Discovering Complex System Dynamics with Intelligent Data Retrieval Tools

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Abstract. This paper presents the theoretical foundations of an intelligent on-line modelling tool capable of processing heterogeneous information on complex techno-economical systems. Its main functionality is to investigate, elicit, and apply rules and principles that govern the development processes of technologies and related markets. Specifically, we will focus on applications of the tool to model the evolution of information technology (IT). We will distinguish several relevant subsystems of the system under study, which describe the demographic, education, global economic trends, as well as specific market factors that determine the demand for and use of IT. The group modelling techniques are implemented in the new tool to enable the collaborative and distributed model building with intelligent verification of entries called 'model wiki'. Based on the information elicited from experts, gathered from the web and professional databases, a discrete-time control model of technological evolution emerges, coupled with a controlled discrete-event system. The latter processes qualitative information and models the influence of external events and trends on the discrete-time control system parameters. We propose novel uncertainty handling techniques capable of processing and combining different types of uncertain information, coming i.a. from Delphi research and forecasts. The quantitative information is dynamically updated by autonomous webcrawlers, following an adaptive intelligent strategy. The resulting model can be used to simulate long-term future trends and scenarios. Its ultimate goal is to perform an optimization process and derive recommendations for decision makers, for example when selecting IT investment strategies in an innovative enterprise.

Keywords: Complex Systems, Model Discovery, Group Modelling Tool, Foresight, Discrete-Time Control, Hybrid Models, Decision Support Systems

1 Introduction

Mathematical modelling has evolved over time to accommodate an increasing number of complex real objects with analytical, analogous, and computer models. The modelling capabilities have been increasingly enhanced by stimuli coming from biology and

Y. Zhang et al. (Eds.): IScIDE 2011, LNCS 7202, pp. 614–626, 2012.

behavioural sciences. Furthermore, as an intrinsic element of scientific methodology, mathematical models used in different areas are often isomorphic or interoperable, ensuring a productive transfer of ideas between different branches of science. Following the development of artificial intelligence and computing systems, we are now able to undertake modelling challenges that were difficult to overcome even a few decades ago [2,8,20], such as building socio-economical models as a generic environment to understand the evolution of science, technology and social structures [8,10,12,23].

This paper presents an online tool allowing us to discover models of complex socioeconomic phenomena that govern the dynamics of technological evolution. Specifically, the motivation for this research comes from the foresight of information technologies (IT) in the economical, political, legal and social context of the Information Society (IS). The latter term is most often interpreted as a "modern, knowledge-based society" [5,23]; here it denotes all objects, events, phenomena, and relations between them, which refer to information creation, exchange and extinction in a pre-defined human population supplemented by autonomous information processing agents. We will show that such a complex environment is necessary to construct an adequate model of knowledge development, focussing on selected information technologies covered by the foresight project [18].

The main problem related to the construction of complex models presented in this paper is no longer the computational complexity of the model algorithms, but rather the definition of novel model identification procedures. The latter should be capable of merging a large amount of diversified information coming from heterogeneous data sources and characterised by different types of uncertainty. Extensive group modelling techniques [3,14,21,22] will be applied, but, in contradistinction to prevailing approaches which aimed at involving stakeholders in modelling, its goal is to decompose the interdisciplinary modelling process into tasks led by key experts in the appropriate fields. Another problem is validating and verifying the model once it has been established. In particular the modeller should be able to deal with non-stationarity of parameters and measurements.

To solve the above problems, we propose a hybrid interactive data gathering and data engineering procedure that merges expert judgments with observable quantitative data. Its characteristic feature is an interlace of quantitative and qualitative phases of data acquisition, and resulting iterative model building, with interlaced statistical identification and expert-based 'intelligent guess' phases. This approach might seem to lack mathematical rigidity at first. However, it is justified due to the relevance of information related to subjective human decisions, which must be considered in a complex socio-economic model, as soon as they are expressed, without waiting for any measurable quantitative effects. In addition, the interdependence of qualitative and quantitative components of the model contributes strongly to its novelty and suitability.

