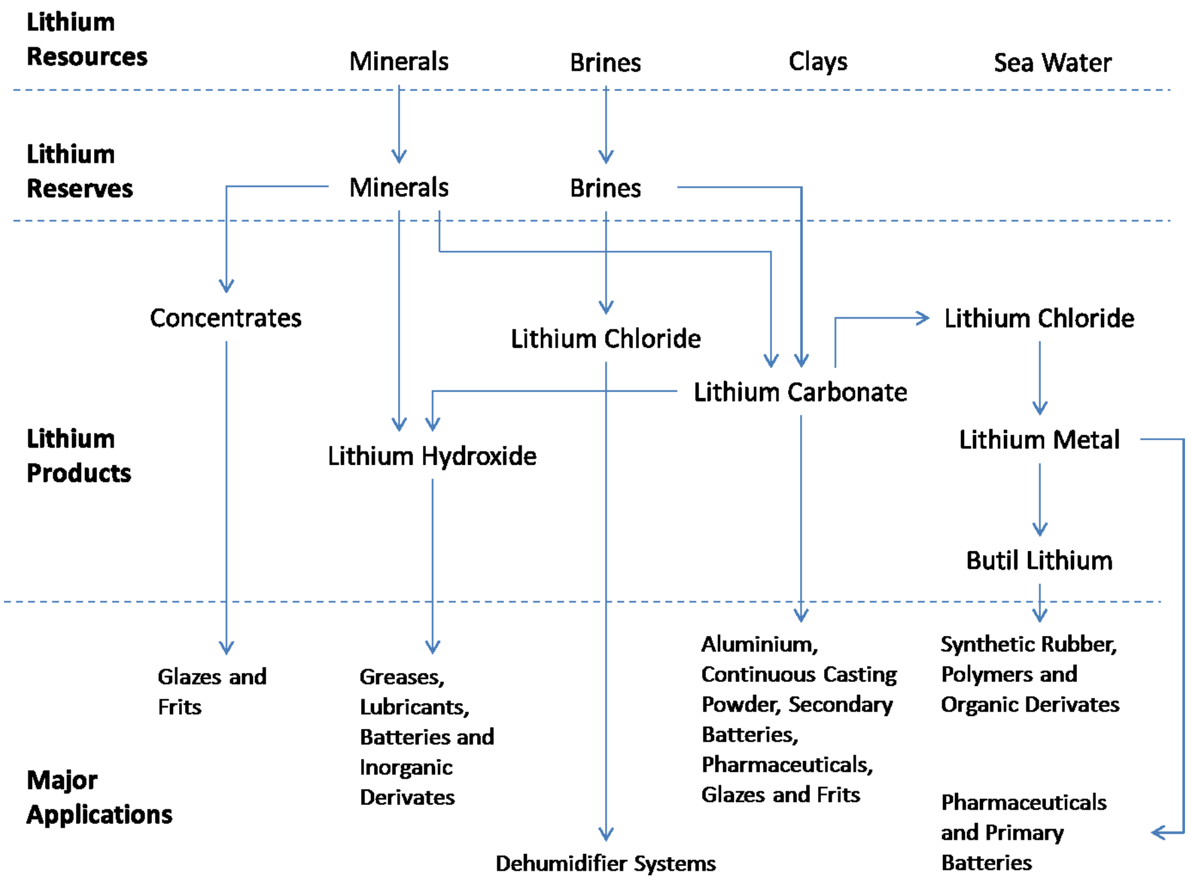
Source: Speirs *et al.* (2013a)

5.2.2 The lithium resource

Lithium is an alkali group metal and is the lightest metal in the periodic table. It is highly reactive and corrodes on contact with moist air. Due to this reactivity, lithium metal does not occur freely in nature and is instead found in four main deposit types: Minerals, brines, sedimentary rocks and seawater. Minerals and brines constitute the world's source of lithium today. Lithium minerals are typically coarse-grained intrusive igneous rocks known as pegmatites, such as spodumene, petalite, lepidolite, amblygonite and eucryptite (Gruber et al. 2011). Lithium brines are currently the largest and cheapest sources of lithium (Yaksic & Tilton 2009) and are mostly found in dry lakes such as the Salar de Atacama in Chile, as well as geothermal deposits and oil fields. The third source of lithium is in sedimentary rocks, notably clays such as hectorite and lacustrine evaporates, such as the newly discovered jadarite (Clarke & Harben 2009; Gruber *et al.* 2011). Finally, lithium is found in diffuse but very large quantities in seawater, where there is potentially 44.8 billion tonnes of recoverable lithium (Yaksic and Tilton (2009). The economic viability of lithium recovery from sedimentary rocks or sea water is uncertain but likely to be uneconomic for some time.

Lithium is not mined in its elemental form but is produced as lithium carbonate, lithium hydroxide, lithium chloride and other forms, shown in Figure 5.4. Different forms of lithium are used in different applications, with lithium carbonate typically used in Li-ion battery manufacture.

Figure 5.4. Sources and chemical forms of lithium and their major applications



Source: Yaksic and Tilton (2009)

Of the major producers of lithium by content (see Figure 5.9), Chile and Argentina both produce Lithium Carbonate from brine, while Australia produces lithium in minerals recovered from spodumene deposits. China's production is split between mineral production and lithium carbonate production from brine, with lithium minerals representing 35% of China's reserves and brines representing 65%.

Mineral Ores

Lithium containing spodumene ores are recovered by quarrying or open cast mining of veins of the ore, which are often only a few meters thick. Concentration of the ore can be carried out by hand-sorting of raw ore. Further separation of ore mineral from waste material is achieved by froth flotation.

A number of authors have reviewed the processing of lithium (Averill & Olson 1978; Bale & May 1989). The ore is first roasted, which improves milling into the powder required for the flotation process. Roasting is carried out at 1050-1100˚C for 15-30 minutes. When cool, the material is crushed to a grain size less than 0.1 mm. This powder is fed to floatation tanks containing anionic fatty acids in alkaline solution or sulphonated oils in acid. Concentration by 70% is achieved.

The powder is treated with an excess of 93% sulphuric acid at elevated temperature in a lined rotary furnace. Lithium sulphate solution is produced, which is leached out of the remaining inert solids with hot water. The liquor is treated with soda lime to remove calcium, magnesium and iron, filtered, then neutralised with more sulphuric acid. The liquor is then transferred to an evaporation vessel and concentrated to 200-250 g/L Li_2SO_4. Lithium is often converted to $LiCO_3$ by addition of sodium carbonate.

In turn, lithium carbonate can be used to produce lithium metal. The carbonate is re-dissolved in hydrochloric acid. The chloride solution is concentrated in a vacuum evaporator and dried. The product, mixed with potassium chloride to lower the melting point, is fused in an electrolytic cell similar to the Downs cell used for sodium production. Electrolysis produces lithium metal and chlorine gas. The metal is used in sacrificial anodes in lithium batteries. (Averill & Olson 1978; Bale & May 1989).

Brines

Economically treatable brines are found in South America, particularly Argentina, Bolivia and Chile and also in the USA and China. Production of lithium carbonate from brines begins with the concentration of brine, often through solar evaporation. This increases the concentration of lithium chloride and precipitates out certain impurities. The concentration process is particularly effective because lithium chloride is highly soluble. Yields are reduced, however, because of the presence of other metals, particularly magnesium. The magnesium can be removed during concentration by treatment with lime. However, this leads to loss of a proportion of the lithium content. The concentration of lithium in lithium chloride liquor rises to about 6%, at which point it is treated with soda ash to precipitate lithium as the carbonate. As above in this form the lithium metal can be produced by electrolysis (Averill & Olson 1978)

Resources and reserves

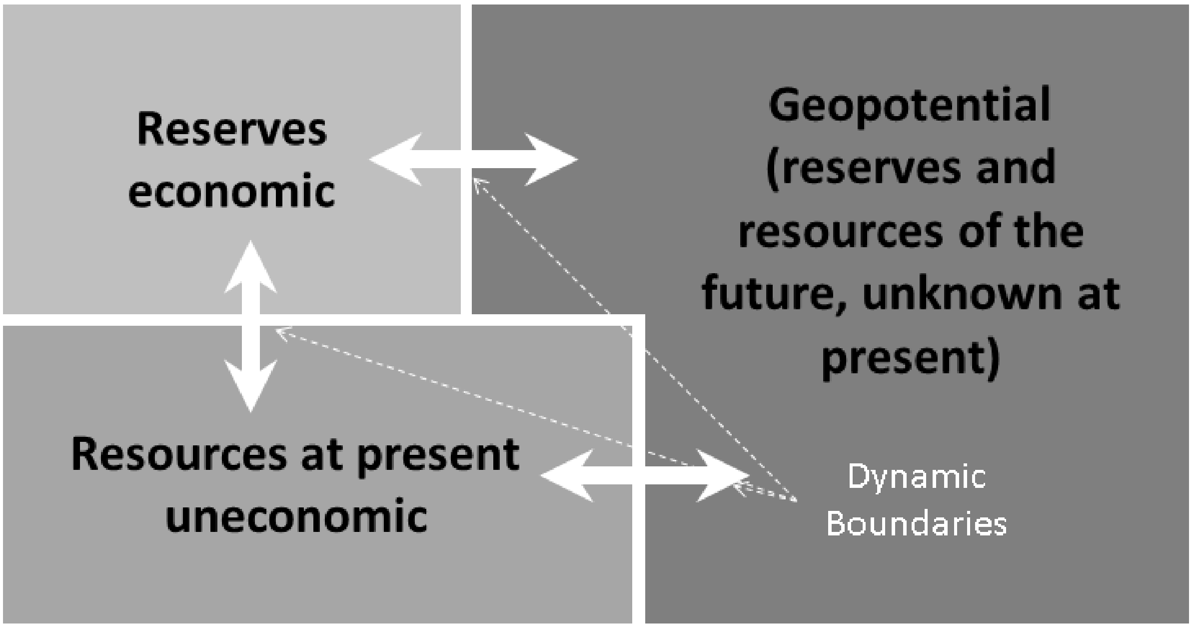
Metal resource classification, as with oil, is a source of confusion and misunderstanding. However, there is a paucity of data and analysis of metal resources in comparison to the available literature on other energy resources. While a range of different resource and reserve terms exist for minerals (see Figure 5.10) the USGS tends to report three different types of resource estimate:

- *Reserves* - the quantity of the resource that can be economically extracted or produced at the time of determination;
- *reserve base* - those parts of the resources that have a reasonable potential for becoming economically available within planning horizons beyond those that assume proven technology and current economics; and
- *resources* - all discovered quantities including identified resources that do not meet the economic criteria of reserves (paraphrased from Appendix C of USGS (2013))

Reserves of lithium can be considered loosely equivalent to reserves of oil, in that they are similarly conservative and likely to be exceeded in the future. They both consider only those resources producible given current technology and economics. Reserve base is a term not referred to in oil reserve classification, but has a lower probability of being exceeded in the future than reserve estimates. This may mean it is more comparable to a 2P or 3P estimate of oil resources, though no probabilistic comparison of these estimates is available. The term ‘resources,’ in mineral classification is likely to be comparable with the technically recoverable resource in oil reserve classification, as they both discount economic constraints.

Wellmer (2008) presents a modified version of the McKelvey box for metal resources, reflecting the similarity between oil and metal resource classification (Figure 5.5). The format of this modified version is somewhat simplified for the non-expert, though this level is appropriate given the lack of available evidence and estimates for metal resources. The total area of the box represents the total resource available over all time, equivalent to the URR in oil resource classification.

Figure 5.5: Simplified version of the McKelvey Box

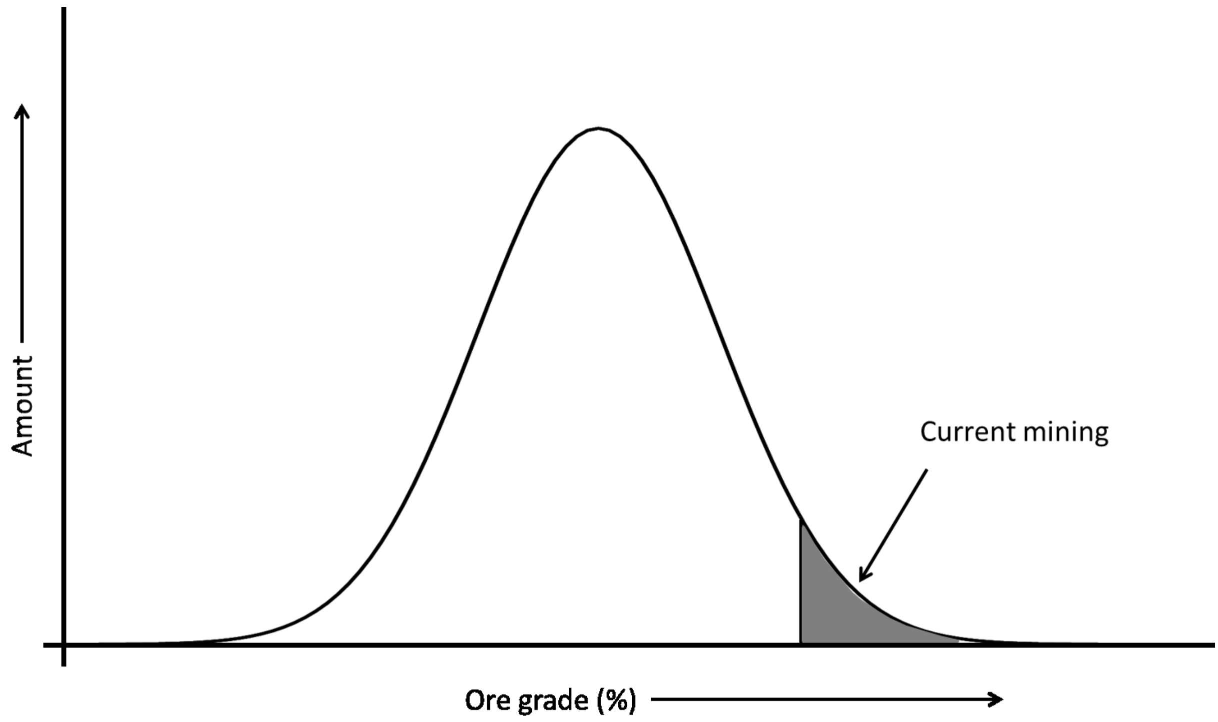


Source: Wellmer (2008)

No URR estimates exist for lithium. It is unlikely that sufficient geological and economic evidence exists to create an estimate of URR for lithium, but it is likely that more than currently stated lithium reserves will be produced in the future.

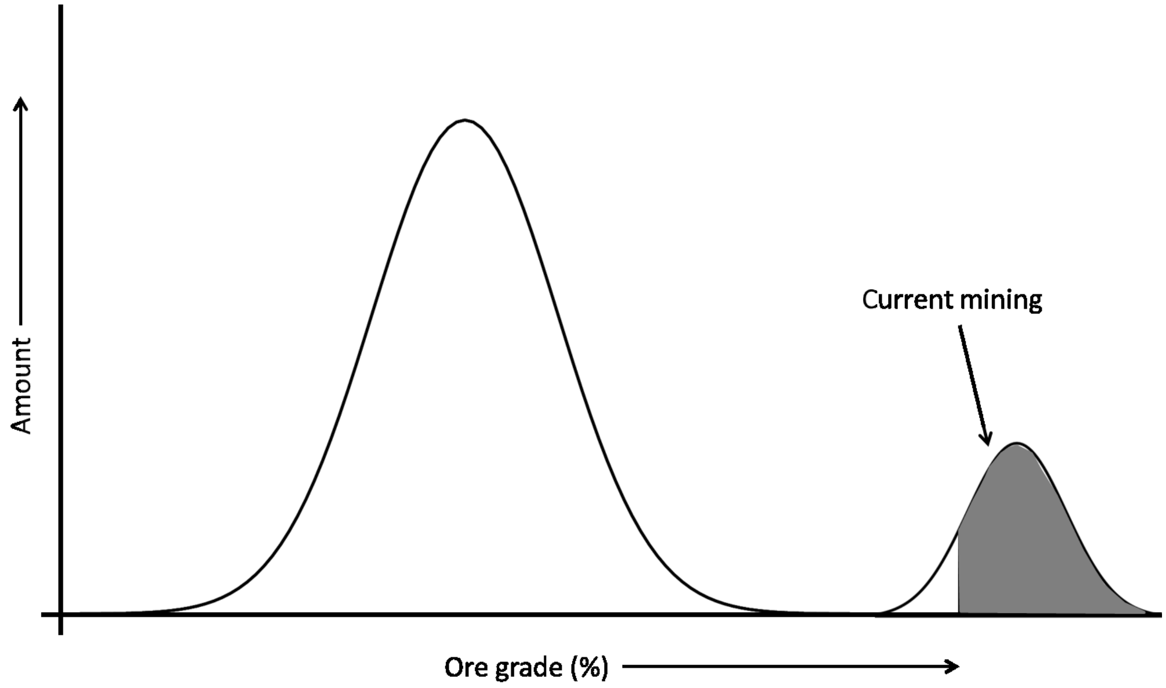
As indicated in Figure 5.5, the boundaries between economic reserves, uneconomic resources and future resources are dynamic and will change over time in response to changes in production costs, resource price and future discoveries. However, the rate at which resources and new discoveries can be booked as reserves is hard to estimate, and is a function of a number of variables. Skinner (1976) suggests that there are two different types of metals - the geologically abundant metals and the geologically scarce metals. He argues that the distribution of these metals in the earth's crust is different, with the abundant metals having a normal distribution of ore concentrations, while the scarce metals are characterised by a bimodal distribution of ore concentrations in the earth's crust (Figure 5.6 and Figure 5.7). The result of this bimodal distribution is, that for the scarce metals, the marginal ore concentration drops precipitously early in the metal's production lifecycle. This will have significant implications for the marginal cost of metals conforming to Skinner's definition of geologically scarce.

Figure 5.6: Skinner's characterisation of the ore grade distribution of geologically abundant metals



Source: Skinner (1976)

Figure 5.7: Skinner's characterisation of the ore grade distribution of geologically scarce metals

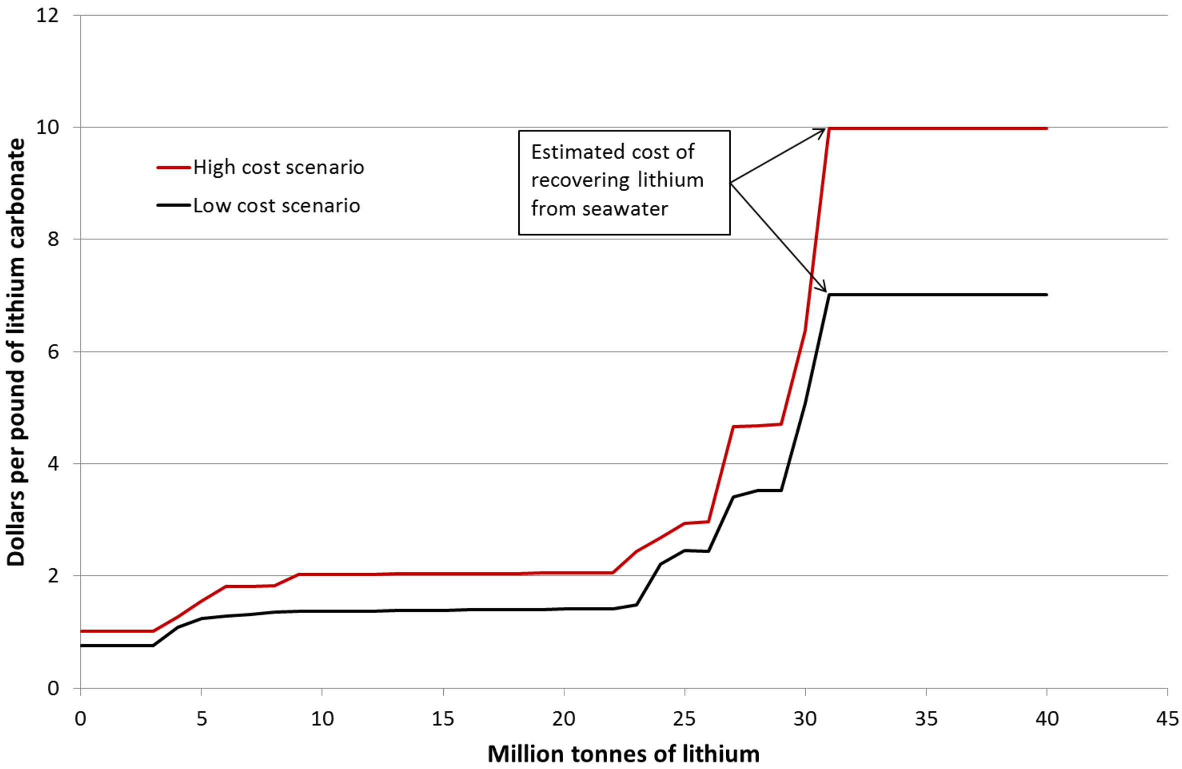


Source: Skinner (1976)

The marginal production cost curve for lithium resources is estimated by (Yaksic & Tilton 2009)(Figure 5.8)[24]. This figure demonstrates the very large quantity of reserves available at high costs, reflecting the very abundant but low concentration lithium resource found in seawater.

[24] Yaksic & Tilton (2009) refer to this as the 'cumulative availability curve'.

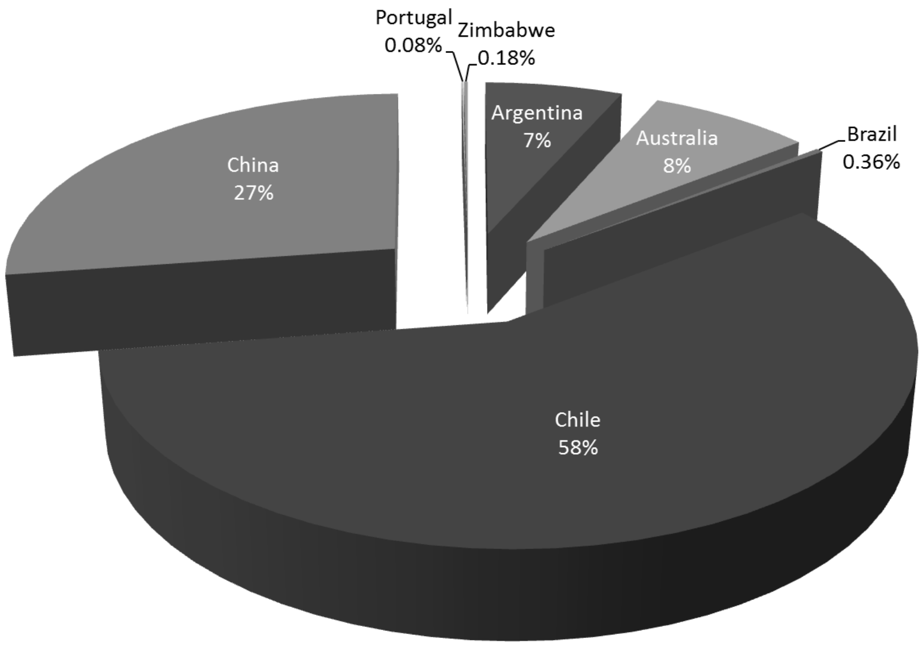
Figure 5.8: Marginal production cost curve for lithium



Source: Yaksic & Tilton (2009)

Known reserves of lithium exist and are produced in a number of countries, the relative distribution of which is presented in Figure 5.9. The largest share of reserves belongs to Chile, which recovers lithium from brine pools located in salt flats.

Figure 5.9: Distribution of lithium reserves in 2012



Source: USGS (2013)

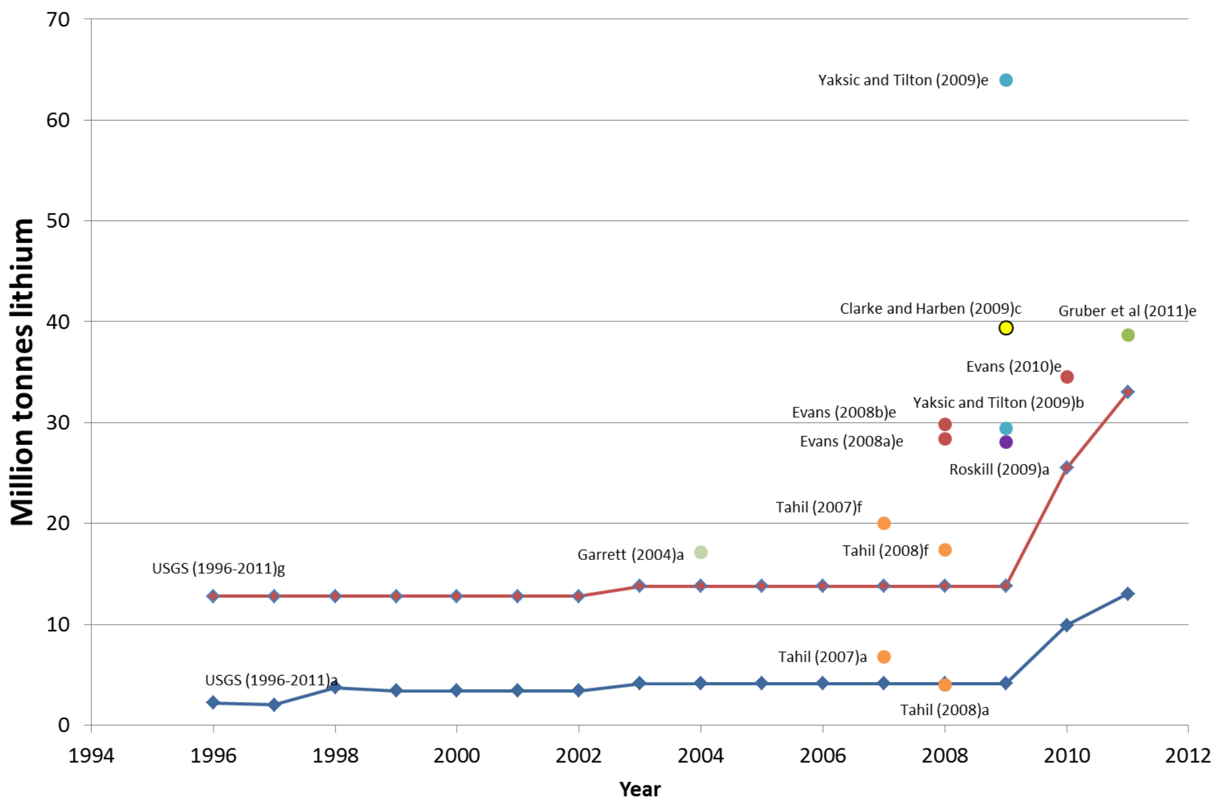
Note: USGS do not disclose US production data

Figure 5.10 presents several different lithium reserve and resource estimates. This figure presents a number of different classifications of resources, and these are acknowledged in the notes below. Where reserve classifications differ, estimates are not directly comparable. This issue is compounded by the fact that explicit descriptions of reserve classifications are not always provided by authors.

The USGS presents figures for reserves and reserve base, although reserve base reporting was discontinued after 2009. Roskill (cited in Engel-Bader (2010)) also presents reserve data for 2009. In 2004, disaggregated reserve figures are presented by Garrett (2004). Reserve and reserve base estimates from Tahil (2007; Tahil 2008) are presented in years 2005 and 2007. In year 2008 reserve and 'in situ' data from Evans (2008a; Evans 2008b) are presented. Finally Yaksic and Tilton (2009) provide estimates of recoverable resources and in situ resources in 2009, which are also included. These data present a considerable range of estimates, with the largest estimate in 2009, being over 700% greater than the smallest.

This can in part be explained by the differing natures of reserve classifications, but this also reflects the range of opinion regarding the future prospects for lithium production. It is also worth mentioning that the USGS refers to additional “resources” for several countries, including Bolivia, which the USGS (2012) estimates to have nine million tonnes of resources, although it as yet has no recorded production or reserves. What prevents any of these resources from being reported as reserves by the USGS is not apparent in the USGS documentation (USGS 2012). The USGS (2012) estimates world resources at 34 million tonnes, over twice the reserve estimate in the 2012 issue of the Mineral Commodity Summaries, but still less than half the in situ estimate in 2009.

Figure 5.10: USGS annual reported reserves and other available estimates from existing literature



Notes:

a. Reserves

b. Recoverable resources

c. Broad based reserves

d. Reserve base

e. In Situ resources

f. Ultimate global reserve base

g. Identified Resources

5.2.3 Lithium production rate

Primary production

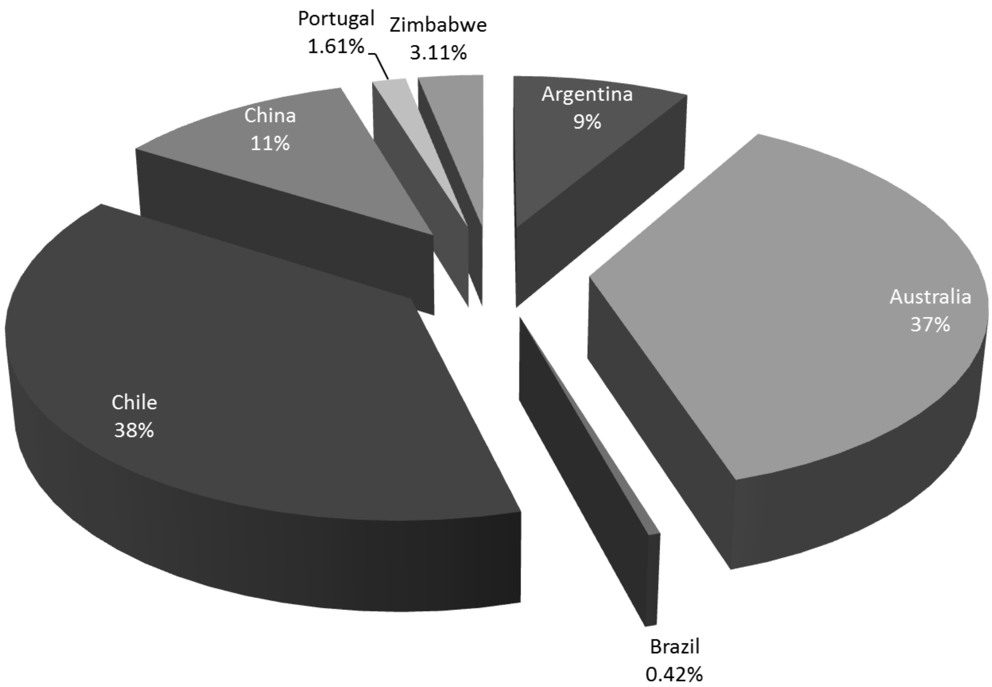
Figure 5.1 presents lithium production data published by the USGS. Data are in metric tonnes of gross product of lithium minerals and brine. Since 1967, lithium production was reported as 'ore and ore concentrates' from mines and lithium carbonate from brine deposits. Calculating the lithium metal weight in lithium carbonate is relatively simple.

However, calculating the metal content of ore and ore concentrate is problematic, given that the composition of these ores and concentrates is unknown.

Despite inconsistencies in data, Figure 5.1 appears to present a resource which is being exploited through an exponential phase of production and displays no indication of a slowing production rate.

The distribution of lithium production is presented below in Figure 5.11. This shows the significant role played by China, Australia and Chile. This closely mirrors the distribution of resources presented in Figure 5.9.

Figure 5.11: Geographical distribution of lithium production in 2013



Source: (USGS 2014b)

As a finite resource, many consider the generic lithium production profile to have similarities to that of oil. Several authors have examined the use of bell curve functional forms to model the production of minerals, (Bardi 2005; Cordell *et al.* 2009; May *et al.* 2011; Mohr *et al.* 2011), including the use of logistic curves and their application to lithium specifically Kushnir and Sandén (2012) and Vikström *et al.* (2013). However, curve fitting methodologies for lithium production forecasting are likely to suffer the same issues as curve fitting in oil production forecasting. Specifically, the lack of theoretical basis for the choice of functional form and the uncertainty around the URR are likely to limit the usefulness of curve fitting techniques. (Vikström *et al.* 2013) applied three different functional forms in order to examine the impact of curve functional form on forecasts of future lithium production and concluded that the logistic curve produces the most rapid growth phase and the highest production level at peak production.

Recycling

Historically, recycled lithium has been insignificant (USGS 2011). The United Nations Environment Programme estimates lithium end-of-life recycling rates at less than 1% (UNEP 2011). However, there has been an increase in use recently due to battery applications, and in particular the laws regulating the disposal of waste batteries: in Europe, Member States are obliged to collect 25% of end-of-life batteries by 2012 and 45% by 2016 (European Parliament 2006). This legislation does not necessarily imply nor mandate the recycling of lithium metal content. For example, the recently built Umicore battery recycling facility in Belgium recycles cobalt and nickel hydroxides but not lithium, which instead is removed as slag (Buchert et al. 2009).

Nevertheless, the potential for recycling of lithium from end-of-life batteries is estimated to be significant. Gaines and Nelson (2009) estimate that over 40,000 tonnes of contained lithium could be recycled in the US by 2050, assuming 100% recycling rates and a 10-year battery life. In the modelling study by Gruber et al (2011), recycled lithium constitutes between 50 and 63% of cumulative demand over the 2010-2100 period, assuming recycling rates of 90-100%. Buchert et al (2009), however, note that while the large growth in battery production implies a significant recycling potential, there is currently a lack of economic incentive to recycle lithium given its relatively low price[25].

A primary issue in recycling lithium from end-of-life batteries is the sorting of collected waste batteries. Not all collected batteries will be Li-ion batteries, e.g. in the automotive sector many will still be NiMH, and not all Li-ion batteries have the same chemistry. In order

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[25] Lithium price is often reported as the price of lithium carbonate. In 2011, the average price of lithium carbonate was approximately $4.3/kg (Jevons 1865).

to develop an efficient recycling process, it is necessary to know the composition of the batteries to be treated (Contestabile et al. 1999). A number of automatic sorting systems have now been developed for waste batteries, using magnetic or electrodynamic sensors, photo recognition of the label and x-ray imaging, all resulting in varying levels of purity in the separated fractions (Bernardes et al. 2004).

There are a number of existing Li-ion battery recycling processes, mostly hydrometallurgical (Bernardes et al. 2004), although many of these are primarily focused on recycling cobalt due to its high concentration and price incentive (Lain 2001; Sloop 2008). Other metals are also recycled due to flammability or toxicity concerns (Castillo et al. 2002; Bernardes et al. 2004). For example, the Sony process, named after the company to which the patent is assigned, does not recover lithium (Lain 2001; Bernardes et al. 2004). On the other hand, the Toxco process (McLaughlin 1994) uses cryogenic processes followed by mechanical shredding and mixture with water to produce lithium hydroxide as a main product. This is then converted to lithium carbonate. More recently, processes have focused on lithium and lithium carbonate recovery (Castillo et al. 2002; Kondás et al. 2006). Xu et al (2008) review the processes available for recycling Li-ion batteries and list six treatment methods for the processing of Li-ion cathode materials, further divided into two distinct groups. Physical treatment methods are mechano-chemical, thermal or dissolution processes, while chemical processes involve acid leaching, bioleaching or solvent extraction (Xu et al. 2008). If future lithium availability constraints were to arise, processes that recover lithium (Toxco) are likely to be favoured over those that do not (Sony).

The recovery of lithium from spent batteries remains a niche market (Buchert et al. 2009), and the battery industry does not currently produce batteries using recycled material (Kotaich & Sloop 2009). For recycled lithium to contribute half of future supply as suggested by Gruber et al (2011) appears likely to be difficult to achieve without more targeted legislation or a clear economic incentive.

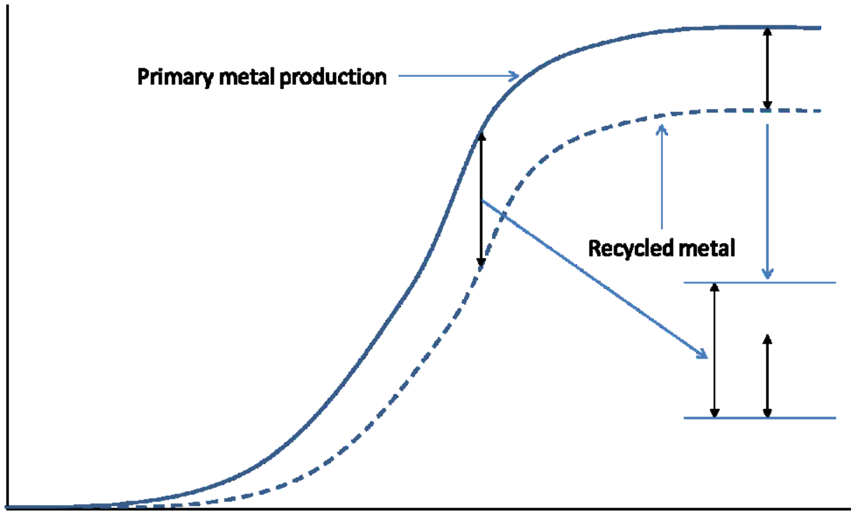
In addition, it has been proposed that automotive Li-ion batteries could be reused after their useful life in electric vehicles. The National Renewable Energy Laboratory (Neubauer & Pesaran 2011) is investigating the potential revenue and BEV/PHEV cost reductions achievable through the use of end-of-life electric vehicle batteries in secondary applications for utility energy storage, such as storage for wind and solar power. However, this form of recycling would extend the delay in availability of recycled material for new EV battery manufacture.

The impact of recycling on future metal availability is subject to a number of factors. First, the lifetime of a product delays the availability of its components to the recycling market. Li-ion batteries for example, may be expected to last for 10 - 20 years (2009; Chris Brandrick 2010; BBC 2014), with post electric vehicle uses of batteries likely to extend this lifetime to the upper end of this range (Neubauer & Pesaran 2011; BBC 2014). Access to recycle the critical metals contained within those modules is therefore delayed by the same period of time. In most cases the recyclable quantity of this metal will be less than 100%, and estimating the future recovery rate[26] is difficult given that it is likely to be a function of technical capability and economic factors 30 years in the future. The relative contribution of recycling during different phases of the production cycle is also important. While production is growing, the quantity of recyclable material is always a fraction of what is produced from mines in any given year. This is due to the recovery rate, and the product lifetime delay. Where the rate of production growth is steep, the relative proportion of recyclable material is likely to be smaller than periods where the production rate plateaus. This means that periods where demand is growing most quickly coincide with periods where recycling can contribute a smaller proportion relative to production.

Despite these limitations, there is an incentive for countries or regions that are net importers of critical metals to encourage recycling as a means to reduce the relative level of imports. This may mean incentivising the design of products to be easily recycled, and policy support and regulation for recycling capability.

[26] The recovery rate is defined as the percentage of a metal that can be recycled from the total metal container in end of life products.

Figure 5.12: The relative impact of recycling during exponential growth and plateau phases of critical metal production.



Source: Adapted from Speirs *et al.* (2014b)

5.2.4 The lithium price

Lithium is not traded on exchanges like oil as it has no futures market (FDC 2013). The price is therefore established through bilateral trading between producers and industrial consumers. Third party investment in lithium it therefore confined to trading of stocks in lithium companies or through exchange traded funds. Other than this difference, price discovery happens through a similar process to that described for oil above. Companies who extract lithium either refine it themselves, or sell to refineries where consumers of lithium such as battery manufacturers buy it. The refiners will offer a lithium price based on their expectation of the market conditions, including how much lithium they believe is available on the market and how high demand is for lithium at any given time. However, these expectations are subject to imperfect and delayed information and the actual price is discovered iteratively based on buyers' response to the refiners expected price (Metal-Pages Ltd 2014).

The lack of transparency in pricing information potentially delays the price discovery process, although there are efforts to collate price data and improve price transparency. Price canvasing of market participants is often conducted by industry associations and commercial organisations, although comparability and other issues affect these efforts

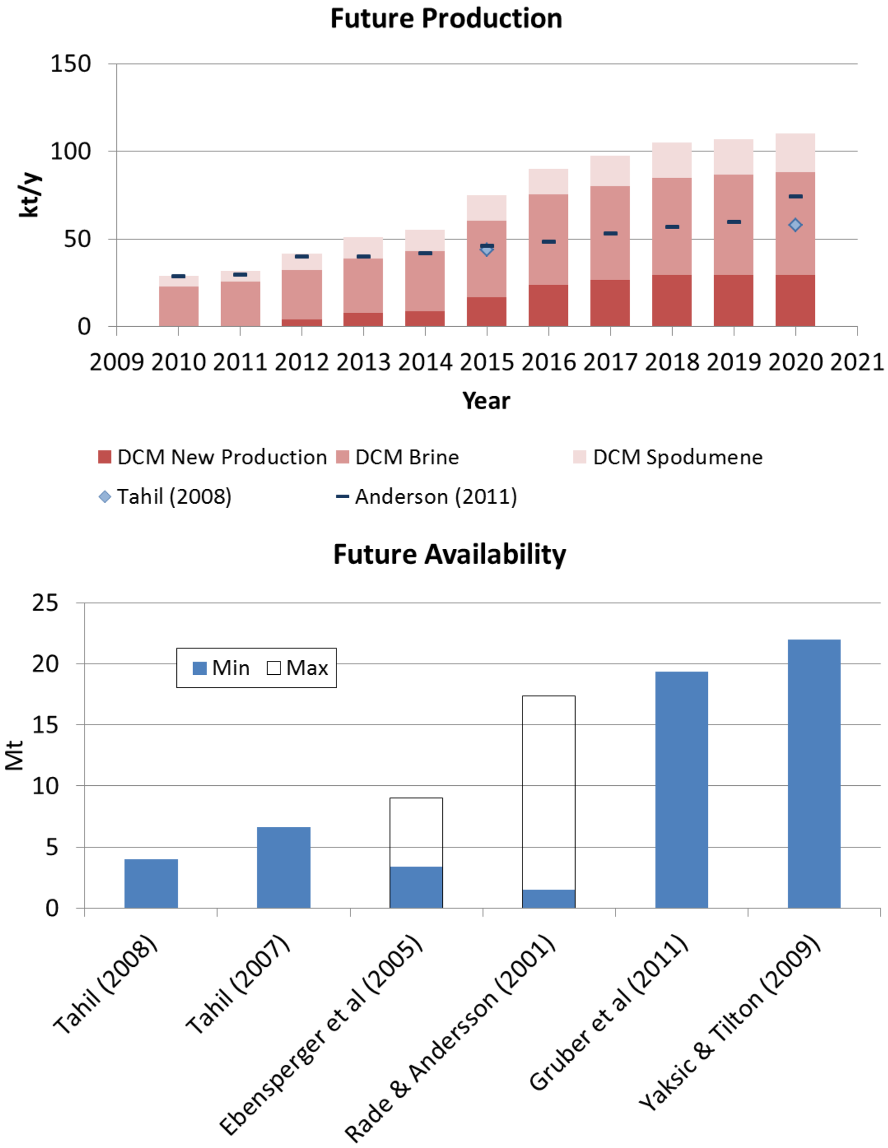
(Metal-Pages Ltd 2014). The pricing methodology adopted by such companies is often explicitly stated, and involves 'the detailed canvasing of buyers and sellers at set periods by reporters, who specialise in the markets they are pricing (Metal Bulletin 2011). Spot price trades involve metals of different quality, different chemical and physical forms, different quantities and different delivery and warehousing conditions. Producers and consumers are also likely to manipulate the price information they give to canvassing agencies to their own benefit. Editorial judgement is therefore used in collating price information but this subjective measure is also a source of inaccuracy. There are a number of proposals to improve this situation, such as establishing commodities exchanges for all metals, and creating a regulatory agency to cover all metals, though these are as yet not implemented (Metal-Pages Ltd 2014).

5.3 Estimates of future supply

There is a lack of lithium supply or resource system models, largely a function of the relatively small economic importance of lithium when compared to commodities such as oil. A number of estimates of future supply exist, though these are not explicitly linked to modelling efforts and do not integrate the assessment of all the dynamic aspects of resource systems.

Figure 5.13 presents estimates of both future production and future resource availability. These estimates are in the order of ~60 to ~110 kt/y of lithium metal production in 2020 and ~2 to ~20 Million tonnes (Mt) of lithium metal available over the century to 2100 or over all time. The methods used to calculate these values and the values themselves are discussed below.

Figure 5.13: Available estimates of future annual production and future cumulative availability of lithium



Source: (Speirs et al. 2013a)

The future production chart in Figure 5.13 contains estimates from three sources. A report by Dundee Capital Markets (DCM 2009) presents their projection for lithium supply to 2020. This data is subdivided into lithium production from brines, lithium production from spodumene minerals, and lithium from new production capacity forecast to come onstream from 2012. These data are represented by the red bars in Figure 5.13 and forecast lithium production of ~110 thousand tonnes per year (kt/y). Anderson (2011) presents a similar supply forecast to 2020, with slightly more conservative lithium production figures of

~75kt/y. Finally, Tahil (2008) presents two spot estimates for future lithium production, estimating 44kt/y in 2015 and 58kt/y in 2020.

The future resource availability chart in Figure 5.13 presents estimates from six sources. Tahil (2008) provides an estimate of the lithium he considers producible. This figure is based on the USGS reserve figure for lithium in that year. This can therefore be viewed as a conservative estimate since reserves estimates are likely to increase for a range of reasons (Clarke 2010). As presented in Figure 5.10, USGS reserve estimates have grown in more recent years and, by 2011, reserves were estimated at 13Mt, over three times the Tahil (2008) estimate.

In an earlier report, Tahil (2007) estimated future availability by calculating an URR[27] of lithium at 35Mt of lithium carbonate (or 6.6Mt of lithium metal). This figure is derived by applying a 50% recovery factor to estimates of lithium resource to arrive at a value of 33.55Mt lithium carbonate which is rounded up to 35Mt. This figure excludes any spodumene ore deposits which the author describes as 'not economically or energetically viable for Li-ion batteries'.

Ebensperger (2005) presents two estimates of future availability, 3.4Mt and 9Mt, both taken from Crowson (2001). These are presented in Figure 5.13, with the higher of the two estimates represented by the black outline.

Andersson and Rade (2001) present a low and high estimate of future availability, 1.5Mt to 17.34Mt, which represents a significant range. This value is derived by assuming a quantity of metal available from the earth's crust, adding the availability from future recycling of lithium and subtracting the lithium used by markets competing with the BEV market. As such this estimate represents the material available to automotive battery markets and not the total metal available. This is a relatively sophisticated methodology for calculating future availability, although the range presented covers a large proportion of the range of all estimates in Figure 5.13.

[27] The concept of URR is described in UKERC (2009)

Gruber et al (2011) present a figure for the minimum recoverable resource of 19.34 Mt. This is derived by summing the in-situ resources from known brines, pegmatites and sedimentary rock deposits, and applying a 50% recovery factor. This provides one of the largest estimates in Figure 5.13.

Finally, Yaksic & Tilton (2009) present a cumulative availability curve for lithium (Figure 5.8). This curve presents a range of marginal resources, their estimated quantity and the price of lithium needed to make them economic. This therefore presents an increasing quantity of lithium available as the price of lithium increases. This curve describes a low cost and a high cost scenario which give a narrow range of lithium price per unit weight. Given a lithium price of $2/lb lithium carbonate the curve suggests a lithium availability of ~22Mt. However, the curve also suggests that at higher prices, the availability increases significantly. If the lithium carbonate price rose to $7.20, about 44.8Mt of lithium would become available according to the authors[28]. This, they suggest, is an unlimited supply for all practical purposes.

Vikström *et al.* (2013) provide one of the few examples of lithium production modelling by applying a Hubbert-esque curve fitting approach to lithium production forecasting. Based on the available literature on available resources they develop a base case and a high case for ultimately recoverable lithium resources. Historical production was then curve-fit using three separate curve functional forms and constrained by the two URR cases. The results are presented in Table 5.6. These results show the trade-off between delaying the peak and maximum production rate, a result of the assumption of a bell-shaped production profile.

Table 5.6: Peak year and maximum production in thousand tonnes (kt) of lithium for the different curve functional forms and URR cases

	Base case: 15.5Mt			High case: 30.5Mt		
	Logistic	Gompertz	Richards	Logistic	Gompertz	Richards
Peak year	2074	2098	2078	2088	2129	2095

[28] At this price, the authors estimate that lithium extraction from seawater will become economic, producing the high estimate.

Maximum production (kt)	208	81	165	403	134	305

Source: Vikström *et al.* (2013)

5.4 Summary

Lithium demand has increased significantly in recent years in response to the growing consumer electronics market where it is used in Li-ion batteries. However, Li-ion batteries are also the likely technology to be used in electric vehicle technologies. Future demand for electric vehicles is forecast by many to be significant, and the size of batteries in these vehicles will be significantly larger than those used in consumer electronics. These facts lead many to forecast significant lithium demand growth in the coming decades.

Lithium resources and production are similar in many respects to the other energy resources, with similar definitions of resources, similarly increasing marginal production costs, and a similar production trajectory. However, lithium can also be recycled, providing an additional source of supply in the future as recycling rates improve and Li-ion batteries reach the end of their useful lifespans.

The formation of the lithium price is also similar, though the market is less sophisticated, with only spot metal trades between lithium producers and lithium consumers.

The estimation of future lithium supply, demand and price through modelling receives significantly less effort than similar estimations of oil resources. Lithium modelling is commonly limited to simplistic techniques and analysis rarely considers supply, demand and price in one integrated framework.

Important concepts discussed here, such as the impact of demand driven by low-carbon policies, and the impact of recycling on production are used in Chapter 7 to develop an indium resource system model, differentiated in these ways from a generic resource system model. The following chapter presents a case study of the resource system issues surrounding indium, which is used in Chapter 7 to develop an indium resource system model.

Chapter 6: Case study – Indium and thin-film photovoltaics

"I'd put my money on the Sun and Solar Energy, what a source of Power! I hope we don't have to wait until oil and coal run out, before we tackle that."

Thomas Edison

“"I have no doubt that we will be successful in harnessing the sun's energy. If sunbeams were weapons of war, we would have had solar energy centuries ago."

George Porter

Indium is a soft and malleable metal, and is relatively rare. It was discovered in 1863 but did not become widely used until the 1990s, where it became a component of flat screen display technologies. Its use as a component of the photoelectric material in some thin film PV technologies has triggered concerns regarding its future availability, and indium appears in many ‘metal criticality assessments’ where it is highlighted as a metal that may experience availability constraints in the future.

In this chapter the various issues surrounding the future supply of and demand for indium are explored. First, this chapter presents a brief history of indium, from its discovery to its modern uses and the emerging concerns regarding its availability for future PV manufacturing. The chapter then examines the range of factors that characterise the indium resource system. This section begins by examining indium demand, then indium production, finishing with a brief overview of indium price formation. The last section of this chapter reviews the approaches to modelling the indium resource system.

6.1 Brief history of indium

Indium is a group 13 metallic element, with an atomic weight of 114.82. It has an estimated crustal abundance of 0.1ppm (Suess & Urey 1956), comparable to that of silver (0.05-0.1ppm). It was discovered in 1863 by F. Reich and T. H. Richter while conducting spectrometric analysis of sphalerite ores, an important source of the metal today (Felix 2000). Indium was named after the indigo blue spectral lines which led to its identification.

Until the mid-20th century there were relatively few industrial applications for indium. In 1924 it was discovered that indium had a stabilising effect when alloyed with nonferrous metals (French 1934). Subsequent end-uses were developed throughout the 20th century, including light emitting diodes, bearing coatings and semiconductors. Indium was used in nuclear control rods from the 1970s, and its use as a coating in liquid crystal displays became the dominant end-use by the early 1990s (Schwarz-Schampera 2002). In the future, many expect that the thin film solar photovoltaic technology copper indium gallium diselenide (CIGS) will become the most significant end-use of indium, driven by decarbonisation policy and the uptake of solar electricity generation (Speirs *et al.* 2011).

Indium does not occur in its native state and is found in trace amounts in various ore types. Sphalerite, one of the most important for modern production, is mined primarily for the base metal zinc. It contains widely varying concentrations of indium, from typical concentrations of 10-20 ppm to around 10,000 ppm (1% by weight) in some extreme cases. These concentrations are considered high relative to other indium containing ore (Table 6.1). Indium is therefore most commonly associated with zinc production, though copper, tin, lead and other base metal bearing ores also contain indium (Table 6.1). In this thesis indium is referred to as a by-product metal, with the associated base metal referred to as the host metal.

Table 6.1: Minerals associated with indium

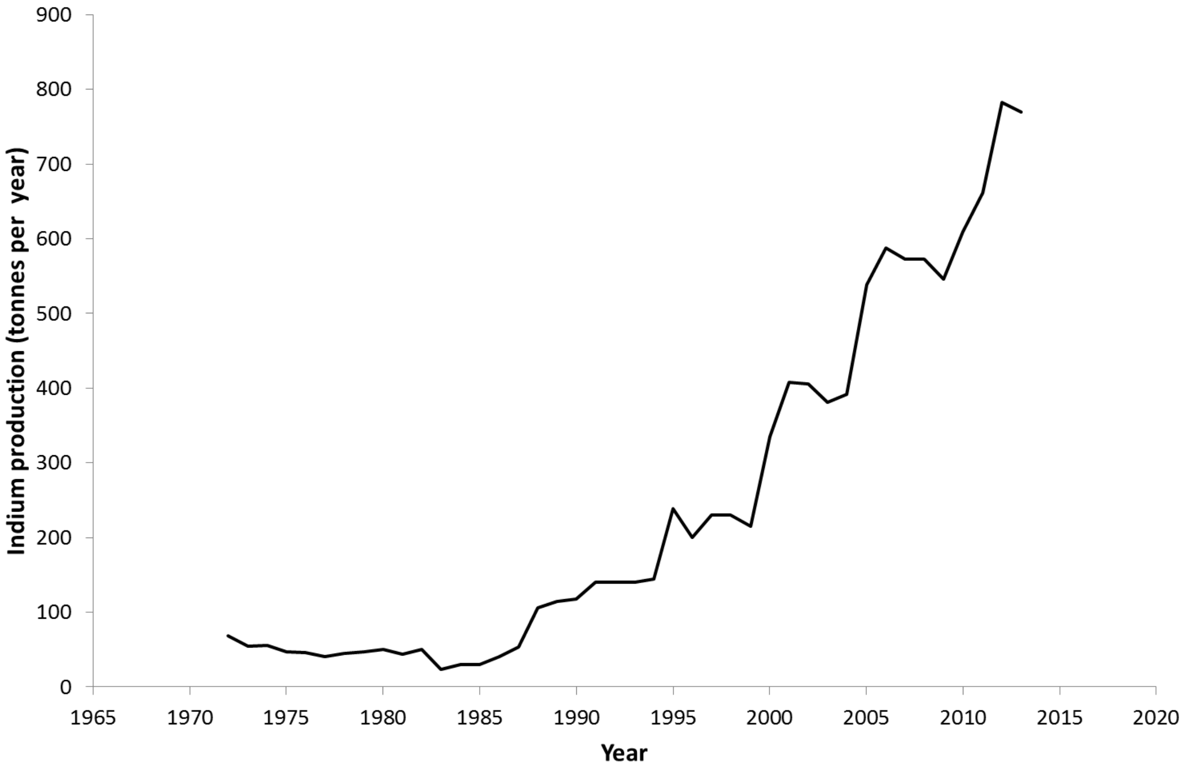
Mineral	*Composition*	*Indium content*
		Ppm
Sphalerite	ZnS	0.5–10,000
Galena	PbS	0.5–100
Chalcopyrite	$CuFeS_2$	0–1500
Enargite	Cu_3AsS_4	0–100
Bornite	Cu_5FeS_4	1–1,000
Tetrahedrite	$(Cu,Fe)_{12}Sb_4S_{13}$	0.1–160
Covellite	CuS	0–500
Chalcocite	Cu_2S	0–100
Pyrite	FeS_2	0–50
Stannite	Cu_2FeSnS_4	0–1,500
Cassiterite	SnO_2	0.5–13,500
Wolframite	$(Fe,Mn)WO_4$	0–16
Arsenopyrite	FeAsS	0.3–20

Source: Felix (2000)

Historical production of indium was relatively low and flat throughout the 1970s and 1980s as the nuclear industry was one of its few uses (Figure 6.1). The use of indium in flat screen displays began to drive demand significantly from the 1990s and from this period, production data shows a significant rate of growth. This rapid growth rate has been sustained by the new uses in thin film PV, which has contributed to demand over the last decade.

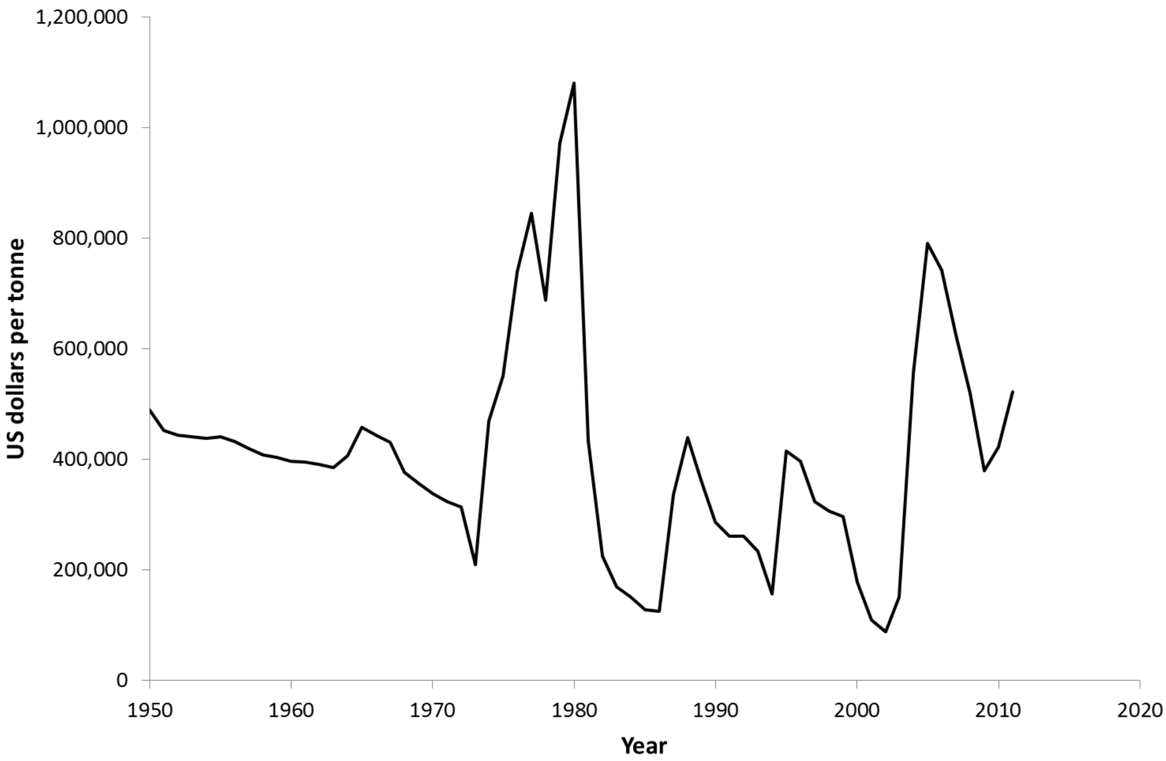
The historical indium price is volatile, likely due to a combination of rapidly changing demand drivers and the relative inflexibility of the by-product nature of its recovery (Figure 6.2). A significant price spike in the 1970s likely represents the new indium use in the nuclear sector, while the subsequent volatility is likely a response to the development of the flat screen display and thin film PV markets.

Figure 6.1: Historical production of indium from 1972 to 2013



Source: USGS (2013)

Figure 6.2: Global indium price in 1998 dollars between 1950 and 2011



Source: USGS (2013)

6.2 Indium resource system

6.2.1 Indium demand

In this thesis demand for CIGS thin film PV is considered the most significant driver of demand in the future. This topic is discussed first. Other demands such as thin film displays are then considered separately below.

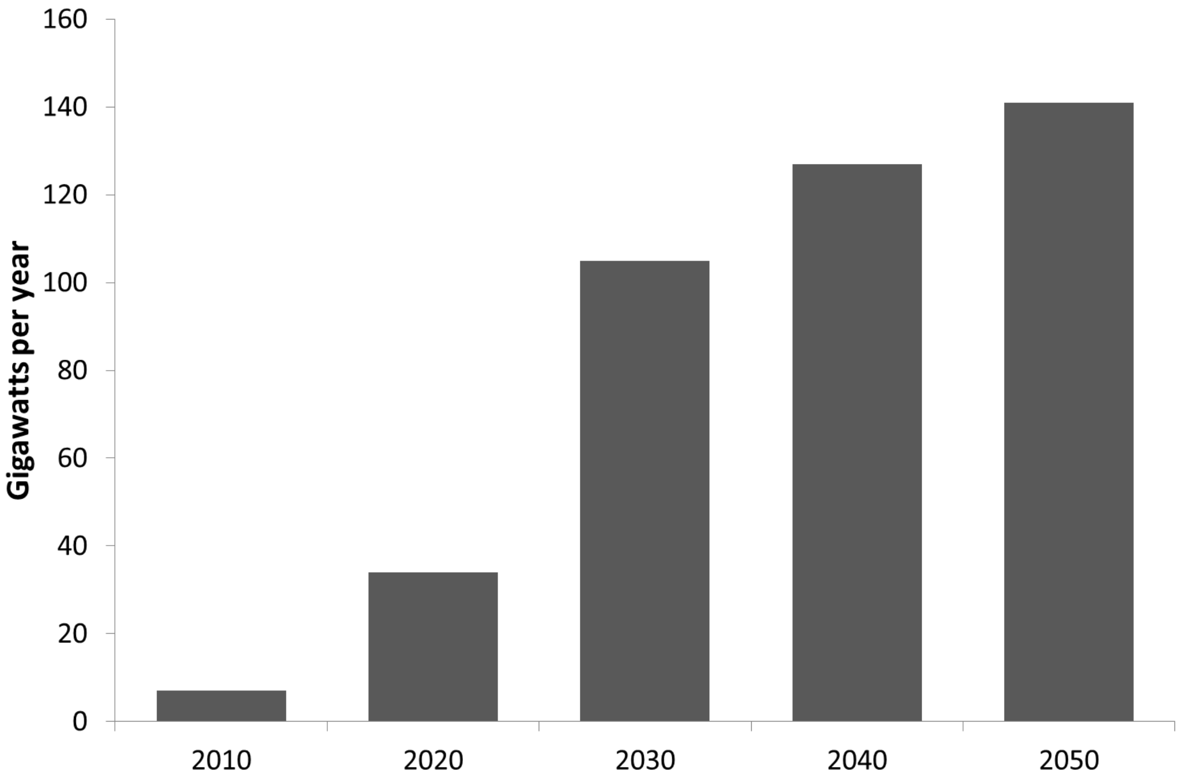
Demand for indium in CIGS thin film PV

The PV sector has grown significantly in the past decade, largely driven by the global decarbonisation agenda, and increasing emissions reduction targets. This growth is forecast to continue (Figure 6.3), with PV generation becoming a significant contributor to the global energy mix in the future[29]. Several PV technologies are expected to contribute: 1st generation crystalline silicon (c-Si); 2nd generation inorganic thin film; and 3rd generation

[29] PV is forecast to contribute 11% of global electricity by 2050 (IEA 2010b)

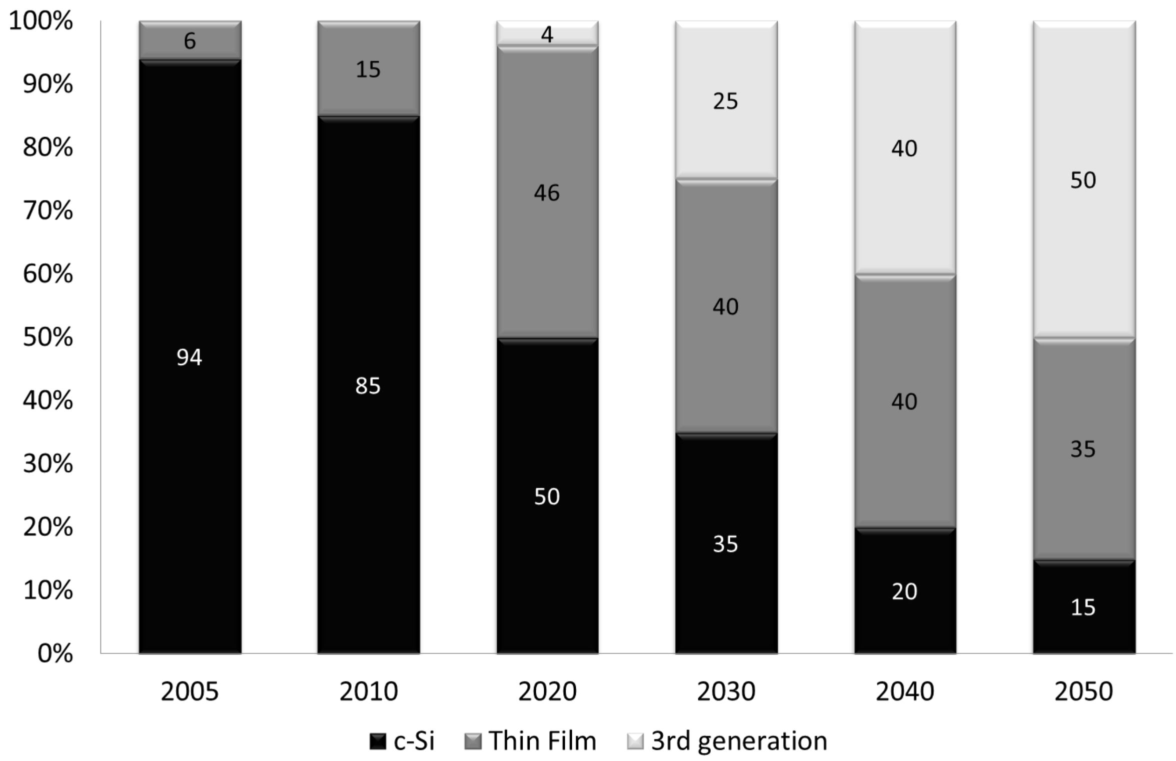
technologies including organic PV and other technologies relatively far from commercialization. Due to their low cost and relative technological readiness, 2nd generation inorganic thin film technologies are expected to take an increasing share of the PV market in the future (Figure 6.4). CIGS is included in this group of thin film technologies, and the impact on indium demand of this growth in thin film technologies is therefore dependant on the relative proportion of CIGS in the future PV energy mix, as well as the quantity of indium used per watt of CIGS PV cell produced.

Figure 6.3: IEA PV Roadmap



Source: IEA (2010a)

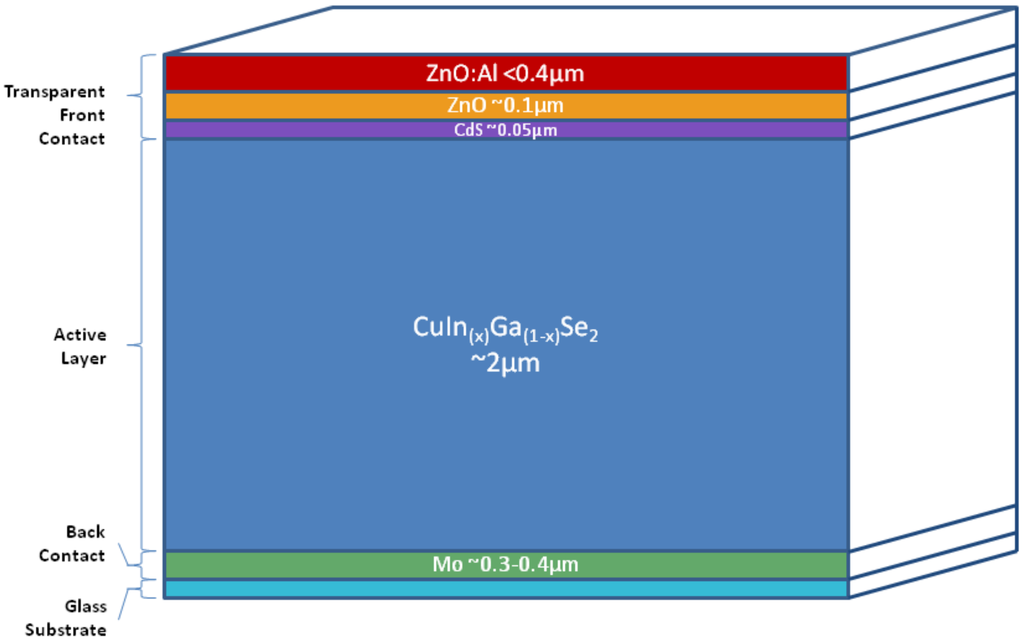
Figure 6.4: IEA estimate of future PV market share



Source: IEA (2008)

The indium material intensity in thin film PV modules depends on a range of variables relating to, amongst other things, the components of thin film PV cells. The structure of those cells is therefore relevant to the calculation of material demand. Figure 6.5 presents typical structure of CIGS thin film PV cells. The top contact layer is a Transparent Conductive Oxide (TCO) and the bottom contact layer is molybdenum. Other layers exist to provide these functions though this is assumed to have no bearing on the analysis here. The active layers consist of Cu $In_{(x)}Ga_{(1-x)}Se_2$ which is an alloy consisting of copper indium diselenide (CIS) and copper gallium diselenide (CGS). The relative weight of indium in a layer of Cu $In_{(x)}Ga_{(1-x)}Se_2$, is therefore related to the relative quantities of CIS and CGS in the alloy. Differing alloy compositions exist, therefore impacting indium demand. The ratio is represented in the chemical notation by x, which is an integer between 0 and 1, with 0 representing pure CGS and 1 representing pure CIS. In practice this number is usually between 0.5 and 0.85.

