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Quantitative Analysis of Technology Futures. Part I: Techniques, Contexts, and Organizations

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Abstract

As a gentle introduction to quantitative foresight techniques we begin by providing a working definition of Future-Oriented Technology Analysis (FTA) and discussing its role, uses, and popularity over recent decades. We select 22 FTA techniques identified as the most important quantitative FTA techniques. We introduce these techniques, discuss their main contexts and uses and classify them into groups with common characteristics, positioning them along four key dimensions: descriptive/prescriptive; extrapolative/normative; data gathering/inference; and forecasting/foresight.

Keywords: Foresight, Data, Futures, Prediction

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Executive Summary

Technological progress has huge impacts on society and economic development, and improving our understanding of likely future developments of technology is becoming increasingly important. The goal of Future-oriented Technology Analysis (FTA) is to enable a better understanding of the directions that existing technological trajectories will take, and decisions making about desired potential states that will help 'create' the future. Policy can play a significant role in shaping technology and its directions given the path dependent nature of technology, and the fact that small changes to current technologies may be amplified in their impacts in the future.

A definition of FTA is provide by Eerola and Miles (2011): 'Future oriented technology analysis (FTA) is an umbrella term for a broad set of activities that facilitate decision-making and coordinated action, especially in science, technology and innovation policy-making. [...] Indeed, understanding the dynamics of technological change is just one part of a broader mandate' [p. 265]. 'So, FTA has many faces and comes in many "flavours", drawing on many different research traditions and methods. Practically any source of insight into the dynamics of science and technology [...] can be utilised as knowledge inputs into FTA' [p. 267]. Thus, FTA includes a number of activities usually indicated in the literature as technology foresight, forecasting, intelligence, roadmapping and assessment (Porter, 2010).

Our focus is on the quantitative techniques used in FTA. Quantitative techniques have become increasingly important in the current era of Big Data and increased computational power, and enable us better to project into the future. New quantitative techniques such as webometrics and prediction markets are complementing existing techniques. In this first working paper, we survey these techniques, and collate them and discuss them synthetically, guiding the reader "through the maze" and discussing the contexts in which these techniques are most appropriate, and the extent to which they claim to increase our knowledge of the possible outcomes and their probabilities of occurring. In the second Working Paper (Ciarli et al., 2013), we discuss these quantitative techniques in the light of the analytical framework of (Stirling and Scoones, 2009).

In this Working Paper, we review the literature on technology foresight, technology forecasting, scenario shaping, and futurology. Focusing on quantitative techniques, we examine the tools and methodologies available, and discuss the contexts in which they are most widely used. We select 26 quantitative techniques which we assign to 10 groups. We distinguish among their uses (Descriptive vs Prescriptive; Positive vs Normative; Data gathering vs. Inference; Foresight vs Forecasting) and classify according to examine their characteristics (Drivers; Locus; Time horizon considered; Purpose; Participation). These techniques are arranged and organized and presented in summary tables.

In the second Working Paper, we position these quantitative techniques according to how they represent the knowledge about the occurrence of different outcomes, and about the probability of different states of the world occurring. While each of these techniques modifies the perception of the state of incompleteness of our knowledge, we show that they differ in their claims to providing knowledge about outcomes and probabilities. Most techniques are perceived as contributing to our understanding of the probabilities attached to certain outcomes. However, we can distinguish also by the extent to which they ‘open up’ or ‘close down’: some techniques open up our awareness to new possibilities, others close down on possible future scenarios and analyse them in greater depth. We also discuss how new techniques that exploit the large amounts of data generated on the web change this perception, and investigate the different stake-holders involved in analyzing futures.

1 Introduction

Technological change is so pervasive that we have begun to regard it as a 'natural' and necessary phenomenon. However, technological change has had such an impact on the course of humanity, that it would be anomalous were we not to try to understand its sources and consequences of its impacts. Technological change cannot be taken for granted, and does not happen according to some 'natural' law particularly with respect to the directions it takes. There are at least three reasons why we need to understand the sources and impacts of technological change and its trajectories, at a given moment. First, small changes in technological events have an impact on the very distant future, precluding most historical paths with respect to others – namely with respect to the only one observed. For example, Diamond (1997) shows how small differences in initial endowments across the planet have strongly and irreversibly determined the shape and divisions of the modern world. On a smaller scale, a large number of studies have identified the sources of path dependency in technological choices, such as sunk costs, network externalities, architectural standards, economies of scale, and the irreversibility of investments. Probably the most famous example is David (1985), which shows that a series of historical accidents and encounters determined the so far unbeaten success of the QWERTY keyboard despite its lower efficiency with respect to alternative designs. Similarly, Arthur (1989) shows how, under given conditions, simple random buying decisions of identical consumers are sufficient to determine the pattern of a dominant technology between two that initially are identical, and determine lock-in to the winning product/technology. Cowan and Gunby (1996) analyze in depth how the choice of farmers, in a very short period, determined the supremacy of chemical pesticides at the expense of competing, socially superior, technologies such as Integrated Pest Management. In other words, the trajectory of technological change is determined in a way that is not reversible and that has dramatic consequences on the world in which we live.

Second, as the examples above suggest, the direction of technological change is influenced as much by apparently everyday choices as by strategic choices. In other words, the direction is in part the outcome of a large number of institutional factors that may appear mundane (MacKenzie, 1998; Pinch and Bijker, 1984; Rip et al., eds, 1995).

Third, the social and political effects of a technology depend on the direction it takes. An early example is the analysis by the Club of Rome on energy and raw materials shortages, and the unsustainable environmental impact caused by the exponential patterns of growth in the industrialized economies (Meadows et al., 1972). More recent examples might be the free access to the Internet, which enables initiatives such as Wikipedia and knowledge sharing among all those with access to a computer, and the Internet. Other types of Internet developments that requires a fee, might have led to paid access, which is common for many biomedical technologies. A large variety of qualitative and quantitative techniques are used to explore and analyze the future to forecast the direction of technological change and its effects on society, and to manage risk under changing uncertainties.

For example, Porter et al. (2004) surveyed around 50 different FTA techniques around about half of which are based on quantitative analysis.

The analysis of the future has been mainly the prerogative of governments and large companies. Foresight activities can also influence future events, and shape technologies, social relations, and cultures. For instance, in early foresight activities – then called forecasting – in the 1960s 'every society [...] is consciously committed to economic growth, to raising the standard of living of its people, and therefore to the planning, direction and control of social change' (Kahn and Wiener (1967), p. xxv, cited in Johnston (2008)). Following the 1974 oil crisis in particular, foresight diffused throughout the corporate sector (Johnston, 2008) but it is only during the 1990s, following the pioneering work of Irvine and Martin (Irvine and Martin, 1984; Martin and Irvine, 1989) and the foresight activities pioneered by the Japanese government, that technology foresight and forecasting have become widespread activities attracting a large attention and investment from practitioners and academics.

Following the diffusion of FTA 'Exploring the future should never be identified with forecasting. Whereas forecasting is founded on determinism, futures research encompasses a view of the world based on freedom of choice' (Fontela, ????, p. 8) Technology foresight and forecasting are only two of the ways we can explore future scenarios, and two FTA (Porter, 2010).[1] Here we use the abbreviation FTA to refer to analytical tools that allow to find suitable ways to study possible future scenarios that could shape social and economic conditions, and bring relative advantage. Where suitable refers to the ability of FTA to provide an understanding of current conditions and problems, project them, and forecast changes to technology that fall as close as possible to the event(s) observed in the future and to the direction that technology should take to address pressing social and economic needs. FTA contains both positive and normative elements: some exercises are aimed at studying short and long term trends; others are aimed at deciding about which actions should be taken to engineer the course of the future.

In both cases FTA comprises a strong performative element: by imagining the future – and reading the present – FTA also creates the future. Referring back to the examples cited above, while computing possible disastrous world growth patterns (based on observable trends and a number of simplifying hypotheses), the Club of Rome provided a powerful imaginary of the future state of the world and the consequences of human activity (Forrester, 1971; Meadows et al., 1972).

The present paper provides a reasoned review of (1) the literature on the different activities that are part of the large family of FTA, and (2) the quantitative techniques, tools, and methodologies available. The review, we which latter we hope will provide the reader with a reasonably thorough understanding of (a) the strengths and weaknesses of a large number of techniques, (b) the main contexts and organizations in which they are used, (c) their main drivers and purposes for which they are best suited, (d) the time

[1] TFA and FTA have been used as alternatives. However, foresight scholars now prefer to refer to Future-oriented Technology Analysis rather than Technology(-oriented) Future Analysis (Johnston, 2008).

horizon considered, (e) whether they are used mainly for data gathering or inference, and how these two activities complement each other, and (f) how they represent knowledge about outcomes and the likelihood of events. We also survey recent quantitative techniques that emerged especially following the availability of Big Data, but which have yet to be integrated in the FTA literature and traditional practice.

In this paper our aim is not to evaluate the different techniques, particularly in terms of their success/effectiveness (for this see, e.g. the chapter by Georghiou and Keenan (2008)). However, we review the different techniques also with respect to the breadth of inputs (e.g. types of data, issues considered), and the degree to which the outputs have the effect of 'opening up' associated policy debates on technology futures. The second paper on FTA provides an assessment of these techniques (Ciarli et al., 2013) – henceforth WP2.

The paper is organized as follows. The next section provides our working definition of FTA, which builds on the numerous definitions of different types of FTA. The following section reviews the large and complex literature on the different types of FTA. After a brief overview of the history of FTA and the debates around its significance, we review the main classifications proposed in the literature, and extract the population of quantitative techniques mentioned so far. We also report on a number of techniques suitable for FTA that the literature has overlooked so far; some of these are in use particularly at the corporate level. Based on the population of techniques available, section 3 describes their selection. Finally, the section 4 summarize the techniques with respect to the several dimensions that define their suitability for different contexts and organizations.

2 Future–oriented Technology Analysis

2.1 A working definition of FTA

Before reviewing the literature and the most important quantitative techniques we need a working definition of FTA. At its most basic, the idea of FTA is to provide analytical tools that allow the identification of 'suitable' ways to study possible future scenarios that could shape social and economic conditions, and provide relative advantage. 'Suitable' refers to the ability of FTA to help our understanding of current conditions and problems, project them into the future, and promote thinking about changes to technology that relate to potential future event(s) and to the direction that the technology should follow to address social and economic needs.

According to Eerola and Miles (2011) 'Future oriented technology analysis (FTA) is an umbrella term for a broad set of activities that facilitate decision-making and coordinated action, especially in science, technology and innovation policy-making. [...] Indeed, understanding the dynamics of technological change is just one part of a broader mandate' [p. 265] 'So, FTA has many faces and comes in many "flavours", drawing on many different research traditions and methods. Practically any source of insight into the dynamics of science and technology [...] can be utilised as knowledge inputs into FTA' [p. 267].

Thus, FTA includes a variety of related but different activities which the literature describes as technology foresight, forecasting, intelligence, roadmapping and assessment (Porter, 2010). Here, we refer mainly to foresight and forecasting, two activities sometimes considered synonymous, and sometimes seen as different, as we will see in the next section (Miles, 2010; Martin, 2010).[2]

2.2 The changing literature on FTA

A number of studies shows that interest in FTA increased significantly in the 2000s (e.g. Porter, 2007). To see this we computed the number of articles published on FTA in the last few decades. We ran an exercise on the Web of Science (WoS) database[3] searching for articles that contained one of the terms referring to FTA: 'technology forecasting', 'technology foresight', 'technology intelligence', 'technology roadmap', and 'technology assessment' (Porter, 2010).[4] Figure 1 shows that the interest in the scientific, social sciences and humanities literatures – those contained in the WoS – in FTA increased significantly at the beginning of the 1990s. This interest seems to have reached a plateau around the millennium or a thoughtful pause, before showing quite dramatic growth starting in 2003. This finding is in line with the results presented in Porter (2007) for the period 1996-2006, which provides a more detailed analysis, disaggregating by the main FTA techniques, disciplines, sectors, journals and organizations.[5] Even more interesting is the loss of momentum for the growing interest in FTA since 2008, showing reduced interest. Data on 2012 publications confirm this reduced interest.[6] One explanation for this might be the financial crisis. There was a similar loss of interest in FTA in the early 1970s: initial growth was halted and did not recover until the early 1990s. This earlier reduced interest might be explained by the reduced confidence in foresight activities following the oil crisis. Similarly, the financial crisis and the inability of foresight activities to hint at its possibility, may have induced scholars and users of FTA to turn to different methods from those traditionally used.

Since its early phases the literature on FTA has taken off in different directions. Although technology foresight and forecasting activities often overlap, and the differences in

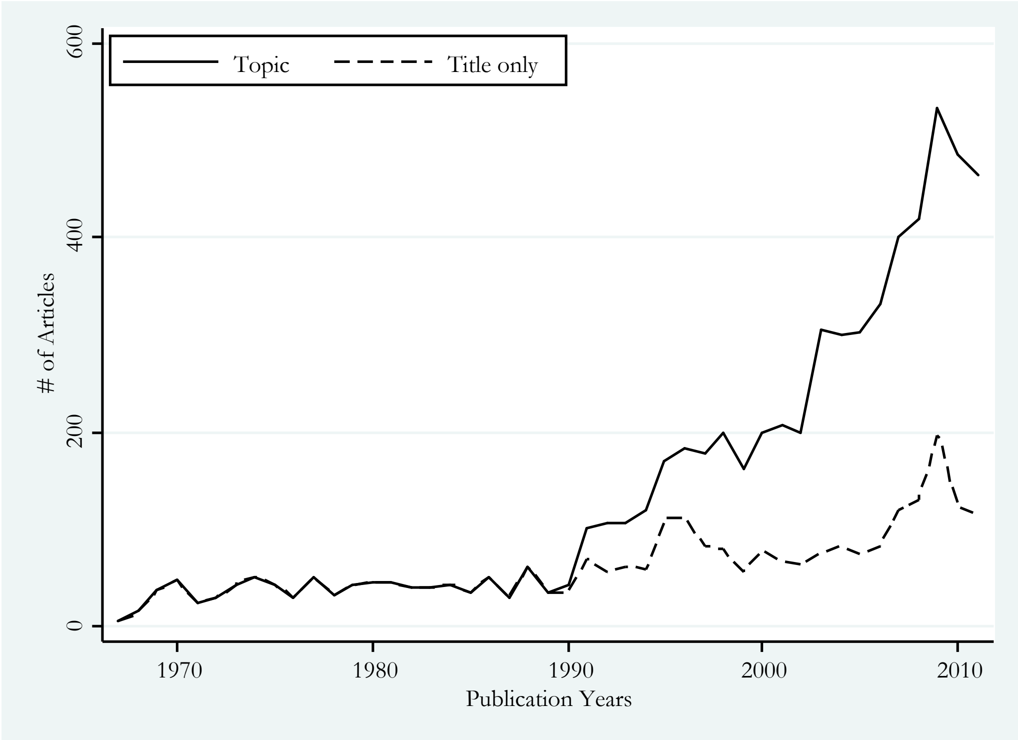
[2]There are also differences in the ways that foresight and forecasting are referred to in different parts of the world. Although following Irvine and Martins introduction of foresight (technology foresight) most organizations adopted the term foresight rather than forecasting; in the USA, a number of activities that would be considered foresight activities in Europe, continued to be referred to as forecasting (Martin, 2010).

[3]See Porter (2007) for a discussion on the pros and cons of this choice in the case of this particular search.

[4]Our search string contained the following terms to capture the different forms of technology/technological and, e.g., forecast/forecasting: "technol* forecast*" OR "technol* foresight*" OR "Technol* intelligence" OR "Technol* roadmap*" OR "Technol* Assessment". The data were retrieved on the 7^{th} July 2012.

[5]Results for 1996-2006 are available from the authors.

[6]If we double the number of published papers in the WoS in July 2012 (which assumes that the same number of articles is published in the first and second half of the year) the data show an even larger decline.



Source: own elaboration based on Web of Knowledge data

Figure 1: ***Number of articles published in Web of Science on Future Technology Analysis between 1967 and 2011.*** *The search includes one of the following strings: 'technology forecasting', 'technology foresight', 'technology intelligence', 'technology roadmap', and 'technology assessment'. The solid line shows the results for keywords found in the abstract, keywords or title (introduced in WoS only since 1991); for consistency with the 1967-1990 dynamics, the dashed line shows the results searching only article titles.*

definitions across the Atlantic Ocean blur, we report here the main differences between the two.[7]

The fathers of technology foresight (Martin, 2010) define it as 'the techniques, mechanisms and procedures for attempting to identify areas of basic research beginning to exhibit strategic potential' (Irvine and Martin, 1984, p. 7) where strategic potential refers to 'areas [...] that are beginning to show promise of constituting a knowledge base that, with further funding, might eventually contribute to the solution of important practical problems' (Irvine and Martin, 1984, p. 7)[8] [p. 6]. In subsequent work Martin and

[7]These definitions are based on FTA undergoing in Europe (starting with the UK), the US, and Japan. For a broader understanding we direct the interested reader to the NESTA report on foresight activities in developmental states (Ely et al., 2012).

