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Modelling for Knowledge Exchange: Global Aspects of Software for Science and Mathematical Modelling[3]

Abstract

The knowledge-based economy and information societies are defined similarly by knowledge and information becoming an essential or even dominant productive factor. In order to reflect on their impact on global science, it is essential to better understand the distinction between information and knowledge. Various types of understanding of the concept of knowledge are discussed in this paper, but one - which is characteristic of hard sciences in the information age - is related to synthesising information into mathematical models that can be analysed by using computers. Data mining in very large data sets is also related to finding patterns or models that synthesise characteristics of data relevant for a given purpose. Most of the methodological conclusions related to mathematical modelling and data mining are not restricted to computer science, but have an interdisciplinary character and support interdisciplinary research.

Knowledge and information become either more commercialised in a knowledge-based economy – or, if supported by public funding, more accessible for public use. Thus, it also becomes more important to make more knowledge accessible in the form of mathematical models used by various scientific disciplines, or in the form of patterns derived from large data sets. Easy exchange of computerised mathematical models will help in better verification and validation of research results for a knowledge-based economy and information society. However, in order to increase such accessibility, better standards and software tools for the analysis of mathematical models should be developed. The development of such standards and tools should become one of the priorities of science policy.

1. Information civilisation: megatrends and challenges

The global information infrastructure, the information society and the knowledge-based economy will be considered here jointly as the *information civilisation*, since their main

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aspect is information and knowledge becoming a dominant aspect of economic activities. More precisely, *information civilisation* is understood here to be the era of the development of the *information society* or –practically equivalent – of *knowledge economy* (because a common definition of both these concepts stresses the dependence of this society and economy on information and knowledge as the increasingly dominant production factor). Under the term *megatrends* we understand here important tendencies in social or technical development that can be observed and predicted for a longer time horizon.

It is important to note that there are reasons to forecast the length of the period of information civilisation for many future decades, perhaps for the entire twenty-first century. The megatrends discussed below will also last for several decades. The reasons for these long-lasting megatrends are as follows. Many new ideas and developments of contemporary science and technology are not being implemented as fast as would seem to be indicated by the rapid progress of science, and to be possible from a purely technological point of view. Delays in their implementation are a result of diverse social and economic factors. One example of this is the development of digital television. Its theoretical foundations were laid over 40 years ago – and its wide implementation has not yet been fully achieved. If technological reasons were the only decisive factor, then the time required to implement digital television could have been shortened to 20 years. Social and economic reasons were responsible for much longer implementation time. There are many other such examples. For these reasons, today we can forecast rather precisely – in qualitative terms – which megatrends will be decisive for the future development of information civilisation; the uncertainty stems from the scale and timing of full implementation as well as future technological details.

The selection of trends that should be recognised as most important and relevant depends on the evaluation of their economic, social, technological and intellectual impacts. From this perspective, three basic megatrends can be selected (see Wierzbicki, 1999) as being decisive for the development of the information society and as generators of many resultant trends of more specific character:

technological megatrend of integration or convergence,

social megatrend of changing and creating new professions,

intellectual megatrend of conceptual challenges.

The **megatrend of technological integration or convergence** concerns media, methods and systems of transmitting and processing information, but also the practical use of information. It starts with a general *digitalisation* of the methods and systems transmitting and processing information, but includes also the trends of:

a) *multimedia communication,*

b) *mobile telecommunication,*

c) *fast increase of transmission rates* in telecommunication networks,

d) *integration of new telematic services* into complex service systems,

e) *e-commerce, e-banking,* etc.

The last trend illustrates also *two facets* of this technological megatrend. While the megatrend is based on exploiting the technological advantages and possibilities of integration provided by the digitalisation of all information, it is also driven by market gains and by commercial applications. The same will concern the development of knowledge-based economy: while being enabled by technological integration, it will be driven by gains obtained from commercialisation of knowledge exchange.