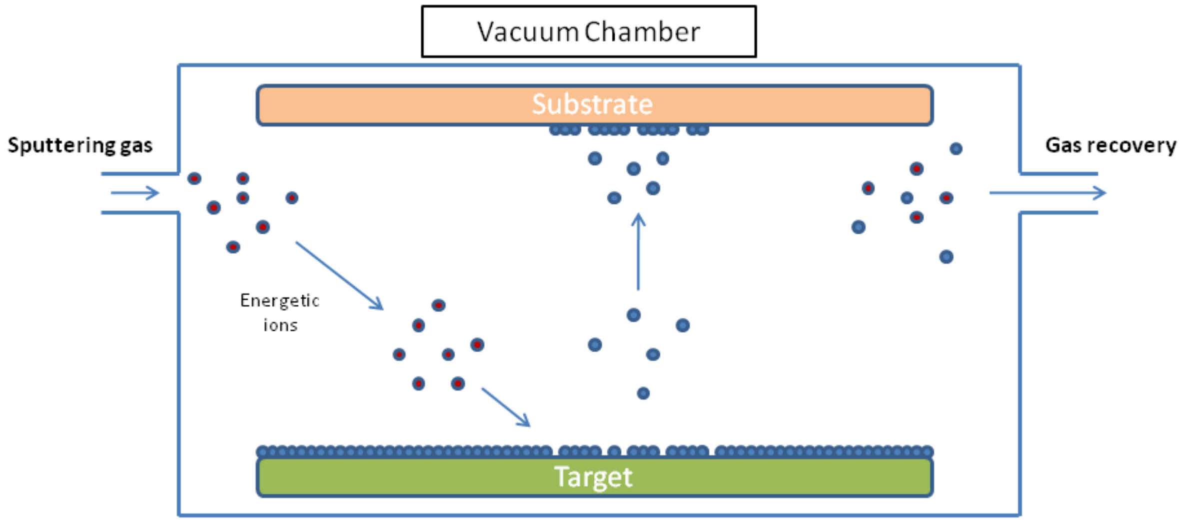
Figure 6.5: Typical structure of CIGS PV cells



Note: these diagrams are for illustration only, and do not represent any specific commercially available cell design.

The active layer thickness also impacts on the demand for indium and minimising the thickness of this layer, while maintaining efficiency, is one of the key challenges faced by PV manufacturers. There are several different deposition techniques used by thin film PV manufacturers to deposit active layer materials. Vacuum based processes dominate current thin film PV manufacturing, including sputtering and chemical vapour deposition (currently used by First Solar (NREL 2010)). Other deposition techniques exist, such as roll-to-roll processes, where active materials are deposited on rolls of substrate (such as aluminium foil) using a system analogous to ink-jet printing (Kessler *et al.* 2005). The efficiency with which active layers are deposited and recycled within the manufacturing process is referred to here as utilisation. In sputtering for example, a substrate is placed in a vacuum chamber adjacent to a 'target' made from the active layer material. The chamber is then bombarded with charged particles, which collide with the target material, aerosolising particles of the target. These particles then settle on the substrate, forming a thin layer. Figure 6.6presents a generic representation of the sputtering process. Particles also settle on the chamber wall and a large quantity of active layer material is left in spent targets. Some of these materials are recovered from the chamber wall and through the reprocessing of spent targets. A quantity of material is usually left however, and the efficiency of this recovery process may have a significant impact on the utilisation rate of PV manufacturing.

Figure 6.6: Generic description of sputtering process



The yield rate is another variable in the manufacturing process which impacts on the demand for materials. Some produced cells will not reach the market due to quality control issues. These cells may be reprocessed in order to recover the component materials but recovering 100% of materials is unlikely. Finally, the finished cell has a measured efficiency, defined as the single junction efficiency of converting light to electricity under standard test conditions (1000W/m^2). The efficiency impacts on the material demand per unit of energy capacity. The relationship between these variables is discussed below.

The range of variables relevant to the demand for materials from PV technologies can be summarised as:

- **Density of active material,** in this case either CIGS or CdTe;
- **Thickness of active layer,** measured in microns (µm);
- **% of material in layer,** in this case measuring the share of Indium in CIGS and calculated by formula weight;
- **Utilisation,** a measure of efficiency of material use in the manufacturing process

- **Yield,** a measure of the material lost due to faulty cells; and

- **Efficiency,** a measure of the amount of energy captured per square meter under standard test conditions (STC), being an energy intensity of $1000W/m^2$.

These estimates can be combined in the following mathematical relationship:

$$M_R = \frac{\rho F \mu}{UYS\eta}$$

6.1

where M_R is the material requirement in g/Wp, ρ is the density of the active layer material, F is the % of material in layer, μ is the thickness of the layer in microns (μm), U is the utilisation factor, Y is the yield, S is the insolation under standard conditions (1000W per m^2) and η is the electrical conversion efficiency of the PV cell.

By multiplying M_R by an assumed annual PV manufacturing rate, the total annual demand for a specific material can be determined. Conversely, by assuming a total annual material availability and dividing this by M_R,a total achievable PV manufacturing rate can be estimated.

There are several studies examining the future demand for indium from thin film PV (Andersson 2000; Keshner & Arya 2004; Fthenakis 2009; Wadia *et al.* 2009). Many assumptions for the variables listed above are discussed in these studies and these are presented in Table 6.2. Since most authors do not discuss yield separately, it is assumed to be 100% in all cases.

Some authors present assumptions that appear conservative given the current state of development (Andersson 2000; Fthenakis 2009). Other authors present highly optimistic assumptions based on theoretical limits that are unlikely to be achieved (Wadia *et al.* 2009). This variability in assumptions results in a range of material intensity assumptions from 0.0002 to 0.0382g/Wp, two orders of magnitude variation. Identifying the likely range of future PV demand is therefore not transparent based on the available literature.

Table 6.2: Assumptions on indium requirement in CIGS manufacturing

Author	Density (g/cm^3)	Thickness (μm)	% In in layer	Utilisation (%)	Efficiency (%)	Material Requirement (g/Wp)
Andersson (2000) Base Case	5.5[1]	2	26.5[5]	100	10	0.0291
Andersson (2000) 2020 Expansion potential	5.5[1]	0.5	18.3[6]	100	14	0.0036
Fthenakis[2] (2009) Conservative	5.8[3]	1.2	20[7]	90	14	0.011
Fthenakis[2] (2009) Most likely	5.8[3]	1	20[7]	90	15.9	0.0081
Fthenakis[2] (2009) Optimistic	5.8[3]	0.8	20[7]	90	16.3	0.0063
Keshner & Arya (2004) Current production	5.8	2	30[8]	75	12	0.0382
Wadia (2009)	5.6	0.05	24[1,9]	100	33	0.0002

Note:

[1]Back calculated using stated assumptions and the relationship in Equation 6.1

[2]Fthenakis estimates for 2020

[3]Not stated by Fthenakis (2009). Assumed from Keshner & Arya (2004)

[4]Based on data extracted using Engauge digitizer

[5]$CuIn_{(x)}Ga_{(1-x)}Se_2$ assumption x=0.75

[6] $CuIn_{(x)}Ga_{(1-x)}Se_2$ assumption x=0.5

[7] $CuIn_{(x)}Ga_{(1-x)}Se_2$ assumption x=0.55

[8] $CuIn_{(x)}Ga_{(1-x)}Se_2$ assumption x=0.85

[9] $CuIn_{(x)}Ga_{(1-x)}Se_2$ assumption x=0.67

[10] Andersson (2000) states that 7GWp is the constrained annual production possible with 290 tonnes of indium annual production. However, with a stated metal requirement of 2.9g/m^2, an efficiency of 10% and a manufacturing rate of 7GW/y the demand for materials would be ~204t/y. The paper does not explain this disparity.

Speirs *et al.* (2011) take a range of material intensity cases based on the range of assumptions found in the literature and derive a low material intensity case of 0.0032 g/Wp and a high material intensity case of 0.0464 g/Wp. As a result of this analysis Speirs *et al.* (2011) concluded that despite uncertainties about future demand, if the CIGS PV market were 20GW/y this could account for 12% to 170% of the current production of indium. Whether the CIGS market will ever reach this level of manufacturing, or how long that would take, is uncertain.

Table 6.3: Range of potential indium intensities in grams per watt peak based on the range of variable assumptions in the literature

Variable	Lowest material use	Highest material use
Layer Thickness (µm)	0.5	2
Utilisation (%)	100	75
Efficiency (%)	16.3	10
Indium Content (%)	18	30
Indium intensity (g/Wp)	0.0032	0.0464

Source: Adapted from Speirs *et al.* (2011)

Notes: Yield is assumed to be 100%

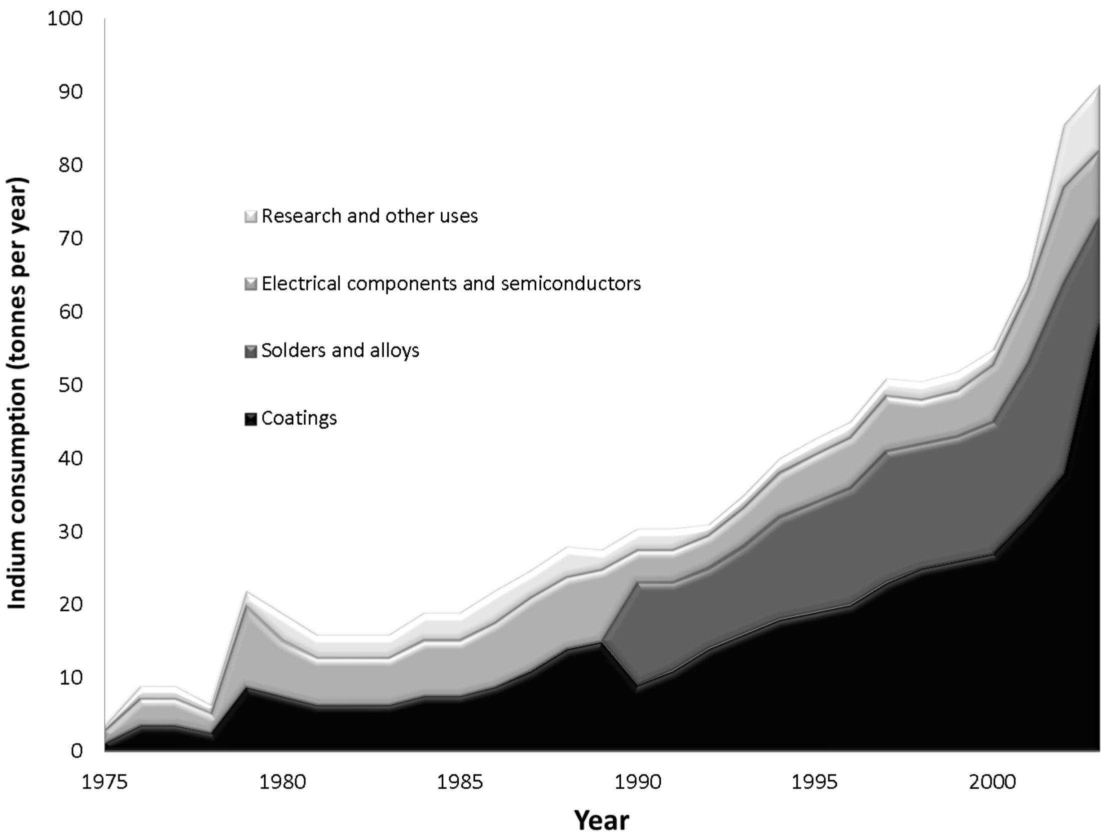
Other demand

There are several end uses other than thin film photovoltaics that have some bearing on indium demand. Some reflect indium's properties as a conductor or semiconductor, others its physical properties. The significant rise in indium production presented in Figure 6.1 appears largely driven by growth in demand for indium tin oxide (ITO), a transparent conductive oxide used in flat panel displays (USGS 2009a; USGS 2011). The growth in flat panel display technologies like LCD TV screens and flat screen computer monitors has driven ITO demand and therefore demand for indium (USGS 2009a; USGS 2011).

Other uses of indium include: in its metallic form in vacuum seals for low temperature sealed storage containers; in the electrolyte of zinc alkali batteries; ITO in sodium vapour lamps for improved efficiency; and in LED applications such as fibre optic communication technologies and to a lesser extent in LED displays (USGS 2011). Indium is also a constituent of several low melting point alloys used in a variety of industrial applications and consumer products.

Data on end-use consumption is not widely available, but Figure 6.7 presents some indicators of the trend in indium consumption in the United States. US consumption over the period 1975-2006 shows significant growth in indium demand in coatings applications, including ITO coatings in flat panel display technologies. Over this period, coatings as a share of total indium consumption in the US grew from 31% to 66%.

Figure 6.7: US indium consumption by end use



Source: USGS

Note: Coatings includes ITO

Data on PV market share in demand for indium are not common. Current estimates suggest photovoltaic use of indium accounts for an estimated 2-5% of the primary indium production, with use of ITO in flat panel displays accounting for 65% of annual indium production and around 30% used in other electrical and industrial applications (Fthenakis 2009; Shon-Roy 2009).

Efficiency

Efficiency of indium use in CIGS thin film PV modules is an integral part of PV manufacturers' ongoing drive to reduce costs. Reduction of layer thickness, increasing efficiency, increasing utilisation rate and increasing yield are all components of this drive to reduce costs, and all of those factors will also reduce indium intensity. Since the range of CIGS indium intensities discussed above includes both relatively contemporary estimates and theoretical maxima, the full extent of potential efficiencies in indium use have already been explored. The likely minimum indium intensity achievable is significantly greater than the theoretical limits explored by Wadia *et al.* (2009) however. Realistic future indium intensities are likely to lie in the order of the midpoint between these values and the current values for electrical efficiency, utilisation and layer thickness or approximately 0.02 grams per watt.

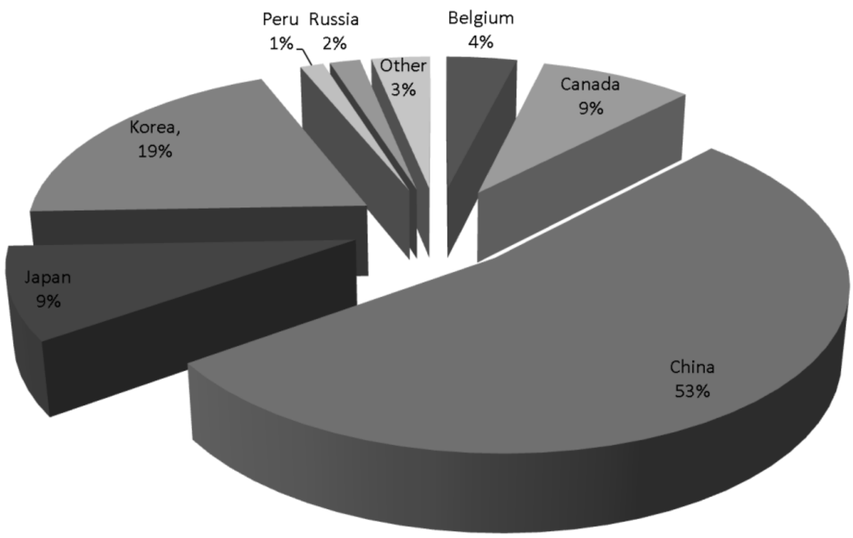
Substitution

The potential for substitution of indium in PV applications is significant. In the composition of CIGS active layer material the quantity of indium can be varied by increasing the relative proportion of copper gallium diselenide in the alloy (Speirs *et al.* 2011). However, reducing indium from CIGS below commonly used proportions is likely to negatively impact electrical efficiency, cancelling out any indium intensity improvements. However, other thin film technologies like amorphous silicon or cadmium telluride could both substitute for CIGS with no use of indium, assuming that their transparent top contact is not an indium compound (see 6.2.1). Moreover, 1st generation crystalline silicon cells, and future technologies such as organic PV could also substitute for CIGS. The range of potential substitution impacts could therefore range extremely from CIGS representing all new PV, to CIGS representing a vanishingly small proportion of future PV manufacturing.

6.2.2 Indium production

Historical indium production is presented in Figure 6.1, showing the approximate exponential production growth. The geographical distribution of production in 2013 is presented in Figure 6.8. This demonstrates the significant contribution China makes to global production. This geographical distribution closely follows zinc given the host/by-product relationship between zinc and indium. China is the largest producer of zinc, making up approximately 35% of global production (USGS 2014b).

Figure 6.8: Geographical distribution of indium production in 2013



Source: (USGS 2014b)

By-product indium production

Indium is a *by-product* metal, meaning that it is not recovered for its own economic value, but as a by-product of the extraction and refining of a *host* base metal. Indium is a by-product of zinc refining. The vast majority (~95%) of zinc mined is from sulphide ore deposits in which the sphalerite (ZnS) is mixed with sulphides of Cu, Pb and Fe. Zinc content is usually between 3 and 10%. Direct mining of indium may be possible at prices of $500,000 and above, but previous brief periods above this price have not initiated this type of production (Green 2009).

There are many different processes used to recover indium from zinc or other base metal ores. Some of these are described in Felix (2000), demonstrating the variety and complexity of refining processes.

Indium recovery processes typically have low extraction efficiency, which may incentivise end of life recycling in the future. Given this complexity, low efficiency, and the low concentrations relative to the host metal, the economics of by-product metal extraction are more complicated than other mineral resources. The incentive to produce indium is not only driven by the indium price, but also by the price of zinc, value of other trace elements and the type of ore extracted, as well as the cost of the production processes used.

Though absolute concentrations of indium can be measured in the ore it is recovered from (see Table 6.1), not all of this material will be produced. Some of these ores are processed at refineries that have no indium recovery capability. The indium in these ores is therefore discarded in tailing and other wastes. For those refineries that have indium recovery capability the extraction of indium is subject to a recovery factor of less than 100%, with the remaining indium also discarded. The Indium Corporation estimates that currently only 30% of indium extracted in zinc ore is produced, with the remaining 70% discarded in wastes (Mikolajczak 2009). Wastes containing indium are difficult to treat but may potentially be used as a resource of indium in the future (Mikolajczak 2009), though the economics of this recovery are likely to be less favourable than exploitation of more conventional resources. Authors have estimated indium recovery factors from zinc processing concentrates at between 50% and 80%, though the literature does not explain this variation, or how much this recovery factor can be increased in the future (Fthenakis 2009; Mikolajczak 2009). The examination of potential increase in recovery rate, particularly the potential to recover indium from tailings, is an important area for future research.

Finally, the produced indium, often at concentrations of between 95% and 99.9% purity, must be refined to purities of 99.9999% for many semiconductor uses. This typically involves electro refining, where indium electrodes are placed in an electrolyte through which electric current is passed. Impurities collect in anode slimes, where they are isolated and extracted. This process is repeated until the desired purity is reached.

Recycling

Large quantities of material are wasted in many of the common industrial processes which utilise indium, creating a significant opportunity for recycling to improve process utilisation. However, this is typically considered a process efficiency issue, represented by the 'utilisation' variable in Section 6.2.1 . The process used to deposit ITO on flat panel displays is a particular example, with most of the indium remaining in unused target material in overspray and other wastes. Only 30% of the ITO target is actually deposited on the substrate (USGS 2011). An estimated 60 – 70% of the target is recycled (Hsieh *et al.* 2009; Mikolajczak 2009; USGS 2009b). Often the user returns this recovered material to the supplier who reprocesses it into new indium targets, closing the material supply loop. Around 1000 tonnes per annum of indium is recovered in this way (Mikolajczak 2009) and is additional to mined metal supply. The result is that more indium circulates in this industrial resource loop than is demanded in mine produced indium. For simplicity, however, the mine produced indium into this industrial process is considered equal to the weight of indium leaving the system on flat panel displays, plus the quantity of material lost during the process. Based on the data above, the material lost may be between 5% and 10% in the case of flat panel display manufacturing. This experience may indicate the potential for process recycling in CIGS manufacturing, which has similarly low utilisation in the 30%-50% range[30] (Fthenakis 2009).

Given the complex nature of indium primary extraction and refining processes and the inherent low efficiency of the process, recycling of indium from end-of-life products containing the metal is likely to be incentivised for economic and environmental reasons. However, details on the recycling market and its future potential are scarce. The USGS state that there is a process to recover indium directly from used displays, though no details are provided on the quantities of recyclates produced. Lab based efficiencies of 92% have been reported for such recycling processes (Hsieh *et al.* 2009). In principle waste flat screens using ITO could also become a significant source of indium, given the relatively short life of many consumer electronic products this may emerge within the next ten years. Recycling

[30] In the case of two stage selenization deposition process based on sputtering, one of the deposition techniques currently mostly used in CIGS manufacturing.

rates for other end-uses of indium are not known, but are expected to be small given the size of those markets.

The potential to recover indium from end of life PV modules is uncertain. The similarity between the structure of flat panel displays and PV modules may indicate that high recycling efficiencies are possible and some authors include end of life recycling estimates of 80%, comparable to current ITO end of life recycling (Fthenakis 2009; Hsieh *et al.* 2009).

6.2.3 The indium price

The formation of the indium price follows a similar path to that of lithium. Indium has no futures market, with all indium traded for instant delivery (the spot market). Indium is produced in smaller quantities and is significantly more expensive than lithium per tonne. Indium has experienced significant price pressure from ITO demand, which has driven significant recovery efficiency improvements (Green 2009). However, the production of indium for its own economic value has not yet been forthcoming despite this price pressure, highlighting the economic issues associated with by-product metals.

6.3 Modelling the indium resource system

Simple metrics

Again, efforts to model the indium resource system are scarce. At their most simple, efforts to project future availability of indium involve simple metrics akin to the R/P ratio.

One type of estimate for the future production of these metals uses ***current production*** as a metric against which estimates of future demand for the metal from the PV market are compared (Andersson 2000; Keshner & Arya 2004; Wadia *et al.* 2009). However, while this type of comparison may provide an interesting illustration, it does not convey any useful information regarding the future supply potential of a material.

Another approach is to present some form of ***reserve estimate***, assume that this is a fixed stock and estimate the future PV production potential if a given proportion of that reserve were used to manufacture PV cells under different PV demand assumptions (Andersson *et al.* 1998; Andersson 2000; Feltrin & Freundlich 2008; Wadia *et al.* 2009). This approach: a) ignores the rate at which this reserve can be produced; b) assumes that current knowledge of the discovered reserves is accurate; and c) assumes that no reserves will be discovered in the future. These assumptions are unlikely to hold true, undermining the value of this type of future availability assessment.

Simple forecasts

A more sophisticated approach is to formulate an estimate of future production based on assumptions which influence the change in annual production rate over time (Andersson 2000; Keshner & Arya 2004; Fthenakis 2009). These can be relatively simple assumptions or more detailed time series models.

Four studies present 'future production' based estimates of indium availability (Andersson 2000; Keshner & Arya 2004; Fthenakis 2009; Wadia *et al.* 2009). Anderson (2000) provides an estimate of annual availability achievable by 2020, while Fthenakis presents two scenarios for availability between 2008 and 2100[31]. Keshner & Arya (2004) and Wadia *et al* (2009) present future availability potential without specifying the time horizon. Andersson (2000) and Keshner & Arya (2004) also present an availability figure based on production in the year their studies were published.

Anderson (Andersson 2000) presents two figures for CIGS PV manufacturing potential, based in part on two separate assumptions of future indium availability. The first, used in Andersson's 'Base Case', assumes annual material availability of 290 t/y, based on indium production in 1997. The origin of this data is not clear since USGS data for 1997 is only 230t/y and Andersson notes that "Refinery data for all metals, except for [...] indium, are taken from the US Geological Survey." Andersson does not state which other source is used to derive the indium figure, though Crowson (1994) is a source cited for production data of other materials.

The second figure, used in Andersson's 'Expansion Potential' case, is an estimate of availability in 2020 based on increased mining of primary metal (in this case zinc) and increased recovery of indium from those ores. By increasing overall availability by a factor of 1.2, indium availability is increased to 348t/y in 2020.

[31] Only the scenario data to 2050 is presented.

The two estimates presented by Andersson are very conservative in view of modern production rates. In the 13 years since Andersson's work, indium production has increased to approximately three times the base case estimate and twice the expansion potential case.

Keshner and Arya (2004) provide two assumptions of future indium availability, designated 'current production' and 'potential production'. The first assumption is based on production of indium in 2000, estimated by the USGS as 335t/y. The potential production assumption is based on indium availability of 26,143t/y, two orders of magnitude greater than production in 2000. This estimate is arrived at based on a fixed percentage of crustal abundance estimates, though the percentage, or crustal abundance assumed, is not disclosed. However, basing estimates on crustal abundance does not account for variability in ore concentration and the resulting economic viability of production. The appropriateness and usefulness of this estimate is therefore questionable.

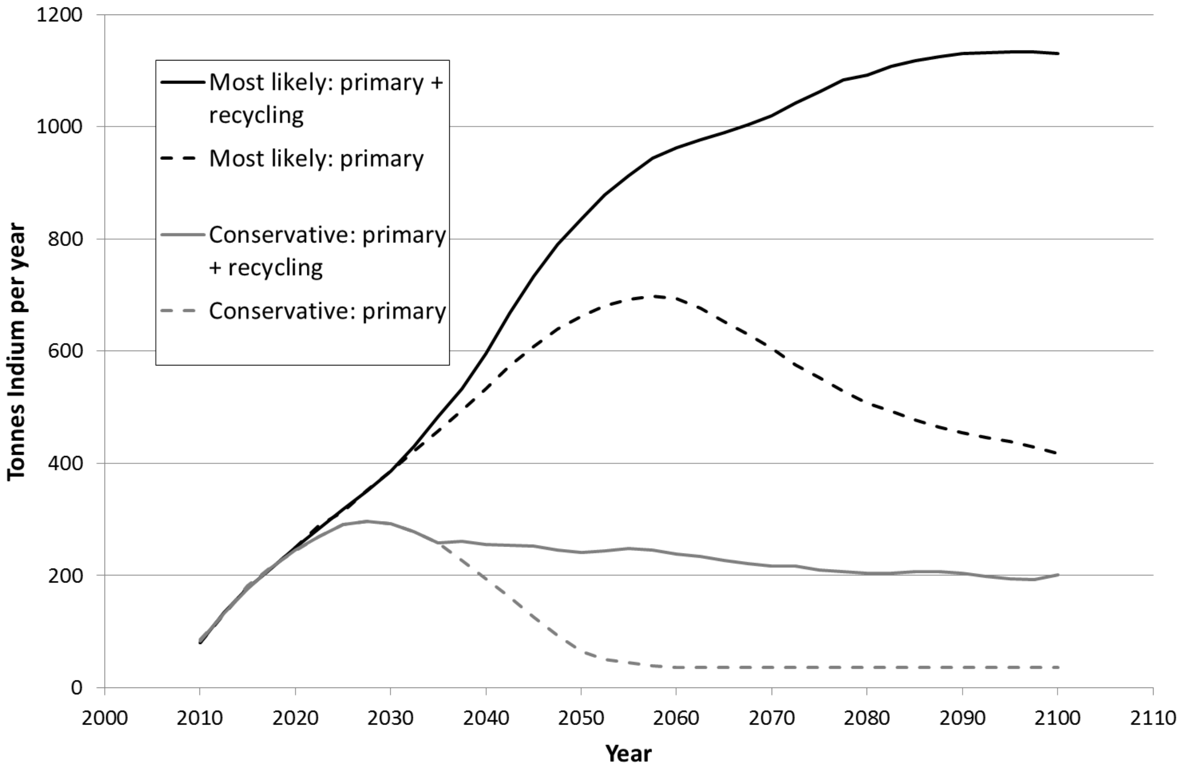
Fthenakis (2009) presents the most sophisticated basis for assumptions on future availability of indium using the simple forcasting methods, giving a time series of production from 2008 to 2100. Two cases are presented: a 'conservative case' and a 'most-likely' case[32]. For indium, Fthenakis derives these cases by first assuming future zinc supply. Fthenakis notes that zinc extraction has grown at 3.2% between 1910 and 2002 and that growth in the last one to two decades is consistent with the historical average (Gordon *et al.* 2006; USGS 2008). Fthenakis takes the average refinery production between 2007 and 2008 to be 545t/y and then applies to this a growth rate of 3.2%, with a peak in production in 2025 for the conservative case and 2055-2060 in the most likely case. This peaking profile is assumed based on the similarities Fthenakis draws between zinc and copper[33], and reflects the copper/tellurium scenario adopted in reference to Fthenakis' CdTe analysis. A recovery efficiency of 70%-80% is stated, though Fthenakis does not state his assumption for indium content in zinc ores. Finally Fthenakis assumes that current competing uses, such as flat

[32] An 'optimistic' case is also referred to, though the material availability profile is not presented.

[33] Fthenakis cites a similar reserves to production (R/P) ratio between zinc and copper as justification for assuming the same production profile. However, authors have written previously about the inadequacy of R/P ratios for analysis of future production (Bentley *et al.* 2007; Sorrell *et al.* 2009), suggesting that this may not be the best basis to defend this analogy.

panel displays, will increase in the future and therefore allocates only 50% of future indium production growth to the PV market (Figure 6.9).

Figure 6.9: Fthenakis' conservative and most likely estimates of future indium availability for thin film PV including recycling



Fthenakis applies a level of sophistication to availability assumptions which is not replicated by many other authors. However, not all of the assumptions needed to derive these figures are entirely explicit, and it is not possible to judge in all cases whether those assumptions are optimistic, conservative or otherwise.

Finally, Wadia *et al* (2009) estimates CIGS production possible given annual production of indium in 2006. USGS production data were used, which estimated global indium production to be 588t/y. Again this is not an estimate of future production potential and as set out previously it is unlikely that this will prove representative of indium production in the future.

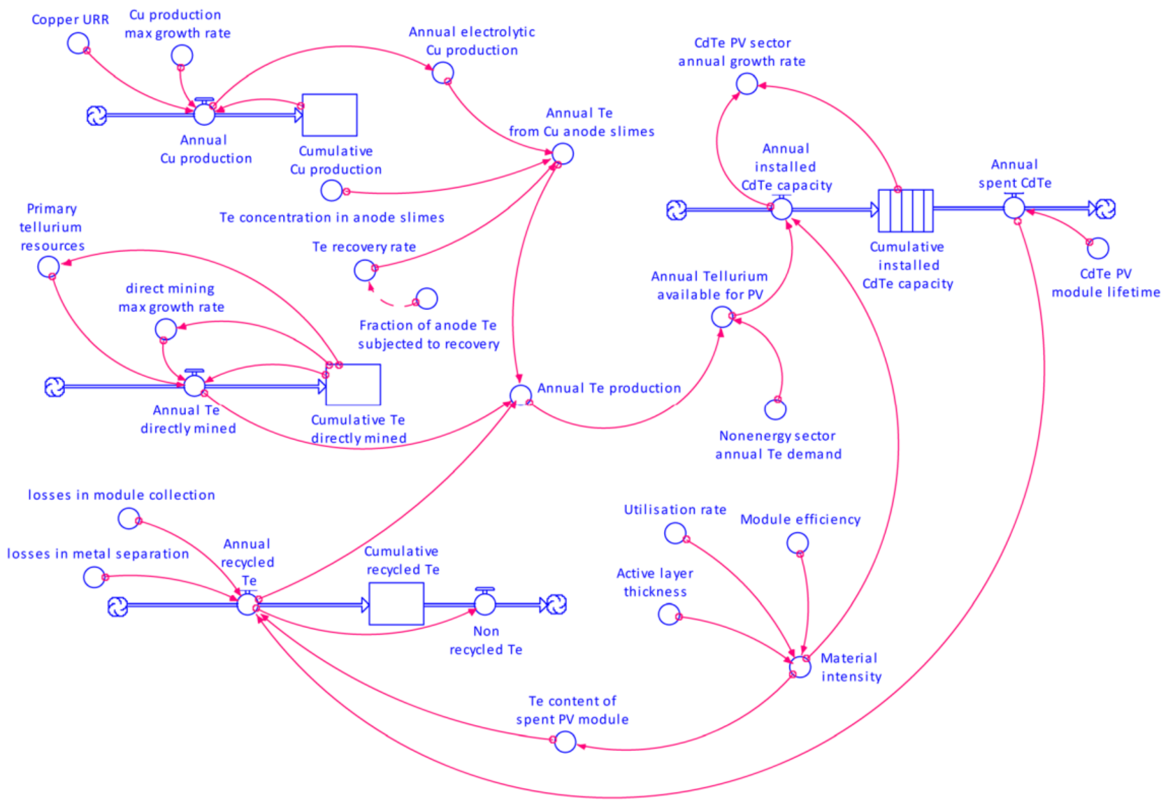
System dynamics

The modelling methodologies presented above are simplistic in many respects and there is a lack of more sophisticated approaches applied to modelling any aspects of indium resource system. System dynamics has been used to model the interaction of the thin film PV market and the development of tellurium resources (Houari *et al.* 2013), and this resource system has many similarities to the indium resource system in that:

- tellurium is recovered as a by-product of base metal extraction and refining;
- tellurium is traded in small volumes for a relatively high price;
- direct mining of tellurium is possible, but not yet economic in significant quantities; and
- tellurium is recyclable, but is not recovered from end-of-life products in any significant quantities commercially.

In this model, supply variables include the growth in host metal production (copper), the recovery rate of tellurium from copper refining, the contribution of direct mining of tellurium, and the contribution of recycling, including PV module lifetime delays on access to end-of-life CdTe modules. The model also includes demand side variables including the rate of technological development of CdTe modules and its effect on tellurium intensity. Though the values for each of these variables are specific to tellurium, the structure of the dynamics is entirely appropriate for modelling the indium resource system.

Figure 6.10: Causal loop diagram of tellurium resource recovery and demand for tellurium including CdTe demand and its development over time.



Source: Houari et al. (2013)

6.4 Summary

Indium demand has increased in recent years due to the demand for flat-screen displays in which indium is used. However, future indium demand increase is expected as a result of its use in thin-film PV cells. The demand increase in the future could be significant depending on the development of the solar PV market, and the CIGS thin-film market in particular.

Indium production is similar to lithium in many respects with one significant exception. The vast majority of indium is produced as a by-product of zinc mining, and the future production capacity of indium and zinc are therefore linked. Zinc production is expected to grow in the future, but if that growth is slower than the demand growth anticipated for indium then indium capacity will likely be a constraint on the indium resource system.

The formation of the indium price is similar to that of lithium, with only a spot market through which the price discovery process occurs.

The level of research examining future estimates of the indium resource system is similar to that of lithium, with relatively unsophisticated estimation methods common in the literature. System dynamics has been used to examine the critical metal tellurium, which has many of the same features as indium, including uses in thin-film PV technology and a by-product production process. However, indium has largely been overlooked by those conducting quantitative modelling of metal resource systems.

Important concepts discussed here, such as the impact of demand driven by low-carbon policies, the impact of recycling on production and the impact of capacity constrained by the link between host and by-product metals are used in Chapter 7 to develop a lithium resource system model, differentiated in these ways from a generic resource system model.

Chapter 7: A system dynamics model comparison of energy resources

"All models are wrong. Some are useful"

George Box, 1987

This chapter describes the mapping, construction and testing of three system dynamics models: the generic resource system model; the lithium resource system model; and the indium resource system model. The models are designed to test how these systems respond to changes in their input variables. In particular, Chapter 8 evaluates the way these models behave in response to short term constraints in capacity, varying contributions of recycling, the impact of by-product constraints on capacity and the impact of varying marginal extraction costs. The models are also used to investigate the impact of increased inventory material substitution. These models are not designed to make forecasts of future system conditions, but to shed light on the types of dynamic behaviour these systems exhibit.

In Chapter 4 the evidence base surrounding common aspects of resource systems is gathered, and these aspects are used here to inform the development of the generic resource system model, including appropriate model elements, the structure of the relationship between those elements, and appropriate exogenous values to set as initial conditions. Chapter 5 and Chapter 6 gather evidence specific to the resource systems of lithium and indium respectively. This evidence highlights several structural differences in resource systems, including differing drivers of demand, recyclability, and by-product/host relationships in resource recovery. This evidence is used here to inform the adaptation of the generic resource system model into a lithium resource system model, and indium resource system model respectively.

The chapter begins by presenting the key variables and other aspects of problem articulation in Section 7.1. The high-level, conceptual structure of the models is then described in section 7.2. This involves explicit boundary definition using boundary diagrams and the mapping of the specific systems through use of subsystem diagrams and causal loop diagrams. The chapter then describes in more detail the model structure for each of the three models, starting with the generic resource system model and developing similar model structures to accommodate the differences of both the lithium and indium resource systems. This includes stock and flow diagrams, which present the detailed structure of the various model elements, and equations representing the underlying mathematical relationships defining this structure. These models are then tested in Section 7.4 and subsequently evaluated against the objectives of this thesis in Chapter 8. This structure follows the five steps of the system dynamics modelling process, laid out in Figure 3.8, namely: 1) problem articulation; 2) developing a dynamic hypothesis; 3) model formulation; 4) model testing; and 5) model evaluation.

7.1 Problem Articulation

The first stage of the modelling process involves the definition of the models' subject matter, its key variables, the time horizon over which the model should operate, and its reference modes, meaning the existing data which describes the types of system behaviour the model is designed to replicate. The theme of this modelling effort is clearly defined in the opening chapters of this thesis. The remaining issues are discussed below.

7.1.1 Key variables

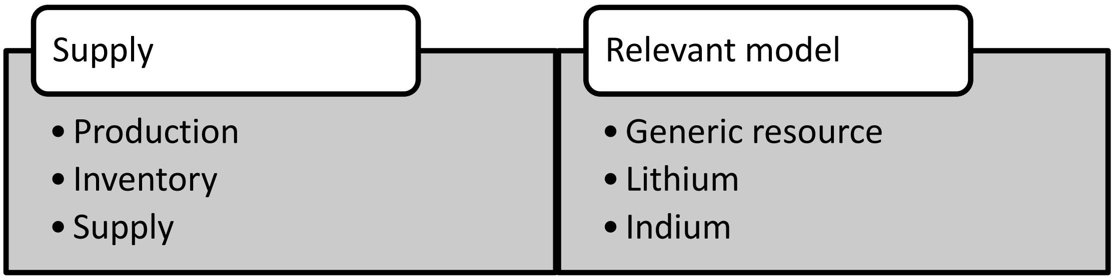
The key variables motivating resource system behaviour can be summarised in several subsystems. The majority of these subsystems are common to all three models and where subsystems are specific to a particular model, this is indicated. The structure of these subsystems is described in greater detail in Section 7.2.

Supply

The function of a resource system is to supply that resource to its consumers. Issues of supply and related variables are therefore central to the development of any resource system model.

There are several parts of the supply subsystem (Figure 7.1). First, supply and production can be separated to represent the difference between extracting a resource and supplying it to the market. By separating these, it is also possible to represent the existing inventory as a variable. Inventory is a useful variable to include as its fluctuation reflects the extent to which supply and demand are in equilibrium. Inventory represents the quantity of produced resource that exists above ground but yet to be supplied to the market. This includes quantities of commodity existing between the well/mine and the refinery, and analogous to oil existing in pipelines and tankers but yet to reach the first consumer (refinery). However, it excludes politically managed quantities of oil such as strategic reserves. The model uses this stock to simulate the buffering effect common to the 'up-stream' side of many resource systems.

Figure 7.1: The elements of the supply subsystem



Capacity

Resource systems typically suffer delay in the feedback of information (Sterman 2000). A significant driver of this delay is the inertia of production capacity. To increase production capacity of a resource requires significant capital investment, which can take in the order of several years (Kaiser & Snyder 2012). This is a critical feature defining the behaviour of the resource system and is therefore a necessary variable to include in a resource system model. The capacity subsystem includes variables for the level of production capacity, the utilisation of that capacity and the desired capacity needed in the future (Figure 7.2).

Capacity utilisation reflects the proportion of existing capacity used for production at any given time. Decreasing commodity price impacts on the profitability of capacity and under these conditions the operators of capacity in a real system may choose to halt some proportion of production. Since increasing or decreasing capacity is either time consuming or economically problematic it is common for resources systems to tend towards some level of spare capacity, and subsequently deal with short term demand and profitability fluctuations by managing the utilisation of existing capacity. The capacity utilisation subsystem simulates this type of system behaviour. National strategic reserves also play a role in responding to changing demand, but quantities of resource such as this are not captured in the capacity subsystems.

Desired capacity is the variable which communicates the need to increase or decrease the available capacity, based on the expected profitability of building new capacity. If all the capacity is being used, then demand increases will go unserved and price will increase. That price increase will increase the perceived profitability of building new capacity. If capacity is underutilised, then all demand is being served and profitability of building new capacity will be low. The model will not build new capacity under these circumstances. Profitability is calculated as the ratio of production costs to commodity price.

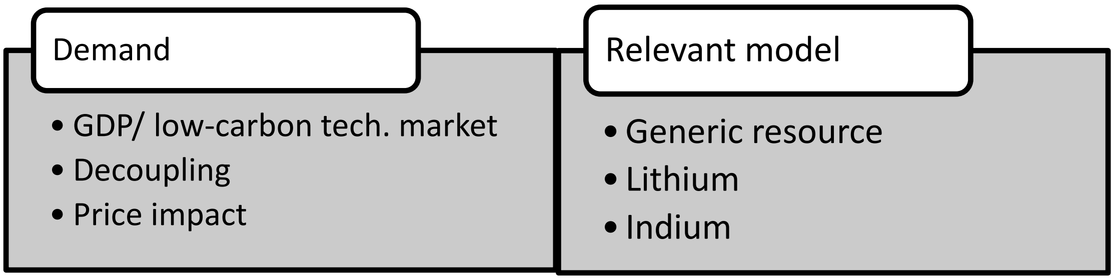
Figure 7.2: The elements of the capacity subsystem

Capacity	Relevant model
• Production capacity • Capacity utilisation • Desired capacity	• Generic resource • Lithium • Indium

Demand

Demand for resources may be driven by a number of things. For example, the demand for oil has long been linked to global GDP (Kaufmann 1992), though recent studies have contested the direction of causality between the two (Narayan & Popp 2012). In addition, the relationship between oil demand and GDP is expected to weaken over time, decoupling the two through some combination of technological change and substitution effects (Kaufmann 1992). Alternatively, a peak in the availability may precipitate a peak in oil demand through dramatically increasing price (Sorrell *et al.* 2009). Demand for critical metals is expected to be driven by a very small number of end uses, such as low-carbon technologies (Angerer *et al.* 2009b). This demand growth is expected to slow as installation of these technologies flattens. Demand is also influenced by the market price of the commodity through the price elasticity of demand (Stiglitz & Walsh 2006). When the price of metal goes up, consumers may be influenced to use less or to develop more efficient ways to use it, decreasing demand. Conversely if the price decreases, demand is likely to increase.

Figure 7.3: The elements of the demand subsystem

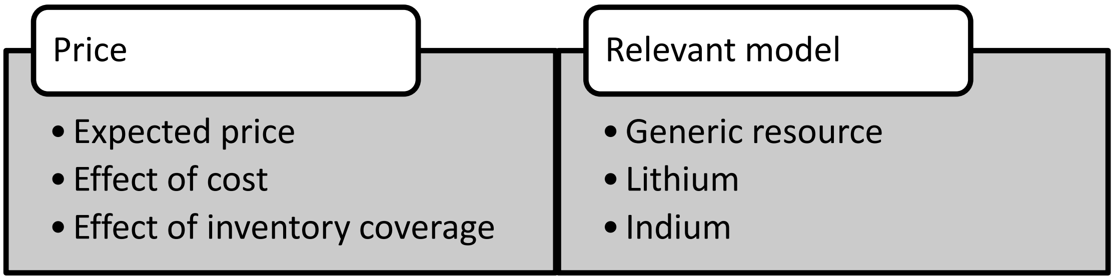


Price

As discussed above, commodity price has a significant influence on resource systems, and representing that price formation within the model is important. Price is defined by three main variables. First is *expected price*, which represents the market's expectation of the resource price in the future. This variable allows for the time delays in price formation and the market's need to make price based decisions in the very short term. This therefore allows the model to represent the kinds of price volatility associated with price uncertainty that are common in resource systems. The effect of resource extraction costs is also important in the price formation process. While companies can produce resources at a cost below market price in the short term, over the medium term the market price is likely to be linked to the marginal cost of production (Mankiw 2011)[34]. An estimate of the cost of production and the effect of that cost on the commodity price are included to incorporate these effects. The extent to which supply and demand are in equilibrium affects the market price of commodities, with markets experiencing rising demand or falling supply, subject to price inflation, and markets with falling demand or rising supply experiencing price deflation (Stiglitz & Walsh 2006). This equilibrium is captured by inventory coverage. Where the proportion of inventory over demand is falling, price will rise, and where the proportion of inventory over demand is rising, price will fall.

[34] The quantity of product that a competitive firm is willing to supply to the market is the quantity where marginal cost and marginal revenue are equal for any given price. An upshot of this is that a firms marginal cost curve becomes its supply curve, hence price and marginal cost are linked.

Figure 7.4: The elements of the price subsystem

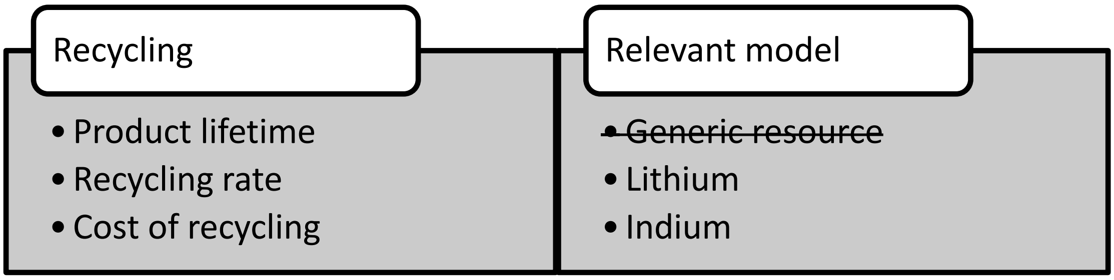


Recycling

While previous subsystems have applied to all three resources discussed in this thesis, the recycling subsystem is specific to the metal resource systems, as the generic resource is not recyclable. This is the first significant structural difference between the three resource systems modelled.

The recycling subsystem is defined by three main variables. The lithium or indium is assumed to be incorporated in low-carbon products or other consumer products, which can be recycled at the end of their useful life. The *product lifetime* defines how long that period is and therefore how long after the metal was originally recovered from a mine it will be available for recycling. Not all of the metal contained in these products will be recycled. Some products will not reach recycling facilities, and those that do will be subject to a recycling process which will recover less than 100% of the metal contained in the product. This is captured by the *recycling rate*. Whether recycling happens at all is a function of the *cost of recycling* and the market price of metal. In the absence of regulation, metal will only be recycled if it is economical to do so (Speirs *et al.* 2013a).

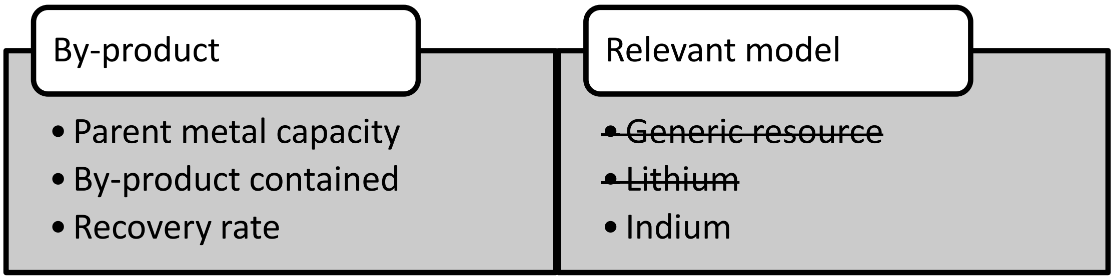
Figure 7.5: The elements of the recycling subsystem



By-product

The final subsystem defines the by-product nature of indium recovery. This is another structural difference between the resource systems modelled and applies only to the indium resource system. The subsystem assumes that the majority of indium is recovered as a by-product of zinc production (a small subsystem also allows for primary indium production to be modelled). This *parent metal capacity* is therefore endogenous to the model. The quantity of indium *by-product contained* is included as a fixed variable, while the *recovery rate* improves over time, tending towards a defined maximum asymptotically.

Figure 7.6: The elements of the by-product subsystem



7.1.2 Time horizon

The models described in this chapter are designed to run over a 100 year time period. This relatively long time scale was chosen for two critical reasons. First, a number of the feedbacks in resource systems are affected by delays in the rate of response. These feedback delays are discussed in the case study chapters above. An illustrative example of this is the time delay experienced in the oil resource system between the decision to increase oil production capacity and the availability of that capacity for production. This is a function of the time it takes to invest in and construct the large infrastructure projects associated with oil production capacity (Kaiser & Snyder 2012). The construction time for such projects can take in the order of several years and the effect of this delay on the system’s response to change can influence the behaviour of variables for significantly longer than the delay period. The 100 year model time horizon allows for these time delays to be reflected fully.

Second, climate change mitigation is typically measured on decadal timescale, and the targets driving uptake of low-carbon technologies are often set at the year 2050. The 100 year time horizon allows for the impacts of these targets on future resource demand to be fully examined.

Finally, any modelling over such long timescales is subject to significant uncertainty, and it becomes increasingly hard to reasonably validate models as the time horizon increases.

7.1.3 Reference modes

In system dynamics modelling the expected behaviour of the system being modelled is examined to provide guidance as to realistic types of expected behaviour, and to validate the model to the extent that this is possible (Sterman 2000) (see Section 7.4). The evidence used to inform expectations of model behaviour is typically time series data on key system variables of interest such as price, or supply rate. These time series are referred to as *reference modes*. It is possible to use either recorded historical trends, or widely expected future forecasts as reference modes depending on the purpose of the modelling effort (Sterman 2000; Contestabile 2012).

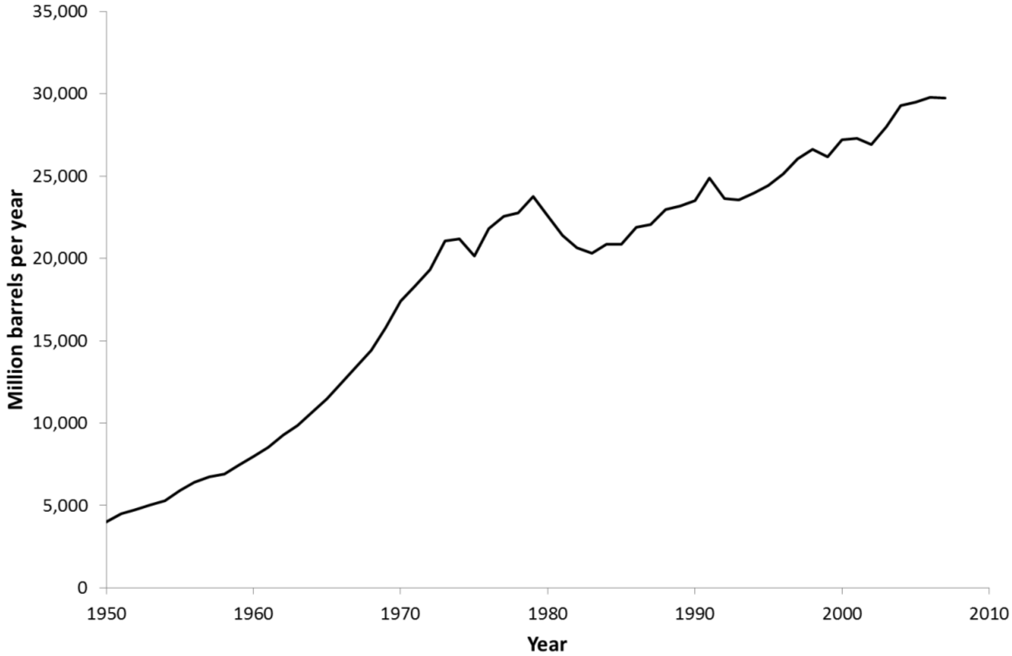
Historical price and historical supply are readily available data sets for lithium and indium and provide appropriate historical reference modes. The reference modes of oil are used as a proxy for the generic resource system (Figure 7.7, Figure 7.8, Figure 7.10, Figure 7.11,Figure 7.13 and Figure 7.14). In addition to the historical reference modes, there are also some forecasts representing possible futures which can inform the modelling process based on the types of dynamic behaviours expected (Figure 7.9 and Figure 7.12). Both of these types of modes are discussed for each of the resources in turn below.

Oil as a proxy for the generic resource system

The historic global production of oil is dominated by two main phases over the past 60 years. In the period to 1970 oil production appears to have grown at an exponential rate. This is followed by a period of oscillation, with an underlying growth trend which appears more linear. In system dynamics this first trend can be replicated by a reinforcing feedback loop, while the second trend is likely to be represented by a balancing feedback loop containing a delay.

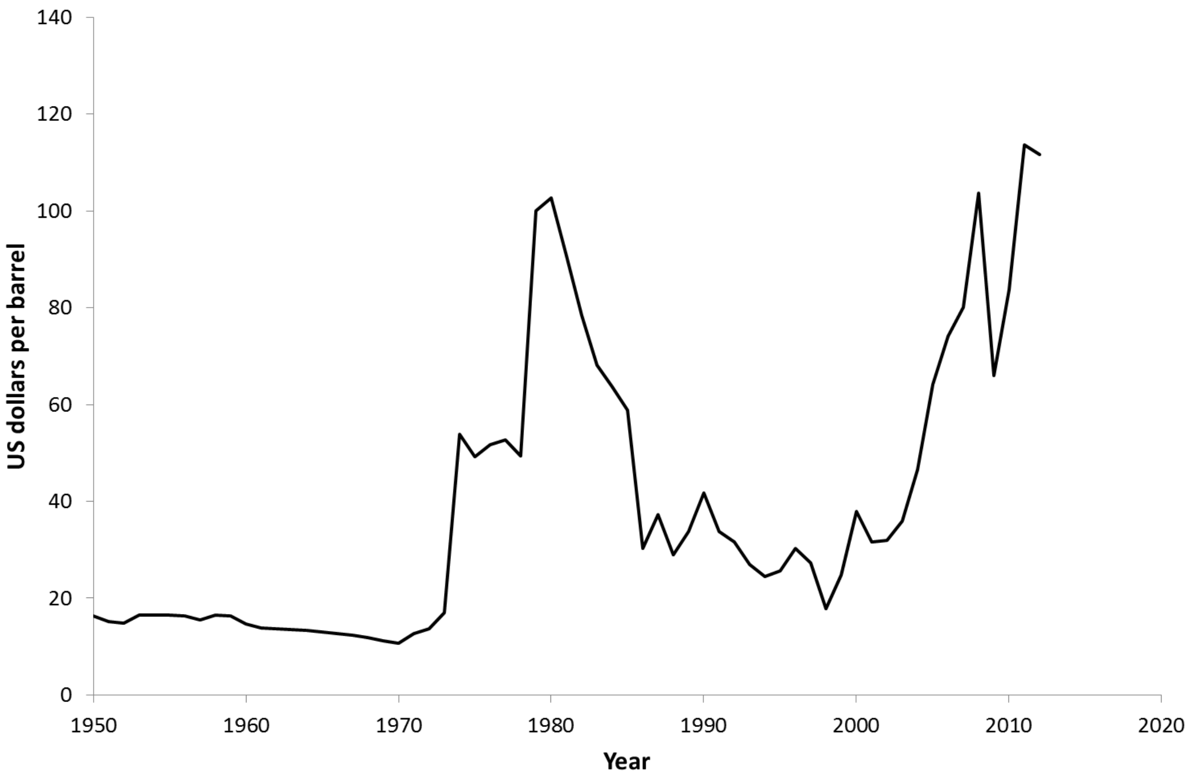
The historical oil price (Figure 7.8) has exhibited significant volatility over the past 60 years. This behaviour can be replicated by a balancing feedback with delay. The extreme nature of some of the oscillations seen in this reference mode can be replicated by making the delay sufficiently long.

Figure 7.7: Global oil production between 1950 and 2007



Source: (Sorrell *et al.* 2009)

Figure 7.8: Global oil price in 2012 US dollars per barrel



Source: BP (2013)

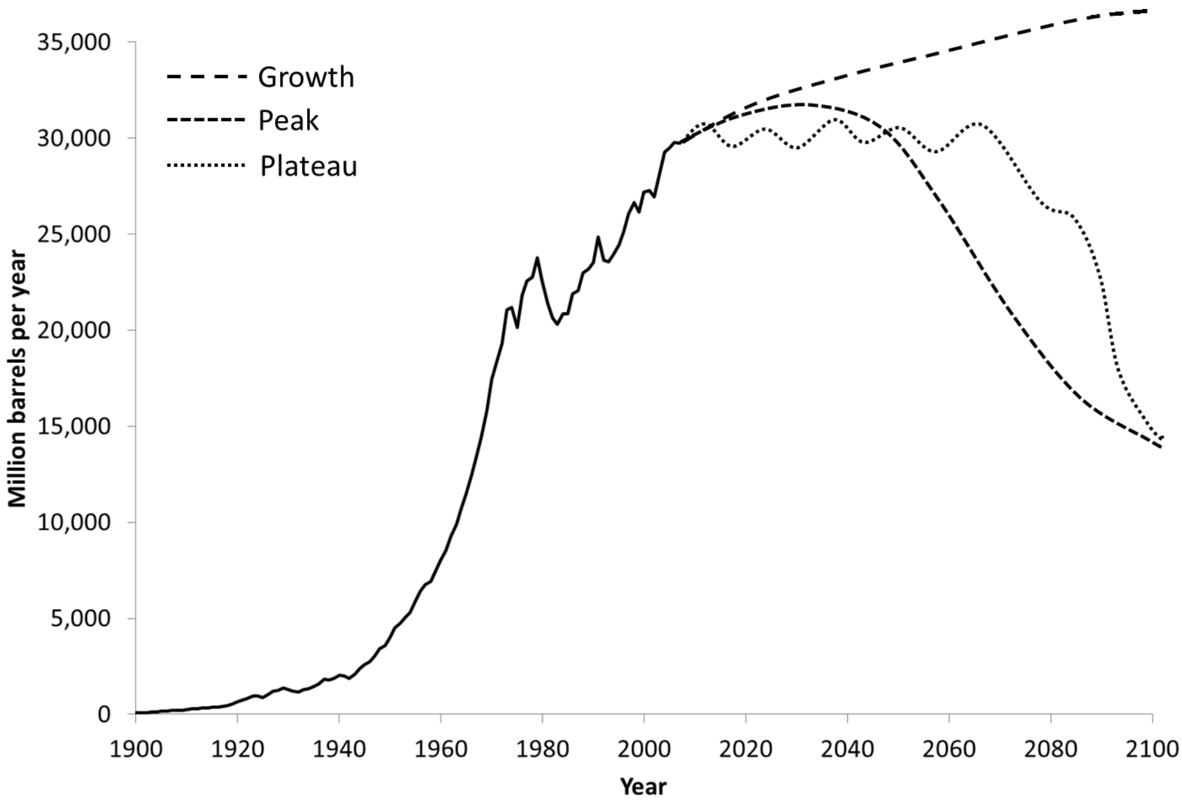
Notes: Oil price based on three separate price indicators: 1861-1944 US average; 1945-1983 Arabian Light posted at Ras Tanura; and 1984-2012 Brent dated.

Available forecasts of future prospects for oil production tend to fall into three main categories: peak; plateau; or growth (Hughes & Rudolph 2011) (Figure 7.9). Peak production is forecast to follow the bell-shaped curve described by Hubbert (1982). While peak oil theory states that this peak will be driven by a peak in oil production, others have suggested that a peak in oil demand should be expected, delivering a similar outcome in terms of bell-shaped supply profile, but with very different macroeconomic implications.

Plateau production is likely to oscillate around an average within a +/- 15% range, though there are different definitions of plateau in the literature (Sorrell *et al.* 2009). This system behaviour is likely dominated by the influence of a balancing feedback loop with delay. After the period of plateau, future oil demand is expected to decrease, following an exponential decline similar to the decline in the peak oil production profile. This decline is likely to be dominated by a balancing feedback loop.

Finally the growth production forecast projects oil production to increase into the future. While those that forecast such growth tend not to look further than mid-century, their forecasts show no period of decline (Sorrell *et al.* 2009). This kind of growth can be represented through a combination of reinforcing and balancing feedback loops, with the relative contribution of each determining the shape of growth.

Figure 7.9: Illustrative example of three possible oil production futures



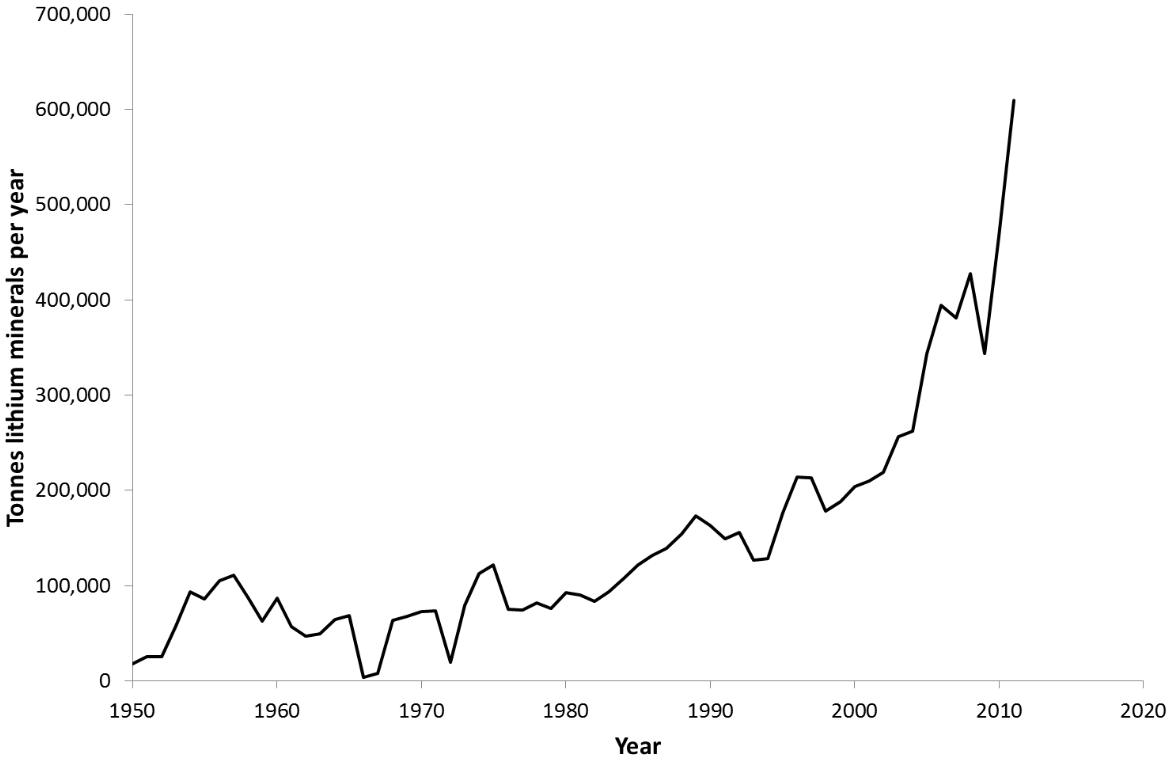
Source: Hughes and Rudolph (2011)

Lithium

Historical production of lithium approaches exponential growth, though there is significant oscillation and volatility within that trend (Figure 7.10). The growth trend can be represented by a reinforcing feedback loop, with the additional oscillation and 'noise' in the data replicated by the combination of reinforcing feedback and balancing feedback with delay.

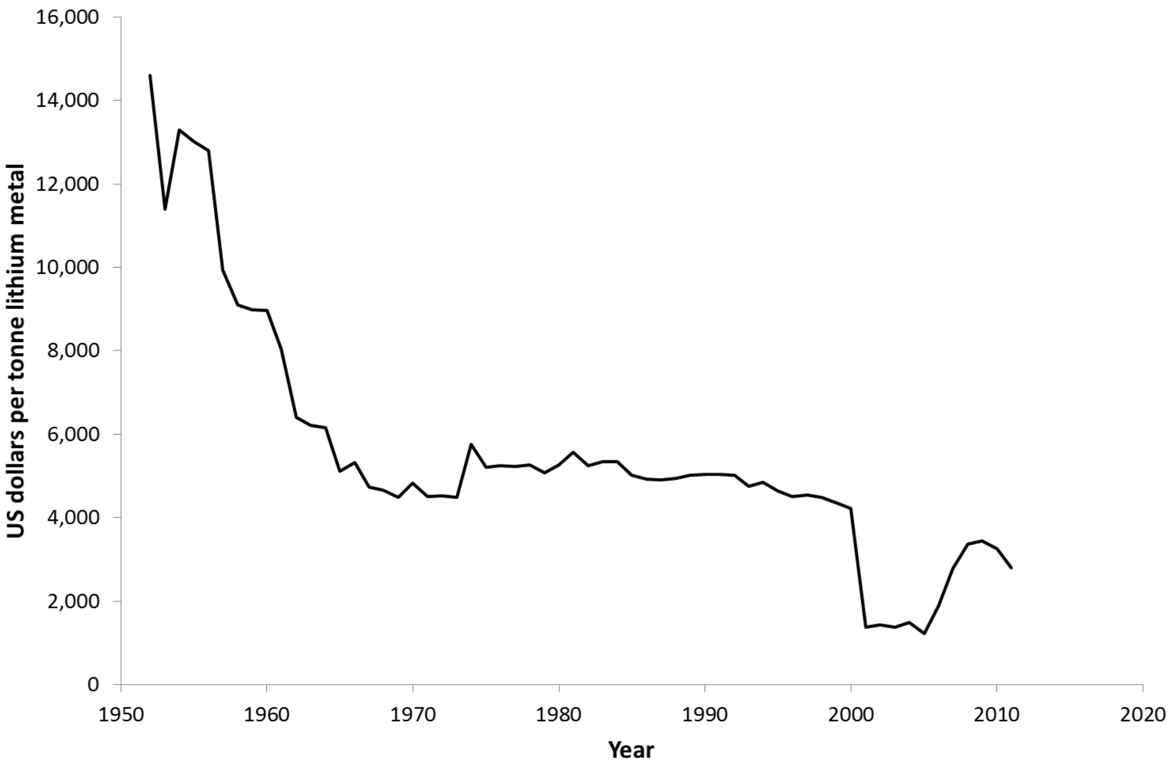
Conversely, the historical price of lithium has declined exponentially since the 1950s. This decline is also subject to the kinds of oscillation and volatility seen in lithium production. A balancing feedback loop with delay can represent that type of system behaviour.

Figure 7.10: Global lithium production between 1950 and 2011



Source: USGS (2013)

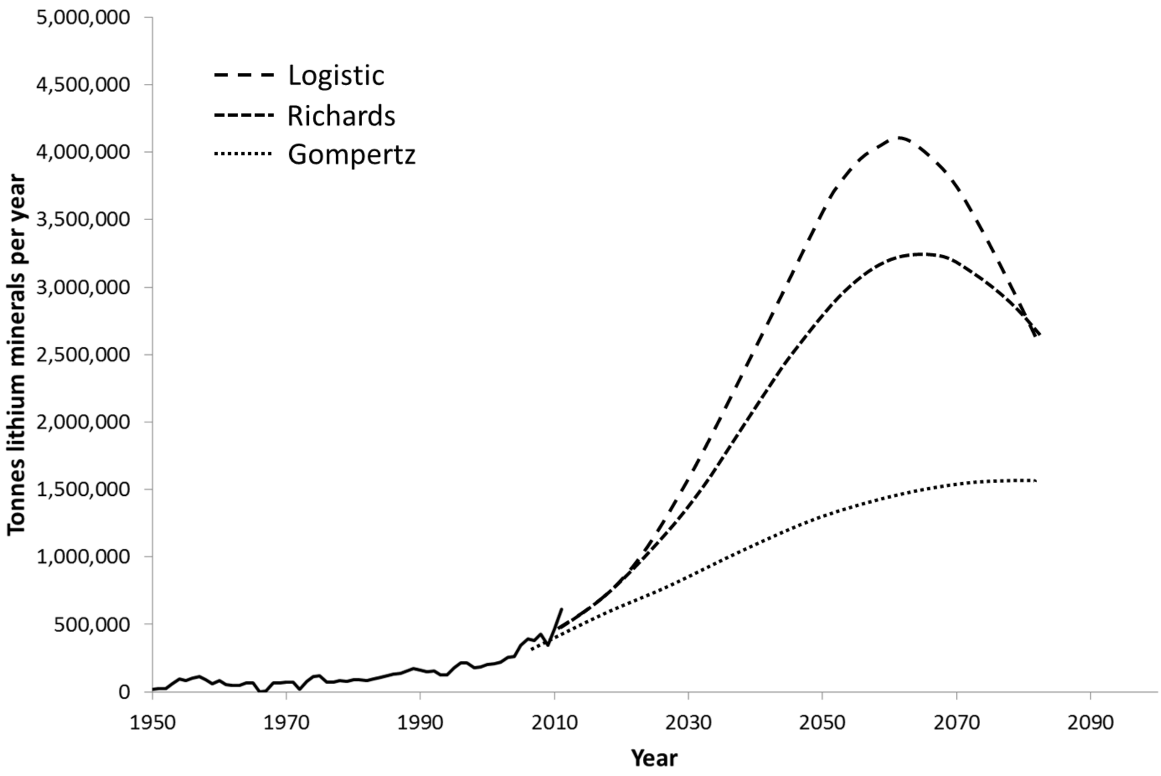
Figure 7.11: Global lithium price in 1998 dollars between 1952 and 2011



Source: USGS (2013)

Forecasters of future lithium production have used very similar techniques to those applied to future oil forecasting, often following a Hubbert-type curve fitting method. This approach can produce multiple types of future production profile depending on the functional form of the extrapolative curve used (Figure 7.12). The resultant forecast production profiles range from a steep curve peaking in the 2060s (logistic curve), to a slow, consistent growth curve with no peak before 2100 (Gompertz curve). These outcomes can be replicated in system dynamics models using a combination of reinforcing and balancing feedback loops, with the reinforcing feedback loop dominating in the early phase and the balancing feedback loop dominating in the later phase of the curve.