[8]A contemporaneous similar definition is given in (Coates, 1985) (cited in Miles et al. (2008a)): 'a process by which one comes to a fuller understanding of the forces shaping the long-term future which should be taken into account in policy formulation, planning and decision making [...]Foresight includes qualitative and quantitative means for monitoring clues and indicators of evolving trends and developments' [p. 343]. This definition is in line with the main activities carried out in the US and emphasizes scanning and forecasting, not specifically related to science and technology (Miles et al., 2008a).

Irvine (1989) add that foresight activity should influence the future development of technology: ‘Foresight provides, at least in principle, a systematic mechanism for coping with complexity and interdependence as it affects long-term decision on research, in particular facilitating policy-making where integration of activities across several fields is vital’ [p. 3]. In contrast, the need to engage with understanding and shaping future (technological) change is emphasized in the definition in Martin (1995): ‘the process involved in systematically attempting to look into the longer-term future of science, technology, the economy and society with the aim of identifying the areas of strategic research and the emerging generic technologies likely to yield the greatest economic and social benefits’ [p. 140].

The first definition focuses on basic research and does not refer to specific techniques, but to all activities that may contribute to the identification of science or technologies. The second definition encompasses more than basic research and includes a variety of future issues (not only technology) including broad economic and societal problems. While neither definition focuses on specific issues – ‘important practical problems’ in the first definition and ‘social and economic benefits’ in the second definition – they refer implicitly to the role that technological change can play in improving the future human condition, which is expressed explicitly in the 1995 definition.

Foresight then is different from activity aimed at forecasting future events and states of the world. This is made clear in Miles et al. (2008a) ‘the aim is not just to produce more insightful “future studies”, more compelling scenarios, and more accurate econometric models. Foresight involves bringing together key agents of change and sources of knowledge, in order to develop strategic visions and anticipatory intelligence’ [p. 11]. Technological forecasting is defined as ‘“Ivory tower” future studies, in which an expert or consultant group produces its vision of the future or of alternative futures’ (Miles et al., 2008a, p. 14).

To sum up, foresight should include the following elements (Miles et al., 2008a, p. 12):

i structured anticipation of needs (technology, society, etc.),

ii interaction of different stakeholders (in contrast to forecasting which uses only experts),

iii creation of a network of stakeholders with different expertise,

iv a strategic vision of the network of stakeholders,

v visions of the future, not utopia, that provide explicit implications for action and decision (policy),

vi communication among different disciplines, able to explain complex phenomena that rarely are partitioned into disciplines.

Both technology foresight and forecasting exercises have employed a range of different quantitative and qualitative techniques which can differ in many dimensions, including their aims, aspects investigated, phase of the exercise, time horizon, organization undertaking or commissioning the study, expertise and so on. In the next section we provide a classification of the different techniques along a number of dimensions. The literature provides several systematizations and classifications of techniques, fitted within a number of dimensions. Our literature review focuses on these contributions since they will be used to build our toolkit.

The first effort to compile the various techniques is usually ascribed to Glenn and Gordon, eds (2003). Their contribution, which was updated in 2009 (Glenn and Gordon, eds, 2009), provides a very useful guide to these techniques and their application, but does not offer a comparison among them. Indeed, it is not straightforward to compare among techniques (Scapolo and Miles, 2006) since it is necessary to make a number of simplifications about how they are applied, to what, by whom and for what purpose, in order to evaluate their contribution accurately. In this paper we attempt a metalevel comparison among different techniques with no claims that two techniques are directly commensurable. We provide the reader not familiar with FTA with an idea of what is available, for what application. In the paper we provide sufficient references to each technique to provide a full understanding of its main features, its advantages and disadvantages, and examples of its use.

Porter et al. (2004) provides the first classification for a comprehensive list of quantitative and qualitative techniques – including Glenn and Gordon, eds (2003), categorizing them into families, distinguishing among those that, e.g. attempt purely creative exercises, from those aimed at providing point estimates of future developments of specific technologies.[9] In between these two extremes are techniques aimed at 'compiling information' and 'understanding interactions among events. Although not all techniques are exclusive to a single family, this preliminary effort makes the significant contribution of relating techniques to different scopes such as time horizon, geographical extent and aggregation level. We return to these categories later.

Popper (2008a) provides two different classifications of foresight techniques – also divided into quantitative, qualitative and semi-quantitative – based on which phase they are likely to be applied, and as a function of the knowledge source.

We first examine his classification according to phase of usage. The literature and practice usually distinguish among different phases in an FTA exercise. With particular reference to technology foresight, Horton (1999), Miles (2002), Warden (2007) and Popper (2008b) suggest several classification. All describe an initial phase when information and stakeholders are assembled:[10] we refer to this as *data gathering*, and assume that the main outcome of the recruitment of experts is functional also to the acquisition of knowledge

[9] The techniques are distributed across nine categories: Creativity, Descriptive and Matrices, Statistical, Expert Opinion, Monitoring and Intelligence, Modelling and Simulation, Scenarios, Trend Analyses, and Valuing/Decision/Economic.

[10] Following Horton (1999) the (i) collection, (ii) collation and (iii) summary of available information (trends, expected and unusual developments); also referred to as 'enactment' by Warden (2007) and as 'pre-foresight' by Miles (2002).

to be used in the FTA, in the form of qualitative or quantitative data. The second phase involves data elaboration to describe and visualize the current state (the type of exercise depends on the objectives of FTA) and elaborate scenarios or possible technology evolutions and states of the world. One expected result from this phase may be selection of the most likely or the most desirable futures:[11] we refer to this as *inference*, assuming that all kinds of analysis in this phase, using any technique, will produce some understanding based on the evidence available (on the past) in order to infer with some degree of accuracy short or long run changes (in theory or in practice). The third phase consists of translating into action the outcome of the first two phases in ways that are relevant to a particular FTA exercise and organization (e.g. publication, communication, policies, firm innovation).[12]

The second classification is based on the knowledge source, differentiating among techniques along two dimensions. The first is concerned more with data gathering activities and ranges from the consultation of a few experts to interaction with a large number of stakeholders. The second dimension is mainly concerned with inference activities and ranges from unstructured creative thinking to evidence-based techniques.

Given that our focus is on quantitative techniques, these two dimensions need to be adjusted, as follows. We consider 'expert' insights to be knowledge that can be applied to any phase in data gathering and inference. For example, expert knowledge can be used to interpret a statistical result or the visualization of Big Data, and is not, as is often the case in the foresight literature and practice, the individuals that provide advice on particular aspects of a technology or issue (e.g. in a Delphi exercise). Similarly, in our classification, creativity is structured and may derive from the use of new techniques, such as social software, which so far have not been considered in the FTA literature. In other words, quantitative techniques can be used to exploit sources of creative information (i.e. blogs and social software), and as inputs to others' 'creative thinking', or to generate creative 'computing' with quantitative scenarios.

Bishop et al. (2007) focus on techniques used in scenario planning exercises, which are not very different from foresight exercises as defined by the authors. Apart from a useful list of advantages and disadvantages of the surveyed techniques, Bishop et al. (2007) contribution adds to the categorizations provided above in two respects. First, most techniques use actual data and information rather than assessments of current states, backcasting from plausible futures. Second, the vast majority of techniques (including qualitative) do not exploit computational power, which opens up a range of possible innovations in FTA. Third, according to Bishop et al. (2007), most techniques are of a very similar intermediate degree of difficulty, which should reduce bias in users choices of a technique suited to a given scope.

[11] Following Horton (1999) the (iv) translation and (v) interpretation of knowledge acquired in the first phase to create understanding of its implications for the future of the organization in question; also referred to as 'selection' by Warden (2007) and the 'generation phase' by Miles (2002).

[12] Following Horton (1999) the (vi) assimilation and (vii) evaluation of the understanding (see above) to produce commitment to action in a particular organization; also referred to as retention by Warden (2007) and as 'action phase' by Miles (2002), which may be followed by a 'renewal'.

We draw on two more surveys written by foresight practitioners, to build our classification of quantitative techniques. The first (Jackson, 2011) is another summary of a selected number (26) of features of techniques. The second (Magruk, 2011) provides a very comprehensive list of techniques. Mag11 defines a large number of variables to characterize the listed methods on the basis of references and personal experience in the field. He runs a cluster analysis and extracts 10 categories. Although the categorization method is interesting, the classification does not provide useful insights in the context of the current work.

Next, we list every technique mentioned at least once in the reviewed work. Eliminating obvious duplicates, this results in a list of 64 quantitative techniques.[13] Some of these are partly overlapping; some differ or not according to different authors. All in all, it is quite a large number of available quantitative techniques, especially if we consider that the list does not include techniques used in some forms of FTA (in the comprehensive definition used here) that have not been included as FTA techniques in the academic literature. As we will see in more detail later (section 3.2), each technique has pros and cons, and is included in one and/or the other category. So how are they chosen for a specific FTA? Does the literature inspire this choice or is it an outcome of different types of learning among the practitioners applying them?

All the contributions discussed so far (as well as our own contribution) use a deductive method; as far as we are aware, Popper (2008b) is one of the only inductive exercise to understand which techniques are used in particular foresight exercises.[14] Popper uses a database of 886 foresight exercises – European Foresight Monitoring Network – EFNM Dynamo – to address the questions above: he looks at the main features of this sample of exercises collected by a number of practitioners and scholars of technology foresight over several years.

The database is part of a project run by EFMN and was constructed by volunteers from EFMN affiliates who contribute by including in the database foresight exercises which they get to know about. This sampling method is not particularly robust and many types of exercises and areas of the world are under-represented. However, it represents a rich source of information for an inductive understanding of the use of different techniques. The paper by Popper analyses how the choice of method is influenced by: (i) the nature of techniques – quantitative or qualitative; (ii) the capabilities – the ability to gather or process the

[13]Some techniques have both quantitative and qualitative aspects; we set a fairly high threshold for the quantitative content for a technique to be considered as quantitative, such that, e.g. Delphi methods are not included.

[14]With the exception of the more focused comparison of Delphi and Cross Impact Analysis done by Scapolo and Miles (2006). In this paper the authors run the same foresight exercise using the two different techniques and consulting the same experts, who then are able to judge which technique applies better to the specific case of the European transport system. Their first result is that the comparative exercise is extremely costly and difficult. Second, these techniques are not harmonized, thus the differences may be due to the way in which they are applied, not to the techniques themselves. Ultimately, there is no conclusive evidence on the most appropriate techniques (subjectivity in measuring the pros and cons): ‘The techniques have somewhat different methodological principles, and may be intended to provide information for different purposes, though the literature is not so clear about what these are’ (Scapolo and Miles, 2006, p. 700). To conclude, the choice remains related to the topic as well as to the study scope.

information based on evidence, experts, interaction among stakeholders, or creativity (see the classification in Popper (2008a)); (iii) the relative R&D expenditure by region; (iv) the sector, industry, or research area covered; (v) the level of geographical aggregation; (vi) the time horizon; (vii) the actors funding the study; (viii) the types of organizations involved; (ix) the number of people involved; (x) the type of output generated – e.g. policy recommendations, scenarios, key technologies; and (xi) the number of methods used.

The results show that the choice of techniques differs according to their nature, geographical R&D intensity and use of different capabilities and techniques, but is insensitive to all other dimensions – particularly sectors, geographical aggregation, time horizon, funding organizations and target groups. In other words, and being cautious in the assessment of these data, analysis of a large number of foresight exercises shows no clear pattern for choice of techniques, suggesting that foresight practitioners, on average, do not consider the same techniques as being a better fit than some others, for particular types of exercises. In fact, much selection of techniques seems to be guided by intuition, impulse or inexperience with the whole range of techniques (Popper, 2008b).

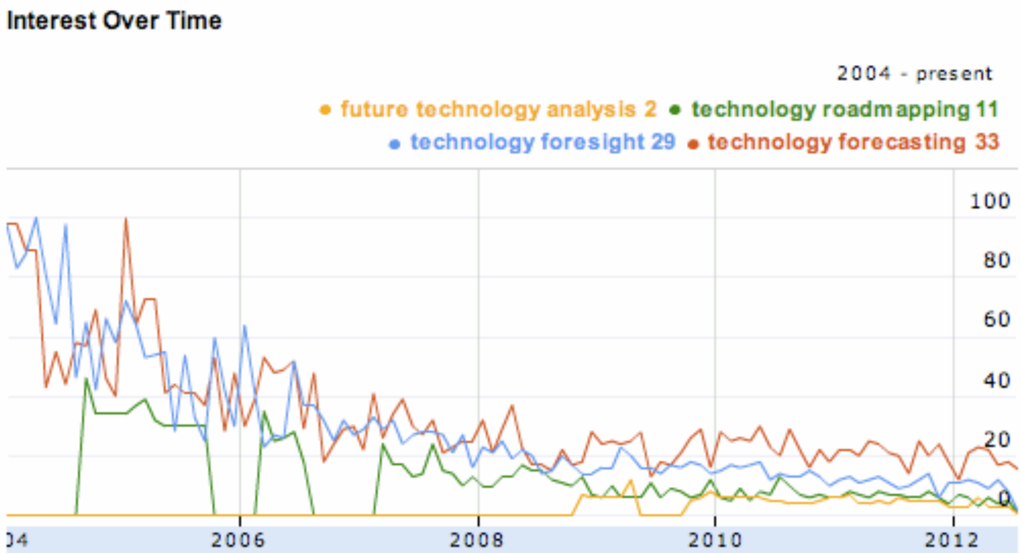
Eerola and Miles (2011) suggest a different problem related to the practice of FTA, which may be an explanation for the results in Popper (2008b): i.e. path dependence in the use of different techniques. '[A]necdotal evidence suggests that many FTA practitioners are simply reiterating the particular approaches with which they have been familiar for many years, with little acquisition of new approaches and little awareness of the costs, benefits and broader implications of alternative methods' (Eerola and Miles, 2011, p. 267). From a different literature – focused more on firm foresight (i.e. not necessarily technology) – Armstrong (2006) and Graefe and Armstrong (2011) suggest that most firms use non-structured face to face meetings as a forecasting tool, which appears not to be very successful compared to many other techniques (such as Delphi).

Ironically, the lack of comparison among techniques occurs in a field where its practitioners continuously question others about the best technologies for the future but do not question which technologies – or techniques – they should use to analyse the future: 'Thus the FTA field itself resembles many of the challenging problems, which are the subject of FTA analysis' (Eerola and Miles, 2011, p. 267).

The above evidence suggests that it is vital to have a comprehensive understanding of the available techniques, their main contexts of application, strengths and weaknesses, and information on the organizations that use them and find them useful. Even more crucial is the exploration and inclusion in the toolkit, of a number of quantitative techniques that have been recently used to analyze future trends, but which have not yet entered the FTA literature (see also Miles et al. (2008b)), e.g. social software, webometrics, altmetrics, Google trends, 'nowcasting' and correlate and prediction markets. To demonstrate the relevance of these recent techniques we analyse the relative weekly frequency of keyword searches in Google from 2004 – the year when the data were first collected – to 2012 using Google Insights.[15] Figures 2 and 3 report the relative number of times that FTA activities

[15]Open access at `http://www.google.com/insights`. The query was last applied on 9 July 2012.

were searched on, from any part of the world, in the eight years 2004-2012. In order to make the series comparable data are normalized (meaning that the figures reported here do not give information on the absolute number of Google searches).



Source: Google Insights

Figure 2: ***FTA traditional activities***. *Google search for Future Technology Analysis, Technology Roadmapping, Technology Foresight and Technology Forecasting, 2004-2012*

Figure 2 reports the results of searches for some of the most commonly-used FTA: Future Technology Analysis, Technology Roadmapping, Technology Foresight and Technology Forecasting. The figure indicates that since 2004 there has been a steady reduction in the number of web searches for FTA activities. This contrasts with the evidence for academic publications (Figure 1), which shows an increase from 2004, with a sharp decrease occurring only after 2008.[16] This difference may be due to a number of reasons, such as, the increased number of publications reduces the need for web searches, or web information is precedes academic publications in this area,[17] or because FTA users are using different techniques and address them using different keywords from foresight and forecasting.

