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Quantitative Analysis of Technology Futures. Part 2: Conceptual framework for positioning FTA techniques in policy appraisal

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Abstract

Quantitative techniques for exploring future developments in Science and Technology (here called Future-oriented Technology Analysis (FTA)) are increasingly important in an era of big data and growing computational power. New quantitative techniques such as social software, prediction markets, and quantitative scenarios are complementing more traditional foresight and forecasting techniques. While these techniques hold great promise, it is unclear how robust and appropriate is their use under different contexts. In order to help users think through their distinct values and limitations, in this paper we discuss quantitative FTA techniques in the light of a general analytical framework. Following Stirling \& Scoones (2009), we position FTA quantitative techniques according to their representation of (the incompleteness) of knowledge --i.e. the extent to which they portray their knowledge on probabilities and outcomes as problematic. This framework illuminates the implicit assumptions about the uncertainty, ambiguity and ignorance that distinct quantitative techniques make when exploring (in some cases ``predicting'') the future. We distinguish between techniques that tend to `open up' awareness of new or unexpected futures, and others that tend to `close down' by pointing out to likely futures.

Keywords: FTA; Policy Appraisal; Big Data; Knowledge

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Executive Summary

Technological progress has a huge impact on society and economic development, and improving our understanding of likely future developments of technology is of increasing importance. The goal of Future-oriented Technology Analyses (TFA) is to enable us to better understand where existing technological trajectories might take us, as well as reflecting and deciding upon desirable future states and playing a role in 'creating' the future. Policy can play a significant role in shaping technology and choosing directions for technology, given the path dependent nature of technology, and that small changes in the present can be amplified to have enormous impacts in the future (Williams and Edge, 1996).

A definition of FTA is offered 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 include a number of activities that in the literature are most often indicated as technology foresight, forecasting, intelligence, roadmapping and assessment (Porter, 2010).

Our focus is on the quantitative techniques used in Future-oriented Technology Analysis. Quantitative techniques are increasingly important in our era of big data and increasing computational power (Gilles, 2012; Miller, 2011), and enable us to better project into the future. New quantitative techniques such as webometrics and prediction markets are complementing existing techniques. In Part 1, we survey the techniques, collating them and discussing them in a synthetic fashion, guiding the reader 'through the maze' and discussing the contexts under which the techniques are most appropriate, and the extent to which they claim to increase our knowledge of the possible outcomes and also their probabilities of occurring.

In Part 1, we reviewed the literature on technological foresight, technological forecasting, scenario shaping and futurology. With a focus on quantitative techniques, we examined the tools and methodologies available, and discussed the contexts in which they are most widely used. More specifically, we selected 26 quantitative techniques, which were then grouped in 10 groups. We distinguished between their uses (Descriptive vs Prescriptive; Positive vs Normative; Data gathering vs Inference; Foresight vs Forecast) and also look at their characteristics (Drivers; Locus; Time horizon considered; Purpose; and Participation). These techniques are arranged and organized in summary Tables.

Here, in Part 2, we discuss these quantitative techniques in the light of a general analytical framework. Following Stirling and Scoones (2009), we position these quantitative techniques in terms of 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 these techniques differ in terms of their claims on the knowledge on outcomes and probabilities. Most techniques are perceived as helping to improve our understanding of the probabilities attached to certain outcomes. However, with regard to the number of outcomes, we can distinguish between 'opening up' and 'closing down' – some techniques open up our awareness to new possibilities, while others close down on possible future scenarios and analyse them in greater depth. We also discuss how new techniques that exploit the large amount of data generated on the web change the perception of the improvement of our understanding of the probabilities attached to certain outcomes and of the inclusion of different stake-holders in analysing futures.

1 Introduction

Predicting, imagining and influencing the future are part of the customary human activities. Peoples have made an extensive use – and in many cases still do – of experts entitled with the power to interpret past and present symbolic evidence to predict future events, such as Oracles, Prophets, Augures, Sibyls and Astrologists. Consulting these experts made the decision maker more confident about the future and about the decision he/she should take under conditions of ignorance or Knightian uncertainty (Knight, 1921). The consultation was common practice, for example, before starting a long trip. The effect of the advice is equivalent to bringing the decision maker out from the state of ignorance or Knightian uncertainty about a specific (set of) event(s) occurring in the future, by defining the plausibility or the probability with which future events are expected to occur, or by suggesting which are the most relevant future outcomes.

For instance, Sybilline books (a collection of oracular utterances) were not used to predict the future, but to find measures to prevent negative future events to occur. In other words, the books identified the relevant outcomes (those the decision maker did not want to happen), and predicted the plausibility of their occurrence in the case of wrong decisions or religious practices. This is akin to making the knowledge about the outcomes unproblematic – Roman rulers had good ideas about the calamities to be avoided – and making the knowledge about the probability of these outcomes occurring less problematic than without the books. Indeed, Oracles, Prophets, Augures and Sibyls were usually considered trustable, and their prophecies and auspices credible. Witness of that is the very high price that Tarquinius Superbus, the last king of Rome, had to pay to acquire them, according to the legend.

Indeed, it is not only through experts that people constructed their knowledge on the future. People's observation of the relation among events occurred in the past allowed them to connect present conditions and actions with future outcomes, reducing the amount of possible outcomes to a smaller number (possibly one single event) and increasing the certainty about future events. "Red sky at night, sailor's delight" is only one of the many examples of sayings used by people to build up knowledge about the future – exploiting the assumption perceived as correct that its relation with the present and past is linear.

The Enlightenment has significantly contributed to substitute Oracles, Prophets, etc, and popular knowledge for scientific advice. For instance, "red sky at night, sailor's delight" was more recently substituted by weather forecasts. Science became the only source of certain knowledge (Klir, 1997). And science, as shown by physics, its most successful discipline, was viewed as requiring the use of quantitative methods: "The conviction [during Enlightenment] was that systematic inquiry using mathematical and quantitative methods will lead to certain knowledge about reality" (van Asselt and Rotmans, 2002, p. 76). People began to perceive the new scientific methods as better suited for predicting, imagining and influencing the future. As suggested by van Asselt and Rotmans (2002), quantitative methods were perceived as producers of certain knowledge, suggesting that

their use would make knowledge about outcomes and their probabilities unproblematic – until that piece of knowledge was falsified.

Since the middle of the last century, organisations and policy makers began to use a large number of techniques to investigate and influence the future (see discussion in Part 1). Several techniques have been proposed since the 1960s, some of which rely on quantitative methods – particularly many of the most recent ones based on the use of internet data. In the first Part of this report Ciarli et al. (2013) – Part 1 – we reviewed and classified 26 techniques employed in Future-oriented Technology Analysis (FTA) grouped in 10 different families, and we discussed the contexts in which they are most widely used. We distinguished these families according to their uses (Descriptive vs Prescriptive; Positive vs Normative; Data gathering vs Inference; Foresight vs Forecast) and to their characteristics (Drivers; Locus; Time horizon considered; Purpose; and Participation).

According to our review, despite the large differences among quantitative techniques, they are all employed to reduce the incertitudes on future states of the world by reducing the space of possible outcomes, and/or by attaching a probability distribution to the occurrence of all possible known instances of an outcome. In the words of the FTA community the aims of FTA are to generate new practical and scientific knowledge in order to: identify and understand "fundamental disruptive transformations" and "grand societal challenges" "in order to allow one to be better prepared for the future and/or shape it in order to realise a favourable future state " (Cagnin et al., 2012, p. 2); "assist decision-makers with relevant analyses, observations and new ideas to be better prepared for the future (assuming that it can be predicted) or shape the future (assuming that it is not fully predetermined by the identified/identifiable trends)" (Cagnin et al., 2012, p. 3); "better understand and shape the future from different methodological perspectives" (Haegeman et al., 2012, p. 1); "collect knowledge about 'posits' or possible futures, their plausibility and limits, their internal consistency and conformity with models and data, their consistency with expert judgement, and their implications for action" (Haegeman et al., 2012, p. 1, citing Eerola and Miles (2011)); a "'formal' assessments of the future", against the other activities aimed at forming expectations (van Lente, 2012); "identify promising technological pathways" and "engage relevant stakeholders and create common visions into action" (Schoen et al., 2011, p. 235); exploring the future to improve decision making in firms and policy (Gordon et al., 2005); "Generating insights regarding the dynamics of change, future challenges and options, along with new ideas, and transmitting them to policy-makers" (Da Costa et al. (2008) cited in van Lente (2012), Table 1); "identify actionable future visions, timely mitigation of negative impacts, guidance and support for the policy process identifying impacts on society and implications for policy" and "develop hypotheses as to how present situations may evolve into the future" (Loveridge and Saritas, 2012, p. 761); allow policy makers to "make decisions about the future" in "long-term policymaking" (Walker et al., 2010, p. 917); particularly needed when the incertitude is "deep" and we cannot rely on extrapolations (Walker et al., 2010, p. 919).

Because FTA quantitative techniques are based on scientific methods and assumptions,

people find it easier to trust FTA techniques than Prophets, Sybilline book or horoscopes. Scientific methods – or, more precisely, the use of techniques based on quantitative methods – lend authority to the analysis of the future, inducing FTA practitioners, policy makers and the public to consider the information delivered as reliable knowledge. A common understanding is that quantitative FTA techniques are based on information on the past that allow to increase the knowledge about the future (Ramirez and Ravetz, 2011; Taylor, 1993), especially with reference to Forecasting techniques – more on the difference between Foresight and Forecast in Section 3.4. For instance, in the introduction of a recent paper on Web mining Radinsky and Horvitz (2013) cite Mark Twain: "the past does not repeat itself, but it rhymes".