Figure 7.12: Illustrative example of three possible critical metal production futures

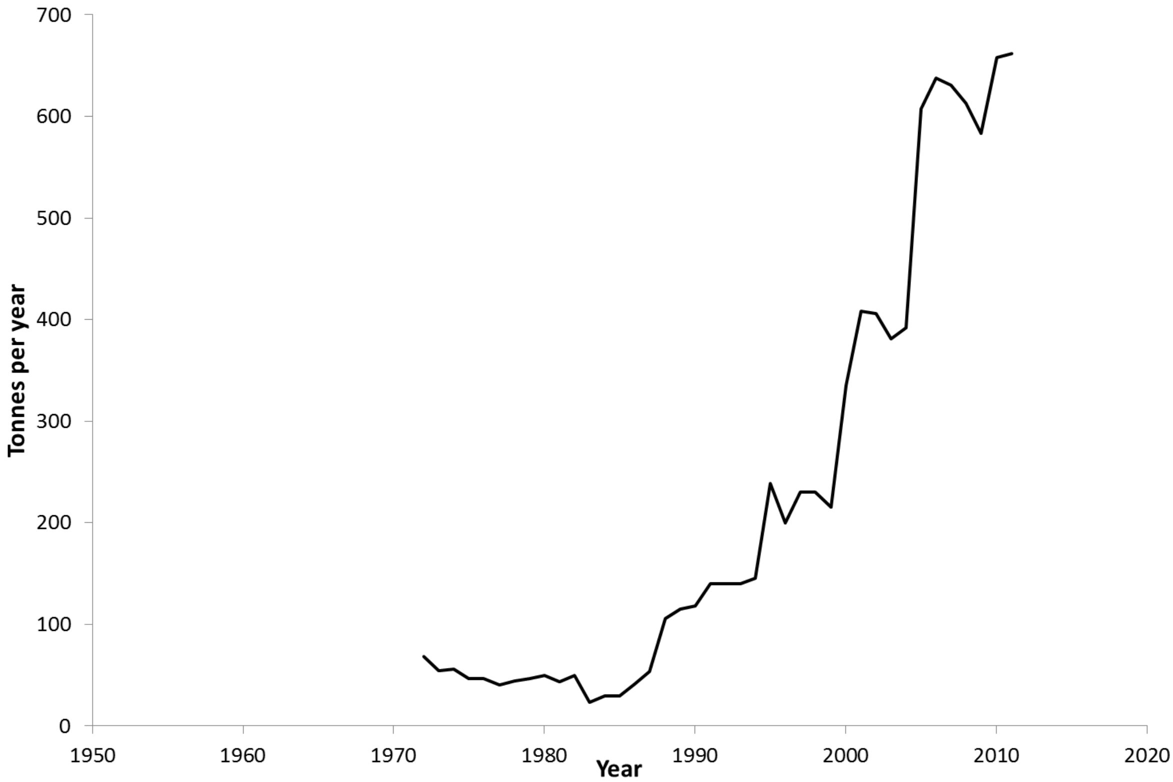


Source: Vikström *et al.* (2013)

Indium

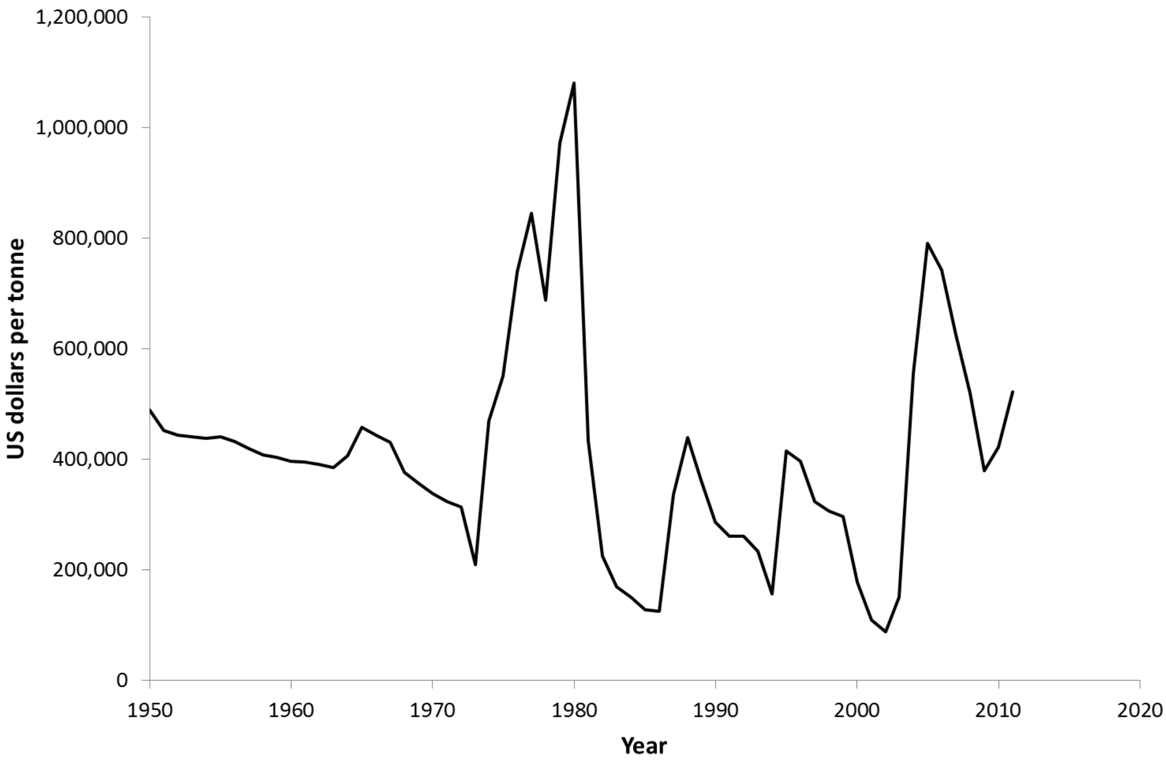
The indium historical reference modes are much the same as those of oil in the most general terms. Indium production appears to have grown exponentially in the last few decades, while its price has been highly volatile over the same period. These system behaviours can therefore be replicated in the same way as for oil, with reinforcing feedback replicating growth, and balancing feedback with delay replicating oscillation and volatility.

Figure 7.13: Global indium production between 1972 and 2011



Source: USGS (2013)

Figure 7.14: Global indium price in 1998 dollars between 1950 and 2011



Source: USGS (2013)

Indium production forecasts are broadly similar to those for lithium, with future prospects from continuous growth, to peaking production within the next 50 years (Fthenakis 2009).

7.2 Dynamic hypothesis

The next stage in the system dynamics modelling process is to develop a stock and flow structure which describes the dynamic system to be modelled. This is often referred to as developing a *dynamic hypothesis*: dynamic, as it must explain the dynamic behaviour of the system and hypothetical, as it is always subject to testing and revision based on developing understanding of the system throughout the modelling process. This section breaks down the two significant stages of dynamic hypothesis formulation. It begins by examining the boundary of the system modelled, listing the variables in the model that are endogenous (defined internally by the model dynamics), those that are exogenous (introduced to the model as external input variables) and those that are excluded (not included in the model at any level). The broad interactions between groups of variables (subsystems) are then examined using subsystem diagrams, allowing high level characterisation of the system structure and examination of the structural differences between resource systems.

7.2.1 Endogenous focus

The goal of system dynamics modelling is to find *endogenous explanations* for phenomena witnessed in the behaviour of complex systems. By seeking to explain the system behaviour through mostly endogenous variables, it is possible to test the system and begin to understand the links between the structure and rules of the system, and its behaviour (Sterman 2000). In contrast, models that describe systems largely through exogenous variables say little about the relationship between system structure and system behaviour, as the structure of the model is largely influenced by inputs that are exogenously assumed (Sterman 2000). Ultimately it is impossible to draw strong conclusions from this type of modelling as there is no way to understand what influenced the variables that have most influence on the model. For this reason it is important to define the most important variables and ensure that they are endogenous to the model structure. To explicitly examine which variables are endogenous, what is exogenous and what is excluded, boundary diagrams are presented below for each of the three resources (Table 7.1).

Table 7.1: Boundary diagrams for each of the three resource models.

Generic resource Model

Endogenous	Exogenous	Excluded
Production	Costs	Finance
Consumption	Resources	Taxes
Price	GDP	Human Resources
Inventory	Policies	Spatial
Demand		
Capacity acquisition an utilisation		

Lithium Model

Endogenous	Exogenous	Excluded
Production	Costs	Finance
Consumption	Resources	Taxes
Price	Policies	Human Resources
Inventory	EV market	Spatial
Demand		
Capacity acquisition an utilisation		
Recycling		

Indium Model

Endogenous	Exogenous	Excluded
Production	Costs	Finance
Consumption	Resources	Taxes
Price	Policies	Human Resources

Inventory	PV market	Spatial
Demand	Co-production capacity	
Capacity acquisition an utilisation		
Capacity limitations		
Recycling		

7.2.2 Mapping the subsystems

The key variables have been previously presented in their various subsystems for each of the three resource systems. Below, these subsystems are presented, with the linkages between them explicitly expressed (Figure 7.15, Figure 7.16 and Figure 7.17). This gives an impression of the overall architecture of each of the three resource models. The specific structure, and nature of the linkages between these subsystems is discussed in detail in 7.3 .

Figure 7.15: Generic resource (GR) model subsystem diagram, showing the linkages between subsystems

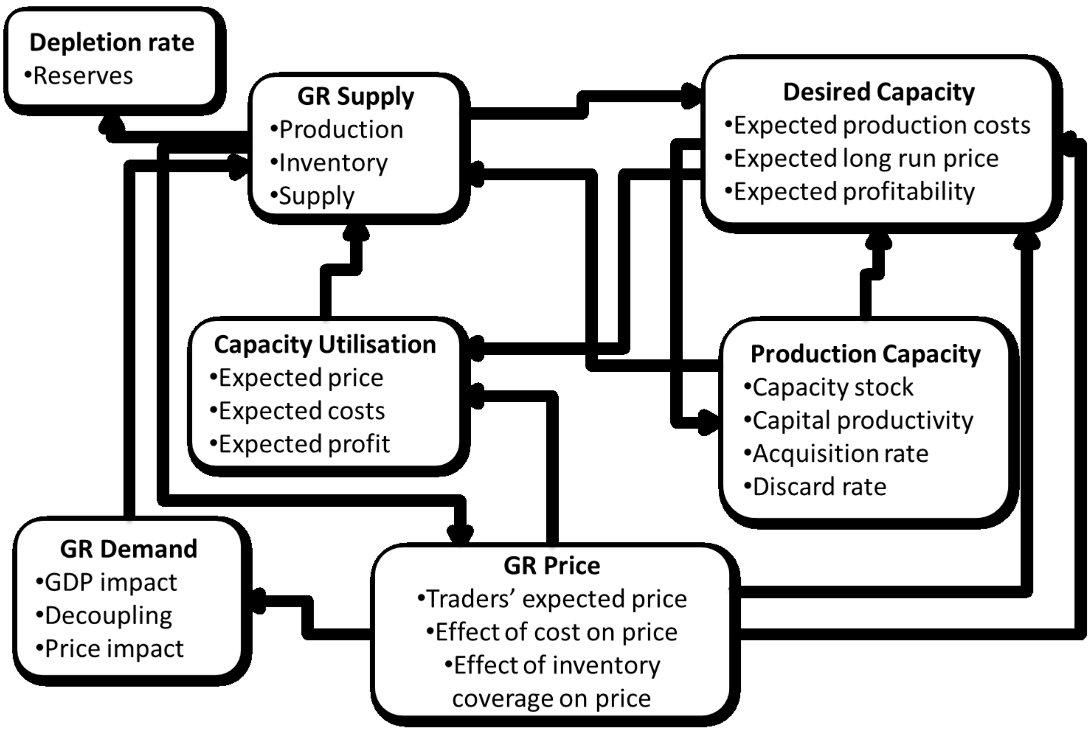


Figure 7.16: Lithium model subsystem diagram, showing the linkages between subsystems and highlighting the recycling subsystem not found in the generic resource model

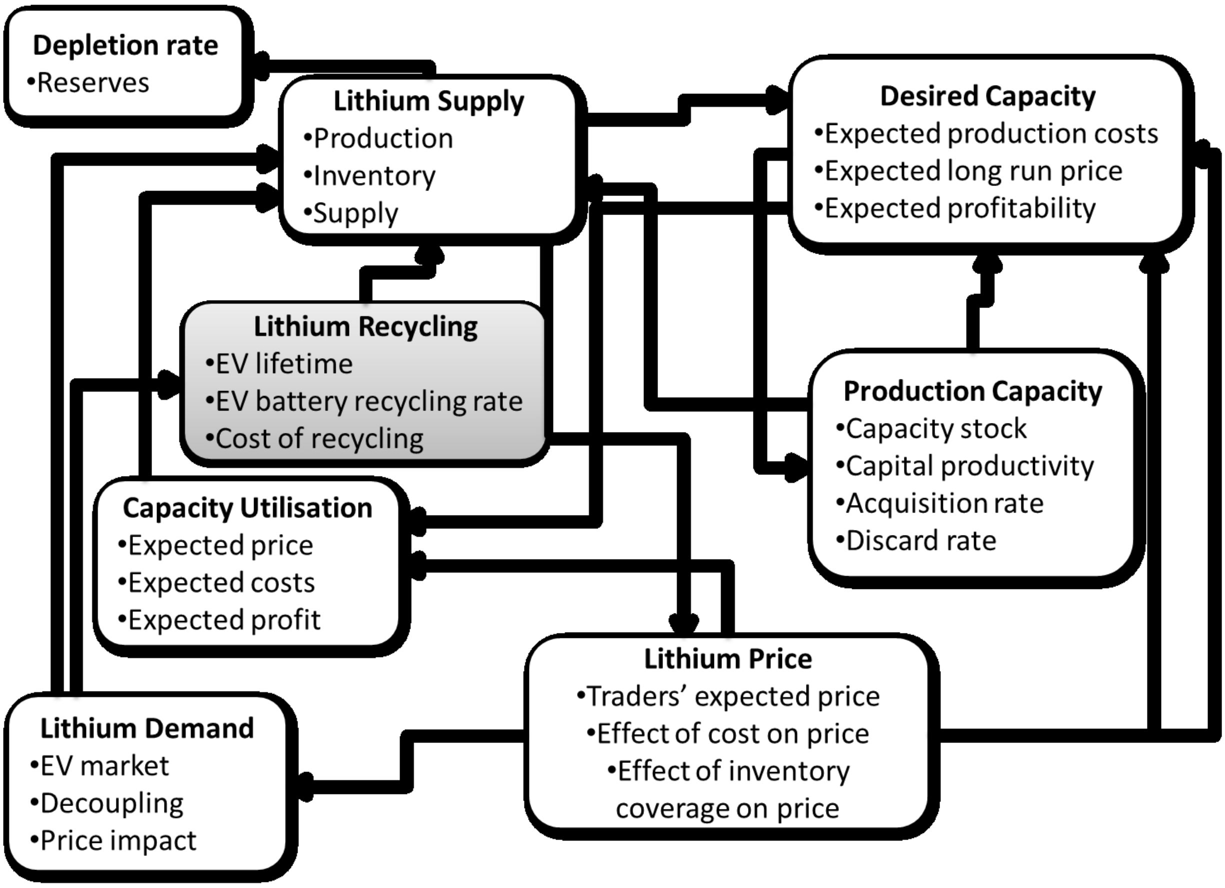
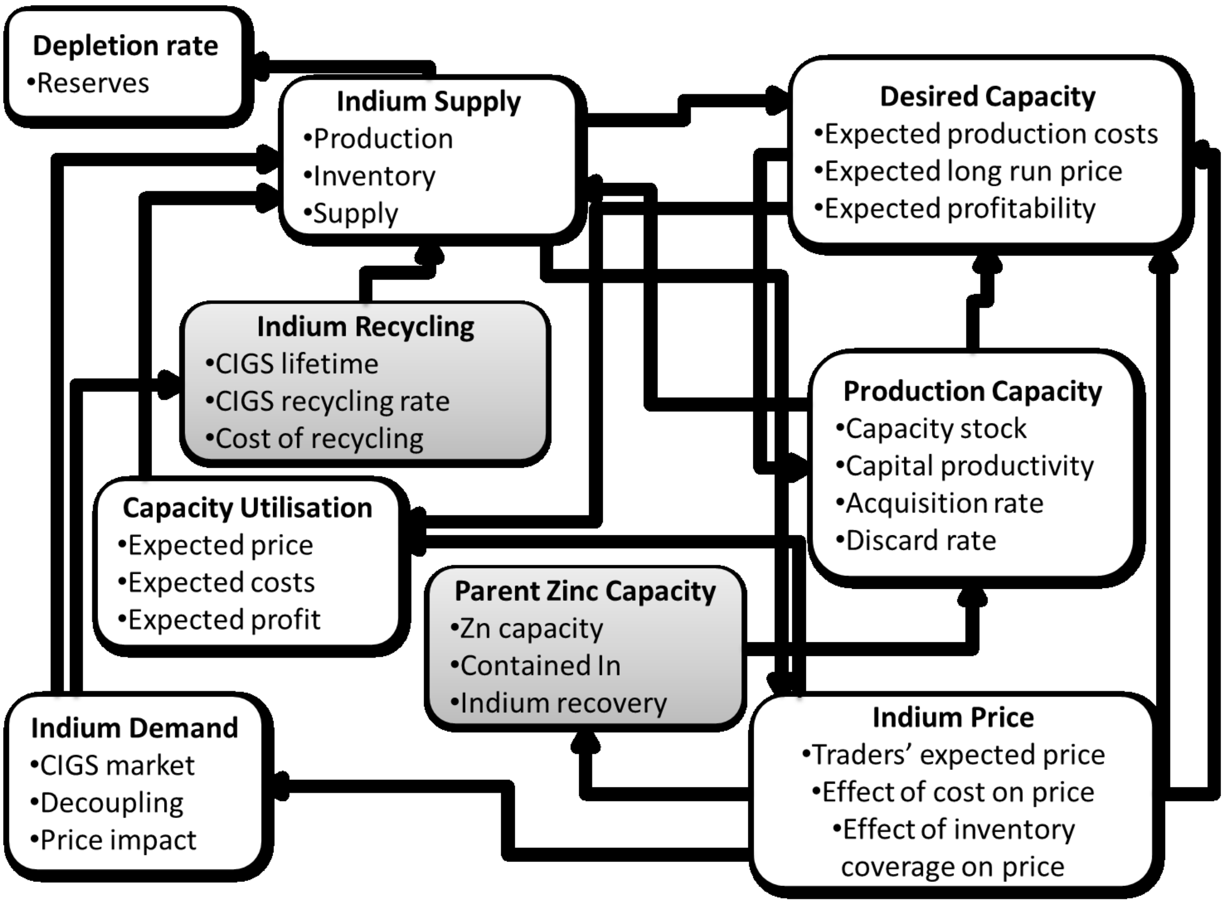


Figure 7.17: Indium model subsystem diagram, showing the linkages between subsystems and highlighting the recycling subsystem not found in the generic resource model, and the parent zinc capacity subsystem, specific to the indium model



7.2.3 Conceptual comparison

At the conceptual level the three models represented in the subsystem diagrams are structurally similar. All models have a *demand* subsystem which is driven by endogenous *price* and an exogenous assumption regarding the wider economic and market drivers of demand (*GDP*, *EV market* or *PV market*). *Supply* is driven by the requirement to meet demand, and the availability of *production capacity*. Price is influenced by the ratio of inventory to the rate of supply (inventory coverage) which indicates the ability of supply to replace inventory used; the supply/demand balance. The three aspects of capacity (*production capacity*, *desired capacity* and *capacity utilisation*) are all linked, with the *desired capacity* and *capacity utilisation* decided as a function of production cost versus price, and the production capacity a function of capacity acquisition and decommissioning.

The first significant difference is the recycling subsystem in both lithium and indium resource system models and not included in the generic resource model. It provides a level of additional supply in future years based on the quantity of metal already produced, the lifetime of products containing the metal, the efficiency of recycling processes, and the expected profitability of recycling. This can contribute significant additional metal supply in future years; though the dynamics of this subsystem are not always intuitive (see Chapter 5).

The second difference between the models is the *parent zinc capacity* subsystem, found only in the indium model. This subsystem expresses the by-product nature of indium production, linking it explicitly to assumptions regarding the production of its parent metal zinc. The subsystem places constraints on the recoverable quantity of indium, and includes a smaller component of primary indium production, which responds to the ratio between price of indium and the costs of primary extraction.

By including these differences endogenously in the models it is possible to test the implications of these differences and achieve results that go beyond the testing of assumptions, exploring the underlying dynamic system behaviours.

7.3 Defining the structure

The following sections present the model structure, broken down by subsystem theme, including detail of the formulae underpinning the model structure. Complete versions of the models in Vensim file type are available online[35], and full model documentation can be found in Appendix C to Appendix E. The process of model development began by adapting a 'generic commodity market model' developed by John Sterman in his book "Business Dynamics" and further detail on many of the elements describe below can be found there (Sterman 2000). The model was first adapted to provide a generic resource system model. This model was then further adapted to represent the lithium and indium resource systems, including their differentiating subsystems. For brevity, the model subsystems will be presented generically, and the differentiating subsystems will be described for each model separately.

[35] https://www.dropbox.com/sh/u69p8m6hsdzrw2r/4JFJKKavJ0

Each of the model diagrams below represents a ‘page’ of the Vensim model they are taken from. The model is split into pages to make the model more manageable. The variables in boxes are stocks, the variables adjacent to the ⧖ symbol are flows, and other variables are auxiliary. The variables in chevrons (e.g. <Production capacity>) are shadow variables, and help link the model structure between different pages.

The following model description includes equations representing the underlying relationships of the model structure presented in Figure 7.18 . Table 7.2 to Table 7.8 present the variables and the symbols used to represent them in the following equations. Symbols starting in upper case represent endogenous variables while those starting in lowercase are exogenous. In those equations δs is a change in time s anytime between initial time (t_0) and current time (t). Several Vensim ‘off-the-shelf’ functions are used in the equations below, which are described in Appendix C. These functions are ‘DELAY FIXED’, ‘DELAY3’, ‘SMOOTH’ ‘MIN’ and ‘MAX’.

7.3.1 Production and capacity utilisation

The diagram below (Figure 7.18) presents the first page[36] of the generic resource model. The page is common to all three resource system models , though it is modified slightly in the lithium and indium models with the insertion of a shadow variable representing recycled material feeds into the inventory stock variable (Figure 7.19).

[36] Modern system dynamics software such as Vensim separates models into ‘pages’ in order to simplify the modelling process.

Figure 7.18: The model diagram representing production and capacity utilisation in the generic resource model.

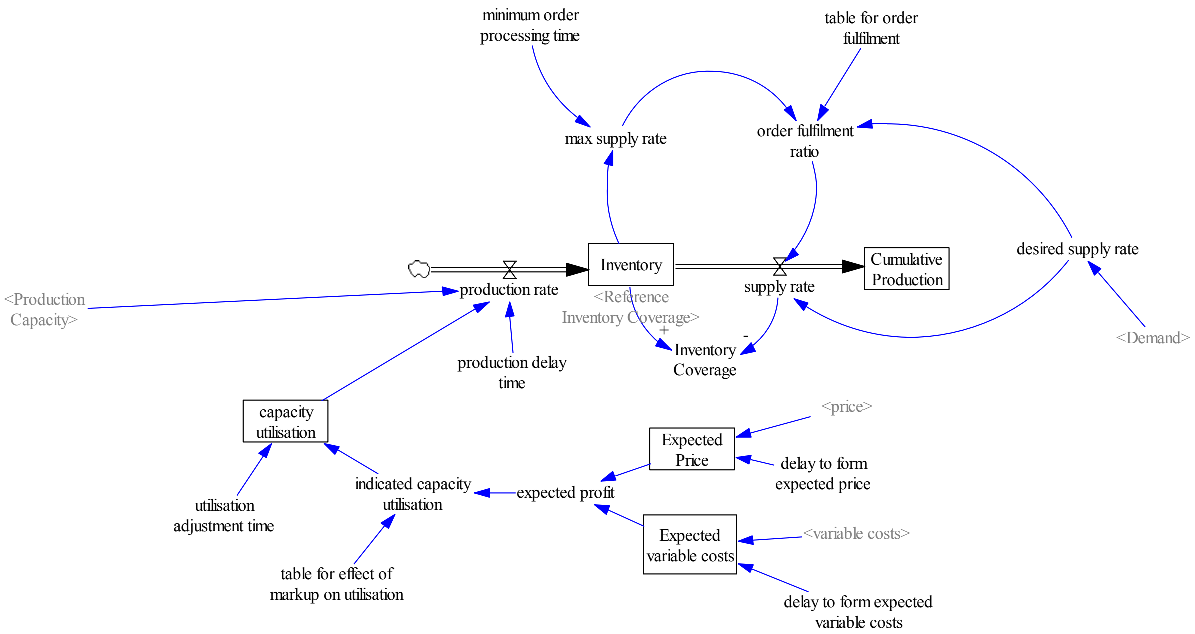
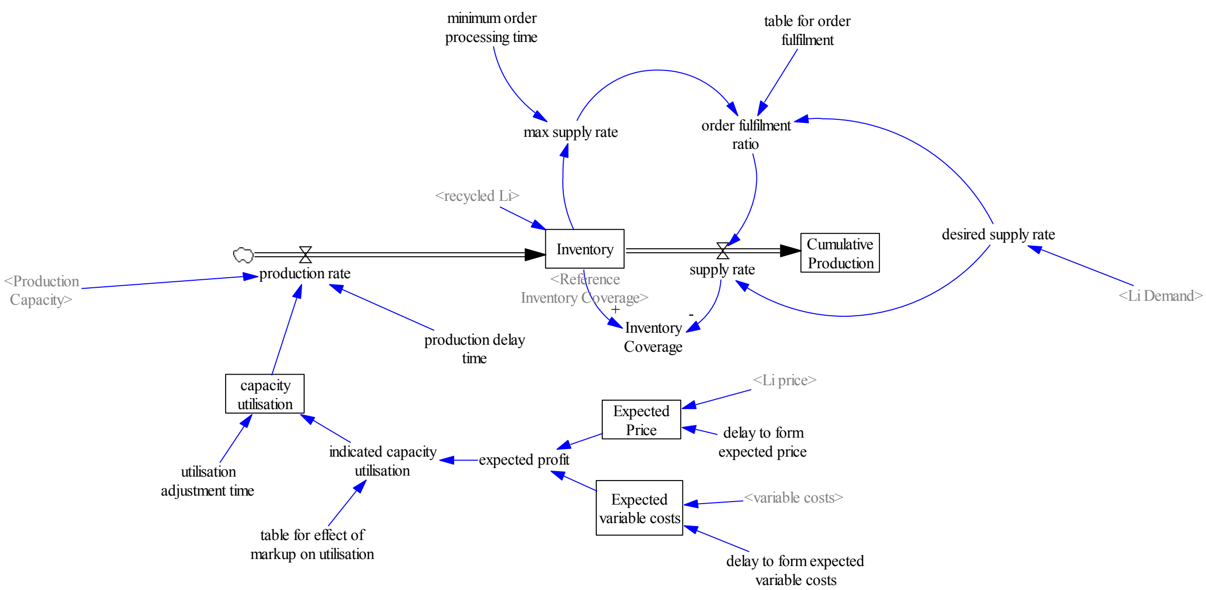


Figure 7.19: The model diagram representing production and capacity utilisation in the lithium resource model



This page is made up of two distinct sections: the two-stock chain representing the *production* of the commodity and found in the top half of Figure 7.18; and the collection of auxiliary variables leading to the *capacity utilisation* stock in the bottom half.

Table 7.2: The variables present in the 'Production and capacity' page of the three resource system models

Variable	Symbol	Model	Units	
Endogenous				
Expected variable costs	C_e	Generic, lithium, indium	$/tonne	
Inventory	I	Generic, lithium, indium	Tonnes	
Inventory coverage	I_s	Generic, lithium, indium	Years	
Order fulfilment ratio	O	Generic, lithium, indium	Dimensionless	
Production rate	P	Generic, lithium, indium	Tonnes/year	
Cumulative production	Q	Generic, lithium, indium	Tonnes	
Supply rate	S	Generic, lithium, indium	Tonnes/year	
Desired supply rate	S_d	Generic, lithium, indium	Tonnes per year	
Max supply rate	S_{max}	Generic, lithium, indium	Tonnes/year	
Capacity utilisation	U	Generic, lithium, indium	Dimensionless	
Indicated capacity utilisation	U_i	Generic, lithium, indium	Dimensionless	
Expected price	V_e	Generic, lithium, indium	$/tonne	
Expected profit	Y_e	Generic, lithium, indium	Dimensionless	
Exogenous				
Variable	**Symbol**	**Model**	**Exogenous value**	**Units**

Delay to form expected variable costs	c	Generic, lithium, indium	1	years
Minimum order processing time	o_{min}	Generic, lithium, indium	0.1	Years
Production delay time	p	Generic, lithium, indium	0.5	years
Utilisation adjustment time	u	Generic, lithium, indium	0.5	years
Delay to form expected price	v_{ed}	Generic, lithium, indium	1	years
Shadow Variable	**Symbol**	**Model**	**Cross reference**	
Variable Cost	C_v	Generic, Lithium, Indium	7.3.4	
Demand	D	Generic, Lithium, Indium	7.3.2	
Reference inventory coverage	i	Generic, Lithium, Indium	7.3.3	
Production capacity	P_{Cap}	Generic, Lithium, Indium	7.3.4	
Recycled resource	R	Lithium, Indium	7.3.5	
Price	V	Generic, Lithium, Indium	7.3.3	

Inventory

The *inventory* is a stock which accumulates the produced commodity until it is delivered to market through the *supply* flow. The *production rate* into the *inventory* stock is defined by the total available *production capacity*, the *capacity utilisation* and a time delay for that process (*production delay time*) (Equation 7.1).

$$I(t) = \int_{t0}^{t} (P(s) - S(s))\delta s + (i_r D(t_0))$$

7.1

Supply rate

The *supply rate* is a function of the *desired supply rate* and the *order fulfilment ratio*. The supply rate is a flow which leaves the inventory stock, at a rate defined by the desired supply rate, and constrained by the maximum supply rate (Equation 7.2, 7.3 and 7.5)

$$S(t) = S_d(t)O(t)$$

7.2

Order fulfilment ratio

The *order fulfilment ratio* is the ratio between *desired supply rate* and the actual *supply rate*. It is constrained by the *maximum supply rate*, which is in turn defined by the available inventory and the minimum time taken to process a delivery of supply (a form of delay).

$$O(t) = f_1(\frac{S_{max}(t)}{S_d(t)})$$

7.3

Where f_1 is a function defined by an exogenous lookup table presented below as '*table for order fulfilment'* (Figure 7.20), and

$$W(t) = \frac{S_{max}(t)}{S_d(t)}$$

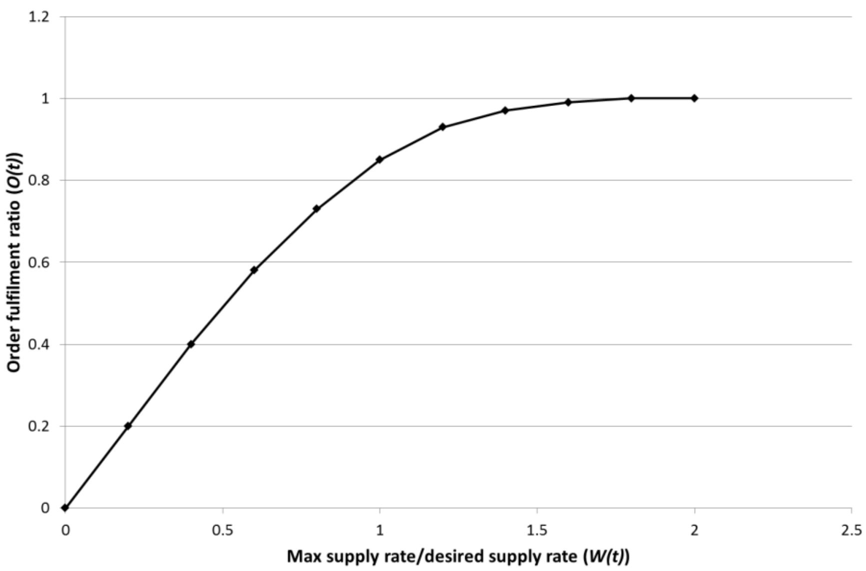
7.4

Maximum supply rate

$$S_{max}(t) = \frac{I(t)}{o_{min}}$$

7.5

Figure 7.20: Table for order fulfilment



Source: Based on Sterman (2000)

<u>*Production rate*</u>

The *production rate* (Equation 7.6) is the rate of production of the commodity from available capacity into inventory. It is modelled as a 3rd order exponential delay (using the DELAY3 function which is native to vensim)[37]. This reflects the fact that delays in the production rate are not always the same, and will vary slightly over time. The concept of 3rd order delays is common in system dynamics modelling (Kirkwood 1998). The equation below provides a reasonable distribution of delays around an average.

$$P(t) = DELAY3(P_{Cap}(t)U(t), p)$$

[37] 3rd order exponential delay varies the actual delay time of delayed units (in this case tonnes of commodity). The variation in delay time of individual units creates a 'smoothed' curve of throughput equivalent to a 3rd order exponential curve (Kirkwood 1998). The system dynamics software package VENSIM contains an 'off the shelf' function 'DELAY3', which creates this smoothed 3rd order exponential delay based on two inputs: the input variable to be delayed; and the delay time.

7.6

Capacity utilisation

Capacity utilisation captures the intensity of production at any given time (Equation 7.7). There is always a given production capacity, and given the time it takes to add new capacity, the market will tend to keep some unutilised capacity in order to respond to demand increases in the short term. Over the longer term additional capacity can be added to the system, as discussed below.

$$U(t) = SMOOTH(U_i(t), u(t))$$

7.7

Capacity utilisation is decided based on the expected profit, which is the ratio between expected costs and expected price. There is also a delay between calculating the expected profit and establishing the capacity utilisation, reflecting the time it takes to coordinate an adjustment to capacity utilisation. A rise in expected profit is an indication of an increase in expected demand. To respond to that demand increase the capacity utilisation will increase. The magnitude of the response is determined by a look-up table, the graph of which is below (Figure 7.21) and the relationship defined in Equation 7.8.

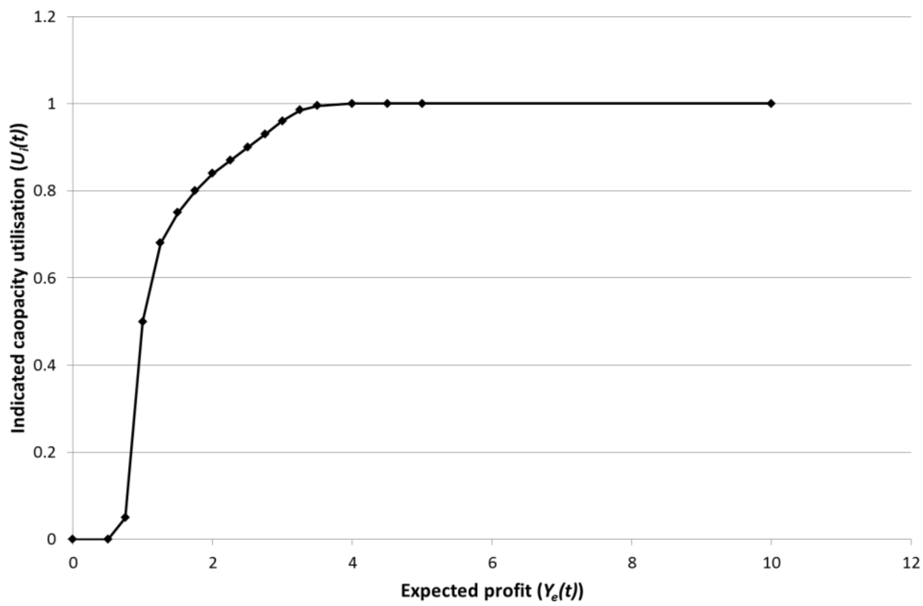
Indicated capacity utilisation

$$U_i(t) = f_2(Y_e(t))$$

7.8

Where *f* is a function defined by an exogenous lookup table presented below as '*table for effect of markup on utilisation'* (Figure 7.21).

Figure 7.21: Table for effect of markup on utilisation



Depletion rate is also modelled as an outcome of the *supply rate* (Figure 7.22, Equation 7.9). *Depletion rate* provides a way to sense check the rate of production against the estimated resources of a commodity (see Section 4.2.6 and Section 7.4.6). Table 7.3 presents the variables used in the 'Depletion rate' page and the associated symbols used to represent them in the equations below.

Figure 7.22: The model diagram representing depletion rate.

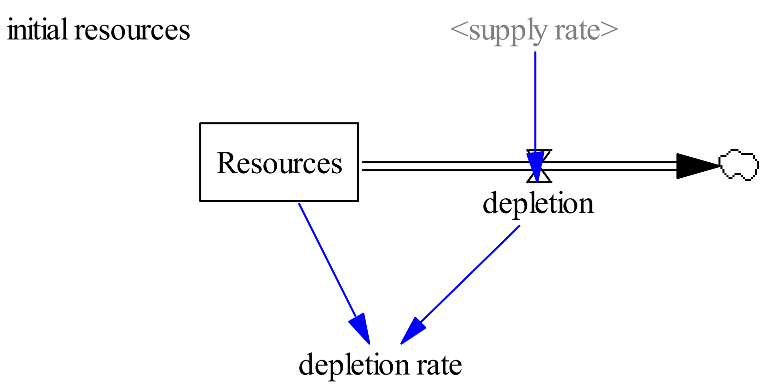


Table 7.3: The variables present in the 'Depletion rate' page of the three resource system models

Variable	Symbol	Model	Units
Endogenous			

Depletion (supply rate)	X_d	Generic, Lithium, Indium	Tonnes/year	
Resources	X	Generic, Lithium, Indium	Tonnes	
Depletion rate	X_s	Generic, Lithium, Indium	Dimensionless	
Exogenous				
Variable	**Symbol**	**Model**	**Values**	**Units**
Initial resources	x_0	Generic, Lithium, Indium	G=3,500 L=1.3e+7 I=300,00	Tonnes
Shadow Variable	**Symbol**	**Model**	**Cross reference**	
Supply rate	S	Generic, Lithium, Indium	7.3.1	

Depletion rate

Depletion Rate is calculated as the inverse of the Reserves/Production ratio, where the rate of production (*depletion*) is divided by the remaining *resources* (Equation 7.10). *Resources* are calculated as the integral of the production rate (*depletion*) leaving the stock of *resources*.

$$X_s(t) = \frac{X_d(t)}{X(t)} 100$$

7.9

Resources

$$X(t) = \int_{t0}^{t} \left(-X_d(s)\right)\delta s + x_0$$

7.10

7.3.2 Demand

The demand page is structured in two parts. The first part establishes a reference demand based on changing market drivers. This differs between the three resource models. The second part introduces the modifications to demand based on price effects. This is the same across all three models.

In the generic resource model the reference demand is established based on estimated global GDP growth, and a Kuznets-like decoupling of demand from GDP growth (Figure 7.23). This provides a peak in demand, defined by a look-up table that represents the profile of decoupling (Figure 7.24). Table 7.4 presents the variables used in the 'Depletion rate' page and the associated symbols used to represent them in the equations below.

Figure 7.23: The model diagram representing generic resource demand.

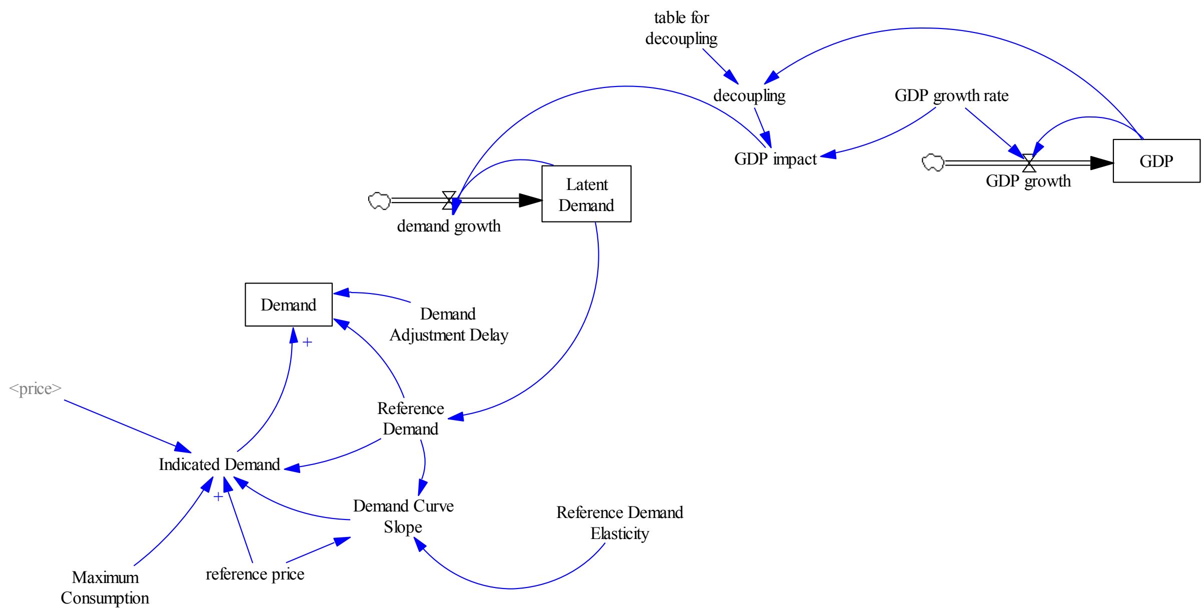


Table 7.4: The variables present in the 'Demand' page of the three resource system models

Variable	Symbol	Model	Units
Endogenous			
Demand curve slope	B	Generic, Lithium, Indium	Dimensionless
Demand	D	Generic, Lithium, Indium	Tonnes/year
Demand growth	D_g	Generic	Dimensionless
Indicated demand	D_i	Generic, Lithium, Indium	Tonnes/year
Latent demand	D_l	Generic, Lithium, Indium	Tonnes/year
EV lithium demand *or* PV indium demand	D_{lm}	Lithium, Indium	Tonnes/year
Reference demand	D_r	Generic, Lithium, Indium	Tonnes/year
GDP	G	Generic	Trillion $
GDP growth	G_g	Generic	Dimensionless
GDP impact	G_i	Generic	Dimensionless
Decoupling	K	Generic	Dimensionless
Fractional rate *or* fractional CIGS growth rate	L_r	Lithium, Indium	Dimensionless
Annual EV sales *or* Annual CIGS sales	L_s	Lithium, Indium	Vehicles
Annual EV sales growth *or* Annual CIGS sales growth	L_{sg}	Lithium, Indium	Dimensionless

Exogenous				
Variable	**Symbol**	**Model**	**Exogenous value**	**Units**
Demand adjustment delay	d	Generic, Lithium, Indium	0.5	Years
Maximum consumption	d_{max}	Generic, Lithium, Indium	G=1000 L=1000 L=1e+8	Tonnes
Other demand	d_{om}	Lithium, indium	L=35,000 I=500	Tonnes/year
Reference demand elasticity	e_d	Generic, Lithium, Indium	0.5	Dimensionless
GDP growth rate	g	Generic	0.01	Dimensionless
Max EV market growth rate *or* max CIGS growth rate	l_{gmax}	Lithium, Indium	L=0.2 I=0.1	Dimensionless
Max EV annual sales *or* max CIGS annual sales	l_{smax}	Lithium, Indium	L=3e+7 I=140	L: Vehicles I: GW/year
Lithium intensity *or* indium intensity	m_i	Lithium, Indium	L=0.00798 I=0.0248	L: tonnes/vehicle I: grams/Wp
Reference price	v	Generic, Lithium, Indium	G=100 L=5000 I=600,000	$
Shadow Variable	**Symbol**	**Model**	**Cross reference**	
Price	V	Generic, Lithium, Indium	7.3.3	

GDP impact

The *GDP impact* on demand is a factor which captures the impact of growing GDP on generic commodity demand, and the decoupling of that relationship over time (Equation 7.11). The rate that this relationship decouples is defined by a lookup table, demonstrated in Figure 7.24, and the *decoupling* factor shown in Equation 7.12.

$$G_i(t) = 0.1G_r(t) - 0.1G_r(t)K(t)$$

7.11

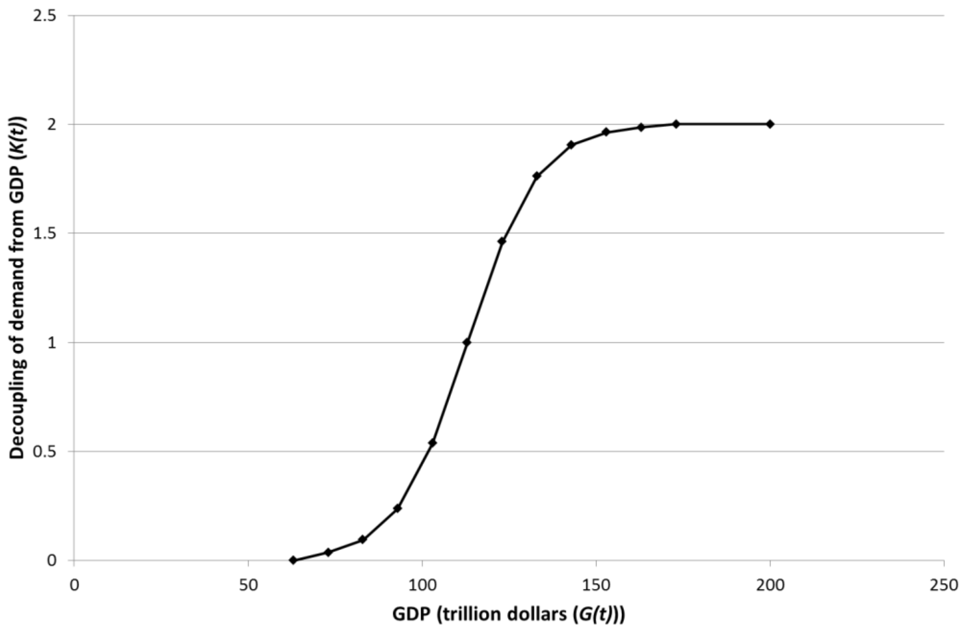
<u>*Decoupling*</u>

$$K(t) = f_3(G(t))$$

7.12

Where f_3 is a function defined by an exogenous lookup table presented below as '*table for decoupling'* (Figure 7.24).

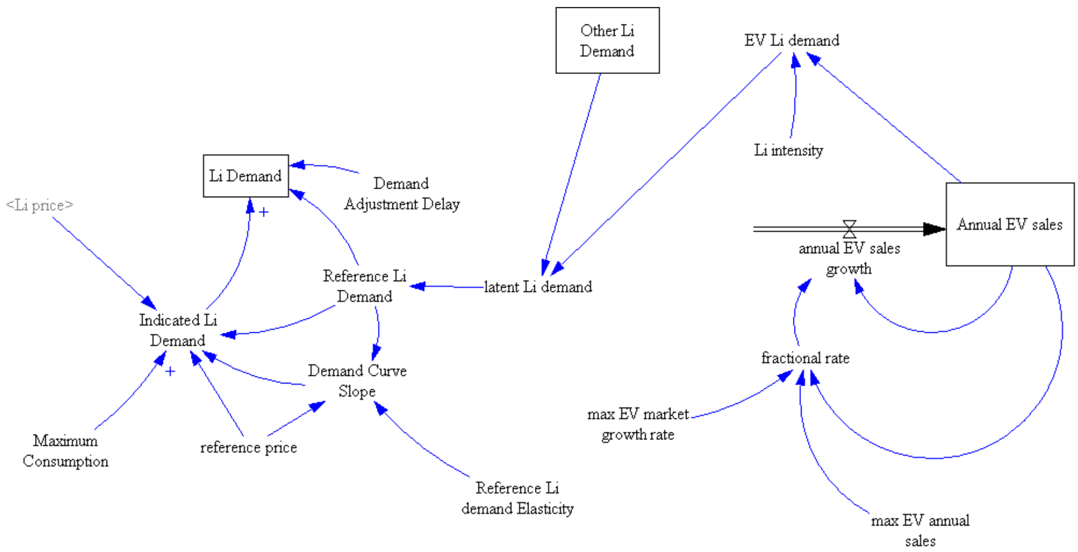
Figure 7.24: Table for decoupling of resource demand from GDP.



Note: Assumed as an approximation of logistic sigmoid growth.

In the lithium resource model the *reference demand* is established as a function of the future market for electric vehicles, with a smaller additional demand representing the other uses of lithium (Figure 7.25). A combination of feedback loops creates a logistic growth function representing the growth of lithium based electric vehicles (*Annual EV sales,* Equation 7.13). The value of 100,000 vehicles is used in this equation to approximate current EV sales. The lithium intensity (*Li intensity*) per vehicle is then used to calculate the growth in lithium demand (*EV Li demand*, Equation 7.14). The elements in the equation creating EV sales growth profile (*Annual EV sales growth* and *fractional rate*) are presented in Equation 7.15 and Equation 7.17.

Figure 7.25: The model diagram representing lithium demand.



Annual EV sales

$$L_s(t) = \int_{t0}^{t} L_{sg}(s)\delta s + 100000$$

7.13

EV lithium demand

$$D_{lm}(t) = L_s(t)m_i$$

7.14

Annual EV sales growth

$$L_{sg}(t) = L_S(t)L_r(t)$$

7.15

Fractional rate

$$L_r(t) = L_{gmax}(W_1(t))$$

7.16

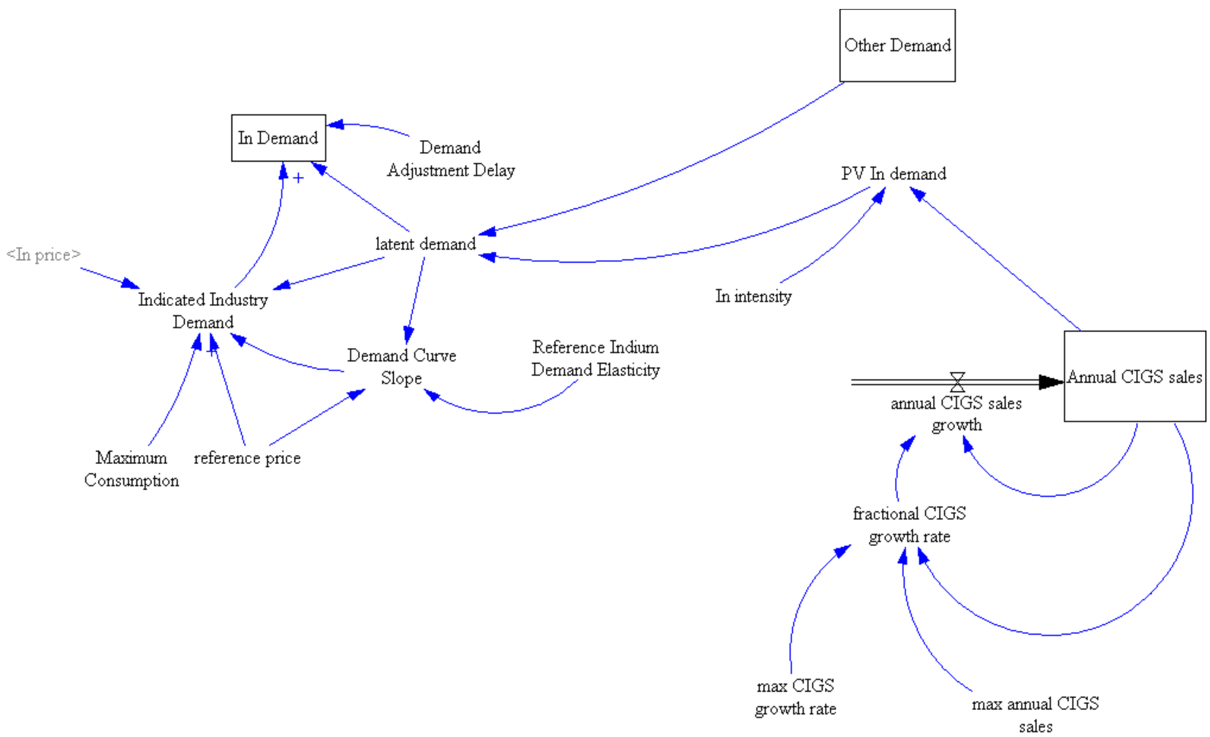
Where

$$W_1(t) = 1 - \frac{L_{sg}(t)}{l_{smax}}$$

7.17

In the indium resource model the reference demand is established in a very similar way to that of lithium (Figure 7.26). The structure and equations are the same as those above for lithium. The only difference is that the market driving indium demand is assumed to be Copper Indium Gallium (di)Selenide thin film PV and not EVs. The differing exogenous assumptions between the lithium and Indium models reflect the different drivers of demand (Table 7.4).

Figure 7.26: The model diagram representing indium demand.



The second part of the demand page (the left of Figure 7.26) defines the effect of price on demand. The *reference demand* (or *latent demand*) variable establishes the demand under conditions where price has no effect. This reference demand is then modified based on the price of the commodity, and the price elasticity of demand. This process also includes a delay in the time it takes price and cost to influence demand (*demand adjustment delay*).

<u>*Demand curve slope*</u>

The *demand curve slope* defines the elasticity of demand (Equation 7.18). The *indicated industrial demand* represents the demand once the impact of price is taken into account (Equation 7.19). *Demand*, *Li demand* or *In demand* represents the price adjusted demand once the time delay has been taken into account (Equation 7.20).

$$B(t) = \frac{-D_r(t\,)e_d}{v}$$

7.18

<u>*Indicated Industry Demand*</u>

$$\boldsymbol{D_i(t) = MIN(D_{max}, D_r)MAX\left(0, 1 + B\frac{V(t) - v}{D_r}\right)}$$

7.19

<u>*Demand, Li demand or In demand*[38]</u>

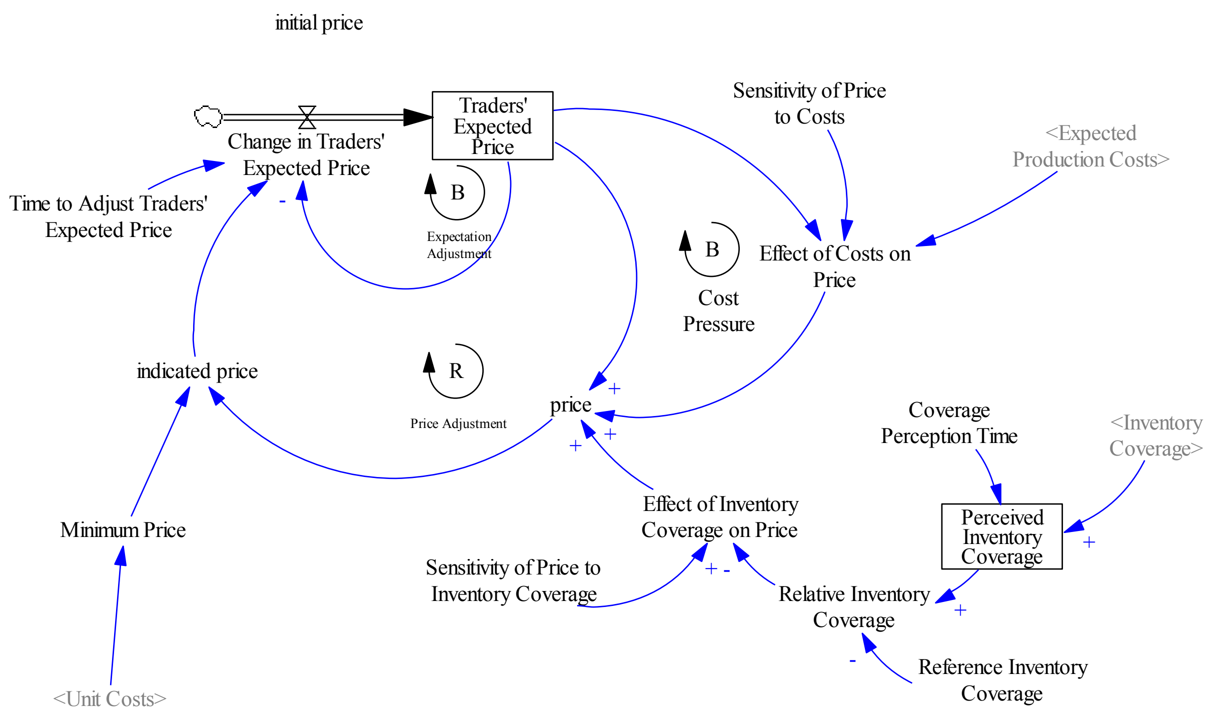
$$D(t) = SMOOTH(D_i(t), d(t), D_r(t))$$

[38] The SMOOTH function is an 'off the shelf' function in the system dynamics software VENSIM that is used to 'smooth' the delay of an input (in this case indicated demand in tonnes) so that the output of a step in input is smoothed as an exponential curve, with the beginning of the curve equal to the delay time.

7.3.3 Price

The page representing *price* in the model begins with an *initial price*, which is modified by cost and by the ability of supply to meet demand (*inventory coverage*). Cost influences price via an auxiliary variable which combines the expected costs with a sensitivity factor. Inventory coverage affects price, first by being measured against reference inventory coverage, and then combined with a sensitivity factor. These two price modifiers are then multiplied and applied to price, with a MAX function to prevent price dropping below zero in extreme conditions (Equation 7.21). Price is modelled in the same way in each of the three resource models. Table 7.5 presents the variables used in the '*Price*' page and the associated symbols used to represent them in the equations below.

Figure 7.27: The model diagram representing price[39]



[39] In the diagram the 'B' indicates a balancing loop, the 'R' indicates a reinforcing loop, and the '+' and '-' indicate the positive or negative impact of the incoming variable.

Table 7.5: The variables present in the 'Price' page of the three resource system models

Variable	Symbol	Model	Exogenous value	Units
Endogenous				
Perceived inventory coverage	I_{sp}	Generic, Lithium, Indium		Years
Relative inventory coverage	I_p	Generic, Lithium, Indium		Years
Price	V	Generic, Lithium, Indium		\$/tonne
Sensitivity of price to cost	v_{cp}	Generic, Lithium, Indium		Dimensionless
Traders expected price	V_e	Generic, Lithium, Indium		\$/tonne
Change in trader's expected price	V_{ec}	Generic, Lithium, Indium		\$/tonne/year
Indicated price	V_i	Generic, Lithium, Indium		\$/tonne
Effect of inventory coverage on price	V_{is}	Generic, Lithium, Indium		Dimensionless
Minimum price	V_{min}	Generic, Lithium, Indium		\$/tonne
Exogenous				
Variable	**Symbol**	**Model**	**Exogenous value**	**Units**
Coverage perception time	i_s	Generic, Lithium, Indium	0.167	Years
Reference inventory coverage	i_r	Generic, Lithium, Indium	0.2	Years
Time to adjust traders expected price	v_d	Generic, Lithium, Indium	1	Years

Sensitivity of price to inventory coverage	v_{is}	Generic, Lithium, Indium	-1	Dimensionless
Initial price	$V(t_0)$	Generic, Lithium, Indium	G=100 L=5,000 I=600,000	\$/tonne
Shadow Variable	**Symbol**	**Model**	**Cross reference**	
Unit cost	C_u	Generic, Lithium, Indium	7.3.4	
Expected production cost	C_{pe}	Generic, Lithium, Indium	7.3.4	
Inventory coverage	I_s	Generic, Lithium, Indium	7.3.1	

Price

Price is the product of the *trader's expected price*, the *effect of cost on price* and the *effect of inventory coverage on price* (Equation 7.21). As the cost of production increases this has an inflationary impact on price, simulating the typical response of commodities to cost inflation. If the relative level of inventory decreases over time this also has an inflationary impact on price, as inventory coverage is used as an indicator of tightness in supply. The equation also makes use of a *MAX* function, which makes sure that price cannot drop below zero. The equations describing *effect of cost on price* and *effect of inventory coverage on price* are presented in Equation 7.23 and Equation 7.24.

$$V(t) = MAX(0, \big(V_e(t)V_{is}I(t)V_{cp}(t)\big))$$

7.21

Effect of cost on price

$$\boldsymbol{V_{cp}(t) = 1 + v_{cp}(W_2(t) - 1)}$$

7.22

Where

$$W_2(\boldsymbol{t}) = \frac{\boldsymbol{C_{pe}}(\boldsymbol{t})}{\boldsymbol{V_e}(\boldsymbol{t})}$$

7.23

<u>Effect of inventory coverage on price</u>

$$\boldsymbol{V_{is}}(\boldsymbol{t}) = (\boldsymbol{I_\rho}(\boldsymbol{t}))^{v_{is}}$$

7.24

<u>Relative inventory coverage</u>

The *relative inventory coverage* (Equation 7.25) measures the *perceived inventory coverage* against the reference inventory coverage. A drop in relative inventory coverage indicates that current production is not sufficient to meet current demand. This increases price through *the effect of inventory coverage on price* variable as it might in a real market where it became apparent that supply was insufficient. The indicated price variable prevents price dropping below the unit costs of production (Equation 7.26).

$$\boldsymbol{I_\rho}(\boldsymbol{t}) = \frac{\boldsymbol{I_{sp}}(\boldsymbol{t})}{\boldsymbol{i_r}}$$

7.25

<u>Indicated price</u>

$$V_i(t) = MAX(V_{\min}(t), V(t))$$

7.26

In a real commodity market the price is set by people making deals to buy and sell quantities of the commodity, whether a physical market, or a paper market. However, the price discovery process is iterative, and those making deals do not necessarily have all the information needed to reflect a fair price. Once evolving issues around the costs of production and the available inventories are established traders may need to reassess their expected price estimates.

Traders' Expected Price

The stock *Traders' expected price* (Equation 7.27) allows for this delayed, iterative price discovery process to be represented in the model. This variable integrates the flow of *Change in traders' expected price* (Equation 7.28), which in turn reflects the *indicated price*, allowing for a time delay.

$$V_e(t) = \int_{t0}^{t} V_{ec}(s)\delta s + V(t_0)$$

7.27

Change in traders' expected price

$$\boldsymbol{V_{ec}(t) = \frac{V(t_0) - V_e(t)}{v_d}}$$

7.28

7.3.4 Capacity

Capacity is dealt with across three different pages in the resource system models. *Capacity utilisation* has already been discussed, and is found on the 'production and capacity utilisation' page. Two further pages deal exclusively with capacity issues: 'capacity' and 'desired capacity'. *Capacity* keeps stock of the balance between capacity building, and capacity decommissioning. *Desired capacity* defines the amount of new capacity needed.

Capacity is dealt with differently between the generic resource model, lithium and indium, due to the existence of the parent '*zinc capacity'* subsystem. The generic resource and lithium model capacity pages capture capacity in a two loop system (Figure 7.28). The capacity stock is the product of new capacity building (*capacity acquisition*) and capacity decommissioned due to age (*discard rate*). The *acquisition rate* is informed by the need to replace the discarded capacity, and the need to adjust capacity based on expected future demand (*desired capacity*). The *discard rate* is simply based on an assumption regarding the useable lifetime of capacity. Table 7.6 presents the variables used in the '*Capacity*' page and the associated symbols used to represent them in the equations below.

Figure 7.28: The model diagram representing capacity

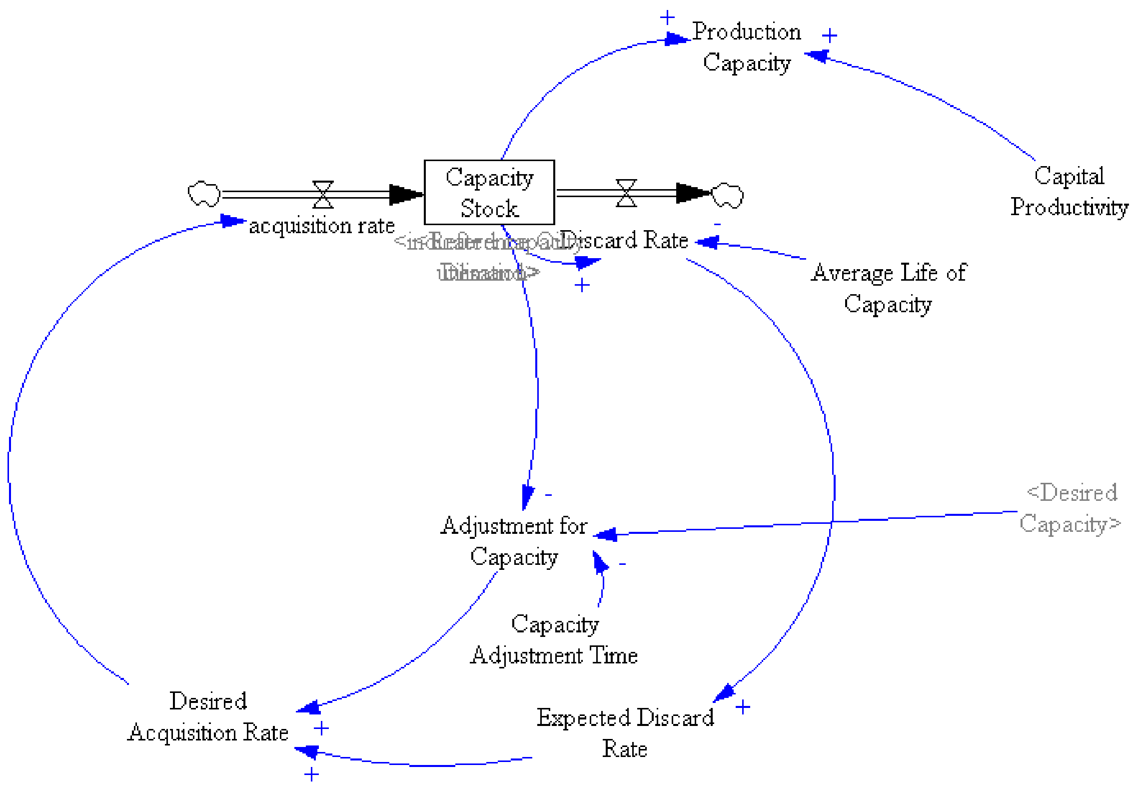


Table 7.6: The variables present in the 'capacity' page of the three resource system models

Variable	Symbol	Model	Units
Endogenous			
Acquisition rate	*A*	Generic, Lithium, Indium	Tonnes/year/year
Desired acquisition rate	A_d	Generic, Lithium, Indium	Tonnes/year/year
Capacity stock	C_{ap}	Generic,	Tonnes/year

		Lithium, Indium	
Zn capacity	H_{cap}	Indium	Million Tonnes/year
Net zinc capacity change	H_{capc}	Indium	Tonnes/year
In recovery change	H_{rc}	Indium	Dimensionless
Difference between current and goal In recovery	H_{rg}	Indium	Dimensionless
In recovery rate	H_{rr}	Indium	Dimensionless
Discard rate	J	Generic, Lithium, Indium	Tonnes/year/year
Expected discard rate	J_e	Generic, Lithium, Indium	Tonnes/year/year
Max In capacity limit	M_{capmax}	Indium	Tonnes/year
Production capacity	P_{Cap}	Generic, Lithium, Indium	Tonnes/year
Primary production capacity	P_p	Indium	Tonnes/year
Adjustment for capacity	Z	Generic, Lithium, Indium	Dimensionless

Exogenous				
Variable	**Symbol**	**Model**	**Value**	**Units**

Average life of capacity	c_{apL}	Generic, Lithium, Indium	20	Years
Capital productivity	c_{app}	Generic, Lithium, Indium	1	Dimensionless
Cost of primary production	c_{Pp}	Indium	600,000	$/tonne
Zn market growth rate	h_g	Indium	0.015	Dimensionless
Max In recovery rate	H_{rmax}	Indium	0.9	Dimensionless
Time to max In recovery rate	h_{rmaxd}	Indium	20	Years
Indium contained	h_{mc}	Indium	9e-005	Dimensionless
Initial In recovery rate	h_{rt_0}	Indium	0.8	Dimensionless
Max primary production capacity	p_{pmax}	Indium	500	Tonnes/year
Capacity adjustment time	t_{cap}	Generic, Lithium, Indium	3	Years

Shadow Variable	**Symbol**	**Model**	**Cross reference**
Desired capacity	C_{apd}	Generic, Lithium, Indium	7.3.4
Reference demand	D_r	Generic, Lithium,	7.3.2

		Indium	
Indicated capacity utilisation	U_i	Generic, Lithium, Indium	7.3.1
Price	V	Generic, Lithium, Indium	7.3.3

Acquisition rate

The flow *acquisition rate* (Equation A*(t)=Ad(t)*
7.29) is equal to the *desired acquisition rate* (Equation 7.30), which is the sum of the *expected discard rate* and the *adjustment for capacity* (Equation 7.31), using a *MAX* function to ensure that the acquisition rate is never negative. The *adjustment for capacity* variable measures the difference between existing capacity (*capacity stock*) and *desired capacity* (discussed below) and includes a delay to represent the time taken for the market to adjust capacity stocks.

$$A(t)=A_d(t) \quad \textbf{7.29}$$

Desired acquisition rate

$$A_d(t) = MAX(0, J_e(t) + Z(t)) \quad \textbf{7.30}$$

Adjustment for capacity

$$Z(t) = \frac{C_{apd}(t) - C_{ap}(t)}{t_{cap}} \quad \textbf{7.31}$$

Discard rate (equal to the *expected discard rate* and presented in Equation 7.32) is a function of an exogenously assumed *average life of capacity.*

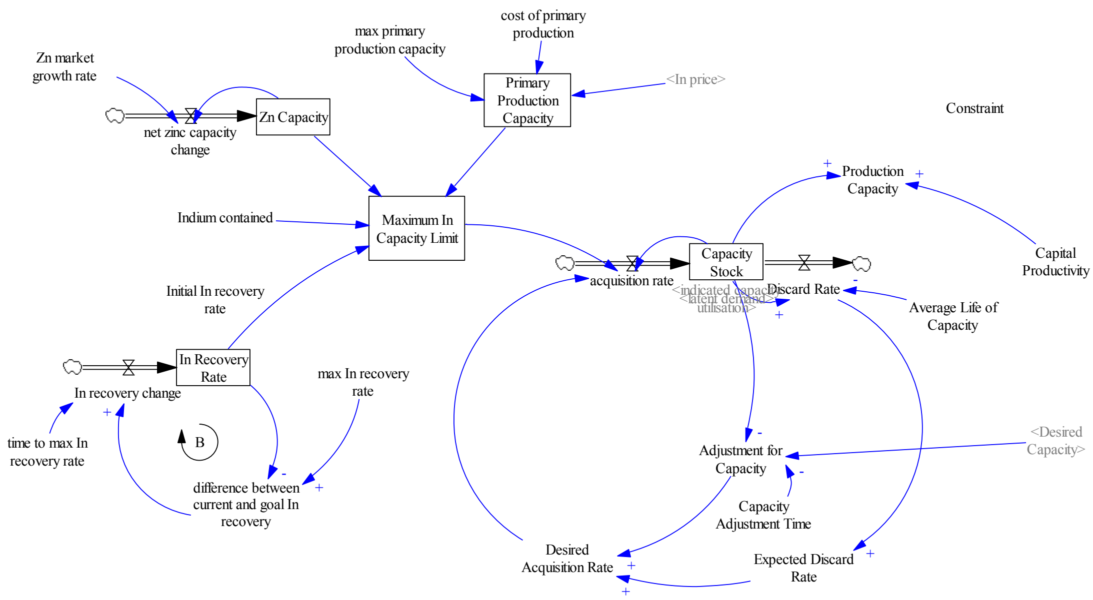
Discard Rate

$$J(t) = \frac{C_{ap}(t)}{C_{apL}}$$

7.32

Indium capacity is dealt with slightly differently given that the indium capacity page contains the parent zinc capacity subsystem (Figure 7.29). The two loop capacity system described above is still present in the indium model (right hand side of Figure 7.29). This system is then augmented by some small feedback systems culminating in a maximum indium capacity (*Maximum In Capacity Limit,* Equation 7.33). The system first creates a trajectory for zinc production. The rate of indium recovery from zinc ore is then modelled in a simple balancing feedback loop. Direct production of indium is also modelled.