The first explanation implies a causal relation between the availability of academic publications (normally not accessible for free) and the acquisition of knowledge by the community involved with FTA exercises (at firm, government or supranational level).

The second explanation implies that the academic community is realizing with a 4 year lag, a reduction in interest in FTA activities, which is when publications start reducing.

The third explanation implies that either there has been a change in terminology, such that academics and users do not use the same keywords to refer to FTA, or that users

[16]Note that the data in these two figures are not comparable in quantitative terms. What we compare here are trends, not actual values.

[17]A phenomenon endorsed by researchers in several fields, particularly with reference to the high cost and slow pace of academic publication compared to the free and almost immediately usable online resources.

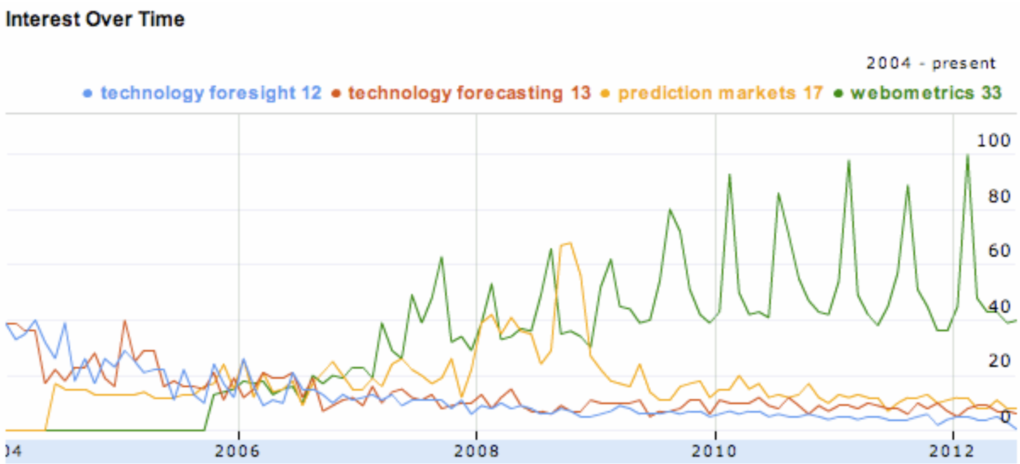
(in particular consultants) are searching for tools not part of the FTA terminology. We cannot say which explanation best fits the real dynamics, which may rely on a combination of reasons. For example, we have a body of material published on more traditional FTA, but much less is available in books or guides on the new tools; therefore, users may use academic references for the former and the web for the latter. Aaltonen and Sanders (2006) comments on this in reviewing the Futures Research Methodology – v2.0 (Glenn and Gordon, eds, 2003), and suggests that we need new (qualitative and quantitative) methods that allow analysis of complex, non-linear relations able to include new conditions and system's criticality: 'When we look at the rest of the methods [excluding SOFI and causal layered analysis], we find out that over four-fifths of them were invented in the 1970s or before' (Aaltonen and Sanders, 2006, p. 30).

In figure 3 we compare the two most common activities in FTA – technology foresight and technology forecasting, – with two widely used new tools – webometrics (a very general term including social software) and prediction markets. The figure shows that non-traditional tools are more frequent search keywords than traditional activities. In addition, webometrics shows an increasing path even when the spikes are smoothed.[18] Finally, at the beginning of the financial crisis there has been a strong increase in searches for prediction markets, but not for FTA activities. This evidence may reflect disaffection with FTA similar to what occurred in the early 1970s after the oil crisis or may, as some experts in FTA suggest, indicate that new users, such as consultants, find that new techniques that use huge datasets made available by the use of the Internet are more useful. However, as mentioned,, neither the Web of Science nor Google evidence constitutes robust scientific evidence of the trends and it is not possible to conduct statistical comparison of series from these two different sources. Therefore, the results presented should be understood as being thought provoking and drawing attention to a phenomenon.[19] As suggested by Boden et al. (2012, p. 136) 'there is a desperate need for new tools, for experimenting different application and combination of existing tools and aligning them to governance systems, to address the complexity of the grand challenges'. In the absence of any systematic way to compare different quantitative techniques (Scapolo and Miles, 2006; Eerola and Miles, 2011), the aim in this paper is not to provide a guide, but merely to map the main strengths and weaknesses of the techniques traditionally used, and those that have yet to enter the FTA literature.

To provide a useful map of existing quantitative techniques, we first systematically select among them. Next, we modify the categorization suggested in Porter (2010) to distinguish between descriptive and prescriptive techniques. Porter (2010) also analyzes two different FTA activities along nine different dimensions. We argue that these dimensions

[18] The spikes in February and August are due to the fact that webometrics is also a university ranking website. However, the results change very little if we search on 'social software', and show an exponential increase if we use the keyword 'Big Data'.

[19] Note that if we add the word 'technology' to the new tools keyword search, replacing, e.g. 'webometrics' with 'technology social software', Google Insight data show that figures are low with respect to FTA, but that keyword searches start in 2007 and increase. Similarly, for prediction markets we were unable to find any exercise or document using prediction markets for technology futures.



Source: Google Insights

Figure 3: ***Google search for Foresight, Forecast, Prediction markets and Webometrics***. *2004-2012*

can be generalized and employed to directly characterize FTA techniques. As we discuss in the next section, these characteristics are useful to map the strengths and weaknesses of different techniques, and how they may be employed in different FTA activities. We then map the main contexts and organizations in which techniques have been used, and how they represent knowledge about future outcomes and probabilities of events (Stirling and Scoones, 2009). Finally, with respect to previous classifications we add recently developed techniques which, because of the lock-in problem referred to in Eerola and Miles (2011), have been overlooked by the literature. Before moving to our classification, we briefly explain our method of selection of the quantitative techniques.

3 Mapping FTA techniques

3.1 The selection of FTA quantitative techniques

In this paper, we adopted the following procedure to select the most important quantitative techniques used in FTA, identified from the literature cited above (Porter et al., 2004; Bishop et al., 2007; Popper, 2008b; Glenn and Gordon, eds, 2009; Magruk, 2011; Jackson, 2011) and the European Commission (EC) Joint Research Centre (JRC) ForLearn website,[20]) and resulting in a list of 64 quantitative techniques.

First, we built the following indicators: (i) number of studies using the method according to EFNM Dynamo data (Popper, 2008b); (ii) number of publications with the name of the technique in the title, abstract or keywords (Web of Knowledge (WoK)); (iii) number of citations to paper in WoK; (iv) number of results in Google scholar containing the name of the technique (in quotation marks); (v) number of results in Google (in quo-

[20] `http://forlearn.jrc.ec.europa.eu/guide/4_methodology/methods.htm` accessed 3 June 2012.

tation marks);[21] and (vi) number of times the technique was mentioned or described in the listed references.

We log transformed indicators i-v to make the figures comparable. Given the low levels of correlation between some of the six indicators, they were summed to obtain an overall proxy for the relative importance of each technique: *Sum*.

Finally, all techniques were ranked with respect to *Sum*, and the main techniques were selected according to their score, correcting for the following three criteria: they should be mainly quantitative – some techniques are mixed; the high *Sum* score does not depend on the name of the technique capturing something different from FTA (e.g. Analogies and Causal models); and evaluation from an extensive reading of the FTA literature.

We grouped some of the techniques under a common term: different contributions ascribe different names to very similar, if not identical, techniques. For example, *Complex Adaptive Systems* (Porter et al., 2004), *Modelling and Simulations* (Magruk, 2011), and *Decision Modelling* (Bishop et al., 2007) are all considered as variations of *Agent Modelling* (Porter et al., 2004).[22] This left us with 26 main quantitative techniques to map and analyze (See Appendix A). Eleven potentially relevant quantitative techniques were not selected, mainly because they referred to methods perceived as being general quantitative approaches rather than specific FTA methods (See Appendix A).

As a result of preliminary analysis of the selected techniques we decided to drop four of them. *Key Technologies* was not retained because we could find no reference to quantitative techniques, and thus relabelled it a qualitative technique. *Force Field Analysis* was dropped because all the references found referred to organizational change, which is far removed from FTA. Structural analysis and Content analysis were dropped because they were perceived as too general.

This procedure resulted in 22 techniques, to which we added 4 new techniques not found in the several reviews analysed above: *Social Software* – which includes Webometrics and Altmetrics, Google tools such as *Google Trends* and *Google Correlate*, *Prediction Markets*, and *Scenario Discovery* – based on Robust Decision Modelling.

In 3.2 we group these 26 techniques into 10 families and describe them. For brevity we describe families of techniques and add some details only for those techniques most representative of a family, if they add significantly different characteristics, or if they are new to FTA.

3.2 Quantitative techniques, contexts and organizations

Different commonly used FTA quantitative techniques have different advantages and disadvantages. Some require different types and sources of data from others; some are more labour intensive or more difficult to operationalize. These quantitative techniques differ also in the proportion of subjective evaluation required, the amount of information col-

[21] Results for both Google scholar and Google were retrieved on the 9 and 10 June 2012.

[22] While *Robust Decision Making* (Glenn and Gordon, eds, 2009) has many common features with *Agent Modelling* it is more appropriate to consider it a Scenario technique.

lected from different numbers of experts or other stakeholders, or the ability to integrate with other quantitative or qualitative techniques in an overall FTA activity. Some techniques have been in use for a number of years and have been refined; others have not been sufficiently tested. These differences, in some cases, are because the use of FTA techniques is subject to fads and path dependency (Popper, 2008b; Eerola and Miles, 2011). Moreover, there is a continuous flow of new techniques developed or borrowed from other disciplines. Some of the recent techniques have been included in the FTA practice to a limited extent – e.g. Robust Decision Making (RDM) (Lempert et al., 2009), hot topics bibliometrics and patents (e.g. Robinson et al., 2011), new applications of Input Output modelling (e.g. Wilting et al., 2008), and prediction markets (Wolfers and Zitzewitz, 2009). Others – such as various forms of social software, social networks, and Google tools – are widely used in FTA-related activities, but have received little attention from the FTA community.[23]

In what follows we briefly review the selected techniques, their strengths (*pros*) and weaknesses (*cons*), their most common applications (*contexts*), and the *organizations* that are more likely to use or to take advantage of them – e.g. national governments, industries, companies, non-governmental organizations and international organizations. We do so by first grouping the techniques according to the families defined in Porter et al. (2004) and Porter (2010). In particular, we distinguish the following 10 families: 'Creative', 'Monitoring and intelligence', 'Descriptive and matrices', 'Statistical methods', 'Trends analysis', 'Economic methods', 'Modelling and simulations', 'Roadmapping', 'Scenarios' and 'Valuing/Decision'.

The classification we propose is a modified version of Porter (2010) which orders the techniques – from Creative to Valuing/Decision – from *descriptive* to *prescriptive*. Second, following this ordering we classify techniques also on the basis of whether they are mainly used for *data gathering* or for *inference*. Third, we provide a first assessment of the features of the techniques and their use (*pros* and *cons*) moving from those that are more aligned to *extrapolative* exercises, to those more appropriate for providing *normative* insights. Finally, with respect to the distinction often discussed in the literature between foresight and forecasting (see e.g. Miles et al., 2008a), we propose that the ordering followed here moves from those techniques more suited to foresight activities to those more suited to forecasting, to return to the foresight-geared techniques at the end of the spectrum.

Next, we categorize the different groups of selected techniques according to how they represent knowledge about 'outcomes' and knowledge about the 'probability' of occurrence of events (Stirling and Scoones, 2009). For a full discussion on the representation of incomplete knowledge, we refer the reader to section 2.2 in WP2. Here '"outcomes" reflect the different relevant things that happen as a consequence of some set of possible interventions or contingent "states of the world". These may be seen as discrete scenarios, or increments on some continuum of consequences' (Stirling and Scoones, 2009, p. 4).

[23] Recent exceptions are Cachia et al. (2007) on social networks, Nugroho and Saritas (2009) on social network analysis (SNA) and Pang (2010) on choice architecture.

Once outcomes have been defined and ordered, '"probabilities" are then conventionally thought of as reflecting the respective objectively established expected relative frequencies associated with each' (Stirling and Scoones, 2009, p. 5). On the one hand, assuming knowledge about 'outcomes' is reflected in the ability to define them and to order them, e.g. along some preference or social welfare scale. On the other hand, assuming knowledge about 'probabilities' is reflected in the ability to measure the distribution of probability of each outcome in a statistically robust way. An example of knowledge about the 'probabilities' of outcomes is that out of 100 coin tosses we can predict that, on average, there will be 50 times an outcome of tails and 50 times an outcome of heads. Using the same example, if among those betting it is agreed that the value of tails is 2 and that of heads is 1, then those betting also have complete knowledge about the 'outcomes'. In this example the knowledge gap on both 'outcomes' and 'probabilities' is closed, and it is possible to compute an expected value. But how do we distinguish between a defined and an undefined 'outcome'? We follow Stirling and Scoones (2009, Fig. 2) and refer to four different states reflecting combinations of assuming highly problematic or non-problematic knowledge about 'outcomes' and 'probabilities'. First, in Fig. 4, top left quadrant we have '*Risk-based Expectations*': when the analyst assumes that she has reliable knowledge of the relevant outcome, on the distribution of possible instances of the outcome and on the value of each instance. An example here would be Moore's Law: we know that the relevant outcome is a perpetual increase in computational speed, and we can predict change in the speed of microprocessors in the short run. Second, in Fig. 4, bottom left quadrant we have '*Uncertainty*': the analyst can assume knowledge on the outcome, – i.e. she assumes perfect knowledge of the outcome she wants to assess, but she has no knowledge of the probability distribution of its occurrences – she cannot assign probabilities to outcomes (and therefore no expected value). Take the example of a flood: we cannot predict it, although it is well defined as a negative phenomenon. Third, in Fig. 4, top right quadrant we have '*Ambiguity*': the analyst can assume reliable knowledge on the probabilities and the final distribution of events, but she does not know what is the desirable outcome, or how to evaluate the outcomes, i.e. we need to explore more than one outcome, and be able to ascertain their respective values. For example, tossing a coin without making a bet on the outcome first, i.e. without being able to identify if heads or tails is the desired outcome. Fourth, in Fig. 4, bottom right quadrant we have '*Ignorance*': we lack knowledge on both the probabilities of the different events and how to evaluate them. In other words, anything might happen. For example, the event of beings from another planet visiting planet earth.

Another caveat is required here: a map representing the knowledge about outcomes and probabilities based on techniques can only be indicative since different techniques can be used for FTAs with different underlying degrees of risk-ignorance. Moreover, whether outcomes and probabilities are perceived as well defined depends also on the context of the analysis. In order to reduce this problem, here we classify the techniques according to which state of knowledge they are perceived to 'bring' the analyst to when she uses them,

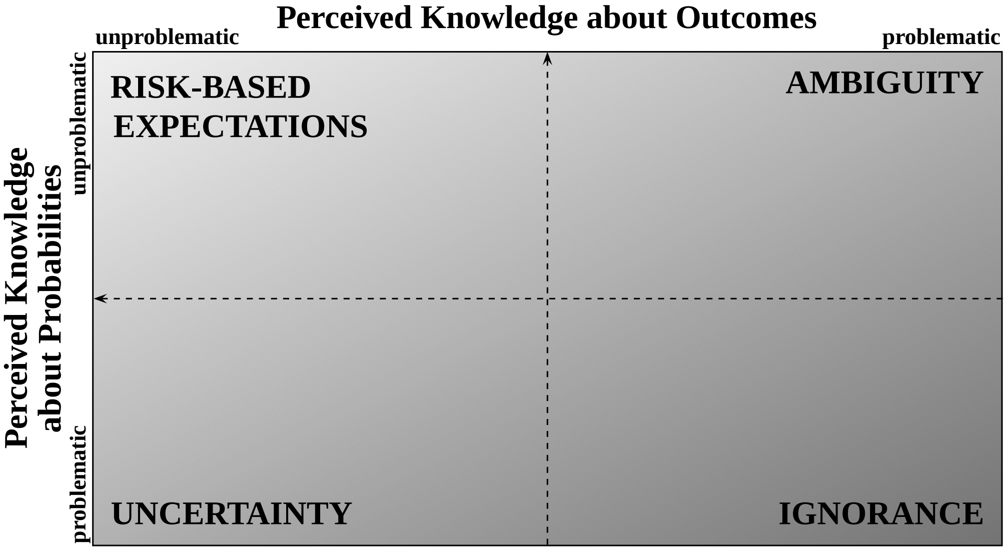


Figure 4: ***Representations of knowledge made by users of different FTA quantitative techniques*** . *Source*: Stirling and Scoones (2009).

and not according to their intrinsic nature.