However, despite the gained authority of quantitative knowledge and the general aims of enquiring and facilitating decisions about the future by acquiring knowledge on the past and the present, there are three major issues that need assessment. First, the extent to which any technique can claim to make the knowledge about the future less problematic using knowledge from the past. Beyond the usual statistical tests on the predictive performance of past events, scholars have questioned the accuracy of knowledge on the past (Ramirez and Ravetz, 2011). Second, the relation between incertitudes (about future events) and knowledge is not linear: an increase in knowledge does not neatly map in a decrease in incertitude, or the other way round (van Asselt and Rotmans, 2002). van Asselt and Rotmans (2002) suggests that we should distinguish two very different sources of incertitudes: knowledge as the property of the analyst (epistemological) from variability as the attribute of the real world (ontological). This is related to the third major issue, which is on the different notions of incertitudes and how these incertitudes are perceived by practitioners and policy makers. A practitioner may perceive the incertitude in different forms, from a simple lack of information – for example because we lack data from the past – to what has been labelled unknown unknowns: that is events that are outside our imagination, probably because they were never observed in the past – for example the polluting impact of a new technology.

In other words, there are incertitudes on future states that quantitative FTA techniques (as well as qualitative) may not or cannot capture. The question is to which extent the analyst is aware of this, at the risk of confusing a change in (scientific) knowledge with a change in incertitude. Moreover, the failure to recognise the existence and non treatability of incertitudes (when not indeterminacy) has a strong effect on closing down policy options. Instead, recognising the existence of a positive degree of incertitude tends to increase the degrees of freedom of the policy maker in defining different adaptable policy options. Walker et al. (2010) suggest that policy failures are often the outcome of the failure to recognise incertitudes, listing a number of useful examples. And this failure to recognise incertitude may be often related to the failure to acknowledge the agency of the different human and non-human actors involved in the phenomena under study.

In this second Part of the report we make explicit the authority of quantitative FTA: we assess the FTA techniques reviewed in Part 1 by asking how practitioners represent

knowledge when they decide to use quantitative techniques for FTA, and how this representation then changes when FTA techniques are used. In other words, we study how the properties of different techniques allow the practitioner to construct different states of knowledge about the future. Following Stirling and Scoones (2009) we focus on two main dimensions: knowledge about outcomes and about probabilities. Under the first dimension knowledge is perceived as more or less problematic with respect to which outcome is more or less relevant when considering future states of the world. For example, economic growth, environmental sustainability, a particular technology, poverty reduction, and so on. Under the second dimension knowledge is perceived as more or less problematic with respect to the probability that specific instances of an outcome will occur in the future. For example, a given rate of economic growth, the probability of a specific environmental catastrophe occurring, the diffusion of a technology, the number of people living under a given poverty line, and so on.

In this paper we take an explicit constructivist approach: the analyst using an FTA technique can only refer to a limited representation of the complexity of the world, and the outcomes of using a technique depend also on the perspective taken by the analyst and used to simplify the world.

Next, we compare the extent to which the use of different families of techniques tend to "open up" ("close down") the range of policy options (i.e. comparable outcomes) resulting from an FTA, and to which extent different techniques broaden (narrow) the range of inputs (i.e. sources of information) used in technology appraisal. We will answer questions such as: how does the use of specific FTA techniques represent knowledge and incertitude, in particular the very incomplete nature of knowledge regarding future technological outcomes? How do they change the way in which we represent knowledge on future events initially considered unknown? Which techniques/organisations tend to be used in a way that results in closing down or opening up of policy options?

We shall make it clear from the outset that to limit the scope of this paper we need to make two arbitrary choices in analysing and classifying the quantitative techniques. First, as it will appear more clearly below, each quantitative technique can be used in different ways. Therefore, the assessment discussed in this paper refers to the way in which techniques are conventionally used, i.e. how they are used in the vast majority of FTA exercises, and not to all potential applications of a technique, or to its application outside the context of FTA. A broader analysis of the single techniques would be very useful in order to provide a much richer toolbox to FTA practitioners, but it requires a much more focussed analysis on each of the groups of techniques.

Second, FTA quantitative techniques are often used as part of a wider future-oriented appraisal process, implying that a foresight exercise may represent knowledge in a different way and could be significantly more (less) open than the use of a specific technique would imply. This is particularly true for the groups of techniques mainly used for descriptive purposes (vs prescriptive), to gather data (vs computing inference) and used in foresight exercises (vs forecast) – more on these differences in Part 1 and in Section 3.4. Keeping

these differences in the use in mind, our focus here is on the techniques and we will evaluate those, irrespective of how they are combined in a wider foresight exercise. We hope that the results presented here will induce more research on the way in which different quantitative FTA exercises (mixing different techniques and different applications) construct knowledge about the future, closing or opening different policy options.

The paper is structured as follows. In the next section we present the theoretical framework we adopt to assess the techniques. This is borrowed from the literature on technological risk assessment and distinguishes two different dimensions in the knowledge represention by FTA users: knowledge about outcomes and knowledge about probabilities. In section 3 we apply the framework to a large number of FTA quantitative techniques surveyed in Part 1. We distinguish how the representation of knowledge changes from before an FTA activity to after the user has applied the technique. We also distinguish how the framework can be used to distinguish between techniques mainly used for foresight and those mainly used for forecast. Next, Section 4 discusses the new techniques and to which extent they contribute to improving FTA. Finally, Section 5 discusses and concludes.

2 Theoretical framework: the incompleteness of knowledge

FTA techniques are used in conditions of incertitude. Within Future Studies a number of scholars have classified different states of imcertitude and how they relate to the incompleteness of knowledge. For example, van Asselt and Rotmans (2002) distinguish between two sources of incertitudes: variability of the phenomenon analysed (ontological) and limited knowledge of the analyst (epistemological). Variability is distinguished by five different sources causing incertitudes, going from randomness to technological surprises (radical changes). Limited knowledge (beyond that originating from variability) is distinguished in seven different ordered cases, moving from inexactness to irreducible ignorance. While for the first cases an increase in measures, data and sources can increase knowledge and reduce incertitude, for the last few cases we have no means to reduce incertitude. Walker et al. (2010) distinguish two extreme cases, determinism – a rare case of no incertitude – and total ignorance – similar to van Asselt and Rotmans (2002)'s irreducible ignorance. In between they distinguish among four levels that differ with respect to the knowledge assumed about different aspects of a policy decision. These levels are similar to the knowns and unknowns evoked by Rumsfeld: at one end is incertitude that can be described in terms of statistical distributions, i.e. risk in the terms of Knight (1921). At the other end are events we do not know the existence of, lack of knowledge about the lack of knowledge, worlds we cannot imagine: uncertainty as defined by Knight (1921). Schippl and Fleischer (2012) further reduce to three levels of knowledge mapped into incertitudes: knowns, known unknowns and unknown unknowns, where the two limits also reflect the Knight (1921) distinction between risk and uncertainty.

The common features among these different classification is that they recognise the distinction between states under which expectations and risk can be computed from states

under which we do not know what to compute. However, these classifications are referred to as objective states of the world, and they refer only to the knowledge about the probabilities.

In order to discuss and compare the different techniques, we borrow a constructivist framework developed for the purpose of studying risk assessment of technologies developed by Andy Stirling and colleagues (Stirling and Scoones (2009) and Leach et al. (2010, p. 52-58)). The similarity between investigating risk assessment and technology futures lies in that, in both cases the incompleteness of knowledge is the key aspect that needs to be explored. The framework adopted adds three significant features with respect to the classifications described above. First, the framework explores how the users of FTA techniques represent knowledge – hence the discussion that follows is about the analyst's perceptions, not about an objective state of knowledge. Second and related, we consider the incompleteness of knowledge also in terms of which outcome is relevant for the user of FTA, not only in terms of the probability of each instance of a given outcome occurring. This means that the knowledge about outcomes includes a subjective evaluation on which outcome(s) is (are) better than others. As we briefly discus below, this second dimension is quite important when considering "opening up" or "closing down" policy decision making (about the future). On the one hand the FTA user may be confident about his knowledge that one single outcome should be considered for future analysis. On the other hand, the FTA user may perceive the knowledge about outcomes as problematic, and consider in the analysis the trade off among a large number of outcomes equally relevant. Third, we forego more or less precise distinctions into different discrete levels of knowledge-incertitude nexus (which are per se valuable exercises) for a continuum in which the knowledge moves from unproblematic (deterministic) to problematic (impossible to assess). This facilitates the task of relating and discussing the 26 different techniques against the two dimensions of the framework: as it will become clearer from the discussion in the next section, it would be misleading to attach each technique to a unique level.

2.1 The incertitude regarding the future: Opening up versus Closing down

Since the exploration of technology futures, such as technology assessment, occurs in the context of appraisal processes that are ultimately aimed at supporting decision-making either in private management or in public organisations, it is important to consider the effect that techniques have in appraisal. The use of some techniques tends to "open up" the decision-making process, in the sense that they have an emphasis on providing an array of potential outcomes of the analysis, forcing the decision-makers to consider between alternatives (Stirling, 2008). Some other techniques have a tendency to "close down", in the sense that their effect in decision making is to reduce the number of possibilities that the decision-makers think that need to be considered.

This difference in the effect of techniques between opening up and closing down is a

key aspect for the impact of an FTA. We discuss this in the context of the perceived type and degree of incertitude or incomplete knowledge that a specific type of analysis of a given technological future poses.

2.2 The representation of incomplete knowledge

When an analyst decides to use a given FTA quantitative technique, she makes a specific representation of knowledge, i.e. she assumes that some or all variables influencing aspects regarding the future technology can be known, others are uncertain, others are unknown and many others are irrelevant. Following Stirling and Scoones (2009), we distinguish two dimensions in the incompleteness of knowledge, as illustrated in Figure 1.

The horizontal axis describes the *perceived* **knowledge about outcomes**. On the left hand side of Figure 1 the analyst considers the outcome of the FTA analysis as not problematic, and assumes that it is fixed. For example, an FTA analysis in the 1950s or 60s might have assumed that urban means of transportation would be based on the combustion engine. Knowledge about the type of the dominant engine technology was perceived as not problematic. However, an analyst in the 2010s on urban means of transportation is likely to represent the possible type of technologies for urban transportation as relevant alternatives to evaluate. Not only there are diverse means (bicycles, cars, tube, tramways), but also she is likely to think that new technological means might appear or their research may be induced. Hence, the knowledge about the outcomes of technological innovation are represented as problematic, or unknown (right side of Figure 1), whereas in the 1960s they were often represented as not problematic, or known (left side of Figure 1).

