A Foresight Support System to Manage Knowledge on Information Society Evolution

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Abstract. In this paper we present an intelligent knowledge fusion and decision support system tailored to manage the information on future social and technological trends. It focuses on gathering and managing the rules that govern the evolution of selected information society technologies (IST) and their applications. The main idea of information gathering and processing here presented refers to so-called on- line expert Delphi, where an expert community works on the same research problems by responding to structured questionnaires, elaborating complex dynamical system models, providing recommendations, and verifying the models so arisen. The knowledge base is structured in layers that correspond to the selected kinds of information on the technology and social evolution, uses, markets, and management. An analytical engine uses labeled hypermultigraphs to process the mutual impacts of objects from each layer to elicit the technological evolution rules and calculate future trends and scenarios. The processing rules are represented within discrete-time and discrete-event control models. Multicriteria decision support procedures make possible to aggregate individual expert recommendations. The resulting foresight support system can process uncertain information using a fuzzy-random-variable-based model, while a coupled reputation management system can verify collective experts' judgments and assign trust vectors to experts and other sources of information.

Keywords: Foresight Support Systems, Complex Socioeconomic Models, Group Model Building, Knowledge Fusion, Intelligent Decision Support.

1 Introduction

The evolution of modern societies cannot be sufficiently explained without a penetrative study of its technological research, economic, political, and social context. A universe of objects, events and dynamical phenomena, and relations between them, has to be taken into account to carry out such a study. These form a complex system [1], [4], [6], [10], [18], [19], usually referred to as the Information Society (IS). Therefore, research on IS modelling methodology can provide clues to building foresight scenarios, eliciting social and technological trends, and planning of future development of information technologies (IT) and their application areas.

K. Aberer et al. (Eds.): SocInfo 2012, LNCS 7710, pp. 246–259, 2012.

A collection of new IS/IT modelling approaches has been elaborated as part of the 'Foresight of the Information Society in the European Research Area' (FISTERA) project [11] financed by the EU within the 5th Framework Programme and applied successfully to model the cohesion processes in the EU New Member States. Some of these methods, in particular the 8-element IS model [11] and the interdependence of trends, events and scenarios constitute the background to define the knowledge base and information processing requirements of the Foresight Support System presented in this paper. Compared to earlier work on IS/IT models [1],[4],[6],[18] the research results presented in [11] have shown that it is possible to model the essential trends and phenomena of an IS as a discrete-continuous event system. However, building a holistic information system that would require large data sets and massive computation was beyond the research goals of earlier EU-funded projects focusing on qualitative analysis of IS phenomena, such as FISTERA. Creating a comprehensive computational model has been therefore left as an open challenge, cf. e.g. [9].

Having studied the findings of the above-mentioned research on IS/IT modelling, it becomes apparent that in order to follow the continuous emergence of essential new IT and consumer usage scenarios, it is necessary to analyze very large data sets that link different aspects of the IS/ITs evolution in one future-oriented model. A straightforward conclusion, relevant to the scope and results of this paper, is that any individual product or technology is embedded in a complex technological, economic and social system in such a way that its evolution cannot be explained without investigating this system in a holistic way. The latter task can be accomplished by establishing an appropriate knowledge base, capable of acquiring, storing and processing information from heterogeneous sources and characterized by different types of uncertainty. Furthermore, the results of the above projects have shown that the sole use of both classical econometric methods and narrative descriptions have proved to be insufficient for achieving adequate IT forecasts or scenarios. Therefore, it has been necessary to elaborate new computational methods based on discrete-event and time-series driven models, and novel decision support methodology to derive foresight-specific rankings and recommendations.

In this paper we provide a report on the design, implementation and use of such an innovative information system equipped with an ontological knowledge base and endowed with analytical data processing mechanisms. It serves as the main component of an IT foresight-oriented decision support system, which will be termed also *foresight support system* (FSS) [20],[14], [2] to emphasize its specificity. The design and implementation of this kind of information system is based on a prior extraction, formulation and analysis of the general rules and principles that govern the evolution of key technologies [14]. In the implementation of the FSS here presented, a special attention is paid to models used in the selected areas of information technology under review [9], in the full context of the information society and digital economy. However, the ideas applied to design the FSS described in this paper explore the general principles of organizing foresight research (cf. e.g. [2],[9],[11]) so that they are applicable to support prospective technological studies in other areas. The studies of different kinds of interactions within an IS led to the joint application of discrete-event systems, multicriteria analysis, and discrete-time control.