Figure 7.29: The model diagram representing indium capacity



Maximum In Capacity Limit

The *Maximum In Capacity Limit* (Equation 7.33) sets the maximum quantity of indium producible at any point in time. This is limited by the total *Zn capacity* (Equation 7.34)*,* the quantity of *indium contained* in a unit of zinc production (an exogenous assumption) and the *In recovery rate* (Equation 7.36) *,* which improves over time through an iterative loop that creates asymptotic growth towards a *max In recovery rate* (exogenous).

$$M_{capmax}(t) = P_p(t) + H_{cap}(t)H_{rr}(t)h_{mc}$$

7.33

Zn Capacity

The level of parent *zinc capacity* is represented in the indium resource model as a stock, which integrates the flow of *net zinc capacity change* (Equation 7.35)*,* governed by an exogenously assumed *Zn market growth rate.* This was calibrated in the model to closely represent expected zinc production forecasts, as discussed in Chapter 6.

$$H_{cap}(t) = \int_{t0}^{t} Z_{capc}(s)\delta s + (1.1 * 10^7)$$

7.34

Net zinc capacity change

$$\boldsymbol{H_{capc}(t) = H_{cap}(t)h_g}$$

7.35

In Recovery Rate

The recovery rate of indium from zinc production is expected to increase in the near future in response to rising demand (Chapter 6). This is represented in the model by a stock named *In recovery rate* (Equation 7.36), which integrates the flow *In recovery change* (Equation 7.37). That flow is in turn a product of the *difference between current and goal In recovery* Equation 7.38) and a time delay in the feedback loop reaching the maximum recovery rate (*time to max In recovery rate*). Both the goal recovery rate (*max In recovery rate*) and the time delay are exogenous assumptions. The result of this feedback loop is an asymptotic growth in indium recovery rate to a maximum recovery rate based on the expected recovery efficiencies discussed in the literature (Chapter 6).

$$In(t) = \int_{t0}^{t} \big(H_{rc}(s)\big)\delta s + h_{rt_0}$$

7.36

<u>In recovery change</u>

$$H_{rc}(t) = \frac{H_{rg}(t)}{H_{rmaxd}}$$

7.37

<u>*Difference between current and goal In recovery*</u>

$$H_{rg}(t) = h_{rmax} - H_{rr}(t)$$

7.38

<u>*Primary Production Capacity*</u>

There is also a small contribution to indium capacity from primary indium production not associated with parent zinc production (*Primary production capacity*, Equation 7.39). This is a small quantity, either available or not depending on whether or not the indium *price* is above the cost of production from this source (*cost of primary production*). The 'IF THEN ELSE' function switches primary production on when price divided by the cost of production is greater than one.

$$\boldsymbol{P_p(t) = IF\ THEN\ ELSE(\frac{V(t)}{C_{Pp}} > 1, P_{pmax}, 0)}$$

7.39

Desired capacity (Equation 7.40) is dealt with in the same way in each of the three resource models. It is based on the *expected profitability of new investment* (Equation 7.42), which is in turn defined by the difference between *expected production cost* and *long run expected price* (Equation 7.43). Expected price is taken from the price page, with a delay introduced to represent the time taken for entities building capacity to interpret price indicators. Expected cost is derived from a *cumulative availability curve* (an exogenous lookup table). Different cumulative availability curves are applied to each of the different models. Where the expected profit is high then desired capacity increases, forcing capacity acquisition in the 'capacity' page. Where the expected profit is low, acquisition is reduced. Table 7.7 presents the variables used in the '*desired capacity*' page and the associated symbols used to represent them in the equations below.

Figure 7.30: The model diagram representing desired capacity

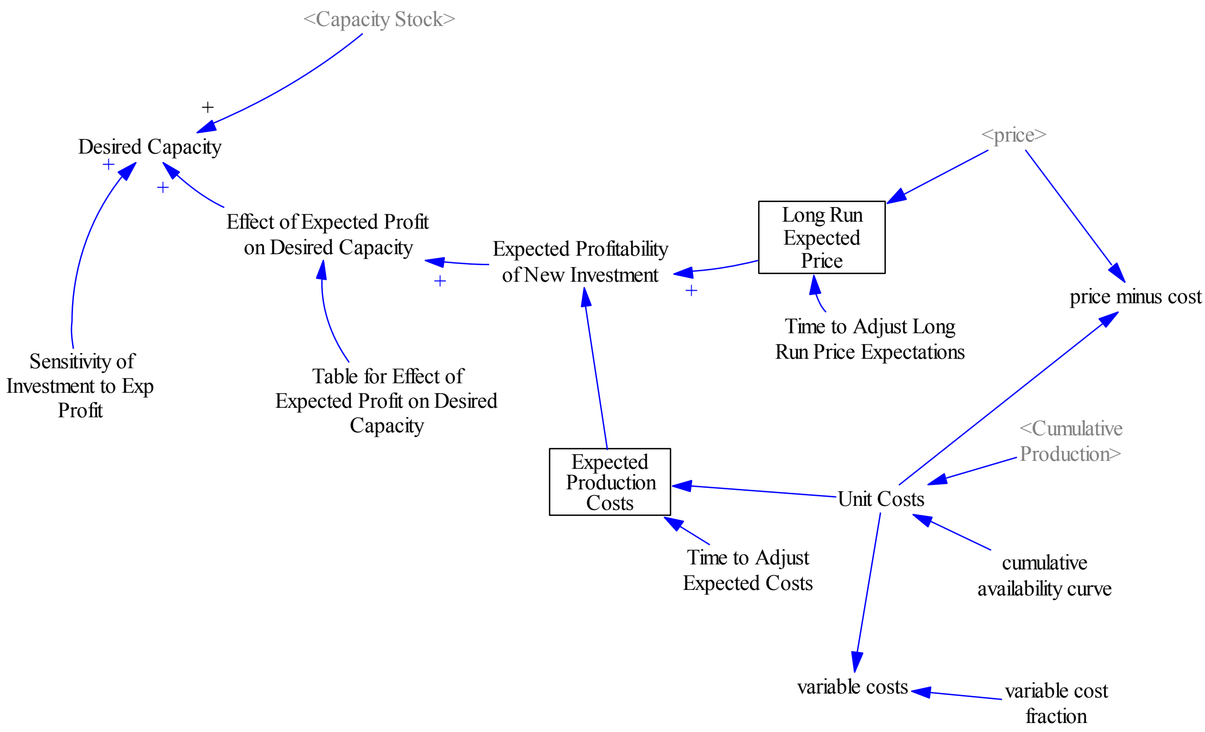


Table 7.7: The variables present in the 'desired capacity' page of the three resource system models

Variable	Symbol	Model	Units
Endogenous			
Desired capacity	C_{apd}	Generic, Lithium, Indium	Tonnes/year
Expected Production Costs	C_{pe}	Generic, Lithium, Indium	$/tonne
Unit cost	C_u	Generic, Lithium, Indium	$/tonne
Variable costs	C_v	Generic, Lithium, Indium	$/tonne
Long Run Expected Price	V_{el}	Generic, Lithium, Indium	$/tonne
Expected Profitability of	Y_{cap}	Generic, Lithium, Indium	Dimensionless

New Investment				
Effect of Expected Profit on Desired Capacity	Y_{capd}	Generic, Lithium, Indium	Dimensionless	
Exogenous				
Variable	**Symbol**	**Model**	**Values**	**Units**
Sensitivity of Investment to Exp Profit	c_{apdy}	Generic, Lithium, Indium	1	Dimensionless
Time to Adjust Expected Costs	c_e	Generic, Lithium, Indium	2	Years
Variable cost fraction	c_{vu}	Generic, Lithium, Indium	0.4	Dimensionless
Time to Adjust Long Run Price Expectations	v_{el}	Generic, Lithium, Indium	2	Years
Shadow Variable	**Symbol**	**Model**	**Cross reference**	
Capacity stock	C_{ap}	Generic, Lithium, Indium	7.3.4	
Cumulative production	Q	Generic, Lithium, Indium	7.3.1	
Price	V	Generic, Lithium, Indium	7.3.3	

<u>Desired capacity</u>

Desired capacity (Equation 7.40) is defined by the existing *capacity stock* multiplied by two factors representing the impact of expected profit (*effect of expected profit on desired capacity* (Equation 7.41)) and the sensitivity of investment to that impact (*sensitivity of investment to exp profit*). The effect of expected profit on desired capacity is defined by an exogenous lookup table that responds to the *expected profitability of new investment* (Figure 7.31).

$$C_{apd}(t) = C_{ap}(t)(1 + C_{apdy}(Y_{capd}(t) - 1))$$

7.40

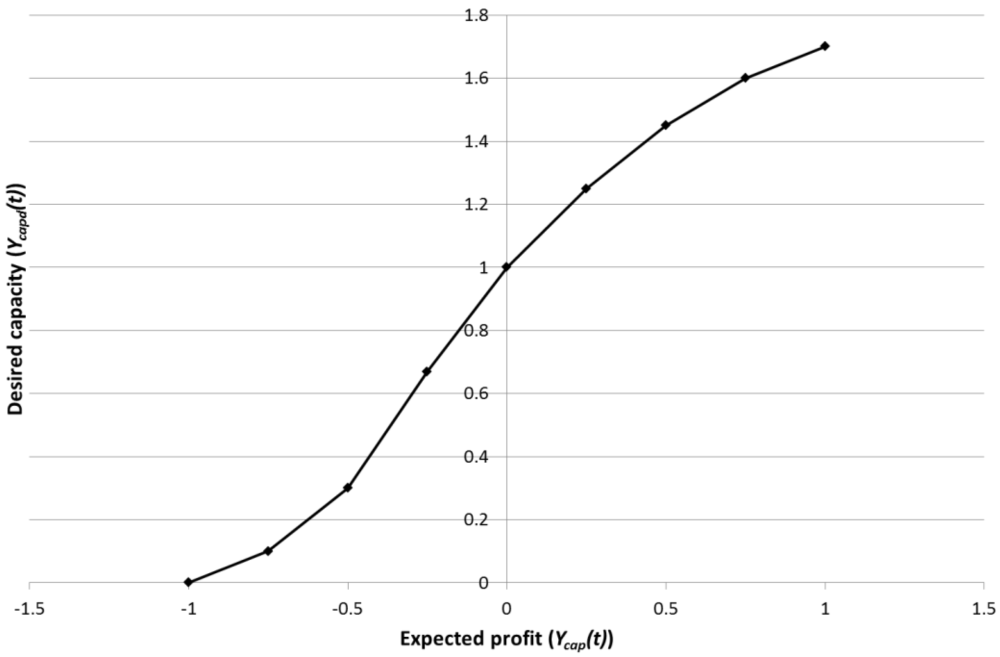
<u>*Effect of expected profit on desired capacity*</u>

$$Y_{capd}(t) = f_4(Y_{cap}(t))$$

Where *f* is a function defined by an exogenous lookup table presented below as '*table for effect of expected profit on desired capacity'* (Figure 7.31).

7.41

Figure 7.31: Table for effect of expected profit on desired capacity



Source: Based on Sterman (2000)

Expected profitability of new investment

Expected profitability of new investment (Equation 7.42) is a function of the balance between expectations of future production cost (*long run expected price* (Equation 7.43)) and future commodity price (*expected production costs* (Equation 7.44)). If price increases relative to costs then expectations of profitability increase, increasing *desired capacity* (Equation 7.40). The unit cost is a function of the *cumulative availability curve*, which takes the form of a lookup table defining the marginal cost curve of the resource. Each resource has an individual *cumulative availability curve*, presented in Figure 7.32, Figure 7.33 and Figure 7.34

$$\boldsymbol{Y_{cap}(t) = \frac{V_{el}(t) - C_{pe}(t)}{V_{el}(t)}} \tag{7.42}$$

Long run expected price

$$\boldsymbol{V_{el}(t) = SMOOTH(V(t), v_{el})} \tag{7.43}$$

Expected production costs

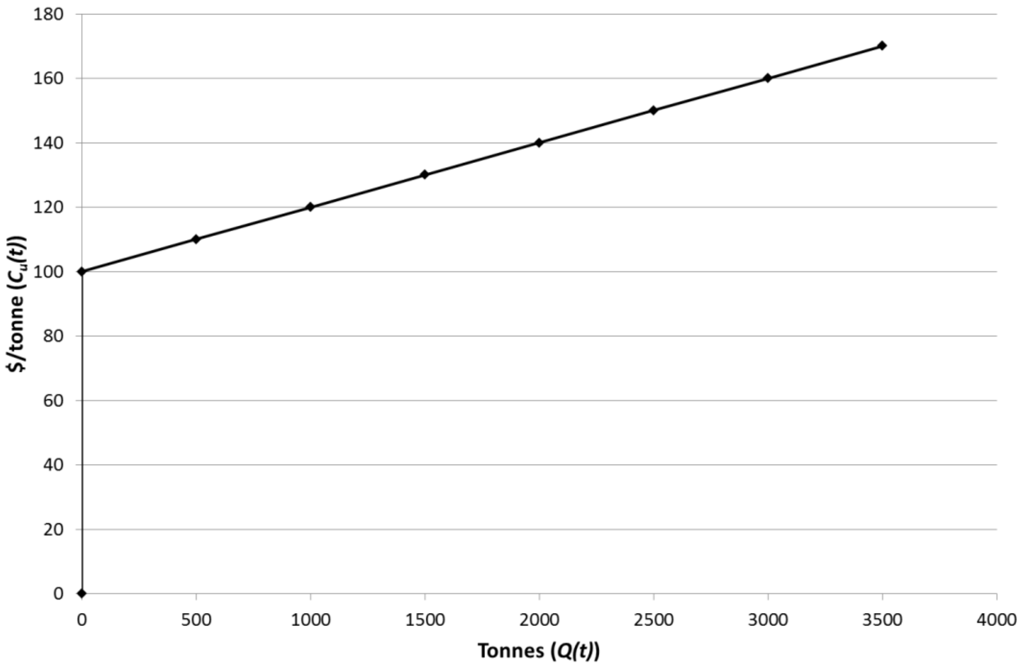
$$\boldsymbol{C_{pe}(t) = SMOOTH(C_u(t), c_e)} \tag{7.44}$$

Unit costs

$$C_u(t) = f_8(Q(t)) \tag{7.45}$$

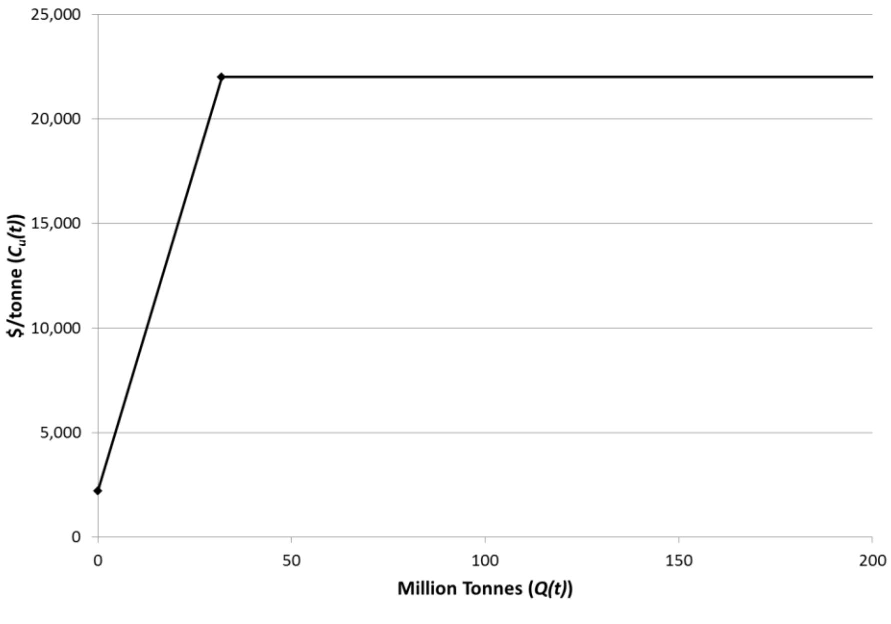
Where f_8 is a function defined by an exogenous lookup table presented below as '*cumulative availability curve'* (Figure 7.32,Figure 7.33 and Figure 7.34)

Figure 7.32: Cumulative availability curve for the generic resource



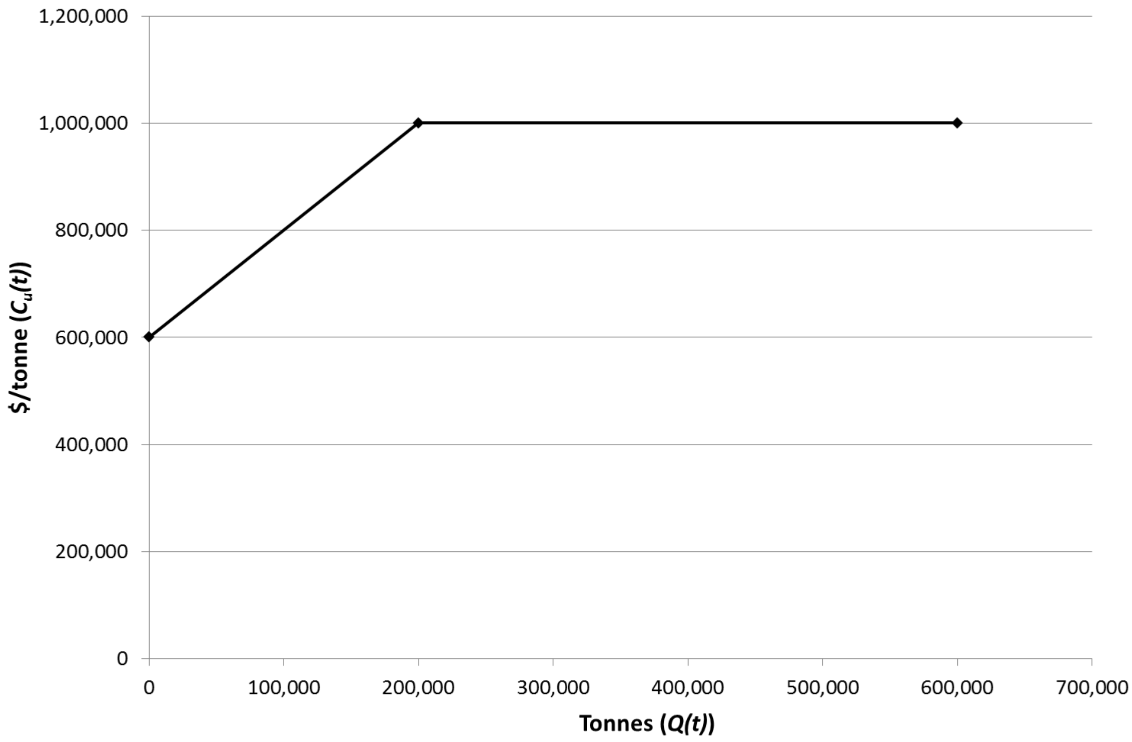
Source: Based on an approximation of IEA (2008)

Figure 7.33: Cumulative availability curve for lithium



Source: Based on an approximation of Yaksic & Tilton (2009)

Figure 7.34: Cumulative availability curve for indium



Source: Based on Mikolajczak (2009)

7.3.5 Recycling

Recycling is the final page and is only present in the lithium and indium models. The quantity of recycled lithium or indium (*recycled Li* or *recycled In*) is a function of the amount of material recycled in two different streams: metal contained in low-carbon products (either CIGS or EVs); and metal contained in other products. Both of these streams operate in exactly the same way. The amount of metal available for recycling in each of the streams is a function of the metal in products (taken from the demand page) after a delay based on the average lifetime of those products, and an assumed efficiency of the recycling process, called the recycling rate. Whether this is recovered is a function of the assumed cost of recycling, and the current price of the metal. As potential profit from recycling increases, the quantity of recycling undertaken by the model increases. Table 7.8 presents the variables used in the '*recycling*' page and the associated symbols used to represent them in the equations below.

Figure 7.35: The model diagram representing lithium recycling

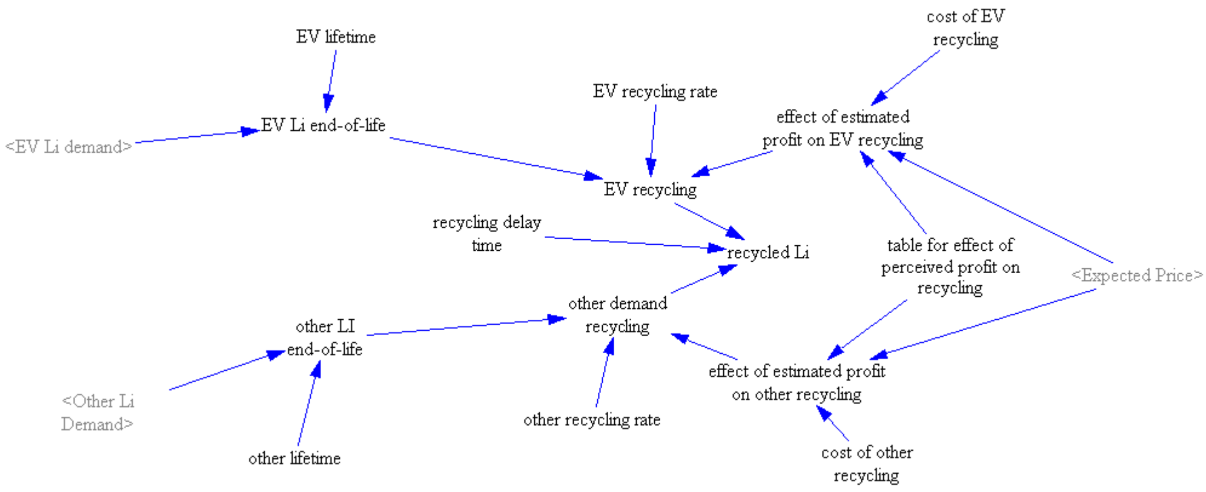


Table 7.8: The variables present in the 'recycled' page of the lithium and indium resource system models

Variable	Symbol	Model	Units
Endogenous			
CIGS In end of life *or* EV Li end of life	M	Lithium, Indium	Tonnes/year
Effect of estimated profit on EV recycling *or* Effect of estimated profit on CIGS recycling	R_y	Lithium, Indium	Dimensionless
EV recycling or CIGS recycling	R_m	Lithium, Indium	Tonnes/year
Recycled Li *or* Recycled In	R	Lithium, Indium	Tonnes/year
Other Li end of life *or* other In end of life	O	Lithium, Indium	Tonnes/year
Other demand	R_o	Lithium, Indium	Tonnes/year

recycling				
Effect of estimated profit on other recycling	R_{oy}	Lithium, Indium	Dimensionless	
Exogenous				
Variable	**Symbol**	**Model**	**Values**	**Units**
CIGS lifetime *or* EV lifetime	e_{ol}	Lithium, Indium	L=20 I=30	Years
Other lifetime	o	Lithium, Indium	10	Years
Cost of other recycling	o_c	Lithium, Indium	L=9,000 I=700,000	\$/tonne
Other recycling rate	o_r	Lithium, Indium	0.6	Dimensionless
Recycling delay time	r	Lithium, Indium	L=0.5 I=1	Years
Cost of EV recycling or Cost of CIGS recycling	r_c	Lithium, Indium	L=9000 I=700,000	\$/tonne
EV Recycling rate *or* CIGS recycling rate	r_r	Lithium, Indium	L=0.6 I=0.8	Dimensionless
Shadow Variable	**Symbol**	**Model**	**Cross reference**	
EV Li demand *or* PV In demand	D_m	Lithium, Indium	7.3.2	
Other demand	D_o	Lithium, Indium	7.3.2	
Expected price	V_e	Generic, Lithium, Indium	7.3.1	

<u>*Recycled lithium or recycled indium*</u>

Recycled metal (Equation 7.46) is a function of recycled metal from both low carbon and other end-of-life sources. The delivery of recycled metal is smoothed using the '*DELAY3*' function to simulate the non-uniform time delay in availability of recycled metal (See Annex D)[37]. The metal recycled (Equation 7.47) is a function of the metal available in EV or CIGS end-of-life products, multiplied by the estimated *recycling rate* (exogenous) and the *effect of estimated profit on recycling* (Equation 7.49). This effect of profit on recycling is a function of a look-up table (*Table for effect of perceived profit on recycling*, Figure 7.36). The contribution of recycled metal from end-of-life products other than EVs or CIGS is calculated in exactly the same way, and feeds into recycled metal as described in Equation 7.46.

$$R(t) = DELAY3\big(\big(R_m(t) + R_o(t)\big), r\big)$$

7.46

<u>*EV recycling or CIGS recycling*</u>

$$R_m(t) = M(t)R_y(t)r_r$$

7.47

<u>*EV lithium*</u> or <u>*CIGS indium end of life*</u>

$$M(t) = DELAY\ FIXED(D_{lm}(t), e_{ol}, 0)$$

7.48

<u>*Effect of estimated profit on EV recycling or CIGS recycling*</u>

$$\boldsymbol{R_{oy}(t) = f_7(W_3(t))}$$

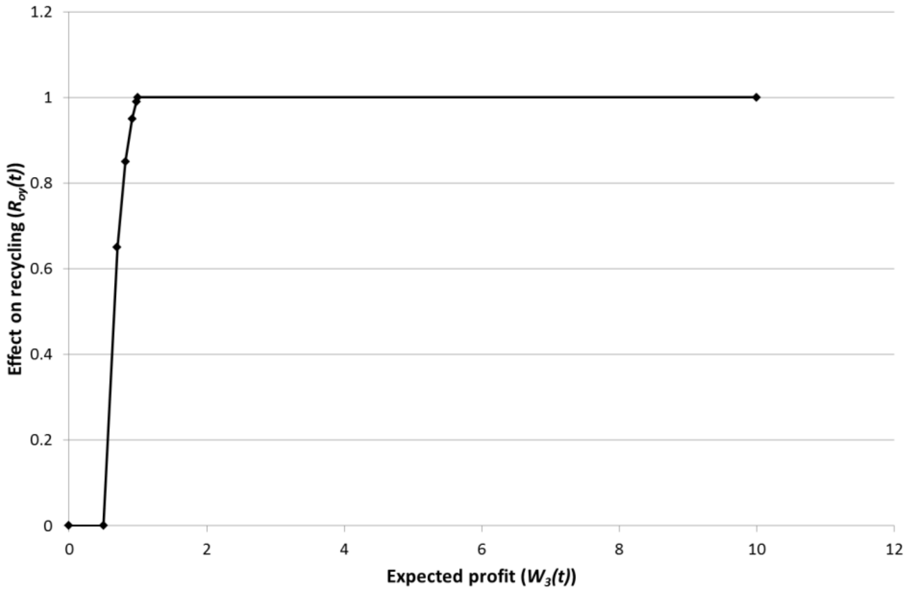
7.49

Where f_7 is a function defined by an exogenous lookup table presented below as '*table for effect of perceived profit on recycling'* (Figure 7.36) and

$$W_3(t) = \frac{V_e(t)}{R_O(t)}$$

7.50

Figure 7.36: Table for effect of perceived profit on recycling



7.4 Model testing and settings

Models are simplified representations of real systems. Once a model is created it is important to understand whether it performs appropriately for its purpose. The phrase 'model validation' is often used in relation to this process, but this phrase is misleading since it is impossible to validate something which is by definition an imperfect representation of a real system. As Forrester (1961) wrote

> *"Any 'objective' model-validation procedure rests eventually at some lower level on a judgment or faith that either the procedure or its goals are acceptable without objective proof."*

For this reason the phrase 'model testing' is used here. In this section, several model tests are carried out to establish the models performance under various conditions. This helps establish that the dynamic system behaviours exhibited by the model are consistent, or at least not in conflict with, the types of behaviour expected in the real system being modelled. Through this process the modeller can begin to build confidence in the model structure, and revise any aspects of the model that clearly conflict with the observed behaviour of the real system being modelled.

First the initial conditions for each model are established. These are the initial values assumed for each of the variables exogenously input into the model. The models have been created to establish relative difference between system behaviours, and not as a forecasting tool for absolute behaviour. The initial conditions used for each model are important however, and the source or justification for the assumptions discussed.

Delta *t* error tests are then carried out to establish that the correct model settings have been applied. System dynamics models are typically solved using some form of numerical integration method, often Euler's integration. Since computers must operate in discrete steps of calculation, this type of approximation works well with computer modelling platforms. The discrete steps of calculation can be defined in the model settings of programs like Vensim, and are often called *time steps*. However, Euler's approximation assumes that values of an equation essentially remain the same over the period of one time step. If the time step is set too long then this assumption is likely to be invalid, and significant errors can occur. Delta *t* error tests are used to establish an appropriate length of time step.

The model can then be evaluated against the identified reference modes. By examining the types of dynamic system behaviour exhibited by the real system, and trying to replicate those behaviours using the model, the appropriateness of the models structure can be judged.

Extreme conditions testing is then carried out, to examine for illogical model behaviour in response to extreme input variables. For example, regardless of how low demand for a product is, the price for that product cannot become negative. There may be examples for some products where this can be the case for very short periods of time, but for commodities this is implausible.

Finally, sensitivity testing is conducted to highlight variable that are very sensitive to the input assumptions, and therefore interesting from an analytical point of view.

7.4.1 Initial conditions

Full details of the initial conditions values can be found in the model documentation in Appendix C to Appendix E. However, for brevity, only a few of the most interesting initial conditions are discussed here. As these models are built on Sterman's generic commodity market model many of the initial conditions are taken from that earlier work (Sterman 2000). However, several modifications have been made to this model to create useful representations of the three commodities systems modelled in this thesis. The initial conditions of these parts of the models are discussed here.

Generic resource model

The initial price is set in the model at $100 per tonne. For the objectives of the modelling exercise conducted in this thesis the initial price is less important than the trends in price resulting from different stimulus. The value of $100 per tonne is therefore sufficient for the purposes of this thesis.

Demand is modified from the original (Sterman 2000) model to incorporate a Kuznets style decoupling between GDP and generic resource demand. The model assumes GDP growth of 1%, a conservative figure based on recent events and trends (Bank 2014). The rate of decoupling is set so that demand peaks between 55 and 60 years into the model time horizon, at 31.4 billion tonnes per year. This ignores any possibility of a supply side peak happening in a shorter time frame. However, it represents a conservative plateau-like future (Hughes & Rudolph 2011).

The cumulative availability curve is another addition to the original Sterman model as a way to represent the cost pressures associated with seeking the marginal tonne of resource. The concept is common in resource economics particularly where evaluating issues of future availability (IEA 2008; Yaksic & Tilton 2009; IEA 2013). The initial curve applied to the generic resource system model (see Appendix C) is based on current estimates of remaining oil resources (Sorrell *et al.* 2009), approximation of current oil production costs (IEA 2008; IEA 2013), and expected future cost trends (IEA 2008; IEA 2013).

Delays associated with adjustment of expected prices or other markets issues are initially set to either one year or half a year (Appendix C). Delays associated with adjustments of physical capital (i.e. capacity adjustments) are initially set to two or three years, reflecting the challenges associate with capital investment in resource extraction.

Lithium model

Initial lithium price in the model is set to $5000/ tonne as an approximation of the historical lithium price (USGS 2013).

In contrast to the generic resource model, demand in the lithium model[40] is driven by demand for electric vehicles, and the lithium intensity of these technologies. The important initial values are therefore the growth rate of electric vehicles and the quantity of metal contained per electric vehicle (lithium intensity). The growth rate is based on a logistic s-curve, governed by two variables: maximum electric vehicle growth and maximum electric vehicle sales. Maximum growth is initially set to 20% while maximum sales are set to 30 million. These values were chosen to closely emulate IEA electric vehicle growth scenarios (Speirs *et al.* 2013a). Lithium intensity is initially set to 0.00798 tonnes per vehicle, based on 380 grams of lithium per kWh of battery and 21 kWh average battery capacity per vehicle (Speirs *et al.* 2013a).

The cumulative availability curve for lithium is an approximation of data in Yaksic & Tilton (2009)

In the recycling model page the lifetime of EVs is set to 20 years, while the lifetime of other uses of lithium (e.g. consumer electronics) is set to 10 years. This reflects current rough estimates of future product lifetimes (Speirs *et al.* 2013a). The lithium recycling rate is set to 60% (Speirs *et al.* 2013a).

Indium model

Initial indium price in the model is set to $600,000/tonne as an approximation of recent indium price trends (USGS 2013).

By-product related initial values in the indium model are based on the findings of (Speirs *et al.* 2011). Zinc market growth rate is set to 1.5 percent to emulate growth estimated in the literature (Fthenakis 2009). The indium contained in a unit of Zn is initially set to a factor of 0.00009 (Speirs *et al.* 2011). The rate of recovery of that indium is based on an initial indium

[40] The indium model follows the same general demand structure, though it is the future PV market driving demand rather than the future EV market

recovery rate (80%), a maximum indium recovery rate (90%) which is reached 20 years from the start of the model timeframe (Speirs *et al.* 2011).

Primary indium production, without reliance on host metal production, is defined by a maximum primary indium production capacity (500 tonnes per year (Speirs *et al.* 2011)) and the indium at which this is profitable is set to $600,000 per tonne. This is set based on the fact that primary production of indium is already a burgeoning market, suggesting that at current the indium price close primary production is viable (Speirs *et al.* 2011).

The initial values for the growth rate in CIGS uptake are based on the PV trajectory presented by the IEA (2010a). This is an optimistic assumption on the future growth rate for CIGS since other PV technologies will likely take some proportion of the IEAs trajectory. However, this optimistic assumption allows for the evaluation of by-product constraints. As discussed in Chapter 8 the by-product constraints begin to impact on the model at the demand growth rates tested.

7.4.2 Delta *t* error test and time step

System dynamics models are commonly solved by numerical integration in discrete time steps. Sometimes when solving these models errors develop relating to the length of these discrete time step. These errors are known as integration error, or delta *t* error (*dt* error). Because the integration methods used to solve these models approximate the results in 'chunks' of time, the longer these chunks are the more likely these approximations will be wrong. However, solving system dynamics models with vanishingly small time steps is impractical given the increasing computational power needed to solve models with increasing number of model iterations. Choosing a time step is therefore important, and needs a 'goldilocks' approach to determine a time step small enough to avoid integration error, but big enough to limit the computational power needed to solve the model.

In addition to time step, many models offer a choice of differing integration methods. Euler integration method is commonly used but alternatives like Runge-Kutta (RK4 Auto) are often also available. In some cases model solutions can be sensitive to the choice of integration method and this is another error to be avoided.

In order to test for both of the potential errors described above the outputs for six variables were recorded at four points in model time. The model was run using several different time steps, and with both types of numerical integration method (Table 7.9).

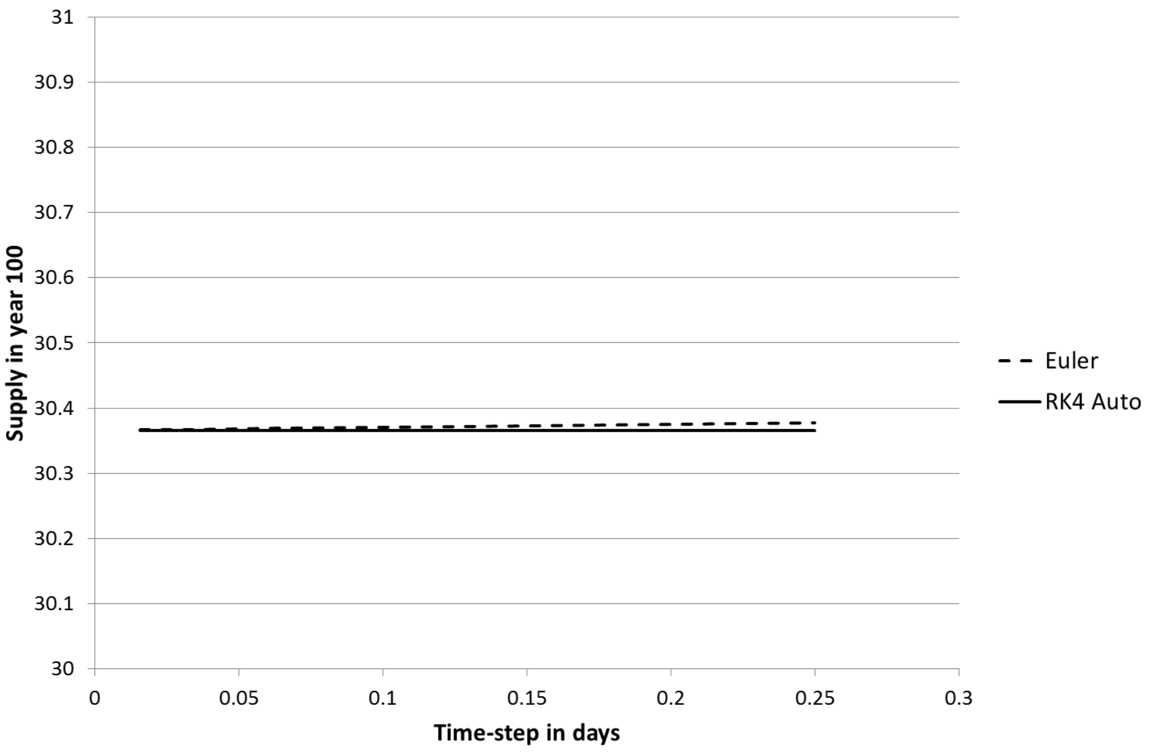
Table 7.9: Outputs recorded, point in model timeframe, time step and numerical integration method used during delta *t* error test.

Outputs recorded	Points in model time (years)	Time steps tested (days)	Numerical integration methods
Supply rate	0	0.007813	Euler
Demand	25	0.015625	RK4 Auto
Price	50	0.03125	
Capacity utilisation	100	0.0625	
Production capacity		0.125	
Desired capacity		0.25	
		0.5	
		1	

This process was conducted for each model, and the results recorded and plotted to establish the presence of any error. Uniformly the results suggested that there were no errors associated with any of the models. This is demonstrated for the case of the generic resource model, where the supply variable in year 100 shows only very slight variation between time step and integration method (Figure 7.37).

Given the apparent absence of errors the time step 0.03125 days was chosen as it was less than a day, but did not significantly affect the length of time taken to solve the model, or limit the number of iterations saveable based on the limitations of the model platform Vensim. The Euler integration method was retained as it appeared to return the more consistent results over different time steps, though this benefit is clearly marginal.

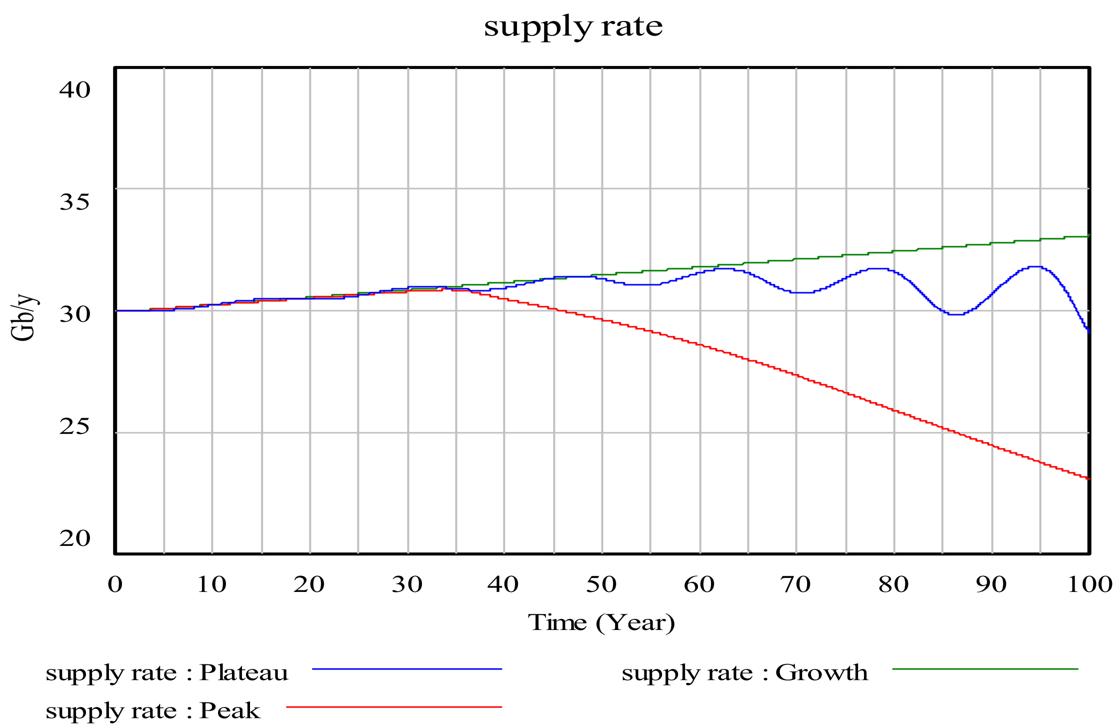
Figure 7.37: DT error test presenting the impact on generic resource supply in year 100 of the model from time-step 0.015625 days to 0.25 days across both Euler and RK4 Auto integration types



7.4.3 Consistency with reference modes

As discussed in Section 7.1.3 , reference modes are typically time series data that demonstrate some kind of system behaviour in the system being modelled. It is common in system dynamics to examine these reference modes, and test model behaviour to see if it is consistent with these reference modes. In Section 7.1.3 reference modes representing historical production, historical price, and forecast production for each of the three resources modelled are presented. The underlying behaviours exhibited in these reference modes were used to inform the construction of the models, and therefore it is reasonable to assume that the models are able to replicate these behaviours. This assumption was tested by changing the input variable of the models and comparing the resulting outputs to the reference modes. In all instances an approximation of the expected behaviour was achieved by the respective models. To provide an example, Figure 7.38 presents three separate runs of the generic resource system model manipulating the input variables to recreate the types of behaviour witnessed in the reference mode for supply rate forecasts. These three runs were created by manipulating the *production time delay*, *cumulative availability curve* and table for decoupling variables to provide growing, peaking and oscillating production simulations. The simulation run representing growth is most likely in a world where future cost of extraction does not increase significantly, and the rate of decoupling of demand from GDP is minimised. The simulation representing peaking behaviour is most likely in a world where either future supply peaks due to physical constraints on capacity, or future demand decreases due to a combination of decoupling of demand from economic growth, and increasing cost of marginal recovery (this simulation represents the latter). The plateau dynamic behaviour simulated is most likely in a world where demand is maintained in a reasonably steady state, but the time delays in the response mechanisms of the system are increased for some reason. This could be the case in a world where the time taken to build capacity, or to respond to demand signals is lengthened due to increasing engineering challenges associated with marginal production or decreasing confidence in industrial intelligence and information.

Figure 7.38: Output of three different simulations in the Generic resource system model representing the types of supply rate behaviour found in the reference modes



Note: Adjustments from initial values –

Growth: table for decoupling set to zero for all levels of GDP and cumulative availability curve flattened at $100/b

Peak: table for decoupling set to double the rate of decoupling and cumulative and cumulative availability curve delayed

Plateau: production delay time increased from 0.5 to 4 years and cumulative availability curve flattened at $100/b

7.4.4 Extreme conditions test

In system dynamics modelling it is common to test the robustness of a model using *extreme conditions testing*. In this type of testing a model input variable is assume to take a sudden and dramatic shift to an implausibly high or low value. The response of the model is examined to see if any implausible behaviour arises from these extreme input variables. For example, regardless of how high the price of a commodity rises, demand cannot drop below zero. If this is a result witnessed during extreme conditions testing then the model structure is likely to need adjustment to improve its robustness.

The three models describe here were tested under extreme conditions by systematically setting each input variable to zero and 10^{10}. The responses to this were recorded and examined for unrealistic behaviour. All models were deemed to have exhibited plausible behaviour.

7.4.5 Sensitivity test

Sensitivity of a model to variation in input assumptions can be carried out in a number of ways. Here the models are exposed to two main types of analysis: Multivariate Monte Carlo simulation, and univariate simulation. The former tests the impact of varying a number of different inputs simultaneously, while the latter varies inputs individually. In both cases variables were assigned an initial value (see 7.4.1), and a maximum and minimum range over which they could be varied. The model then randomises the values for these variables over a set number of iterations, based on a stated probability distribution. In this case the range was set to +/-50% for each initial value, the number of iterations was set to 100 and a random uniform distribution was selected given lack of evidence for the true underlying distribution for most of the model variables. The results of sensitivity analysis for the three models are presented in turn below.

The figures below are sensitivity percentile graphs, providing information about both the range of outcomes and the distribution of those outcomes when subject to changing inputs. The blue line at the centre of the range of outcomes represents the response of the model to the initial values. The yellow, green, blue and grey portions of these figures represent the 50^{th} percentile, 75^{th} percentile, 95^{th} percentile and 100^{th} percentile of the sensitivity analysis outcomes. For example, of the 100 iterations of the sensitivity analysis in each graph, 95 of those iterations produced an outcome that stayed within the blue portion of the graphical output.

The generic resource system model

The variables included in the generic resource model sensitivity analysis, and the range of values used is presented in Table 7.10. Below the results of multivariate analysis are presented, before focusing on some of the interesting findings of univariate analysis.

Table 7.10: Model inputs varied during the generic resource model sensitivity analysis including their units, initial values and variable range

Variable	Units	Initial value	Minimum (-50%)	Maximum (+50%)
Production delay time	Years	0.5	0.25	0.75
GDP growth rate	Factor	0.01	0.005	0.015
Demand adjustment delay	Years	0.5	0.25	0.75
Reference demand elasticity	Factor	0.5	0.25	0.75
Sensitivity of price to costs	Factor	0.5	0.25	0.75
Time to adjust traders expected price	Years	1	0.5	1.5
sensitivity of price to inventory coverage	Factor	-1	-0.5	-1.5
Capital Productivity	Units/year	1	0.5	1.5
Average life of capacity	Years	20	10	30
Minimum order processing time	Years	0.1	0.05	0.15

Multivariate analysis

The results of the multivariate analysis are presented below in Figure 7.39 to Figure 7.43. The impacts of the sensitivity analysis are presented for the output of five key aspects of the model:

- supply rate (Figure 7.39)
- demand (Figure 7.40)
- price (Figure 7.41)
- production capacity (Figure 7.42); and
- Desiredproduction capacity (Figure 7.43)

The following points are worth highlighting with reference to the multivariate analysis outputs below:

- First, supply and demand show very similar sensitivity responses. This is intuitive as one of the functions of the model is to balance supply and demand. In both cases the initial values produce a model response which is reasonably flat initially, and then begins to decrease in response to both decoupling of demand from GDP, and increasing marginal cost of production.

- Price shows only modest sensitivity to varied inputs in 95% of the multivariate sensitivity iterations. However in the most extreme 5% of model iterations price varies significantly, showing significant oscillations. These oscillations are positively biased, suggesting that the models response to more extreme model inputs is more likely to produce a higher generic resource price than a lower one. The initial values create an price that largely follows the marginal cost, as one might expect in a rational economic system.
- Production capacity follows a similar trend to supply and demand, though its response to variation appears greater, creating a broader range. The centre of the range is above the centre of the supply rate range, given that the model favours maintaining spare capacity (see 7.3.1).
- Desired capacity shows a much greater range than actual production capacity. This is a function of the fact that desired capacity defines the goal and can change more quickly than production capacity, which is constrained by additional delay.

Figure 7.39: Generic resource model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on supply rate of varying inputs +/- 50% (Tonnes/y)

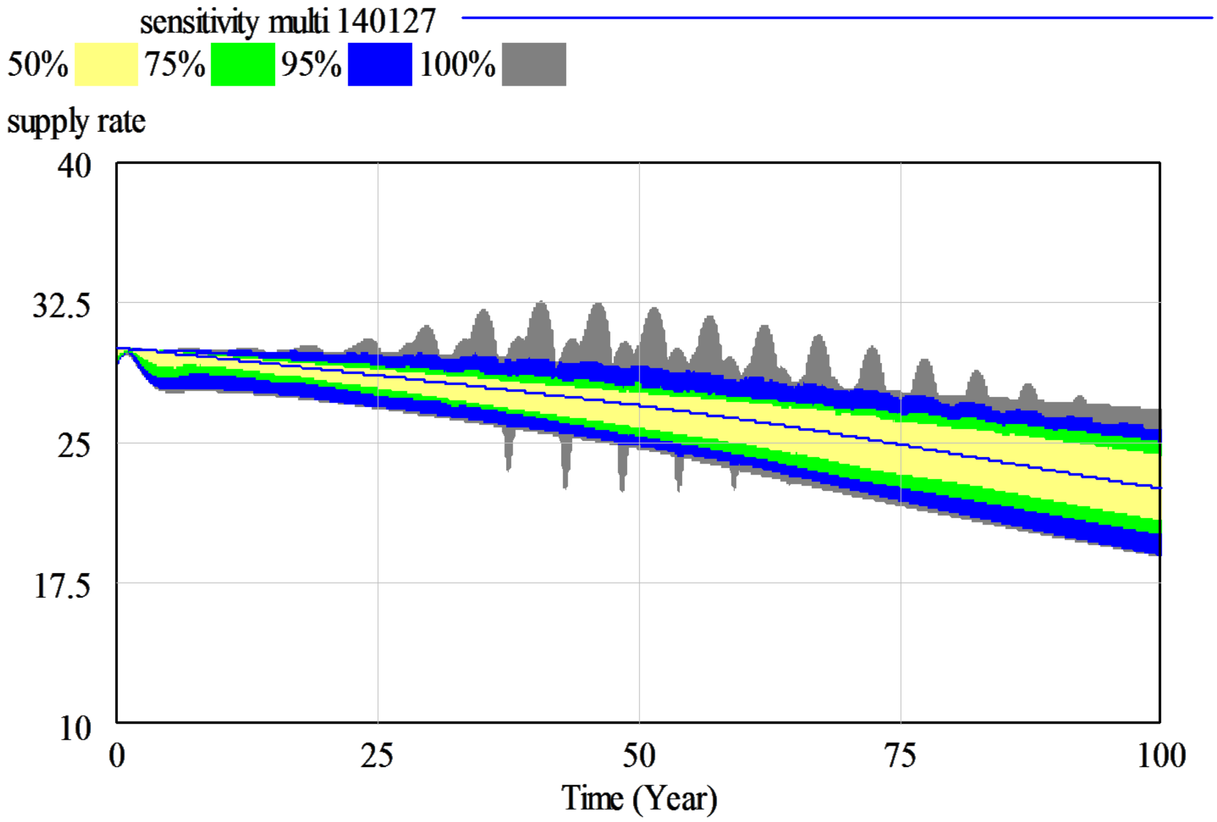


Figure 7.40: Generic resource model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on demand of varying inputs +/- 50% (Tonnes/y)

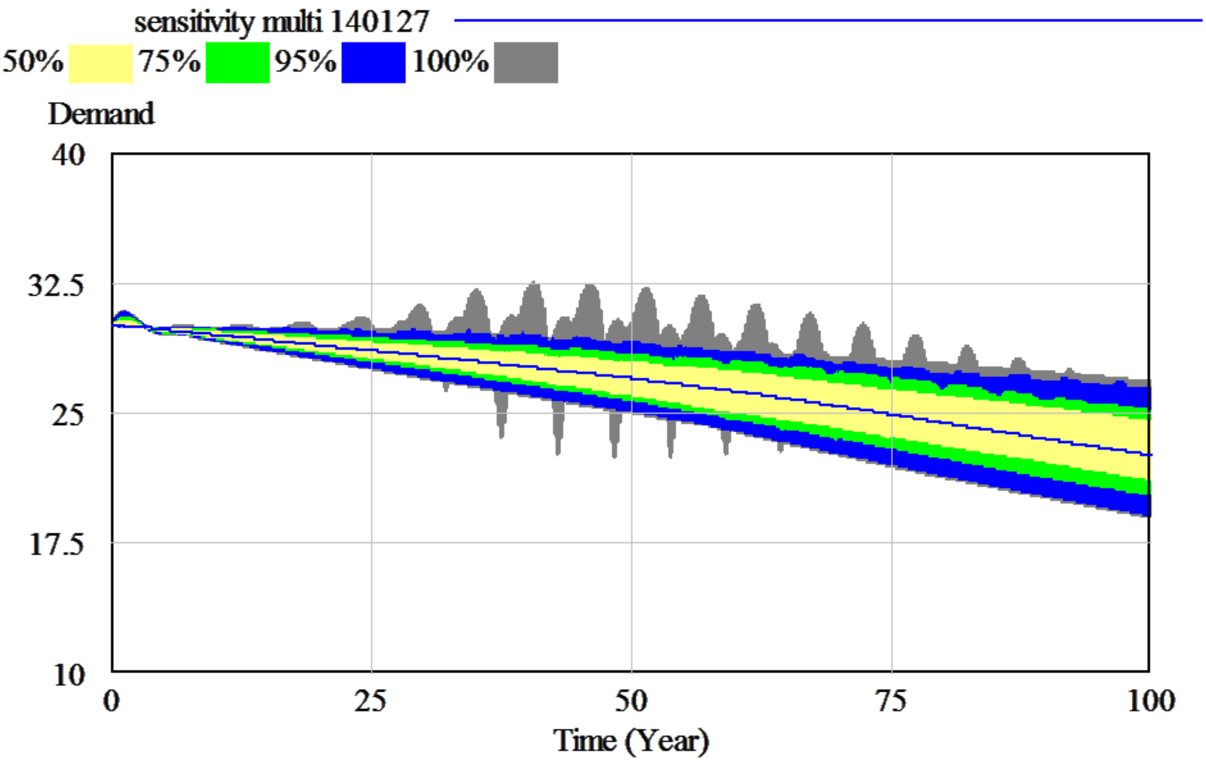


Figure 7.41: Generic resource model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on price of varying inputs +/- 50% ($/b)

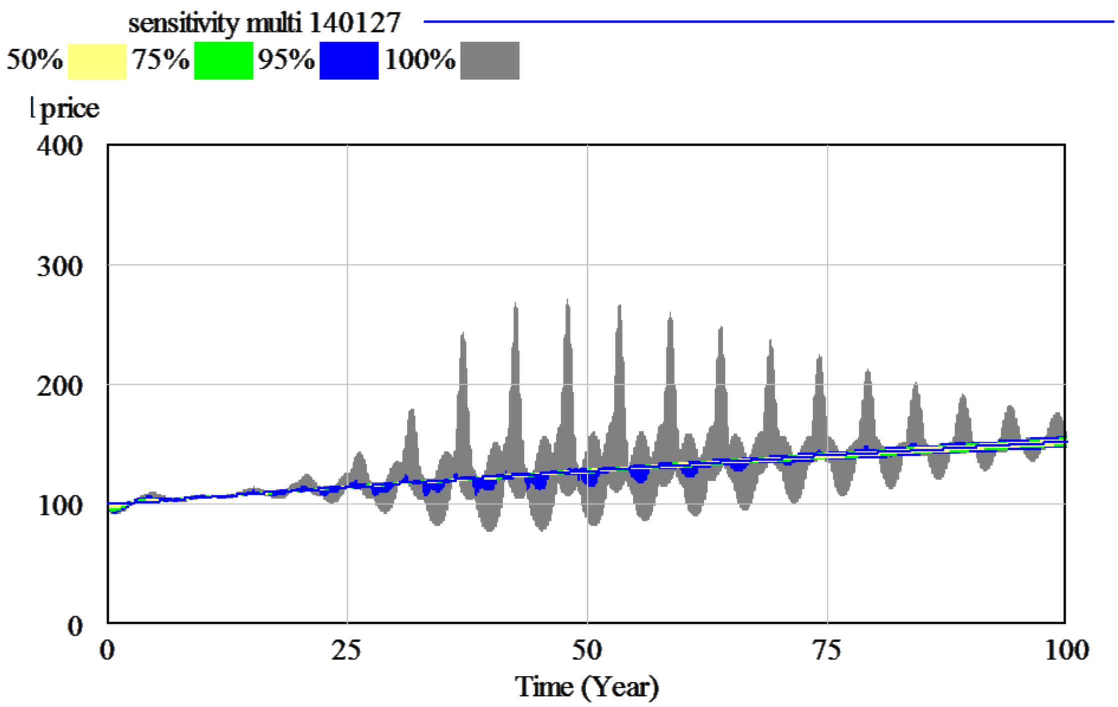


Figure 7.42: Generic resource model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on production capacity of varying inputs +/- 50% (Tonnes/y)

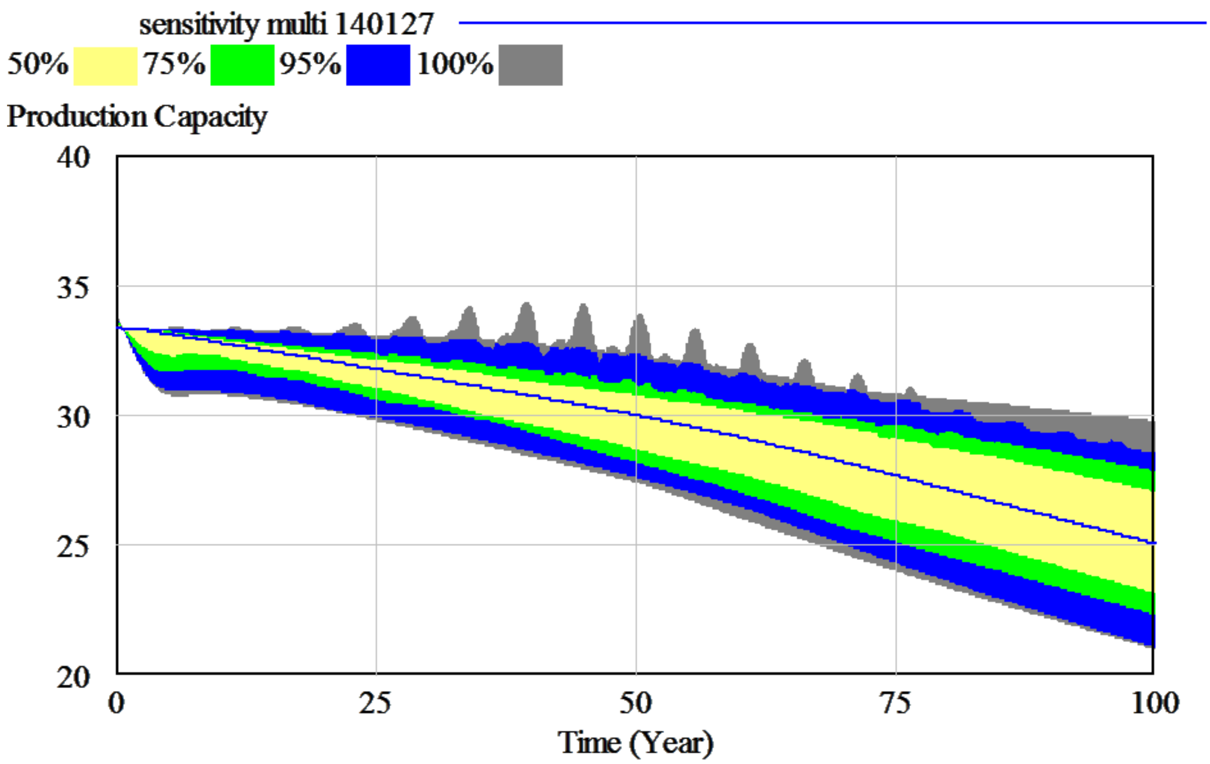
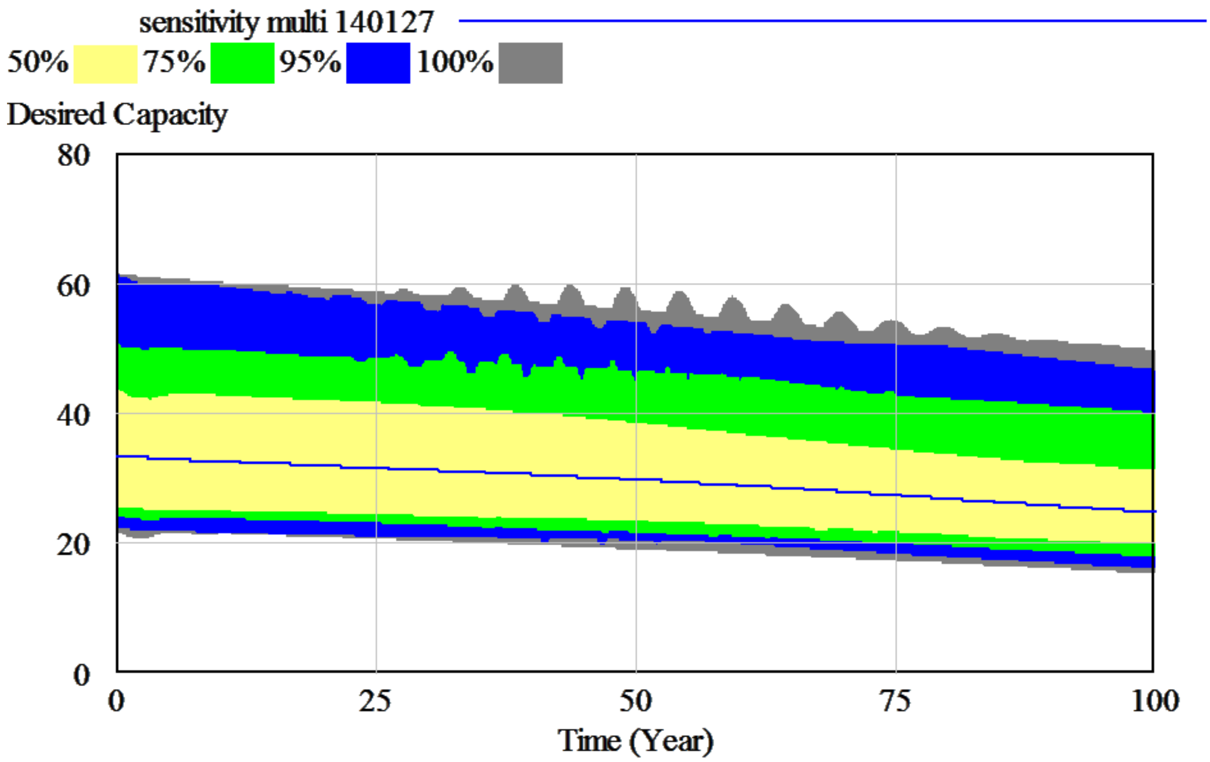


Figure 7.43: Generic resource model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on desired capacity of varying inputs +/- 50% (Tonnes/y)



Univariate analysis

Below are the results for univariate sensitivity analysis of the generic resource system model. The impacts of the univariate analysis are only presented for supply rate for brevity. In the initial values case the model output trajectory is relatively stable. As such the model in this state is not very sensitive to variation of individual variables representing some form of delay. These variables determine how quickly the model responds to change, and these delays are often characterised by oscillation in model outputs. Therefore, only those variables that do respond with interesting sensitivities are presented here.

Varying the GDP growth rate creates a small range in the supply rate, represented in Figure 7.44. Varying the reference demand elasticity, however, has a more significant impact (Figure 7.45). When comparing this sensitivity with that shown for the multivariate sensitivity test impact on supply rate (Figure 7.39) it is clear that the majority of the sensitivity of this model can be explained by reference demand elasticity alone. Therefore, assumptions regarding the slope of the generic resource demand curve are very important to the behaviour of the generic resource system model.

Figure 7.44: Generic resource model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying GDP growth rate +/- 50% (Tonnes/y)

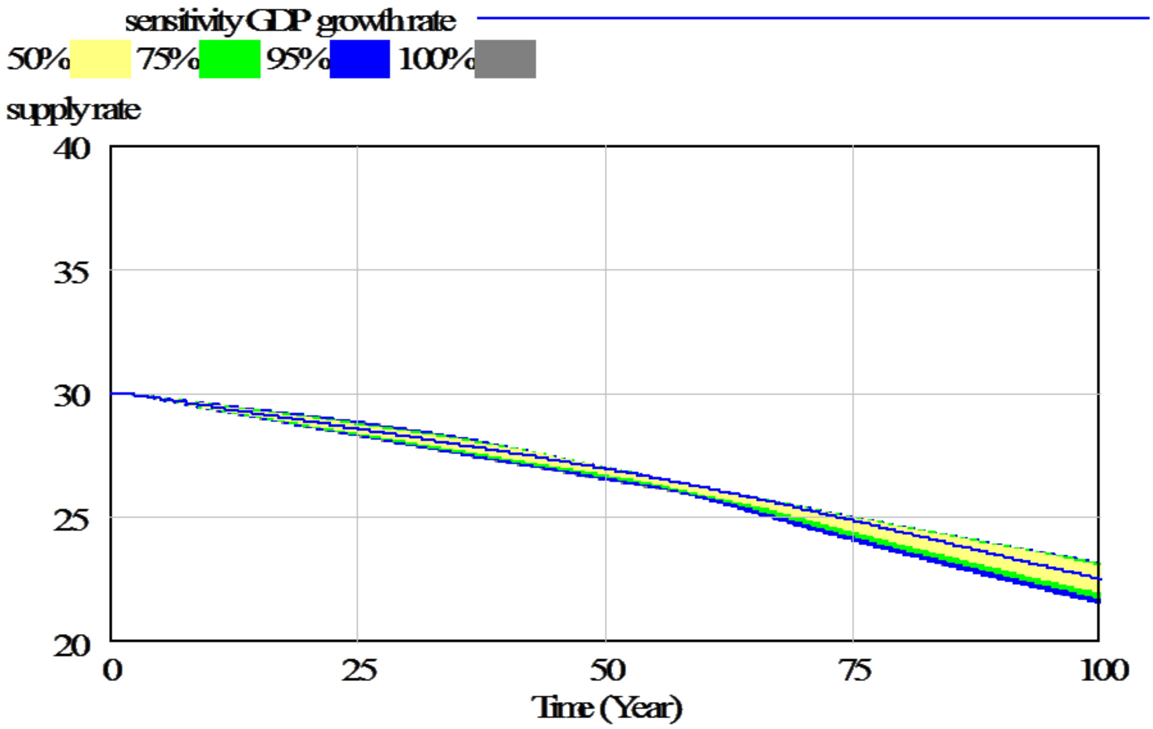
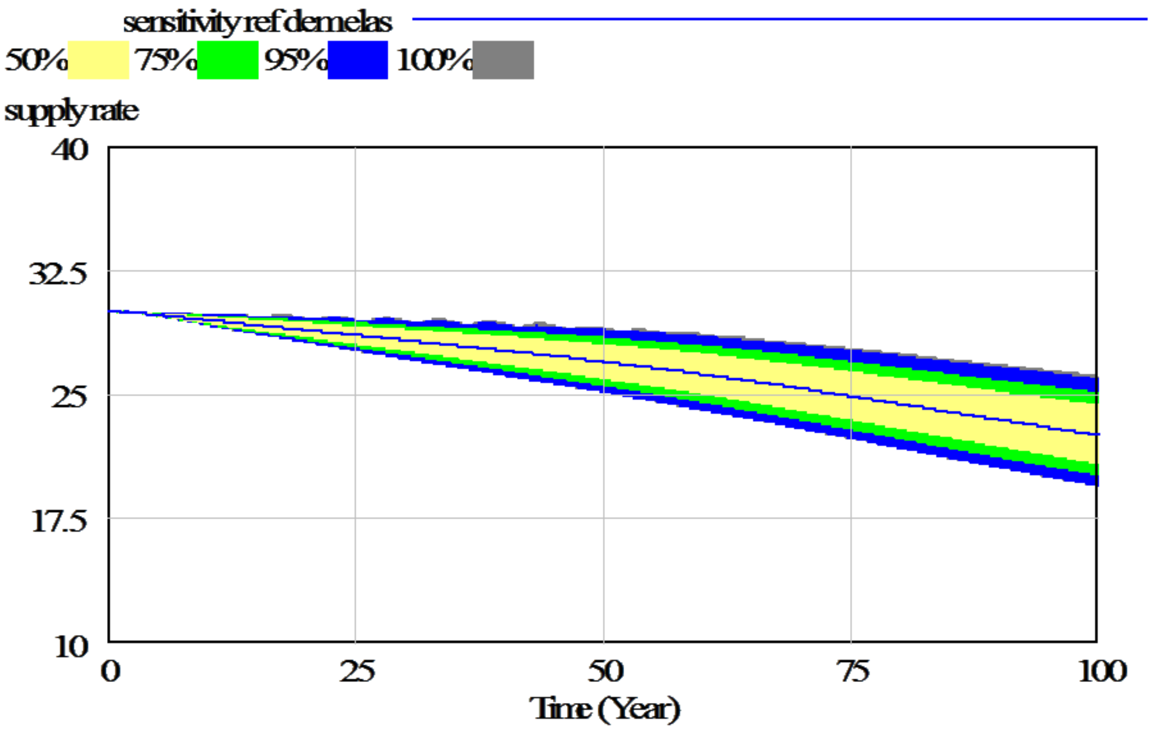


Figure 7.45: Generic resource model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying reference demand elasticity +/- 50% (Tonnes/y)



The lithium resource system model

As previously, the variables included in the lithium model sensitivity analysis and the range of values used, are presented in Table 7.11. Below the results of multivariate analysis are presented, before focusing on some of the interesting findings of univariate analysis.

Table 7.11: Model inputs varied during the lithium model sensitivity analysis including their units, initial values and variable range

Variable	Units	Initial value	Minimum (-50%)	Maximum (+50%)
Other Demand	Tonnes/yr	35000	17500	52500
demand adjustment delay	Yrs	0.5	0.25	0.75
ref Li demand elasticity	Dimensionless	0.5	0.25	0.75
Li intensity	t/vehicle	0.00798	0.00399	0.01197
Sensitivity of price to costs	Dimensionless	0.5	0.25	0.75
Time to adjust traders expected price	Yrs	1	0.5	1.5

sensitivity of price to inventory coverage	Dimensionless	-1	-0.5	-1.5
Capital Productivity	Tonnes/yr/capacity	1	0.5	1.5
Average life of capacity	Yrs	20	10	30
EV lifetime	Yrs	20	10	30
EV recycling rate	Factor	0.6	0.3	0.9
cost of EV recycling	$/tonnes	6000	3000	9000

Multivariate analysis

The multivariate analysis for the lithium model was conducted in the same manner as for the generic resource model above. However, this time an extra model output, recycling is also recorded. The following points of this analysis are notable:

- Again the supply (Figure 7.46) and demand (Figure 7.47) outputs behave in broadly similar ways, for the same reasons as discusses for the generic resource model above. The initial values case grows exponentially over the first few decades as the growing demand from electric vehicles encourages commensurate production increase. Between year 25 and year 50 of the model time horizon this trend abates and the outputs both peak and then begin a slow decline. This is in response to the asymptotic nature of electric vehicle demand and the increasing contribution of recycling (Figure 7.51). As the model reaches this period of peaking the 100th percentile case begins to exhibit oscillating behaviour as the model struggles to balance this changing demand under increasingly eccentric input values.
- The initial values case creates an initial oscillation in price (Figure 7.48) before the model settles down to a steadily growing trend, driven by the growing marginal cost of production assumed in the cumulative availability curve. The lithium model exhibits similar oscillations in the 100th percentile case as in the generic resource model multivariate analysis. However, the lithium model also exhibits a wide range of outcomes in the 50th and 75th percentile cases.
- Both production capacity (Figure 7.49) and desired capacity (Figure 7.50) peak and decline at the same time as demand and supply, in response to the growing contribution of recycling and the plateau in electric vehicle demand. Neither shows a

great deal of oscillation but desired capacity appears more unstable in the years post-peak in comparison to production capacity.