Concerning the **megatrend of changing and creating new professions** we observe that the development of the information civilisation relies on a substitution of old professions by their newer versions or by entirely new professions. Old professions require much physical effort and are badly equipped with information technology tools; new professions require much knowledge and information and utilise increasingly more information technology tools. This implies an increasing *dematerialisation of work***.** There are many conclusions related this megatrend, such as:

a) The formation of new professions and the changes in educational systems necessary for bringing these new professions into effect are the most important of the social phenomena that limit the speed of development of the information society, the knowledge-based economy and civilisation.

b) New technologies always give opportunity to get rich - for those, who know how to use this opportunity. However, at the beginning of the era of information civilisation, this phenomenon is particularly significant: the megatrend of changing professions causes another trend, that of *increasing social stratification,* sometimes called *a new divide.*

c) The condition of the success of the information society is the *human innovativeness in inventing new professions,* that will provide employment for the majority, not only a small part of the population in the knowledge economy and will thus limit the impact of the new divide.

d) Many decades of increased demand for education can be predicted. This concerns education at all levels, but in particular university education and life-long continuing education. Together with other technological trends discussed above, this results in a *trend of multimedial life-long and continuing education.*

The **megatrend of intellectual challenges** might be even more important than the previous two: it is formed by the great challenges concerning the way of understanding the world, resulting from the spread of the information civilisation. The *mechanical way of understanding the world* - as a great machine, turning its wheels with the inevitability of celestial matter - *will be replaced by a new way, systemic and chaotic.* The world will be seen as a great but complex dynamic system, in which there are some laws, but chaotic behaviour, resulting from nonlinear dynamics with strong feedback is likely. A chaotic system is more similar to an avalanche or a tornado than to a big machine; anything can happen there, and small changes in initial conditions can essentially change its path. Everything which used to seem a natural and common sense phenomenon in the old way of understanding the world might be questioned in information civilisation. Thus, we might have many new and great conceptual, intellectual challenges.

This concerns quite basic concepts and problems: the way of understanding markets, economy, democracy, human rights, ethical problems, etc. We shall not discuss this megatrend in any more detail here. However, it should be noted that the subject of this paper – the issue of modelling for knowledge exchange - is strongly related to this third megatrend, though it also results clearly from the definition of the knowledge-based economy and is related to both megatrends discussed earlier. It should be also noted that it is the third megatrend that constitutes the greatest challenge to science policy: without seeing the new knowledge-based economy in new terms, we might miss the most important policy aspects.

2. Diverse concepts of information and knowledge

When discussing the future of knowledge-based economy, in order to respond to its intellectual challenges, we must better understand the meaning of the term *knowledge.* An encyclopaedic definition of knowledge usually stresses at least two aspects of this concept. One understanding of knowledge corresponds to the entire contents of an individual mind, resulting from experience and learning. Another understanding of knowledge stresses its objective and socially utilitarian character: knowledge denotes all information that results from confrontation with the real world, be it incorporated in theoretical reflection or be it not based on a theory, but just useful in applications. In this paper, we are not concerned with the individual, but with the social aspect of knowledge. However, both above definitions are very general, while in the time of the information society and knowledge-based economy we need a more technical definition of knowledge. Recall that the known technical definition of the quantity of information[4] contributed essentially to the understanding of this concept, even if various qualitative aspects of information, such as its security, quality, etc., are of more importance today. However, the concept of knowledge is more demanding that that of information, and we shall consider it from various perspectives: so-called *soft sciences* (humanities and social sciences) versus the so-called *hard sciences* (natural sciences and technology).

Both in soft and hard sciences, we often use the concept of a *model.* This concept is quite general. Besides its traditional social or professional interpretations, it might mean a small representation or a copy of some object, a pattern on which we base a new version of a system, etc. However, in professional, scientific language, the concept of a model denotes *a synthetic description of a part of reality, constructed for a given purpose.*

Following the *falsification* approach in the philosophy of science - see Popper (1983) - we can interpret any *scientific law* as a *model of reality,* valid only subject to falsification attempts (which failed to falsify this model). The Popperian approach to the philosophy of science is today considered strict and demanding, at the same time there are also even more relativistic approaches. For example, Feyerabend (1987) denies any fully objective character of knowledge. However, the most convincing seems the approach of evolutionary epistemology (see e.g. Lorentz, 1965, Wutetits, 1984): objective knowledge and its social transfer are useful for the evolution of humans. We can treat the principle of falsification by Popper as an useful tool for checking the objectivity of knowledge, needed in the evolution of human civilisations. We can summarise the above discussions thus: *models express knowledge while no knowledge is absolute.*