The vertical axis describes the *perceived* **knowledge about the likelihoods** about a certain aspect of a technology, a plausible instance of one of the outcomes (the different technologies). If the analyst perceives that a certain instance can be calculated in a probabilistic manner with a known generation mechanism of the probability distribution and an expected probability of its occurrence, then she is assuming that the knowledge about likelihoods is not problematic. For example, one analyst in the 1960s may have assumed that combustion car ownership trends in a given city were sufficient to "predict" the number of automobiles in the years to come. One analyst in the 2010s might instead think that knowledge about the likelihood of combustion car ownerships is extremely problematic since it depends on a series of variables (public opinion on climate change, governmental regulations on pollution, public health measures, petrol cost, and so on), which have behaved in an erratic way for the last 40 years.

This analytic framework leads to four potential "ideal" manners of representing knowledge. It is in relation to these ideal representations of knowledge that we can now think on how different FTA techniques are conventionally perceived and used. We should emphasise that there is some flexibility in how an analyst's use of a given FTA represents knowledge. Here we describe the conventional uses of the FTA techniques.

When neither knowledge about likelihoods nor knowledge about outcomes is repre-

sented as problematic, the analysts engage in **risk-based expectations** (top left of Figure 1). Here there is a "neat" focus on a given technology and a method to estimate one of its aspects. This would be the case of many simple quantitative FTA techniques, such as trend extrapolation. This is the type of approach which is often associated with scientific techniques, possibly because it allows quantification in a similar way that physics does. However, these (scientific) methods are only valid to the extent that they ensure that exogenous conditions are controlled and fixed so that only the variables under investigation may have an effect on the outcomes. Yet, in practice, technology futures in the mid and longer terms unfold with many variables beyond control (public perceptions, energy source prices, other technologies, political and organisational preferences, events that cannot be known), changing radically and releasing unforeseen signals, having major effects on technological development.

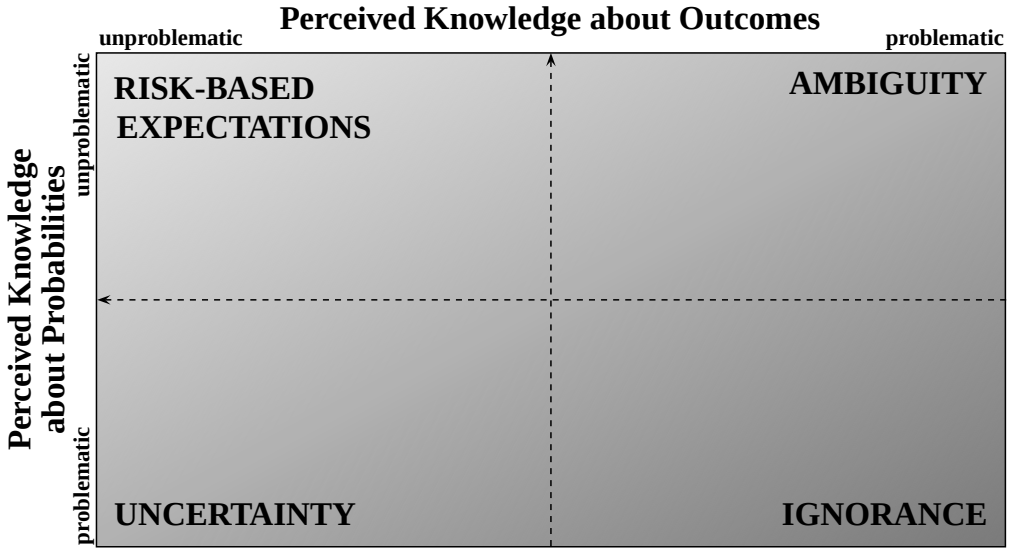

Figure 1: ***Representations of knowledge that users of different FTA quantitative techniques may make***. *Source*: Stirling and Scoones (2009).

Indeed, when dealing with future technologies, all sorts of changes in conditions – both endogenous and exogenous to the closed system analysed – assumed as stable may disturb the assumptions made by risk-based expectations FTA. If the analyst focuses on well-defined outcomes but represents the system as not being amenable to probabilistic analysis, then she moves into an area of **uncertainty** (bottom left in Figure 1). Roadmapping, which often includes quantitative description of technological trajectories, would be one such case. There is a consensus on the type of outcome desired, and hence the actors involved focus on achieving some given technological specifications. However, the roadmapping exercise is carried out without making assumptions on the likelihood of each instance of the outcome being achieved. A good example is the case of the International Technology Roadmap for Semiconductors (ITRS, `http://www.itrs.net`) which specifies expected outcomes, while acknowledging uncertainty without carrying out probabilistic assumptions.

Another way of representing the state of knowledge is to assume that probabilities are not problematic, but that the knowledge of outcomes is problematic, because of conflicting assessments on the desirability of these outcomes. Such state is characterised by **ambiguity**. In principle, one cannot find many examples of quantitative FTA techniques leading to ambiguity because in quantitative approaches incomplete knowledge of type of outcomes often occurs with incomplete knowledge on likelihoods (while the reverse is not true: one analyst can assume she knows the outcomes, but not their likelihood). However, many approaches using risk-based expectation type of assessment over diverse potential outcomes could fall into ambiguity. This would be the case, for example, of an exercise looking into the future of urban transportation where the stakeholders agreed on the likelihood that various technologies (bicycles, cars, tube, etcetera) were used in a near future on the basis of trend extrapolation, but the stakeholders did not agree on the desirability of those. One of the quantitative techniques that yields ambiguity is scenario modelling, a simulation based technique considering different potential outcomes while comparing different probabilistic instances of the outcomes, the probability of which depends on the values given to those parameters that are considered to be unknown.

Finally, the state of knowledge can be represented as **ignorance**. This is the state of knowledge that the US Defence Secretary made famous with his quote on "unknown unknowns", namely those "things we do not know we don't know." In short, when an analyst considers that she is in a state of ignorance, she assumes that she does not know what are the potential types of outcomes (or their desirability), nor the probability that they occur. One might think that ignorance is the most sensible way to represent technological futures, given that futurology or forecasting have an extremely bad record on prediction (Geels and Smit, 2000). But ignorance is a difficult state to work with (and moreover, it is not seen as a scientific contribution). One can try to carry out forecasting or foresight with some known potential outcomes, but which data should one use to characterise the unknown? Qualitative foresight exercises may investigate the unknown building on experts' imagination (as in the case of Delphi studies). Science fiction is also a method to explore fully unknown areas. Another approach is to monitor technological developments, horizon scanning with tools such as bibliometrics or networks analysis in search of new technologies, i.e. technologies that were "not known".

3 The representation of knowledge by users of FTA techniques: outcomes and probabilities

3.1 The representation of knowledge at the outset of an FTA

When a user seeks to employ FTA techniques it is often because the knowledge on the relevance of future outcomes of technologies or states of the world is seen as problematic, and always because the knowledge on the likelihood that specific instances of an outcome will occur in the future is problematic. FTA techniques are used under conditions in which

the user (an analyst, a sponsoring agency of the state, a firm or a group of them) perceives the knowledge about the future as problematic, uncertain. "FTA's future orientation means that it deals with matters characterised by uncertainty and ignorance" (Loveridge and Saritas, 2012, p. 756).

In Figure 2 we map the 10 groups of FTA quantitative techniques surveyed in Part 1 according to their *relative* position with respect to the representation of knowledge about outcomes and probabilities that a user has **before** an FTA exercise. A special mention with regard to techniques that fall under the categories "description and matrices" and "statistical methods" in Part 1 (Table 1) follows: these techniques are used exclusively to inform other FTA techniques and do not make any previous assumption on the representation of outcomes and probabilities. Therefore, a priori they could equally tend towards Ignorance or Uncertainty. As argued, for all techniques the knowledge on probabilities is

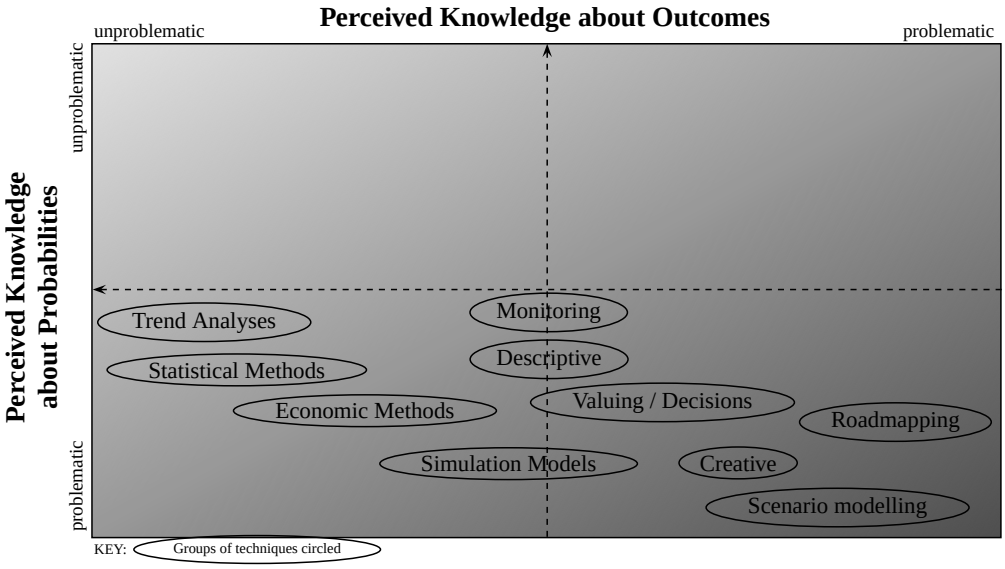

Figure 2: ***The representation of knowledge about outcomes and probabilities before an FTA***.

represented as problematic. Techniques vary to a large extent with respect to how the knowledge on outcomes is represented. Some techniques are prevalently employed when the outcome is already perceived as relatively certain. For example, the use of Trend Analyses to describe the diffusion of a technology in terms of the share of users. Other techniques are employed when the knowledge about outcomes is presented as highly problematic. For example, in the case of Scenario Modelling, when the user needs to compare the trade off existing among different outcomes associated with different scenarios.