To provide decision support to industrial enterprises, research institutions and governing bodies concerning IT-related R&D management and investment strategies, as well as the definition of legal regulations, a research project has recently been carried out in Poland [9]. Its results are to be constructively applied to developing technological policies and strategies at different levels, from corporate to international. A number of partial goals have been defined, which might help to achieve the ultimate objective described above, as well as being independent research aims in their own right. These include:

- Implementation of an ontological knowledge base which stores heterogeneous data together with suitable technological models, trends and scenarios in the form of so-called proceedings (records of operations) containing data together with records of their step-by-step analyses, results and assessments.
- Elaborating or adjusting methods of multicriteria rankings suitable for IT management and capable of generating constructive recommendations for decision makers as regards the prioritization of IT investments.
- An in-depth analysis of several real-life industrial applications of the decision support system so arisen. The selected technological areas are submitted by industrial partners cooperating on the implementation of the project results.
- A detailed analysis of technological trends and scenarios in areas such as 3D-based e-commerce, expert systems, decision-support systems, recommenders, m-health, neurocognitive technologies, quantum and molecular computing.

Any of the above partial objectives should provide useful solutions to the technology management problems presented by the industrial stakeholders involved in the exercise. This would allow them to apply the knowledge gained to set strategic technological priorities and formulate IT and R&D investment strategies. This is discussed further in Sec.4.

Although the general applicability field of the models studied in [9] is generating trends and foresight scenarios, they can also be used to better understand the role of global Information Society Technology (IST) development trends and to elaborate IS and IT policies in an optimal control framework.

To sum up, the data processing methods presented here as a background to elicit trends and elaborate scenarios of decision-support and decision-making systems can be applied as a universal framework in any future-oriented socio-economic or socio-technological study. As an example of application that has been elaborated within the foresight project [9], we will present recommendations concerning the development of some types of decision support systems.

2 The Principles of the Information Society Modeling

A user of a technological knowledge base could pose the following question: how does the development of selected information technology depend on global IT development, diffusion processes and on the integration of the IS around the world, driven by global socio-economic trends? We will investigate this question in more detail in the next sections. As regards the global environment, various factors should be considered such as falling telecommunication prices, growth of the information exchange through the internet, rapid diffusion of information on innovations and technologies, the development of e-commerce, and free access to web information sources. The civil society evolution, driven by the growing availability of e-government services and related web content, has been taken into consideration as well. Finally, the psychological and social evolution of IT users, including all positive and negative i-inclusion phenomena, has to be taken into account as a set of feedback factors influencing the legal and political environment of the IS.

Due to the complex nature of decision technologies that rely heavily on cognitive and social phenomena, it is difficult to create a technology evolution model that is clear, unambiguous and concise. One of the aforementioned earlier findings [11] was that the composite indicators merging data from users with statistical information can rarely provide an adequate description of the technology parameter dynamics. Therefore, when performing the research described in this paper, it was decided that the use of aggregates as the basis of forecasts and recommendations should be restricted to the final visualization of the information retrieved. Instead, during the quantitative analysis phase we have used the basic social, economic and technological data embedded in a new class of input-output models that fit well into the specificity of this kind of technology. For instance, we can separately analyze different groups of potential users characterized by different preferences. Even though their full statistical characteristics are missing, we can explain the development of the market of complementary products that are distinguished by features corresponding to the consumers' preferences. The actual parameters of the groups such as their size, spatial distribution etc. can be estimated *ex-post* based on market data.

In [11] we have defined eight major subsystems of an IS, such as its population, demographics, legislation, IS policies, IT infrastructure, R&D etc. (cf. Fig.1). It has been applied to model the IS evolution in the EU New Member States.