2.1. Concepts of knowledge in humanities and social sciences

Humanities, with their distinction of nomothetic and ideographic sciences, have a quite different concept of knowledge than the so-called hard sciences. There is actually a duality, an opposition of two different concepts of knowledge in humanities. One of them is still a model, although in a rather general, verbal form: *ideal type* (of M. Weber) or a *structure* (of G. Levi-Strauss). The opposite concept stresses not model formation, but *hermeneutic understanding* (with a long history of the development of the concepts of hermeneutics, Husserl, Gadamer, Heidegger). This is a very deep counter-position, a dichotomy of basic concepts: *knowledge as models versus knowledge as understanding.* With the emergence of

[4] Due to Shannon: the amount of information is equal to the binary length of its code.

knowledge science, on the verge of knowledge-based economy, we also need a deeper though rational explanation of this dichotomy.

The explanation of this may be obtained from the rational theory of intuition proposed by one of the authors (Wierzbicki, 1997). Without presenting this theory in full, we shall include here a short discussion of the role of subconscious thought, intuition and non-verbal processing by human mind.

We know today that processing images requires circa 10^4 times more processing capacity than processing words[5]. Humanswere already quite capable of dealing with their environment, before developing language, hence had quite well-developed capacity to process images and other signals in a holistic way; this was related to a subconscious use of multivalued, fuzzy logic, not to binary logic. The development of language started the accelerated evolution of human civilisation, the intergeneration transmission of knowledge. Binary logic was discovered together with language, in order to convince others about necessary actions (by arguments such as: *we must take this action, otherwise very bad things would happen*), but is not naturally related to the description of a real world. This development pushed the original, holistic processing of visual and other information further into the subconscious parts of our mind; we still have the capacity of such reasoning, but we call it *intuition.* From these premises, a rational theory of intuition can be developed, together with practical falsification tests of theoretical conclusions, see Wierzbicki (1997, 2000).

Thus, we need to extend the dichotomy between humanistic models (ideal types, structures) and humanistic understanding (hermeneutics, which can be viewed as intuition formation) to other forms of knowledge and other sciences. We need both the evaluation of various forms of models expressing knowledge and, in order to show the limits of knowledge, a rational theory of intuitive reasoning, if we aim at the development of *knowledge science.* Such a new discipline should not only help us to understand various forms of and limits to knowledge, but also result in a better integration of and transfer of results between diverse disciplines of knowledge and science.

The rational perspective of intuitive reasoning also helps to better understand another distinction between various forms of models expressing knowledge. Hard sciences and, in particular, engineering often use *mathematical models*. However, disciplines such as philosophy, humanities and social sciences – generally called soft (ideographic) sciences[6] - attempt to help in the understanding of an increasingly complex world in various ways. One way is by trying to reach a hermeneutic, intuitive understanding; another way is by using various general types of models - ideal types, structures, other verbal models of difficult issues.

Note that even a verbal discussion of such issues, organised in a structured way, is in fact a model that tries to provide a certain perspective and to increase understanding. The megatrends of the information society, discussed earlier in this paper, provide an example of such a model. We might call such verbal models *humanistic models,* as opposed to mathematical models.

Soft sciences have in the past attempted – sometimes redundantly - to increase the scientific validity of their statements by trying to incorporate mathematical models from hard sciences. Humanistic models however, rely in fact on hermeneutic understanding, at a very high degree

[5] Transmitting images requires 10^2 times more transmitting capacity than transmitting words; processing times grow usually at least with the square of the amount of data.

[6] In a positive sense, as illustrated by the following principle that was formulated by H. Barnett (in a discussion at IIASA, 1980): *Hard models – soft thinking, soft models – hard thinking.*

of synthesis. From the rational theory of intuition it follows that such degree of synthesis is usually attained by intuitive, holistic perception. Choosing words to formulate such models is difficult, because all words have multiple meanings; on the other hand, it is doubtful whether any attempt to make these models " harder" by trying to express them in a mathematical form is constructive or useful.