Summing up, following the framework discussed in Section 2 (Stirling and Scoones, 2009), when an analyst starts an FTA activity using one or more quantitative techniques, she tends towards a condition of Uncertainty – outcomes are represented as known – or Ignorance – outcomes are represented as unknown (they are part of the FTA activity). In the first case, the user of FTA techniques makes assumptions on the relevant outcomes

since the beginning of the exercise, while in the second case the analyst uses the technique as well to evaluate different outcomes. In both cases no explicit assumptions are made on the probability of occurrence of each instance. As we shall see in the next subsection, assumptions are made during the process generating these probabilities.

3.2 How the use of FTA changes the representation of knowledge

As discussed in the introduction, practitioners' use of FTA techniques is aimed at generating new practical and scientific knowledge. Quantitative techniques are employed to reduce the incertitude on future states of the world by reducing the space of possible outcomes, and/or by attaching a probability distribution to the occurrence of all possible known instances of an outcome. In order to achieve these aims, an analyst needs to focus on specific properties of the problem that is the object of future studies (as researchers in any science). This in turn requires assumptions on what is most relevant and what can be left out from the analysis because it is not influential, or because it seems not to be related to the object of study. In other words, the analyst isolates those properties and objects of study that she consider important for future changes of the problem analysed. For instance, if she employs one of the Trend Analysis techniques she will normally consider the series of past events. If the problem investigated is the diffusion of a specific technology such as Genetically Modified Foods she will retain data on their past adoption, maybe on regulations and on consumer preferences, and discard all the remaining information, considered as non relevant for the purposes of the analysis. If instead the analyst employs one of the modelling techniques (economic, simulation or scenarios), these will carry a large number of assumptions on how the model works. She will have to represent more nuanced behaviour of the food consumers and producers, maybe considering exchange rates, the rate of substitution with similar food, the role of retailers, climate change, and a specific discount rate, among other variables.

These assumptions constitute the first admission of knowledge about the future event, by excluding the alternatives to the assumed statements. Often these assumptions are justified by empirical evidence, methodological traditions, or relevance of the analysis.[1] Back to our examples of techniques, in trend analysis it is not uncommon to assume that rate of adoption of a technology will follow the S-curve often observed in the past: initial adoption is hold back by lack of information, risk aversion and learning costs – slow growth in adoption rate; once the technology starts to diffuse, the information is largely available, the risk significantly reduced, and the advantages of the new technology overcome the learning costs (network economies) – quick growth in the adoption rate; as the majority of the population has adopted the new technology, the rate of adoption can only decrease. Assuming that a new technology will follow a similar pattern can overlook a large number of previously unobserved details that can make the prediction totally wrong. As it was

[1] If the analyst is interested in the cure of an illness that is specific to a confined area of the world, she will be more interested in the food consumption pattern of the people inhabiting that area than of those leaving anywhere else.

the case for ancient Prophets, the prediction may hold for a noticeable number of cases, but may sometimes fail.

Similarly, when modelling, one needs to simplify the behaviour of a system's agent. In particular, one tends to eliminate a large amount of uncommon behaviour: if most consumers will buy a good with a lower price, other things being equal, non conforming behaviour – buying more of a good when the price increases – is considered as noise that induces negligible errors in prediction. Things are assumed not to change much if instead these particular cases are acknowledged and modelled: modelling with precision may nonetheless result in large errors if uncommon behaviours are not considered.

In sum, the use of (all) quantitative techniques requires making assumptions reducing the space of potential outcomes and probabilities, and this is the first representation of knowledge done by the analyst.

In addition, the scientific methodology on which FTA quantitative techniques rest, tends to convey a sense of confidence to the analyst, as well as to the public (rightly or wrongly), about their knowledge on outcomes and/or probabilities as a result of their use. In most of the cases the use of techniques allows to close policy options (i) either in terms of finding an expected future state occurring with higher probability than competing states, for a given outcome (when starting from a condition of *uncertainty*),[2]; (ii) or in terms of prioritising one outcome with respect to competing outcomes (when starting from a condition of *ignorance*); or both, focussing on a selected outcome, and finding an expected state of that outcome (when starting from a condition of *ignorance*). In summary, the use of FTA tends to reduce the outcomes deemed relevant, possible or probable. A few techniques, on the contrary, starting from a condition of *uncertainty* allow the analyst to assess different future outcomes, 'opening up' to different policy options (Figure 5).

We discuss how the use of FTA changes the representation of knowledge with reference to Trends Analyses and different types of Modelling with reference to the two dimensional framework representing the perceived knowledge about outcomes and probabilities. In Figures 3 and 4 we represent the direction towards which the families of techniques move on the knowledge map. Because each family usually contains more than one technique, it is possible that some of the techniques that have similar characteristics – according to the classification in Part 1 – are used with quite different effects on the appraisal of future technologies/states of the world.

As discussed in Section 3.1 the choice of techniques that are part of the Trend Analysis family tends to have a closing-down effect since the beginning of an FTA exercise because of the use of very restrictive assumptions. Their use tends to increase the certainty about the representation of knowledge even more (Figure 3). Techniques such as Trend Extrapolation, S-Curves, Technology Substitution and Google Trends and Correlate, usually analyse one single outcome, deriving a prediction (forecast) for one expected event and a relatively small variance. Therefore, similar techniques may be useful when the phenomenon analysed is very well defined, the assumptions are not influential in the

[2]The variance of the expected outcome differs for different techniques and FTA activities.

short period, and policy requires a well defined and closed outcome with no need for an evaluation of alternatives and the representation of different stakeholders. As briefly

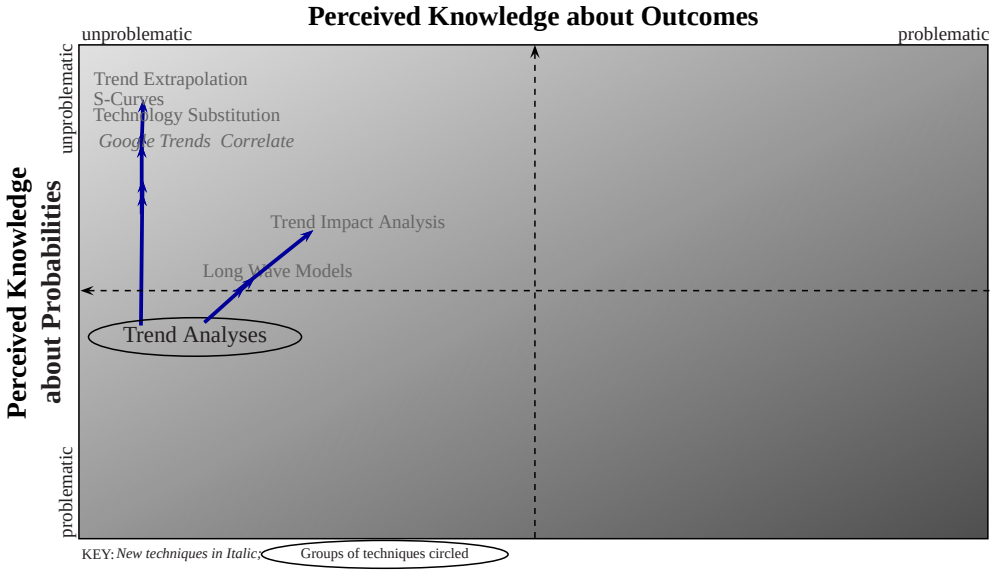

Figure 3: ***The change in the representation of knowledge about outcomes and probabilities using an FTA quantitative techniques.*** The case of Trend Analyses

mentioned, some of these techniques can be used in a less restrictive way: Trend Impact Analysis, for example, integrates more elaborate models – with respect to Gompertz, the Fisher and Pry or the Norton and Bass models (for more detail see Part 1) – to study the effect of unforeseen events that can alter the expected dynamic of a trend based on an historical series. This is the case of Trend Impact Analysis. Long Wave Models usually suggest future patterns that are very open to a number of different outcomes, and are very cautious about making predictions – usually not presented in probabilistic form.

Economic methods are an example of techniques with very different effects on technology appraisal (Figure 4). On the one hand Prediction Markets close down on one single outcome and a well defined expected value with low variance (Risk-Based Expectations). On the other hand, Input-Output models may even open up to different scenarios, although the relevant outcomes are usually defined at the outset. Starting from less restrictive assumptions, Simulation Models usually allow to open to a number of different, even non-predicted outcomes. At the outset they also tend to define which the relevant outcomes are. However, users of simulation models usually do not pre-empt different outcomes to emerge as unforeseen properties of the model. Moreover, outcomes are usually given in distribution form, not as one expected value. Starting from a condition of ignorance – fewer assumptions on the outcomes, Quantitative Scenarios represent one relatively elaborate way to use Simulation Modelling. Their aim is to find conditions under which a large number of different outcomes can be realised. The only reduction in policy space occurs towards a perceived increase of knowledge about the likelihood of the different outcomes. This is achieved thanks to the combination of a large number of conditions defined

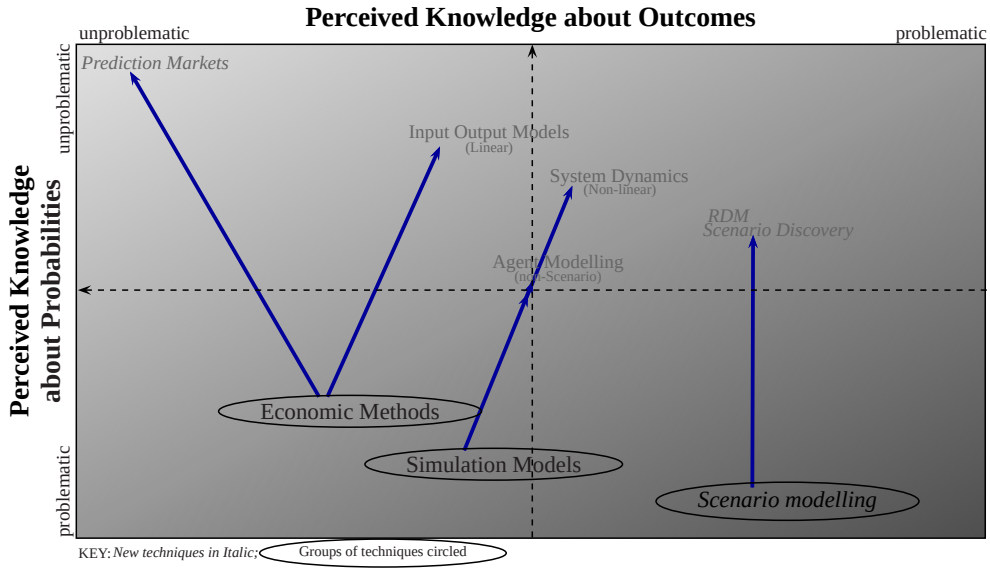

Figure 4: ***The change in the representation of knowledge about outcomes and probabilities using an FTA quantitative techniques.*** The case of different types of modelling: Economic Methods, Simulation Models and Scenario Modelling.

by a number of parameters. By combining different conditions Quantitative Scenarios can also show outcomes or instances thereof that are not imagined at the outset, or cannot be imagined by experts of a particular technology or phenomenon under analysis.