Apart from the above-cited paper [2] describing the information society as a complex system in general terms, without providing any specific model or procedure, there have been few attempts to construct such a holistic model of the social information evolution until recently [4,9,11,15,23]. An innovative IS modelling approach has been proposed within the project [7] and applied to model the IS/IT evolution in the EU New Member States [16]. The above-cited results have provided evidence that it is possible to construct efficient models of the socio-technological evolution using coupled discrete-time-control and discrete-event systems. Therefore the 8-component

IS model presented in [16] serves as a basis for the data engineering and modelling methodology applied in this paper.

The problem of building complex system models in order to elicit its future behaviour can be regarded as one of the hottest research topics. For instance, it is one of the six challenging research themes supported by the European Commission within the FET Flagship initiative [6]. The modelling principles presented in this paper will make use of recent achievements in the area of artificial intelligence and soft computing, such as evolutionary feature identification and variable selection, and multicriteria decision analysis. The model will also allow for an in-depth analysis of selected real-life technological applications submitted by industrial partners and public authorities involved in foresight. A detailed analysis of technological trends and scenarios in areas such as 3D-based e-commerce, expert systems, decision-support systems, recommenders and m-health should provide specialized knowledge to set strategic technological priorities as well as formulate IT and R&D investment strategies. This is discussed further in Sec. 4.

2 Modelling Principles

The outcomes of the above-mentioned research projects [7,18] show that the sole use of either classical econometric methods or narrative descriptions have proved to be insufficient for generating adequate IS/IT forecasts or scenarios. Therefore, new analytical methods, which merge qualitative and quantitative information in one model, are needed. In this section, we describe such a modelling approach. The resulting intelligent tool consists of an expert information module, analytical data processing mechanisms, time series forecasting and knowledge base. Overall, it can serve as an IT-foresight-oriented decision support system [18].

The modelling tool is based on a prior extraction of features of the objects modelled. These are filtered, transformed into state variables or discrete event system states and endowed with a set of rules and relations that can describe the complex system under consideration, such as the information society and key information technologies. The other relevant information available at the pre-modelling stage were scenarios of the future use of the model. This pre-knowledge allowed us to decompose the IS/IT model discovery procedure in the following way:

Procedure 1

Step 1. Define the class of models suitable for the real-life objects to be modelled
Step 2. Determine the modelling timeframe and the desired accuracy (e.g. *ex-ante* forecasting error at given future moments) of results obtained with the model
Step 3. Set the constraints: time, funds and other resources available to build the model; set the upper bound for the dimensions of the state and control vectors
Step 4. Check availability of data, specify its sources and strategy of acquisition
Step 5. Elaborate the modelling strategy: specify the model-building steps based on the expected information gathering results, define the outcomes to comply with the modelling purpose, specify the way they are to be presented to stakeholders.

A prototype model was tested for selected EU countries [16]. The ITs to be investigated in detail have been specified in [18], in particular expert systems, e-commerce and main IS applications such as e-health, e-learning, and e-government. The general immediate purpose of the study was *to provide trustworthy trend estimates for selected IT until 2025*. The ultimate research goal was to provide decision support to industrial enterprises, research institutions and governing bodies when solving problems concerning IT-related R&D, management and investment. It would also provide support to legislative authorities in determining suitable legal regulations. To select the class of models, special attention was paid to those exploring the full context of the digital economy, ensuring the exploitation of available time series, technological and scientific knowledge and expert judgments. It was estimated that the number of independent quantitative variables considered in the model should be preferably higher than 80 (but not more than 100) and grouped into 8 blocks to allow for a smooth interaction with the users when performing simulation experiments. A pre-evaluation of the information available, in particular taking into account that the length of time series on IT indicators and market data rarely exceeds 20 (with IT stock indices as an exception), allowed us to conclude that the data available is insufficient to estimate the statistically relevant coefficients of a nonlinear model. Overall, a linear non-stationary model was regarded as adequate. Furthermore, the study of the nature of differentiated IS/IT factors and their interactions to be considered led to the following procedure included in the modelling strategy:

Procedure 2

Step 1. Acquire expert judgments on the qualitative relations between objects of the system modelled

Step 2. Identify the quantitative variables to be included in the model

Step 3. Experts indicate which variables are controllable; controls correspond to decision variables that can be determined by the model users or stakeholders

Step 4. Identify the structural matrices of the discrete-time control system

Step 5. Identify external and random events that can influence the evolution of the system, and the state transition principles in discrete-event systems (DES) with numeric as well as qualitative parameters

Step 6. Discover the impacts of the DES actions on the control system's parameters

Step 7. Set up the parameters of vector autoregression and Kalman filtering to derive quantitative variable forecasts and combine them with the DES simulation.