An example of such difficulties is the issue of interpreting the statistical models of data preferred today by social sciences. These sciences, such as economics, business management, quality management etc., tend to be fascinated by the possibilities of computer data processing and by deriving statistical models from these data – with no deeper knowledge of the methodology of forecasting which stresses the dangers of interpreting such models. A statistical model is not a causal model, which specifies causes and effects. For development of such a model we need deeper, fundamental knowledge, external to the statistical data. The best illustration of this issue is the strong statistical relation between magnetic storms on Earth and solar spots. Based only on statistical data, one could advance a theory that magnetic storms perturb our vision and thus we see spots on the Sun. Such a theory is false, but consistent with the data. In order to correctly specify that solar spots cause magnetic storms, we need the theory of elementary particles emitted by solar eruptions and their impact on the magnetic field of Earth – a deeper theory, external to the data.
This example also illustrates the conclusion that it is important to develop *knowledge science* but it must include *methodology of model formation and interpretation.*

2.2. Concepts of knowledge in hard sciences

Hard sciences have their own forms of knowledge: though all use mathematical models, they are by no means united about the definition of knowledge. We start thus from a specific discipline in information sciences, called *knowledge engineering.* From the perspective of knowledge engineering*,* knowledge is defined as a *pattern that can be discerned in data.* While this definition is very useful for *data mining* and *knowledge discovery* in large data sets, it is possibly too narrow for broader applications in the knowledge economy. Although knowledge engineering specialists tend to include *models* as a specific forms of *patterns,* the interpretation of this relation in other specialities – including computerised decision support - is just the opposite: *patterns* are considered a specific form of *models.*
We shall follow the second interpretation, since the concept of a *model* is quite general. Besides its traditional social or professional interpretations, it can mean a small representation or a copy of some object, a pattern on which we base a new version of a system, etc. We have already mentioned that in professional scientific language, the concept of a model denotes *a synthetic description of a part of reality, constructed for a given purpose.* The purposes of constructing a model can be diverse, but very often – e.g. in model-based decision support – relate to expressing knowledge about a given situation. The forms of models can be also diverse, starting with a general, verbal form and proceeding to more specific forms of mathematical models.

In a sense, mathematical models today represent the most basic form of expressing and exchanging knowledge in hard sciences, technological knowledge in particular. This is because mathematical models can be easily computerised. We shall discuss this and related concepts in more detail.

3. The importance and typical forms of mathematical models expressing knowledge

A critical element of many scientific investigations – also including such activities as model based decision support - is a mathematical model representing data and relations that are too complex to be adequately analysed based solely on experience and/or intuition of a researcher or a decision maker. Models, when properly developed and maintained, can represent not only a part of the knowledge of a researcher or a decision maker, but also integrate other available relevant knowledge from various disciplines and sources. Moreover, models, if properly analysed, can help their users to extend their knowledge and intuition. Therefore, the quality of the whole cycle of preparing, maintaining and analysing models also determines to a large extent the quality of research conclusions or of a practical decision-making process for any complex decision problem.

There are new developments in modelling methodology and tools that are worth discussing in the context of knowledge integration. In addition to the continuously growing opportunities resulting from the progress in database management and in the foundations of modelling, there are many new opportunities. They have emerged for example, from recent developments in methodologies for and experiences from, model-based decision support systems – see e.g. Wierzbicki et al. (2000) - or from the network-based platform-independent software technologies. New opportunities are also offered by new developments in the applications of World Wide Web for management, policy makers, research and education. Not all such opportunities are yet being efficiently exploited.

There is a need to use all these opportunities to improve the low productivity of model-based work by unifying various representations of a model, facilitating the standardised interfaces to diverse solvers that support different paradigms of model analysis. It is also necessary to improve the knowledge sharing possibilities represented by various models that can be analysed on heterogeneous hardware available in distant locations.

To look at improving such possibilities, we shall first discuss typical forms of mathematical models. They can be divided into *binary models* (based mostly on binary logical relations, e.g. such as patterns discovered in data) and *analytical models,* although this distinction is not always sharp (each model includes logical relations and might include binary ones). However, this general distinction is related in a sense to the basic megatrend of technical integration in information civilisation. This basic trend is based on digitalisation of all forms of information; thus, it is not strange to think that the forms of models expressing computerised knowledge will also be closely related to the most basic, binary form of presenting information.

3.1. The importance and limitations of binary models

There are many examples of this trend to replace all other types of information processing by purely binary processing. Genetic algorithms of optimisation represent one such example; another is the powerful trend towards finding patterns of knowledge in very large data sets. Thus, there is no doubt that *binary forms of computerised models encoding knowledge,* in a sense natural for implementation on digital computers, will become increasingly important in the future. For a computer scientist, who tends to see the world as a giant computer, these forms are the most natural models.