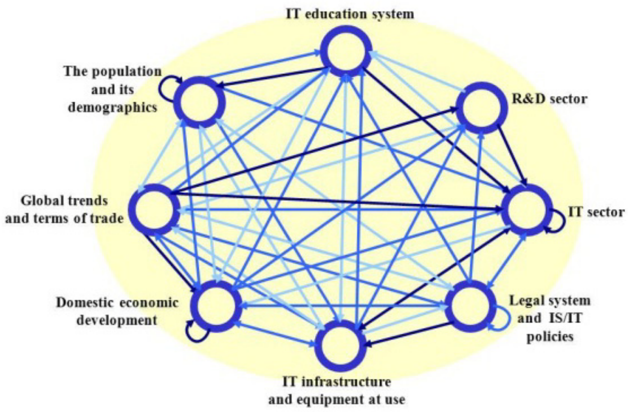

Fig. 1. An example of a causal graph linking the major groups of data used in the IS/IT model

The causal graph presented in Fig.1 contains direct impacts only, i.e. those which show within one modelling step. Indirect impacts may be obtained by multiplying by itself the coincidence matrix associated with the direct impact graph. Dark blue edges denote strong direct dependence, medium blue indicates average relevance of causal dependence, and light blue denotes weak dependence between subsystems. The feed-back directions are not marked as they may vary for different subsystems' variables.

The above assumptions allow us to define the scope of data to be gathered and processed, and they give hints as regards procedures and models to apply. The characteristics of the information stored in the knowledge base are given in Tab.1.

Table 1. The IS model characteristics stored in the knowledge base

No.	Data description	Data type	Data sources	Typical size of a data set
1.	Time series describing quantitative variables in the IS model (macroeconomics, demographics etc.)	monthly to yearly quotes	Eurostat, national statistics	80 to 100 x (20 to 200)
2.	Auxiliary financial time series (stock prices of IT companies, specialized equity indices, exchange rates, IT-related commodity prices etc.)	from tick-by-tick to daily quotes	financial information providers	from 10^4x20 to 10^5x500
3.	Metadata as an ontology: system description, definitions of subsystems, variables, descriptions of event classes, assignment of variables and events to subsystems, relations between them	OWL code, text, graphics, graph incidence matrices	Experts and analysts involved in modelling	Can vary strongly, e.g. about 10 MB in the example in Sec.4
4.	Qualitative and quantitative characteristics of past events with the corresponding states of the system, links to data sources	records with heterogeneous information	event streams, news agencies, experts	100 to 10^5 events, 10kB per record
5.	Qualitative assessments and quantitative characteristics of relations between IS subsystems and between system variables	structured expressions	expert Delphi, statistical calculations	~(10^4 +64) x (no. of experts) assessments
6.	Annotated source files (bibliographic, patent, personal, research projects, research institutions, IT companies etc. databases)	texts, spreadsheets, files with heterogeneous data	automatic updates, manual data input and annotation	from 10GB to 1 TB

During analysis of an IS, each of its subsystems shown in Fig.1. appears as a bundle of discrete events, continuous trends and continuous or discretized state variables. For instance, in the initial model of the Polish IS used in [9] there are 92 variables in total, while the number of variables describing subsystems ranged from 7 for the ICT sector to 17 for the R&D sector. The final set of quantitative characteristics has been selected from a total of 337 variables considered, based on an iterated two-stage procedure: an expert Delphi and calculating statistical relevance of causal relations with standard tests. This approach is justified by the insufficient length of time series (cf. Tab. 1) to rely solely on statistical methods and by the need to verify expert judgments with statistical tests even when their relevance was not perfect.

The dynamics of the system can be derived from past observations forming vector time series. It can be described [15] by the following discrete-time dynamical system

$$x_{t+1}=f(x_t,\ldots x_{t-k},u_1,\ldots,u_m,\eta_1,\ldots,\eta_n), \quad (1)$$

where
$x_t,\ldots,x_{t-k}$, are state variables, $x_j:=(x_{j1},\ldots x_{jN})\in IR^N$,
$u_1,\ldots,u_m$ are controls, $u_i \in [u_{i-}, u_{i+}]$, *for* $i=1,\ldots,m$, and
$\eta_1,\ldots,\eta_n$ are external non-controllable or random variables,
f is linear non-stationary with respect to x, and stationary with respect to u and η.