Additional applications that might help to achieve the ultimate objective of the modelling tool, which are independent research challenges in their own right, include a library of external models of the global economical and political environment, including telecommunication prices, innovation diffusion models, legal regulations concerning e-commerce and cybersecurity, etc.

3 An Intelligent Model Discovery Tool

As already mentioned in the previous section, to cope with the high level of data complexity, the system under consideration should be first decomposed into a small number of subsystems, whose mutual relations should be studied in order to define the fields for in-depth research. For the class of IS/IT models considered in [16,18] we have defined eight major elements of an IS such as its population, demographics, legal environment and IS policies, IT in personal and commercial use, R&D etc. (cf. Fig.1) that can influence technological evolution. These elements correspond to the subsystems of each IS and are related to IT/IS development trends evidenced in the past that should effectively characterise the IS evolution. The relations between different groups of technology users can be described at this level as well.

The first step of Procedure 2 above involves building a causal graph presented in Fig.1, based on qualitative expert judgments. These are gathered during an interactive session with a small group of experts and discussed later independently with another group of experts. The resulting causal graph is then used as a background for the subsequent steps of analysis in Procedure 2. Note that the system evolution will be modelled by iterating the one-time-step causal relations included in the model.

The prevailing types of data gathered during the distributed modelling phase hint at the procedures and models to apply. The characteristics of the information necessary to build the IS/IT evolution model, together with data sources, are listed below [18]:

A. Model metadata: specialised ontologies containing components, subsystems, variables, event classes, and their mutual relations: assignment of variables and events to subsystems, incidence matrices,
B. Quantitative variables of the discrete-time control systems: time series provided from Eurostat, national statistics, chambers of commerce etc.,
C. Other quantitative trends used as external (input) variables: financial time series (stock price quotations, equity indices, exchange rates, selected commodity prices etc.) available from exchanges or provided by commercial data suppliers,
D. Event history: qualitative and quantitative characteristics of past events with the corresponding system states with links to data sources,
E. Qualitative assessments and quantitative characteristics of relations between IS subsystems and system variables gathered from experts in Delphi exercises,
F. Trends retrieved from source files (bibliographic, patent, personal, research projects, research institutions, IT companies etc. databases).

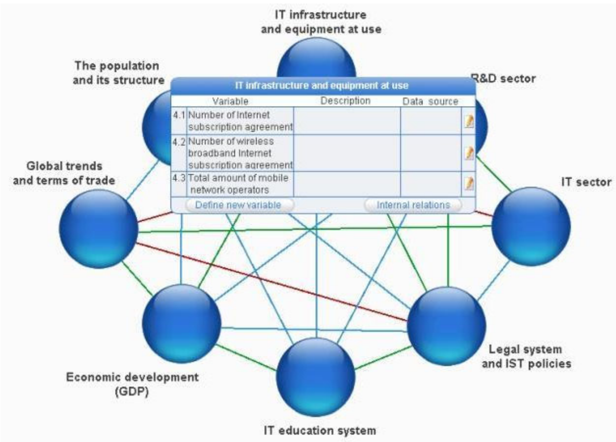

Fig. 1. A sample screen presenting the interactive variable definition phase of IS/IT model building. The variables can be selected from a list of 337 predefined variables or new variables can be defined by experts.

The above information is gathered from experts within Steps 2-5 of Procedure 2 using an interactive on-line tool. Sample screenshots illustrating these phases of model building are presented in Figs.1 and 2.

The tool is available online for registered experts. They can define variables for each subsystem separately, after clicking on the appropriate subsystem on the graph resulting from pre-analysis, as shown in Fig.1. At this step the experts can also

- mark variables regarded as (internal or external) controls,
- define the external trends to be regarded as inputs to the evolution model,
- define the composite indicators for each subsystem, and
- define the relations between variables of the same subsystem.