This does not mean, however, that this form of model will become a universal or even a dominant standard, because for all their uniformity, binary models have some essential drawbacks. These include:

Binary models are in a sense too sharp for representing the real world; multivalued, fuzzy logic expressions and so-called *soft computations* are much more adequate, but already this means a departure from binary models towards analytical models. For more detail on the developments and applications of fuzzy logic see e.g. Zadeh (1978), Zimmermann (1987).

Each discipline of science uses its own characteristic collection of analytical models, which serve as a kind of global language for specialists in this discipline; it would be disadvantageous to the development of science to replace such “languages” by a universal, binary model form. We should recall here several examples. One of the disciplines that has contributed most significantly to the understanding and classification of analytical models is *control science.* It described ways of controlling diverse dynamic processes, which lead to the development of most of modern technology such as automated manufacturing, robotics etc. But control science also relied on earlier developments of various concepts and models developed in other disciplines, such as the concept of *feedback* coming originally from telecommunications, or models describing dynamic processes coming originally from mechanics. Control science included binary models in the form of the *theory of finite automata,* but is much broader and richer than this theory.

The processing of binary models requires usually computing resources that grow faster than polynomially (e.g. exponentially) with the dimensions of these models. This is also true of many analytical models. Classical computer scientists usually argue that the processing power of modern computers is growing fast enough not to be troubled by the non-polynomial computation complexity. However, this argument does not take into account the fact that true specialists in complex computations can always find ways to saturate even the most powerful computers. In fact, the advantage of analytical over binary models is the possibility of finding special algorithms – admittedly, usually only approximate and only for limited and specific classes of analytical models – that can process these models much faster than in the universal case (that is always doomed to non-polynomial complexity).

Finally, we should note that human mind works quite differently than do modern computers and binary models are a very poor approximation of its operation. A better approximation of the human mind are the artificial neural networks, but they are not yet adequate; we can only say that the processing of information in the human mind is certainly parallel and distributed, and certainly more complicated than contemporary artificial neural networks. This argument is also related to the rational definition of intuition discussed earlier in this paper.

3.2. The role and challenges of analytical mathematical modelling

Analytical *mathematical modelling* started as a generalisation of modelling techniques from several disciplines. Models of *operations research* were augmented with a broader methodological reflection of *control science* as well as other disciplines, especially *systems analysis.* Today, the classification of model types in mathematical modelling are well known: *continuous versus discrete, linear versus nonlinear, deterministic versus stochastic, static versus dynamic, open loop versus feedback, single-objective or scalar optimisation versus multi-objective or vector one,* as well as diverse techniques of dealing with all these model types. This powerful body of knowledge can be developed further as one of basic elements of knowledge science, provided we are able to respond to several challenges – all related to the development of the information civilisation and knowledge-based economy. Especially important are the two facets of the megatrend of integration: we need more integration of models used in diverse disciplines and we need clearer principles of using commercially knowledge encoded in models. We shall discuss the first facet here and the second in a further section.

Several challenges can be listed as being related to the facet of integration. The first is the need to integrate, in particular, the results from two disciplines almost separate until now: *knowledge engineering* and *mathematical modelling.* This is related to the former discussion of the binary and analytical forms of models.

The second is to integrate various methodological approaches to the analysis of diverse types of mathematical models used in various scientific disciplines. We recall that mathematical modelling typically uses *model simulation, scenario and sensitivity analysis, single-objective optimisation,* and sometimes *multi-objective optimisation and analysis.* These approaches might be complemented, however, by *multi-objective inverse simulation and scenario analysis,* see e.g. Wierzbicki et al. (2000). However, all these methodological approaches are not widely known by specialists in the various scientific disciplines. While we will discuss these issues in more detail in the next subsection, the related challenge should be noted here : to make the approaches of mathematical modelling and systems analysis known and usable for diverse scientific disciplines.