The coefficients of f can be identified using least-squares or maximum likelihood methods on each subinterval of the modelling period where they were stationary. To cope with the non-stationarity in (1) that usually manifests in abrupt changes of parameters caused by internal (legal system, R&D) or external events, the evolution model was supplemented by a discrete-event system P [7], [10] that represents the dynamics of discontinuous variables, namely

$$P=(Q,V,\delta,Q(0),Q_f) \tag{2}$$

The notation used in (2) is explained in the following Tab.2.

Table 2. The data characterizing the discrete-event component of the IS model

No.	Symbol in eq.(2)	Data description	Data sources	Typical size of a data set
	Q	The set of all feasible states of event-driven model components, stored as labeled narrative descriptions combined with Boolean or fuzzy logic vectors that model the occurrence of predefined state properties	expert analysis of appropriate IS components	10 to 100 per component
	$Q(0)$	The set of initial states of event-driven model components, used together with causal links as a base to derive transformation rules for P	legislation, R&D state-of-the-art	10-20 (=no. of discrete-valued components)
	Q_f	The set of reference (or final) states of event-driven model components corresponding to alerts or to reporting the modelling results	experts involved in modelling	~10 MB (including descriptions
	V	The set of admissible operations over the states of discrete system components, derived from rules governing legislation, principles of generating R&D results and innovations	legislation, expert analysis of R&D	10 to 100 operations per each component
	δ	$\delta : V\times Q \rightarrow Q$ – the transition function governing the results of operations over states, stored in form of rules	expert Delphi, rules inferred from cases	100-1000 rules

Events in P are defined as pairs of states $e:=(q_1,q_2)$, such that $q_2=\delta(v,q_1)$. Following the above assumptions concerning the controlled discrete-event variables, the operations from V may be either controls, i.e. the decision-maker's actions over Q, or may occur spontaneously as the results of random processes. Furthermore, we assume that there exists a set $X(Q)$ of quantitative or ordinal characteristics of states, which can be deterministic, interval, stochastic, fuzzy etc. Although (2) is in principle asynchronous, one of the coordinates of $X(Q)$ can be identified with time to couple (2) with (1).

The evolution of the IS can then be modelled as a discrete-time/discrete-event system, where the mutual impacts of each of its elements are represented either in symbolic form, as causal diagrams, or within state-space models. Some external controls, such as legal regulations and policies, are modelled as discrete-event controls, while the others, such as tax parameters or the central bank's interest rates are included as discrete-time control variables in (1). The exogenous non-controlled variables include exchange rates, energy prices, demographic structure, attitudes towards IT-related learning and so on. Both serve as inputs to the system (1)-(2), while basic social, technological, and economic characteristics are state variables in (1) linked by feedback loops. The parameters of (1) are functions of the states of (2), changing their values when the output $X(Q)$ from (2) is modified by an event. After performing a simulation of external and random variables, and assuming a sequence of controls, output trends can be calculated, allowing us to model the influence of consumer and industrial demand on the IT development, research, production and supply of selected IT or IT-dependent products, as well as on GDP growth rates. Scenarios appear as the results of grouping trends and sequences of events, for different variants of decision variables, random events, and external drivers.

3 The Architecture of the Foresight Support System

The above-presented expert system can serve as a framework to organize the overall information processing during future-oriented research, such as socio-technological foresight. Its main component is the ontological knowledge base fed by collective expert judgments, autonomous webcrawlers and updates by users. The information is verified, then processed by analytical engines. The knowledge base includes ontology management functionality, specifically ontology merging and splitting, evolution registering, operations on metadata and metadata updating protocols as well as the usual data warehousing functionalities such as automatic verification and updating.