Figure 7.46: Lithium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on supply rate of varying inputs +/- 50% (t/y)

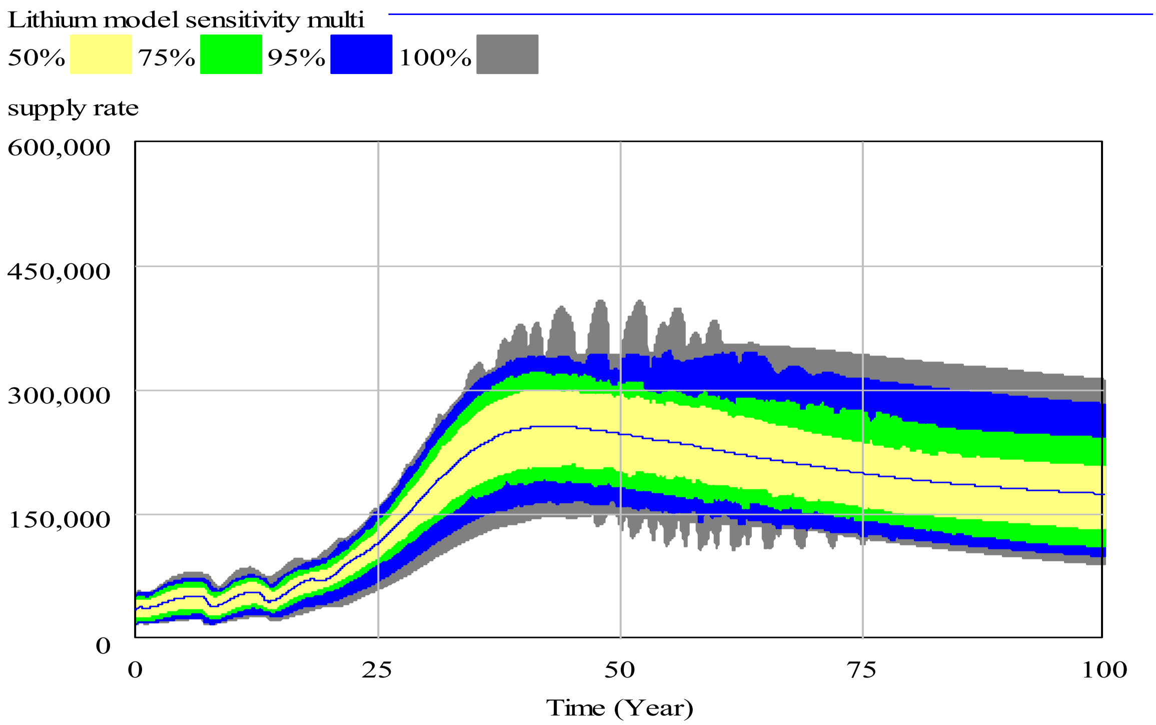


Figure 7.47: Lithium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on lithium demand of varying inputs +/- 50% (t/y)

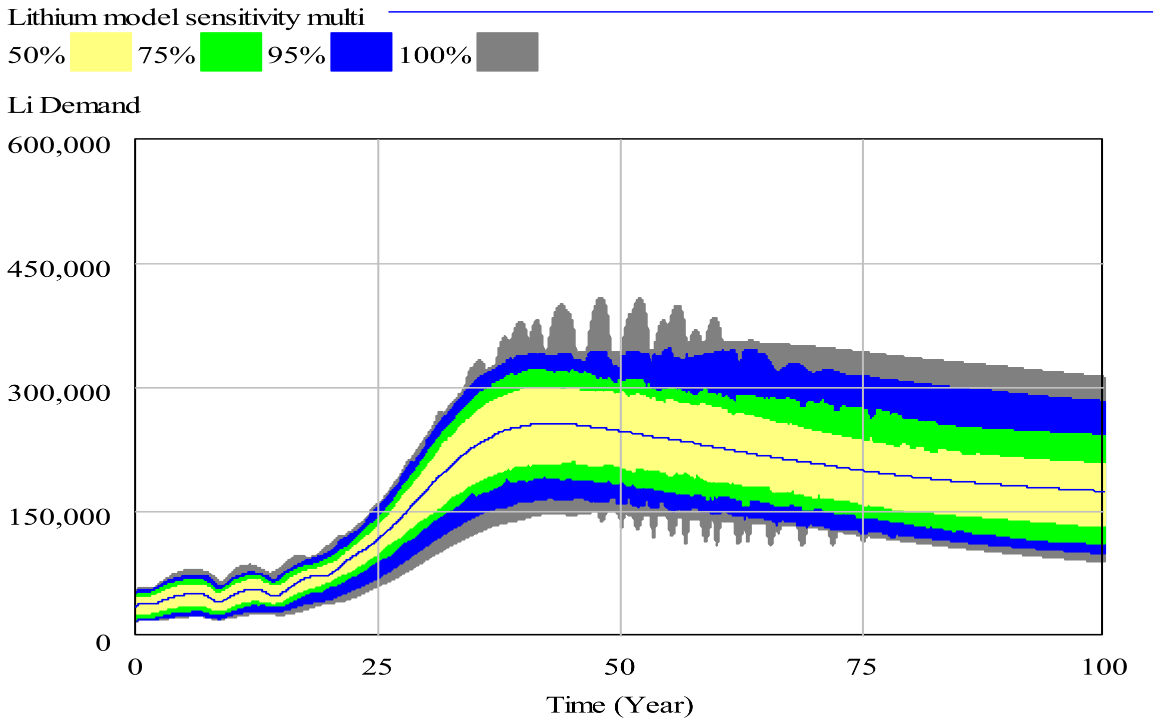


Figure 7.48: Lithium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on lithium price of varying inputs +/- 50% ($/t)

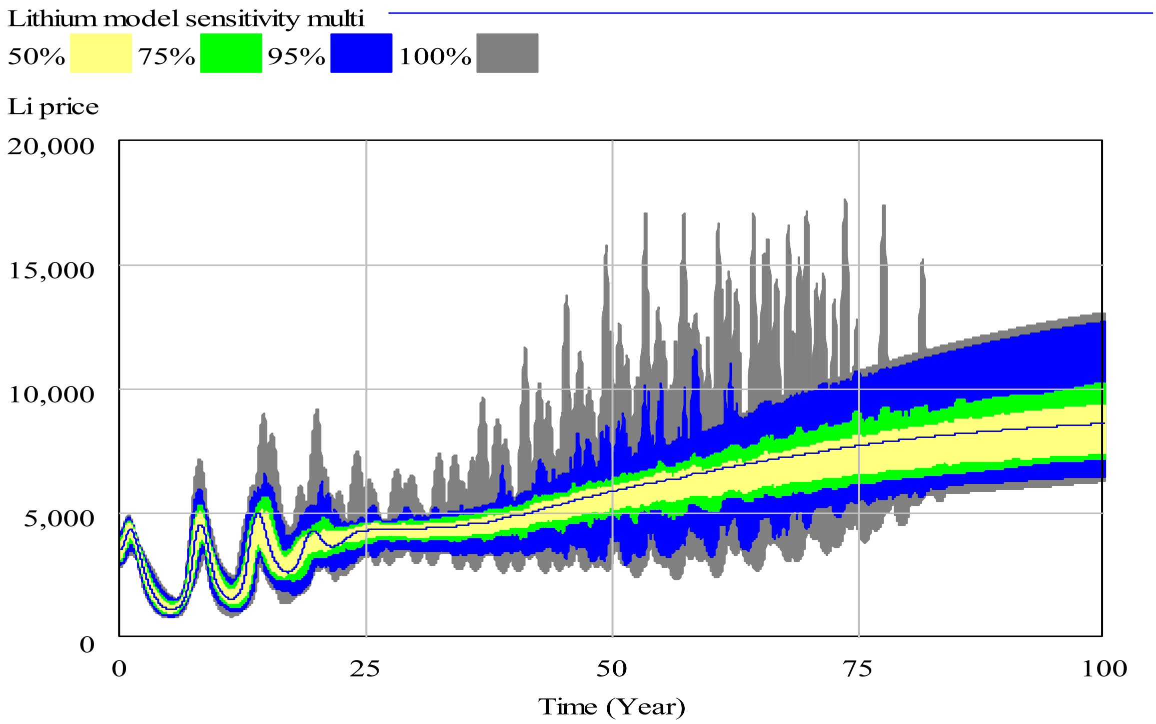


Figure 7.49: Lithium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on production capacity of varying inputs +/- 50% (t/y)

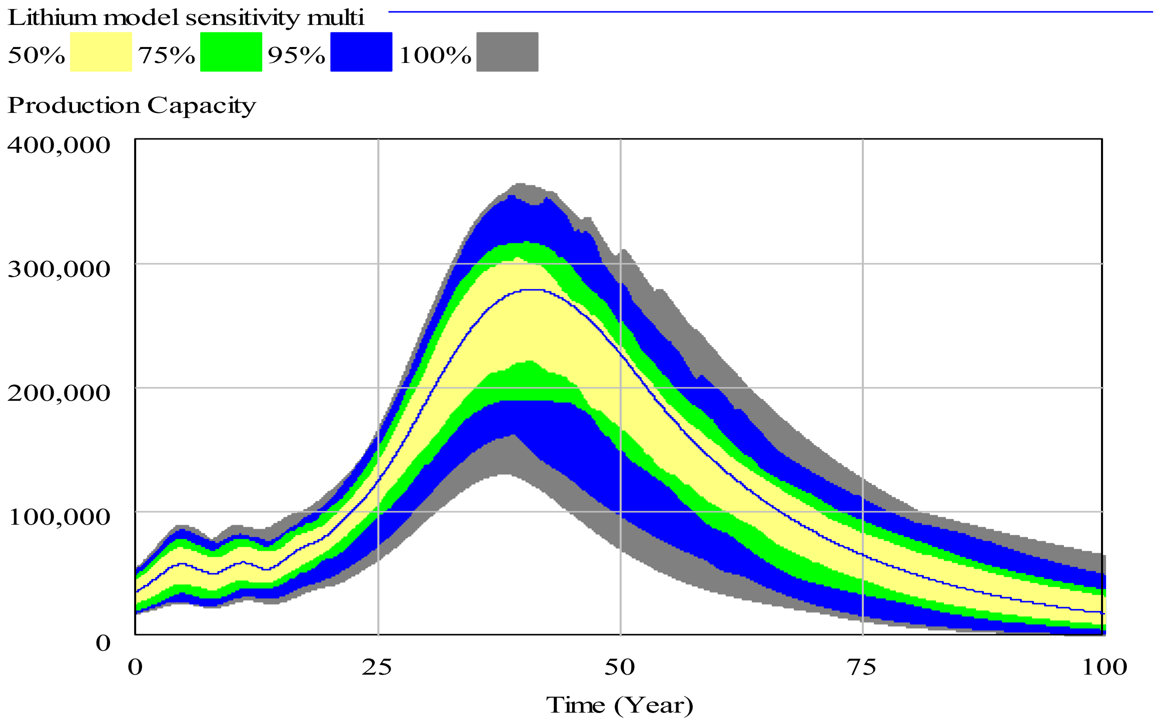


Figure 7.50: Lithium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on desired capacity of varying inputs +/- 50% (t/y)

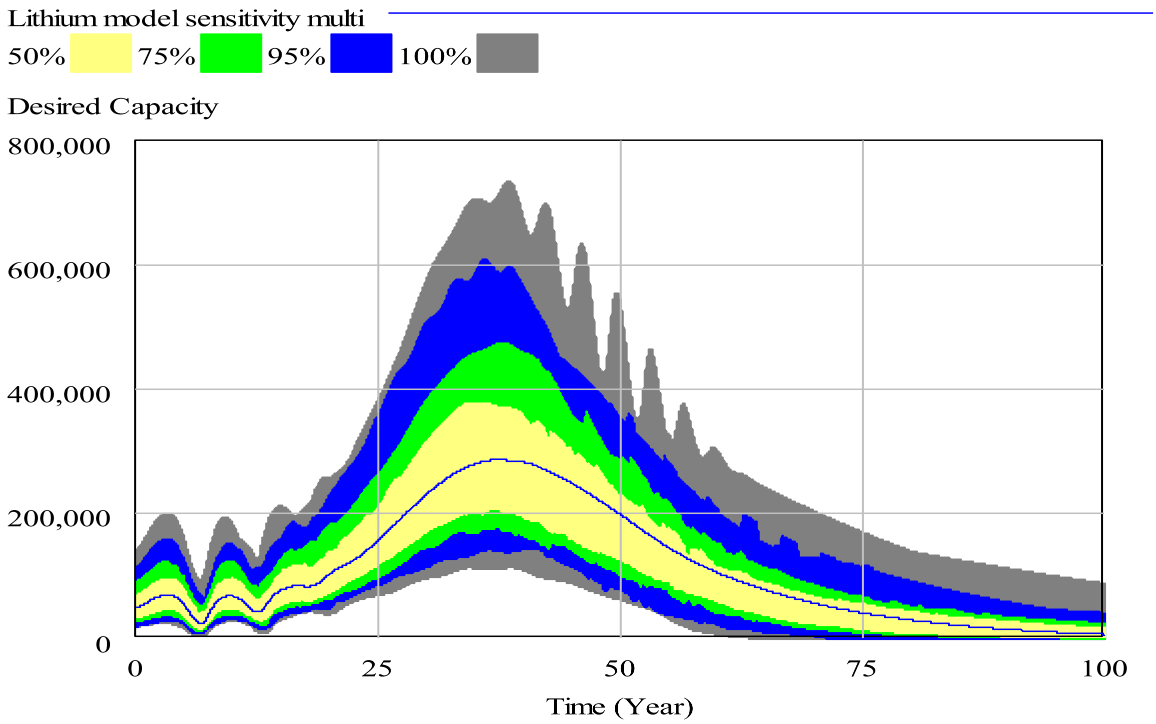
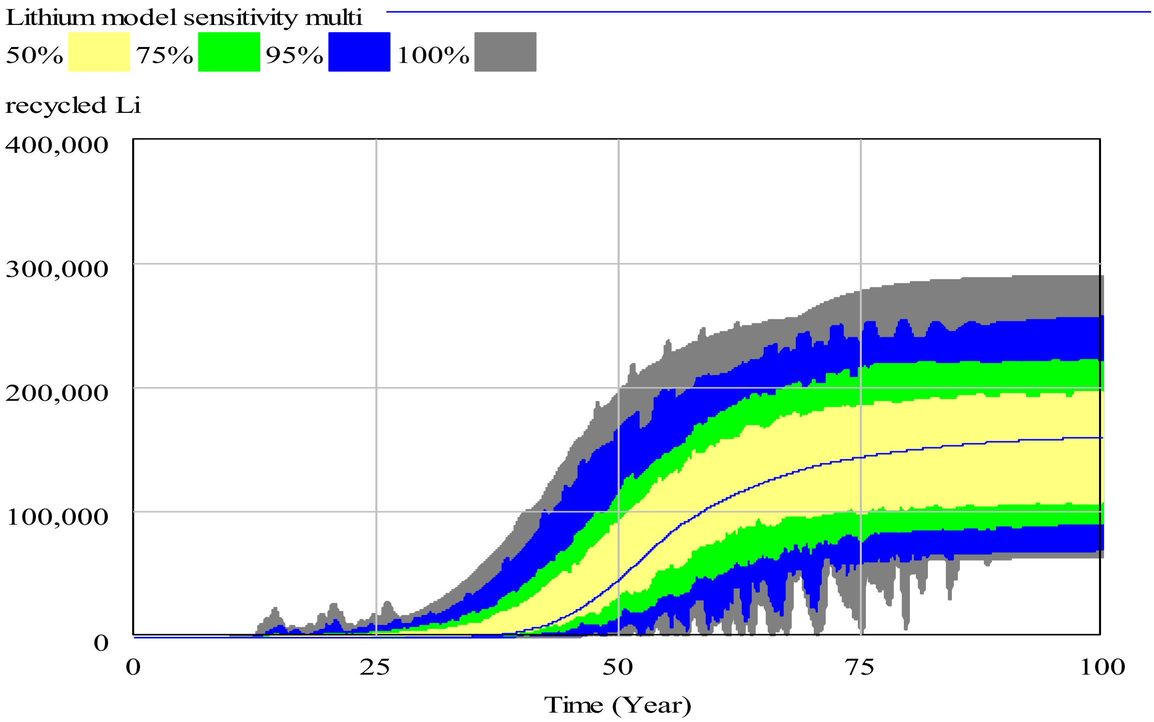


Figure 7.51: Lithium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on recycled lithium of varying inputs +/- 50% (t/y)



Univariate analysis

As with the generic resource model analysis above, only the results of univariate sensitivity analysis demonstrating significant sensitivity are presented below. From the graphical outputs below two notable findings arise. First, a large proportion of the sensitivity range found in the multivariate analysis can be explained by the response of the lithium intensity variable (Figure 7.52). As the assumed lithium intensity of electric vehicles increases or decreases it has a multiplicative effect on total lithium demand, and as that demand rises or falls, the supply curve aims to meet that demand.

Second, the oscillation exhibited by the multivariate test supply rate output is largely explained by demand adjustment delay (Figure 7.53) and reference lithium demand elasticity (Figure 7.54). Demand adjustment delay is the length of time it takes to adjust demand to the changing conditions of price and other demand drivers. As this delay increases the ability of demand to equilibrate is compromised, creating oscillation. Reference demand elasticity, as in the generic resource model, plays a significant part here. In the lithium model, however, it is responsible for creating oscillation. This is due to the models response to very low assumptions for elasticity of lithium demand, which makes it difficult for demand to respond to small changes in price, resulting in the overshoot and overcompensation seen in Figure 7.54.

The remaining figure below represents the impact of varying the electric vehicle recycling rate on the supply rate (Figure 7.55). This variable has an increasing impact in the later years of the model as the in-use stock of vehicles grows and ages to end-of-life. However, this trend happens late in the model life and does not significantly drive the sensitivity of the model.

Figure 7.52: Lithium model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying lithium intensity +/- 50% (t/y)

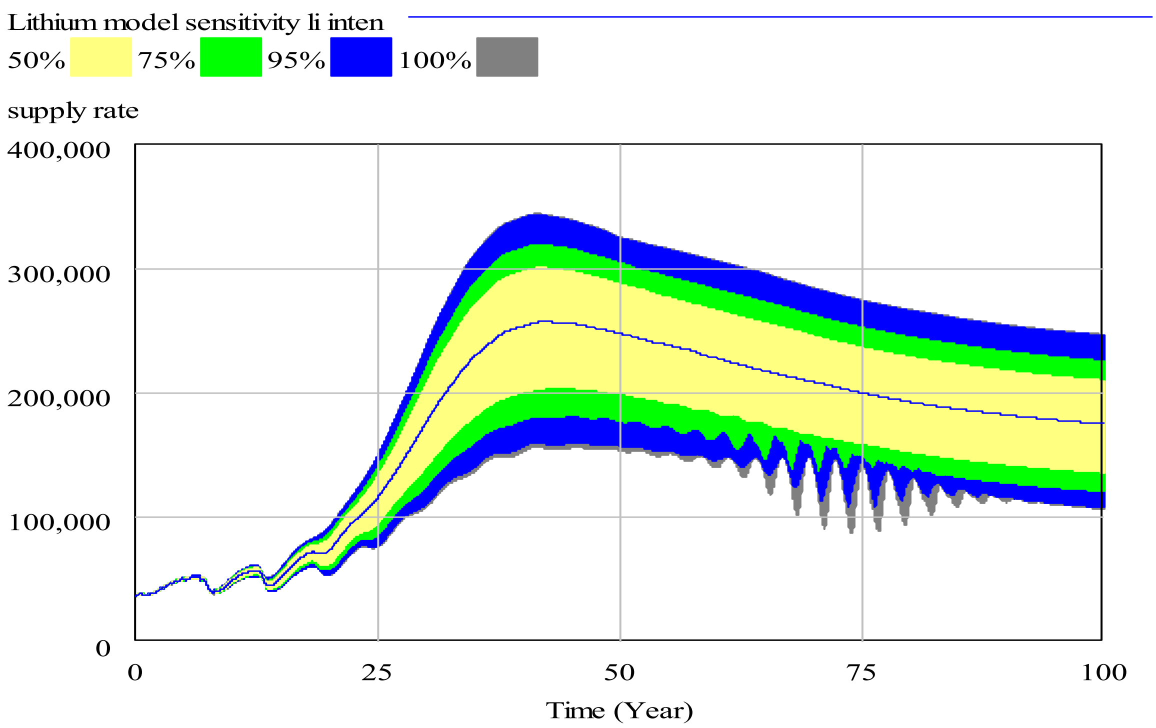


Figure 7.53: Lithium model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying demand adjustment delay +/- 50% (t/y)

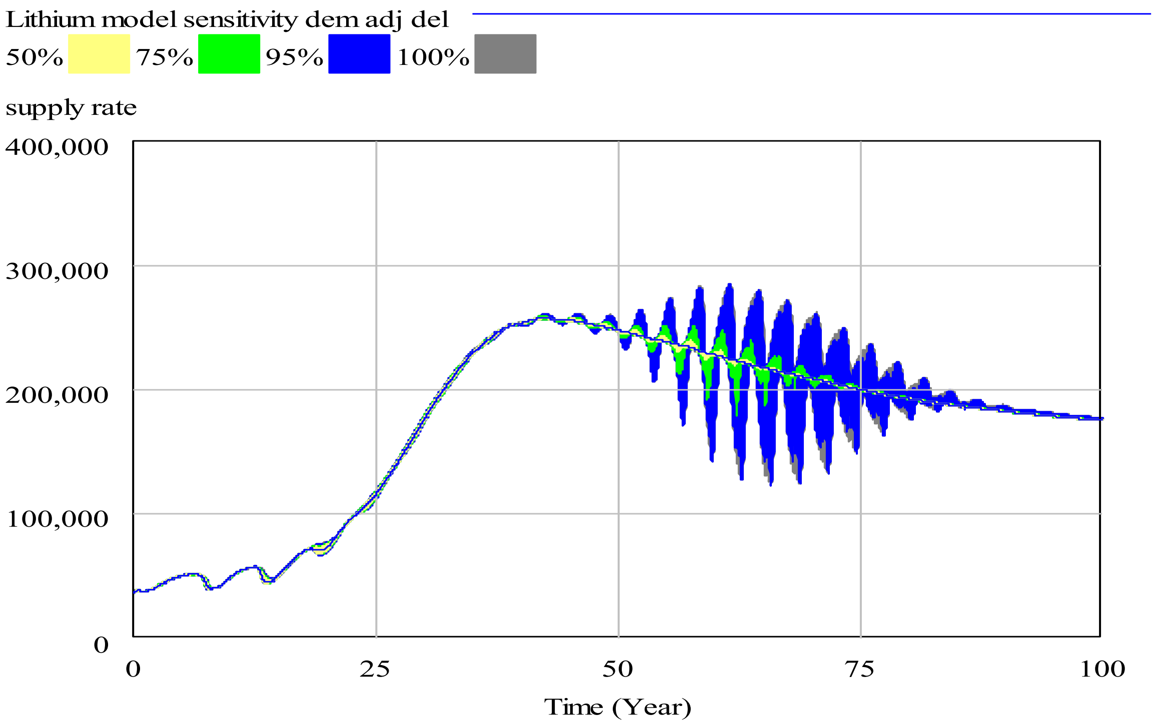


Figure 7.54: Lithium model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying reference lithium demand elasticity +/- 50% (t/y)

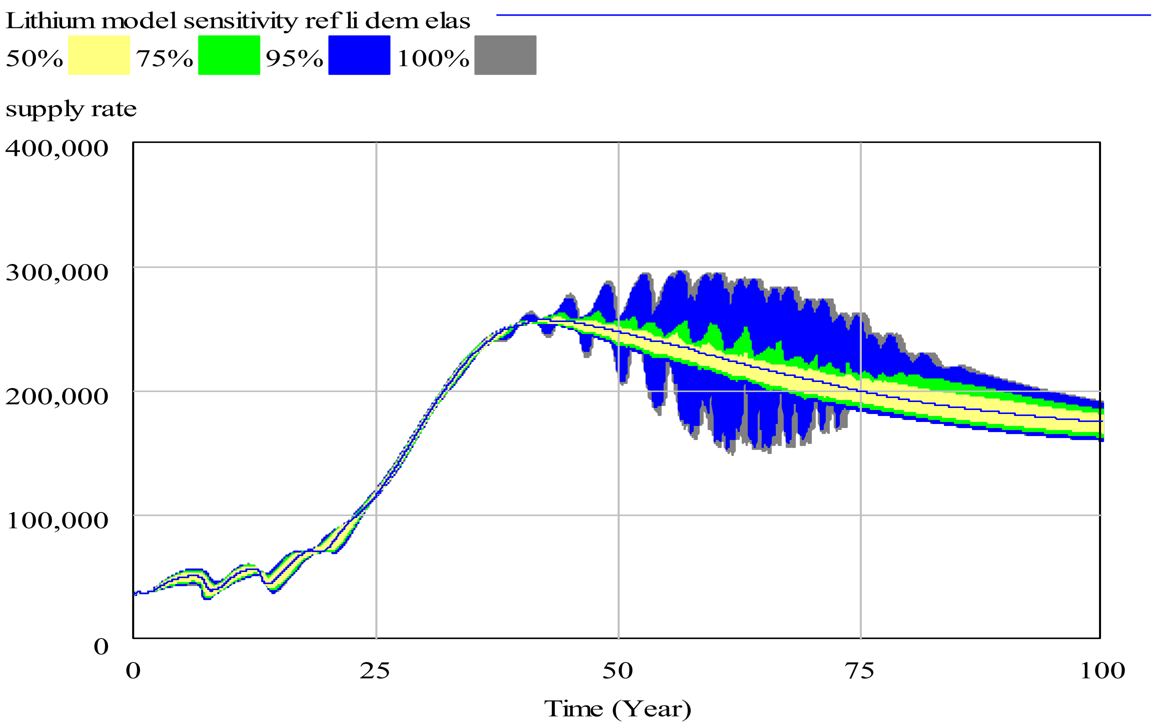
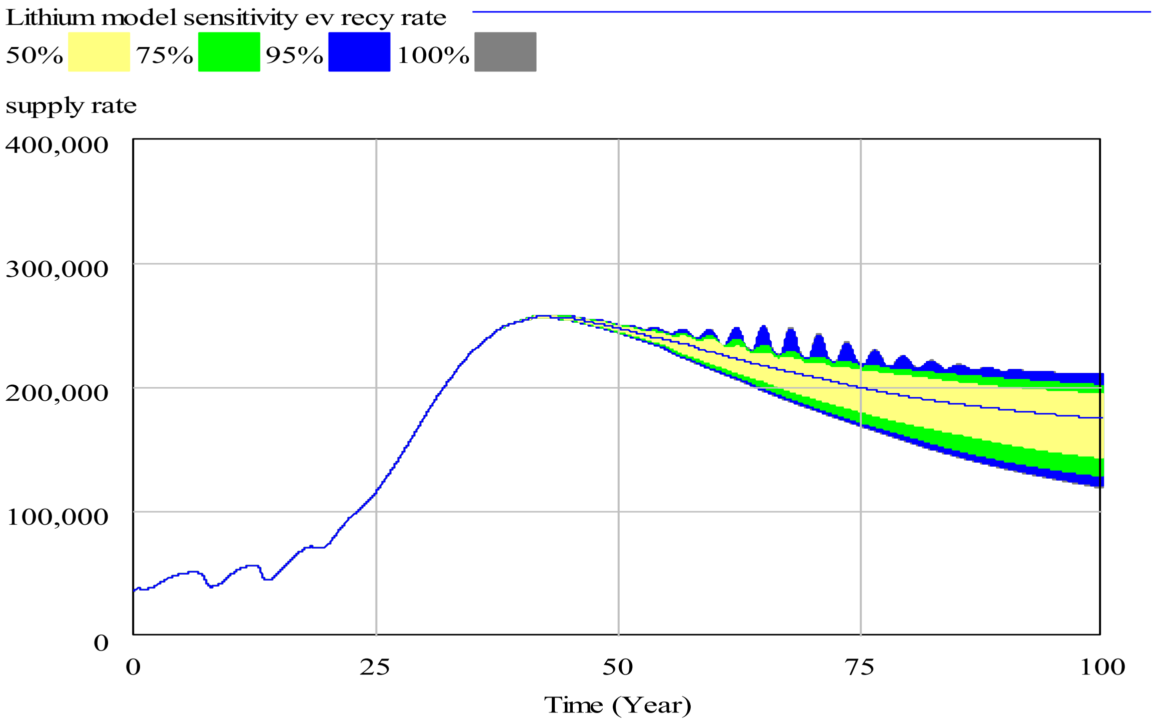


Figure 7.55: Lithium model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying electric vehicle recycling rate +/- 50% (t/y)



The Indium resource system model

Once again the variables included in the indium model sensitivity analysis, and the range of values used is presented in Table 7.12. Below the results of multivariate analysis are presented, before focusing on some of the interesting findings of univariate analysis.

Table 7.12: Model inputs varied during the indium model sensitivity analysis including their units, initial values and variable range

Variable	Units	Initial value	Minimum (-50%)	Maximum (+50%)
minimum order processing time	yrs	0.1	0.05	0.15
production delay time	yrs	0.5	0.25	0.75
Other Demand	tonnes/y	500	250	750
demand adjustment delay	Yrs	0.5	0.25	0.75
ref In demand elasticity	Dimensionless	0.5	0.25	0.75
In intensity	g/Wp	0.0248	0.0124	0.0372
Sensitivity of price to costs	Dimensionless	0.5	0.25	0.75
Time to adjust traders expected price	Yrs	1	0.5	1.5
sensitivity of price to inventory coverage	Dimensionless	-1	-0.5	-1.5
max primary In production capacity	tonnes/y	500	250	750
cost of primary indium production	$/tonnes	600000	300000	900000
indium contained in zinc	Factor	0.00009	0.000045	0.000135
Capital productivity	t/y/capacity	1	0.5	1.5
Average life of capacity	Yrs	20	10	30
CIGS lifetime	Yrs	30	15	45
CIGS recycling rate	Factor	0.8	0.4	1.2
cost of CIGS recycling	$/tonnes	700000	350000	1050000

Multivariate analysis

The multivariate analysis for the indium model was conducted in the same manner as for the lithium model above including recording the recycling model output. The following points of this analysis are notable:

- The initial values case produces a reasonably stable output for supply and demand (Figure 7.56 and Figure 7.57), though supply does not appear to grow in the exponential way that would be demanded under common assumptions regarding the growth rate of CIGS PV manufacturing. This is the result of the production capacity constraints placed on the model by the assumed host metal production trajectory. Again the supply and demand outputs behave very similarly to the multivariate sensitivity analysis, though the indium model appears more volatile in the 100th percentile case than in either of the previous two models. This volatility is again largely a response to the constrained production capacity.

- In response to the constrained production capacity, indium price (Figure 7.58 and Figure 7.59) in the initial values case dramatically increases in the early years of the model time horizon, nearly doubling over a 30 year period. In the 30th year of the model run price enters a phase of slow decline. This behaviour coincides with the assumed lifetime of CIGS PV modules (30 years). Recycling is therefore a significant driver of this price stabilisation and decline, helping make up the supply deficit resulting from constrained production capacity. The extreme volatility in the 100th percentile masks the underlying behaviour of the initial values case. To highlight the underlying behaviour the initial values case is presented on its own (Figure 7.59). This extreme volatility is again driven by the constrained production capacity, which prevents supply from responding quickly enough to limit this oscillation.
- The production capacity and desired capacity outputs show a similar relationship to each other as seen in the previous model sensitivity analyses (Figure 7.60, Figure 7.61). The initial value case shows a steadily growing production capacity, following the trend of the underlying host metal production. This trend is halted with a peak in capacity near the 75th model year, driven by the combination of recycling, plateauing PV demand, and production capacity catching up to latent demand. The range of outcomes grows significantly in the later years of the model time horizon, though this range does not seem to include significant oscillation or instability. The growing range is largely driven by the growing range of recycled indium over the same time period
- Recycled indium appears very sensitive to the multivariate analysis, and exhibits a significant range in the later years of the model (Figure 7.62). This range is due to the range of indium price generated in the multivariate analysis, which is either below the cost of recycling, pushing recycling to zero, or above the cost of recycling, incentivising the maximum level of recycling possible. Since the cost of recycling is also varied in this analysis the impacts of this price/cost relationship are accentuated.

Figure 7.56: Indium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on supply rate of varying inputs +/- 50% (t/y)

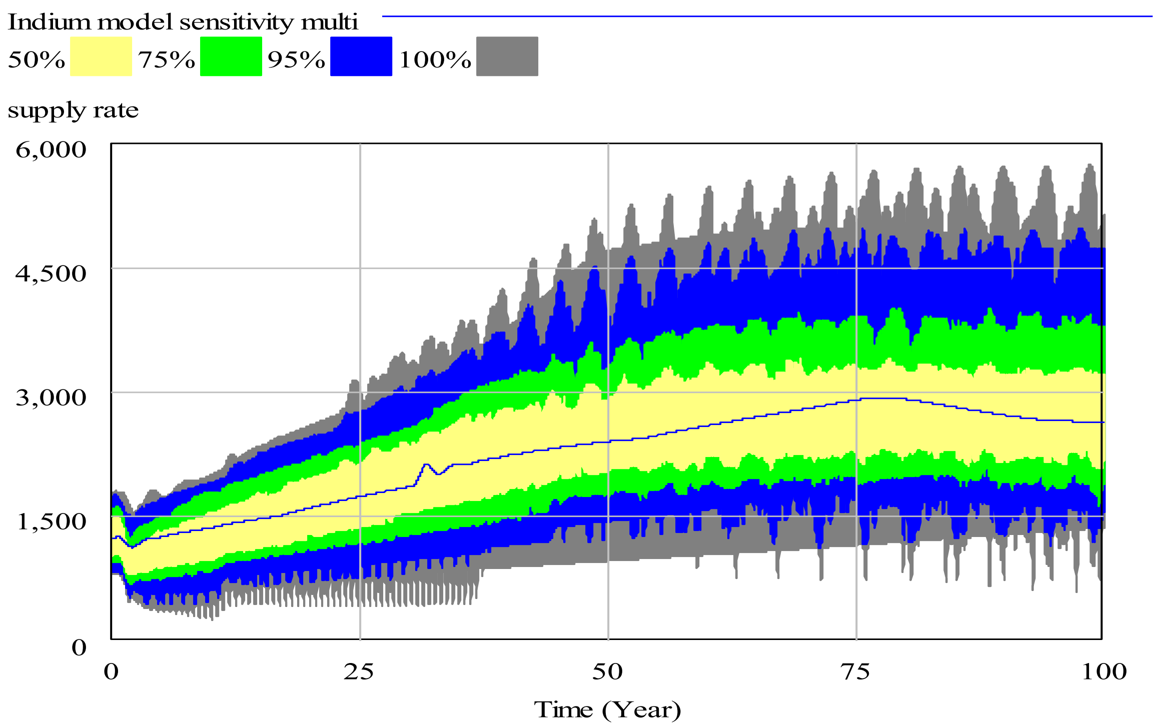


Figure 7.57: Indium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on indium demand of varying inputs +/- 50% (t/y)

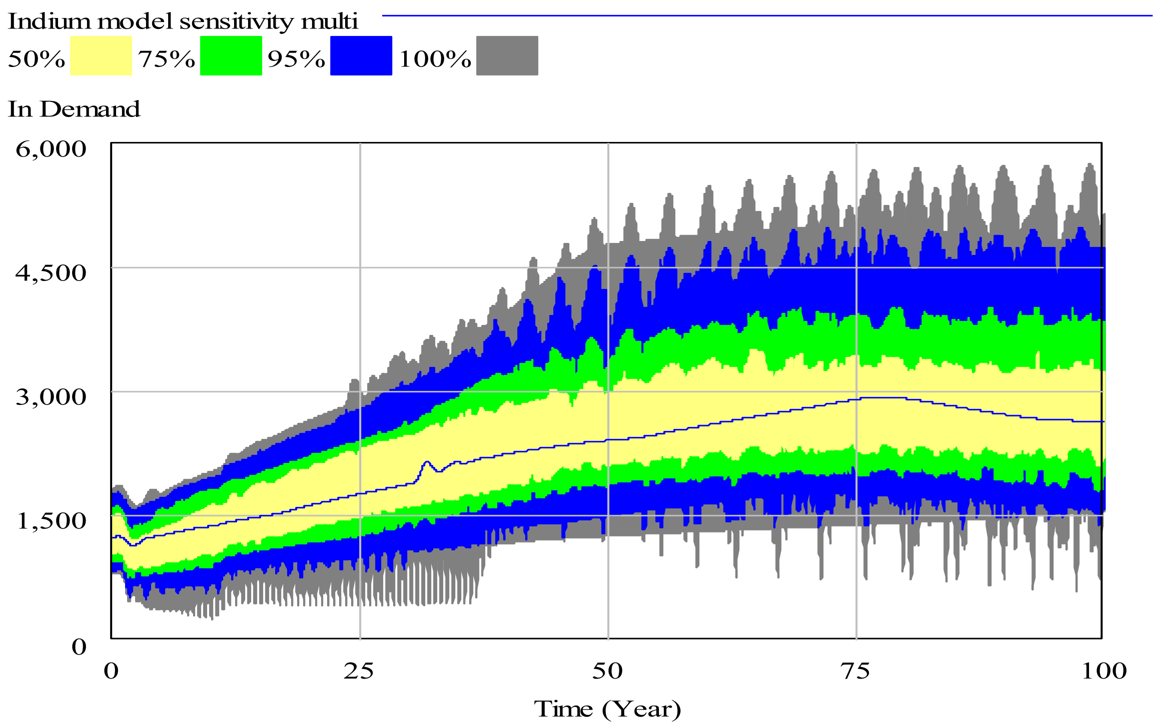


Figure 7.58: Indium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on indium price of varying inputs +/- 50% ($/t)

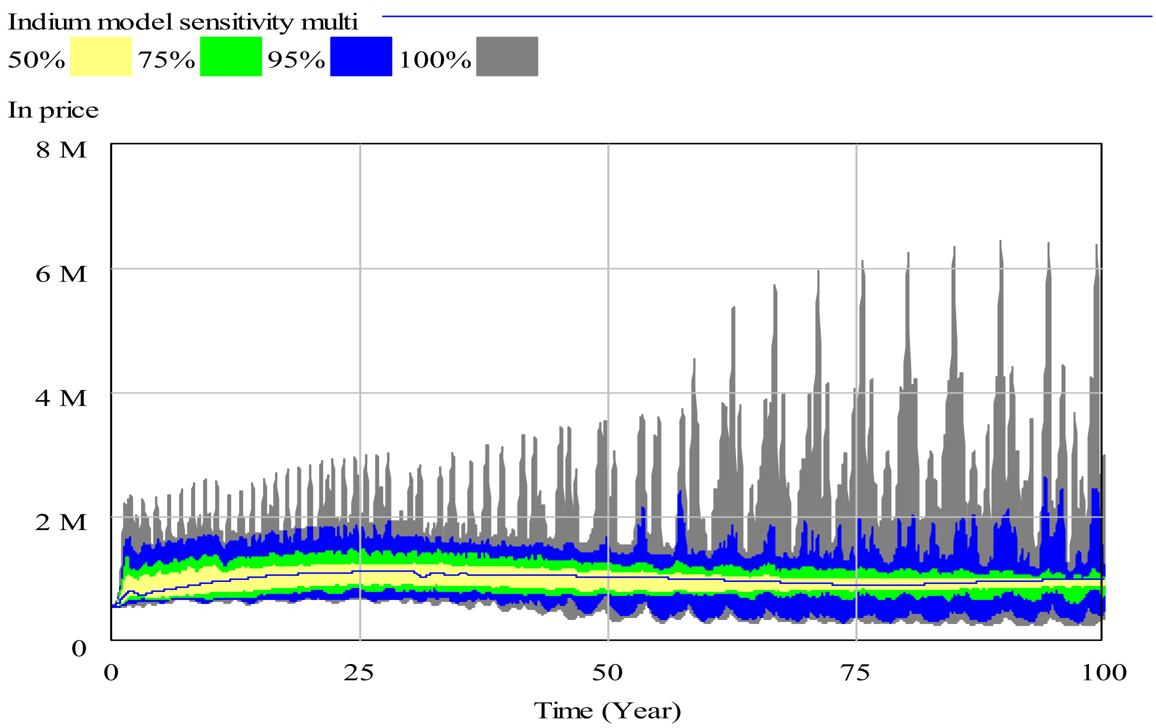


Figure 7.59: The initial values case for indium price ($/t)

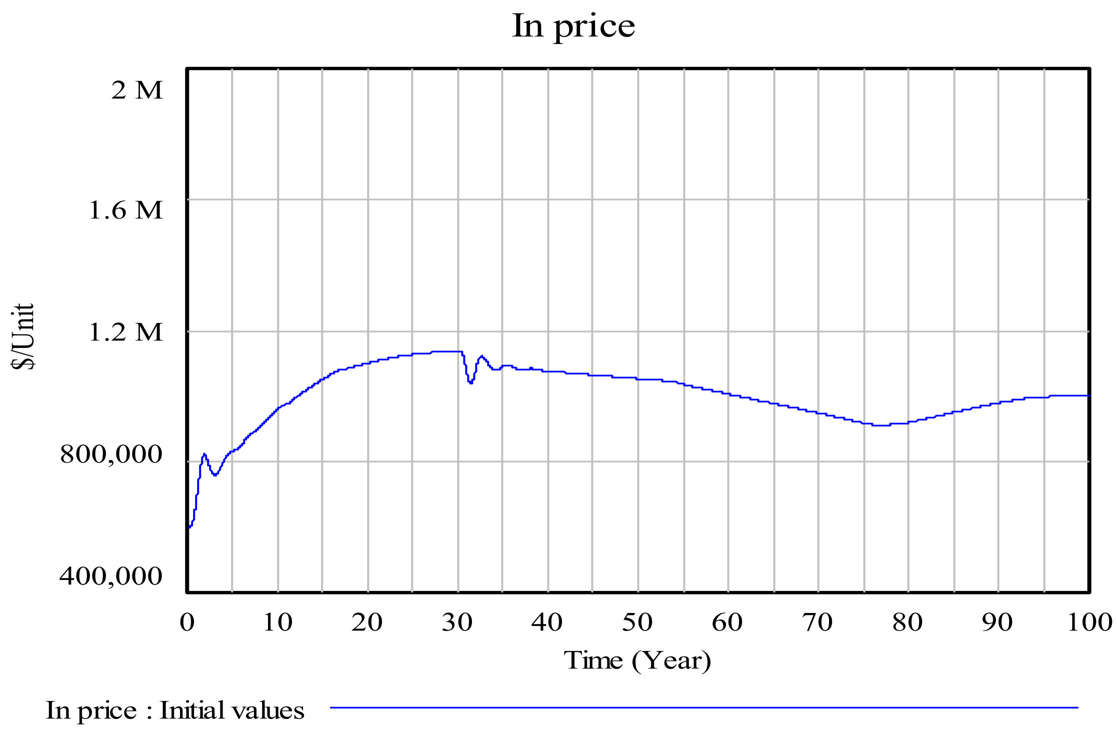


Figure 7.60: Indium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on production capacity of varying inputs +/- 50% ($/t)

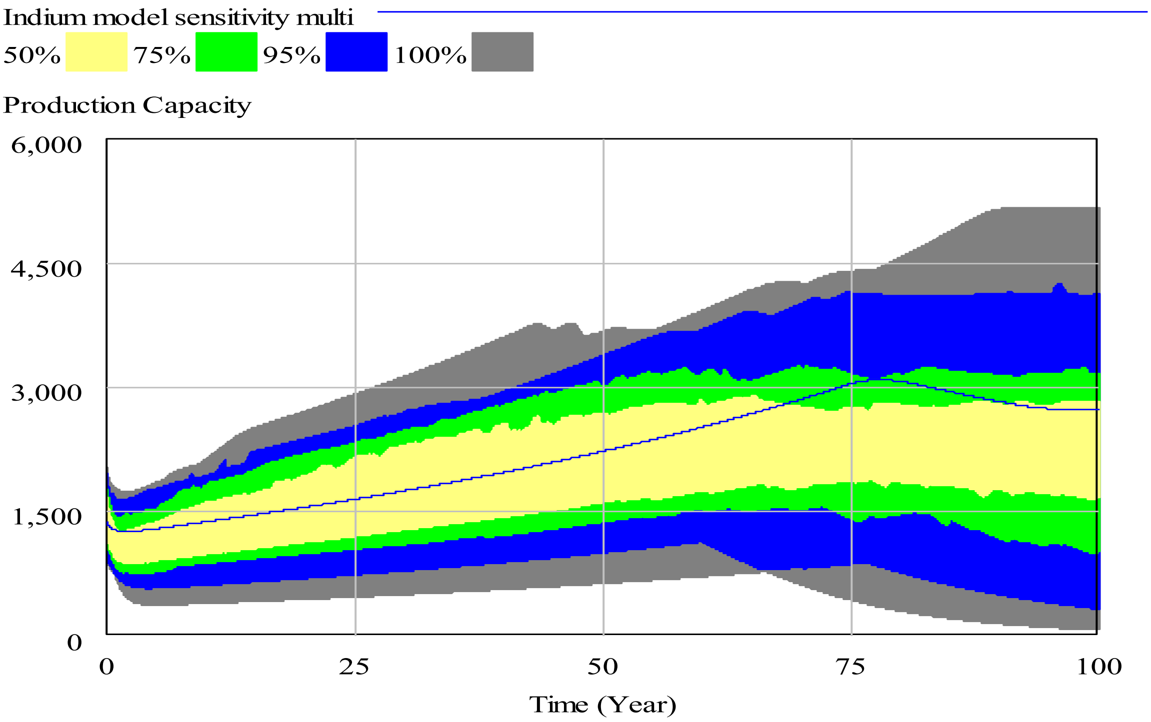


Figure 7.61: Indium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on desired capacity of varying inputs +/- 50% ($/t)

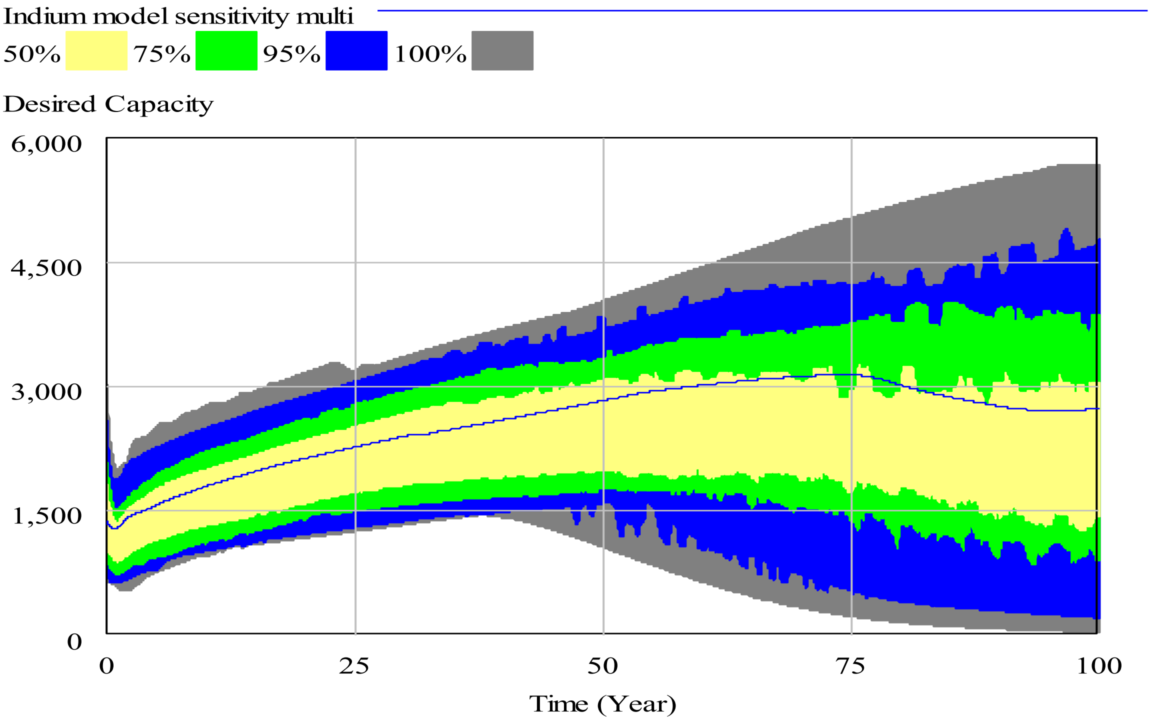
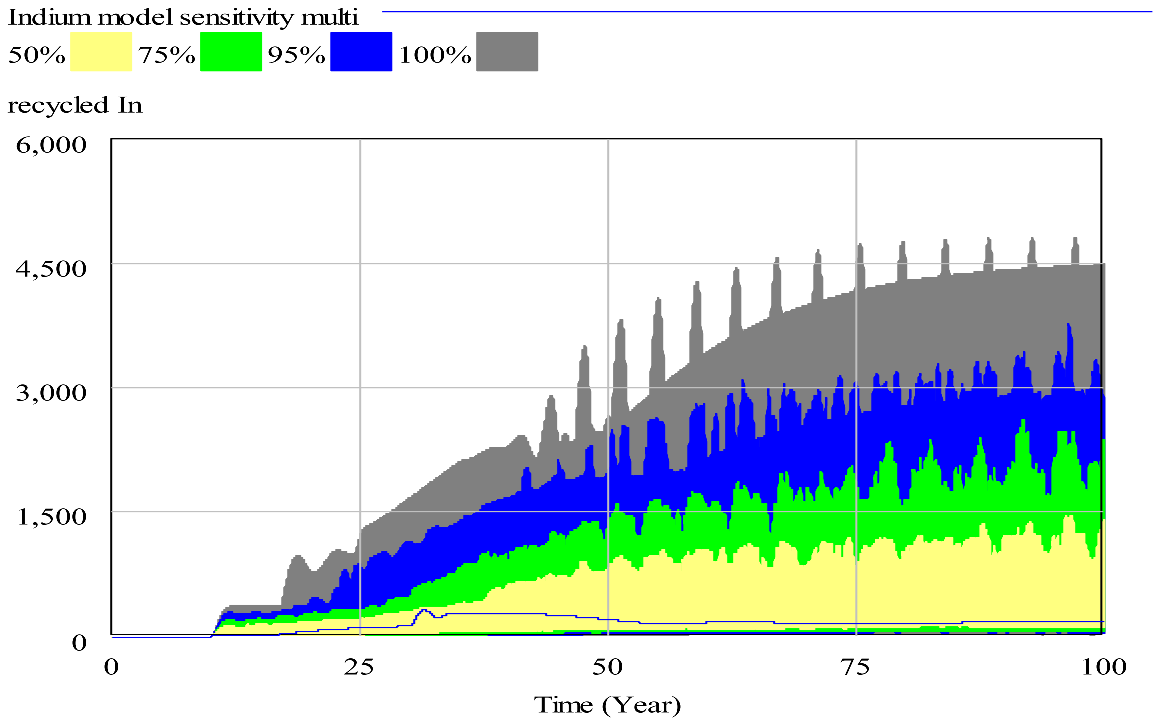


Figure 7.62: Indium model sensitivity analysis based on multivariate Monte Carlo simulation showing the impact on recycled indium of varying inputs +/- 50%($/t)



Univariate analysis

As with the analyses above, only the results of univariate sensitivity analysis demonstrating significant sensitivity are presented below. Based on the outputs presented in the figures below there are two points of note. First, reference demand elasticity (Figure 7.64) is again an important variable, as it has been shown in the analysis for the two previous models. Second, the variables that appear to describe the majority of the sensitivity presented in the multivariate analysis all respond to the central driver of that behaviour; i.e. the models constrained production capacity due to host metal interactions. These variables are: the indium intensity of CIGS modules (Figure 7.64); the indium contained in zinc ore (Figure 7.65); the productivity of indium producing capacity (Figure 7.66); and the cost of CIGS recycling (Figure 7.67). While the indium intensity has a significant impact on demand, the indium contained in zinc ore, the productivity of capital, and the cost of recycling all have an impact of indium supply. By comparing these figures to the multivariate analysis output for supply rate (Figure 7.60) it is clear that a large proportion of the sensitivity of this model can be explained by these four variables.

Figure 7.63: Indium model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying reference demand elasticity +/- 50% ($/t)

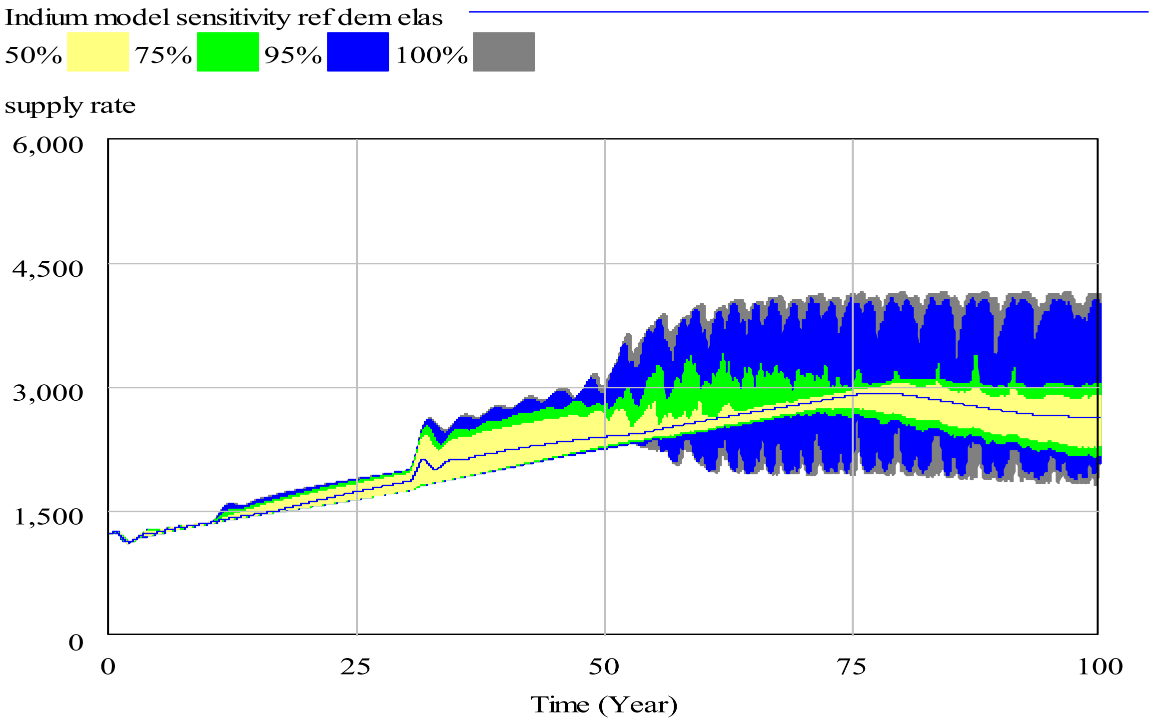


Figure 7.64: Indium model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying indium intensity +/- 50% ($/t)

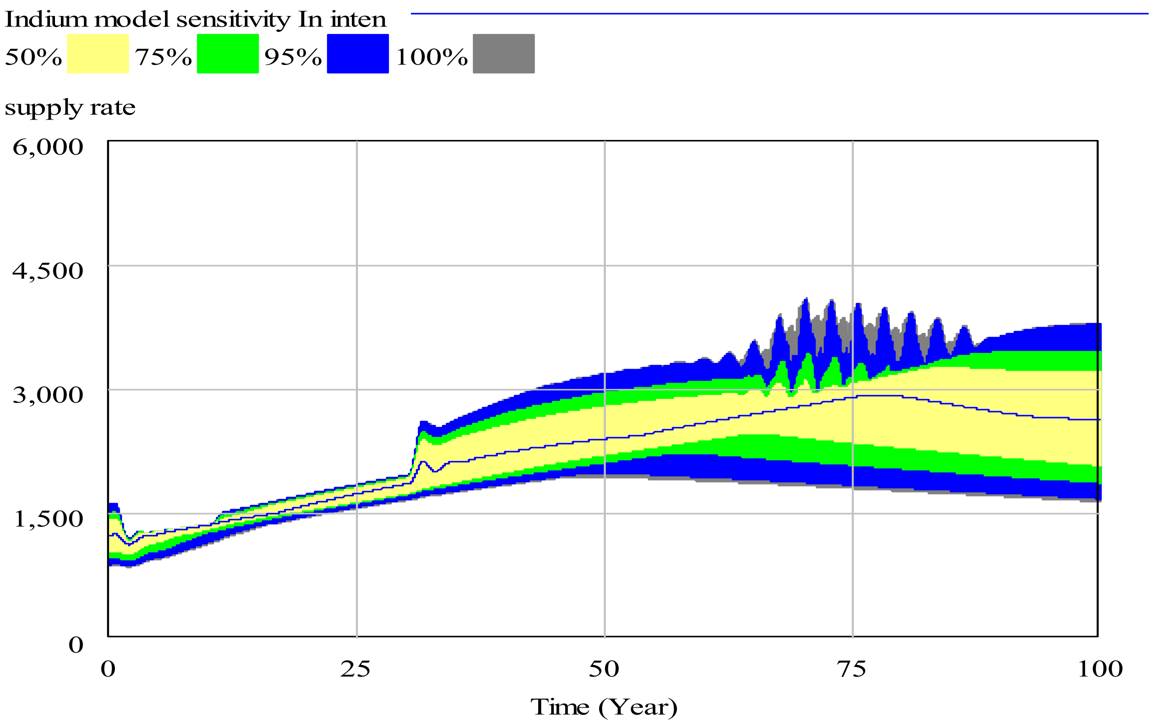


Figure 7.65: Indium model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying indium contained in zinc +/- 50% (t/y)

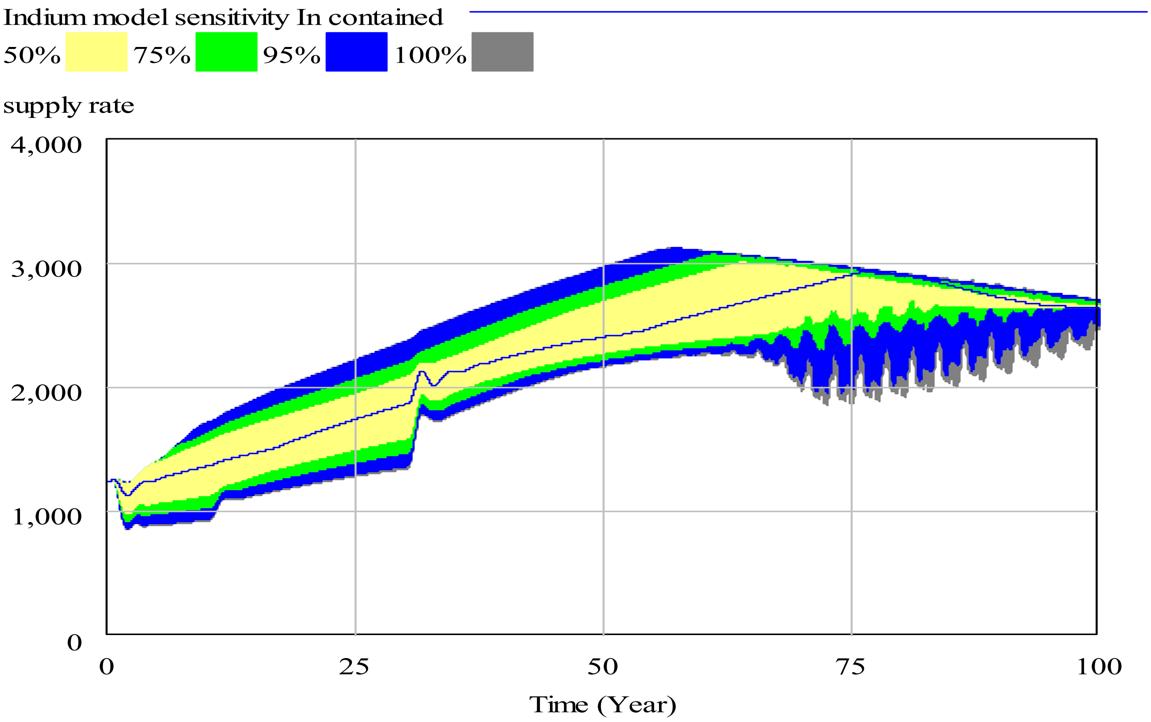


Figure 7.66: Indium model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying capital productivity +/- 50% ($/t)

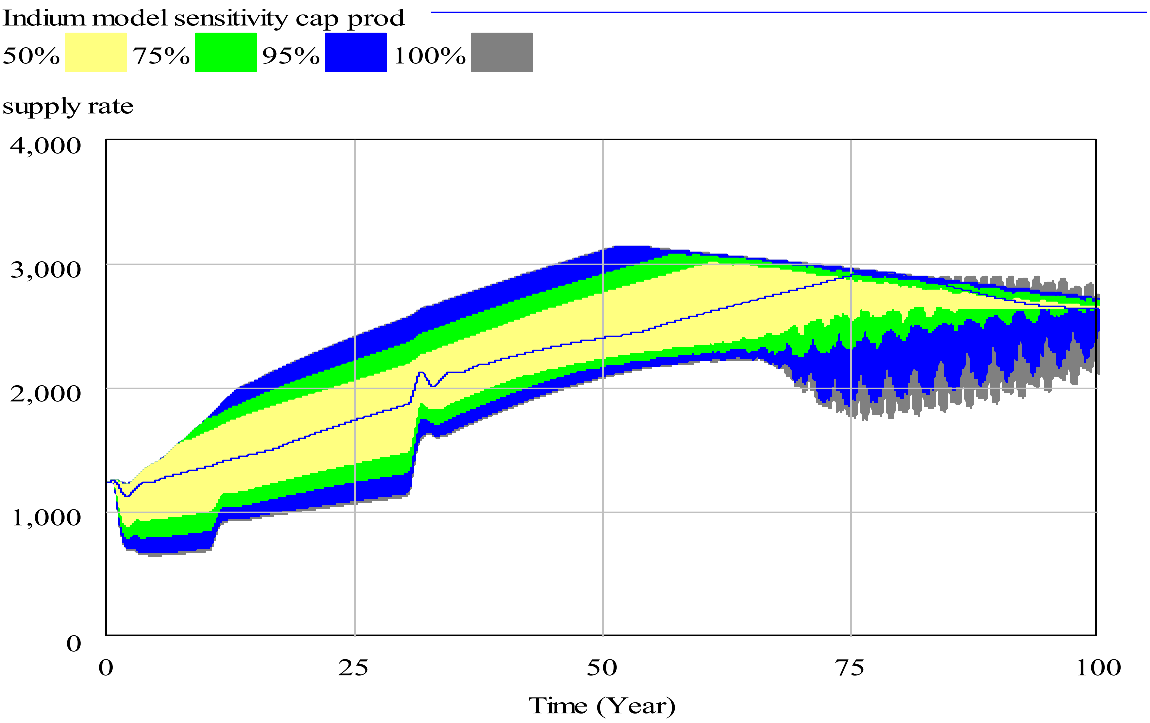
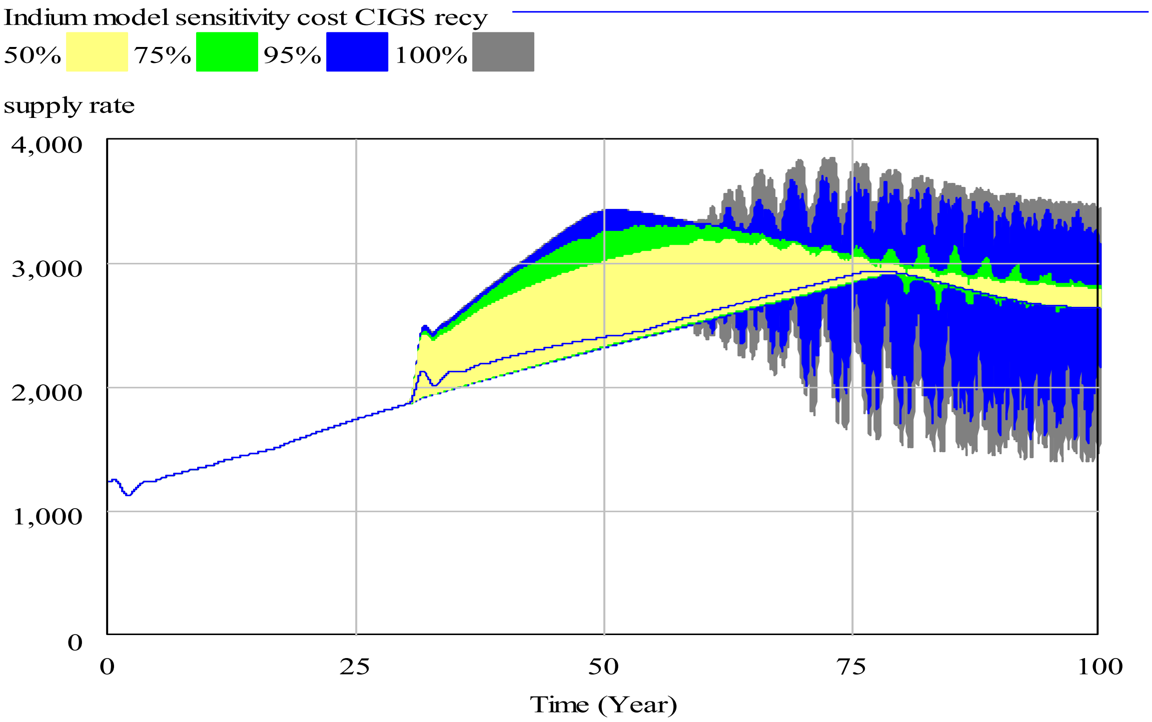


Figure 7.67: Indium model sensitivity analysis based on univariate simulation showing the impact on supply rate of varying CIGS recycling +/- 50% ($/t)



7.4.6 Depletion rate test

To examine the plausibility of the models behaviour in terms of geological availability the model calculates the rate at which resources are depleted. The URR estimate for the generic resource uses the example of oil, and is based on the evidence analysis in Sorrell *et al.* (2009), the lithium resource estimate is based on the estimates in Yaksic and Tilton (2009) excluding sea water resources, and indium reserves based on Mikolajczak (2009) estimates.

In general the models appear to behave in a plausible manner with reasonable depletion rates and leading to long time horizons for the available resources. However, there are the following caveats:

- The most extreme iterations in the indium model expend the total quantity of resources by the very end of the model time horizon.
- The time horizons in the model are very long and the models are not presented as forecasts of the future but tools to test future conditions. The depletion rate tests

should not therefore be viewed as an estimate of when these resources will 'run out'.

- This depletion rate test is to sense check the rate at which resources are depleted by the model runs, and is not a comprehensive examination of the geological aspects of resource systems. The use of cumulative availability curves to define production costs covers aspects of the geological system. However, in order to capture the geological aspects of resource systems more sophisticated treatment of the geological processes of resource discovery and exploitation should be included in resource system models.

Below are the results of the depletion rate test for the generic resource (Figure 7.68), lithium (Figure 7.69) and (Figure 7.70).