The definition of relations between variables of different subsystems is possible after clicking on the edge linking selected subsystems (Fig.2). Note that it may emerge from pre-analysis that some links between subsystems do not exist or are irrelevant for the modelling purposes. This simplifies the overall procedure.

Both the above modelling phases benefit strongly from the collective intelligence features of the modelling tool: the experts involved in model discovery define first their areas of competence and then build the corresponding model components, while an internal data processing mechanism ensures data verification and fusion of complementary information provided. This is accomplished as shown in Tab. 1.

Table 1. Autonomous data processing rules applied during IS/IT model building

Rule No.	Rule description	Data in cache	Data entered by expert	Resulting data or operation
1.	Combining quantitative assessments	Time series	Time series or single data	Time series
2.	Combining qualitative assessments	Graded causal relation, comments	Graded causal relation, comments	Graded causal relation
3.	Combining quantitative assessment with qualitative cache	Graded causal relation	Time series or single data	Updated structural coefficient
4.	Combining qualitative assessment with quantitative cache	Time series or structural matrices	Graded causal relation	Updated structural coefficient
5.	New variable verification (in a subsystem)	List of variables defined previously	New variable	Delete duplicates, otherwise append
6.	Variable type verification	List of variables defined previously	Type update or confirmation	Majority rule applied to types
7.	Combining narrative descriptions of variables and relations	Narrative description	Narrative description	Concatenation after moderation
8.	Combining formulas binding the state, control and output variables	Iterative formula	New formula	Update if entered by a field expert
9.	Determine gaps in the model	All information gathered so far	Verification key pressed	Shows missing coefficients
10.	Alert generation on error	All information gathered so far	Any newly entered information	Checks data consistency

The mechanisms presented in Tab. 1 operate under the supervision of a key expert, who is asked to intervene when an alert is generated by the modelling tool. This may happen if the tool is left by all experts, but there are still gaps in the model or if the inconsistencies in a subsystem's model exceed a certain predefined ratio with respect to all the data concerning this subsystem.

After the verification, fusion, and normalization of the values entered by experts involved in model building, as shown in Tab.1, the dynamics based on time series resulting from past observations, key technological, economic or social trends can be described quantitatively as outputs from a discrete-time dynamical system

$$x_{t+1}=f(x_t,\ldots x_{t-k},u_{t,1},\ldots,u_{t,m},v_{t,1},\ldots,v_{t,n},\eta_{t,1},\ldots,\eta_{t,p}), \qquad (1)$$

where $x_{t-k},\ldots,x_t,x_{t+1}$, are state variables, $x_t:=(x_{t1},\ldots,x_{tN})\in IR^N$, $(u_{t,1},\ldots,u_{t,m})\in IR^m$ are controls, $(v_{t,1},\ldots,v_{t,n})\in IR^n$ are decision variables of external agents, and $\eta_{t,1},\ldots,\eta_{t,p}$ are external input or random variables for the modelling period $t=1,\ldots,T$. In the models analyzed so far, f has always been linear non-stationary with respect to x, and stationary with respect to u,v and η. The outputs from (1) are given as

$$y_{t+1}=g(x_t,\ldots x_{t-k},u_{t,1},\ldots,u_{t,m},\ v_{t,1},\ldots,v_{t,n},\eta_1,\ldots,\eta_n), \qquad (2)$$

where the output vectors $y_t:=(y_{t1},\ldots y_{tK})\in IR^K$, for $t=k+1,\ldots,T$, g is linear, and $x_t,\ldots x_{t-k}$, $u_1,\ldots,u_m$, $v_{t,1},\ldots,v_{t,n}$, and $\eta_1,\ldots,\eta_n$ are the same as defined in (1). A specified subset of coordinates of y_t can be regarded as performance criteria of the system (1), either as a fixed value for $t:=T$, or as a trajectory criterion. Additional criteria can be defined as

$$F(x_t(u),\ldots,x_1(u),\ u)\rightarrow opt, \qquad (3)$$

where $F=(F_1,\ldots,F_M)$, $u:=(u_{t,1},\ldots,u_{t,m},u_{t-1,1},\ldots,u_{t-1,m},\ldots,u_{1,1},\ldots u_{1,m})$ and the optimum is usually a Pareto minimum with additional preference information supplied by the stakeholders. F has usually been a linear or linear-quadratic combination of x and u.