The main functionality of the above knowledge-based system, together with its analytical capabilities and automatic or supervised knowledge acquisition, update and verification, is to respond to queries submitted by users and to support their decisions. Further functionalities, such as content marketing, can be included as separate modules. The structure of the system is illustrated in Fig.2 on the next page. It shows the generic structure of the knowledge base, while the architecture of a particular instance of the system will depend on the scope of applications. The focus areas of the research reported in this paper, which are also reflected in the scope of the knowledge gathered and processed and in the system's architecture, are listed below:

- Key IS application areas (e-government, e-health, e-learning, e-commerce)
- Expert systems, including decision support systems and recommenders
- Machine vision and neurocognitive systems, including man-machine interfaces

The use of the system consists in applying the research and modeling results in the first two focus areas listed above to elicit development trends and scenarios for more specific IT areas that depend on basic technological trends and socio-economic processes. Thematic databases store the area-specific information, while a common data block contains interdisciplinary information, such as macroeconomic data, social characteristics (employment, education, demographics), geographic information and other potentially useful data. The common block is used for providing decision-making support during specific thematic analyses.

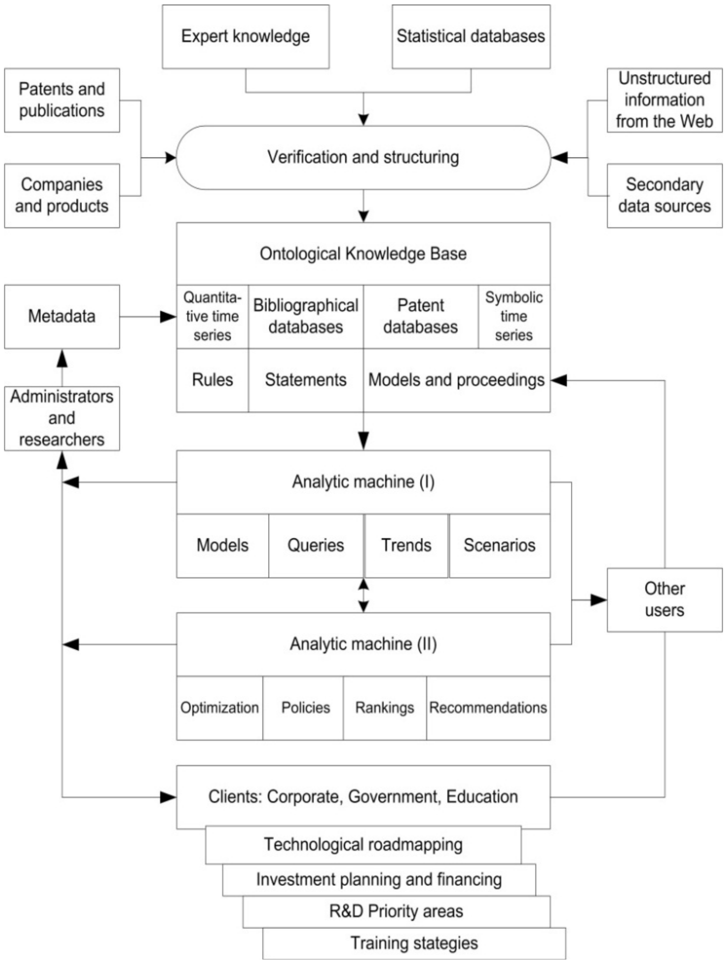

Fig. 2. The scheme of the knowledge base within the foresight support system

The Analytic Machine I contains specialized data fusion algorithms such as:

- Delphi questionnaire analysis, where each Delphi question is associated with a trend or a future event in (1)-(2),
- trend-impact and cross-impact analysis based on experts' judgments,
- consumer preference models, which are to be integrated according to [3], [9],
- specific sector and market models concerning education, health care services, media, internet advertising, quantitative information markets,
- a package of simulation procedures, adaptive trend algorithms and autoregressive time series forecasts.

The R&D trends are derived primarily from biblio- and patentometric data that are partitioned according to the time of appearance and the syntax of the query as proposed in [17]. Other relevant sources of information are technical products' characteristics.

As a result of heterogeneous data fusion and processing, an instance of the system (1)-(2) is obtained. Specifically, the data stored in the knowledge base is used to derive the parameters of coupled discrete-event and discrete-time control systems thus providing a tool to elicit trends of state variables as trajectories to (1)-(2). The foresight scenarios are constructed as sequences of output trends and events. Mutually contradictory scenarios are filtered out using causal-anticipatory models [16].