Figure 7.68: Generic resource model sensitivity analysis of reserve depletion based on multivariate Monte Carlo simulation varying inputs +/- 50% (Tonnes)

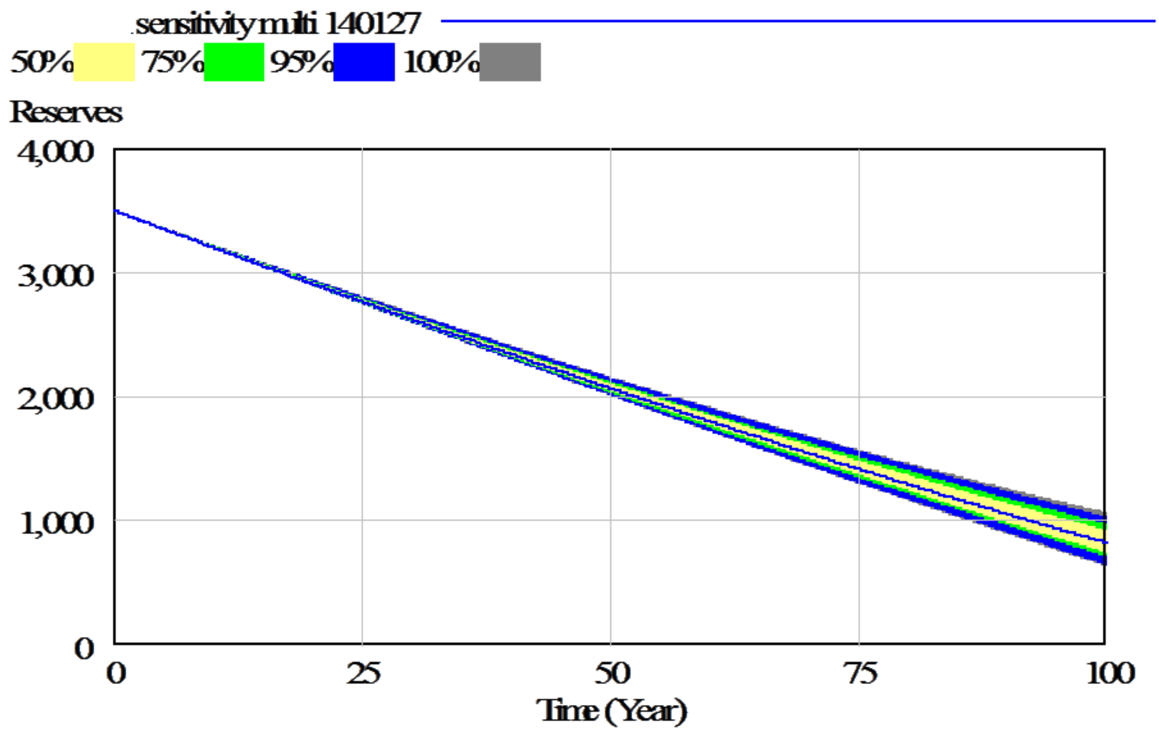


Figure 7.69: Lithium model sensitivity analysis of reserve depletion based on multivariate Monte Carlo simulation varying inputs +/- 50% (tonnes)

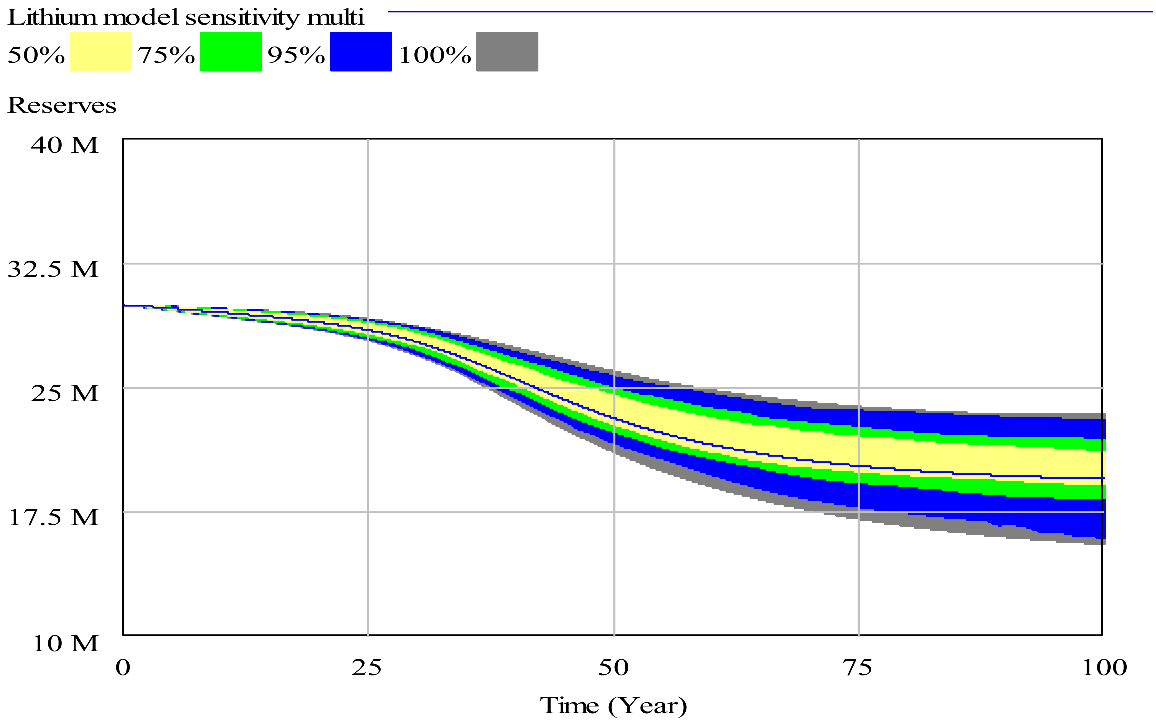
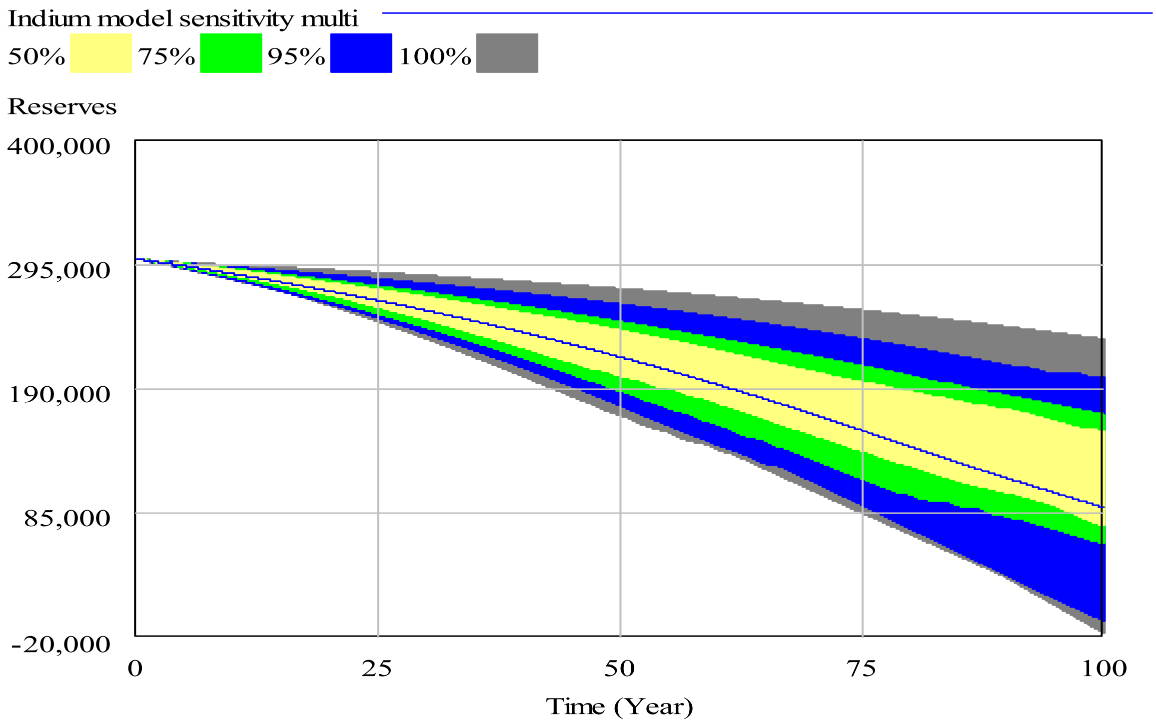


Figure 7.70: Indium model sensitivity analysis of reserve depletion based on multivariate Monte Carlo simulation varying inputs +/- 50% (tonnes)



7.5 Summary

This chapter documents the construction of three system dynamics resource system models covering three resources: the generic resource, lithium and indium. The chapter then presents the results of several model tests designed to build confidence in the models structure and validity. These tests examine the models response in respect to changing time step (*Dt* error tests), the historical and forecast reference modes, extreme initial conditions, depletion rate, and the sensitivity of the model to varying inputs. The model structures were iterated over during this testing and the models documented here are robust in response to these tests.

The sensitivity tests provide insight into the variables that have most influence on the models. In the generic resource model these are

- GDP; and
- Price elasticity of demand

In the lithium model these are:

- Lithium intensity in electric vehicles;
- The delay time in adjusting demand to changing system conditions;
- Price elasticity of demand; and
- The future recycling rate in electric vehicles.

In the indium model these are:

- Price elasticity of demand;
- The indium intensity in CIGS PV;
- The assumed indium contained in zinc ores
- The productivity of production capital; and
- The future rate of CIGS PV recycling.

In the following chapter the three resource models documented here are evaluated to examine their behaviour in various system conditions, in particular their response to periods of capacity constraint.

Chapter 8: Model evaluation

> *"Since the measuring device has been constructed by the observer … we have to remember that what we observe is not nature itself but nature exposed to our method of questioning"*

Werner Karl Heisenberg, 1958

The previous chapter presented three resource market models, described their structures and highlighted the conceptual differences between them. This chapter explores the impact of those differences on the models' responses to constrained future availability. The central motivation of this thesis is to determine whether or not the resources studied here respond in similar ways to constraints in future supply. The chapter is structured to examine each of the main areas where there are significant distinctions between the models. First, recycling and by-product metal issues are explored given that these are the significant structural differences between the three models. The impacts of differences in marginal cost are then explored. Marginal cost is likely to influence price significantly under traditional views of economic systems, and the potential differences between the marginal cost curves of the three resources may have interesting implications for the future behaviour of these systems. Finally, the impacts of potential policy responses to scarcity are examined to explore whether these resource system models can inform the development of sensible material availability policies.

8.1 Impact of recycling

This section exposes the three models to a 'capacity constraint event' at three different points in the model timeframe (year 25, year 50 and year 75) and examines the impact of recycling on the models' response. The capacity constraint event is a period of one year where 5% of capacity is made unavailable. In a real world scenario this type of event might represent a period where a geopolitical event such as civil conflict, export embargo or cartel activity constrained capacity for a short period of time. The lithium and indium models are exposed to these capacity constraint events under conditions of both low and high recycling costs. By assuming a very high cost of recycling the models will not recycle lithium or indium. This run can then be compared to model runs using a low recycling cost where metal recycling will occur. This isolates the impact of recycling on the models' responses to the capacity constraint event. Table 8.1 presents the different model cases applied to each model, including the key inputs varied in each case.

Table 8.1: The model cases applied to the generic, lithium and indium models to investigate the effects of recycling and constrained availability

	Case	Cost of recycling ($)	Timing of 5% capacity constraint event (year)		
Generic	Base case	N/A	0	0	0
	Capacity constraints	N/A	25	50	75
Lithium	Base case	6000	0	0	0
	Capacity constraints	6000	25	50	75
	Capacity constraints high recycling cost	60000	25	50	75
Indium	Base case	700000	0	0	0
	Capacity constraints	700000	25	50	75
	Capacity constraints high recycling cost	7000000	25	50	75

8.1.1 The generic resource models response to availability constraint

The generic resource model has no recycling subsystem, and therefore responds to the impacts of capacity constraint through the effects of price on capacity and its utilisation. Figure 8.1 presents the impacts of the capacity constraint events on supply rate, and Figure 8.2 presents the impact on price. In each case the supply rate initially decreases, with the unserved demand producing an increase in price. As price rises the supply rate begins to increase back towards the previous trajectory, but overshoots due to the impacts of the models delay. This oscillation takes approximately 10 years to stabilise, and at its greatest supply fluctuates by approximately +/-5%. The price response generating this oscillation also takes approximately 10 years to stabilise. However, price fluctuates by approximately +/-

10% in the year 25 capacity constraint event, twice the impact experienced by supply. The impact reduces in absolute terms between the three cases in response to decreasing supply rate, meaning that the impact on price in the year 75 capacity constraint event is less, at approximately +/-7%. This is due to the capacity constraint event being a percentage of supply, and not an absolute number. The oscillation in price decreases over time despite the increase in price over the time period of the model as the oscillation is relative to the supply rate rather than the price.

These capacity constraint events may seem small in comparison to the inventory that exists in the model, which the model seeks to keep at 20 percent of demand. However, since price in the model responds to even slight changes in *relative inventory coverage* even small unforeseen, instantaneous constraints in available capacity should have an impact on the model.

Figure 8.1: Impact of capacity constraint on the generic resource model supply rate

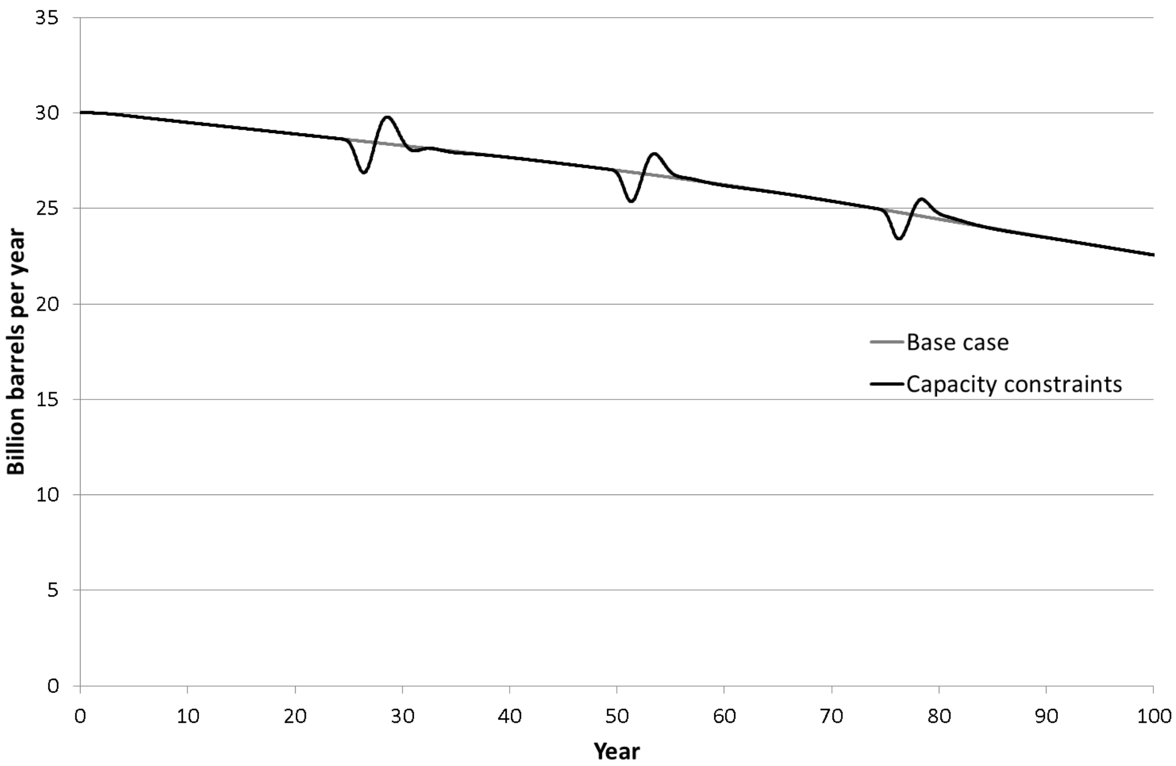
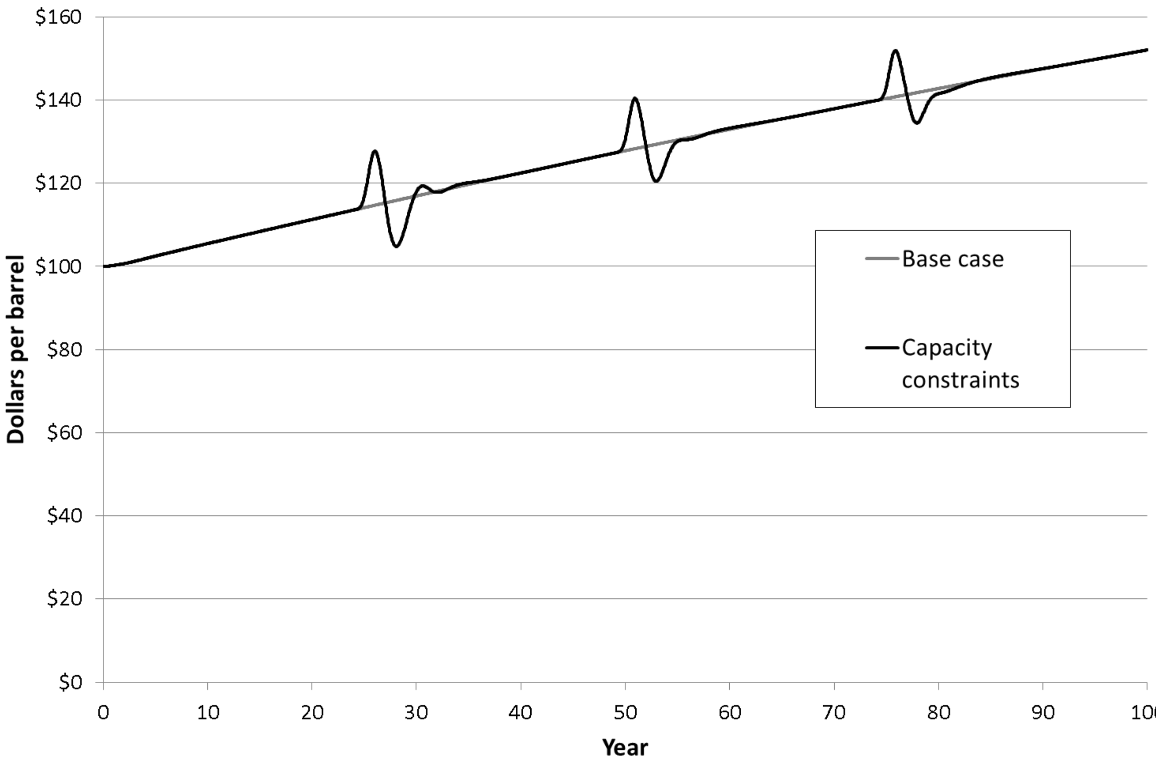


Figure 8.2: Impact of capacity constraint on the generic resource model price



8.1.2 The lithium models response to availability constraint under variable recycling cost

The lithium model was run under three different cases: one case reflects the base case assumptions using the initial values; once case exposes the initial values to the same capacity constraint events as described above, with capacity reduced by 5% for one year in year 25, year 50 and year 75; and finally one case exposes the model to both the capacity constraint events and a high recycling cost. This high recycling cost means that the model is unlikely to undertake any recycling, and the effect that recycling has on the model can therefore be deduced by comparison of this case with the first two. The results of these runs are presented in Figure 8.3 and Figure 8.4.

In the early years of the three model cases there is some oscillation, particularly in lithium price (Figure 8.4). By comparison of the base case with the high recycling cost case it appears that recycling alters this oscillation, reducing it to an extent. The underlying reason for the oscillation is difficult to isolate but likely to be an artefact of the difference between the models initial values and the supply demand equilibrium in the early years. However, between year 25 and year 30 this oscillation subsides, and all three models follow a very similar path as supply rate increases dramatically in line with rapidly rising demand for electric vehicles. This follows expectations regarding the impact that recycling can have during a period a dramatic supply increase (see section 5.2.3). These issues are discussed in more detail in Chapter 9.

After supply peaks and begins to decline the model cases begin to diverge. This highlights two important factors of the models response to metal recycling. First, recycling does begin to produce a noticeable impact on the supply rate where the supply rate is no longer increasing dramatically, or indeed decreasing over time. Again this is in line with expectations of the impact of recycling. This is also reflected in price, where the availability of recycled material helps to keep the price of metal below that expected in the absence of recycled metal. Second, the impact of the capacity constraint events is significantly diminished where recycled material is available. In year 50 the oscillation in supply rate in the 'capacity constraints' case is approximately half that seen in the 'capacity constraints high recycling cost' case. Assuming that the constraint in supply comes from an event affecting only primary production the recycled proportion of metal is unaffected by the constraint event, and helps to mitigate the effects of the capacity constraints. Since recycling can happen in any number of different countries, and at small and well distributed scale, it is reasonable to assume that a capacity constraint event as described above would not affect recycling availability. The impact on lithium price is similarly diminished in these models, given that price responds to the supply deficit which has been mitigated by recycling.

Figure 8.3: Impact of capacity constraint on the lithium model supply rate under both high recycling costs and base case recycling cost values

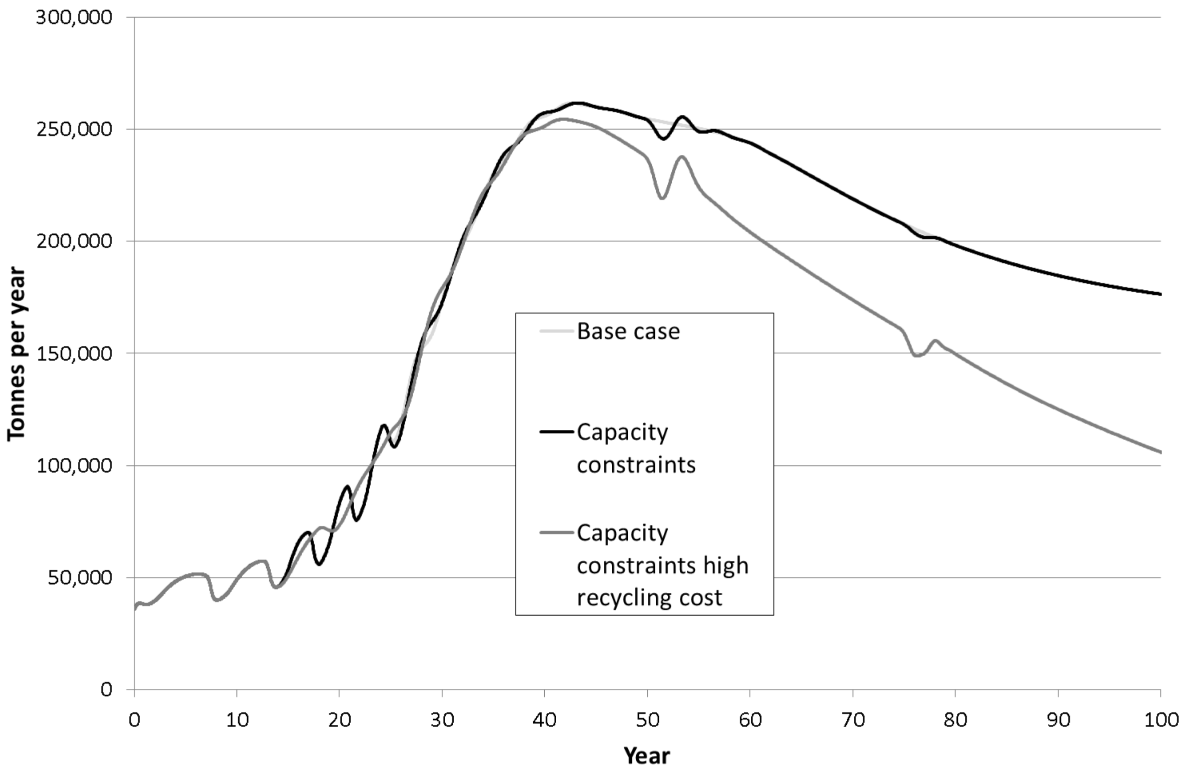
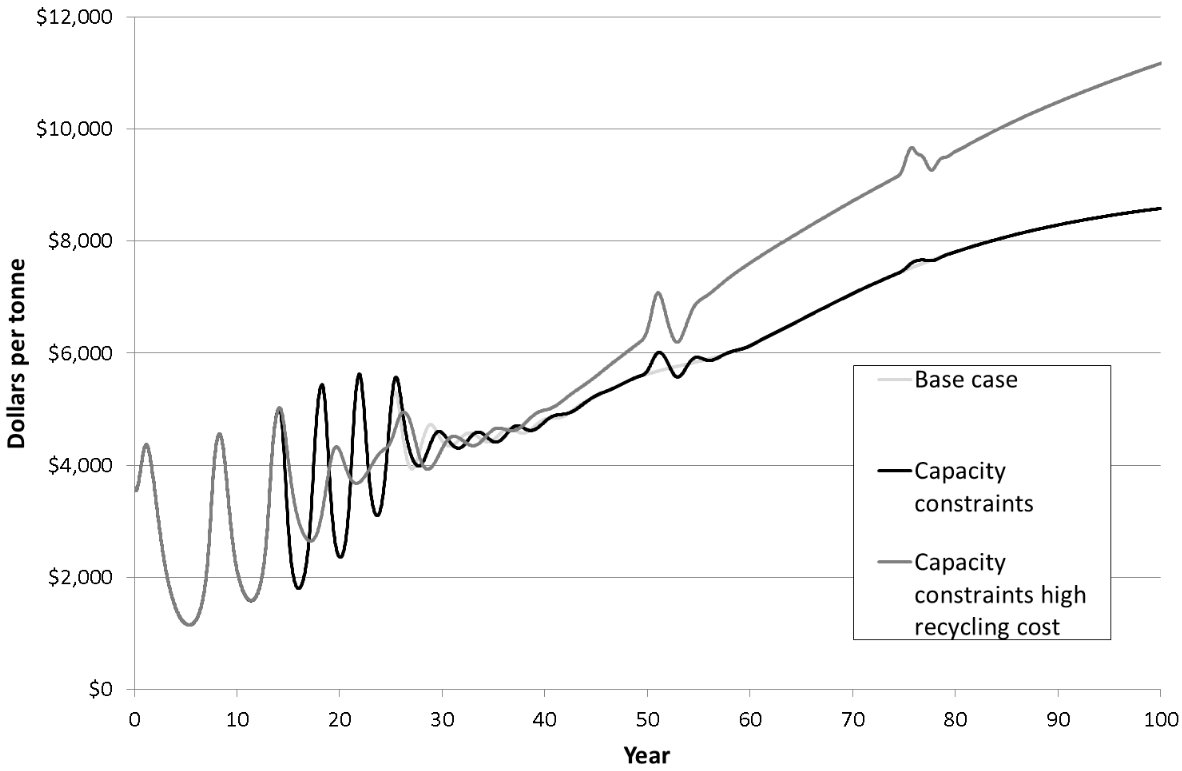


Figure 8.4: Impact of capacity constraint on the lithium model price under both high recycling costs and base case recycling cost values



8.1.3 The indium models response to availability constraint under variable recycling cost

The indium model behaves slightly differently to the lithium model when exposed to similar assumptions regarding the costs of recycling, and capacity constraint events (Figure 8.5 and Figure 8.6). The model produces slightly more metal under the ‘capacity constraints’ and ‘base case’ model runs than in the ‘capacity constraints high recycling cost’ case, but the difference is not as significant as in the later years of the lithium model. The impact of recycling on the effect of capacity constraint events is also muted, with little difference seen in the oscillations in years 25, 50 and 75. This difference is a result of the fact that the indium model supply growth is constrained by the availability of indium due to the by-product nature of its production. This constraint keeps indium production below the reference demand for the majority of the model time period. Indium price is similarly affected, with little differentiation of price throughout the model, and similar responses to the capacity constraint events across the model cases.

An interesting point in the indium model is in year 80, where the model runs invert, and there is a change in trend in the model cases, with supply peaking and going into decline, and price reaches a floor and begins to climb. The constraint in supply due to the by-product nature of indium production induces a high and rising price of indium in the early years of the model as demand for PV outstrips supply of indium. As growth in demand for PV slows, and the rate of recycling increases the indium price begins to decrease back towards the rising marginal cost of production, defined by the cumulative availability curve. In year 80 the price of indium and the marginal cost of production intersect, and price follows the marginal cost from that point forward. The inversion in model runs is unintuitive, but is a result of the oscillations caused by the capacity constraint event in year 75. The model runs converge as they approach year 100, correcting this inversion to a more intuitive position.

Figure 8.5: Impact of capacity constraint on the indium model supply rate including under a high cost of recycling

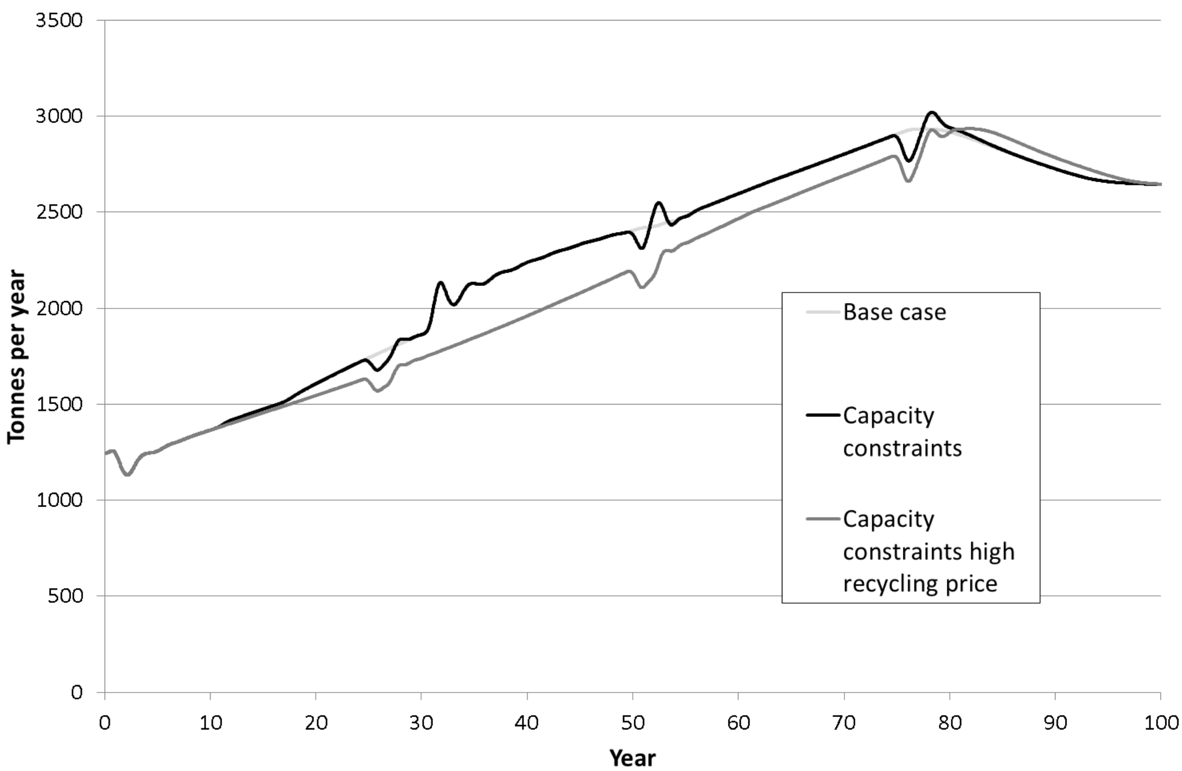
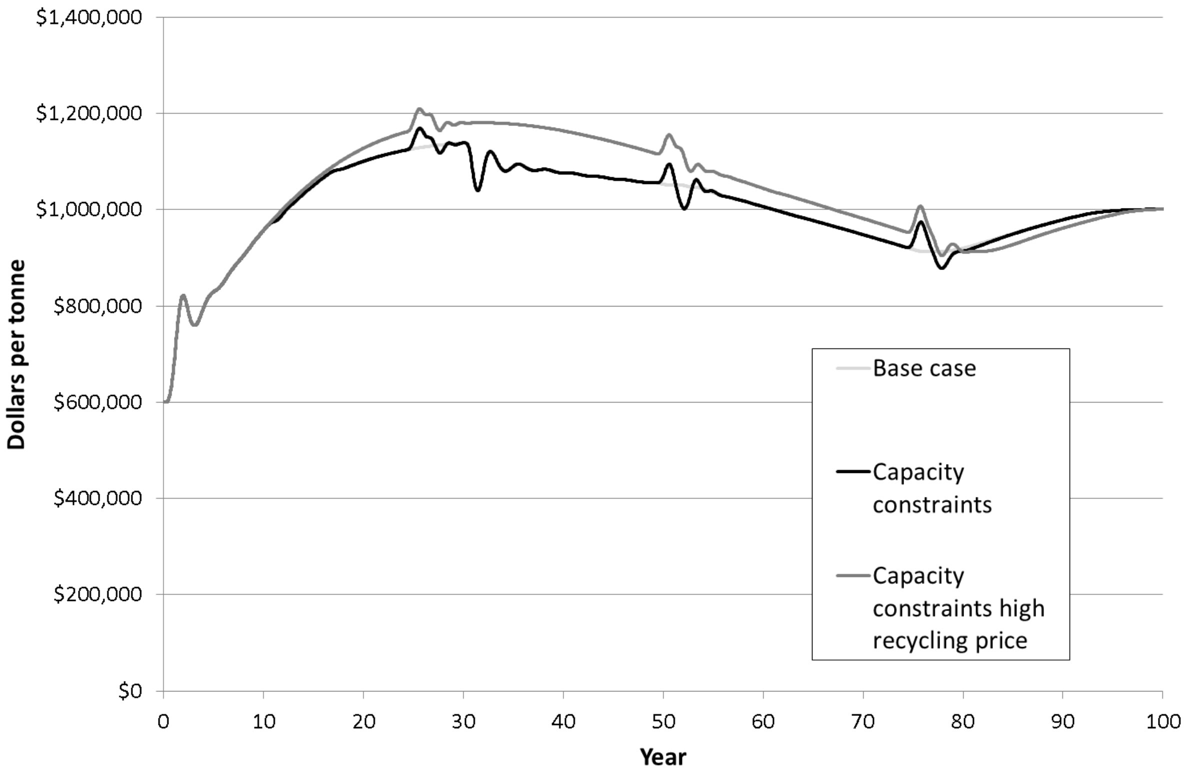


Figure 8.6: Impact of capacity constraint on the indium model price including under a high cost of recycling



In summary, the effect of recycling can have a significant effect on both supply and response to sudden constraint events. However, this effect is least potent when supply is growing significantly. Further, where supply might be constrained by by-product metal production the effects of recycling are likely to be muted.

8.2 Impact of by-product metal production and its constraint on production growth

To isolate the impact of by-product indium production from the effects discussed above the indium model was run again under conditions which relax the by-product related supply constraints. By running the model under the assumption that zinc ore contains an unrealistically high quantity of indium, production is unconstrained by the rate at which zinc is produced (Table 8.2). The result of this run, along with the base case and capacity constrains cases presented in the previous section, are seen below (Figure 8.7 and Figure 8.8).

Table 8.2: The model cases applied to the indium model to investigate the impact of by-product production and capacity constraint events

	Case	Indium contained in zinc ore	Timing of 5% capacity constraint event (year)		
Indium	Base case	0.009%	0	0	0
	Capacity constraints	0.009%	25	50	75
	High indium contained	1%	25	50	75

The impact of by-product indium production on the supply rate is quite significant, exposing a large quantity of unserved reference demand, shown by the differential between the 'capacity constraints'' case and the 'high indium contained' case in Figure 8.7. This is also reflected in the indium price, which is significantly reduced in the early years of the model if by-product constraints are removed (Figure 8.8).

The impact of capacity constraints appears relatively unaffected by the by-product nature of indium production. The oscillations resulting from the capacity constraint events appear larger in the 'high indium contained' case, but are very similar as a percentage of the underlying supply rate.

In summary, by-product indium production has a significant effect on supply rate, but relatively little effect on the models response to capacity constraint events.

Figure 8.7: Impact of capacity constraint on the indium model supply rate including under conditions of high indium content in zinc ore.

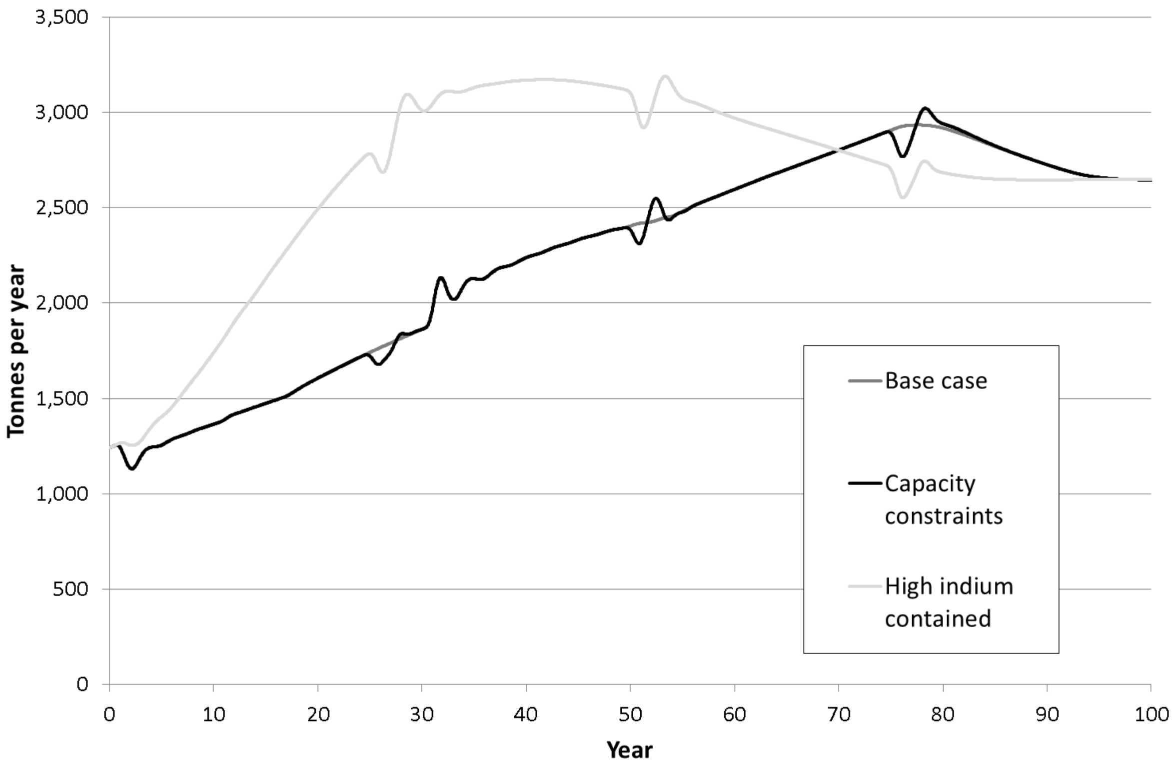
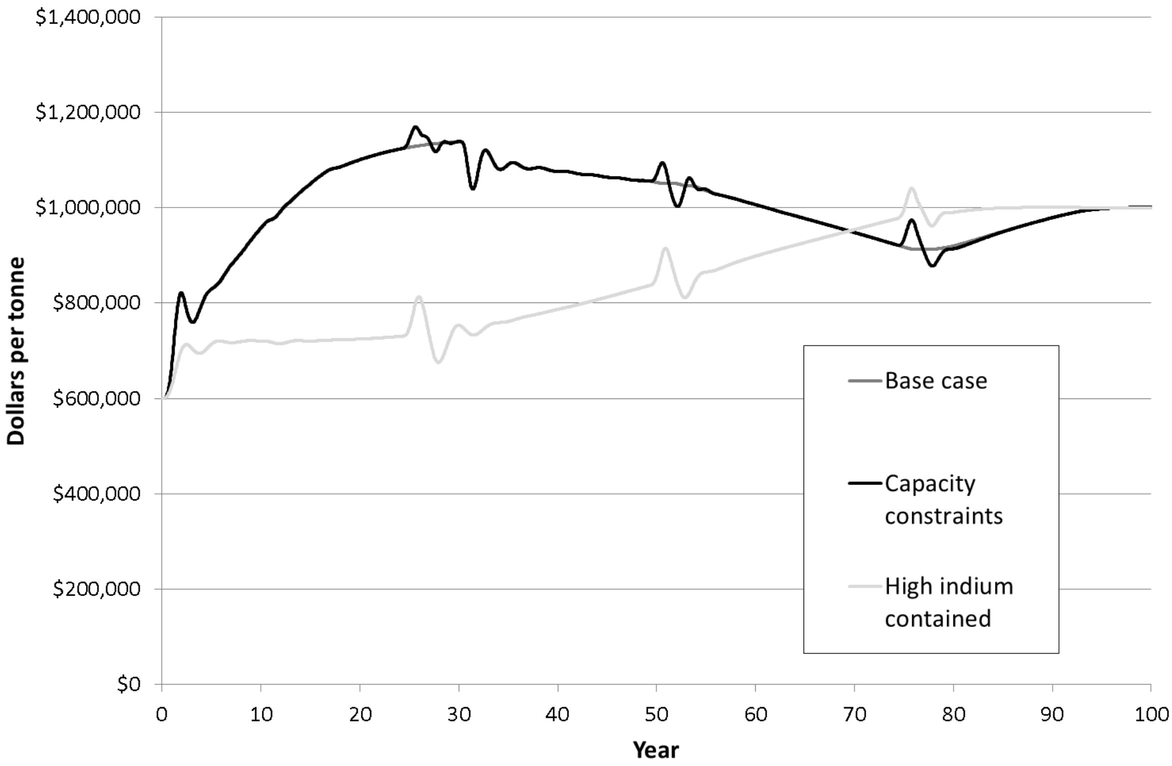


Figure 8.8: Impact of capacity constraint on the indium model price including under conditions of high indium content in zinc ore.



8.3 Impact of marginal cost

The cumulative availability curve dictates the increasing cost associated with production of the marginal resource. Since the marginal cost of production is a strong factor in the establishment of price then variations in this input can have significant impacts on the model outputs. In order to examine the impact that marginal cost has on the response of the three resource models each was run with a flat cumulative availability curve (Table 8.3). In the figures below the 'base case' and 'capacity constraints' model runs are also presented for comparison.

Table 8.3: The model cases applied to the generic resource, lithium and indium models to investigate the impact of the cumulative availability curve and capacity constraint events

	Case	Cumulative availability curve	Timing of 5% capacity constraint event (year)		
Generic resource	Base case	Initial values	0	0	0
	Initial values cumulative availability curve	Initial values	25	50	75
	Flat cumulative availability curve	Flat: $100/tonne	25	50	75
Lithium	Base case	Initial values	0	0	0
	Initial values cumulative availability curve	Initial values	25	50	75
	Flat cumulative availability curve	Flat: $2,200/tonne	25	50	75
Indium	Base case	Initial values	0	0	0
	Initial values cumulative availability curve	Initial values	25	50	75
	Flat cumulative availability curve	Flat: $600,000/tonne	25	50	75

8.3.1 The generic resource model response to availability constraint under static marginal cost

The generic resource model initial values assume that the cost of extracting the resource increases by $10 with every 500 billion tonnes produced. This assumption is based on marginal resource cost curves published by the (IEA 2008; IEA 2013). However, some envisage a future where the extraction of marginal resources is actually relatively low cost, largely due to the advent of horizontal drilling and hydraulic fracturing technologies (Maugeri 2012). In this type of future the marginal cost of production might be relatively static, or ‘flat’. Figure 8.9 and Figure 8.10 present the results of applying a flat cumulative availability curve of $100 per tonne to the ‘capacity constraints’ model run for both supply rate and price. The ‘base case’ and ‘capacity constraints’ model runs are also presented for comparison.

First, the rising marginal cost in the ‘base case’ and ‘capacity constraints’ cases appears to be largely responsible for the decline in supply seen in these model runs (Figure 8.9). When a static cumulative availability curve is applied to the model supply grows very slightly in the first half of the time horizon, peaking round year 50 and declining for the remainder of the time horizon. In this ‘flat cumulative availability curve’ case the initial growth in supply is driven by growth in demand due to rising GDP. The subsequent peak and decline is a result of the decoupling assumed in the model run, reflecting the fact that through decarbonisation and efficiency measures it is increasingly possible for GDP to grow without also increasing demand for energy. Supply in the ‘flat cumulative availability curve’ case is therefore significantly above that seen in the capacity constraints case. This is intuitive as a lower resource price (Figure 8.10), driven by a lower marginal cost of production, is likely to increase demand.

The response to the capacity constraint events is modified slightly by the change in cumulative availability curve. The oscillation in supply rate resulting from these events creates larger oscillations in the ‘flat cumulative availability curve’ case, but these oscillations appear to be similar in magnitude relative to the underlying supply rate. However, the duration of the oscillation, and the time period until the oscillation subsides appears to be longer than in the ‘capacity constraints’ case. This appears again to be due to the fact that the higher supply rate in the ‘flat cumulative availability curve’ case creates larger oscillations which take longer to return to equilibrium.

Figure 8.9: Impact of capacity constraint on the generic resource model supply rate including under conditions of static marginal cost of production.

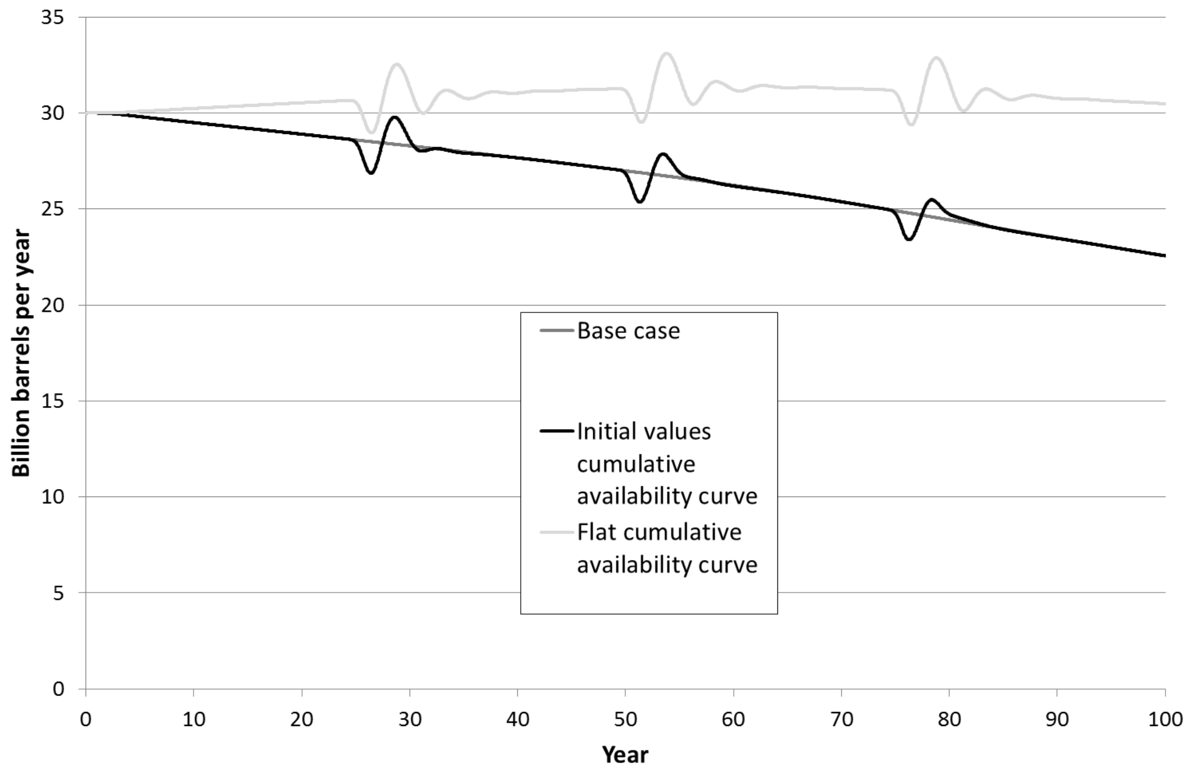
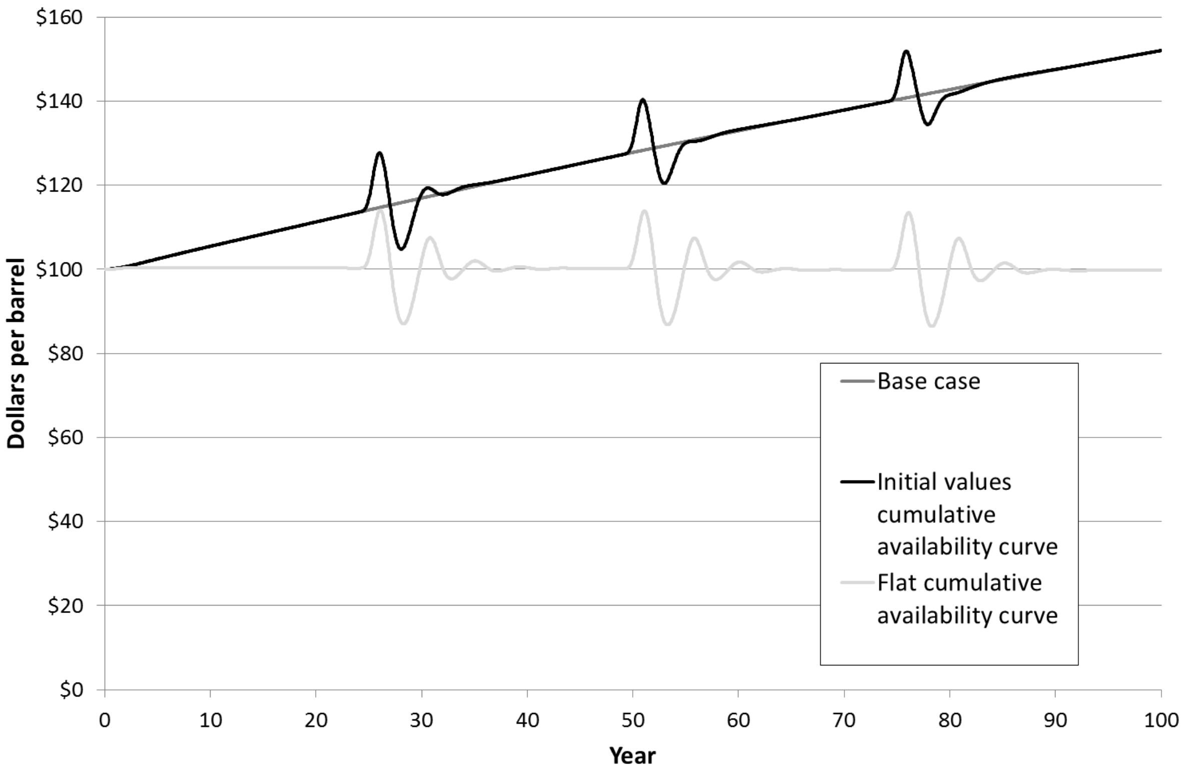


Figure 8.10: Impact of capacity constraint on the generic resource model price including under conditions of static marginal cost of production.



8.3.2 The lithium model response to availability constraint under static marginal cost

The base case for the lithium model again assumes that the marginal cost of production is increasing, from an initial value of $2,200 per tonne, to $22,000 per tonne at cumulative production of 32,000,000 tonnes. This assumption is based on academic literature estimating the slope of this cumulative availability curve (Yaksic & Tilton 2009). In Figure 8.11 and Figure 8.12 the base case and capacity constraints cases are presented, and a third case where the cumulative availability curve is set at a static $2,200 per tonne of metal.

Lithium supply rate grows more quickly under static assumptions on the marginal cost of lithium production (Figure 8.11). However, once supply approaches the plateau of lithium reference demand (approximately 275,000 tonnes per year) it enters a phase of significant oscillation. This oscillation is also reflected in lithium price (Figure 8.12) and remains for the rest of the model time horizon. The ongoing low cost of lithium production drives the magnitude of this oscillation, creating the conditions for the supply of metal to approach the reference demand plateau too steeply, making it difficult for the model to reach equilibrium due to the model delays. This level of oscillation is unlikely in the real world and probably reflects some level of unrealism in the models assumptions on delay in interpreting the equilibrium price. The oscillation also masks the impact of the capacity constraint events, making it difficult to interpret the models response to these events under static assumptions on marginal cost of production.

Figure 8.11: Impact of capacity constraint on the lithium model supply rate including under conditions of static marginal cost of production.

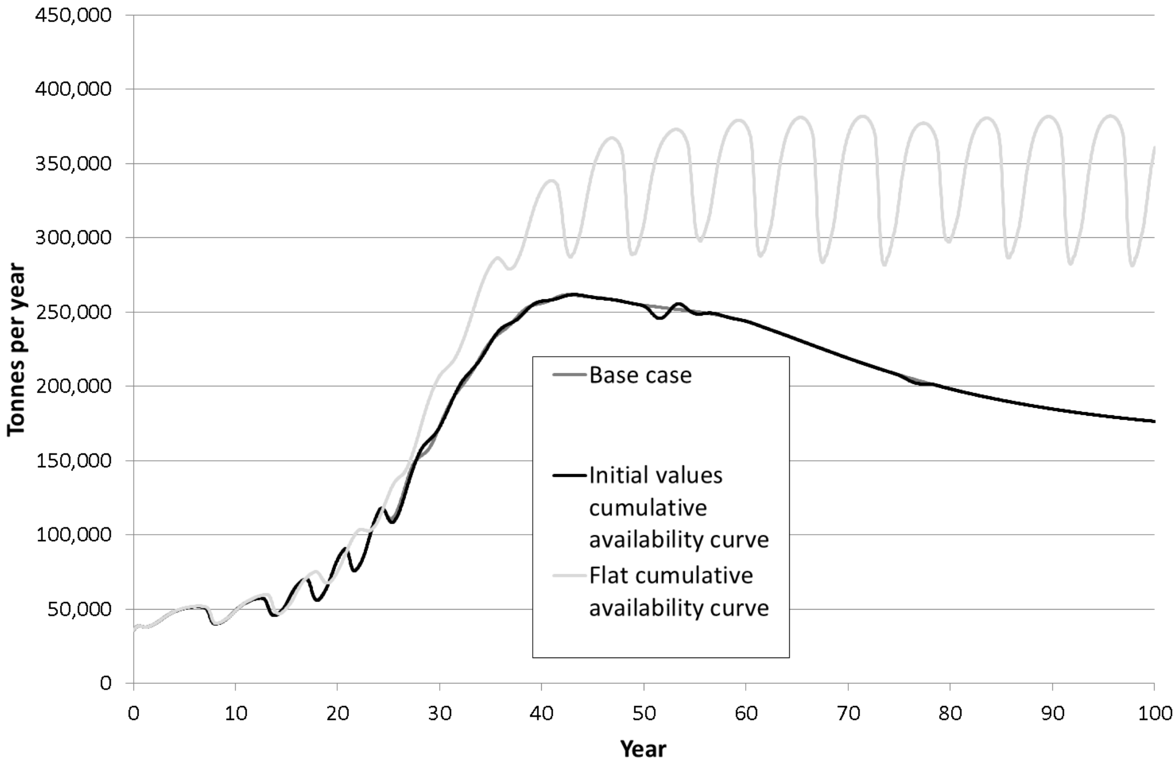
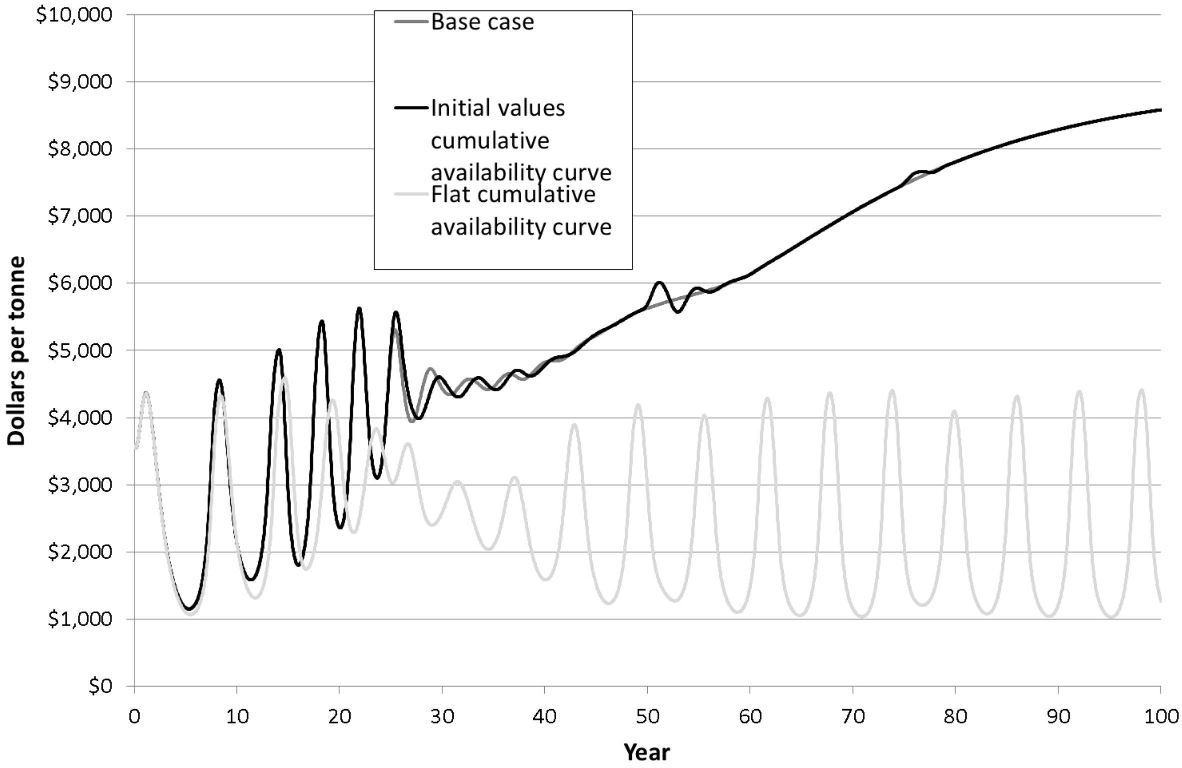


Figure 8.12: Impact of capacity constraint on the lithium model price including under conditions of static marginal cost of production.



8.3.3 The indium model response to availability constraint under static marginal cost

In the early phase of the indium model (approximately 0 to 50 years) the cumulative availability curve has little impact since the demand for indium is not constrained by the price but rather by the constrained supply due to by-product indium production. However, once the inflection point in year 80 is reached the model runs diverge, and the 'flat cumulative availability curve' case continues to increase, while the base case and 'capacity constraints' cases decline. At this point in the model the driver of dynamic behaviour in the 'base case' shifts from the capacity constraint of by-product indium production to the rising marginal cost of production, and resulting rising price (Figure 8.14).

There is also very little difference between the model runs in terms of their response to the capacity constraint. Even in the year 75 where there is already some convergence between the capacity constraints' and flat cumulative availability curve cases there appears to be little difference in the oscillations associated with capacity constraint event.

Figure 8.13: Impact of capacity constraint on the indium model supply rate including under conditions of static marginal cost of production.

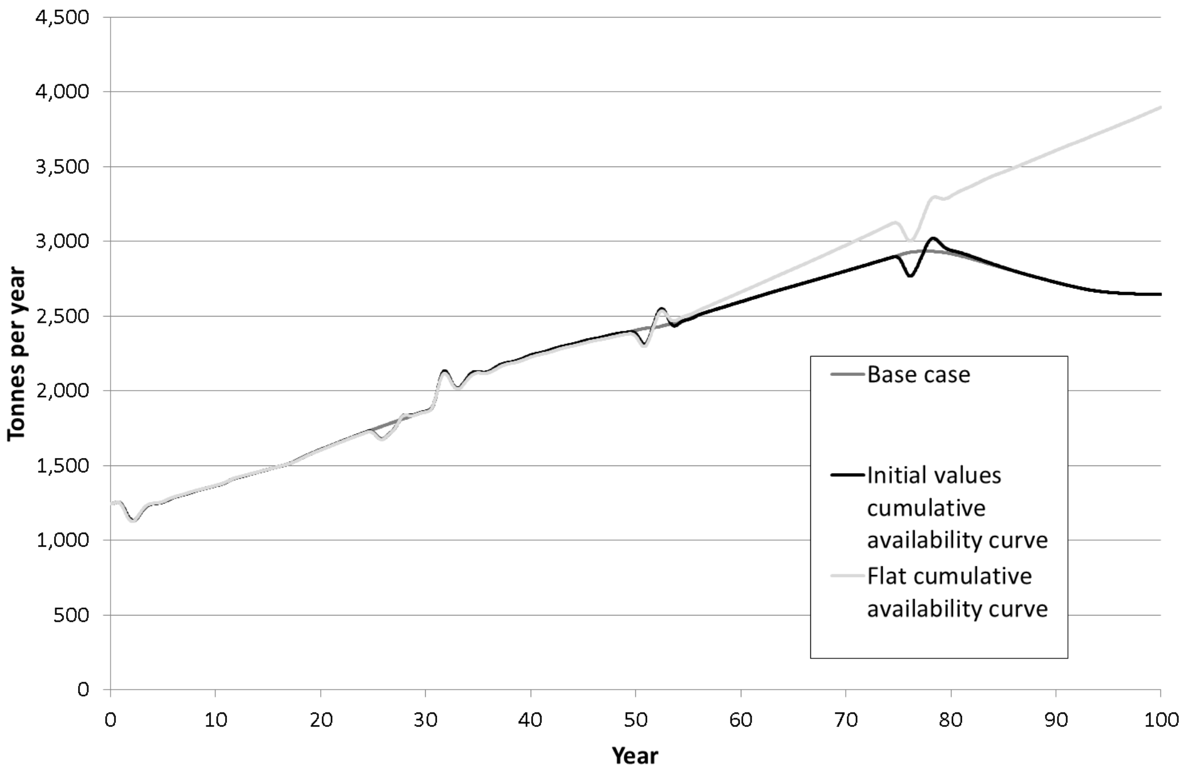
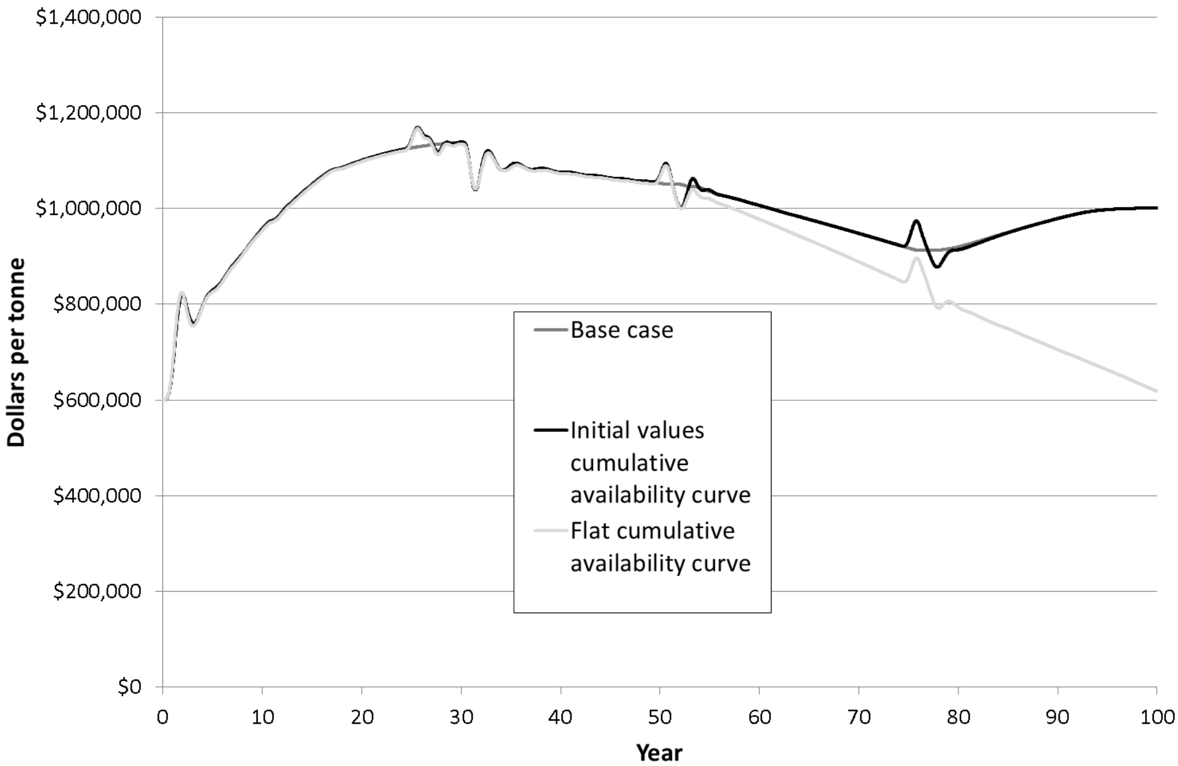


Figure 8.14: Impact of capacity constraint on the indium model price including under conditions of static marginal cost of production.



8.4 Impact of response measure

The generic, lithium and indium resource models can be used to test the impact of some of the policy measures that may be employed in response to capacity constraint, and provide some insight into their relative effectiveness. There are a number of possible policy responses to constraints in resource availability. Policy makers may seek to modify demand for a constrained resource by incentivising resource efficiency such as fuel efficiency standards for vehicles (NHTSC 2010). Demand may also be influenced by encouraging the research and development of substitute technologies or materials (CBO 1982).

A number of supply side measures may also be taken in response to constrained resource availability. Governments can choose to support domestic exploration and production activities in order to create additional resource production (HCST 2010). Strategic reserves of certain resources may also be maintained in order to mitigate sudden availability constraints and provide some level of reassurance to the resource market (CBO 1982; IEA 2007). Policy makers may also wish to explore supply options through international diplomacy to secure bilateral agreements with foreign exporters (CBO 1982). Recycling can also mitigate supply constraints, and policy makers may wish to encourage recycling through legislation, financial incentive, and design-for-recycling standards (UNEP 2011).

Given the structure of the models it is difficult to simulate the impact of the country specific measures such as bilateral import agreements or support for domestic exploration and production. However, three particular types of resource policy measure can be examined:

- The management of strategic reserves
- Support for the development of substitutes; and
- Recycling incentives.

The impact of increased recycling is examined in Section 8.1 where it was found that for metals with no production constraints recycling can have an impact on both the quantity of metal produced and the severity of the oscillations in supply and price in response to capacity constraint events. This is particularly the case where primary metal production has plateaued. The impacts associated with strategic reserves and substitution are tested below.

8.4.1 The effect of strategic reserves on resource availability

Strategic reserves of oil and certain metals are held in a number of countries and economic regions (IEA 2007; Areddy 2011). To test the impact of strategic reserves on responses to capacity constraint events the 'reference inventory coverage' in each of the three models was varied. The reference inventory coverage dictates the quantity of resource that the model aims to keep in inventory as a proportion of supply. In the base case the reference inventory coverage is set to 20% of the annual supply rate. In the analysis below two additional cases are run which modify the reference inventory coverage to 30% and 50% of the supply rate to test the impact of increasing inventory on the model outputs and their response to capacity constraint events (Table 8.4).

In reality, a strategic reserve of a commodity will be utilised as a policy decision, and the decision making process is as much a political one as it is a rationally economic one. As such it is very difficult to model the 'draw down' decision making process. Using the inventory coverage as a proxy for strategic reserve as described above assumes that this draw down decision making process is an economically rational one, and that the reserve is utilised in direct proportion to the shortfall between capacity utilisation and demand. This approach therefore misses the dynamics of politically motivated draw down of strategic reserves, the implications of which are examined in Chapter 9.

Table 8.4: The model cases applied to the generic, lithium and indium resource models to investigate the impact of cumulative availability costs and capacity constraint events

	Case	**Reference inventory coverage**	**Timing of 5% capacity constraint event (year)**		
Generic resource	Capacity constraints (20% inventory)	Initial values (20%)	25	50	75
	30% inventory	30%	25	50	75
	50% inventory	50%	25	50	75
Lithium	Capacity constraints (20% inventory)	Initial values (20%)	25	50	75
	30% inventory	30%	25	50	75
	50% inventory	50%	25	50	75
Indium	Capacity constraints (20% inventory)	Initial values (20%)	25	50	75
	30% inventory	30%	25	50	75
	50% inventory	50%	25	50	75

The generic resource model response to availability constraint under increased inventory

The generic resource models response to changing inventory coverage is presented below in Figure 8.15 and Figure 8.16. First, as inventory increases the magnitude of oscillation in supply and price in response to capacity constraint events decreases. In the 50% inventory case supply oscillates 4.4% from the base case, while the initial values case oscillates 5.7%. The impact on price is greater, with the 50% inventory oscillating 8% and the initial values case oscillating 11%. This model response is due to the mitigating effect of 'drawing down' from an inventory during times of constrained supply. However, as the inventory is increased the time the model takes to return to equilibrium increases. For example, the generic resource supply takes 12 years to return to equilibrium in the 'capacity constraints' case while the model returns to equilibrium in 14 years in the 50% inventory case. This extended period of oscillation is due to a combination of the increased demand associated with 'buying back' the inventory used in response to the capacity constraint, and the possible overshoot and oscillation in re-establishing the desired level of inventory.

The impact of increasing inventory on the generic resource models response to capacity constraint events is limited given the quantity of inventory needed to change the response of the model by only small amounts. For example, current global strategic inventories of oil total approximately 4.1 billion barrels (Reuters 2011). This is only 7.5% of annual production. To increase this to 50% of annual production would mean storing an additional 11 billion barrels of oil. This would be a significant financial and logistical challenge, and may not deliver significant mitigation for capacity constraint events based on the conditions tested here.

Figure 8.15: Impact of capacity constraint on the generic resource model supply rate including under conditions of increased inventory.