The third challenge relates to the fact that computerised mathematical models have diverse standards not only between the various scientific disciplines, but also within each discipline. This makes knowledge exchange cumbersome and difficult and it also impedes the comparison of models devoted to the same subject.[7] There initiatives in existence aimed at responding to this challenge, including the idea of *structured modelling language,* see Geoffrion (1989) and further discussions of modelling tools in Wierzbicki et al. (2000). However, it is not only standards of modelling languages that should be further developed, but also the methods and tools related to model analysis should be integrated into such languages. Thus, much more work is yet to be done before this challenge can be adequately met.

Other challenges relate to that facet of commercialisation of knowledge which requires a better understanding and also the development of clear guidelines for utilising model-encoded knowledge in several domains. However, as it is not limited to analytical mathematical modelling we will discuss it in a further section together with science policy issues.

3.3. An example: computerised decision support systems

Some necessary developments can be best described using the example of model-based computerised decision support systems. Any decision maker, before making final selection of a decision, wants to understand the consequences of his/her possible decisions in a best possible way. Particularly, in more complex situations, decision makers typically need help in finding decisions that best correspond to their preferences. These preferences cannot be precisely defined in advance, because they often change while a decision maker is learning about the decision problem. Experiences show that such learning is an important element in the development and use of a decision support system for any complex problem, such that the intuition and expertise of the decision maker are not enough for predicting the consequences of various decisions. However, decision makers typically also want to examine the consequences of the decisions that they define, often by using their own intuition and/or experience to modify decisions obtained from analysis or suggested by somebody else.

A modern decision maker is confronted with more complex decision problems than were previous generations, but also has a much better knowledge of decision making processes and

[7] An example relates to models of climate, particularly global ones: due to the lack of compatibility of modelling standards, it is extremely difficult to compare the assumptions and conclusions of various studies of global climate.

access to analytical tools and teams of experts and advisors. Therefore, such a decision maker is not keen to accept the classical ways of decision support which relied on using, as a basis for a decision, a given solution of a mathematical model that is assumed to represent a well structured problem. A modern decision maker needs a decision support system that can be used for various types of analysis, and that can help to extend the decision maker's knowledge about the problem on the one hand, and allow them to use their experience and intuition on the other hand. In order to achieve this, a good decision support system should be composed of two mutually linked parts of a quite different nature:

> A **mathematical model** that represents the part of a decision problem for which logical and physical relations exist and have to be handled in model form rather than by the intuition and experience of the decision maker. We shall call this model a *core model* or *substantive model*.
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> **Tools for a comprehensive analysis** of the core model. Up to now we have concentrated more on the diverse types of models; here we shall add some comments on the *tools for model analysis.*

Mathematical and computer models are widely used in many areas of science and industry for predicting the behaviour of a system under particular circumstances, when it is undesirable or impossible to experiment with the system itself. The understanding of the system gained through a comprehensive examination of its model can greatly help in finding *decisions* (in managerial terms; in technical terms they might be called *controls*) whose implementations will result is a desired behaviour of the system. The systems that are modelled have diverse characteristics - including the nature of the underlying physical and economic processes, their complexity, size, types of relations between variables etc. There is also a great diversity in the use of models that depends on various factors – such as the nature of the decision making process, the background and experience of users of the models, etc. However, the process of formulating and analysing a model, abbreviated to *the modelling process*, have many similarities even if the systems being modelled are quite different. This type of modelling process is typically composed of problem formulation, model specification, implementation, verification and validation, analysis and management. The modelling process is a combination of craft, art and knowledge, and its quality is critical to any results achieved.

There are two classical approaches to model analysis: *descriptive* (also called *predictive*) and *prescriptive* (or *normative*). Descriptive modelling is used for predicting the behaviour of the modelled system without attempting to influence it. Prescriptive modelling is aimed at providing information about decisions (or controls) that can result in a desired behaviour of the modelled system. In other words, descriptive modelling helps to answer the question *"what will happen if ...",* whereas prescriptive modelling provides answers to the question *"what decisions are best for achieving specified goals".*

For the prescriptive model analysis, typical tools are *optimisation techniques.* They consist of selecting the decision or solution (from the set of admissible decisions or solutions) that is considered the best in a specified sense. Usually, this sense denotes a solution that results in the best (minimal or maximal) value of a performance index - goal function, objective function, utility or value function, etc. The classical approach assumed that the mathematical model, including the performance index, describes the reality well, including the preferences of the decision maker; thus, it would suffice to optimise the performance index in the model and the best decision would result. Modern approaches question such assumptions at least partially: even if a model describes the reality reasonably well, it usually describes the human preferences rather inadequately; hence the advice not to model preferences and to limit the core or substantive model to knowledge that is as objective as possible. Even so, optimisation might be used for model analysis, but not as the goal of the exercise, only as a technical tool; for example, by using optimisation techniques we might check whether a set of desired outcome values in the model is attainable by admissible decisions, or not.