All quantitative techniques are based on assumptions that incorporate a given representation of knowledge on probabilities and outcomes. Before taking account of the assumptions underlying the use of the technique for an analysis, and referring to the techniques in abstract form, there will be very few that do not fall into the *ignorance* or at best *uncertainty* class. It by taking assumptions that knowledge about outcomes and probabilities is defined and performed. In other words, it should be emphasized that each technique in using these assumptions takes a particular representation of knowledge. For example, trend analysis assumes that only one outcome is relevant and provides the mathematical tools to take the analyst from a condition of uncertainty to a condition of risk-based expectations. Alternatively, when the analyst builds a simulation model, in principle, she is in a condition of *ignorance* because she makes assumptions about the characteristics of the model but outcomes and likely realizations of the model will result from its analysis. Thus, the analysis can lead the analyst either to a condition of ambiguity or to a condition of risk-based expectations, depending on whether she considers the outcomes of the model to be narrow predictions or different scenarios depending on the assumptions and parametrizations. We describe the use of the techniques and how they allow us to move in the probability-outcome space in WP2 when we assess the various techniques.

The adoption of a given technique does not necessarily pre-suppose a specific representation of knowledge in terms of assumptions about outcomes and probabilities. This is because most techniques can be applied in several different ways. *Data gathering* techniques are particularly flexible in this respect. Data collection, in fact, can be aimed at one or another outcome and can supply the analyst with more or less knowledge on the probability of an event.

Finally, the advantages (*pros*) and disadvantags (*cons*) of techniques, and their appropriateness for different *contexts* and *organizations*, are reviewed by assigning to the different groups and techniques the following five characteristics (Porter, 2010, Tab. 10): '*Drivers*' – science (research), technology (development) and innovation context (problem solving); '*Locus*' – company, institution, sector, nation/region and global; '*Time horizon*' – short, mid range or long; '*Purpose*' – informational and action-oriented; and '*Participation*' – narrow, intermediate or representative process. The dimension '*Participation*' refers to the range of different stakeholders that participate in the FTA process. We extrapolate its meaning by considering the breadth of stakeholder perspectives that are included in the FTA, even if this is not direct ' participation', but mere use of text mining techniques aimed at capturing the views of diverse stakeholders.

As in previous classifications of FTA techniques, it is important to remember that the combination of two or more techniques under the same heading is intended to facilitate the reader's orientation and choice among a large number of different techniques. However, the boundaries between groups should not be taken as rigid. As we will see, the same technique can fall into more than one group depending on how it is used. Also, if we enter the different types of FTA activities, we can apply different classifications. For example, particularly in the context of foresight, different techniques may be better suited to different phases in the foresight exercise (Saritas, 2006; Saritas and Aylen, 2010), and a foresight activity will usually combine more than one technique.

In Table 1 we distribute techniques according to the 10 families listed above; in Table 2 we summarize the characteristics of each family outlined above.

3.2.1 Creative

The main technique for creative exercises is the Theory of Inventive Problem Solving or TRIZ,[24] aimed at finding inventive solutions for technological problems. TRIZ emphasizes that patterns of improvement and refinement are common across industries and scientific fields and that innovations from other domains can often be introduced with positive effects. The progressive nature of technical progress in the TRIZ framework takes place as improvements are made along existing technological trajectories within their respective technological paradigms (Dosi, 1982). The concept of 'evolutionary potential' describes how much progress can be made along an existing trajectory (Mann, 2003). TRIZ seeks out regularities in the patterns of evolution of the technologies. Efforts have been made to find an algorithmic approach to obtain insights into the invention of new systems and the refinement of existing systems. TRIZ considers that inventions occurred via trade-offs between two contradictory elements, with the solution often emerging at a 'superior' level that overcomes the tension between these two elements. For example, 'Dairy farm operators could no longer dry cow manure for use as fertilizer due to an increased cost of energy. They were faced with a technical contradiction between dry manure (good) and

[24] From the Russian: teoriya resheniya izobretatelskikh zadatch.

Descriptive ⟶ *Prescriptive*
Extrapolative ⟶ *Normative*
Data gathering ⟶ *Inference*
Foresight ⟶ *Forecast* ⟶ *Foresight*

Creative	**Monitoring & intelligence**	**Descripive & matrices**	**Statistical methods**	**Trends analyzes**	**Economic methods**	**Simulation Models**	**Quantitative Scenarios**	**Roadmaps**	**Valuing/ decision**
TRIZ	Bibliometrics	Bibliometrics	Cross impact analysis	Long wave models	Input Output	Agent modelling	*RDM*	Roadmapping	Multicriteria decision analysis
	Conjoint analysis	Cross Impact analysis	SMIC Prob Expert	Trend extrapolation	*Prediction markets*	(Modeling & simulations)	*Scenario discovery*		AHP
	Social network analysis	State of the future	Scientometrics	Trend impact analysis		(Decision modeling)			Life cycle an. / sustainability
	Social Software (Webometrics)	Conjoint analysis		S-curves		(Robust Decision Making)			
		Social network analysis		Technology substitution		System dynamics			
		Social Software (Altmetrics)		Megatrend analysis					
				Time series / Indicators					
				Google trends & correlate					

Source: our own elaboration based on Porter (2010) (see Sections 3.1 and A)

Table 1: ***Classification of techniques***. *Quantitative techniques are categorized in 10 groups (in bold). Groups/techniques are ordered along the dimensions indicated at the top of the table. Italics refer to techniques that are new to FTA.*

Descriptive → → *Prescriptive*
Extrapolative → → *Normative*
Data gathering → → *Inference*
Foresight → *Forecast* → *Foresight*

	Creative	**Monitoring & intellig.**	**Descripive & matrices**	**Statistical methods**	**Trends analyzes**	**Economic methods**	**Simulation Models**	**Quantitative Scenarios**	**Roadmaps**	**Valuing/ decision**
Outcomes - Prob.	Ignorance	Ignorance / Uncertainty	Ignorance / Uncertainty	Uncertainty	Uncertainty	Uncertainty	Uncertainty	Ignorance	Ignorance / Uncertainty	Ignorance
Drivers	Science & Technology	Innovation and context	Science & Technology	Technology & Innovation	Technology & Innovation	Context	Context	Context	Science & Technology	Context
Locus	National, industry, companies	Companies & institutions	Companies & Governments	Sector & Nation	Sector & Nation	Nation / Region	Nation	Companies & Nation	Companies / Sector / Nation	Companies & Nation
Time horizon	Long	Short	Mid range	Mid range	Short	Long	Short / Long	Long	Mid/ Long	Mid range
Purpose	Informational	Info & action	Info & Action	Action	Informational	Informational	Informational	Action	Action	Action
Particip.	Narrow	Intermediate / *Diverse*	Narrow / *Diverse*	Narow-Intermediate	Narrow / *Diverse*	Narrow / *Diverse*	Narrow	Intermediate	Intermediate / Diverse	Diverse mix

Source: our own elaboration based on Porter (2010) and Stirling and Scoones (2009).

Table 2: ***Main features of the groups of techniques***. *Each group of techniques is described along the following dimensions (column 1): Knowledge on Outcomes and Probabilities, Drivers, Locus, Time horizon, and Participants. The groups are ordered along the dimensions indicated at the top of the table.*

cost (bad). TRIZ led the operators to a drying method used for the concentration of fruit juice, which required no heat'.[25] Although TRIZ is a technique related to creativity, it does not build on the creativity of the researcher, but requires the researcher to consider the predictability and reliability of patterns of technological progress. It is therefore mainly used under conditions of *uncertainty*.

TRIZ can be employed in many FTA activities (Jackson, 2011) and is mainly *descriptive* and *extrapolative* (*data gathering*). With respect to the other dimensions, the main *drivers* are Science and Technology problems, the *loci* of activities are the national, industry and company levels (Clarke Sr., 2000), the *time horizon* is relatively long and it has mainly an informational *purpose*.

The benefits *Pros* of TRIZ are that it can be applied to a wide range of problems (whether well-known or relatively unknown); its disadvantages *Cons* are that it is complex, time consuming and requires that the researcher has been specially trained. For these reasons its *participation* is quite narrow.

3.2.2 Monitoring and intelligence

A number of techniques can be classified under this group, such as Bibliometrics, Conjoint Analysis, *Webometrics*, (*Social Software*) and *Social Network Analysis* (SNA). The last two are new to FTA and we rely more on their applications in practice than on reviews in the literature.

These techniques are used mainly to gather information from individuals on their preference, relations, attributes, etc. They are *data gathering* techniques, *extrapolative*, and close to *foresight* methods. Some of these techniques, such as Conjoint Analysis, focus on small numbers of individuals and gather structured information on trade-offs among alternative outcomes, and the ordering of preferences on specific outcomes, which can range from products to projects. Conjoint Analysis is used with selected groups of individuals with different characteristics: individuals are given a set of features of a project/good/technology and are asked to order these features, thus revealing their preferences. For example, they may be given several cards listing the same attributes but with different values. Their ordering of these cards reveals which types of individuals (information on their characteristics is also collected) prioritise certain attributes with respect to others (Lukban, 1997).[26] The data can then be analysed using econometric techniques, bringing Conjoint Analysis applications closer to *inference*. The *pros* of Conjoint Analysis are the very precise information it provides on users (for large samples) and the ability to order preferences on the attributes that usually form trade-offs.

Among the newer FTA techniques, data available on the web offer a wealth of possibil-

[25] From `http://www.mindtools.com/pages/article/newCT_92.htm`, accessed 23 July 2012.

[26] Two papers use Conjoint Analysis to evaluate objective attributes of technologies (Yoon and Park, 2007; Xin et al., 2010). E.g. Yoon and Park (2007) use number of citations to a patent to proxy for its 'value'. The attributes of the patents are determined first using morphology analysis. The value of each attribute is then estimated in order to run the Conjoint Analysis and establish the relative value of the technology.

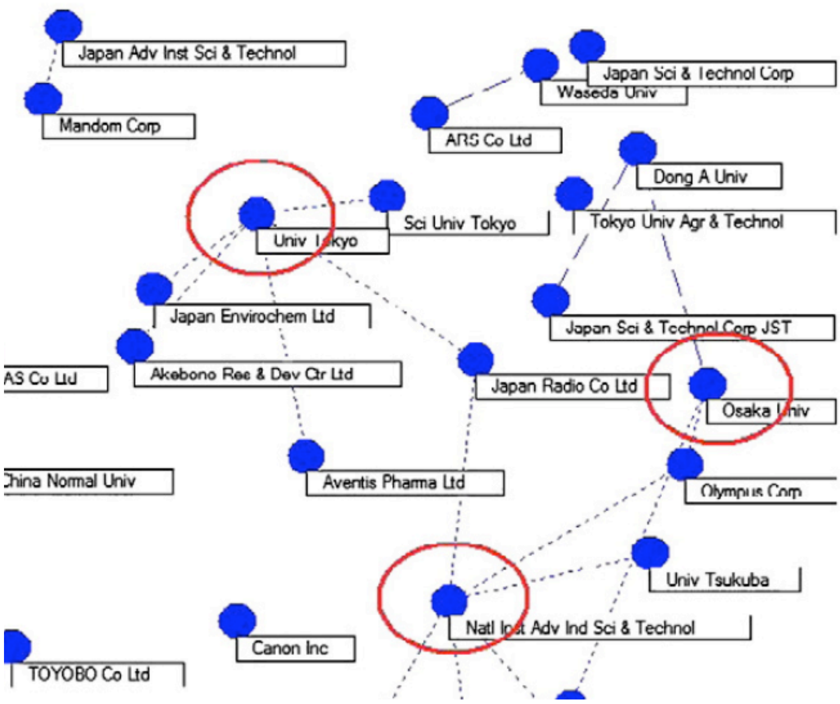
ities for data mining. There is a body of anecdotal evidence showing that tools based on information available on the web are being used to track technological developments. The extent to which these sources have been used to investigate technology futures is unclear, but companies such as Quid, RecordedFuture and Treum are providing tools that help to map technologies using web data. The information gathered from the web can be used as background information for more direct future-oriented activities such as technology roadmapping (Section 3.2.9). The sources of web-based data are quite diverse and include online news publications, blogs, trade publications, government web sites. Unlike the information available from bibliometric or patent databases, web-based information is generally unstructured. As a result, complex (often time-consuming) algorithms are needed to process these data and identify entities (persons, companies, etc.) and events (meetings, company acquisitions, protests, etc.), and to locate them in space and time in order to generate trends and networks. One of the *pros* of these analyses is that trends and clusters are annotated with visual tags, which greatly facilitates understanding of information. On the *cons* side, the knowledge produced can be unreliable. A major problem in these studies is that the open-ended nature of the web means that it is unclear what constitutes the reference or base. For example, to study trends over time it is necessary to compare perceived growth of the technology being analysed (e.g. lab-on-a-chip) with the general growth in the information generated about that technology, something that, in an expanding web universe is likely to be very rapid (more and more information is being generated per unit of technology). This problem already applies to the Web of Science, which has substantially increased its journal coverage; the result of this is that some topics can appear to be expanding, when in reality it is the database that is expanding!

As in qualitative *foresight* techniques such as Delphi, these techniques encourage the gathering of information from different stakeholders. However, in contrast to foresight techniques such as Delphi, the stakeholders do not build relationships with one another, they do not confront each other's ideas, and, often, they are not active participants, but rather actors who produce traces that are subsequently analysed. However, a major advantage (*pro*) of these techniques (particularly Webometrics and Tech mining) is that *'participation'* is very diverse: they gather extremely large amounts of information, from experts and non-experts indifferently, and include many more opinions. However, the sample is still biased towards a specific group of stakeholders: those with access to the Internet and who use it intensively for (social) communication. In sum, there is a trade-off between expertise and continuity of exchange on the one side, and bottom-up representation, an aspect that should be considered carefully by foresight practitioners and clients.

SNA is a technique that investigates a social phenomenon by analysing the structure of the relationships (links) among entities such as actors, concepts or artefacts (nodes). The key assumption in network analysis is that the network structure and relative positions of the entities in the network are potentially important for understanding the outcomes of the collective. Despite its wide use in social sciences, SNA is quite new to FTA (Nugroho and Saritas, 2009), although Network Analysis has been used implicitly as a tool, e.g.

FTA studies using science maps generally are based on network analysis of bibliometric data (van den Besselaar and Leydesdorff, 1996).

In what sense can network analysis be considered a type of technology analysis that is future-oriented? The different potential uses of SNA in foresight exercises, as discussed by Nugroho and Saritas (2009), illustrate that techniques such as SNA can be employed in FTA in many different ways. For example: (i) in the scoping phase of foresight, SNA can be used to define and delineate the field or issues under investigation by looking at how different clusters of topics relate to each other; (ii) in the recruitment phase, SNA can help to identify key actors and their positions in relation to other actors or to topics and/or organizations; (iii) in the action phase, SNA can become a management tool to foster interdisciplinary interactions and/or effective collaboration (Nugroho and Saritas, 2009, p.30). As examples of applications, Saritas and Nugroho (2012) use SNA to show the relation between topics in a questionnaire administered to FTA experts: the network shows which topics are the most strongly related (e.g. Scarce Natural Resource is related to Climate Change). A typical example of the application of SNA in FTA is analysis of inter-organizational collaboration networks (Figure 5): here, the insights gained can be used to understand groupings of collaborators with potentially different interest, visions or research agendas. An important *pro* of SNA compared to other techniques is that it can



Source: **ADD SOURCE**

Figure 5: ***Inter-organizational collaboration is Japanese nanobiosensor research***

help to convey the systemic, relational and situated nature of technological developments.

The main *drivers* for using monitoring and intelligence techniques are related to innovation and context. Similarly, the main *loci* are companies and institutions. In fact, Conjoint Analysis is used mainly for marketing purposes, i.e. for promoting new goods (e.g. Tseng et al., 2012), although the context can differ among pricing of new goods, environmental consciousness Eggers and Eggers (2011); Lin et al. (2010) and value chains (Luo et al., 2007). Given the type of information collected, the *time horizon* is short, and the *purposes* of the FTA are both informational and action-oriented.

3.2.3 Descriptive and matrices

The techniques included in this group are in a mid ground between pure monitoring and pure statistical methods, and include*Scientometrics* (Bibliometrics and Patent Analysis), *Cross-Impact Analysis* (CIA), *State of the Future Index* (SOFI), *SNA*, *Social Software* such as Webometrics and *Altmetrics*, and *Conjoint Analysis.* We refer to these techniques as *data gathering* and *extrapolative* techniques, structured (some more than others) in statistical indicators. Compared to the previous group, the techniques in this group refer to aggregate indicators rather than individuals. Scientometrics and Bibliometrics are good examples here.