A user's query input to the system may define the time span and parameters for simulations, specify variables or events to be displayed or a composite output function to be calculated from the system variables. The user can also specify the data to be taken into account as a subset of resources available in the knowledge base and provide assumptions as regards his own or a stakeholder' future decisions in the form of rules. They are then taken into consideration during the simulation. The knowledge gathered in the system is continuously updated, represented and processed using causal networks, rule generation from cases, and anticipatory feedback. The system is capable of indicating which data is missing to obtain trustworthy results, thus allowing for interaction with the user, who can input new data, extend its scope under consideration, or start a new round of data acquisition from experts and external sources.

Responding to a query, the system performs the required calculations and returns the specified trends, scenarios and indicator forecasts. All parameters of the model used, including the scope of data, and the results of calculations can be stored in the dedicated object-oriented database as simulation proceedings. They are available for further analysis by Analytic Machine II, for modifications or comparative analysis by the user, who can investigate model sensitivity to parameter change.

The optimization and recommendation results are generated by Analytic Machine II based on outputs from Analytic Machine I. Its engine makes use of multicriteria optimization, outranking methods, ranking forecasts [12] and so on. Consequently, when using models (1)-(2) to generate optimal technological strategies or investment policies, the criteria and goals should be quantified by the user or external customer and associated with state variables, events and decision scenarios. A generalization of the multicriteria shortest-path algorithm [10] combined with discrete-time optimal control [14], [15] can then be applied to variable-structure networks that appear in the simultaneous optimal control of discrete-events [10] and discrete-time dynamical systems.

If the recommendations require multicriteria rankings, one has to take into account their dynamic character, i.e. future changes in the customer's priorities after certain goals have been achieved or as a result of changing external circumstances. In the present implementation of the model, dynamic prioritization algorithms have been developed as tailored for IT ranking problems.

While Analytic Machine I can reply mostly to research-related questions, any query from an external client will usually refer to the capabilities of Analytic Machine II. However, it must be processed making use of all the system components and databases, even if the global trends and general development models used are not visible in a reply. At this stage, if context-dependent information related to the specific area of the query is missing, the system may require additional input data, and to combine them with those input to the Analytic Machine I.

In the next Sec.4 we provide an example application of the above system to derive development trends for decision support and autonomous decision-making systems, which has been selected as the first focus area for the prospective study. The data necessary to describe the development of decision-support technologies and related social, economic, and technological evolution characteristics has been extracted from the knowledge base created within the research project [9].

4 An Application Example

After selecting the social, technological and geographical focus areas, which can correspond to an instance of the knowledge base outlined in Sec.3, the first task of an analyst is to obtain rankings of the technologies, markets, and application areas with the most potential to be subjects of a detailed study. These rankings result from an expert and practitioner pre-delphi, which are merged interactively with the analytical outcomes from the knowledge-based system above. This stage of the prospective study is least formalized as it should be tailored to the specific needs and customs of stakeholders. The common feature is a simple on-line questionnaire research, called "Delphi round 0", where the users mark the most relevant items. Then the experts assess the results, review the data resources available in the knowledge base and determine the effort to gather the additional necessary information. The final selection of specific topics and a time horizon for the study is a result of a trade-off between the users' needs expressed by aggregated ranks and resource requirements.

In the case of decision support systems (DSS) and recommenders, which have been selected as the exploratory focus area in [9], cf. also [13], the pre-delphi phase resulted in the identification of the following key subareas, listed according to their pre-delphi relevance scores (best first):

- recommenders for e-commerce (excluding banking and finance)
    - graphical (content-based) recommenders for multimedia
    - graphical (content-based) recommenders for 3D-e-commerce
- recommenders for security and commodity trading
- intelligent intermediary agents for negotiations, partner matching, e-commerce.

Then for each of the subareas selected the experts retrieved the keywords, geographic, temporal and other characteristics to be used when surveying the information in the knowledge base and acquiring additional data. A topical DSS-related ontology was created, that ended the preparatory phase of the study.