Indeed, a similar exercise on how FTA quantitative techniques change the representation of knowledge can be done with all families of techniques surveyed in Part 1. Although we do not go through all of them in the same detail, for completeness we show the effect of their use on the representation of knowledge in the two dimensional graphs (Figure 5). For instance, when the analyst views herself as being in a condition of Ignorance, most techniques tend to increase the perceived knowledge on outcomes. This is the case for example with Value and Decision Making techniques, aiming at facilitating decisions on the most desired future outcomes, and finding probabilities of their occurrence – in the case of Analytic Hierarchic Processes. In the case of roadmaps, instead, the actors have decided where they want to go (closing outcomes), and the quantitative exercise is about how to get there (trying to reduce uncertainty). The only "closing down" effect in this case occurs towards a perceived increase of knowledge about the outcomes that should be realised in the future.

3.3 The representation of knowledge after an FTA

The use of quantitative FTA techniques shifts the representation of knowledge of the analyst about relevant outcomes and the probability of realisation of specific instances of an outcome. As shown in Figure 5, knowledge is, in most cases, represented as less problematic. The use of quantitative techniques certifies this change in knowledge and incertitude about future events, entitling the policy maker to use this information to take

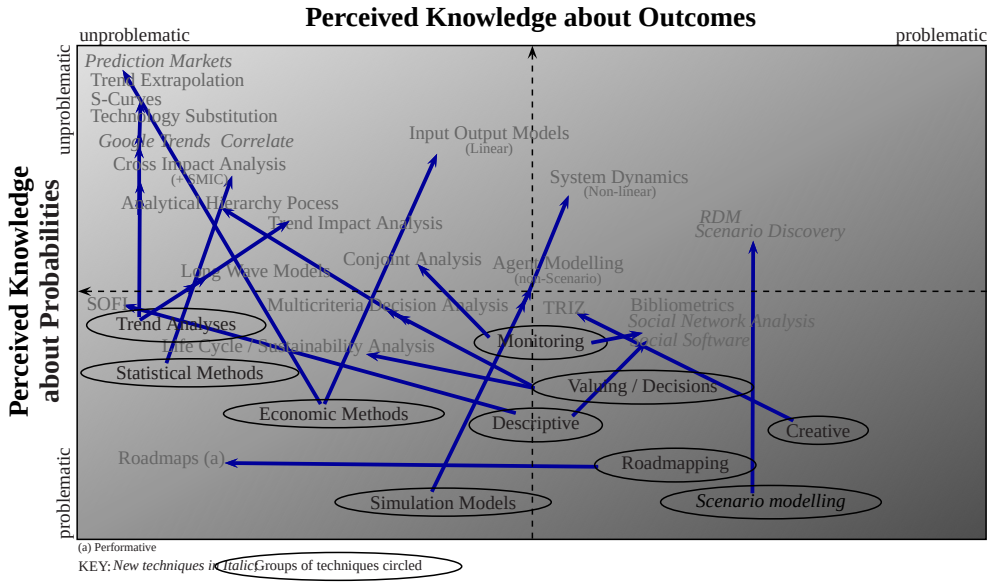

Figure 5: ***The change in the representation of knowledge about outcomes and probabilities: using techniques***.

future oriented decisions. As we have argued, however, many of the FTA quantitative techniques tend to limit substantially the evaluation of decision makers, by closing down policy options to a small number. For instance, using Analytical Hierarchy Process (AHP) an analyst may be asked to priorities the main industry/technology in which a Government should invest, for example by building an industrial park. Given the final objective (critical industries) the analyst devises what she believes (or she is told) are the main criteria that should be used for the decision making process. The criteria selection already contain the assumed prioritisation, leaving out those that are not considered as relevant. Criteria included may be, for example, consumer demand, trade, land used, capital intensiveness. Criteria excuded may be, for example, employment opportunities, availability of educated workforce, or value added. To be sure, there is a limited number of criteria that the analyst can use in AHP. Next, the analyst selects the different alternatives to be assessed using the selected criteria. As a result of the AHP exercise done with the help of experts – see Part 1 for more details – the analyst ends up with one preferred industry/technology. During the exercise the analyst also attributes specific probabilities to the different technologies. In other words, the analyst's perception of knowledge moves from a condition of initial Ignorance to a condition closer to Risk-based Expectations.

In what follows, we illustrate how the different quantitative FTA techniques are represented on the map of outcomes and probabilities, relative to one another. We position the techniques on the same map representing the perceived knowledge on outcomes and probabilities and we identify five different groups of techniques, which include techniques from different families (as defined in Part 1). The positions on the map should be understood in relative rather than in absolute terms. It is also important to note that most of these techniques can be used in different ways, occupying a large area of the map, rather

than a well defined static position. This is shown by drawing a dotted area around some of these techniques.[3]

The first group of quantitative techniques (Figure 6) provides information on the future that is perceived as unproblematic both with respect to the outcome defined and the likelihood that specific instances occur. It includes different types of trend extrapolations and two new techniques: Prediction Markets and Google Trend and Correlate. In all these cases the choice on which outcome is relevant is done before the FTA activity. These techniques are more suitable for very circumscribed issues occurring in the short term, such as the diffusion of a technology, the diffusion of a virus or the sales of a good. An example is the prediction of Apple laptop sales in Wu and Brynjolfsson (2009).

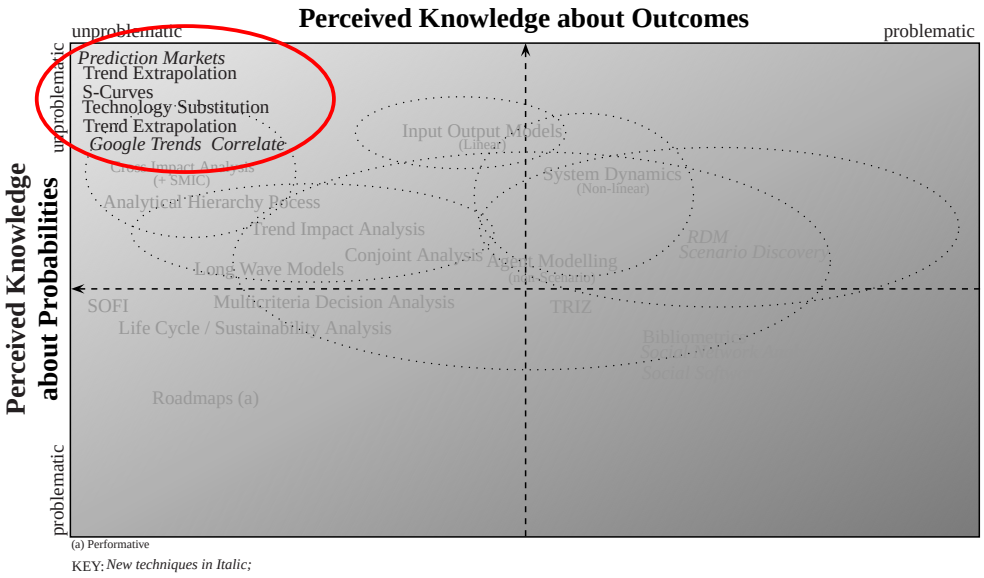

Figure 6: ***The representation of knowledge about outcomes and probabilities after an FTA activity: Unproblematic futures.*** Relative positioning of techniques

The second group of techniques, in Figure 7, shares a similar perception about the knowledge on the outcome (be it a technological development or any other state of the world). However, while the outcome is assumed since the beginning, in the case of Trend Impact Analysis and Long Wave Models, the use of Cross Impact Analyses and Analytical Hierarchy Processes is to define the most relevant outcomes in probabilistic terms. The techniques clustered in the second group differ from the first group mainly with respect to the degree of incertitude in relation to the probability of each instance of an outcome occurring. For all these techniques the knowledge about probabilities is represented as limited. For instance, in the case of Trend Impact Analysis and Long Wave Models the analyst usually provides a distribution of different possible instances of the same outcome, depending on events that are not predictable and that recognise incertitude as a source of information and arbitrary choice and adaptation of future policies. In the case of Cross Impact Analyses and Analytical Hierarchy Processes the analyst provides

[3]We did not draw this area for all techniques, which would make the map difficult to read, but for those for which we know of different uses.

one single probabilistic outcome, which is perceived as less certain than with techniques in the first group. The extent to which the knowledge about future events is left open depends substantially on the application of these techniques, as the dotted line around them suggests.