Data contained in bibliometric databases, such as the Web of Science or Scopus, and patent databases, such as the Derwent World Patents Index (DWPI), can be analyzed in a variety of ways in order to investigate technology futures. These structured databases on publications and patents provide a rich set of information on each bibliometric (publication) or technometric (patent) record: title, keywords, authors (inventors), organizational affiliations of authors (inventors or assignees), references or citations in the record. The main *pro* of bibliometric and patent analysis approaches is that the databases are standardized, which provides quite reliable time series. The *cons* are the lack of accuracy in searches for records related to a technology (due to technologies whose names change, and idiosyncrasies in titles and abstracts), and the fact that information contained in publications and patents refers to early stage R&D. Another problem is that the data will be some 1-3 years old at the time of the analysis given the time between submission of a publication (or patent application) and appearance of a record in the database. The data gathered are usually employed to extrapolate future trends (see Section 3.2.5). They can be used also for network analysis such as investigation of shifts in topic clustering in the evolution of a network (Kajikawa et al., 2008). In this case, the bibliometric data are used to analyze trends in different areas of the network, which provides information on trends in competing clusters (options) related to an emerging technology, e.g. Silicon vs GaAs solar cells.

A number of tools has been developed recently to expand the databases used to analyse bibliometric records, using social media to assess immediate impact and diffusion of scientific publications and related topics. Such ‘alternative’ metrics are referred to as Altmetrics (Priem et al., 2012).[27] These alternative metrics retrieve the citations of papers from open online sources ranging from knowledge sharing tools such as Wikipedia, social

[27]Tools currently available on the web are PLOS Article-Level Metrics (ALM), Reader Meter, CiteIn, Total-Impact and Altmetric (Priem et al., 2012).

network such as Delicious, Twitter and Facebook, publication sharing tools, and online reference managers such as Mendeley, Zotero and CiteULike, blogs, comments, and so forth. Depending on the types of sources included, Altmetrics need normalized data that are structured and to use algorithms to avoid duplication, use of different names, automatic downloads by web-crawlers, etc. The use of Altmetrics is in its infancy and its usefulness and reliability are strongly debated (E.g. Jump, 2012). However, Priem et al. (2012), for example, find that: (i) the distribution of the number of activities on the web per paper is strongly skewed, as is that of citations in the Web of Science or Scopus; (ii) activity on the web related to articles changes markedly over time with respect to use of different tools, e.g. sharing and commenting decays in a few weeks, while downloads are more persistent, showing the different uses of scientific information; (iii) the correlation among the different metrics is observed when using similar metrics – 'Altmetrics and citations track forms of impact that are distinct, but related; neither approach is able to describe the complete picture of scholarly use alone.' (Priem et al., 2012)

Altmetrics, then, on the one side tends towards structured databases, such as those used in traditional Scientometrics, and on the other side, tends towards unstructured databases, such as those used in Webometrics that have wider application (than measuring the production of scientific outputs (Section 3.2.2)). Careful use of Altmetrics can resolve the *pros* and *cons* of these two extremes. However, there are important limitations with respect to data quality and the possibility to easily alter some of these metrics.

SOFI is a very different technique in this family: it collapses the information into a set of (economic) variables, e.g. unemployment, population growth, food availability and R&D, to build an index that provides a 10-year projection into the future. Some indicators follow an improving trend over time (e.g. Gross Domestic Product (GDP) per capita and literacy), others tend to become worse over time (e.g. CO2 emissions, forest cover, unemployment). In order to build a SOFI, the analyst needs to consider: (i) which variables to include; (ii) how to compare and combine them in one index; (iii) how to forecast them; and (iv) their weights (Gordon, 2003). The main *pro* of SOFI is that reducing the future to a single number, it makes it easier to grasp for policy makers, although it is of course a grotesque simplification that masks variations across regions and groups (e.g. masks potential trends in inequality). However, SOFI can be used at the level of individual regions or countries rather at world level.

The *drivers* of the techniques in the descriptive and matrices family, particularly for Social software, Scientometrics, SNA and CIA, less so for SOFI, are generally science and technology, and mainly science-based emerging technologies such as fuel cells (Daim et al., 2006, p. 992), or emerging applications such as food safety technologies (Daim et al., 2006, p. 1000), which have both informational and action-oriented *purposes*. The *loci* are mainly governmental agencies involved in S&T or military research, and large corporations in science-based industries such as chemicals. The *time horizon* is generally mid-range and *participation* is usually very narrow (expect for Conjoint Analysis, see above, and CIA, see below).

3.2.4 Statistical methods

All statistical method techniques are *data gathering* and *extrapolative*. We distinguish between techniques that gather secondary data from large data bases – Bibliometrics and Patent analysis discussed earlier (Sec 3.2.3) – from those that gather data from experts such as CIA. CIA is closer to the original idea of *foresight* methods of gathering opinion from stakeholders. However, all these methods are closer to *foresight* than to *forecasting*, and recent use of Big Data described in Sections 3.2.2 and 3.2.3 can be seen as a huge expansions in the involvement of different stakeholders. However, in this latter case, nobody is asked for information on their choice; it is inferred from the data.

Having already discussed large data-sets, we focus here on CIA. The technique consists first of selecting a series of possible events related to the topic of analysis. These possible events are judged by a group of experts. Events need to be clearly stated in probabilistic terms, such that the experts are not in doubt about the different possible outcomes or how to evaluate their likelihood. The experts can be asked to assess the probabilities of single events or to assess the conditional probabilities directly. Events that should be included are those related to the topic being studied and which are not independent, i.e. not influencing and not influenced by any other included event. The number of events should be limited, due to the exponential growth of interactions to assess in the number of events selected. The events usually will be included on the basis of the literature and the experts' advice. In the next step, a number of technical procedures are used to assess the consistency of the probabilities of related events, to measure the impact of one event on the conditional probabilities, and to measure the sensitivity of the conditional probabilities to single events (Gordon, 2009a). CIA is often used in conjunction with simulation models to adjust expert opinion to obtain a set of predictions that are coherent in statistical terms, and to elaborate future scenarios, e.g. CIA and Matrices (SMIC) (Duperrin and Godet, 1975), EXPLOR-SIM (Fontela and Gabus, 1974), KSIM (Kane, 1972) and INTERAX (Enzer, 1980a,b).

The *pros* of CIA are its main method which forces the experts to compare their opinions,[28], to think about causal relations between events and to consider explicitly the occurrence of a number of events. However, these activities can be long and difficult, especially for large numbers (over 10) of events to interact. It is important to keep the number of events small. In any case, it becomes difficult for the experts to maintain consistency of opinion and to keep in mind the probabilities assigned to previous interactions of events, and to avoid thinking about more than one interaction at a time (Gordon, 2009a; Scapolo and Miles, 2006).

The main *drivers* in this group of techniques are technology and innovations, with the main *loci* being sectors (industries) and nations. CIA has been used in a number of industries, to forecast the development of a number of technologies, e.g. information and communication technology (ICT), to analyze national or supranational events such

[28] I.e. in a more precise way than when using Delphi (Scapolo and Miles, 2006).

as flood risks and geopolitical changes, and the evolution of industries e.g. nuclear and automotive. The *time horizon* depends on the experts' abilities to assess future events, but tends to be mid range. The *purpose* is mainly action-oriented, and *participation* is quite narrow.

With respect to outcomes and probabilities, statistical methods such as CIA are used when knowledge about outcomes is assumed, i.e. contained in the questions to the experts, but knowledge about the relative importance of events, the probability of each event occurring within a given time horizon and the conditional probabilities reflecting the interactions of events is small (Scapolo, 1996). Following Stirling and Scoones (2009), we refer to this condition as *uncertainty*.

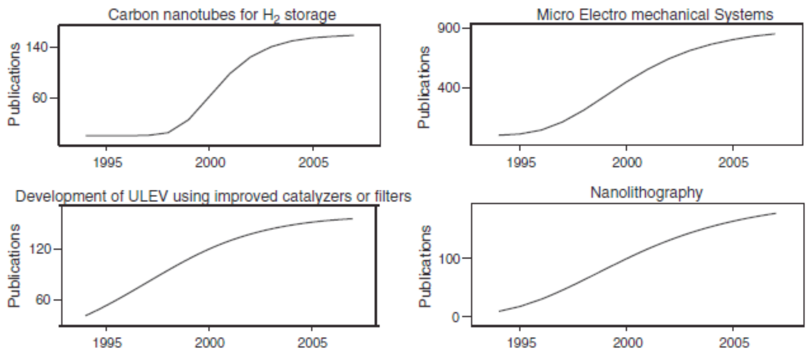
3.2.5 Trend analyzes

There are numerous techniques that use historical data (such as those described above) to infer future trends: *Indicators/Time Series Analysis* (I/TSA), *Long Wave Analysis/Models* (LWA), *Trend Extrapolation*, *Trend Impact Analysis* (TIA), *S-Curves*, *Technology Substitutions*, *Megatrends Analysis*, and Google tools such as *Google Trends* and *Google Correlate*. We are thus moving from data gathering to examine *inference* oriented techniques, which are more useful for *forecasting* than for foresight exercises. However, these techniques are still more useful for *extrapolative* (rather than normative) exercises and are more *descriptive* than prescriptive. Some of these techniques differ only with respect to the initial assumptions and/or the specific application. To illustrate, below we outline the differences between Trend Extrapolation, Technology Substitutions, TIA, Megatrends Analysis and LWA.

In general, I/TSA starts with the selection of some numerical indicators that can be tracked over time to highlight key developments. The indicators can come from a wide variety of domains: economic, social, environmental, scientific, technological, etc. The choice of indicator will be determined by the particular problem and the needs (as well as the imagination) of the researcher (Popper, 2008a).

More specifically, Trend Extrapolation extrapolates historical technology trends into the future. These trends can be based on data on research on the technology (e.g. bibliometric data), its potential commercialization (patents) or its adoption (e.g. number of Internet users). Although Trend Extrapolation can refer to any historical series, it is often used for diffusion or adoption of technologies. Historical studies of technology diffusion (Rogers, 1962) suggest that technologies follow a life-cycle that includes an early period with just a few adopters, followed by a mid-life period with rapid rates of adoption, which decelerate as the technology saturates the population of potential adopters. Hence, the adoption rate follows a sigmoid curve. This conceptual model has also been used to map technology emergence.

The related literature usually refers to S-curves or Technology Substitutions. S-curves are diffusion models identified in the historical analysis in Rogers (1962). These longitudinal models, including the popular Gompertz model and the more recent Richards model, are purely descriptive, i.e. they do not use explanatory variables for the trends (Marinakis, 2012; Ryu and Byeon, 2011). They can be used, e.g. to assess a 's stage of technological advancement (Ryu and Byeon, 2011), or the future development of a technology. For instance, based on growth in the number of publications reported in Figure 6, Bengisu and Nekhili (2006) suggest investment in the represented technologies.



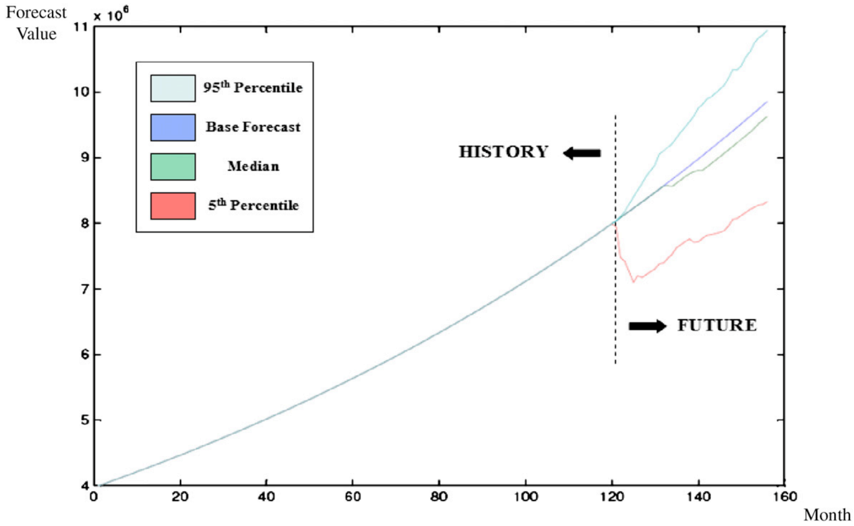
Source: **Bengisu and Nekhili (2006), p. 843**

Figure 6: ***Growth curves of some emerging technologies***

Technology substitution adds to the diffusion dynamic substitution of an incumbent technology/product by a new technology. The idea of technology substitution was proposed by Fisher and Pry (1971-1972). They show how the sigmoid curve that describes early, slow substitution followed by rapid increase, which later fades as the technology reaches saturation, could be fitted to the cases of 17 observed technology substitutions, including synthetic and natural fibres, plastic and leather, synthetic and natural rubber, etc. (Fisher and Pry, 1971-1972). Following Fisher and Pry (1971-1972), Nakicenovic (1979) introduced a model in which more than one technology is introduced in the market in series (multi-generations). Another multi-generation model based on Fisher and Pry (1971-1972) was introduced by Norton and Bass (1987), in which the diffusion of new generations of technology is positively influenced by the earlier adoption of the old generation. All these models fit quite well with the data and have been used widely to forecast the diffusion patterns of new technologies.

TIA was proposed as a further extension to extrapolation and substitution: it investigates how the forecasted trajectory would change if there were unanticipated events Agami et al. (2008); Gordon (2009c). The method develops a computational algorithm, supported by expert input, which explores different potential scenarios, with different probabilities of occurrence, as illustrated in Figure 7 (Agami et al., 2008).

Megatrends analysis broadens the scope of analysis in time (various decades) and topic (broad issues), and includes general social issues (Oner et al., 2007). Megatrends analysis usually represents broad tendencies such as progress in information science and computing, nano-scale research, or body-enhancing technologies (Roco, 2002, pp. 10-11).



Source: **Agami et al. (2008), p. 1449**

Figure 7: ***Scenarios generated with Trend Impact Analysis***

LWA, is wider in scope compared to Trend Extrapolation, TIA and Technology Substitutions. Since Schumpeter, Mensch and Kondratiev, LWA represents long term patterns in the behaviour of technology and society. For example, long wave cycles lasting about 50-60 years have been identified as coinciding with the rail-road boom, the eras of steel, oil/coal and, eventually, the current information technology era. If this pattern continues, we can expect the next technological 'boom' led by biotechnology to occur around 2024 (Linstone, 2002, p. 318).

As already noted, new FTA techniques emerge particularly from the use of Big Data available from the web. Google Trends and Google Correlate are two examples of short term forecasting (nowcasting). These two tools exploit very simple behaviour among Internet users, the search for solutions to specific problems on the internet using Google. These searches are conducted using keywords. Since 2004, Google has recorded these keywords, and makes available these Internet tools to investigate the time series of web searches: i.e. what people search for in specific locations, at specific times of the year, or close to specific events. Google Insights is a sophisticated version of Google Trends, which breaks down the data by location, time range and category, and allows these data to be saved. It provides a 'time series index of the volume of queries users enter into Google in a given geographic area' (Choi and Varian, 2011, p. 3). The index approximates the normalized ratio of the searches on a given query (in the given region) with respect to the total number of queries.[29].

These data are used to improve the predictions in several time series, by adding information on the behaviour of individuals. For instance, Wu and Brynjolfsson (2009) show that, after the bursting of the real estate bubble in the US, i.e. in a period when the housing market is not predictable, immediately available Internet search data allow fairly

[29]See Choi and Varian (2011) for a detailed description of approximation, sampling and normalization

precise predictions about house sales: ‘Specifically, we find that a 1% increase in search frequency about real estate agent is associated with quarterly sales of an additional 67,700 homes in a US state’ (Wu and Brynjolfsson, 2009, p. 3). Wu and colleagues suggest also that tools, such as Google Trends, can be used to predict technological trajectories related to the competition between rival technologies (e.g. HD DVD and Blue-Ray). For instance, they compare the series of the Google searches for Apple laptops with Apple laptop sales (Figure 8). They find that the inflection points in the searches are visually correlated with laptop sales.

Source: **Wu and Brynjolfsson (2009), p. 12**

Figure 8: ***Comparison between Google search for and sales of Apple laptops***

These correlations can be tested using another Google tool, Google Correlate. Google Correlate allows study of the correlation between different queries or, and even more interesting, between real (monthly or weekly) data and queries (such as the sale of goods as in the example above, or between job searches and unemployment rates).