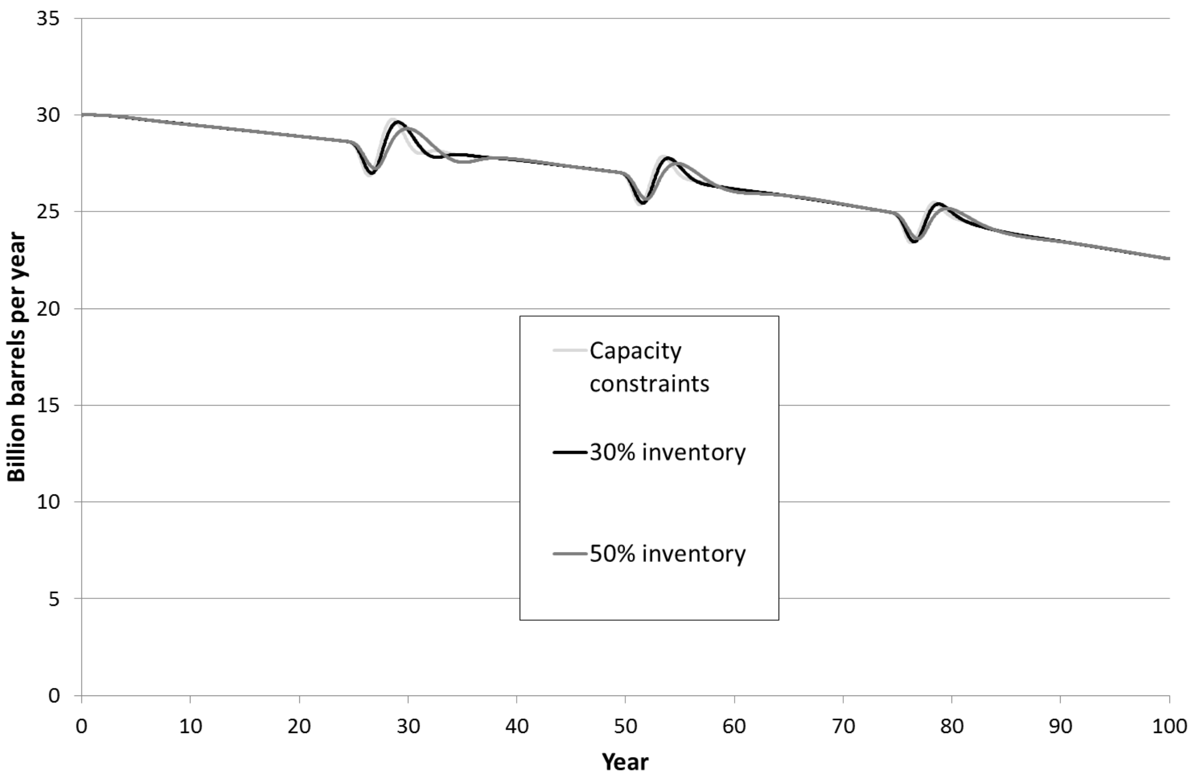
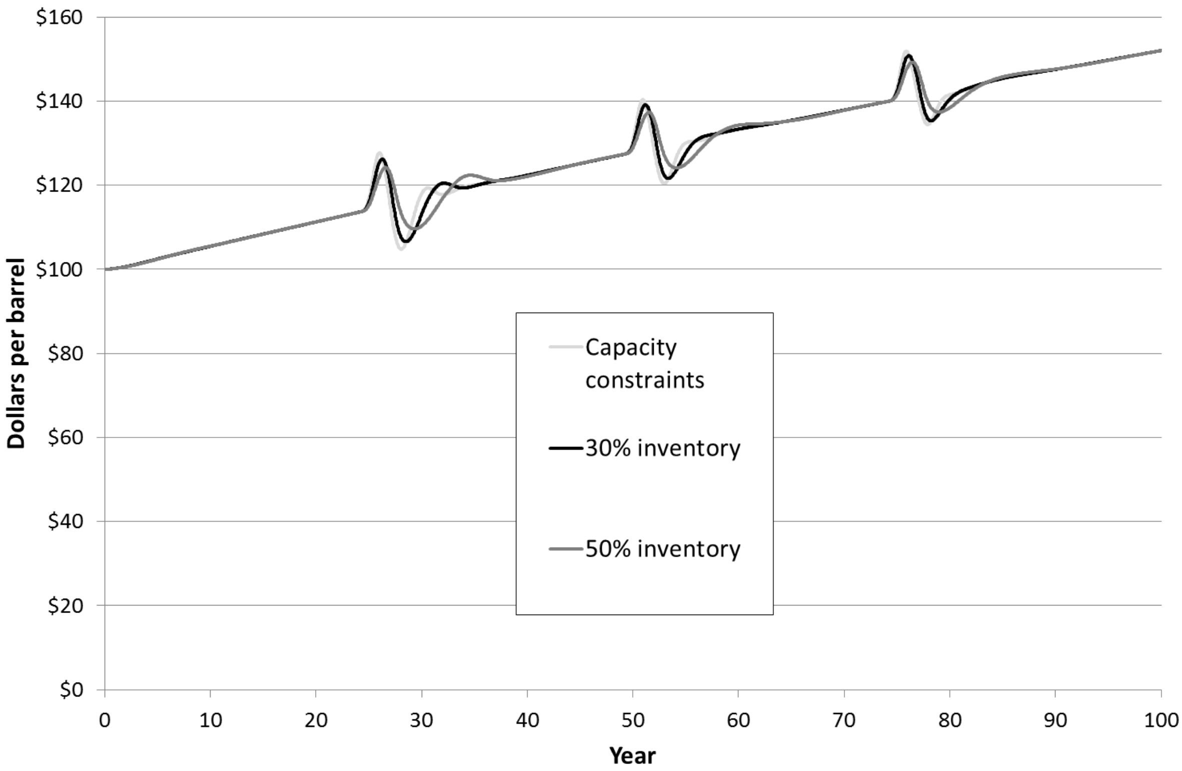


Figure 8.16: Impact of capacity constraint on the generic resource model price including under conditions of increased inventory



The lithium model response to availability constraint under increased inventory

The lithium model response to capacity constraint events under changing inventory coverage are presented in Figure 8.17 and Figure 8.18. In the early years of the models the background oscillations in supply rate (Figure 8.17) and price (Figure 8.18) mask the impact of the capacity constraint event in year 25. In the later years the impact of recycling appears to mitigate the impacts of capacity constraint to the extent that there is very little difference between the model cases. In year 50, both supply rate and price appear to behave in a similar way to the generic resource model outputs (Figure 8.15 and Figure 8.16), though the response is diminished, and there is very little measurable difference between the model runs. In the year 75 constraint event the impact is negligible, owing to the contribution of recycled metal.

Based on the analysis above it appears then that the maintenance of a strategic reserve is unlikely to have a significant impact on response to capacity constraint events for metals that have either dramatic supply growth with volatility, or a proportion of supply through recycling. This is explored further in Chapter 9.

Figure 8.17: Impact of capacity constraint on the lithium model supply rate including under conditions of increased inventory

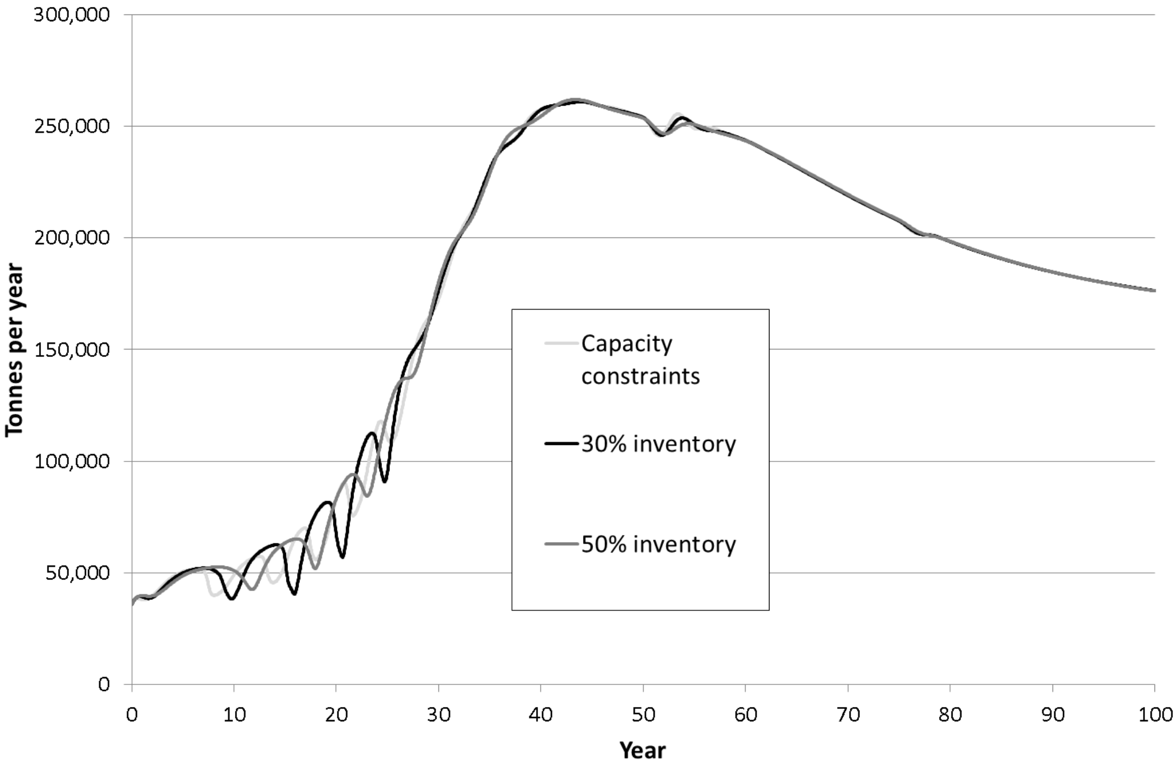
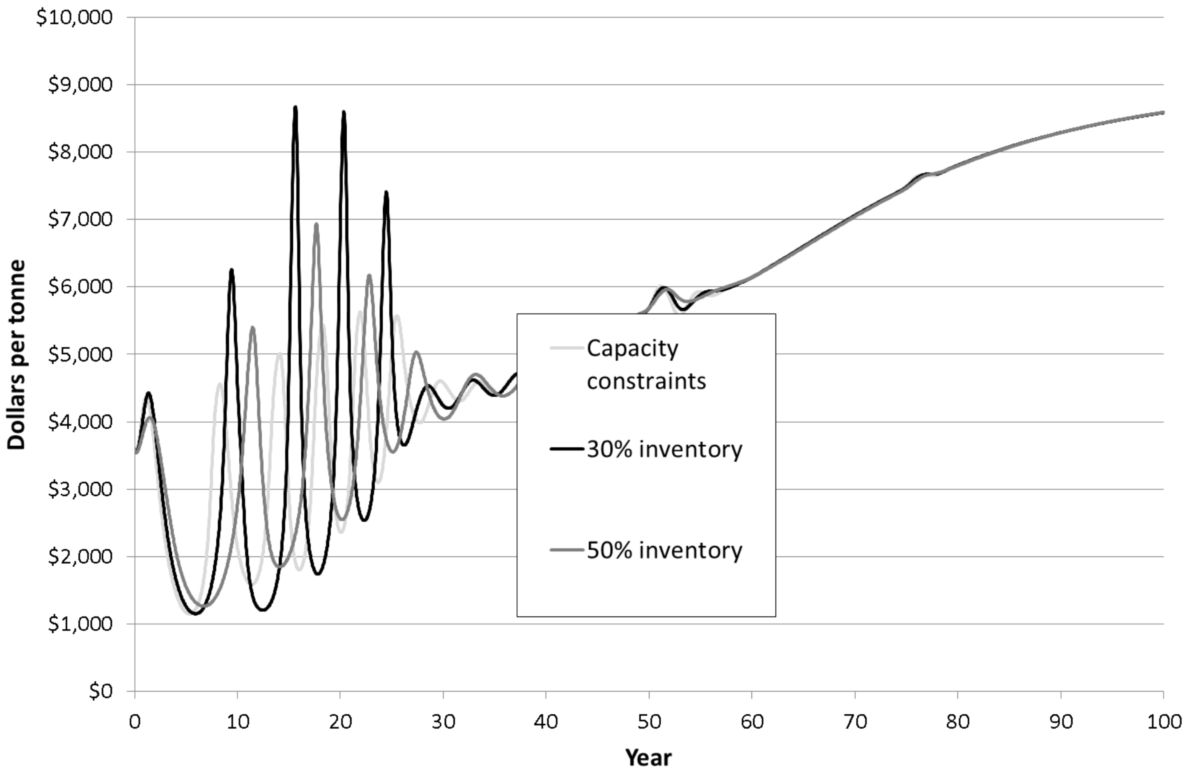


Figure 8.18: Impact of capacity constraint on the lithium model price including under conditions of increased inventory



The indium model response to availability constraint under increased inventory

The impact of changing inventory coverage in the indium model is presented in Figure 8.19 and Figure 8.20. The impact on supply rate (Figure 8.19) of changing indium inventory coverage appears to follow a similar pattern to the generic resource model outputs in the year 75 capacity constraint event, with oscillations in response to capacity constraints reducing in magnitude with increasing inventory, but having longer duration. However, the variation between model runs is minimal. In the year 25 and year 50 capacity constraint events the underlying volatility affects the models response, altering the expected relationship seen in year 75. In year 25 the model supply rate and price outputs do not appear to vary significantly with increasing inventory coverage. In year 50 the supply and price outputs clearly vary with increasing inventory coverage, though unexpectedly the 50% and 30% inventory cases appear to react more to the capacity constraint event than the 20% inventory 'capacity constraints' case, though this effect appears marginal. This is the case for both supply rate and price (Figure 8.20).

Given the results of this analysis it is possible to conclude that, under these model conditions, with both by-product constraints in supply, and recycling, unintuitive responses to increasing inventory coverage can occur. In this instance increasing inventory has no impact on response to capacity constraints at best, and at worst, actually increases the supply and price volatility associated with these capacity constraint events.

Figure 8.19: Impact of capacity constraint on the indium model supply rate including under conditions of increased inventory

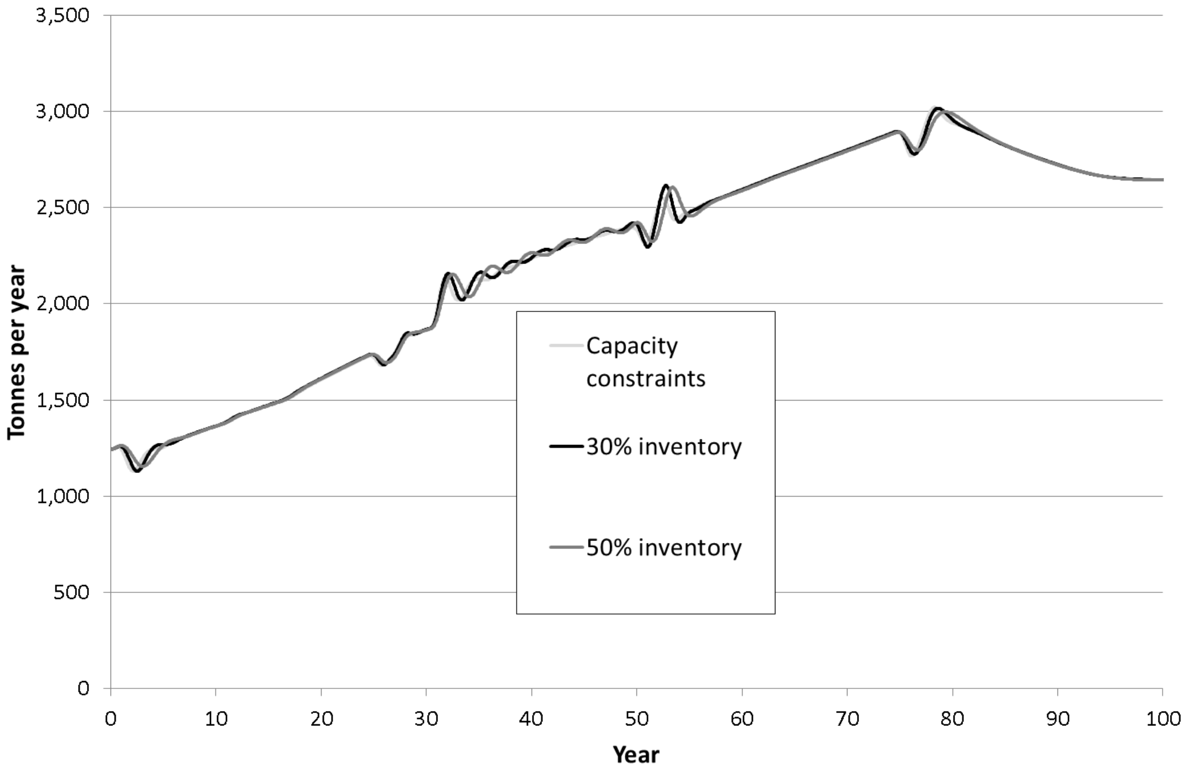
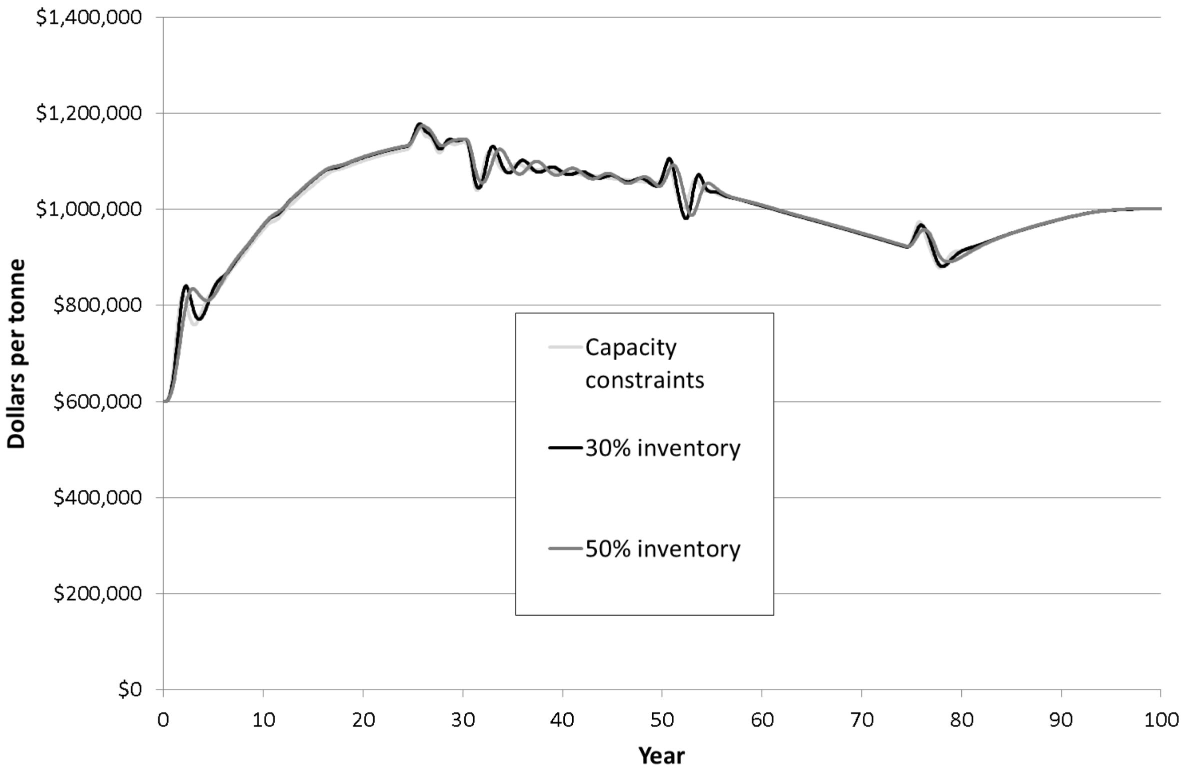


Figure 8.20: Impact of capacity constraint on the indium model price including under conditions of increased inventory



8.4.2 The effect of substitution

Technological and material substitution has a significant potential to reduce the demand for particular resources. Given this potential seeking to incentivise substitution is a legitimate policy approach and has been pursued successfully in the past (CBO 1982). In order to simulate the effect of substitution an additional element was inserted into each of the three models. This substitution subsystem (Figure 8.21) substitutes a given proportion of demand (the 'substitution level') over a 50 year time frame, using a logistic progression (defined in a lookup table in the model called 'table for substitution' (Figure 8.22)). After the first 50 years of the model the substitution has proceeded to completion, and the remainder of the timeframe is governed by the remaining dynamics of the system. A logistic rate of substitution is used based on evidence in the literature on the nature of technological substitution, though the political and regulatory drivers of substitution in the cases below may alter the trajectory of any substitution process in the real world (Foster 1986; McGrath 1998). The subsystem was used to create two new cases to compare with the 'capacity constraints' case. These are the '25% substitution' case, and the '50% substitution' cases. These cases are presented in Table 8.5.

Figure 8.21: The substitution subsystem

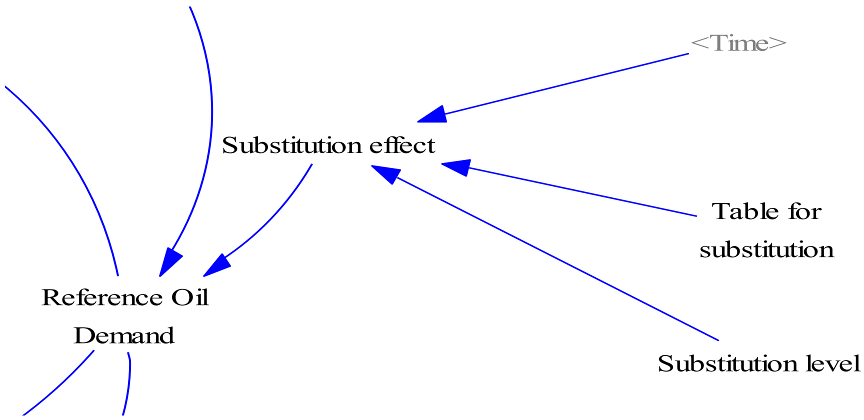


Figure 8.22: Table for substitution

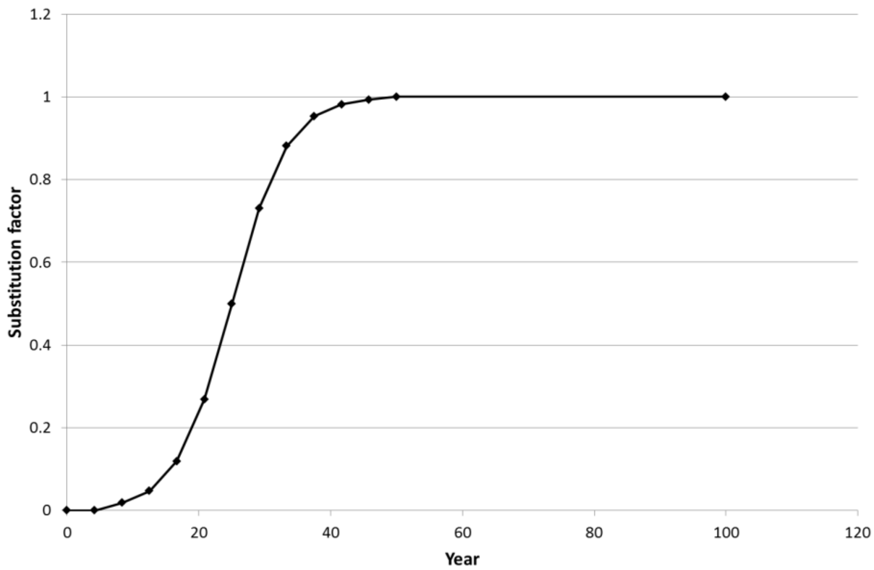


Table 8.5: The model cases applied to the generic, lithium and indium resource models to investigate the impact of cumulative availability costs and capacity constraint events

	Case	Substitution level	Timing of 5% capacity constraint event (year)		
Generic resource	Capacity constraints	0%	25	50	75
	25% substitution	25%	25	50	75
	50% substitution	50%	25	50	75
Lithium	Capacity constraints	0%	25	50	75
	25% substitution	25%	25	50	75
	50% substitution	50%	25	50	75
Indium	Capacity constraints	0%	25	50	75
	25% substitution	25%	25	50	75
	50% substitution	50%	25	50	75

The generic resource model response to availability constraint under increased substitution

Substitution in the generic resource model represents any effort to limit the demand for a resource through development of new technologies. In the example of oil transport fuel is a significant proportion of oil demand, and substitution technologies include electric vehicles, vehicle drivetrain hybridisation and hydrogen fuel cell vehicles. Substitution is implicitly included in the decoupling component of the demand subsystem but separating additional substitution in this subsystem allows for fair comparison across the three resource models.

The generic resource model responds to increased levels of substitution in a relatively intuitive way. Supply (Figure 8.23) decreases as substitution level increases, with the most significant reductions happening in the first 30 years of the model. There appears to be little impact on the response to capacity constraint events, with the oscillation decreasing proportionally to the level of supply.

Resource price (Figure 8.24) decreases with increasing substitution. However, in year 100 a 21% reduction in supply between the 'capacity constraints' and '25% substitution' cases there is only an 11% reduction in price. There is an increased amount of price volatility associated with the very steep reductions in supply in the early years of the model time horizon. The oscillation resulting from the steep supply decline is, however, significantly smaller than the oscillation associated with the capacity constraint events.

In summary under the conditions defined in the generic resource model demand and resulting supply can be significantly reduced through substitution. However, there is a much less significant reduction in price resulting from this substitution. This is primarily because price is more sensitive to the marginal cost of production, defined by the cumulative availability curve. The response to availability constraints in both supply and price is not significantly affected by substitution other than the fact that the oscillation response is proportional to the level of supply, and as supply decreases through substitution, so too does the magnitude of the oscillation.

Figure 8.23: Impact of capacity constraint on the generic resource model supply rate including under conditions of increased substitution

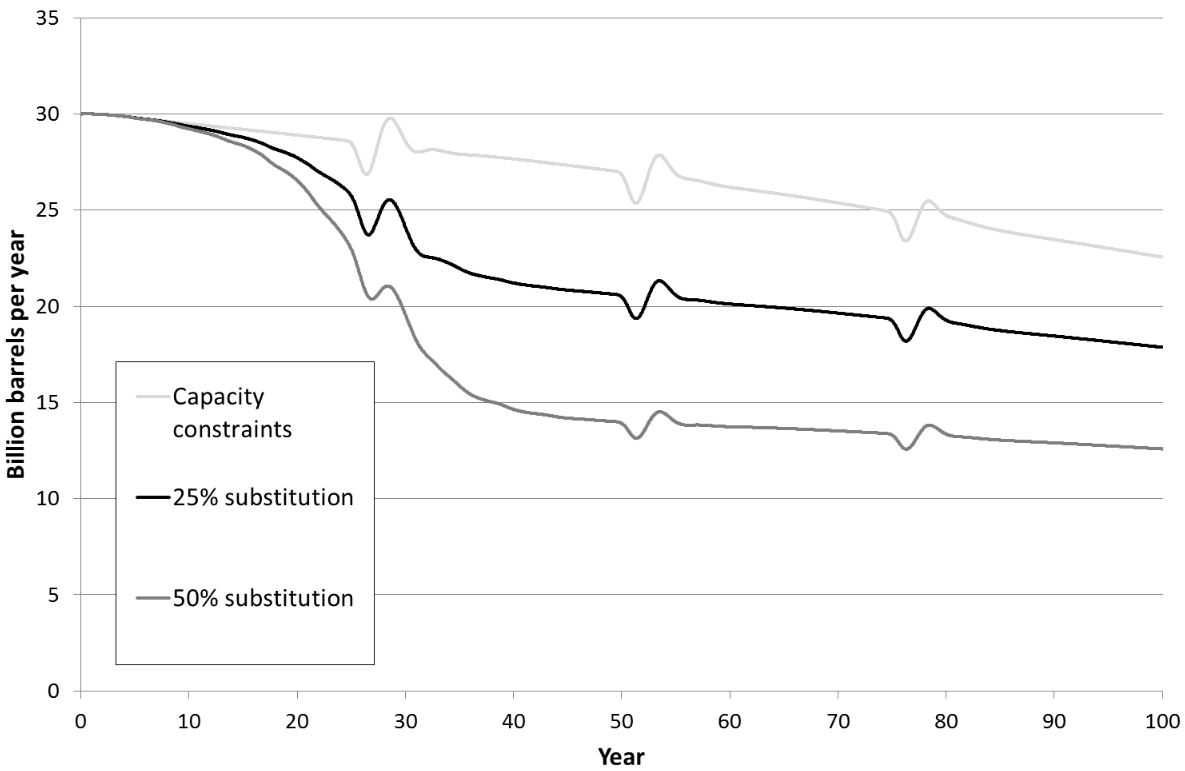
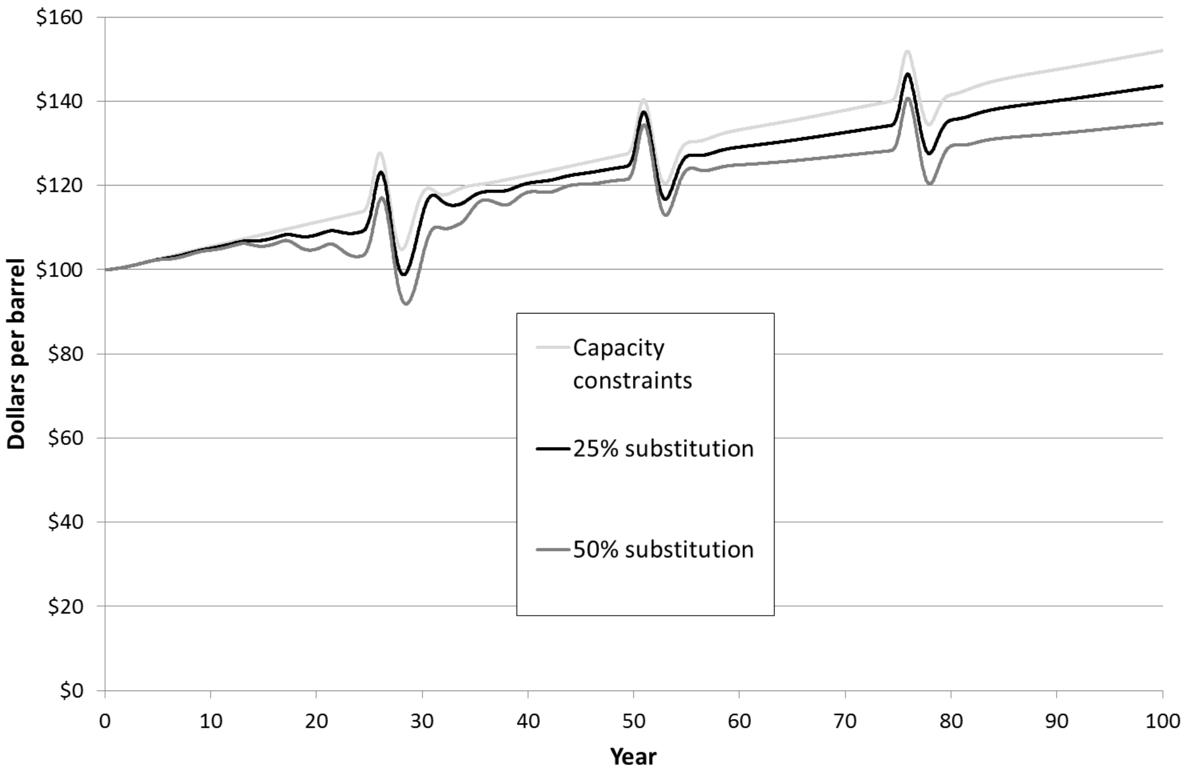


Figure 8.24: Impact of capacity constraint on the generic resource model price including under conditions of increased substitution



The lithium model response to availability constraint under increased substitution

Lithium demand in the lithium resource model is largely defined by the growth in use of lithium as a battery component in low-carbon vehicles. Lithium substitution in this context could therefore represent other low-carbon vehicle types which use less, or no lithium, such as fuel cell vehicles, or vehicles using non-lithium battery chemistries.

Lithium supply (Figure 8.25) is reduced significantly by the increasing substitution level by year 50 in the time horizon, and from that point the three different model cases converge. The 'capacity constraints' and '25% substitution' cases converge almost completely by year 100, whereas the '50% substitution' case remains significantly lower. This is because the 50% substitution case does not reach the price threshold needed to trigger full lithium recycling while the other cases do.

The volatility in price (Figure 8.26) in the early years of the model time frame masks the impact of the substitution. However, once this volatility subsides price in the three cases diverges considerably, with a much more significant difference in price than exhibited in the generic resource model substitution analysis.

The response to capacity constraint events does not appear to be significantly impacted by the level of substitution in any of the three cases tested. Oscillations around the capacity constraint events are limited in all cases as the impact of recycling masks the impact of these events, as discussed above in Section 8.1 .

Figure 8.25: Impact of capacity constraint on the lithium model supply rate including under conditions of increased substitution

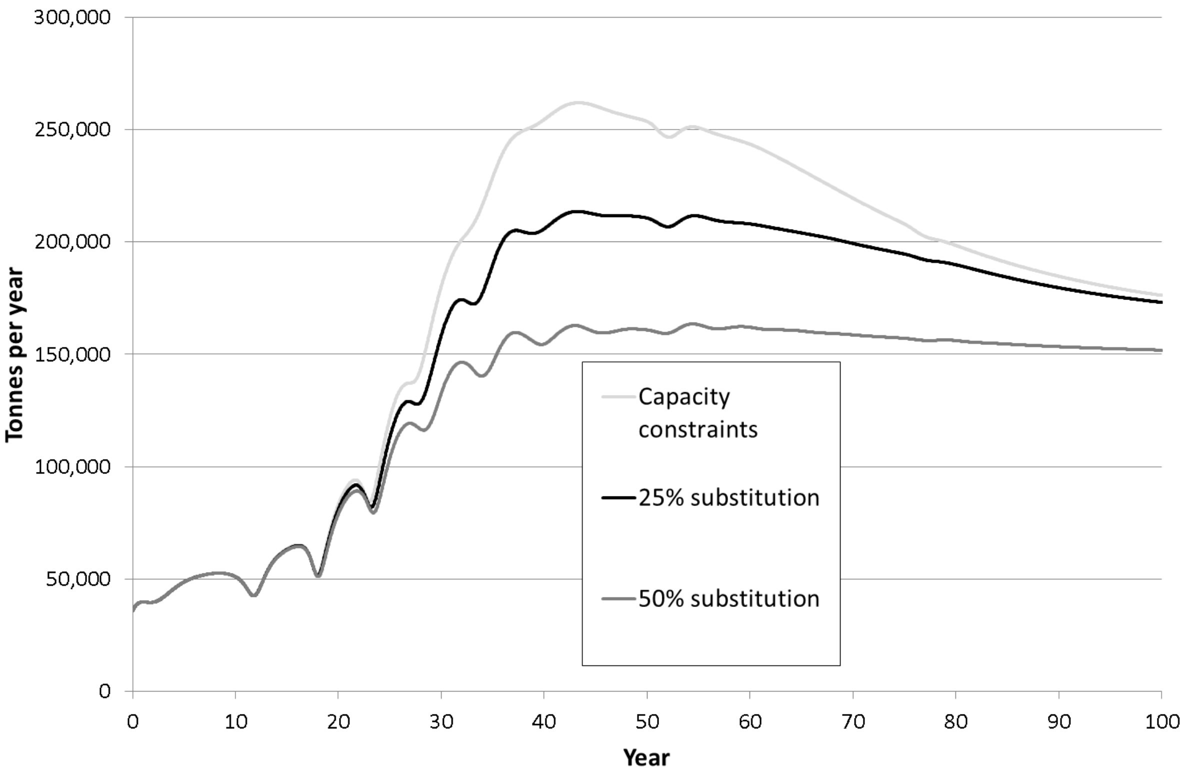
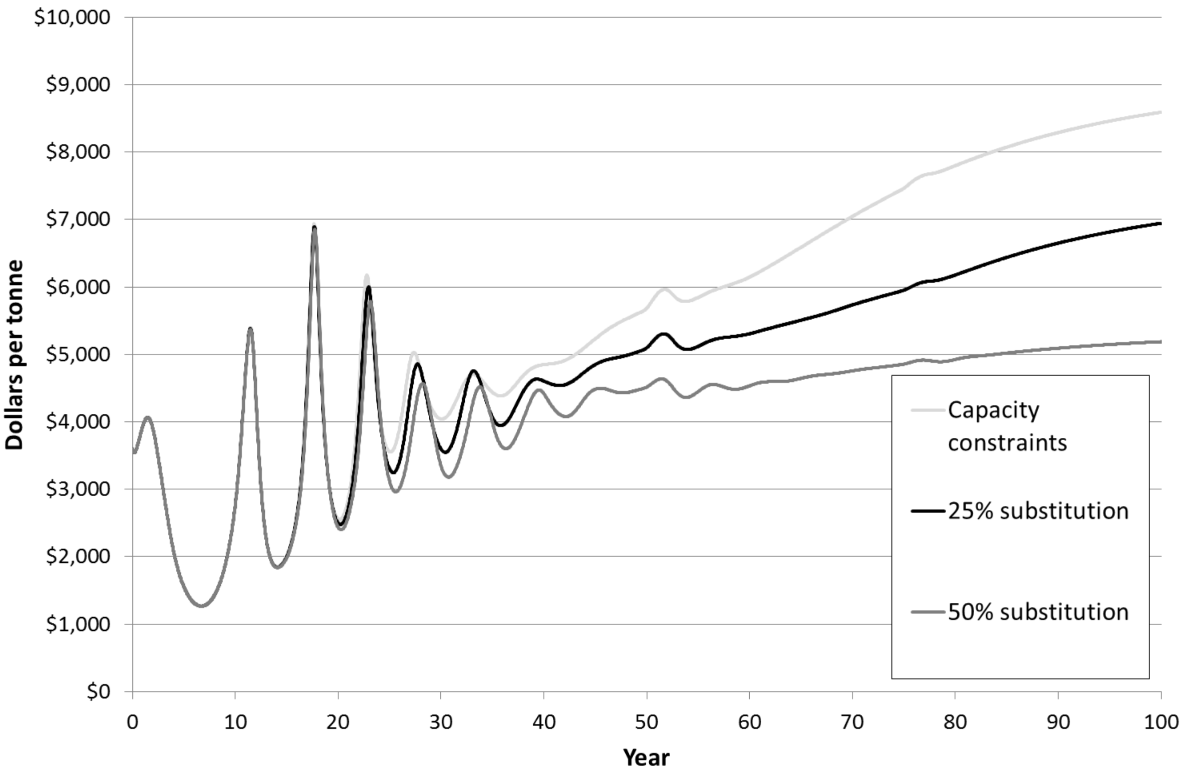


Figure 8.26: Impact of capacity constraint on the lithium model price including under conditions of increased substitution



The indium model response to availability constraint under increased substitution

Demand for thin-film PV is the primary driver of indium demand in the indium resource model. However, other thin-film technologies, and non-thin-film technology alternatives exist, and these can substitute for CIGS PV modules, reducing indium demand.

Indium supply (Figure 8.27) increases until approximately year 80 in the 'capacity constraints' case, at which point supply peaks and begins to decrease. As substitution increases the point at which supply peaks and begins to decline is sooner in the model time horizon. Towards the end of the model time horizon there is approximately 500 tonnes of indium per year between each of the three model cases (or a sixth of peak indium supply in the 'capacity constraints' case.

Indium price (Figure 8.28) and its response to increasing substitution can be summarised in three stages. In the early stage (approximately 0 to 20 years) price increases significantly in response to the by-product capacity constraint and all three cases follow a very similar trajectory before the substitution levels begin to differentiate. In the central stage (approximately 20 to 70 years) the price trajectories of the three model cases differentiate themselves significantly as the level of substitution reduces the extent to which demand exceeds the by-product constrained demand. In the final phase (approximately 70 to 100 years), price in the three cases converges as the cumulative availability curve intersects with the by-product capacity constraint, and price in all cases follows the marginal cost.

The response to the capacity constraint events appears to be relatively unaffected by the changing levels of substitution as in the case of the generic resource and lithium models.

Figure 8.27: Impact of capacity constraint on the indium model supply rate including under conditions of increased substitution

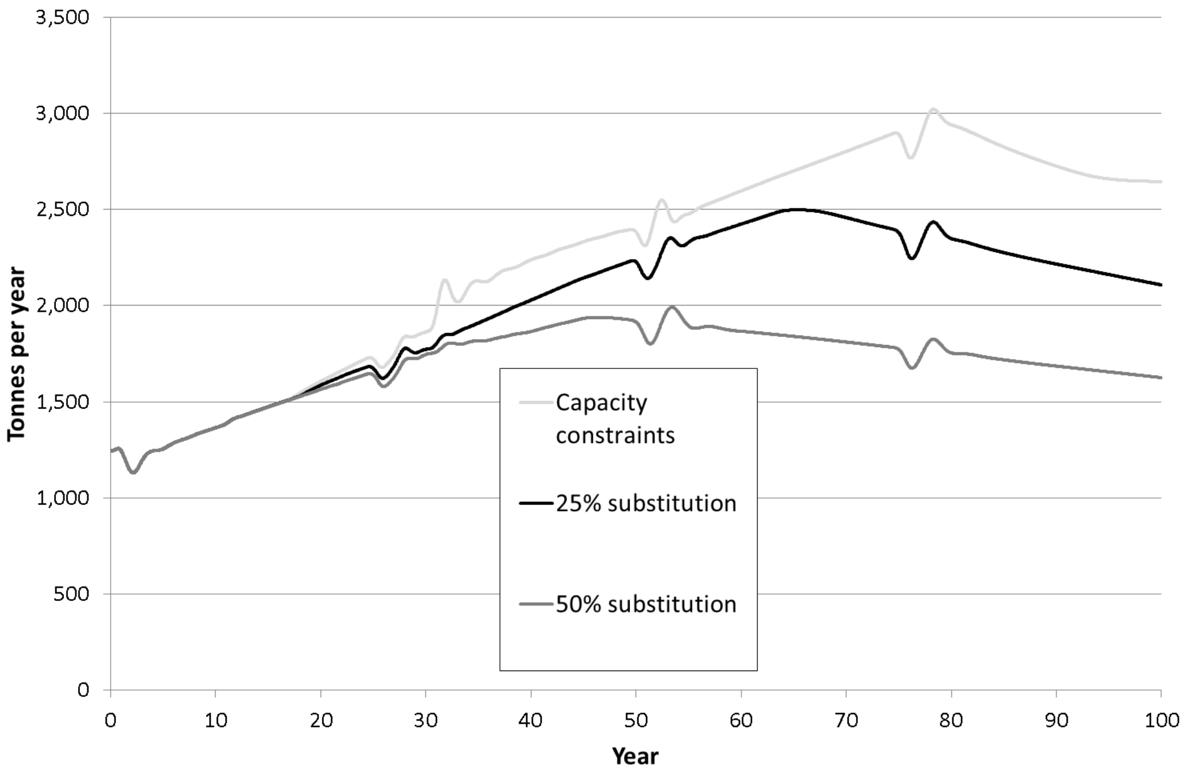
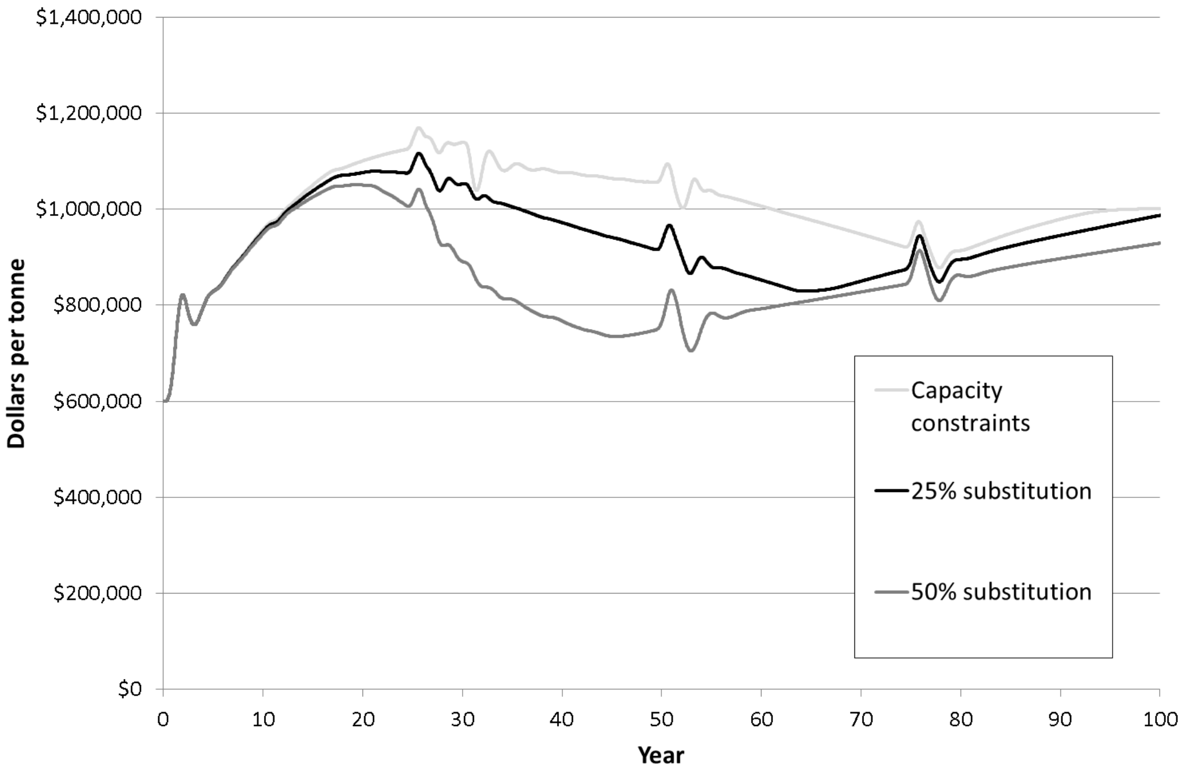


Figure 8.28: Impact of capacity constraint on the indium model price including under conditions of increased substitution



8.5 Summary

This chapter has explored the three models responses to sudden constraints in availability of production capacity. First, the model runs suggest that resources that can be recycled may benefit from this source of supply under periods of unanticipated production capacity constraint. The availability of recycled material which is unaffected by the supply constraint events helps to reduce the supply deficit, buffering the resulting oscillation in both supply and price. This effect is most potent when annual demand is relatively stationary, and in periods when demand and supply are growing this effect is diminished. However, if by-product supply issues are already placing a constraint on capacity then recycled metal is unlikely to be sufficient and the impacts of capacity constraint events will go relatively unmitigated.

The modelling suggests that by-product metal supply can place a significant constraint on availability, causing significant price rises. This is most likely under circumstances where the demand growth for the by-product metal is significantly greater than the growth in supply of the host metal. However, real world demand may not grow as aggressively as modelled here given the optimistic assumptions in the model on CIGS uptake.

Marginal cost is also an important variable with significant implications for the dynamic behaviour of resource systems. In the case of the generic resource model, reducing the marginal cost increases demand, and the increasing marginal cost assumed in the base case is a significant driver of demand and supply decline in the future. In the case of lithium the marginal cost is shown as an important constraint of future production in the model, and assuming a flat marginal cost allows the model to increase production more quickly than the model can establish equilibrium given the model delays. In the case of indium the by-product supply constraints dominate the model outcomes until late in the model timeframe, where assumptions about marginal cost begin to influence the models dynamic behaviour. At this point reducing marginal cost increases supply.

The impact of strategic reserves is marginal. However, increasing strategic reserves reduces the magnitude of oscillation caused by constraint events, and increases the time period over which the oscillation occurs.

Reducing demand through substitution reduces the oscillations associated with capacity constraint. These reductions are in in proportion to the reduction in demand and supply, given that the magnitude of oscillation is a function of the absolute level of supply.

These points and their wider implications are discussed in more detail in the next chapter and Table 8.6 presents them and the section where they are discussed in Chapter 8.

Table 8.6: Summary of key points from model evaluation

Effect	Model			Section
	Generic resource	Lithium	Indium	
Recycling		Reduces commodity price and the impact of capacity constraint events	Impact of recycling suppressed by by-product constraints on production	8.1
By-product			Supply constrained significantly by zinc production rate.	8.2
Marginal cost	Reducing marginal cost increases supply	Reducing marginal cost increases supply and creates oscillation	Reducing marginal cost has no impact until late in the model	8.3
Strategic reserve	Marginally reduces oscillation of constraint event	Marginally reduces oscillation of constraint event	Marginally reduces oscillation of constraint event	8.4.1
Substitution	Reduces magnitude of oscillation of constraint event	Reduces magnitude of oscillation of constraint event	Reduces magnitude of oscillation of constraint event	8.4.2

Chapter 9: Discussion of the research results and conclusions

In Chapter 1 the research question proposed for this thesis was:

How do the resource systems surrounding fossil fuel and metal resources critical to the future energy system behave in response to constrained availability in the future and are these responses similar?

Three resource systems have been explored in detail in Chapters 4, 5 and 6 and three system dynamics models representing these resource systems were created. These models were then tested Chapter 7 and evaluated Chapter 8 to examine their dynamic responses to different initial conditions. These tests and evaluations were designed specifically to examine the models in the context of the research question, examining the similarities and differences between their responses.

In light of the results of this thesis the following conclusions can be made.

1. **While there are significant similarities in the structure of the generic resource, lithium and indium resource systems modelled, the structural differences between these systems has a significant impact on both the future trajectories of supply, demand and the response of these systems to constrained availability in the future. These structural differences are:**
    a. **The differing nature of the drivers of demand;**
    b. **The recyclability of metals in contrast to non-recyclable resource; and**
    c. **The by-product nature of indium recovery.**
2. **The differing demand drivers are likely to create significant growth in lithium and indium demand, while demand for mature resources like fossil fuels is more likely to plateau.**
3. **The recyclability of metals can mitigate the impacts of constraints in primary supply. However, if by-product constraints are also present the benefits of recycling will be diminished.**

4. Strategic reserves need to be very large to have only small impact on the response to constraints in supply, suggesting that this is an ineffective way to mitigate the effects of capacity constraint.
5. Reducing demand through substitution does not have a significant effect on the models response to capacity constraints, but reducing the demand significantly reduces indium price where by-product constraints would otherwise force prices higher

This chapter brings together the findings of the previous chapters. First, this chapter examines the structural similarities and differences between the systems. The structure of these systems is very similar, but there are several features that distinguish them from each other. Next, the similarities in the dynamic behaviours of these three models are examined. As discussed in Section 3.3, the dynamic behaviour of a system is a result of its underlying structure and the impact of the differences in structure on the dynamic behaviour of these models is therefore examined. The chapter then discusses the limitations of the work and recommendations for future research before summarising these findings in the light of the research question.

9.1 Structural similarities and distinctions between the resource system models

9.1.1 Similarities

The creation of the three resource system models is documented in Chapter 7, including details of the conceptual structure of these models, with subsystem and causal loop diagrams. There are many similarities between the three resource systems and these similarities have been represented in the structure of the three models. There are four main similarities in the structure of the three models, summarised in the following points:

- Supply is dealt with similarly in each of the models, being a function of the available capacity, the level of capacity utilisation and the level of demand. This is true of many resource systems, where in the short run capacity is fixed, and the utilisation of that capacity accounts for any short run production dynamics. The quantity of resource in inventory provides a buffer over this short run, and in the three models the changing level of inventory is used as a proxy for the equilibrium between supply and demand, which is fed back into price formation.

- The available capacity and its utilisation is a function of expected profit in all three models, with the expected profit being measured by the difference between price and cost. The quantity of capacity therefore responds to price in all three models, with additional capacity being built in response to rising price, and subject to significant delay representing the time it takes to finance, build and make operational new mining projects. The utilisation of this capacity also responds to the difference between price and cost, and operates with considerably less delay, making adjustments in utilisation a short run response, while adjustments in capacity represent long run responses to expected profit. This structure for capacity and its utilisation overlooks some of the geological factors that dictate future production, such as the discovery process, and the maximum rate at which capacity can be brought on stream. Neither of these factors are constrained in the model, though in the real world these factors have finite, yet hard to measure, limits. To counter this inadequacy, extraction cost is represented through a marginal extraction cost curve (see below) and a depletion rate calculator is included, which can measure the rate at which reserves are depleted. The depletion rates measured look at least plausible, though the length of the time horizon, and the limited sophistication of this metric, mean that these models should not be considered forecasts of long term depletion trajectories.
- Price in all three models is formed as a function of the cost of extraction and the balance between supply and demand. The cost of extraction is represented through a marginal cost curve which responds to the depletion rate and can be set to represent any profile. By increasing costs as a function of marginal resource depletion, some of the geological dynamics of the discovery process and depletion can be represented, but this model structure explicitly assumes that all constraints to production are economic, and that fundamental physical barriers to depletion rate are never experienced. The balance between supply and demand is measured through the inventory coverage, which is the ratio of inventory to demand. The price component has a reference inventory coverage against which the inventory coverage is benchmarked.

- Demand in all models is influenced by price through an elasticity factor. The price elasticity factor represents the impact that a change in price has on demand, with an increase in price typically decreasing demand.

9.1.2 Differences

The three resource models have several differences, not just between the generic resource and metals models but also between the metals themselves. The three main differences in the structure of the three models are presented in the following summary points:

- Although demand in all models is influenced by price in the same way, each model has a distinct type of demand driver. Demand in the generic resource model is driven by economic growth and the demand-reducing influence of the decoupling of the demand/GDP relationship. Demand for metals is a function of the growth of their respective low-carbon technologies. This is in some way linked to the concept of decoupling traditional energy resource demand, as growth in these low-carbon technologies will help reduce demand for oil. As a result of these differing drivers of demand, the generic resource model is likely to produce a peaking or decreasing demand trajectory, while the metals models are likely to have significantly increasing demand during the early years of the model.
- Recycling is another factor which leads the models to differ. Exhausible resources such as fossil fuels have no potential for future recycling in most of their uses while the metals do, and this potential source of future supply is represented in the lithium and indium models. This second source of supply responds to price, along with other variables including the recovery rate of metal from recyclates, and the low-carbon technology lifetime, which creates a significant delay between a metal's primary production and its recovery as recycled metal. The impact of this difference is that recycled material can mitigate the impacts of a capacity constraint event, as this source of supply is separate from primary supply and not subject to the capacity constraint event.
- Finally, the by-product nature of indium's extraction creates a difference between the capacity structure of the indium model and the structure found in the lithium and generic resource models. The result of this difference is that under very high

indium demand conditions the available capacity might become a constraint as zinc capacity grows more slowly than indium demand and limits the rate of indium capacity growth. This growth is a function of the zinc capacity and the content of indium in zinc. Improving the recovery rate of indium from zinc can only play a minor role, as the model already assumes indium recovery of between 80% and 90%. This constraint means that indium is not as free as the resources in the other models to respond to price signals, with the potential that the indium model may generate very high prices due to the inelasticity of indium supply in the face of increasing demand.

9.2 Behavioural similarities and distinctions

In Chapter 7, the dynamic behaviour of the three resources models was tested using extreme conditions testing and sensitivity analysis. The models were then evaluated in Chapter 8 to examine their dynamic behaviour in response to constraints in available capacity. The behaviours in the models are in some respects similar, but notable differences in dynamic behaviour arise in response to the differing structures between the three models. These similarities and differences in dynamic behaviour are examined in the following paragraphs.

9.2.1 Similarities

The following three dynamic model behaviours are examined in all three models:

- Capacity constraint events initially cause a reduction in supply, which is compensated for after a period of time, leading to an oscillation lasting a number of years in the model time horizon. The models then tend back towards an equilibrium state.
- In response to this constrained supply and the resulting reduction in inventory, the price increases in all three models. This price increase leads to a reduction in demand through the price elasticity of demand function.
- These demand and price dynamics are what lead the three models back to an equilibrium state after capacity constraint events.

These similarities are very broad, and within these general trends there are significant differences in the three models' dynamic behaviour.

9.2.2 Differences

The differences between the dynamic behaviour of each of the three models is discussed below, starting with the generic resource model behaviour and then contrasting that case with the lithium and indium models in turn.

The generic resource model

The difference in the structure of the demand subsystems in the three models drives differing dynamic behaviour of demand. Under the initial variable assumptions, the generic resource model demand peaks quickly and declines until the end of the model time horizon. This trend is also reflected in the supply trajectory, given the model's goal to balance supply and demand. This trend is a function of the assumed growth in GDP, the rate of decoupling of the GDP/generic resource demand relationship, and the rising marginal cost of generic resource extraction. The nature of the generic resource model demand trajectory reflects the maturity of traditional energy resources and their uses. For example, given that transport is the major end use of oil, increasing oil demand more quickly than the rate of GDP growth would involve some heroic assumptions regarding the growth of internal combustion engine (ICE) sales and usage. At the same time, an increasing array of policy measures and incentives are aimed at decoupling the relationship between GDP and demand. These policies and measures try to exploit a range of mechanisms to achieve decoupling, including increasing ICE efficacy, replacing ICEs with electric, hybrid, and hydrogen fuel cell technologies and incentivising transport mode shifting. The historically high oil price from 2008 to 2014 has also encouraged consumers to pursue lower use of oil products. Relaxing the assumptions on marginal cost of oil production to reduce the model's future price trajectory leads to much greater oil demand in the later years of the model. Whether the oil price will decrease in the future remains to be seen, but some suggest that developments in unconventional oil could lead to a lower future oil price (Maugeri 2012). In this event it is plausible that oil demand may begin to increase, though this would then be dependent on, the progress of decarbonisation of the global economy, amongst other variables.

In the generic resource model the magnitude of oscillation in response to the capacity constraint events decreases as the supply rate decreases, due to the capacity constraint events being a percentage of supply. However, constraints in available capacity are likely to arise in the traditional energy resource markets due to things like weather events or conflicts in countries producing these resources and these constraints are unlikely to be a function of total global supply. Nevertheless, reducing demand in the generic resource model is still likely to have a beneficial effect on resilience to capacity constraint events as this will limit the exposure of the global economy to unexpected changes in production capacity. Some of the measures that may be implemented to reduce impact of capacity constraints are tested in Chapter 8 and discussed in more detail below.

Lithium model

Demand in the lithium model is structured as a function of the demand for its end-uses, particularly in electric vehicle batteries. Since demand for these vehicles is expected to increase significantly in the coming years, this is likely to lead to significant increase in demand for lithium, and the lithium model replicates this behaviour. This is in contrast to the generic resoruce model and highlights the mature nature of demand for traditional energy resources such as oil and gas, versus the burgeoning demand for lithium in the global transition to a low-carbon future economy.

The lithium model is also distinguished from the generic resource model as a result of its recycling subsystem. Though lithium is not currently recycled at any great scale, a future market with significant quantities of lithium in use, and a pressure for lithium supply is likely to recover significant quantities of recycled lithium from end-of-life products. This recycled lithium is a separate supply stream from primary lithium production and is unlikely to be subject to the same capacity constraint events that primary lithium production is subject to, creating some security of supply chains through diversity of supply.

Recycling in the early years of the model has only a limited capacity to mitigate any capacity constraints in primary production, since the recyclable indium is delayed by the lifetime of in-use products. The current lifetime of lithium-ion electric vehicle batteries is short, but manufacturers hope to improve that in the future to the point where batteries might last in the order of 20 years. Proposed uses for these batteries after their useful life in EVs is likely to extend the time period before batteries are available for recycling (see Section 5.2.3). Given this significant time lag, demand is likely to remain significantly greater than the available recycled material until demand growth plateaus, allowing the quantity of recyclable lithium to 'catch up' that time delay.

Once the demand plateau is reached, recycling appears to significantly mitigate the volatile response to capacity constraint events. Given that this supply stream is not affected by the capacity constraint event, recycling supply can make up the deficit in primary supply, helping to maintain the inventory coverage and smoothing the impact of the event. This suggests that incentivising recycling is a legitimate policy response to increasing a country's resilience to resource capacity constraint events. This is a significant departure from the responses exhibited by the generic resoruce model, which has no recycling capacity and is limited to its price balancing mechanism as a way to respond to capacity constraints.

Indium model

Demand in the indium model is subject to similar subsystem structure of lithium, with latent demand increasing as demand for CIGS thin film PV increases. However, the indium model contains the by-product capacity subsystem, an additional subsystem not found in either the lithium or generic resource system models. The by-product subsystem limits the maximum indium production capacity, based on the production rate of its host metal zinc, and an assumed maximum recovery rate. Given the high CIGS growth rate assumed in the model runs, the by-product constrained indium capacity is insufficient to meet latent demand in the early years of the model time horizon. A proportion of indium is available from mines developed for indium production specifically, but this quantity is assumed to be small and is insufficient to make up the deficit between by-product production and latent demand. The by-product constraints on production capacity, and the significant impact on inventory coverage as a result, forces significant price rises, which in turn limit demand through the price elasticity of demand.

The by-product constrained capacity and its impacts dominate the dynamic behaviour of the model and significantly impair the system's capacity to deal with unforeseen capacity constraint events. Unlike the lithium model, recycled indium is insufficient to compensate for the reduced production during a capacity constraint event. The combined impact of both the ongoing by-product capacity constraints and the additional capacity constraint events is significant. The deficit between the available supply and the level of demand the model would seek with no constraints overwhelms the additional metal available through recycling. The capacity constraint events therefore create large oscillations, more similar to those seen in the generic resource model than those of the lithium model.

The assumption on the growth of CIGS PV modules is ambitious, and though this growth rate may be too optimistic, it does help to illustrate the dynamic behaviour experienced when by-product constraints impinge on the ability to meet future demand. Reducing the level of demand is likely to relieve the symptoms of by-product capacity constraints, as demonstrated in Figure 8.7. If these constraints were experienced in a real world resource system, then demand could be reduced through reducing the material intensity, or increasing substitution of CIGS PV.

Given the findings of the indium and lithium models the implications of capacity constraint events seem very different. Where recycling provides a sufficient buffer for capacity constraint events in the lithium model, it is insufficient to offset the combined capacity constraints of the indium model. This leads to the conclusion that where policy might be applied to improve resilience to capacity constraint events, those policy measures should be tailored to the specific structure of the resource system in question. For a resource system like lithium, where ongoing capacity constraints are not an issue, recycling may be sufficient to offset short, unforeseen capacity constraint events. However, where a long-term ongoing capacity constraint issue exists, as in the case of the by-product recovery of indium, recycling efforts are unlikely to be sufficient to offset the limitations of capacity, and measures aimed at reducing demand are more likely to be effective.

9.3 Reflections on the resource availability debate

The resource availability debate is often characterised as a polar debate between those who predict future resource supply scarcity and prescribe policy intervention, and those who expect the economic mechanisms of resource systems to overcome the challenges of supply constraints, assuming that policy intervention will only disrupt this feedback system. This thesis highlights this aspect of the debate in Chapter 2. However, the modern debate contains a spectrum of analysis and opinion, reflecting the range of approaches and positions in this field of research.

The analysis in this thesis does not focus on absolute questions of whether the availability of exhaustible, non-recyclable resources, lithium or indium will impact the security of civilisation in the future, but it does examine the responses of resource systems to short term unforeseen constraints in capacity. One thing that is apparent from these models is that the ability of the economic feedbacks in resource systems to balance supply and demand, even during periods of unforeseen capacity constraints, is significant. What this does not address is whether accurately anticipating these constraints and taking policy measures in advance could significantly reduce the economic cost of resource system response to scarcity. The very high price resulting from constraint and the time lag in the systems response through efficiency or substitution or other routes to demand reduction means that an economy will pay a price to adapt to scarcity. However, policy measures taken as proactive responses to future scarcity will also have a cost, which may entirely offset any gains resulting from accurate anticipation and reaction to scarcity. It is the author's opinion that this choice between policy intervention and pure market response is at the heart of the resource availability debate. Resolving this debate, however, is outside the scope of this thesis.

9.4 Implications for policy

A number of policy measures may be introduced with the intention of improving the resilience of resource systems to unforeseen constraints in capacity. Two of these measures are examined in Chapter 8:

- The use of a strategic reserve; and
- The encouragement of substitution away from the constrained commodity.

These are discussed in turn below.

9.4.1 Strategic reserve

Many countries and regions maintain a quantity of commodity in reserve, to be released to the market in the event that capacity constraints limit supply. In Chapter 8 tests suggest that increasing the quantity of commodity held in inventory has only a small impact on the response to unforeseen capacity constraints. However, the tests conducted assume that this reserve is utilised in an economically rational way, with the strategic reserve being immediately released when inventory is reduced and price begins to rise. In real commodity markets, where strategic reserves are maintained, the release of reserves is a political decision, and not necessarily taken on a purely economic basis. How these dynamics should be best represented, and how this would change the model results, is unknown.

In the context of the models tested here, the large quantities of reserve needed to create only a small impact on the response to capacity constraint events suggests that this is a relatively inefficient way of increasing system resilience. For traditional energy resources such as oil or gas, the very large quantities consumed on a daily basis means that to physically store a reserve capable of covering even relatively short periods of capacity constraint is a significant undertaking. For metals such as lithium and indium this is likely to be less challenging as their physical quantities are likely to be much smaller, and their solid form is easier to store. Nevertheless, the benefits of managing a strategic stockpile of lithium or indium are unlikely to be significant unless those stockpiles are of a very significant quantity.

9.4.2 Substitution

In the model evaluation conducted in Chapter 8 the impact of substitution on resource systems and their response to capacity constraints is tested. This evaluation suggests that while substitution reduces demand, the capacity constraint event is still a function of the background level of supply.

As discussed in Chapters 4, 5 and 6, there are technological substitutes that could reduce demand for commodities. However, not all resources are equally substitutable. For example, given the volumes of oil consumed daily and the difficulty in producing a substitute for the ICE that provides similar utility at similar cost, it is likely that oil is harder to substitute for than either lithium or indium. Given the relatively undeveloped nature of the low-carbon uses of those metals, and their relatively low economic importance in comparison to oil, the challenge of replacing them is likely to be less significant. The relative difference in the substitutability of different resources may mean that the levels of substitution tested in Chapter 8 are not equally achievable for all types of resources.

The potential for disruptive innovation to drive the substitution of one or all of the commodities is not tested in this thesis. It is plausible that a development in technology could rapidly increase the rate of substitution of any of the resources examined here. However, when such a substitute might arise, how how quickly that substitution event would propagate, or what impact that event would have on other resource demand is difficult to predict and is therefore not modelled here.

Resources that are easily substituted have a significantly greater price elasticity of demand than those that are less easily substituted, and the concept of price elasticity of demand is linked to substitution elasticity such as the cross price elasticity of demand (Stiglitz & Walsh 2006). As the sensitivity analysis conducted in Chapter 7 shows, the price elasticity of demand can have a significant impact on the outcome of the model under conditions of changing price. However, the ideas of substitutability and elasticity of demand are not formally linked in the models in this thesis.

9.5 Limitations of work and usefulness of the approach

The use of system dynamics in the examination of different dynamic resource systems has provided a way to both conceptually and quantitatively compare them. However, it is worth discussing a number of issues that are not addressed by the application of this approach.

9.5.1 Geological limitations

First, while the economic and market aspects are reasonably well covered in the three resource models, the geological aspects of resource recovery are underrepresented. The process of resource discovery and the rate at which those resources are depleted are endogenous variables in other types of models, though it was considered impractical to attempt to create similar model structure in this thesis. The result of this could be that the models attempt to increase production capacity at an unrealistic rate Attempts have been made to identify this exogenously and correct assumptions where necessary.

9.5.2 Technological limitations

In the lithium and indium models, the assumptions relating to the quantity of metal used in low-carbon technologies have a significant impact on metal demand. However, although these variables are tested in the sensitivity analysis in Chapter 7, they are not examined in any detail in Chapter 8. In addition these variables are expected to change over time as technological learning opens up cost saving measures, which have knock-on impacts for metal intensity of products. These learning rates are not reflected in the structure of the lithium and indium models, and the assumptions on metal intensity are static through the model time horizon. For example, in the indium model a single, fixed assumption is made for indium intensity in CIGS PV modules, which helps to maintain simplicity in the demand subsystem. However, the material intensity of indium in CIGS modules is a function of a number of factors that are likely to improve over time as researchers and manufacturers improve knowledge (see Section 6.2.1). Although material intensity assumptions that have been used to represent plausible future conditions this does not allow for the dynamic variability of these variables over time. This use of a single aggregated assumption for intensity also prevents any analysis of which variables are most interesting for future research. However, this omission is unlikely to dramatically alter the broad trends emerging from the model evaluation (Chapter 8).

9.5.3 Economic limitations

The three resource models capture a number of the economic elements that define resource market systems. However, it is worth discussing a number of economic functions that the three resource models don't capture. First, the sensitivity analysis in Chapter 7 highlights the sensitivity of the three models to the price elasticity of demand. Price elasticity of demand was not evaluated independently in Chapter 8. This is in part due to the focus on aspects of the model that are structurally different, and partly due to the difficulty in finding evidence on which to base assumptions of elasticity for lithium and indium. The demand elasticity for each of these resources is assumed to be the same. However, in reality they are liklely to be different. If demand elasticity of one of these resources is overestimated relative to others then demand for that resource is likely to be underestimated.

The relationship between substitutability, price and demand discussed above highlights another economic aspect of these models that could be examined in more depth. For example, in the indium model the by-product constrained capacity leads to significant price increases as the model struggles to maintain inventory coverage. In a real-world system a period of high price would incentivise the improvement of material efficiency in the manufacturing of indium-containing products, and the development of suitable substitutes. However, in the models described here price, is not linked to material intensity in any way, and is linked to substitutes only by the static assumptions on price elasticity of demand. This helps to maintain the simplicity of the models, though the omission likely results in overestimation of material intensity in periods of high price.

9.5.4 Policy limitations

In Chapter 8, some potential policy responses are tested. However, this analysis is brief, and a number of aspects of the policy response to capacity constraint could be further researched. First, when examining the use of strategic reserve to mitigate the impacts of unforeseen capacity constraints, the models assume that a maintained inventory is used in an economically rational way, with any reduction in inventory coverage immediately triggering a proportion of strategic reserve release. However, strategic reserves are managed by policymakers, who may decide on the release of strategic reserves for reasons other than purely economic ones. For example, policy makers may decide to suffer price rises for a period of time to test the normal market responses to capacity constraints, and decide to release strategic reserves only when the market responses fail to reduce price. In addition, traders who base their expected price on a system with full strategic reserves may become significantly less confident in the market if strategic reserves are being depleted and this might significantly affect their price setting process. However, introducing these components to system dynamics models such as these would be challenging, and it is unknown whether they would create a significant bias in the current model results.

To test the implications of increased substitution, the model assumes decreased demand through an assumed declining s-curve to varying degrease of substitution. However, a number of policy initiatives may be used to encourage substitution and these are not modelled. Policy initiatives might include increased or targeted funding for research and development of substitute technologies, subsidy to encourage the deployment of substitute technologies approaching commercial readiness, or the taxation of incumbent technologies to incentivise the market towards substitutes. Initiatives like these will have broad and unintuitive impacts on dynamic systems, including the macroeconomic conditions.

The macroeconomic and cost implication of these possible policy measures are not represented in the three resource models. Although the maintenance of strategic reserves, the funding of research and development, the cost of subsidy and the macroeconomic impacts of taxation will all have implications for the behaviour of the dynamic systems examined here. Ignoring them potentially underrepresents the impacts of policy decisions, and might lead to a overestimation of the effectiveness of using these policy measures. However, incorporating the full range of issues was impractical in this thesis, given the main research objectives laid out in Chapter 1.

9.5.5 Spatial limitations

The three resource system models are focused on global level dynamics. This was the only practical approach, since levels of special disaggregation add significant levels of complexity. However, a number of issues have a spatially disaggregated dimension and it is important to recognise these.

Different countries have very different resources, and countries with the largest quantities of resources are not necessarily the countries with the highest demand. This leads to a distinction between exporters and importers. Countries with such different levels of net export are likely to respond in very different ways to capacity constraint in the global market, and these kinds of divergent behaviours cannot be represented in the models examined here.

Strategic reserves of different commodities are also conducted at a regional level, and release of these reserves is not necessarily coordinated internationally. This may mean that, depending on the nature of capacity constraints, and the different policymakers' sensitivity to them, only a proportion of the total global strategic reserve will likely be made available to the market. This uncertainty will likely affect actors in the resource market such as traders.

The demand for resources is also spatially heterogeneous. This heterogeneity is influenced by a range of factors including regional levels of economic development, regional subsidy and taxation regimes, and the regional price differentials of commodities.

The incentives to recycle are also likely to be regional. Countries with significant endowment of a particular metal resource are unlikely to pursue recycling unless it becomes a cheaper source of that resource than primary production. However, countries that import the majority of their metal resources might be greatly incentivised to foster recycling supply chains to help reduce their regional price and help mitigate the impacts, particularly price impacts, of capacity constraints.

9.5.6 Usefulness of the approach

This thesis uses case study and system dynamics to address the question laid out in Chapter 1. The limitations and criticisms of both case study and system dynamics are presented in Chapter 3. This section deals briefly with the usefulness of both of these research methods.

The use of case study to assess the wide and varied aspects of resource systems has provided a significant level of detail with which to inform the construction of system dynamics models. For the critical metals, analysis of the issues around their availability is often restricted to very high level comparative multi-criteria analyses. These assessments are too shallow and broad to capture all of the important aspects of these systems, and too generic to capture the metal-specific aspects that are so important in defining the structure of these resource systems. A small number of studies do assess specific metals but these assessments often have very limited scopes and simplistic analysis techniques. Case study has therefore been a suitably broad and inclusive approach to evidence gathering.