According to the scheme presented in Secs. 2 and 3, the subsequent knowledge acquisition, processing and analysis has been performed within the following five steps:

Step 1. A common discrete-time model of the IS in Poland (1) with 92 variables has been updated to include the recent economic data and input price trends. The model parameters have been re-calculated and verified using the Granger causality tests. After the model iteration for the blocks of variables with statistically relevant A-matrix (1) coefficients, or trend extrapolation for the remaining ones, we received the forecasts of GDP per capita, digital literacy indicator, unemployment, mobile technologies penetration and other relevant trends. They all have been input to the new analysis instance (called DSS2025) in the knowledge base.

Step 2. The DSS-related ontology served to retrieve from the knowledge base the list of most relevant technologies, methods and models to be used in the DSS. This phase was based on an automatic webcrawler search in external information sources (bibliographic and patent databases, smart web search for products and technologies [14]). It yielded a.o. the following results:

- GIS technologies able to evaluate or elicit geographic preferences within a specified area, capable of using advanced visualization techniques coupled with GPS,
- DSS endowed with cognitive features, making it possible to avoid the negative consequences of decisions made by an irrational decision maker etc.
- Mobile decision support technologies that can explore a Personal Preference Record available in the cloud.

Step 3. An on-line expert Delphi was performed to complement the data gathered so far: verify the causal relations in the models (1)-(2), identify the market trends and the external events that may influence the model parameters, such as expected legislation, political decisions and IPR impact. It included the elements of risk analysis as well: the respondents could identify barriers, opportunities, threats and challenges for the DSS production and use.

Step 4. The fusion of all information gathered so far has been the most crucial point in the overall study as the quality of output information influences directly the success chances of the users. A dedicated information processing method has been elaborated as a merger of discrete-event simulation (2) and the well-known trend-impact analysis [8]. All events have been originally regarded as 0-1-valued functions on the predefined time interval Ω, in our case Ω=[2012,2025]. Then, depending on the event character, the event variables have been converted to continuous functions, using the Delphi responses and technological trends elicited from the bibliographic and patent analysis. They have been interpreted either as fuzzy (partial) events or cumulative distribution of the event occurrence probability, or as a combination of both. The influence of events generated from (2) on the outputs from (1) was performed by multiplying the latter by the event variables. The whole process was repeated iteratively until the convergence was reached. Finally, the following salient trends concerning future development of decision support systems (DSS) until 2025 have been obtained (cf. Tab.3 below).

Table 3. Selected DSS-related trends until 2025

Technological/consumer trend description	Present value	Value in 2020	Value in 2025
Penetration of the mobile DSS in OECD countries (in % of mobile phone users)	3%	60%	80%
Seeking advice from an online medical DSS (in % of Internet users, EU)	18%	45%	70%
Share of financial investment decisions made with DSS (in %, OECD)	65%	80%	95%
DSS as a component of social media	5%	60%	95%
Share of DSS using multicriteria analysis (except simple scoring)	35%	50%	80%

Source: Delphi and causal trend analysis in [9],[13]

Step 5. The quantitative results have been described in form of recommendations to the software analysts and researchers, specifically, we claim that:

- the role and degree of sophistication of OR-based methods applied in DSS will grow, especially multicriteria optimization, uncertainty models and management,
- the class of decision problems regarded as numerically non-tractable will shrink,
- DSS will converge with search engines and intelligent data mining agents; the latter will complete missing data that might help in solving decision problems supplied in the client's queries.

The above presented example shows how the results produced by the information system allow the users to characterize the evolution of selected technologies as well as rank and position the companies, countries or regions under review in terms of development of a particular technological area. For instance, the above presented future characteristics of the DSS market are helpful in assessing the competitiveness of DSS suppliers. The systematic specification of key technologies, focus areas, methods and models within the above presented approach allows us, in turn, to perform targeted research on trends and scenarios concerning the objects selected in an efficient way. Its results can then be used to re-examine technological evolution principles in the knowledge base, thus forming a consistent interactive and adaptive model.