Several papers have explored the robustness of query data and applied them to various issues. For instance, Ettredge et al. (2005) found a positive relation between Internet job search and subsequent unemployment data in the US. More recently Askitas and Zimmermann (2009) found a similar positive relation between job searches and monthly unemployment rates in Germany, and confirms the robustness of Internet search data. Baker and Fradkin (2011) found that job searches are related also to changes in unemployment insurance, including timing of unemployment benefits and changes to insurance policies. Guzman (2011) pushes the interpretation of the macrodynamics even further by explaining inflationary expectations, using Google search data on inflation as a proxy for people's revealed expectations: high frequency search data seem to outperform lower frequency surveys usually used to predict inflationary expectations. On a more micro scale, Preis et al. (2010) find that the volumes of transactions of companies registered in the S&P500 index are related to the volumes of those companies' Internet searches. People have used queries trends to predict the close future also outside of economics. Radinsky et al. (2008) find that past searches are able to predict a good part of what appears in the news a few days later. Polgreen et al. (2008) and Ginsberg et al. (2009) kicked off the analysis of the relation between Internet searches related to influenza and influenza epidemics. They show that Internet searches have very strong predictive power related to the diffusion of this disease in populations highly connected to the Internet, with very short lags.

Despite this persistent diffusion of and experimentation with Internet queries, data in disparate disciplines, including rather traditional disciplines such as economics, to our knowledge similar techniques and data have not been explored or applied in the FTA literature.

The main *pros* of traditional trend analysis techniques is that they rely on simple and intuitive models which are not data intensive, and they provide a reasonably good fit with a large body of evidence on diffusion processes. Techniques based on use of Internet data benefit from a vast source of information that reveals peoples' needs, preoccupations, expectations and so on. In other words, they can be used to predict a large number of economic and social dynamics related to technological change (including user adoption). On the *cons* side, with reference to diffusion and substitution models, first the replacement of technologies is usually not as clear cut as it is implied in Norton and Bass (1987): old generation technologies coexist with new ones and, in some cases, more than one product/technology enters the market simultaneously (Tseng et al., 2009). Second, these models represent very simple dynamics that are not very explanatory. Third, such models are deterministic and assume that 'once the substitution starts, it will proceed unidirectionally to the final level of saturation/displacement' (Gordon, 2009b). Fourth, they generally need quite long data time series on the initial diffusion of a technology in order to forecast its future state (Gordon, 2009b), although techniques using few data have begun to be developed (Meade and Islam, 2006). Internet data are still being tested, and their openness and structure are a cause for concern. For example, like social software (Sections 3.2.2 ad 3.2.3), they provide information on only a specific portion of the population(and the reliability of this information remains to be proven).

With the exception of Megatrends Analysis and LWA that target broad socio-economic issues, the main *drivers* of traditional trends analysis techniques are technology and innovation. Techniques that use Internet search data (Google Trends and Google Correlate) are more focused and context oriented. Trends analysis is used mainly by industries and governments (*loci*) aimed at analysing the disruptive potential of new technologies (e.g.

Ryu and Byeon, 2011). The use of Internet search data is limited mainly to academia and to a limited extent to government agencies (e.g. to predict an influenza outbreak) and companies (e.g. to predict seasonal markets). The exercises usually focus on short or medium *time horizons*, have mainly informational *purposes*, and require rather narrow *participation*. Google Trends and Google Correlate may differ in terms of 'participation' mainly because they gather information from very large numbers of passive stakeholders: the information used is extracted from all Internet users who employ search engines revealing a number of information on their behaviour. Although this information does not derive from 'participation', its basis is the revealed behaviour of the stakeholders involved.[30] However, in analyses based on Internet searches which lack a unique theoretical framework, the time lag seems to be shorter: Choi and Varian (2011) [p. 1] present these data as useful to 'predict the present', or as others describe it for 'contemporaneous forecasting' or 'nowcasting.'

Most trend extrapolation techniques treat outcomes and probabilities as unproblematic or as originally given. They usually are based on theoretical models with already defined relations between inputs and outputs, and require only estimates of the curvature of a given direction, i.e. the pace at which outputs follow from inputs and, sometimes, whether these relations are linear. Some methods, such as TIA, consider only one outcome (the technology under study), but take into account of unexpected events in the likelihood of results. All these techniques are used in conditions of *uncertainty*.

3.2.6 Economic Methods

In relation to the need to design and implement economic policies economics is concerned with *forecasting* analysis, mainly with reference to macroeconomic fundamentals such as inflation, unemployment, growth rates and accounting variables including foreign trade. However, these types of exercises are not directly relevant to FTA. Economic policy (and forecasting) exercise mainly use Dynamic Stochastic General Equilibrium (DSGE) models based on the theoretical foundations of the new Neoclassical synthesis, with little or no reference to technological or structural dynamics. Agent-based models in the Schumpeterian tradition, take technology and structural change more seriously and, since the financial crisis, more consistently Fagiolo and Roventini (2012), but are of limited relevance to FTA.

More related to FTA is the use of *Input-Output analysis* (I/O) and the recent development of *Prediction Markets*.

I/O analysis models the relations between different sectors in an economic system, where the outputs from one sector are used in one or more other sectors. While the first version included sectors such as industries, later developments include different aspects of demand, natural resources, waste, international trade, and so on. I/O were initially used to forecast the state of the world, and the income gap between the developed and developing countries (Leontief et al., 1977), and have been extended to include endogenous

[30] We discuss participatory issues in more length below and in WP2.

technological change, prices and household micro behaviour. These developments enable the construction of scenarios if there are sufficient data to calibrate the initial exogenous factors. More importantly, the matrix of real variables that form the I/O framework can be used to account for flows of energy and resources, and outflows of pollution (Fontela and Rueda-Cantuche, 2004). This is usually accomplished by constructing a social account matrix (SAM) to model the relations between technology factors (use of inputs across sectors, i.e. inter-industry flows of inputs and outputs), flow of goods, income and activities purchased by different institutions, use of factors and resources and distribution of income among organizations (transfers of income between the various sectors of the economy) (Duchin and Hubacek, 2003). The models describe the relations between real variables and, if data on a model's parameters are known, SAM can be used to build scenarios by manipulating the parameters values.

Thus, I/O models are mainly used to construct *inferences* from available data, but they are more *descriptive* rather than prescriptive, and are both*extrapolative* and *normative* when, as it is usually the case, the assumptions underlying the modelling are based on normative aspects.

Relevant examples of recent I/O developments are the models built to analyse the environmental impact of economic activity – DIMITRI Faber et al. (2007); Wilting et al. (2008). These models build different technology scenarios based on technology extrapolation, to define how technological change affects the use of the different inputs employed in production (the coefficients). Changes in the coefficients can occur due to (i) changes in the process of primary production (e.g. organic changes the input mix), and (ii) changes that affect all sectors such as demand, labour productivity, imports and exports. This enables analysis of the effect of technological change (the trend) on emissions, and which investments are likely to be the least polluting. Figure 9 provides an overview of the different dimensions of an economy, the ways in which they are related, and how each dimension directly or indirectly affects polluting emissions.

A relatively recent technique, which, to our knowledge, has not yet entered the FTA literature or practice despite its inclusion in the latest Futures Research Methodology Version 3.0 (Glenn and Gordon, eds, 2009) (see Wolfers and Zitzewitz, 2009),[31] is Prediction Markets.

The simple idea of Prediction Markets is using price mechanism to signal the likelihood of the occurrence of a future event. Price is given as an outcome of the transactions between players that buy and sell contracts, and promise to pay a given amount in the case that the event occurs (and nothing otherwise). Wolfers and Zitzewitz (2009) [p. 1] describes it as: 'Prediction Markets [...] are markets where participants trade contracts whose payoffs are tied to a future event, thereby yielding prices that can be interpreted as market aggregated forecasts.' As expectation of the probability of realisation of the event increases, demand for security (or the contract) increases, pushing up its price; if, on the

[31] 5 years later Prediction Markets were surveyed in an article in the *Journal of Economic Perspectives* (Wolfers and Zitzewitz, 2004).

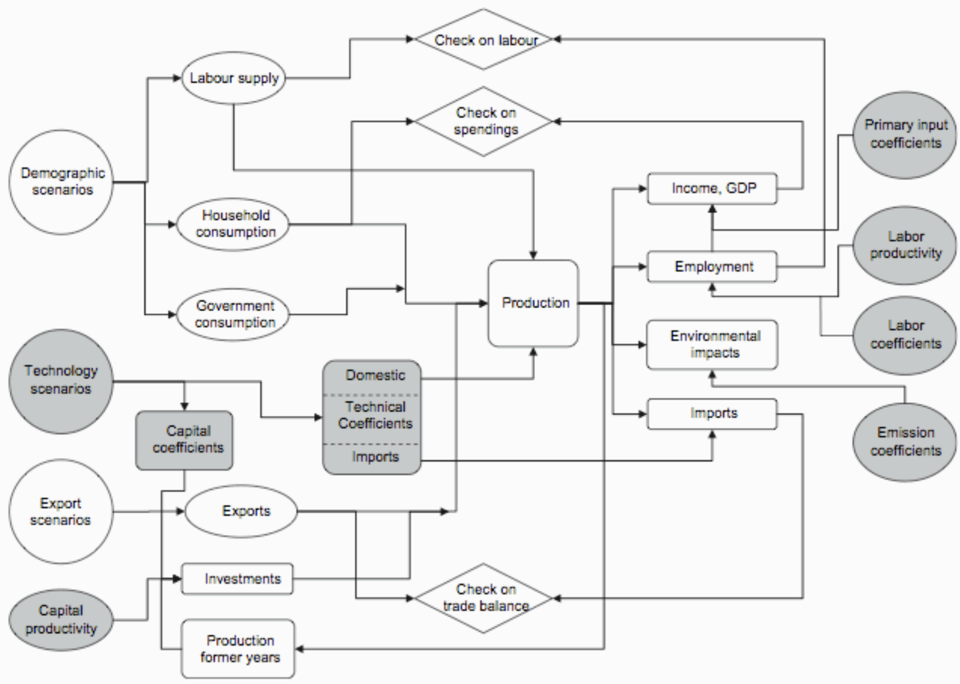


Fig. 1. Outline of the DIMITRI modelling structure (grey shades show coefficients influenced by technology scenarios).

Source: **Wilting et al. (2008), p. 103**

Figure 9: ***DIMITRI I/O model structure of the economy***

contrary, people believe that the event is unlikely to occur, the security is sold and the price becomes lower. That is, depending on how the market and the gamble are designed, the price provides an indication of the likelihood of the event occurring, as perceived by the players. Anyone can be a player; these securities are offered by gaming companies and sometimes organizations, as in the case of forecasting election results implemented by the University of Iowa, earlier forecasts of geopolitical risks developed by the Pentagon, or forecasting of other critical issues by the Defense Advanced Research Projects Agency (DARPA).

Due to the market design, the event must be well defined and there must be no doubt about verifying the occurrence or not of the event. For this reason Prediction Markets can be used only to predict whether events will occur by a an established date. Wolfers and Zitzewitz (2004) show that the accuracy of the prediction improves as the given date gets closer: time allows for more information to be released and allows players to actively seek more information. Prediction Markets work to aggregate information that is dispersed among different users (in similar ways as the web-based techniques described above).

The literature on Prediction Markets has grown dramatically, especially within economics, but it appears not to have had a traceable impact on any type of FTA. Partial exceptions might be Bell (2006), who suggests that use of Prediction Markets to promote new scientific discoveries and art is a more efficient tool than patents, and Graefe et al. (2010) who suggest use of Prediction Markets as a foresight tool to improve firm performance in turbulent markets.

Apart from the mentioned uses in macroeconomic policies, the main application of I/O models is related to environmental impacts. Its *pros* include the ability to represent a real economy with many features, and the relative availability of data (sectoral I/O matrices are available for many countries). The *cons* of I/O matrices are their behavioural simplifying assumptions and constrained equilibrium dynamics, which do not allow for criticalities and crises. These models need to integrate more interdisciplinary research, from both futures studies and behavioural science. However, this might represent a move towards agent modelling (see next section (3.2.7)).

The main *pros* of Prediction Markets is to have a relative advantage over other mechanisms in the ability to aggregate diverse opinions: (i) they provide an incentive to seek accurate information (especially as the price of the security increases); and (ii) they provide incentives to reveal truthful information. Their main *cons* is a consequence of the precision required to design the prediction market which forecloses a large number of applications where a precise date for an occurrence is not relevant, or where well defined outcome cannot be assumed at the outset. However, there are also potential problems related to attracting uninformed players, accounting for the trade off between interest and contractability, avoiding manipulation of the event, and ensuring that individuals can manage small probabilities despite evidence to the contrary Wolfers and Zitzewitz (2006). Graefe and Armstrong (2011) suggest that firms should use Prediction Markets only in combination with other forecasting methods.

The main *drivers* of economic methods are contextual, e.g. the environmental impact of production and consumption or the occurrence of specific events. I/O and Prediction Markets are used predominantly at the national and regional *loci* by government agencies, (which are also those who collect I/O data). I/O provide information on fairly long *time horizons* of one or more decades, while Prediction Markets are bounded to rather short *time horizons* – few people will bet on events that will occur after the value of the bet has been fully discounted. The main *purpose* of I/O models and prediction markets is informational, but they lead also to action. *Participation* in an I/O exercise is limited to a small number of analysts investigating a specific issue. Conversely, *participation* in Prediction Markets can include different actors, although not as many as web based techniques, – and aggregate information from a large number of participants.

Both I/O and prediction markets techniques are applied in conditions of *uncertainty*. The outcomes are given by the *context* in which the problem is framed in both cases, and by the event specified in a Prediction Market. The probabilities are investigated in I/O models by calibrating the input data, and in Prediction Markets by extracting information from the players.

3.2.7 Simulation Models: Agent modelling and complexity

The interaction among different objects performing simple actions can lead to complex dynamics. A number of modelling methods are designed to deal with this complexity, in the attempt to understand it and/or accounting for it when considering possible future dynamics (or scenarios). These methods include *System Dynamics* and a number of methods and tools that can be included under the heading *Agent Modelling* – Cellular Automata (e.g. Wolfram, 2002), Chaotic Systems (e.g. Gordon and Greenspan, 1994), Agent Based Models (ABM) (e.g. Epstein and Axtell, 1996; Gilbert and Troitzsch, 2005), Agent-based Computational Economics (ACE) (e.g. Tesfatsion, 2006), and others.[32]

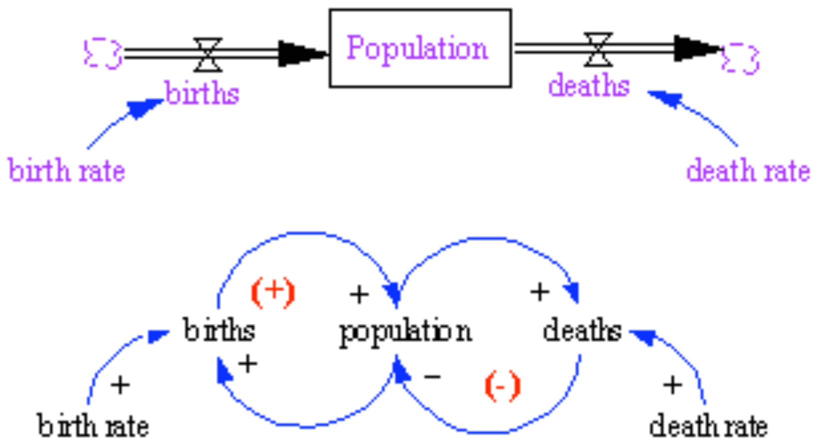
Modelling is one way to stylize a system in order to: (i) understand the logical relations that lead to its results; (ii) isolate the key elements – variables or parameters – that represent these logical relations; and (iii) use the knowledge on relations and variables to forecast possible outcomes. The techniques are *descriptive* as much as *prescriptive* in relation to defining assumptions, variables, parameters and the system represented. They serve both *extrapolative* and *normative* purposes and, in some cases, are used as tools to build *foresight* – to understand the system, and in other cases to *forecasting.*They are also useful as *inference* exercises, sometimes using data gathered elsewhere.

System Dynamics is a modelling method mainly concerned with the structure of the system and the feedbacks among its variables. No exogenous variation is assumed since all dynamics depend on the feedback relations among the endogenous variables. The feedbacks are a source of complexity. System Dynamics became famous in foresight after it was used to forecast the non-sustainability of the world economic system (Meadows et al., 1972). A System Dynamics model is foremost a map of the causal relations among variables, including feedbacks among the main variables. When a system of feedback loops is represented in a system of equations that in turn represent the relations among the different variables, it can be used to forecast different scenarios which depend on the initial conditions, the relation modelled and the parameters of the equations.