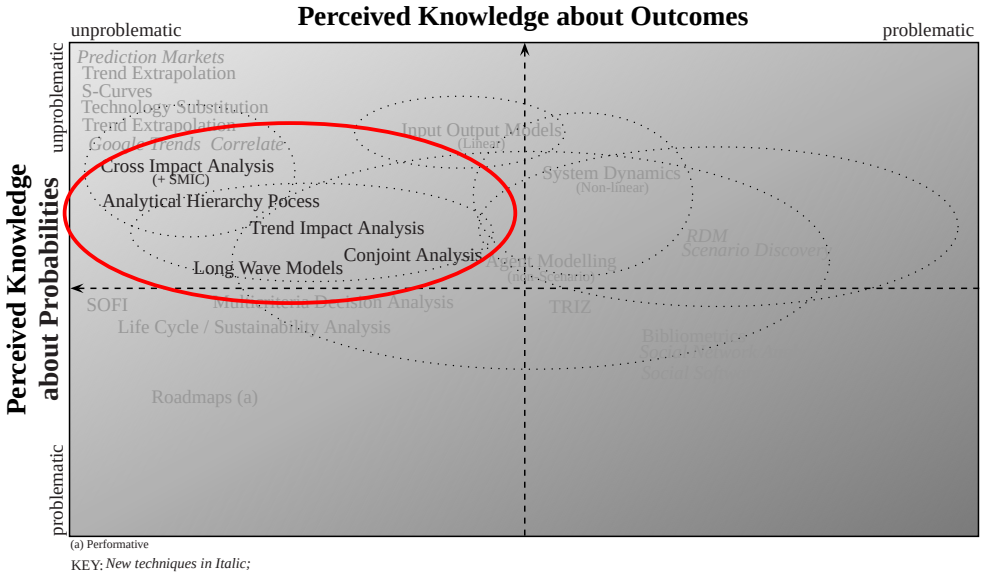

Figure 7: ***The representation of knowledge about outcomes and probabilities after an FTA activity: Defined outcome, problematic probabilities.*** Relative positioning of techniques

The third group of techniques is employed to assess a relatively larger number of possible outcomes (Figure 8): Input-Output Models, System Dynamics, Agent Modelling and Scenario Modelling. By representing the knowledge about the outcomes as problematic, the analyst is in a position to compare different possible outcomes, usually with trade-offs that need to be assessed (for example, comparing the effect of a policy on income growth and global warming). These are all models that have a number of parameters representing the initial condition of the system and the behaviour of the human or non-human actors modelled. Each of the parameters represents a degree of lack of knowledge (degree of freedom in the choice of the analyst) and can be used to compare different instances of an outcome. It follows that all four techniques represent the knowledge about likelihood as problematic.

However, the four techniques do differ with respect to how the knowledge about outcomes is represented, and as suggested by the dotted lines, they can be applied in very different ways, with very different effects on the perceived knowledge on outcomes and probabilities. When using Input-Output models the analyst has already in mind one or two outcomes, and she employs the technique to predict different scenarios under different parameterisations. In the case of System Dynamics, a number of outcomes are usually compared, as in the famous example of the model of the Club of Rome used to discuss the relation between the use of resources, pollution, and economic growth. Agent-Modelling

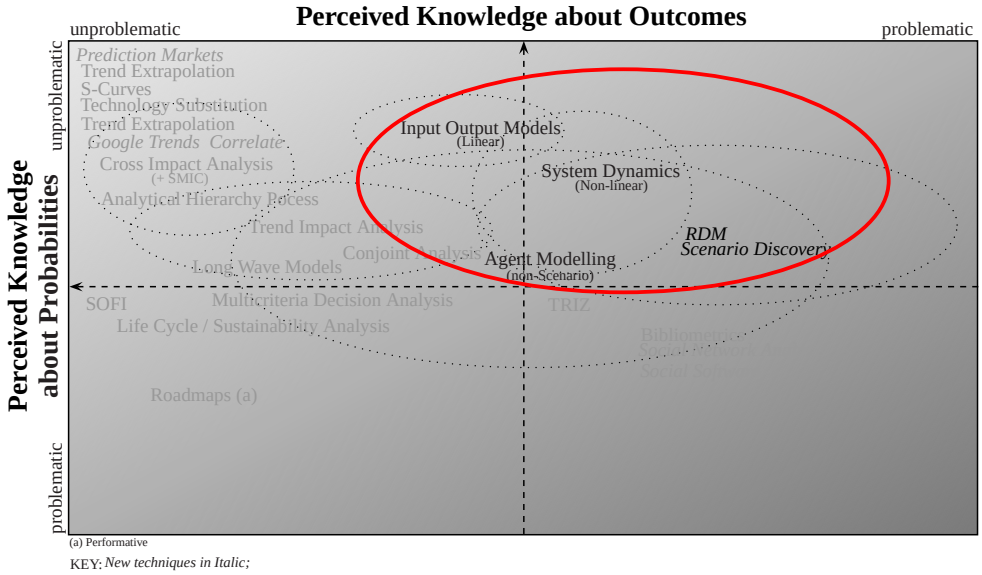

Figure 8: ***The representation of knowledge about outcomes and probabilities after an FTA activity: Open Outcomes and Probabilities.*** Relative positioning of techniques

is very flexible and can be used in a very closed as well as in a very open way. Indeed, the "philosophy" behind Agent-Modelling is that the analyst observes the outcome as an emerging property of the individual actions and behaviour. Therefore, while in some cases the outcome is pre-defined and the analyst is only interested in how the different instances vary for different parameterisations – the use of the model is similar to an Input-Output model where the analyst studies the effect of the parameters, in many other cases the analyst observes unexpected outcomes as a result of the agent's interactions.

Scenario Modelling, although it is presented as a different family of techniques for reasons illustrated in Part 1, is a combination of one or more agent models. The purpose of Scenario Modelling techniques, such as Robust Decision Making (RDM), is to compare different outcomes and the probability that they occur, under different parameterisations. In other words, the analyst represents knowledge on outcomes as incomplete, presenting to the policy maker the conditions (combination of parameters) under which different instances of different outcomes are likely to occur. Scenario Modelling tools are actually seen as techniques that can uncover outcomes and probabilities that cannot be imagined by experts with qualitative scenario methods, as they are not part of the knowledge or imaginary set of the analyst.

The fourth group, Figure 9, includes quantitative techniques that are aimed at defining a unique outcome/pattern for which there is little or no knowledge about the probability of its realisations. All the techniques in this group of techniques pertain to the most normative families of quantitative techniques: Roadmaps and Valuing and Decision Making (see Part 1). These are the State of the Future Index (SOFI), Life Cycle Analysis, Multicriteria Decision Analysis (when different from Analytical Hierarchy Process) and Roadmaps. Such techniques are mainly prescriptive and normative used by decision makers to indicate

trajectories for future technological developments, for which there is little knowledge on how to follow these trajectories. Closing down on possible outcomes is not only a perception in this case, but the main objective, for example establishing the standard of a technology.

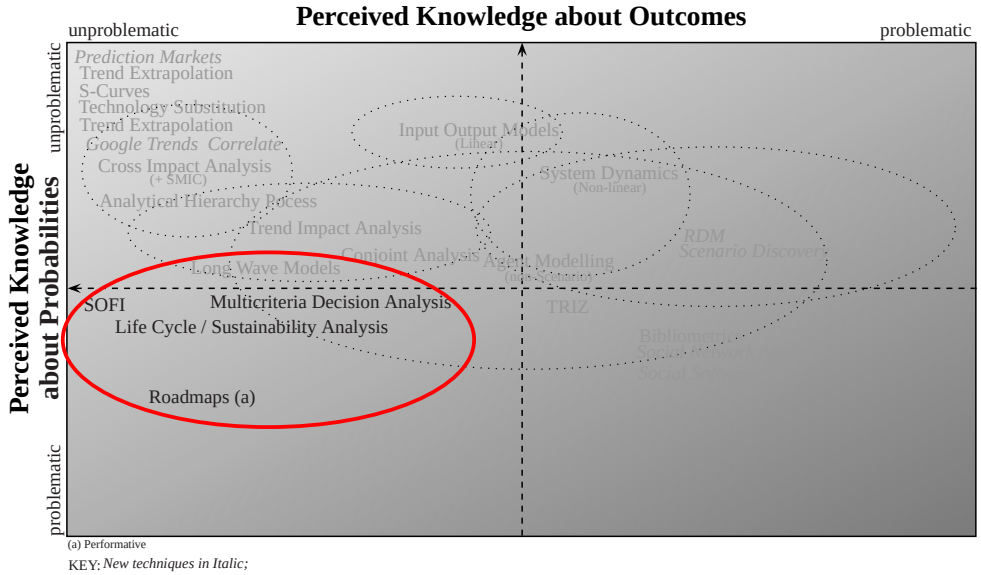

Figure 9: ***The representation of knowledge about outcomes and probabilities after an FTA activity: Defined Uncertain Outcomes.*** Relative positioning of techniques

The last and fifth group, Figure 10, includes techniques that are on the opposite side of the descriptive-prescriptive spectrum (see Part 1 for details). These are all techniques that fall under the Creative, Monitoring and Descriptive families. Their main role is to inform about past directions of a technology (or another phenomenon under investigation), the actors involved, the organisation and clustering of discourses and research, and so on. Some of these (new) techniques, such as Social Software, are employed to inform instead about current hot topics, fads, sentiments and networks of Internet users. Both sets of information (on past trends, on current issues) are not conclusive on future outcomes and probabilities of occurrence. They show statistical properties that are used in broader FTA activities to reduce the incompleteness for knowledge about the future. Taken alone, they do not close down on potential outcomes, they may actually serve the opposite function of opening up previously unseen potential outcomes.