Descriptive methods of model analysis are useful when *verifying* a model. Not only should a good model represent objective knowledge in a possibly best way while conforming to formal specifications, but also all possible discrepancies between the results of its analysis and the intuitive judgement of model user (a decision maker, an analyst, etc.) should be resolved. Such inconsistencies show that either the intuitive judgement, or a part of model specification (assumptions, data, parameters) is wrong and must be modified. Without such verification, the user will not trust the model, hence the model cannot be used for decision support.

Typical tools for descriptive model analysis are *simulation techniques.* Decisions (or controls) are then defined either correspondingly to typical data, or varied randomly, or specified by intuitive judgement of model user; various outcomes defined by the model are computed and presented to the user as results of the simulation. In fact, more advanced simulation techniques mix simulation with optimisation; for example, so-called *inverse simulation* consists of specifying desired outcomes and using optimisation in order to find corresponding decisions or controls.

The usage of simulation and optimisation could be ideally compared as follows:

> In simulation, decision variables are inputs and goals are outcomes. This technique is good for exploring the intuition of a decision maker, not only for model verification but also for examining the consequences of applying certain decisions in terms of goals and constraints. Simulation can be considered as an option-focused method of analysis that aims at examining alternatives defined by a decision maker.
>
> Optimisation can be considered as a value-focused (or goal-oriented) approach that aims at creating options. Optimisation is driven by the hope of reaching a set of goals (while the basic goal is to optimise the value of a given performance index). Therefore, goals are a driving force and the values of decision variables are outcomes. This is very appealing, but has certain disadvantages. First, not all real objectives are usually included into the goals formulated for the optimisation. Second, an optimal solution is selected between members of the set of admissible solutions. If a decision maker prefers to change this set, a new optimisation problem must be considered.

Therefore, an interchangeable use of both simulation and optimisation techniques has obvious advantages, but a joint implementation of both techniques in classical models is difficult. This has resulted in development of *multiobjective model analysis* methods and *vector optimisation* tools that combine advantages of these two classical approaches.

Advances in methods and tools for specification and analysis of analytical models have allowed for implementations of such models in various policy making problems for which traditional crisp optimisation and/or simulation modelling tools do not offer enough support. Modern model based decision support explores a cluster of enhanced traditional methods combined with multicriteria model analysis. This provides advantages in examining trade-offs between various conflicting criteria and helps to identify attainable goals and decisions which lead to achieving such goals. Various techniques can be used for multicriteria model analysis; best developed are *reference point approaches* that can be considered as a generalisation and enhancement of known *goal programming* techniques. Reference point approaches (see

Wierzbicki et al., 2000) include techniques for *soft and inverse simulation* as well as examining *soft constraints*.

Decision support systems based on reference point approaches are usually built from a modular collection of software tools, to which belong:

Model generation tools. Generation of a core model or a substantive model (which is a representation of all logical and physical relations between variables representing the decision problem being examined, without including models of the preferential structure of a decision maker) requires special tools. Various *modelling environments, modelling languages, problem specific model generators,* etc., can be used for this purpose.

Model analysis tools. As discussed above, model analysis can have various tasks and tools: simulation, optimisation, vector optimisation, soft and inverse simulation, examination of soft constraints, etc.

Computation tools: Model analysis often requires solving a series of auxiliary optimisation or simulation problems; this in turn requires robust and efficient solvers that can handle the related computational tasks in a robust way that is transparent to the user.

The diversity of such modelling tools and types of model raises the issue of *model standardisation.* Many research institutions develop analytical models that are of broader interest. However, there are no standards for a model specification and analysis. Therefore, not only is much work required for the development of models but also the analysis of a model is often restricted to a limited number of approaches for which tools appropriate for the particular model class are available.