For instance, Figure 10 represents a very simple system of the dynamics of a population. The left hand side loop is positive: the increase in births leads to a larger population, which leads to a larger number of births. The right hand side loop is negative: the increase in population increases the number of deaths, which reduces the population. The resulting dynamic is an s-shaped curve, with initially low population growth, increasing quickly due to the positive loop, up to a population size where negative feedback predominates and the population increases at a decreasing rate.

System Dynamics models usually can represent multiple mechanisms. For example, in the Salter cycle (Warr and Ayres, 2006) – Figure 11 – the discovery of new fossil fuel resources reduces the cost of capital, which substitutes for labour and reduces the costs of production (due also to technological progress and learning in conversion of energy).

[32] There are a number of websites that survey large numbers of agent models such as `http://www2.econ.iastate.edu/tesfatsi/`.



Source: `http://www.iiasa.ac.at/Research/POP/pde/htmldocs/system.html`

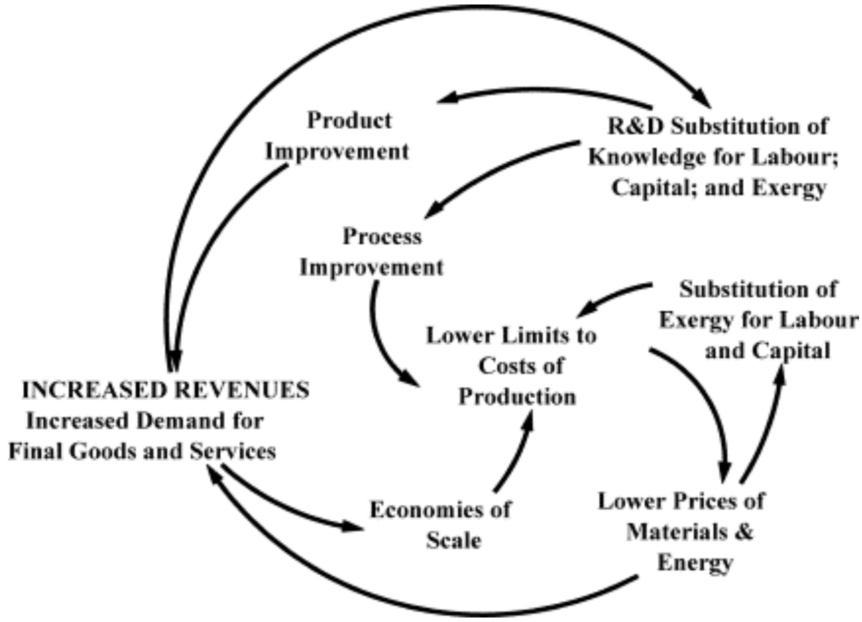
Figure 10: ***Causal loop diagram of a population growth, and the stock and flow corresponding diagram***

Reduced costs translate into price, increasing final demand and putting more pressure on demand for production factors. The corresponding increases in wages provide a further incentive to substitute labour for fossil fuel energy, which increases investment, economies of scale and technological change in the energy sector, and the cycle begins again.

In Agent Modelling, the source of complexity comes from the interaction among objects that, individually, follow simple dynamics. In addition, objects do not perform only automatic actions and reaction, but can also make autonomous decisions, generating complex relations leading to unpredictability. This applies to systems that include social objects, i.e. actors. Straightforward examples include the distribution over time of communities in a city, which regularly result in segregation or different social groupings (Schelling, 1971), and the configuration of a classroom of auditors, which regularly results in the rows to the rear being more populated than those at the front (Schelling, 1978).

Modelling the behaviour of single agents and their interaction using (behavioural) algorithms rather than systems of differential equations, allows us to study the behaviour of a system and its emergent structure, without their being imposed from the top down. In other words, Agent Modelling enables more realistic assumptions about the behaviour of agents (e.g. urban settlers, or traders in a stock market) and to understand how the overall system behaves as an outcome of the agents' interactions.

Agent Modelling is used to represent large numbers of systems such as markets, firms' organizations, products. and technology diffusion (whose properties are too complex to be represented by S-Curves or Technology Substitutions models), income growth, technological change, industry cycles, pollution dynamics and so on. Behavioural rules are usually assumed with reference to observed behaviour (averaged or distributed across different agents), including limits to agents' rationality, knowledge, adaptation, strategies



Source: **Warr and Ayres (2006), p. 336**

Figure 11: ***The Salter cycle***

and incentives. Agents differ in their initial status, but follow similar behavioural rules. For example, all agents in a market model aim at making a market transaction, but may do this under different conditions, with different preferences or information sets.

Agent Modelling usually comprises a large number of parameters that represent the properties of the agents and their system. When a model is implemented, it is first tested against empirical evidence (validation), then the combinatorial space of the parameters is used to analyse the model and build scenarios. This can be done in various ways: calibrating all parameter values against the data, and/or analysing the effect of different parameters on the emerging results. Different combinations of the parameter values enable a corresponding number of scenarios.

The main *pro* of the different forms of System Dynamics and Agent Modelling is the ability to deal with complex open systems where results emerge from underlying behaviour and which allow for ambiguity (Aaltonen and Sanders, 2006), which represents a real economy with multiple features, easy combination with real data (mainly System Dynamics), reasonable assumptions about micro behaviour and computational flexibility. On the *cons* side, System Dynamics are mainly used in operational research and less so for more complex problems related to foresight (Forrester, 2007). Their predictive capacity is limited, see e.g. the Club of Rome model. Also, while reproduction of time series is used frequently to demonstrate model robustness (e.g. Dosi et al., 2010), it is not sufficient proof of their usefulness for forecasting (Forrester, 2007). Efforts are underway to improve the forecasting power of Agent Modelling.

The above discussion shows that the techniques in this group are mainly context *driven*, although applications in science, technology and innovation are numerous (particularly

Agent Modelling). Given the technicalities involved and the types of use, these models are mainly developed in the *locus* of national organizations (and mostly for academic/research purposes, not strictly for FTA). The *time horizon* varies substantially, ranging from no prediction (explanatory models) to models that make forecasts on the distant future, especially System Dynamics models. The *purpose* of these models is mainly informational, and *participation* is narrow, being limited to a very few analysts (although some large interdisciplinary groups have attempted to build very large models). It should be remembered that Agent Modelling is used extensively as a basis for scenario discovery, as discussed in Section 3.2.8.

Similarly to trend analysis and economic methods in the case in which agent modelling techniques are used to predict (forecast), the variables that the analyst observes (outputs) are given from the beginning of the exercise. That is, outcomes are given at the outset. However, in contrast to the models related to the previous two groups of techniques, particularly in the case of Agent Modelling the analyst does not usually have prior about how aggregated outcomes emerge from non-aggregated agent dynamics. Thus, these modelling techniques are used mainly under conditions of *uncertainty*.

3.2.8 Quantitative Scenarios

Future scenarios are built using a number of techniques that allow evaluation of the probability of different events occurring in the future, and the outcomes attached to those events. Many of the techniques discussed above, which were categorized as *inference* and *forecasting*, can thus be seen as 'scenarios makers'. Similarly, techniques in the decision and valuing group (Section 3.2.10), such as Analytical Hierarchy Processes, are sometimes referred to as scenarios techniques. However, a definition of scenarios as techniques that 'combine multiple elements to convey alternative futures' (Porter, 2010, p. 41) is too general for our categorization. For instance, some of the techniques grouped under trend analyzes (Sec 3.2.5) provide a forecasting for a limited number of futures, economic methods (I/O, Sec 3.2.6) forecast a large number of futures and modelling and simulations open up to the emergence of a large number of futures (3.2.7). In order to distinguish quantitative scenarios from these other families of techniques we consider the techniques employed in 'scenario development' rather than 'scenario planning' (Bishop et al., 2007). This avoids inclusion of forecasting methods that provide 'alternative futures', but which are not scenario development techniques (Bishop et al., 2007).

Scenario planning tends primarily to be a qualitative activity, 'stories that anticipate the future' (Saritas and Aylen, 2010, p. 1064) and can be both extrapolative and normative, although the *normative* and *prescriptive* aspects of choice of the future prevail. Development of scenarios retains an element of *foresight*, while the construction of different policy options is closer to *forecasting*. Quantitative based scenarios use large amounts of data and generate *inference*. Here, we refer mainly to those techniques that use agent modelling and statistical methods to evaluate long term policy options, such as the recently developed Robust Decision Modelling (RDM) (Lempert, 2002) and Scenario Discovery (Bryant and Lempert, 2010).

RDM uses agent modelling to describe the relations between a number of input variables and outcome indicators. As discussed in Section 3.2.7, the combinatorial space of all the parameters generates deep uncertainties over a large number of dimensions, corresponding to the number of parameters (Lempert, 2002). Next, using an experimental design, a large number (several thousands) of scenarios can be generated, each reflecting a different combination of the parameter values. These different scenarios are not ordered according to a given subjective value function defining the optimal one; rather, groups of scenarios are created which perform similarly with respect to a number of criteria identified by the policy maker. These are referred to as robust criteria, as opposed to a single optimal criterion Lempert and Groves (2010). These criteria identify minimum conditions, such as, e.g. the maximum probability that a drought will occur, the minimum level of pollution abatement, or the minimum rate of GDP growth. In practice, the analyst defines the vulnerabilities of the scenarios, i.e. those scenarios that do not meet the minimum criteria.

In Scenario Discovery a number of analytical tools are used to identify the combinations of input (parameter) values that predict satisfactory scenarios ('cases of interest'), i.e. scenarios that are within the decision maker's bounds of acceptance. Several measures, referring to the different groups of input combinations, are built to compare scenarios, i.e. how many different satisfactory scenarios a group of inputs can predict, their predictive power, the facility to interpret the role of inputs on final outcomes (e.g. if they are explained by a small number of parameters the results are easier to interpret). The different scenarios are eventually tested and evaluated. 'In brief, RDM first helps decision makers characterize the vulnerabilities of a series of candidate strategies and then helps these decision makers identify and choose among alternative means for ameliorating the vulnerabilities. Scenario discovery facilitates this first step, concisely summarizing a wide range of future states of the world in a way that helps decision makers more clearly understand the strengths and weaknesses of candidate strategies' (Bryant and Lempert, 2010, p. 36).

Similar to several other FTA techniques, RDM and Scenario Discovery are used under conditions of 'deep uncertainty' (Lempert et al., 2003, p. xii), i.e. when the analyst has little knowledge about outcomes and probabilities. In our framework this is referred to as a state of *ignorance*. The identification of alternative groups of options is one of the main *pros* of scenario development: being able to deal with a large number of factors and high uncertainties about the future (Saritas and Aylen, 2010), dealing with and choosing among a number of uncertain alternatives, accepting the realistic conditions that uncertainty cannot be eliminated, but may be exploited. With respect to qualitative scenario development methods, RDM and Scenario Discovery offer a choice of alternative futures that is less arbitrary and less strongly linked to particular interests: i.e. they include in the analysis futures that may be erroneously regarded as not feasible, and lead more easily to consensus (Bryant and Lempert, 2010). Their *cons* include the black-boxing of a large part of the analysis, mainly for the end user, but partly also for the analyst. This includes modelling assumptions, the a priori choices made to simplify the problem represented, and the analysis being limited to the effect of the parameters on the chosen outcomes.

It follows that *participation* is narrow with respect to analytical aspects, and intermediate with respect to the involvement of stake-holders in the choice of outcomes. The high level of technicality and specificity of the models implies also that the main *drivers* are contextual, and the main *loci* are government or related agencies, although a number of corporations also employ RDM. For the latter the *time horizon* of scenarios development is likely to be short or medium, while government agencies are likely to use them for long term future analysis. In both cases, the *purpose* is to collect information and attempt to shape the future.

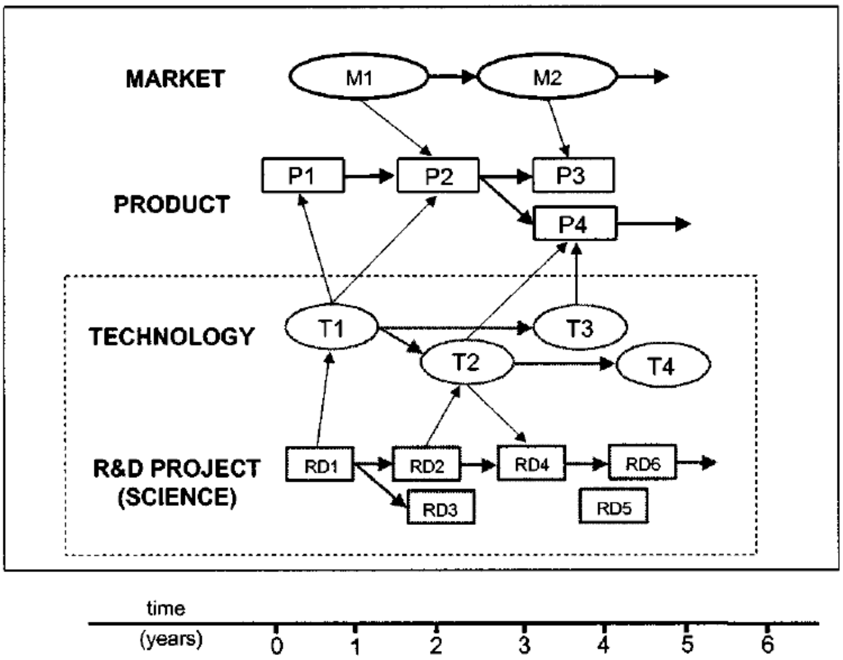
3.2.9 Roadmaps

Technology roadmapping is an umbrella term used to describe a group of (quantitative and qualitative) techniques that help to plan and co-ordinate S&T development at various levels. A roadmap is a layout of relationships that can be expected to occur between science, techniques and products over time, in the process of a technology achieving practical application and/or reaching the market (see Figure 12).

While Roadmapping techniques are sometimes employed for *forecasting*, they mainly serve to collect shared views on S&T development, in line with *foresight* methods. Roadmapping is particularly useful to provide a common vision for the whole organization (or an organizational group) by bringing together diverse types of cross-functional and/or cross-disciplinary views of technologies and applications (Kostoff and Schaller, 2001, p. 135). The quantitative-based approaches are derived from analysis of publications, patents, technical reports and other data sources, e.g. press releases on company webpages. As described in Sections 3.2.3 and 3.2.4, these quantitative techniques cannot by themselves predict future relations, but they provide trends and contextual understandings of the scientific, technological, social and organizational proximities that make certain relations more likely compared to others. Despite these efforts to 'mechanize' roadmapping, 'much of it remains off the books. Roadmapping is political and involves negotiation and re-negotiation' (Radnor (1998) cited by Kostoff and Schaller (2001, p. 136)).

Therefore, while these exercises use data gathered using other quantitative techniques, they are more *prescriptive* than descriptive, and more *normative* – based on data extrapolation – rather than being extrapolative. Because of their dominant prescriptive and normative features, we refer to this group of techniques as neither data gathering nor inference.

A major *pro* of Roadmapping resides in the roadmapping process, i.e. in the activities leading to information exchange and construction of shared views, rather than in



Source: **Kostoff and Schaller (2001), p. 133**

Figure 12: ***Generic S&T roadmap***

the roadmap outcome itself.[33] The *pros* and *cons* of Roadmapping can be seen as resulting from the same source: the coordination of visions and the rhythms imposed by a roadmap which promote application of the technology, at the expense of developing other applications at other rhythms.

The main *driver* of Roadmapping activities is S&T both as a technology-push factor (e.g. in bio- or nanotechnologies in search of application) or as a demand-pull factor (e.g. search for low-carbon energy technologies). The main *loci* of Roadmapping are companies and industry associations although government organizations, such the US National Institutes of Health and the EC, have been active in developing roadmaps in areas considered strategic such as nanotechnology (e.g. nanomedicine roadmap) or energy.[34] Depending on the organization undertaking the exercise, the *time horizon* is mid to long range. As already mentioned, the main *purpose* is to inform action, and *participation* can be quite diverse.

The search for common visions by bringing together diverse cross-functional and/or cross-disciplinary views of the technologies and applications involved, is conducted under conditions of sparse knowledge about either the outcomes of the technologies and applications or the probabilities that these outcomes will occur. Thus, they are mainly used

[33] This is particularly important in technologies that require shared standards, such as ICT. E.g. the International Technology Roadmap for Semiconductors (ITRS) is considered the crucial coordination mechanism for this industry.

[34] Respectively `http://www.etp-nanomedicine.eu/public/press-documents/publications/etpn-publications/091022_ETPN_Report_2009.pdf` and `http://ec.europa.eu/energy/energy2020/roadmap/index_en.htm`.

under conditions of *ignorance*.