The last figure (Figure 11) describes all the techniques surveyed in Part 1 on the same graph, in order to appreciate their relative position. The grouping of techniques that emerge from Figures 6-10 aligns quite well with previous classifications of FTA techniques. In Part 1 we discuss one such classification, based on previous efforts of FTA scholars. As we have already mentioned, most techniques in Figure 10 (Undefined Outcomes and Probabilities) pertain to three families: Creative, Monitoring and Intelligence and Descriptive and Matrices; and the techniques grouped in Figure 9 (Defined Uncertain

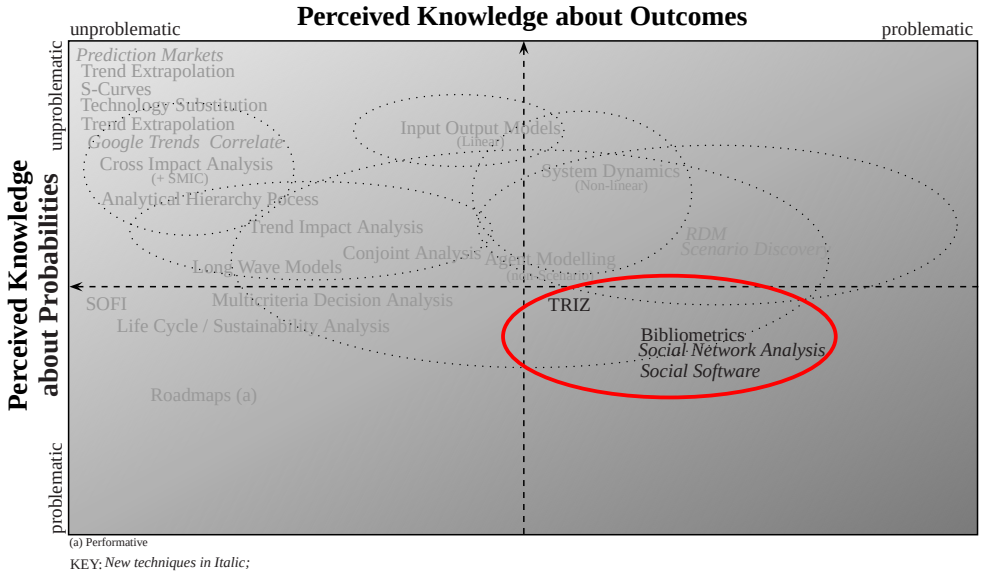

Figure 10: ***The representation of knowledge about outcomes and probabilities after an FTA activity: Undefined Outcomes and Probabilities.*** Relative positioning of techniques

Outcomes) are mainly listed under the Roadmaps and Value/Decision families. Looking at the remaining groups, the techniques listed in Figure 8 (Open Outcomes and Probabilities) are those listed under three families: Economic Methods (with the exception of Prediction Markets), Simulation Models and Scenarios. Group 6 (Unproblematic futures) encompasses quite neatly the techniques usually referred to as Trends Analyses. Finally, Group 7 (Defined outcome, problematic probabilities) is more mixed, hosting techniques from Trend Analyses, Statistical Methods and Descriptive. Essentially, the techniques clustered here are either an opening up of usually closed Trend methods, or a closing down of statistical methods employed for forecasting purposes.

This leads us to discussing how the different techniques lend themselves to the different practices of FTA, distinguishing between those employed for descriptive and data gathering purposes, from those employed for prescriptive and inferential purposes. Once again the framework adopted here seems to relate quite neatly the perceived knowledge about outcomes and probabilities with the current use of the techniques. We discuss this in the next subsection.

3.4 Distinguishing between foresight and forecasting

In summary, the framework that we propose sets the type of knowledge representation used as a key factor for understanding the effect that an FTA technique may have in policy making. FTA techniques that focus on a given outcome and specific properties in order to provide allegedly quantitatively rigorous approaches (generally falling in the risk-based expectations zone, Figure 6), do so at the expense of putting blinders to phenomena which are very difficult to quantify and which may dramatically alter the results of the

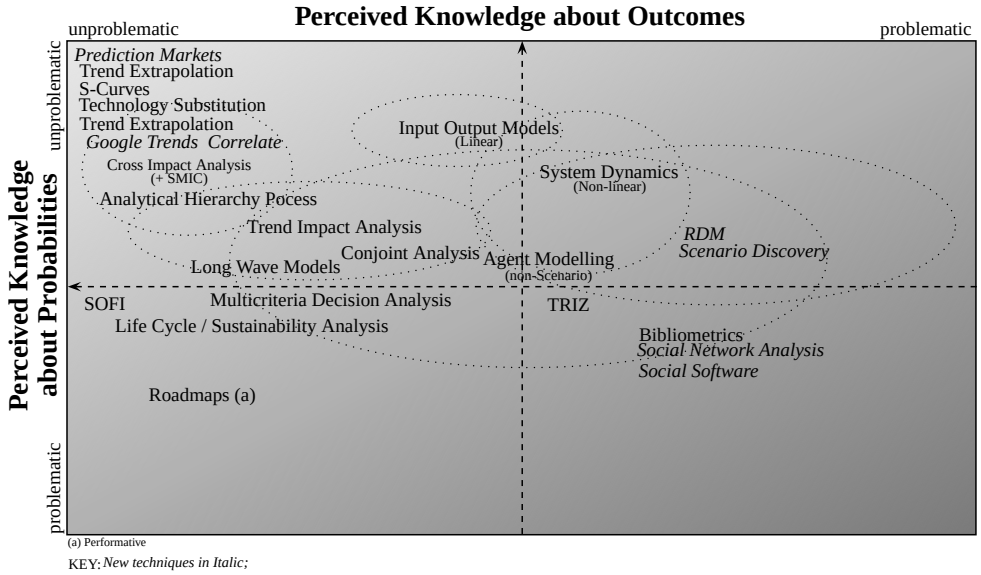

Figure 11: ***The representation of knowledge about outcomes and probabilities after an FTA activity: All Techniques.*** Relative positioning of techniques

"prediction" (an unexpected war, conflict, or terrorist attack, or less dramatic events that scale up to reach critical unstable points). These are the type of approaches that resemble in one way or the other the traditional forecasting literature (Figure 13). As we will discuss, the use of new web-based data or extremely large databases does not change the fact that these methods are highly reductive of dimensions. Therefore, they only "work" under the assumptions that all other variables remain within stable ranges, as dramatically illustrated in the case of the recent financial crisis. But in open systems, other variables do happen to change sooner or later, often much sooner than expected.

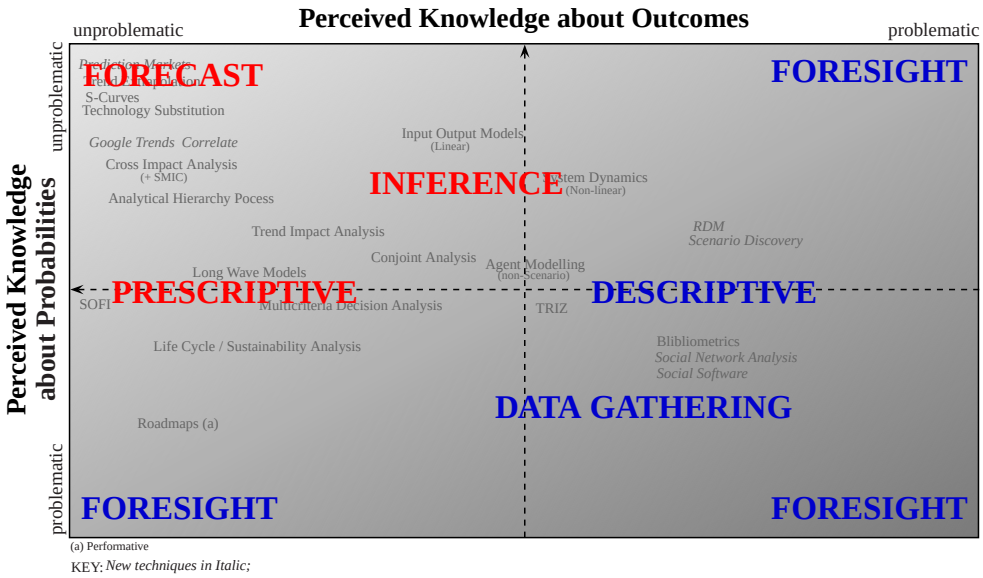

Figure 12: ***The representation of knowledge about outcomes and probabilities and their role in Forecast and Foresight FTA.***

As a result of the repeated failure of forecasting exercises, policy-oriented analysis of future technologies puts the emphasis on foresight rather than quantitative forecasting (see review in Part 1 and in the work by Ely et al. (2012)). This practical focus acknowledges that the usefulness of foresight lies in opening up a process to discuss technological futures in the face of insurmountable incertitudes, rather than trying to predict the future. The contribution of quantitative techniques to foresight seems to be generally achieved via FTA techniques that represent knowledge as incomplete, either in terms of the probability of known outcomes or in the type of outcomes.

Among those we distinguish three groups, already identified above. The techniques in the lower left area of the framework (Uncertainty), represented in Figure 9 (Defined Uncertain Outcomes) acknowledge the incertitudes, and deal with them in a prescriptive way, attempting to define standards that facilitate technological co-ordination and reduce incertitude (if they succeed). A second group of techniques, represented in the lower right area of the framework (Ignorance) and in Figure 10 (Undefined Outcomes and Probabilities) have mainly a descriptive function, providing and structuring the data for further analysis. Finally, the techniques that fall in the upper right are of the framework, represented in Figure 8 (Open Outcomes and Probabilities) provide educated conjectures and inference about plausible and alternative futures, with different degrees of openness. Scenario and simulation modelling are significantly more open than economic methods. These are also more prescriptive than purely data gathering techniques, but to an extent that leaves many degrees of freedom to decision makers and that incorporates the role of incertitudes.

4 Breadth of inputs and "participation" in FTA: the role of new quantitative techniques

In Section 3.3 we have discussed the role of some of the new techniques in FTA and how they are perceived in terms of defining outcomes and the probability that they realise: Prediction Markets, Google Trends and Google Correlate, and Scenario Modelling. Less clear is the role of a number of new monitoring techniques which serve to collect information to be used by other FTA activities. These are statistical techniques that analyse large amounts of data from the World Wide Web (WWW): "Social Software" and "Social Network Analysis."