The use of system dynamics in this thesis has allowed the analysis of complex and dynamic resource systems, combining both aspects of supply and demand. Resource models often treat these aspects separately, and this integrated approach is therefore additional. This is particularly the case for critical metals, which have until recently only received very simplistic analysis methods. The economic aspects of critical metal supply, specifically price and its feedbacks, is largely lacking from the existing literature. Given the significant impact that these economic factors have on the behaviour of these subsystems their omission is a significant issue for much of the existing critical metals analysis.

The research here has also highlighted unanswered research questions that can be pursued in future research. A number of these are addressed below.

9.6 Recommendations for future research

The various limitations discussed above give rise to a number of opportunities for future research, which are discussed below.

9.6.1 Future research into geological issues

Two aspects of the geological nature of resource systems could be further explored in future research. First, the discovery process modelling literature might provide a way to better represent geological factors in resource system models. This could potentially provide some endogenous geological limitations to production growth rates.

Another approach might be to better characterise the cumulative availability curves for resources being modelled. This research would require efforts to understand the costs of production in different geological areas, therefore necessitating collaboration with the extractive industries. Sufficient cooperation from such companies may not be forthcoming as they may be sensitive to the sharing of proprietary information. However, accurate and comprehensive characterisation of cumulative availability curves could significantly improve the accuracy of estimates of marginal production costs and help improve future supply estimates.

9.6.2 Future research into technological variables

The technological variables that define material intensity are aggregated in resource models in this thesis to a single static assumption. In the future it may be useful to disaggregate these in the model and allow for their dynamics over time. This could include their response to changing resource price and their reduction in line with existing learning curves. This approach has been used in other models and examples of this approach could be adapted for incorporation into the resource system models described in this thesis.

Another technological aspect of these models is the recycling subsystem. Aspects of this subsystem create dynamic behaviour that is discussed in Chapter 8, but some issues are not addressed and could possibly be examined in more detail in the future. One factor worth examining in greater depth is the expected product lifetime. The length of useful life of low-carbon technology delays the availability of its components for recycling by the same time period. The greater this period, the more likely it is that valuable resources will be unavailable when most needed. However, given the burgeoning nature of these technologies there is significant uncertainty regarding their useful lifespan. Examining the impact of varying the assumptions could highlight whether this uncertainty is a significant issue for future resource availability assessment.

9.6.3 Future research into economic factors

If future examination of these models was to further examine the economic aspects of resource systems, then more analysis could be undertaken of the implications of price elasticity of demand and its implications for model outputs. The sensitivity analysis in Chapter 7 identified this as a sensitive variable but the topic is not explored further in this thesis. Detailed examination of the impact of changing elasticity could better characterise the sensitivity of these models to that particular assumption. Deeper examination of the relationship between price and demand in the historical data of specific resources could also help define the sensible boundaries for varying these assumptions in the model.

The relationship between price elasticity of demand and substitution is interesting and worth further investigation. In particular it would be worth investigating whether changing assumptions of price elasticity would be sufficient to fully address the relationship between these two factors, or whether a new model structure needed to represent the relationship between elasticity and substitution.

9.6.4 Future research into policy responses

The enhanced modelling of strategic reserves and their use to mitigate the impacts of capacity constraints could provide some very interesting insights. The challenge is to incorporate both spatial and non-economic decision-making protocols into the modelling of strategic reserve management. An agent-based modelling approach might provide the opportunity to represent the different strategic reserves managed by different governments and their differing decision making protocols and approaches. There are examples of incorporating agent based modelling into system dynamics, making it possible to adapt the existing models described in this thesis if desired.

This thesis also touches on the link between future success of decarbonisation policy and the resulting impact on critical metals demand. Significant uptake of electric vehicles and solar PV to generate the electricity that powers them will have a decreasing impact on oil demand. However, decreased demand for oil will reduce its price, changing the economics of deploying decarbonised technologies. This is a feedback loop that could be testable through system dynamics and linking the lithium and indium models to the oil market in some form may provide a tool to examine this premise and explore its impacts.

Finally, a very interesting area of research that this thesis only touches on is whether well timed policy responses in anticipation of supply constraints could significantly reduce the economic costs of market responses and corrections in the face of unforeseen resource scarcity. This is a fundamental question to the wider scarcity debate and is likely hard to resolve. To address such a question would involve a model with greater economic detail than the models described here.

9.7 Summary conclusions in reflection on the research question

In response to the central research question the three resource systems investigated here are sufficiently different in structure that their resulting behaviour in response to capacity constraints is very likely to be different. Therefore the development of systems thinking, models and resulting forecasts of future resource behaviour should always seek to represent the detailed specifics of individual resource systems. Relying on analogy to inform judgments on the likely future of resource systems will lead to flawed heuristics or formalised resource models which will poorly represent the structure and behaviour of resource systems.

The structural differences between the models examined here produce significantly divergent behaviours when projected into the future. The most important of these are:

- The difference in fundamental drivers of demand between the three models;

- The recyclability of metals in comparison to non-recyclable nature of the generic resource model; and
- The by-product nature of indium production in comparison to the lithium and generic resource models, both produced for their own economic value.

The differences in behaviour of the three resource systems are critical for policymakers and should be accounted for in any attempt to respond to availability concerns through policy. The results of this thesis suggest that different resoruces are likely to have very different demand futures, and very different responses to capacity constraint. Any analysis that explicitly or implicitly assumes analogy between resources, and does not account for these differences is likely to form the wrong conclusions.

In response to the objectives laid out in Chapter 1, Table 9.1 presents summary comments.

Table 9.1: The objectives laid out at the beginning of this thesis against the section of the thesis that addresses that objective and any summary comments on that objective's outcomes.

Objective	Section	Summary comments
1: Create an analytical framework	3.1	Approach: Case study➢Conceptual comparison ➢➢Quantitative comparison
2: Modelling methodology	3.3	System dynamics: Provides a platform for both conceptual and quantitative analysis. Feedbacks represent economics of supply and demand well.
3: Key characteristics of generic resource system	4 and 7.2.2	**Supply** - function of demand and capacity **Demand** - function of GDP and price **Price** - function of cost and equilibrium price **Capacity** - function of expected profit
4: Key characteristics of lithium and indium	5, 6 and 7.2.2	Distinguished from generic resource by: **Demand** function of decarbonisation and price **Supply** also function of recycling **Indium** capacity also function of zinc capacity
5: Dynamic structure of generic, lithium and indium resource systems	7.2.2 and 7.3	Causal loop diagrams presented in Section 7.3
6: Define the model formulae and test	7.3 and 7.4	Functional relationships underlying the model structure detailed in Section 7.4
7: Evaluate the models	8	Models suggest that significantly different behaviour arises from the small differences in model structure
8: Conclusions	9	Set out in this chapter

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Appendix A: Glossary

AER	All-Electric Range
BEV	Battery Electric Vehicle
BoE	Bank of England
BRICS	Brazil, Russia, India, China, South Africa
CAFE	Corporate Average Fuel Efficiency
CCC	Committee on Climate Change
CdTe	Cadmium Telluride
CERA	Cambridge Energy Research Associates
CGS	Copper Gallium(di)Selenide
CIGS	Copper Indium Gallium (di)Selenide
CIS	Copper Indium (di)Selenide
DCA	Decline Curve Analysis
DOE	Department of Energy
E&P	Exploration and Production
EC	European Commission
EIA	Energy Information Administration
EOR	Enhanced Oil Recovery
EV	Electric Vehicle
FCV	Fuel Cell Vehicle
Gb	Giga Barrels or billion barrels
GDP	Gross Domestic Product
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
IEA	International Energy Agency
In	Indium
ITO	Indium Tin Oxide
JRC	Joint Research Centre
LCD	Liquid Crystal Display
LED	Light Emitting Diode

li	Lithium
li-ion	Lithium-ion
LPG	Liquid Petroleum Gas
NGL	Natural Gas Liquids
NiMH	Nickel Metal Hydride
ODT	Optimal Depletion Theory
OEM	Original Engine Manufacturer
OPEC	Organisation of Petroleum Exporting Countries
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaic
R/P	Reserve to Production ratio
REE	Rare Earth Elements
SUV	Sports Utility Vehicle
TCO	Transparent Conductive Oxide
UN	United Nations
UNEP	United Nations Environment Programme
URR	Ultimately Recoverable Resource
USGS	United States Geological Survey
WEO	World Energy Outlook
WPA	World Petroleum Assessment
WTI	West Texas Intermediate
xSi	Crystalline Silicon
YTF	Yet-to-find

Appendix B: Units

b	Barrels (sometimes BBLS)
kb	Thousand barrels
Gb	Giga barrels or billion barrels
b/d	Barrels per day
t	tonne
kt	Kilotonne
Mt	Million tonnes
kt/y	Kilotonnes per year
µm	Micrometres
ppm	Parts per million
km	Kilometres
km/h	Kilometres per hour
Ah/g	Ampere-hours per gram
V	volts
kWh	KiloWatt hour
g/Wp	grams per watt peak

Appendix C: The generic resource model - Full model equations and initial conditions

The variables referred to in this annex are defined in the variable tables in Chapter 7, Section 3. This and the following two appendices use Vensim 'off-the-shelf' functions, described in the footnotes here.

Production and capacity utilisation

Stocks

- Inventory= INTEG (production rate-supply rate,Reference Inventory Coverage* Demand)

Units: Tonnes

$$I(t) = \int_{t0}^{t} (P(s) - S(s))\delta s + (i_r D(t_0))$$

Where (s) represents any time between initial time t_0 and the current time t.

- Cumulative Production= INTEG (supply rate, 0)

Units: Tonnes

$$Q(t) = \int_{t0}^{t} \big(S(s)\big)\delta s + Q(t_0)$$

Where (s) represents any time between initial time t_0 and the current time t.

Flows

- production rate=

DELAY3[41]((Production Capacity*capacity utilisation),production delay time)

Units: **undefined**

$$P(t) = DELAY3(\left(P_{Cap}(t)U(t)\right), p)$$

- supply rate=desired supply rate*order fulfilment ratio

Units: Tonnes/y

$$S(t) = S_d(t)O(t)$$

Auxiliaries

- max supply rate=

  Inventory/minimum order processing time

Units: Tonnes/y

$$S_{max}(t) = \frac{I(t)}{o_{min}}$$

- order fulfilment ratio=

  table for order fulfilment(max supply rate/desired supply rate)

[41] DELAY3 is an 'of the shelf' function used in system dynamics to return a third order exponential delay of an input variable for a specific delay time. This is used to vary the delivery time of delayed inputs in order to 'smooth' the delayed inputs availability. This function is equivalent to the equations below, as stated in the VENSIM user manual. Further discussion of this function can be found in Kirkwood (1998)

DELAY3=LV3/DL
LV3=INTEG(RT2-DELAY3,DL*input)
RT2=LV2/DL
LV2=INTEG(RT1-RT2,LV3)
RT1=LV1/DL
LV1=INTEG(input-RT1,LV3)
DL=delay time/3

Units: Dimensionless

$$O(t) = f_1(\frac{S_{max}(t)}{S_d(t)})$$

Where *f* is a function defined by an exogenous lookup table presented below as '*table for order fulfilment'* (Figure 7.20), and

$$W(t) = \frac{S_{max}(t)}{S_d(t)}$$

- desired supply rate=Demand

Units: Tonnes/y

$$S_d(t) = D(t)$$

- Inventory Coverage=Inventory/supply rate

Units: Years

$$I_s(t) = \frac{I(t)}{S(t)}$$

- capacity utilisation=
  SMOOTH[42](indicated capacity utilisation,utilisation adjustment time)

Units: Dimensionless

$$U(t) = SMOOTH(U_i(t), u(t))$$

- indicated capacity utilisation=

[42] SMOOTH is an 'off the shelf' function that is used in system dynamics to create exponential smoothing of a time delay process. This delivers a smooth transition in the time that delayed inputs are available as output. This is equivalent to the equation below as stated in the VENSIM user manual. More information on the smooth function can be found in Kirkwood (1998)

$$U(t) = \int_{t0}^{t} (U_i(s) - U(s)/u(s))\delta s + U_i(t_0)$$

table for effect of markup on utilisation(expected profit)

Units: Dimensionless

$$U_i(t) = f_2(Y_e(t))$$

Where f_2 is a function defined by an exogenous lookup table presented below as '*table for effect of markup on utilisation'*

- expected profit=

  Expected Price/Expected variable costs

Units: Dimensionless

$$Y_e(t) = \frac{V_e(t)}{C_e(t)}$$

- Expected Price=

  SMOOTH(price,delay to form expected price)

Units: $/Unit

$$V_e(t) = SMOOTH(V(t), v_{ed})$$

- Expected variable costs=

  SMOOTH(variable costs,delay to form expected variable costs)

Units: **undefined**

$$C_e(t) = SMOOTH(C(t), c)$$

<u>Exogenous variables</u>

- minimum order processing time

$$o_{min}=0.1$$

Units: Years

- table for order fulfilment ([(0,0)-(4,1)],(0,0),(0.2,0.2),(0.4,0.4),(0.6,0.58),
(0.8,0.73),(1,0.85),(1.2,0.93),(1.4,0.97),(1.6,0.99),(1.8,1),(2,1),(2,1),(4,1))

Units: Dimensionless

- table for effect of markup on utilisation ([(0,0)-(5,1.2)],(0,0),(0.5,0),
(0.75,0.05),(1,0.5),(1.25,0.68),(1.5,0.75),(1.75,0.8),(2,0.84),(2.25,0.87),(2.5,0.9),(2.75,0.93),(3,0.96),(3.25,0.985),(3.5,0.995),(4,1),(4.5,1),(5,1))

Units: Dimensionless

- production delay time

$$p=0.5$$

Units: Years

- utilisation adjustment time

$$u=0.5$$

Units: Years

- delay to form expected price

$$v_e=1$$

Units: Years

- delay to form expected variable costs

$$c_e=1$$

Units: Years

Demand

Stocks

- Latent Demand= INTEG (demand growth,30)

$$D_l(t) = \int_{t0}^{t} D_g(s)\delta s + 30$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: Tonnes

- GDP= INTEG (GDP growth,63)

$$G(t) = \int_{t0}^{t} G_g(s)\delta s + 63$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: **undefined**

Flows

- demand growth=Latent Demand*GDP impact

$$D_g(t) = D_l(t)G_i(t)$$

Units: **undefined**

- GDP growth=GDP*GDP growth rate

$$G_g(t) = G(t)g(t)$$

Units: **undefined**

Auxiliaries

- decoupling=table for decoupling(GDP)

Units: **undefined**

$$K(t) = f_3(G(t))$$

Where f_3 is a function defined by an exogenous lookup table presented below as '*table for decoupling'.*

- GDP impact=(GDP growth rate*0.1)-(GDP growth rate*0.1*decoupling)

$$G_i(t) = (G_r(t)0.1) - (G_r(t)0.1K(t))$$

Units: **undefined**

- Demand=SMOOTHI(Indicated Demand,Demand Adjustment Delay,Reference Demand)

$$D(t) = SMOOTH(D_i(t), d(t), D_r(t)$$

Units: Units/Year

Industry demand adjusts to the indicated demand with a delay,

representing the time required for consumers of the good to find substitutes or change their consumption after a change in price.

- Reference Demand=Latent Demand

$$D_r(t) = D_l(t)$$

Units: Units/Year

Initial value of customer orders.

- Indicated Demand=MIN[43](Maximum Consumption,Reference Demand)*MAX[44](0,1+Demand Curve Slope*(price-reference price)/Reference Demand))

$$D_i(t) = MIN(D_{max}, D_r)MAX\left(0{,}1 + B\frac{V(t) - v}{Dr}\right)$$

Units: Units/Year

The indicated demand for the commodity given the current price.

Indicated demand is the demand consumers would like given the current price. Actual demand adjusts to indicated demand with a delay. The demand curve is linear, with slope set so that the elasticity of demand at the reference price is equal to the reference industry demand elasticity, set by the user.

- Demand Curve Slope=(-Reference Demand*Reference Demand Elasticity)/(reference price)

$$B = (-D_r e_d)/v$$

Units: Unit*Units/($*Year)

The slope of the industry demand curve, as a function of the

price elasticity at the reference price level

<u>Exogenous variables</u>

- reference price

[43] 'MIN' is an 'off the shelf' function that returns the lowest of two values A and B in the form MIN (A,B)

[44] 'MAX' is an 'off the shelf' function similar to 'MIN' that returns the highest of two values A and B in the form MAX(A,B)

$$v = 100$$

Units: **undefined**

- GDP growth rate

$$G_r = 0.01$$

Units: **undefined**

- table for decoupling([(63,0)-(200,2)],(63,0),(73,0.036),(83,0.094),(93,0.238),(103,0.538),(113,1),(123,1.462),(133,1.762),(143,1.906),(153,1.964),(163,1.986),(173,2),(200,2))

Units: **undefined**

- Demand Adjustment Delay

$$d=0.5$$

Units: Years

The average time required for consumer demand to respond to a change in price.

- Maximum Consumption

$$D_{max}=1000$$

Units: Units/Year

The maximum demand for the commodity, no matter how low price goes.

- Reference Demand Elasticity

$$e_d=0.5$$

Units: Dimensionless

Demand elasticity at the reference price

Price

Stocks

- Traders' Expected Price= INTEG (Change in Traders' Expected Price, initial price)

$$V_e(t) = \int_{t0}^{t} V_{ec}(s)\delta s + V(t_0)$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: $/Unit

The price market makers and traders believe would clear the market if demand and supply were in balance, and no other pressures to change price existed.

Flows

- Change in Traders' Expected Price=(indicated price - Traders' Expected Price)/Time to Adjust Traders' Expected Price

$$V_{ec}(t) = \frac{V(t_0) - V_e(t)}{v_d}$$

Units: $/Unit/Year

Traders' beliefs about the underlying equilibrium price adjust in response to the gap between the indicated price and the current belief. Expected underlying price adjusts via first-order adaptive expectations to the actual price, constrained to be greater than a minimum level.

Auxiliaries

- Effect of Costs on Price=1+Sensitivity of Price to Costs*((Expected Production Costs/Traders' Expected Price)-1)

$$\boldsymbol{V_{cp}(t) = 1 + v_{cp}(W_2(t) - 1)}$$

Where

$$W_2(\boldsymbol{t}) = \frac{\boldsymbol{C_{pe}(t)}}{\boldsymbol{V_e(t)}}$$

Units: **undefined**

- indicated price=MAX(Minimum Price,price)

$$V_i(t) = MAX(V_{\min}\quad(t), V(t))$$

Units: **undefined**

- price=MAX(0,(Traders' Expected Price*Effect of Inventory Coverage on Price*Effect of Costs on Price))

$$V(t) = MAX(0, \left(V_e(t)V_{is}I(t)V_{cp}(t)\right))$$

Units: $/Unit

- Effect of Inventory Coverage on Price=Relative Inventory Coverage^Sensitivity of Price to Inventory Coverage

$$V_{is}(t) = I_\rho(t)^{v_{is}}$$

Units: Dimensionless

Price rises when inventory coverage is less than normal, and falls when it is greater. The Sensitivity of Price to Inventory Coverage controls the magnitude of the response.

- Relative Inventory Coverage=Perceived Inventory Coverage/Reference Inventory Coverage

$$I_\rho(t) = \frac{I_{sp}(t)}{i_r}$$

Units: Dimensionless

Perceived inventory coverage relative to the normal level needed to ensure desired service levels in the market.

- Perceived Inventory Coverage= SMOOTH(Inventory Coverage,Coverage Perception Time)

$$I_{sp}(t) = SMOOTH(I_s(t), i_s(t))$$

Units: Years

Perceived coverage is formed by smoothing actual coverage. It takes time to recognize changes in coverage.

- Minimum Price=Unit Costs

$$V_{min}(t) = Y(t)$$

Units: $/Unit

Trader's do not believe prices can fall below the variable cost per unit of production.

<u>Exogenous Variables</u>

- initial price=100

$$V_{t0} = 100$$

Units: **undefined**

- Sensitivity of Price to Costs

$$V_{cp} = 0.5$$

Units: Dimensionless

Controls the response of price to discrepancies between the expected price and the expected cost of production.

- Time to Adjust Traders' Expected Price=1

$$v_d = 1$$

Units: Years

Trader's belief about the underlying equilibrium price adjust to actual prices over this period.

- Sensitivity of Price to Inventory Coverage=

$$V_{is} = -1$$

Units: Dimensionless

Controls the response of price to inventory coverage. Must be negative for high inventory to lead to lower prices. Higher absolute values lead to greater price changes for any given inventory coverage level.

- Coverage Perception Time

$$i_s = 0.167$$

Units: Years

The average time required to perceive and react to inventory coverage.

- Reference Inventory Coverage

$$I_\rho = 0.2$$

Units: Years

The normal inventory coverage required to ensure desired levels

of service (the desired ability to fill orders).

Capacity

Stocks

- Capacity Stock= INTEG (acquisition rate-Discard Rate,(Reference Demand/indicated capacity utilisation)/Capital Productivity)

$$C_{ap}(t) = \int_{t0}^{t} (A(s) - J(s))\delta s + \frac{D_r(t)/U_i(t)}{C_{app}}$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: Capacity Units

The capital stock accumulates acquisitions less discards.

Initialized to the initial equilibrium level.

Flows

- acquisition rate=Desired Acquisition Rate

$$A(t)=A_d(t)$$

Units: **undefined**

- Discard Rate=Capacity Stock/Average Life of Capacity

$$J(t) = \frac{C_{ap}(t)}{C_{apL}}$$

Units: Capacity Units/Year

The average life of capacity determines the rate at which it decays and is discarded.

Auxiliaries

- Production Capacity=Capacity Stock*Capital Productivity

$$P_{Cap}(t) = C_{ap}(t)C_{app}$$

Units: Gt/y

Production capacity is determined by total capital stock in service and its productivity.

- Adjustment for Capacity=(Desired Capacity - Capacity Stock)/Capacity Adjustment Time

$$Z(t) = \frac{C_{apd}(t) - C_{ap}(t)}{t_{cap}}$$

Units: Capacity Units/Year

Producers seek to close the gap between desired and actual capacity over the Capacity Adjustment Time

- Desired Acquisition Rate=MAX(0, Expected Discard Rate + Adjustment for Capacity)

$$A_d(t) = MAX(0, J_e(t) + Z(t))$$

Units: Capacity Units/Year

The rate at which new capacity should be acquired, given the expected discard rate and the adjustment to bring the stock of capacity in line with the desired stock.

- Expected Discard Rate=Discard Rate

$$J_e(t) = J(t)$$

Units: Capacity Units/Year

The expected discard rate is assumed to equal the actual discard rate.

Exogenous variables

- Capital Productivity

$$C_{app}=1$$

Units: Unit/Year/Capacity Units

The productivity of capital is assumed exogenous and constant. One unit of capital is defined as the capital stock required to generate one unit of output per year (at normal utilization), so productivity =1.

- Average Life of Capacity

$$C_{apL}=20$$

Units: Years

The average life of capacity.

- Capacity Adjustment Time

$$t_{cap}=3$$

Units: Years

The average time over which producers seek to close the gap between desired and actual capacity.

Desired capacity

Auxiliaries

- Desired Capacity=

  Capacity Stock*(1+Sensitivity of Investment to Exp Profit*(Effect of Expected Profit on Desired Capacity-1))

$$C_{apd}(t) = C_{ap}(t)(1 + C_{apdy}(Y_{capd}(t) - 1))$$

Units: Capacity Units

Desired capital stock is based on current capital, adjusted up or down according to the expected profitability of new investment.

- Effect of Expected Profit on Desired Capacity=Table for Effect of Expected Profit on Desired Capacity(Expected Profitability of New Investment)

Units: Dimensionless

$$Y_{capd}(t) = f_4(Y_{cap}(t))$$

Where f_4 is a function defined by an exogenous lookup table presented below as '*table for effect of expected profit on desired capacity*'

Desired capacity is adjusted above or below current capacity in response to the expected profitability of new investment.

- Expected Profitability of New Investment=(Long Run Expected Price - Expected Production Costs)/Long Run Expected Price

$$Y_{cap}(t) = \frac{V_{el}(t) - C_{pe}(t)}{V_{el}(t)}$$

Units: Dimensionless

The expected profitability of new investment is the difference between long run price expectations and expectations for the unit costs of new investment, including fixed and variable costs. Fixed cost includes the normal profit margin required. The expected profit is normalized by price to give a dimensionless measure of profit, analogous to the percentage return per unit.

- Long Run Expected Price=SMOOTH(price,Time to Adjust Long Run Price Expectations)

$$V_{el}(t) = SMOOTH(V(t), v_{el})$$

Units: $/Unit

Long run price expectations are formed by first-order

exponential smoothing (adaptive expectations).

- Expected Production Costs=SMOOTH(Unit Costs,Time to Adjust Expected Costs)

$$C_{pe}(t) = SMOOTH(C_u(t), c_e)$$

Units: **undefined**

- Unit Costs=cumulative availability curve(Cumulative Production)

Units: $/Unit

$$C_u(t) = f_5(Q(t))$$

Where f_5 is a function defined by an exogenous lookup table presented below as '*cumulative availability curve'*

Unit costs including fixed and variable costs.

- variable costs=Unit Costs*variable cost fraction

$$C(t) = C_u(t)C_{vu}$$

Units: **undefined**

Exogenous variables

- Sensitivity of Investment to Exp Profit

$$C_{apdy}=1$$

Units: Dimensionless

The Sensitivity of Desired Capacity to expected profit.

- Table for Effect of Expected Profit on Desired Capacity([(-1,0)-(1,2)],(-1,0),(-0.75,0.1),(-0.5,0.3),(-0.25,0.67),(0,1),(0.25,1.25),(0.5,1.45),(0.75,1.6),(1,1.7))

Units: Dimensionless

The adjustment of desired capacity above or below the current level depends on this function of the expected profitability of new investment.\!\!\!

- Time to Adjust Long Run Price Expectations

$$v_{el}=2$$

Units: Years

The time required to update long-run price expectations.

- Time to Adjust Expected Costs

$$c_e=2$$

Units: Year

The time required for market participants to glean information about costs and adjust their beliefs to the new information. Since cost information is difficult to get, unreliable, and differs from producer to producer, expected costs adjust slowly.

- cumulative availability curve([(0,0)-(3500,200)],(0,100),(500,110),(1000,120),(1500,130),(2000,140),(2500,150),(3000,160),(3500,170))

Units: $/t

- variable cost fraction

C_{vu} =0.4

Units: **undefined**

Depletion Rate

Stock

Resources= INTEG (-depletion,initial resources)

$$X(t) = \int_{t0}^{t} \big(-S(s)\big)\delta s + x_0$$

Units: **undefined**

Flow

- depletion=supply rate= desired supply rate*order fulfilment ratio

$$S(t) = S_d(t)O(t)$$

Units: Tonnes/y

Auxiliaries

- depletion rate=depletion/resources*100

$$X_s(t) = \frac{S(t)}{X(t)}100$$

Units: **undefined**

Exogenous variables

- initial resources

$$x_0 = 3500$$

Units: **undefined**

Appendix D: The lithium model - Full model equations and initial conditions

The variables referred to in this annex are defined in the variable tables in Chapter 7, Section 3.

Production and capacity utilisation

Stocks

- Inventory= INTEG (production rate + recycled Li)-supply rate,Reference Inventory Coverage* Demand)

Units: Gt

$$I(t) = \int_{t0}^{t} ((P(s) + R(s)) - S(s))\delta s + (i_r D(t_0))$$

Where (*s*) represents any time between initial time t_0 and the current time *t*.

- Cumulative Production= INTEG (supply rate, 0)

Units: Tonnes

$$Q(t) = \int_{t0}^{t} \big(S(s)\big)\delta s + Q(t_0)$$

Where (*s*) represents any time between initial time t_0 and the current time *t*.

Flows

- production rate=

DELAY3[45]((Production Capacity*capacity utilisation),production delay time)

Units: **undefined**

$$P(t) = DELAY3(\left(P_{Cap}(t)U(t)\right), p)$$

- supply rate=desired supply rate*order fulfilment ratio

Units: Tonnes/y

$$S(t) = S_d(t)O(t)$$

Auxiliaries

- max supply rate=

  Inventory/minimum order processing time

Units: Tonnes/y

$$S_{max}(t) = \frac{I(t)}{o_{min}}$$

- order fulfilment ratio=

  table for order fulfilment(max supply rate/desired supply rate)

[45] DELAY3 is an 'of the shelf' function used in system dynamics to return a third order exponential delay of an input variable for a specific delay time. This is used to vary the delivery time of delayed inputs in order to 'smooth' the delayed inputs availability. This function is equivalent to the equations below, as stated in the VENSIM user manual. Further discussion of this function can be found in Kirkwood (1998)

DELAY3=LV3/DL
LV3=INTEG(RT2-DELAY3,DL*input)
RT2=LV2/DL
LV2=INTEG(RT1-RT2,LV3)
RT1=LV1/DL
LV1=INTEG(input-RT1,LV3)
DL=delay time/3

Units: Dimensionless

$$O(t) = f_1(\frac{S_{max}(t)}{S_d(t)})$$

Where *f* is a function defined by an exogenous lookup table presented below as '*table for order fulfilment'* (Figure 7.20), and

$$W(t) = \frac{S_{max}(t)}{S_d(t)}$$

- desired supply rate=Demand

Units: Tonnes/y

$$S_d(t) = D(t)$$

- Inventory Coverage=Inventory/supply rate

Units: Years

$$I_s(t) = \frac{I(t)}{S(t)}$$

- capacity utilisation=
  SMOOTH[46](indicated capacity utilisation,utilisation adjustment time)

Units: Dimensionless

$$U(t) = SMOOTH(U_i(t), u(t))$$

- indicated capacity utilisation=

[46] SMOOTH is an 'off the shelf' function that is used in system dynamics to create exponential smoothing of a time delay process. This delivers a smooth transition in the time that delayed inputs are available as output. This is equivalent to the equation below as stated in the VENSIM user manual. More information on the smooth function can be found in Kirkwood (1998)

$$U(t) = \int_{t0}^{t} (U_i(s) - U(s)/u(s))\delta s + U_i(t_0)$$

table for effect of markup on utilisation(expected profit)

Units: Dimensionless

$$U_i(t) = f_2(Y_e(t))$$

Where f_2 is a function defined by an exogenous lookup table presented below as '*table for effect of markup on utilisation'*

- expected profit=

  Expected Price/Expected variable costs

Units: Dimensionless

$$Y_e(t) = \frac{V_e(t)}{C_e(t)}$$

- Expected Price=

  SMOOTH(price,delay to form expected price)

Units: $/Unit

$$V_e(t) = SMOOTH(V(t), v_{ed})$$

- Expected variable costs=

  SMOOTH(variable costs,delay to form expected variable costs)

Units: **undefined**

$$C_e(t) = SMOOTH(C(t), c)$$

<u>Exogenous variables</u>

- minimum order processing time

$$o_{min}=0.1$$

Units: Years

- table for order fulfilment ([(0,0)-(4,1)],(0,0),(0.2,0.2),(0.4,0.4),(0.6,0.58),(0.8,0.73),(1,0.85),(1.2,0.93),(1.4,0.97),(1.6,0.99),(1.8,1),(2,1),(2,1),(4,1))

Units: Dimensionless

- table for effect of markup on utilisation ([(0,0)-(5,1.2)],(0,0),(0.5,0),(0.75,0.05),(1,0.5),(1.25,0.68),(1.5,0.75),(1.75,0.8),(2,0.84),(2.25,0.87),(2.5,0.9),(2.75,0.93),(3,0.96),(3.25,0.985),(3.5,0.995),(4,1),(4.5,1),(5,1))

Units: Dimensionless

- production delay time

$$p=0.5$$

Units: Years

- utilisation adjustment time

$$u=0.5$$

Units: Years

- delay to form expected price

$$v_e=1$$

Units: Years

- delay to form expected variable costs

$$c_e=1$$

Units: Years

Demand

Stocks

- Annual EV sales= INTEG (annual EV sales growth,100000)

$$L_s(t) = \int_{t0}^{t} L_{sg}(s)\delta s + 100000$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: vehicles

Flows

- annual EV sales growth=Annual EV sales*fractional rate

$$L_{sg}(t) = L_S(t)L_r(t)$$

Units: **undefined**

Auxiliaries

- Li Demand=SMOOTHI(Indicated Li Demand,Demand Adjustment Delay,Reference Li Demand)

$$D(t) = SMOOTHI(D_i(t), d(t), D_r(t))$$

Units: Units/Year

Industry demand adjusts to the indicated demand with a delay,

representing the time required for consumers of the good to find substitutes or change their consumption after a change in price.

- Reference Li Demand=Latent Li Demand

$$D_r(t) = D_l(t)$$

Units: Units/Year

Initial value of customer orders.

- Indicated Li Demand=MIN(Maximum Consumption,Reference Li Demand*MAX(0,1+Demand Curve Slope*(Li price-reference price)/Reference Li Demand))

$$D_i(t) = MIN(D_{max}, D_r)MAX\left(0{,}1 + B\frac{V(t) - v}{Dr}\right)$$

Units: Units/Year

The indicated demand for the commodity given the current price.

Indicated demand is the demand consumers would like given the current price. Actual demand adjusts to indicated demand with a delay. The demand curve is linear, with slope set so that the elasticity of demand at the reference price is equal to the reference industry demand elasticity, set by the user.

- Demand Curve Slope=(-Reference Demand*Reference Demand Elasticity)/(reference price)

$$B(t) = (-D_r(t\ )e_d)/v)$$

Units: Unit*Units/($*Year)

The slope of the industry demand curve, as a function of the price elasticity at the reference price level

- EV Li demand=
  Annual EV sales*Li intensity

$$D_{lm}(t) = L_s(t)m_i$$

Units: tons/y

- fractional rate=max EV market growth rate*(1-Annual EV sales/max EV annual sales)

$$L_r(t) = L_{gmax}(W_1(t))$$

Where

$$W_1(t) = 1 - \frac{L_{sg}(t)}{l_{smax}}$$

Units: **undefined**

- latent Li demand=EV Li demand+Other Li Demand

$$D_l(t) = D_{lm}(t) + D_{om}(t)$$

Units: **undefined**

<u>Exogenous variables</u>

- reference price

$$v = 5{,}000$$

Units: **undefined**

- Demand Adjustment Delay

d=0.5

Units: Years

The average time required for consumer demand to respond to a change in price.

- Maximum Consumption

$$d_{max}=1000$$

Units: Units/Year

The maximum demand for the commodity, no matter how low price goes.

- Reference Demand Elasticity

$$e_d=0.5$$

Units: Dimensionless

Demand elasticity at the reference price

- Max EV annual sales

$$l_{smax} = 3e + 7$$

Units: vehicles

- Max EV market growth rate

$$l_{gmax} = 0.2$$

Units: **undefined**

- Other Li Demand

$$d_{om}=35000$$

Units: tons

- Li Intensity

$$m_i=0.00798$$

Units: Tonnes per vehicle

Price

Stocks

- Traders' Expected Price= INTEG (Change in Traders' Expected Price, initial price)

$$V_e(t) = \int_{t0}^{t} V_{ec}(s)\delta s + V(t_0)$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: $/Unit

The price market makers and traders believe would clear the market if demand and supply were in balance, and no other pressures to change price existed.

Flows

- Change in Traders' Expected Price=(indicated price - Traders' Expected Price)/Time to Adjust Traders' Expected Price

$$V_{ec}(t) = \frac{V(t_0) - V_e(t)}{v_d}$$

Units: $/Unit/Year

Traders' beliefs about the underlying equilibrium price adjust in response to the gap between the indicated price and the current belief. Expected underlying price adjusts via first-order adaptive expectations to the actual price, constrained to be greater than a minimum level.

Auxiliaries

- Effect of Costs on Price=1+Sensitivity of Price to Costs*((Expected Production Costs/Traders' Expected Price)-1)

$$\boldsymbol{V_{cp}(t) = 1 + v_{cp}(W_2(t) - 1)}$$

Where

$$W_2(\boldsymbol{t}) = \frac{\boldsymbol{C_{pe}(t)}}{\boldsymbol{V_e(t)}}$$

Units: **undefined**

- indicated price=MAX(Minimum Price,price)

$$V_i(t) = MAX(V_{\min}\quad(t), V(t))$$

Units: **undefined**

- price=MAX(0,(Traders' Expected Price*Effect of Inventory Coverage on Price*Effect of Costs on Price))

$$V(t) = MAX\left(0, \left(V_e(t)V_{is}I(t)V_{cp}(t)\right)\right)$$

Units: $/Unit

- Effect of Inventory Coverage on Price=Relative Inventory Coverage^Sensitivity of Price to Inventory Coverage

$$V_{is}(t) = I_\rho(t)^{v_{is}}$$

Units: Dimensionless

Price rises when inventory coverage is less than normal, and falls when it is greater. The Sensitivity of Price to Inventory Coverage controls the magnitude of the response.

- Relative Inventory Coverage=Perceived Inventory Coverage/Reference Inventory Coverage

$$I_\rho(t) = \frac{I_{sp}(t)}{i_r}$$

Units: Dimensionless

Perceived inventory coverage relative to the normal level needed to ensure desired service levels in the market.

- Perceived Inventory Coverage= SMOOTH(Inventory Coverage,Coverage Perception Time)

$$I_{sp}(t) = SMOOTH(I_s(t), i_s(t))$$

Units: Years

Perceived coverage is formed by smoothing actual coverage. It takes time to recognize changes in coverage.

- Minimum Price=Unit Costs

$$V_{min}(t) = Y(t)$$

Units: $/Unit

Trader's do not believe prices can fall below the variable cost per unit of production.

Exogenous Variables

- initial price=100

$$V_{t0} = 100$$

Units: **undefined**

- Sensitivity of Price to Costs

$$V_{cp} = 0.5$$

Units: Dimensionless

Controls the response of price to discrepancies between the expected price and the expected cost of production.

- Time to Adjust Traders' Expected Price=1

$$v_d = 1$$

Units: Years

Trader's belief about the underlying equilibrium price adjust to actual prices over this period.

- Sensitivity of Price to Inventory Coverage=

$$V_{is} = -1$$

Units: Dimensionless

Controls the response of price to inventory coverage. Must be negative for high inventory to lead to lower prices. Higher absolute values lead to greater price changes for any given inventory coverage level.

- Coverage Perception Time

$$i_s = 0.167$$

Units: Years

The average time required to perceive and react to inventory coverage.

- Reference Inventory Coverage

$$I_\rho = 0.2$$

Units: Years

The normal inventory coverage required to ensure desired levels

of service (the desired ability to fill orders).

Capacity

Stocks

- Capacity Stock= INTEG (acquisition rate-Discard Rate,(Reference Demand/indicated capacity utilisation)/Capital Productivity)

$$C_{ap}(t) = \int_{t0}^{t} (A(s) - J(s))\delta s + \frac{D_r(t) / U_i(t)}{C_{app}}$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: Capacity Units

The capital stock accumulates acquisitions less discards.

Initialized to the initial equilibrium level.

Flows

- acquisition rate=Desired Acquisition Rate

$$A(t)=A_d(t)$$

Units: **undefined**

- Discard Rate=Capacity Stock/Average Life of Capacity

$$J(t) = \frac{C_{ap}(t)}{C_{apL}}$$

Units: Capacity Units/Year

The average life of capacity determines the rate at which it decays and is discarded.

Auxiliaries

- Production Capacity=Capacity Stock*Capital Productivity

$$P_{Cap}(t) = C_{ap}(t)C_{app}$$

Units: Gt/y

Production capacity is determined by total capital stock in service and its productivity.

- Adjustment for Capacity=(Desired Capacity - Capacity Stock)/Capacity Adjustment Time

$$Z(t) = \frac{C_{apd}(t) - C_{ap}(t)}{t_{cap}}$$

Units: Capacity Units/Year

Producers seek to close the gap between desired and actual capacity over the Capacity Adjustment Time

- Desired Acquisition Rate=MAX(0, Expected Discard Rate + Adjustment for Capacity)

$$A_d(t) = MAX(0, J_e(t) + Z(t))$$

Units: Capacity Units/Year

The rate at which new capacity should be acquired, given the expected discard rate and the adjustment to bring the stock of capacity in line with the desired stock.

- Expected Discard Rate=Discard Rate

$$J_e(t) = J(t)$$

Units: Capacity Units/Year

The expected discard rate is assumed to equal the actual discard rate.

Exogenous variables

- Capital Productivity

$$C_{app}=1$$

Units: Unit/Year/Capacity Units

The productivity of capital is assumed exogenous and constant. One unit of capital is defined as the capital stock required to generate one unit of output per year (at normal utilization), so productivity =1.

- Average Life of Capacity

$$C_{apL}=20$$

Units: Years

The average life of capacity.

- Capacity Adjustment Time

$$t_{cap}=3$$

Units: Years

The average time over which producers seek to close the gap between desired and actual capacity.

Desired capacity

Auxiliaries

- Desired Capacity=

Capacity Stock*(1+Sensitivity of Investment to Exp Profit*(Effect of Expected Profit on Desired Capacity-1))

$$C_{apd}(t) = C_{ap}(t)(1 + C_{apdy}(Y_{capd}(t) - 1))$$

Units: Capacity Units

Desired capital stock is based on current capital, adjusted up or down according to the expected profitability of new investment.

- Effect of Expected Profit on Desired Capacity=Table for Effect of Expected Profit on Desired Capacity(Expected Profitability of New Investment)

Units: Dimensionless

$$Y_{capd}(t) = f_4(Y_{cap}(t))$$

Where f_4 is a function defined by an exogenous lookup table presented below as '*table for effect of expected profit on desired capacity*'

Desired capacity is adjusted above or below current capacity in response to the expected profitability of new investment.

- Expected Profitability of New Investment=(Long Run Expected Price - Expected Production Costs)/Long Run Expected Price

$$Y_{cap}(t) = \frac{V_{el}(t) - C_{pe}(t)}{V_{el}(t)}$$

Units: Dimensionless

The expected profitability of new investment is the difference between long run price expectations and expectations for the unit costs of new investment, including fixed and variable costs. Fixed cost includes the normal profit margin required. The expected profit is normalized by price to give a dimensionless measure of profit, analogous to the percentage return per unit.

- Long Run Expected Price=SMOOTH(price,Time to Adjust Long Run Price Expectations)

$$V_{el}(t) = SMOOTH(V(t), v_{el})$$

Units: $/Unit

Long run price expectations are formed by first-order

exponential smoothing (adaptive expectations).

- Expected Production Costs=SMOOTH(Unit Costs,Time to Adjust Expected Costs)

$$C_{pe}(t) = SMOOTH(C_u(t), c_e)$$

Units: **undefined**

- Unit Costs=cumulative availability curve(Cumulative Production)

Units: $/Unit

$$C_u(t) = f_6(Q(t))$$

Where f_6 is a function defined by an exogenous lookup table presented below as '*cumulative availability curve'*

Unit costs including fixed and variable costs.

- variable costs=Unit Costs*variable cost fraction

$$C(t) = C_u(t)C_{vu}$$

Units: **undefined**

Exogenous variables

- Sensitivity of Investment to Exp Profit

C_{apdy}=1

Units: Dimensionless

The Sensitivity of Desired Capacity to expected profit.

- Table for Effect of Expected Profit on Desired Capacity([(-1,0)-(1,2)],(-1,0),(-0.75,0.1),(-0.5,0.3),(-0.25,0.67),(0,1),(0.25,1.25),(0.5,1.45),(0.75,1.6),(1,1.7))

Units: Dimensionless

The adjustment of desired capacity above or below the current level depends on this function of the expected profitability of new investment.\!\!\!

- Time to Adjust Long Run Price Expectations

v_{el}=2

Units: Years

The time required to update long-run price expectations.

- Time to Adjust Expected Costs

c_e=2

Units: Year

The time required for market participants to glean information about costs and adjust their beliefs to the new information. Since cost information is difficult to get, unreliable, and differs from producer to producer, expected costs adjust slowly.

- cumulative availability curve [(0,0)-(4e+008,40000)],(0,2200),(3.2e+007,22000),(4e+008,22000) Units: $/t

- variable cost fraction

C_{vu} =0.4

Units: **undefined**

Recycling

Auxiliaries

- effect of estimated profit on EV recycling=table for effect of perceived profit on recycling(Expected Price/cost of EV recycling)

$$R_y(t) = f_7 \frac{V_e(t)}{r_c}$$

Where f_7 is a function defined by an exogenous lookup table presented below as '*table for effect of perceived profit on recycling'*

Units: **undefined**

- effect of estimated profit on other recycling=table for effect of perceived profit on recycling(Expected Price/cost of other recycling)

$$\boldsymbol{R_{oy}(t) = f_7(W_3(t))}$$

Where f_7 is a function defined by an exogenous lookup table presented below as '*table for effect of perceived profit on recycling'* and

$$W_3(t) = \frac{V_e(t)}{R_O(t)}$$

Units: **undefined**

- EV Li end-of-life=DELAY FIXED[47] (EV Li demand,EV lifetime,0)

$$M(t) = DELAY\ FIXED(D_{lm}(t), e_{ol}, 0)$$

[47] DELAY FIXED is an 'off the shelf' function which returns the value of the 'input' delayed by the 'delay time'. The 'input' is the value of the variable on the left-hand side of the parentheses. The 'delay time' is the central constant in parentheses. On the right of the equation is the 'initial value', in this case 0.

Units: **undefined**

- EV recycling=EV Li end-of-life*effect of estimated profit on EV recycling* EV recycling rate

$$R_m(t) = M(t)R_y(t)r_r$$

Units: **undefined**

- other demand recycling=other LI end-of-life*other recycling rate*effect of estimated profit on other recycling

$$R_o(t) = M(t)o_r(t)R_{oy}$$

Units: **undefined**

- other LI end-of-life=DELAY FIXED(Other Li Demand,other lifetime,0)

$$O(t) = DELAY\ FIXED(D_o(t), o, 0)$$

Units: **undefined**

- recycled Li=DELAY3((EV recycling+other demand recycling),recycling delay time)

$$R(t) = DELAY3\big((R_m(t) + R_o(t)\big), r)$$

Units: **undefined**

Exogenous variables

- cost of EV recycling

r_c =9000

Units: $/ton

- cost of other recycling

$$o_c = 9000$$

Units: $/ton

- EV lifetime

$$e_{ol}=20$$

Units: **undefined**

- EV recycling rate

$$r_r=0.6$$

Units: **undefined**

- Other lifetime

$$o=10$$

Units: **undefined**

- Other recycling rate

$$o_r=0.6$$

Units: **undefined**

- Recycling delay time

$$r=0.5$$

Units: **undefined**

- table for effect of perceived profit on recycling([(0,0)-(1,1)],(0,0),(0.5,0),(0.7,0.65),(0.82,0.85),(0.92,0.95),(0.98,0.99),(1,1),(10,1))

Units: **undefined**

Depletion Rate

Stock

Resources= INTEG (-depletion,initial resources)

$$X(t) = \int_{t0}^{t} \left(-S(s)\right)\delta s + x_0$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: **undefined**

Flow

- depletion=supply rate= desired supply rate*order fulfilment ratio

$$S(t) = S_d(t)O(t)$$

Units: Tonnes/y

Auxiliaries

- depletion rate=depletion/resources*100

$$X_s(t) = \frac{S(t)}{X(t)}100$$

Units: **undefined**

Exogenous variables

- initial resources

$$x_0 = 3E + 7$$

Units: **undefined**

Appendix E: The indium model - Full model equations and initial conditions

The variables referred to in this annex are defined in the variable tables in Chapter 7, Section 3.

Production and capacity utilisation

Stocks

- Inventory= INTEG (production rate + recycled Li)-supply rate,Reference Inventory Coverage* Demand)

Units: Gt

$$I(t) = \int_{t0}^{t} ((P(s) + R(s)) - S(s))\delta s + (i_r D(t_0))$$

Where (s) represents any time between initial time t_0 and the current time t.

- Cumulative Production= INTEG (supply rate, 0)

Units: Tonnes

$$Q(t) = \int_{t0}^{t} \big(S(s)\big)\delta s + Q(t_0)$$

Where (s) represents any time between initial time t_0 and the current time t.

Flows

- production rate=

DELAY3[48]((Production Capacity*capacity utilisation),production delay time)

[48] DELAY3 is an 'of the shelf' function used in system dynamics to return a third order exponential delay of an input variable for a specific delay time. This is used to vary the delivery time of delayed inputs in order to

Units: **undefined**

$$P(t) = DELAY3(\left(P_{Cap}(t)U(t)\right), p)$$

- supply rate=desired supply rate*order fulfilment ratio

Units: Tonnes/y

$$S(t) = S_d(t)O(t)$$

Auxiliaries

- max supply rate=

  Inventory/minimum order processing time

Units: Tonnes/y

$$S_{max}(t) = \frac{I(t)}{o_{min}}$$

- order fulfilment ratio=

  table for order fulfilment(max supply rate/desired supply rate)

Units: Dimensionless

'smooth' the delayed inputs availability. This function is equivalent to the equations below, as stated in the VENSIM user manual. Further discussion of this function can be found in Kirkwood (1998)

```
DELAY3=LV3/DL
LV3=INTEG(RT2-DELAY3,DL*input)
RT2=LV2/DL
LV2=INTEG(RT1-RT2,LV3)
RT1=LV1/DL
LV1=INTEG(input-RT1,LV3)
DL=delay time/3
```

$$O(t) = f_1(\frac{S_{max}(t)}{S_d(t)})$$

Where f_1 is a function defined by an exogenous lookup table presented below as '*table for order fulfilment'* (Figure 7.20), and

$$W(t) = \frac{S_{max}(t)}{S_d(t)}$$

- desired supply rate=Demand

Units: Tonnes/y

$$S_d(t) = D(t)$$

- Inventory Coverage=Inventory/supply rate

Units: Years

$$I_s(t) = \frac{I(t)}{S(t)}$$

- capacity utilisation=
  SMOOTH[49](indicated capacity utilisation,utilisation adjustment time)

Units: Dimensionless

$$U(t) = SMOOTH(U_i(t), u(t))$$

- indicated capacity utilisation=
  table for effect of markup on utilisation(expected profit)

Units: Dimensionless

[49] SMOOTH is an 'off the shelf' function that is used in system dynamics to create exponential smoothing of a time delay process. This delivers a smooth transition in the time that delayed inputs are available as output. This is equivalent to the equation below as stated in the VENSIM user manual. More information on the smooth function can be found in Kirkwood (1998)

$$U(t) = \int_{t0}^{t} (U_i(s) - U(s)/u(s))\delta s + U_i(t_0)$$

$$U_i(t) = f_2(Y_e(t))$$

Where f_2 is a function defined by an exogenous lookup table presented below as '*table for effect of markup on utilisation*'

- expected profit=

  Expected Price/Expected variable costs

Units: Dimensionless

$$Y_e(t) = \frac{V_e(t)}{C_e(t)}$$

- Expected Price=

  SMOOTH(price,delay to form expected price)

Units: $/Unit

$$V_e(t) = SMOOTH(V(t), v_{ed})$$

- Expected variable costs=

  SMOOTH(variable costs,delay to form expected variable costs)

Units: **undefined**

$$C_e(t) = SMOOTH(C(t), c)$$

<u>Exogenous variables</u>

- minimum order processing time

$$o_{min}=0.1$$

Units: Years

- table for order fulfilment ([(0,0)-(4,1)],(0,0),(0.2,0.2),(0.4,0.4),(0.6,0.58), (0.8,0.73),(1,0.85),(1.2,0.93),(1.4,0.97),(1.6,0.99),(1.8,1),(2,1),(2,1),(4,1))

Units: Dimensionless

- table for effect of markup on utilisation ([(0,0)-(5,1.2)],(0,0),(0.5,0),

(0.75,0.05),(1,0.5),(1.25,0.68),(1.5,0.75),(1.75,0.8),(2,0.84),(2.25,0.87),(2.5,0.9),(2.75,0.93),(3,0.96),(3.25,0.985),(3.5,0.995),(4,1),(4.5,1),(5,1))

Units: Dimensionless

- production delay time

$$p=0.5$$

Units: Years

- utilisation adjustment time

$$u=0.5$$

Units: Years

- delay to form expected price

$$v_e=1$$

Units: Years

- delay to form expected variable costs

$$c_e=1$$

Units: Years

Demand

Stocks

- Annual CIGS sales= INTEG (annual CIGS sales growth,30)

$$L_s(t) = \int_{t0}^{t} L_{sg}(s)\delta s + 30$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: GW/y

Flows

- annual CIGS sales growth=Annual CIGS sales*fractional rate

$$L_{sg}(t) = L_S(t)L_r(t)$$

Units: **undefined**

Auxiliaries

- In Demand=SMOOTHI(Indicated In Demand,Demand Adjustment Delay,Reference In Demand)

$$D(t) = SMOOTHI(D_i(t), d(t), D_r(t)$$

Units: Units/Year

Industry demand adjusts to the indicated demand with a delay,

representing the time required for consumers of the good to find substitutes or change their consumption after a change in price.

- Reference In Demand=Latent In Demand

$$D_r(t) = D_l(t)$$

Units: Units/Year

Initial value of customer orders.

- Indicated In Demand=MIN(Maximum Consumption,Reference In Demand*MAX(0,1+Demand Curve Slope*(In price-reference price)/Reference In Demand))

$$D_i(t) = MIN(D_{max}, D_r)MAX\left(0,1 + B\frac{V(t) - v}{Dr}\right)$$

Units: Units/Year

The indicated demand for the commodity given the current price.

Indicated demand is the demand consumers would like given the current price. Actual demand adjusts to indicated demand with a delay. The demand curve is linear, with slope set so that the elasticity of demand at the reference price is equal to the reference industry demand elasticity, set by the user.

- Demand Curve Slope=(-Reference Demand*Reference Demand Elasticity)/(reference price)

$$B(t) = (-D_r(t\,)e_d)/v)$$

Units: Unit*Units/($*Year)

The slope of the industry demand curve, as a function of the

price elasticity at the reference price level

- CIGS In demand=

  Annual CIGS sales*In intensity

$$D_{lm}(t) = L_s(t)m_i$$

Units: tons/y

- fractional rate=max CIGS market growth rate*(1-Annual CIGS sales/max CIGS annual sales)

$$L_r(t) = L_{gmax}(W_1(t))$$

Where

$$W_1(t) = 1 - \frac{L_{sg}(t)}{l_{smax}}$$

Units: **undefined**

- latent In demand=EV In demand+Other In Demand

$$D_l(t) = D_{lm}(t) + D_{om}(t)$$

Units: **undefined**

Exogenous variables

- reference price

$$v = 600{,}000$$

Units: **undefined**

- Demand Adjustment Delay

d=0.5

Units: Years

The average time required for consumer demand to respond to a change in price.

- Maximum Consumption

d_{max}=100,000,000

Units: Units/Year

The maximum demand for the commodity, no matter how low price goes.

- Reference Demand Elasticity

e_d=0.5

Units: Dimensionless

Demand elasticity at the reference price

- Max CIGS annual sales

$$l_{smax} = 140$$

Units: GW/y

- Max CIGS market growth rate

$$l_{gmax} = 0.1$$

Units: **undefined**

- Other In Demand

d_{om}=500

Units: tons

- In Intensity

m_i=0.0248

Units: g/Wp

Price

Stocks

- Traders' Expected Price= INTEG (Change in Traders' Expected Price, initial price)

$$V_e(t) = \int_{t0}^{t} V_{ec}(s)\delta s + V(t_0)$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: $/Unit

The price market makers and traders believe would clear the market if demand and supply were in balance, and no other pressures to change price existed.

Flows

- Change in Traders' Expected Price=(indicated price - Traders' Expected Price)/Time to Adjust Traders' Expected Price

$$V_{ec}(t) = \frac{V(t_0) - V_e(t)}{v_d}$$

Units: $/Unit/Year

Traders' beliefs about the underlying equilibrium price adjust in response to the gap between the indicated price and the current belief. Expected underlying price adjusts via first-order adaptive expectations to the actual price, constrained to be greater than a minimum level.

Auxiliaries

- Effect of Costs on Price=1+Sensitivity of Price to Costs*((Expected Production Costs/Traders' Expected Price)-1)

$$\boldsymbol{V_{cp}(t) = 1 + v_{cp}(W_2(t) - 1)}$$

Where

$$W_2(\boldsymbol{t}) = \frac{\boldsymbol{C_{pe}(t)}}{\boldsymbol{V_e(t)}}$$

Units: **undefined**

- indicated price=MAX(Minimum Price,price)

$$V_i(t) = MAX(V_{\min}(t), V(t))$$

Units: **undefined**

- price=MAX(0,(Traders' Expected Price*Effect of Inventory Coverage on Price*Effect of Costs on Price))

$$V(t) = MAX(0, \left(V_e(t)V_{is}I(t)V_{cp}(t)\right))$$

Units: $/Unit

- Effect of Inventory Coverage on Price=Relative Inventory Coverage^Sensitivity of Price to Inventory Coverage

$$V_{is}(t) = I_\rho(t)^{v_{is}}$$

Units: Dimensionless

Price rises when inventory coverage is less than normal, and falls when it is greater. The Sensitivity of Price to Inventory Coverage controls the magnitude of the response.

- Relative Inventory Coverage=Perceived Inventory Coverage/Reference Inventory Coverage

$$I_\rho(t) = \frac{I_{sp}(t)}{i_r}$$

Units: Dimensionless

Perceived inventory coverage relative to the normal level needed to ensure desired service levels in the market.

- Perceived Inventory Coverage= SMOOTH(Inventory Coverage,Coverage Perception Time)

$$I_{sp}(t) = SMOOTH(I_s(t), i_s(t))$$

Units: Years

Perceived coverage is formed by smoothing actual coverage. It takes time to recognize changes in coverage.

- Minimum Price=Unit Costs

$$V_{min}(t) = Y(t)$$

Units: $/Unit

Trader's do not believe prices can fall below the variable cost per unit of production.

Exogenous Variables

- initial price=100

$$V_{t0} = 100$$

Units: **undefined**

- Sensitivity of Price to Costs

$$V_{cp} = 0.5$$

Units: Dimensionless

Controls the response of price to discrepancies between the expected price and the expected cost of production.

- Time to Adjust Traders' Expected Price=1

$$v_d = 1$$

Units: Years

Trader's belief about the underlying equilibrium price adjust to actual prices over this period.

- Sensitivity of Price to Inventory Coverage=

$$V_{is} = -1$$

Units: Dimensionless

Controls the response of price to inventory coverage. Must be negative for high inventory to lead to lower prices. Higher absolute values lead to greater price changes for any given inventory coverage level.

- Coverage Perception Time

$$i_s = 0.167$$

Units: Years

The average time required to perceive and react to inventory coverage.

- Reference Inventory Coverage

$$I_\rho = 0.2$$

Units: Years

The normal inventory coverage required to ensure desired levels

of service (the desired ability to fill orders).

Capacity

Stocks

- Capacity Stock= INTEG (acquisition rate-Discard Rate,(Reference Demand/indicated capacity utilisation)/Capital Productivity)

$$C_{ap}(t) = \int_{t0}^{t} (A(s) - J(s))\delta s + \frac{D_r(t) / U_i(t)}{C_{app}}$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: Capacity Units

The capital stock accumulates acquisitions less discards.

Initialized to the initial equilibrium level.

- Zn Capacity= INTEG (net zinc capacity change,1.1e+007)

$$H_{cap}(t) = \int_{t0}^{t} \left(Z_{capc}(s)\right) \delta s + (1.1 * 10^7)$$

Where (s) represents any time between initial time t_0 and the current time t.

Units: mt

- In Recovery Rate= INTEG (In recovery change,Initial In recovery rate)

$$In(t) = \int_{t0}^{t} \left(H_{rc}(s)\right)\delta s + h_{rt0}$$

Units: Units

The state of the system accumulates its net inflow rate.

Flows

- acquisition rate=Desired Acquisition Rate

$$A(t)=A_d(t)$$

Units: **undefined**

- Discard Rate=Capacity Stock/Average Life of Capacity

$$J(t) = \frac{C_{ap}(t)}{c_{apL}}$$

Units: Capacity Units/Year

The average life of capacity determines the rate at which it decays and is discarded.

- net zinc capacity change=Zn Capacity*Zn market growth rate

$$H_{capc}(t) = H_{cap}(t)h_g$$

Units: **undefined**

- In recovery change=difference between current and goal In recovery/time to max In recovery rate

$$H_{rc}(t) = \frac{H_{rg}(t)}{H_{rmaxd}}$$

Units: Units/Period

The net inflow a fraction of the discrepancy between the desired and actual state each period. The adjustment time determines what fraction of the gap is corrected each period.

Auxiliaries

- Production Capacity=Capacity Stock*Capital Productivity

$$P_{Cap}(t) = C_{ap}(t)C_{app}$$

Units: Gt/y

Production capacity is determined by total capital stock in service and its productivity.

- Adjustment for Capacity=(Desired Capacity - Capacity Stock)/Capacity Adjustment Time

$$Z(t) = \frac{C_{apd}(t) - C_{ap}(t)}{t_{cap}}$$

Units: Capacity Units/Year

Producers seek to close the gap between desired and actual capacity over the Capacity Adjustment Time

- Desired Acquisition Rate=MAX(0, Expected Discard Rate + Adjustment for Capacity)

$$A_d(t) = MAX(0, J_e(t) + Z(t))$$

Units: Capacity Units/Year

The rate at which new capacity should be acquired, given the expected discard rate and the adjustment to bring the stock of capacity in line with the desired stock.

- Expected Discard Rate=Discard Rate

$$J_e(t) = J(t)$$

Units: Capacity Units/Year

The expected discard rate is assumed to equal the actual discard rate.

- Primary Production Capacity=IF THEN ELSE[50](In price/cost of primary production>1,max primary production capacity,0)

$$P_p(t) = IF\ THEN\ ELSE(\frac{V(t)}{C_{Pp}} > 1, P_{pmax}, 0)$$

Units: **undefined**

- Maximum In Capacity Limit=Primary Production Capacity+(Zn Capacity*Indium contained*In Recovery Rate)

$$M_{capmax}(t) = P_p(t) + (H_{cap}(t)H_{rr}(t)h_{mc})$$

Units: **undefined**

- difference between current and goal In recovery= max In recovery rate - In Recovery Rate

$$H_{rg}(t) = h_{rmax} - H_{rr}(t)$$

Units: Units

The gap between the desired and actual state of the system.

[50] 'IF THEN ELSE' is an 'off the shelf' conditional statement function. It returns one of two values depending on whether the conditional statement is satisfied or not. In parentheses the first formulation is the conditional statement, the next is the value returned if the conditional statement is satisfied, and the final is the value returned if the conditional statement is not satisfied.

Exogenous variables

- Capital Productivity

$$C_{app}=1$$

Units: Unit/Year/Capacity Units

The productivity of capital is assumed exogenous and constant.

One unit of capital is defined as the capital stock required to generate one unit of output per year (at normal utilization), so productivity =1.

- Average Life of Capacity

$$C_{apL}=20$$

Units: Years

The average life of capacity.

- Capacity Adjustment Time

$$t_{cap}=3$$

Units: Years

The average time over which producers seek to close the gap between desired and actual capacity.

- Zn market growth rate

$$h_g=0.015$$

Units: **undefined**

- max primary production capacity

$$p_{pmax}=500$$

Units: tons/y

- cost of primary production

$$c_{Pp}=600{,}000$$

Units: $/t

- Indium contained

h_{mc}=9e-005

Units: undefined

- Initial In recovery rate

H_{rt0}=0.8

Units: Units

The initial quantity in the stock.

- max In recovery rate

H_{rmax}=0.9

Units: Units

The desired, or goal state for the system.

- time to max In recovery rate

h_{rmaxd}=20

Units: Period

The time period over which discrepancies between the desired and actual state of the system are corrected.

Desired capacity

Auxiliaries

- Desired Capacity=

Capacity Stock*(1+Sensitivity of Investment to Exp Profit*(Effect of Expected Profit on Desired Capacity-1))

$$C_{apd}(t) = C_{ap}(t)(1 + C_{apdy}(Y_{capd}(t) - 1))$$

Units: Capacity Units

Desired capital stock is based on current capital, adjusted up or down according to the expected profitability of new investment.

- Effect of Expected Profit on Desired Capacity=Table for Effect of Expected Profit on Desired Capacity(Expected Profitability of New Investment)

Units: Dimensionless

$$Y_{capd}(t) = f_4(Y_{cap}(t))$$

Where f_4 is a function defined by an exogenous lookup table presented below as '*table for effect of expected profit on desired capacity*'

Desired capacity is adjusted above or below current capacity in response to the expected profitability of new investment.

- Expected Profitability of New Investment=(Long Run Expected Price - Expected Production Costs)/Long Run Expected Price

$$Y_{cap}(t) = \frac{V_{el}(t) - C_{pe}(t)}{V_{el}(t)}$$

Units: Dimensionless

The expected profitability of new investment is the difference between long run price expectations and expectations for the unit costs of new investment, including fixed and variable costs. Fixed cost includes the normal profit margin required. The expected profit is normalized by price to give a dimensionless measure of profit, analogous to the percentage return per unit.

- Long Run Expected Price=SMOOTH(price,Time to Adjust Long Run Price Expectations)

$$V_{el}(t) = SMOOTH(V(t), v_{el})$$

Units: $/Unit

Long run price expectations are formed by first-order

exponential smoothing (adaptive expectations).

- Expected Production Costs=SMOOTH(Unit Costs,Time to Adjust Expected Costs)

$$C_{pe}(t) = SMOOTH(C_u(t), c_e)$$

Units: **undefined**

- Unit Costs=cumulative availability curve(Cumulative Production)

Units: $/Unit

$$C_u(t) = f_8(Q(t))$$

Where f_8 is a function defined by an exogenous lookup table presented below as '*cumulative availability curve'*

Unit costs including fixed and variable costs.

- variable costs=Unit Costs*variable cost fraction

$$C(t) = C_u(t)C_{vu}$$

Units: **undefined**

Exogenous variables

- Sensitivity of Investment to Exp Profit

$$C_{apdy}=1$$

Units: Dimensionless

The Sensitivity of Desired Capacity to expected profit.

- Table for Effect of Expected Profit on Desired Capacity([(-1,0)-(1,2)],(-1,0),(-0.75,0.1),(-0.5,0.3),(-0.25,0.67),(0,1),(0.25,1.25),(0.5,1.45),(0.75,1.6),(1,1.7))

Units: Dimensionless

The adjustment of desired capacity above or below the current level depends on this function of the expected profitability of new investment.\!\!\!

- Time to Adjust Long Run Price Expectations

$$v_{el}=2$$

Units: Years

The time required to update long-run price expectations.

- Time to Adjust Expected Costs

$$c_e=2$$

Units: Year

The time required for market participants to glean information about costs and adjust their beliefs to the new information. Since cost information is difficult to get, unreliable, and differs from producer to producer, expected costs adjust slowly.

- cumulative availability curve [(0,400000)-(600000,1e+006)],(0,600000),(200000,1e+006),(600000,1e+006)

Units: $/t

- variable cost fraction

C_{vu} =0.4

Units: **undefined**

Recycling

Auxiliaries

- effect of estimated profit on CIGS recycling=table for effect of perceived profit on recycling(Expected Price/cost of CIGS recycling)

$$R_y(t) = f_7 \frac{V_e(t)}{r_c}$$

Where f_7 is a function defined by an exogenous lookup table presented below as '*table for effect of perceived profit on recycling'*

Units: **undefined**

- effect of estimated profit on other recycling=table for effect of perceived profit on recycling(Expected Price/cost of other recycling)

$$\boldsymbol{R_{oy}(t) = f_7(W_3(t))}$$

Where f_7 is a function defined by an exogenous lookup table presented below as '*table for effect of perceived profit on recycling'* and

$$W_3(t) = \frac{V_e(t)}{R_O(t)}$$

Units: **undefined**

- CIGS In end-of-life=DELAY FIXED[51] (CIGS In demand,CIGS lifetime,0)

[51] DELAY FIXED is an 'off the shelf' function which returns the value of the 'input' delayed by the 'delay time'. The 'input' is the value of the variable on the left-hand side of the parentheses. The 'delay time' is the central constant in parentheses. On the right of the equation is the 'initial value', in this case 0.

$$M(t) = DELAY\ FIXED(D_{lm}(t), e_{ol}, 0)$$

Units: **undefined**

- CIGS recycling=CIGS In end-of-life*effect of estimated profit on CIGS recycling* CIGS recycling rate

$$R_m(t) = M(t)R_y(t)r_r$$

Units: **undefined**

- other demand recycling=other In end-of-life*other recycling rate*effect of estimated profit on other recycling

$$R_o(t) = M(t)o_r(t)R_{oy}$$

Units: **undefined**

- other In end-of-life=DELAY FIXED(Other In Demand,other lifetime,0)

$$O(t) = DELAY\ FIXED(D_o(t), o, 0)$$

Units: **undefined**

- recycled In=DELAY3((In recycling+other demand recycling),recycling delay time)

$$R(t) = DELAY3\big(\big(R_m(t) + R_o(t)\big), r\big)$$

Units: **undefined**

Exogenous variables

- cost of CIGS recycling

$$r_c = 700{,}000$$

Units: $/ton

- cost of other recycling

$$o_c = 700{,}000$$

Units: $/ton

- CIGS lifetime

$$e_{ol}=30$$

Units: **undefined**

- CIGS recycling rate

$$r_r=0.6$$

Units: **undefined**

- Other lifetime

$$o=10$$

Units: **undefined**

- Other recycling rate

$$o_r=0.6$$

Units: **undefined**

- Recycling delay time

$$r=0.5$$

Units: **undefined**

- table for effect of perceived profit on recycling([(0,0)-(1,1)],(0,0),(0.5,0),(0.7,0.65),(0.82,0.85),(0.92,0.95),(0.98,0.99),(1,1),(10,1))

Units: **undefined**

Depletion Rate

Stock

Resources= INTEG (-depletion,initial resources)

$$X(t) = \int_{t0}^{t} \left(-S(s)\right)\delta s + x_0$$

Where (*s*) represents any time between initial time t_0 and the current time t.

Units: **undefined**

Flow

- depletion=supply rate= desired supply rate*order fulfilment ratio

$$S(t) = S_d(t)O(t)$$

Units: Tonnes/y

Auxiliaries

- depletion rate=depletion/resources*100

$$X_s(t) = \frac{S(t)}{X(t)}100$$

Units: **undefined**

Exogenous variables

- initial resources

$$x_0 = 300{,}000$$

Units: **undefined**