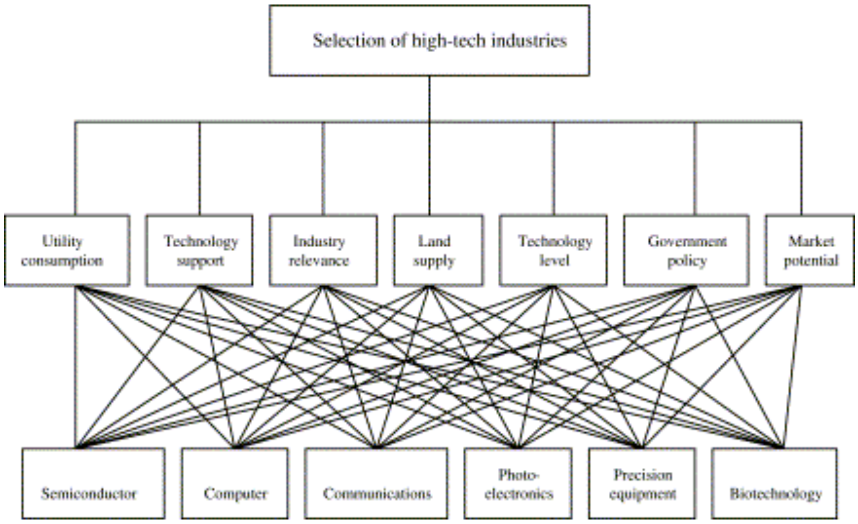
3.2.10 Valuing/Decision making

The techniques identified in the group of valuing and decision making are Multicriteria Decision Analysis (MCDA), including Analytical Hierarchy Process (AHP) and Life Cycle/Sustainability Analysis (LCA). This group of techniques serves mainly *prescriptive* functions, enabling policy-makers' decisions about desired future outcomes. This implies that these techniques are highly *normative*. To be able to assess different outcomes these techniques make use of the information collected using more extrapolative techniques. Similar to roadmapping, value and decision making techniques are not used for either data gathering or inference. We would also not classify them as either forecasting or foresight techniques.

MCDA are concerned with 'the deployment of systematic methods to help address problems characterized by incommensurate objectives, multiple stakeholders and conflicting interests' (Salo et al., 2003, p. 236). MCDA is a process that involves various phases including identification of stakeholders, development of goals, criteria and technological options/alternatives, elicitation by stakeholders of scores for and weights of alternatives, and computation of performance measures. One way to use MCDA in FTA is as a tool to create a shared problem representation in which different potential technological options, and the criteria required to assess them, are explained and contrasted. MCDA can also be used as a communication tool to describe the potentially contrasting perceptions of various stakeholders of the technologies (this is particularly relevant for controversial technologies). Finally, MCDA methods can be creativity tools which help stakeholders to imagine ways to solve problems.

AHP is usually considered a MCDA quantitative techniques and is aimed at assessing a number of different options with the same objective, resulting in the selection of priorities – in our context, with respect to choices regarding the future. The way it works is by decomposing the problem into a hierarchical structure of sub-problems which are easier to evaluate (Saaty, 2008). See e.g. a hierarchical tree used to prioritize high tech industries for an industrial park in Taiwan (Figure 13). The top layer represents the overall problem; the middle layer is the criteria to be used to evaluate the main goal; the bottom layer is the different alternatives to be assessed using these criteria. All options on the same level are compared pairwise, and each pair comparisons are assigned a relative value. These are transformed into a matrix of 'votes', where each option is represented in one column and one row (see e.g. Table 3 for the pairwise comparison of criteria in Figure 13). The elements of the matrix are the relative judgements, and the diagonal of the matrix consists of '1' (an option is equivalent to itself). The scores for one level are then aggregated at the next level in the hierarchy, up to the main choice. The aggregation can be done using various methods (Saaty, 2008).

LCA is a widely used technique to assess the cumulative impact on, e.g., the environ-



Source: **Chen and Huang (2004), p. 842**

Figure 13: ***An AHP tree for selecting high tech industries investment***

Relative importance	Pairwise comparisons								
	Utility consumption	Technology support	Industry relevance	Land supply	Technology level	Government policy	Market potential	Priority	Ranking
Utility consumption	1	0.746	0.707	1.046	0.493	0.456	0.488	0.092	7
Technology support		1	0.923	1.561	0.802	0.794	0.542	0.129	4
Industry relevance			1	1.188	0.804	0.624	0.523	0.123	5
Land supply				1	0.511	0.611	0.545	0.097	6
Technology level					1	1.119	0.642	0.169	2
Government policy						1	0.697	0.169	2
Market potential							1	0.222	1
							C.R.	0.005	

Source: **Chen and Huang (2004), p. 844**

Table 3: ***Pairwise comparison of criteria with respect to the goal***

ment during the life cycle of a product. It can involve large amounts of data since inputs from various contributing factors, stakeholders and related parties are taken into account. In situations where the end point of the life cycle is uncertain, the researcher may prefer to focus on a 'midpoint' beyond which uncertainty is judged to be too high (Finnveden et al., 2009).

The main *pros* of these decision techniques are that they explicitly recognize the openness (uncertainties) of future outcomes and the diversity of preferences among stakeholders. AHP provides a structured decision problem, in which the structure helps to identify the problem, the alternatives are weighted, group opinions are aggregated, they allow for a flexible time horizon, and tools for consistency analysis are incorporated(Bañuls and Salmeron, 2008). However, the main *cons* of decision/valuing techniques is that they are static exercises carried out at one point in time. In relation to AHP, it requires large numbers of inputs (Bañuls and Salmeron, 2008), some implementations can lead to rank reversal, it is based on simplistic rationalism (while the experts are concerned about the technicalities of the calculation of indicators, policy makers are more worried about the type of information considered), they can be cumbersome to implement and, as in most quantitative techniques, consistency and rigour may hinder learning and the sharing of useful information (Miles et al., 2008b).

The main *driver* of these techniques is context specific with the their *locus* ranging from companies to countries. MCDA are particularly useful in the context of environmental issues (Biloslavo and Dolinsek, 2010), urban management (roads, waste, water, etc.) and in a variety of operations research and engineering contexts. AHP has been used by public administrations for ICT projects Banuls and Salmeron (2007), allocation of strategic resources, relocation of populations when cities have been destroyed by natural disasters, and political relations and treaties between countries (Saaty, 2008). It has been used by companies for the selection of product technologies, evaluation of technologies, allocation of resources and short term planning (Vaidya and Kumar, 2006). The *time horizon* of these activities is mainly mid range and the *purpose* is definitely action oriented, although MCDA and AHP exercise are aimed mainly at collecting information from different sources, which involves broad textitparticipation.

Decision/valuing techniques are used under conditions where outcomes need to be specified as part of the exercise, and there is no clear information about the probabilities of the event occurring because this will be a consequence of the action implemented as a result of the exercise. These techniques are applied in conditions of *ignorance* with respect to outcomes and probabilities.

4 Discussion

Technical change and the appearance and diffusion of new technologies are having increasing impacts on the economy and society. FTA can help us reflect on the likely directions of technologies, manage the risks involved and shape technological trajectories in order to improve the long term benefits to society. In this paper we surveyed the large (and growing) number of quantitative techniques designed to help our understanding of and thinking about future technologies.

The main findings of this paper are that FTA quantitative techniques are extremely diverse, and that the choice of FTA techniques appropriate for a given foresight exercise depends on the characteristics of specific cases. Hence, the quality of an FTA does not depend on an 'ideal' or intrinsic quality of the FTA technique itself, but rather on achieving a satisfactory match between the goals of the foresight exercise and the particular FTA technique that will fulfil them. In order to help in the selection of an appropriate FTA technique, we classified techniques into classes with common characteristics.

Adapting a classification suggested by Porter (2010), we ordered the FTA quantitative techniques into 10 families. We discussed the main features of these classes, including the main advantages (pros) and disadvantages (cons) of the different classes of techniques, in which contexts (drivers) they were applied more often and by which types of organization (locus). We investigated whether there is any regularity across classes with respect to time horizon, main purposes (leading to acquisition of information or actions) and the number of different stakeholders involved. To do so, we ordered the families of techniques according to whether they are mainly descriptive and extrapolative (not necessarily extrapolating from time series) or mainly prescriptive and normative (from left to right in Tables 1 and 2). This distinction also reflects the main use (purpose) of each technique, and in which stage of the FTA exercise it is most helpful.

Techniques at the left hand side of Table 1 are mainly used for data gathering (extrapolating and describing available information from a number of different sources including stakeholders, the World Wide Web, patents, publications, people's perceptions and choices, etc.). If the data are analysed using descriptive/extrapolative techniques, the analysis is purely descriptive. In other words these techniques are used to describe observed statistical properties based on information collected in various forms and from a variety of sources. The techniques on the right hand side of Table 1 tend to be used to make inferences or to find optimal solutions for the future, based on elaboration of the information gathered. These techniques are used to analyse possible future outcomes, establish and define knowledge about the future, and nudge it. Knowledge about the future is established by defining desired outcomes and the probability of the occurrence of different instances of these outcomes.

The uses of the techniques along the left-right dimension are related to the type of FTA exercise. Note that, techniques at the extreme ends of the classification (left and right in Tables 1 and 2) are mainly used for foresight activities, while those in the centre of the scheme are more commonly used for forecasting. We can differentiate also among the time horizons of foresight activities: those that use techniques at the left hand side in Tables 1 and 2 are aimed at understanding the past; those using techniques on the right hand side are aimed at influencing the future.

If we move from left to the right of Table 2 a few more regularities emerge with respect to number of uses and characteristics of the techniques. First, most techniques, from creative to the trends analysis, are used in FTA activities driven mainly by science, technology and innovation. As we move from techniques within the economic methods class towards the right hand side of Table 2 most of the techniques are used in FTA activities driven by specific contexts. These contexts can range from evaluation of the environmental impact of economic activities (Input-Output analysis, I/O), likelihood of a specific event occurring, e.g. an election, political instability, a natural disaster (Prediction Markets), applications in operational research (System Dynamics), water management (Robust Decision Making), key technologies (Analytical hierarchy process), and so on.

Second, the techniques included in the classes at the left side of Table 2 tend to be more suited to studying short to medium-term time horizons; those in classes towards the right hand side of Table 2 apply to the study of longer time horizons. In general, this reflects the fact that forecasting activities tend to be over a shorter time horizon than foresight activities. However, there are also differences among foresight and forecasting oriented techniques. For example, most Trend Analyzes have rather short time horizons, while

Simulation Models seek to provide insights over a long time horizon. Among quantitative foresight techniques, Roadmaps tend to apply to more distant future techniques listed under Monitoring and Description, i.e. Conjoint Analysis and Cross Impact Analysis. As is discussed in more detail in WP2 this difference is related also to the assumptions required for different techniques about the knowledge on outcomes and probabilities of events. When the knowledge about outcomes and probabilities is perceived as fairly unproblematic, then the time horizon used by the analyst is likely to be shorter.

Third, following from the ordering of the classes according to the data gathering / inference continuum, i.e. from descriptive to prescriptive, techniques classified on the left hand side of Table 2 are used more for informational purposes than for defining action (although a few techniques set the stage to design actions in subsequent steps). As we move towards the right hand side of Table 2 – scenarios, roadmaps and valuing/decision making classes – the main purpose of the techniques is to implement specific actions. As discussed in Sections 3.2.2, 3.2.3 and 3.2.4, Monitoring, Descriptive and Statistical methods families of techniques serve the purpose of collecting and systematizing information, which may inform future analysis or action. On the other hand, techniques such as Roadmaps are employed explicitly to define common visions of and standards for future technological developments. Similarly, scenario exercises are developed for very specific contexts and issues, where policy makers or large corporations want to identify potential solutions. The decision-making feature is related to another characteristic that seems to indicate a rather regular pattern, i.e. context specificity. On average, techniques on the right end side of Table 2 are more context specific than those on the left hand side.

Fourth, we consider the extent of 'participation' of various stakeholders, in the loose sense used in this paper, in the FTA activities. If we exclude the techniques new to FTA, we can identify a pattern, moving from classes of descriptive techniques to classes of prescriptive techniques. In the former, the participation of stakeholders is mostly narrow, with a few exceptions such as Conjoint Analysis and Cross Impact Analysis which require an intermediate level of participation. This applies also to some techniques that require advanced technical training and understanding of the techniques. The last three families on the right hand side of Table 2, involve a wider mix of stakeholders taking part in the decision process. This may be related to the stronger prescriptive nature of these techniques, which are aimed more at context specific issues rather than at general science and technology studies. If, instead, we include techniques that are new to FTA, the picture changes with most classes on the descriptive side featuring techniques aimed at collecting information/opinions from a quite large and diverse number of passive stakeholders and/or subjects. In WP2 we discuss how the 'broadening out' of the acquisition of information by some of the new techniques differs substantially from the broad participation that characterizes foresight activities. This broadening allows us to capture the views of much bigger constituencies (thousands of individuals), but is passive.

Fifth, we were unable to identify a pattern related to the types of organizations that use the techniques categorized. Companies and governments tend to use different techniques, but for reasons that lie in a number of features that are not captured by the ordering of our classification. For example, companies tend to prefer more context-specific and action-oriented techniques, and those that are most useful in relatively short time horizons. Instead, broad participation is required for certain FTA activities by both firms and governments, and narrow participation for others. A mapping of (classes of) techniques with respect to (types of) organizations would require a sharper focus on both techniques and organizations and few studies provide such information. See e.g.Popper (2008b) and more generally the EFNM Dynamo project.

Finally, the descriptive classes of techniques are used mainly under conditions of uncertainty in which knowledge about outcomes is assumed to be unproblematic, but knowledge about probabilities is problematic; while prescriptive classes are used mainly under conditions of ignorance, where knowledge about both outcomes and probabilities is problematic. This is discussed in more length in the WP2.

The classification we proposed in this paper and which we discussed with respect to the different uses – Descriptive-Prescriptive, Extrapolative-Normative, Data gathering-Inference and Foresight-Forecasting, and their characteristics – Drivers, Locus, Time horizon, Purpose, Participation and assumed incompleteness of knowledge about outcomes and probabilities (uncertainty), provide useful information on the advantages and disadvantages of some techniques with respect to others, for different FTA activities. However, these dimensions only partially define the advantages of different techniques. Indeed, these techniques are also performative: first, their use affects the knowledge that is crafted by the analyst with respect to the probability of the different events and evaluation of their corresponding outcomes. Second, different (classes of) techniques involve a number of assumptions about probabilities and their outcomes (e.g. statistical properties, behavioural assumptions in modelling). Third, in many cases techniques are employed to reduce perceived uncertainty about probabilities and outcomes. To what extent do the techniques broaden or restrict the initial sources of information used (see also the characterization of classes in terms of participation)? And, to what extent do the techniques allow the analyst and the policy maker to evaluate alternative (closure) options? Finally, we know little about some of the newest techniques in relation to what they add to the standard techniques, and what instruments they provide analysts and policy makers, to 'open up' alternative outcomes.

In WP2, we evaluate the contribution of these quantitative techniques, referring to the Stirling and Scoones (2009) framework to highlight the contributions made by these techniques to 'opening up' to increase the number of options to be considered, or 'closing down' to narrow the focus to a smaller number of more likely outcomes.

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A List of reviewed techniques

The 26 main techniques initially selected were:

- Agent modelling (including Complex adaptive systems, Modelling and simulations, Robust Decision Making, and Decision modelling)
- Analytical hierarchy process (AHP)
- Bibliometrics (including Scientometrics, Research profiling, patents, and tech mining)
- Conjoint analysis
- Content analysis
- Cross impact analysis
- Force field analysis
- Indicator/Time Series Analysis
- Input Output Analysis
- Key technologies
- Long Wave analysis
- Megatrend analysis
- Multicriteria decision analysis (including data envelopment analysis and other methods),
- Roadmapping
- S-Curves
- SMIC Prob expert
- Social Network Analysis
- State of the future index (SOFI)
- Structural Analysis
- Sustainability analysis (life cycle)
- Systems simulations (including system dynamics and KSIM)
- Technology substitution
- Trend extrapolation

- Trend impact analysis
- TRIZ
- Webometrics

Other 11 less relevant techniques non selected in the initial sample were:

- Classification trees
- Critical Influence analysis
- Diffusion modeling
- Markov
- Precursor analysis
- Probability trees
- Regression analysis
- Requirement analysis (needs analysis, attribute X tech matrix)
- Rule based forecast
- Statistical analysis
- Stochastic forecast