To understand why a standardisation is a possibility, we have to recall the evolution of database management theory and technology. The data management revolution occurred in response to severe problems with data reusability associated with file-processing approaches to application development. The need to share data resources resulted in the development of data base management systems that separate data from the applications that use data. Following this historical example, model management systems can be developed. Models could not only be developed in a much more efficient way but they could also be used in a more efficient way, if standards for model specification and analysis were agreed upon. We observe thus that model management is at about the same stage of evolution as data management was during its transition from file processing to database processing. It should also be noted that data management has recently been subject to a fundamental change, related to the data warehouse concepts. The ability to capture data from multiple operational source databases, to date data consistently, to retrieve it efficiently across many different dimensions has always been a key issue for timely delivery of useful information needed for actual decision making; data warehouses respond to such needs.

The comparison of data bases and analytical models clearly illustrates the challenge: what moved database technology forward - voluntary de facto standardisation around a rigorous, principled representation formalism of great generality - is what we need to move model management forward. Standardised interfaces for model analysis would in turn, allow much broader access of both institutions and individuals to a vast amount of information and knowledge that is currently available mainly for researchers and experts. Non-specialists will not learn detailed ways of analysing diverse model types, but many may be willing to learn user-friendly ways of analysis of various models that can be made publicly available. Then a broad access to knowledge encoded in models can greatly contribute to the education of societies and can help in public discussions of various issues, such as social security reforms, population ageing, climate change, air quality, etc. Finally, standardisation of models is necessary for integration of models from diverse disciplines, thus for advancement of trans-disciplinary and interdisciplinary knowledge.

4. Science policy issues

All of the above discussions have some implications for science policy. We list only some of these:

1. Essential for a good formulation of science policy on the verge of knowledge-based economy, particularly in terms of the megatrend of intellectual challenges, is a deeper understanding of the concept of knowledge, in several aspects such as:

   We need further analysis and comparison of diverse concepts and definitions of knowledge, their interdisciplinary interdependence, to formulate science policy for stimulating interdisciplinary research that will become increasingly important in knowledge-based economy.

   In particular, we need stimulation of development of new economic models of production and new economic theory of knowledge-based economy.

2. Essential for issue for science policy in knowledge-based economy is a good balance of knowledge utilisation in various domains:

   Private domain concerns issues of intellectual property rights for model-encoded knowledge as well as the development of new protection mechanisms (since it is difficult to imagine patenting model-encoded knowledge).

   Commercial domain concerns issues of marketing and commerce in model-encoded knowledge.

   It should be stressed, however, that for all the development of commercialisation of knowledge, much of it would certainly remain in *public domain***.** Free access to at least some parts of knowledge is advantageous for the evolution of human civilisation and many scientists will insist on making public some of their results. But the issues of knowledge in public domain are by no means simple. The distinction between the private, commercial and public domains is a deeply ethical question. The discussion of this question will remain one of main intellectual challenges related to the third megatrend of intellectual challenges.

3. Societies and countries that support a faster development of knowledge-based economy will have a better position in the information civilisation. Thus, science policy should specifically support those areas of research that might contribute most significantly to the development of knowledge-based economy. We shall mention here some of such areas:

   Knowledge science as a transdisciplinary synthesis of diverse approaches to knowledge formation, based not only on knowledge engineering, but including also on other forms of model-encoded knowledge such as in mathematical modelling, as well as basic philosophic reflection on the concepts of knowledge. An essential issue in knowledge science is the dichotomy between *knowledge as models versus knowledge as hermeneutic or intuitive understanding;* this issue should be studied further in order to deepen the foundations of knowledge science.

   Since knowledge is becoming increasingly more commercialised, another essential issue in science policy is the support for the development of *standards of knowledge encoding,* including modelling languages integrated with methods and tools related to the analysis of models of diverse types encountered in various scientific disciplines.

5. Conclusions

There are many conclusions that might be drawn from this quite general discussion of the concepts of megatrends of information civilisation and the role of modelling for knowledge exchange; only some of them are stressed here:

A new understanding of the coming civilisation era is extremely important for science policy; such an understanding might be helped by the megatrends of information civilisation, discussed above as a simple model of this coming era.

Science policy should include a better balance of knowledge utilisation in various domains: private, commercial and public.

Science policy should also support the development of better tools for knowledge exchange, including such as standards of knowledge encoding and modelling languages.

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