A real-life example of a typical industrial user of the above research results is an investment fund focused on 3D and virtual reality technologies for modern e-commerce applications. When making investment decisions the management of the fund takes into account IT development trends and rankings of prospective products, technologies and markets elicited during a foresight exercise. At a higher decision-making level, dynamic ranking methods [12] are used to rank corporate development policies, which concern the sector, size, or regional preferences regarding targeted markets or portfolio structure [8]. At the lower decision-making level, rankings are implemented as investment rules, by assigning funds to specific undertakings. Each assignment is a function of time and of external logical variables, the latter representing the changes in higher-level ranking and the states of external socio-economic (including the financial markets) situation and research environments. The trends and scenarios generated by the system (1)-(2) are used to establish future investment rankings in an adaptive way. In particular, based on the feasible scenarios found at moment t_0, the management of the fund can calculate corresponding future rankings for $t= t_0+1, t_0+2,\ldots,t_0+k$. This makes it possible to input into fund allocation planning more knowledge coming from systematically updated foresight results in the form of future recommendations and real options. Apart from rationalizing the time order, financing IT and market expansion projects, investment policy ranking may also help to determine organizational structure, future human resource and budgetary needs, and actions to be taken when priorities change as a result of external events [12].

5 Conclusions

The main user group of the recommendations and future prospects produced by the system described in Secs. 2 and 3 are policy makers at different levels as well as R&D and educational institutions on the key directions of development, and on the demand for IT professionals. Moreover, the global trends concerning the economy- and consumer-behavior-driven diffusion of IT innovations and technological characteristics of the IS evolution can provide clues to innovative IT companies seeking technological recommendations and advice concerning R&D priorities. This information will also be useful for corporations from different sectors that invest in IT. Foresight outcomes can situate the IT project portfolio management and fund allocation strategies within the macroeconomic, political, technological and research environment by providing recommendations, relative importance rankings, trends and scenarios [12]. More objective and quantifiable future technological and economical characteristics will enable us to define more appropriate policy goals and measures to implement. The quantitative characteristics of the technological evolution can provide direct clues to IT providers, specifically DSS, as regards future demand for their products.

Comparing quantitative and descriptive approaches to elicit technological trends and build scenarios, it is noticeable that the approach of extracting evolution rules prior to a scenario analysis proved especially useful in the case of converging information societies, as exemplified by the IS/IT trends in the EU States which acceded in 2004 and 2007 [11]. The progress of the cohesion process seven years after the IS foresight results in these countries were published [11] confirms the adequacy of the modelling methods developed by a good coherence of forecasts and their ex-post verification. Furthermore, the architecture of the knowledge base designed originally as a foresight support system, and the hints resulting from its applications can contribute to the mainstream of knowledge science development (cf. e.g. [5]), as an example of an information system based on participatory modelling by experts and stakeholders.

The foresight results provided in [11] can be used as arguments supporting our claim that trustworthy Information Society trends, scenarios and rankings for the following 12-15 years can be derived using the methods applied in [9], some of them described in this paper. Such results can have useful applications in planning corporate strategic IT development. In particular, the investigation of selected technology areas within the IT foresight project [9] can provide constructive recommendations to companies interested in the development of DSS for e-commerce applications.

Another type of result that can be derived from the information gathered in the knowledge base is the model of adaptation of new software versions to the changes in the consumers' behaviour and the technological progress. The product line evolution model described by (1)-(2) together with the research on the evolution of the consumers' preferences can provide clues to IT providers about future demand. They can also give R&D and educational institutions some idea of the most likely directions of development and demand for IT professionals, exploring the interdependence of the corresponding components of the model (1)-(2). Moreover, the general IS evolution model presented in Secs.2 and 3 can be useful for the analysis of global socio-economic trends that influence the development of the digital economy in a country or region, being thus useful to the policy makers at national or regional levels.

Acknowledgment. The results presented in this paper have been obtained during the research project "Scenarios and Development Trends of Selected Information Society Technologies until 2025" financed by the ERDF within the Innovative Economy Operational Program 2006-2013, Contract No. WND-POIG.01.01.01-00-021/09.

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