The advantage in using these techniques is that they collect information from a very large number of users, rather than from a small number of experts or from structured sources that acquired an authoritative status such as patent and scientific publication datasets. In other words, they broaden the source of inputs, including outputs and opinions that were not usually included in FTA. One may even push the argument and maintain that the use of information from, for example, open source repositories of publications (such as open access journals, Mendeley and Slideshare – see the reference to Altmetrics in Part 1)

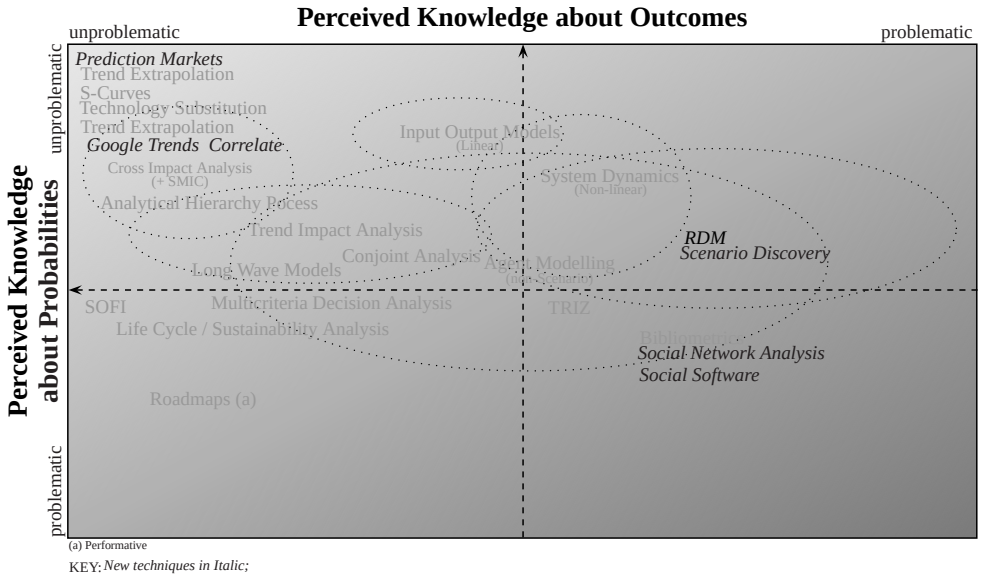

Figure 13: ***New techniques for FTA***.

or regular Internet users, increases significantly what could be called the "participation" in FTA – where "participation" here is used is the restrictive sense of attention to different types of information sources.

Indeed, by monitoring the opinions and sentiments on blogs and social network such as Twitter, it is possible to use more or less spontaneous opinions about past, present and future events (the degree of spontaneity is increasingly problematic: monitoring is already resulting in manipulations). For instance, the use of Altmetrics (`http://altmetrics.org/manifesto/`) to assess research outcomes takes into consideration the diffusion of research output, accounting for its impact in a way that seems more useful than the self referential account of research within the academic communities, when it comes to assess the contribution of scientific research to a broader societal goal (Priem et al., 2010).[4]

Using a large Yahoo-based social network, Goel and Goldstein (forthcoming) examine whether social relations affect purchasing behaviour: they find that adopter's peers are more likely to adopt themselves. Goel et al. (2012) compare a number of different online social networks to study if the diffusion of adoption follows a cascade from initial adopters down to peers of peers. Using these large sources of data they find that diffusion is restricted to one or two steps (neighbours) and only very rarely produces a cascade, accounting for a small share of the total adoption. The reader may note that, besides the illustration of the new methods, these results put the main Trend Analysis methods based on diffusion under discussion. Recently Radinsky and Horvitz (2013) have collected 22 years of news archived from the New York Times and use them to compute the likelihood of future events occurring – natural or human – following a sequence of news. In order to provide for the context of the news they also use more general context data from a number of sources. Simulating past events they show a high precision and a mid level sensitivity.

[4]See also other online services such as `http://impactstory.org/`

Using twitter data from UK users – 484 million tweets from around 9.8 million people – Lansdall-Welfare et al. (2012) analyse individuals' sentiments (fear, anger, joy and sadness). Apart from expected results linked to festivities, the authors find some interesting results related to the announcements of cuts in social spending – which induces anger and fear sentiments that last for many months after the announcement – and related to the riots happened in UK main cities in summer 2011 – preceded by a significant increase in anger.

While these are a small sample of recent work and forecasting companies using Internet data, they are representative of how people's opinion is used to suggest intuitions on future events. However, a few important caveats should be mentioned. First, "participation" (diversity of information sources) is clearly still restricted to capture the views of those that have regular access to the WWW, and that voluntary decide to express their opinions in some form over the internet. In other words, the use of WWW sources faces a problem of self-selection bias among those who have access to the internet. Moreover, among those self selected users the communication is very unequally distributed: some users account for the majority of the information distributed, while most users have no influence on the diffusion of information (see for example the work by Wu et al. (2011)). Hence again the question: whose participation is relevant?

Secondly, this kind of participation is passive. In other words, the views collected were not uttered with the goal of being assessed as informing on a certain issue, as it is the case with experts.

Moreover, when we move to the use of the data collected, the use of big data falls into some of the simplest categories of forecasting tools: trend extrapolations and monitoring. We have already discussed an example with Google Trends and Google Correlate in Part 1. These are based on massive information on what people connected to the Internet search for, and this is sometimes useful to predict short term dynamics.

Although these methods collect very diverse types of information and therefore they broaden up the number (and often the variety) of information sources, they do not necessarily have an opening up effect in policy or decision making. Let us think for example about carbon-based nanotechnologies. The exponential boom in presence of fullerenes and carbon-nanotubes in databases and the web in the 1990s meant that most quantitative FTA techniques would have focused on the impact of these two types of carbon materials. This focussing (closing-down) effect might have had a blinding effect, overlooking ongoing research on other carbon-based nanomaterials, and hence it would have missed out the possibility that graphene, another carbon-based nanomaterial, would become important. Instead a simple qualitative study that discussed diverse carbon-based nanomaterials could have mentioned graphene, since it had been studied theoretically for decades. This example illustrates that quantitative power does not imply capacity for seeing more alternative futures – an opening up of perspectives.

As noted in the case of Twitter data (Wu et al., 2011), the risk is to concentrate the sources of information and outcomes, in a cumulative process that generates the frequently-

observed power law distributions. That is, technologies that for some reason are initially captured by strong communication hubs, they are also diffused through the Internet more rapidly, they become relatively significant in the Internet noise, they become interesting sources of funding, and therefore they diffuse even more their presence on Internet and social media. This generates a cumulative process that leads to a distribution of potential technologies, where a small number of them are over-researched and a very large number are under-explored. This is similar to what happens with "picking the winner" technologies. Policies that focus on a few technologies with high potentials can have scale advantages, but they also risk closing down many possible outcomes. Initial openness, and continuously investigating different trajectories, may be more promising for a technology policy.

The difference between using new techniques for opening-up or closing-down does not depend on having more or less computational power. In some cases, FTA will be concerned with closing down – choosing the winners in the short run. In this case, new methods can also be useful in providing robust trend extrapolation for short periods – but the analyst should be aware that this only works over very short periods. However, very often, quantitative FTA will be concerned with longer term analysis within some type of foresight methodology. Then opening up is recommended, and opening up is achieved by discussing a variety of potential technological outcomes – and new monitoring methods such as web-scraping may be helpful in providing early detection of small signals rather than trying to predict.

5 Final considerations

People believe in numbers, especially if reflected in simple statistical properties such as the mean or the standard deviation of a distribution. Numbers are presented to the audience as reliable sources of knowledge when they are the result of complex algorithms, used for data gathering, or to build models that encompass a large number of endogenous phenomena. And so for policy makers: numbers may be a source of legitimacy and expediency. Therefore, policy makers provide incentives to fabricate figures that are easy to explain, even if their construction is a 'black-box.' So far, the representation of knowledge by users of FTA techniques does not sound very different from the representation of knowledge constructed by reading symbols in the natural elements, such as bird flights (they are both 'black boxes' to the policy maker and the public).

The main difference is that numbers are based on allegedly scientific methods that are more robust than the subjective interpretation of bird's flights. And this is precisely because these numbers can be replicated, if the same assumptions on their construction and the same data are maintained – which is usually the case when comparing the predictions with past events because they are based on previous observations, which have only happened once under identical conditions. In other words, for a given shape of a flock, the scientists applying the same technique always provide the same prediction, while the

Augures are likely to provide different interpretations entailing different predictions. It is because of the perceived objectivity and replicability that scientific knowledge quickly gains more credit (Mokyr, 2005, 1998) and numbers become Oracles for policy makers.

The fact that FTA are perceived as trustable can be problematic if the increase in trust from an Oracle to an FTA using a quantitative technique is larger than the increase in the reliability of the analysis. In other words, the use of quantitative techniques can induce false perceptions about the actual probabilities that a predicted instance of an outcome will occur, or about the necessity of a particular outcome foreseen. One famous example is the prediction by Meadows et al. (1972) regarding the short term exhaustion of resources, criticised by Cole et al., eds (1973) on the basis that the system dynamics models used for the predictions did not consider technological change.

As discussed in the previous section, the improvements in computational capabilities are resulting in the creation of new FTA techniques that promise great improvements in their capacity to generate reliable predictions. The analytical framework we proposed in this second report should help discern the type of contribution that they can make.

Given that many of the new methods have not yet been published in scientific articles, we have not been able to review the full range of available techniques. However, anecdotal evidence suggests that many of the methods rely on assumptions reducing incertitude and outcomes. This allows them to produce low-dimensional outputs, such as trend extrapolations that have a forecasting role, making predictions. When this is the case, no matter how big the data sources on which they rely, the analyst should be wary and sceptical about the validity of the expected-values since the implicit assumptions might not hold.

Instead, our analysis suggests that the most promising quantitative methods for conducting FTA in a sophisticated manner are those that allow the analysis to explore states of ignorance – in which neither future technology outcomes nor their probability are known – and bring the user to a state of ambiguity, in which future outcomes are compared against different probabilities of occurring, and users can evaluate a number of trade-offs. These exercises are not capable of predicting instances of outcomes, but they help explore the future in a conditional manner, acknowledging the incompleteness of knowledge. Using the techniques plotted in the ambiguity quadrant of the knowledge map, one can investigate the possibility of reaching certain outcomes under circumstances that are unknown but can be investigated in a conditional manner (if other, uncertain, conditions are in place). We suggest that these types of agent modelling and scenario modelling are the ones which can make a more positive contribution to policy-oriented FTA – by avoiding narrow prediction and allowing plural exploration of future technologies.

Finally, monitoring methods (such raw bibliometrics or web-scraping) may be able to identify potential outcomes and be useful for activities such as horizon-scanning, but they have limited analytical potential on their own to inform on future states of the world. Therefore, their usefulness depends on their implementation within a larger foresight methodology.

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