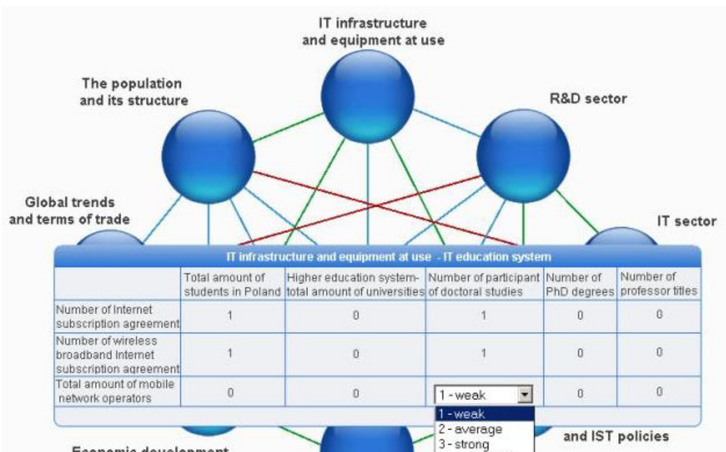

Fig. 2. A sample screen presenting the interactive definition of relations between variables from different subsystems. Experts can choose between the definition of quantitative or qualitative relations.

The usual approach used in foresight to deal with the non-stationarity of eqs. (1)-(2) involves applying trend-impact and cross-impact analysis. A discussion of the reasons for applying a more in-depth kind of modelling is given in [18]. Specifically, we will apply an additional system component modelled by the following discrete-event system [13, 15]

$$P=(Q,V,\delta,Q_0,S,Q_f) \tag{4}$$

where:

- Q is the set of all feasible states of event-driven model components,
- V is the set of all admissible operations over the states Q,
- δ: $V\times Q \supset W \rightarrow Q$ is the transition function defining the results of operations over states; stored as a set of rules; defined for certain pairs of $v\in V$ and $q\in Q$ only,
- $Q_0 \subset Q$, $Q_0\neq\phi$ is the set of initial states of event-driven model components,
- S: $V\times Q \rightarrow IR^s \cup \{\infty\}$ is the transition (multicriteria) cost function; its values are infinite iff a transition is infeasible,
- $Q_f \subset Q$, $Q_f \cap Q_0=\phi$, is the set of reference (or final) states of event-driven model components corresponding to alerts or points of reporting the modelling results.

Causally connected pairs of states $e:=(q_1,q_2)$ of (4), such that $q_2=\delta(v,q_1)$ are termed *events.* Observe that the set W can be identified with the set of all events.

The states Q,Q_0,Q_f and other structures of (4) are defined by experts involved in modelling and stored in a database. The feasibility and duration of events may be coded as Boolean, continuous $[0,1]$-valued, or fuzzy variables defined on a certain time interval $[t_0,T]$, depending on whether a partial occurrence of an event, or a partial achievement of a state is possible and whether a transition is immediate or distributed over time. If the transitions are random, or occurring at random moments, these variables may be defined as cumulative probability distributions of the events' occurrence on the same time interval. The combination of a random and possibly partial occurrence of an event results in a 2-dimensional cumulative probability distribution. The cost S for a fixed event e is coded analogously to the coding of the underlying event. A relevant virtue of the intelligent modelling tool is the capability of an automatic construction of the above variables, based only on a reply to a simple questionnaire that is displayed when defining states Q and admissible operations V. Having completed the description of an event, the questionnaire displays the *impact vector*, which describes the potential changes that may be incurred by the event to the variables of (1)-(2). Again, the experts are assisted with a fixed catalogue of potential impacts.

The discrete-event system (4) allows us to include the influence of new legislation in the model, as well as new technologies, expected R&D results, political decisions and other events of similar nature. The rules governing legislation changes are predefined by core legal experts, the principles of generating innovations and technologies by appropriate technological experts etc., so that the numerical characteristics of impacts can be calculated automatically, once they are pointed out by experts. The catalogue of R&D and technology-related events and potential impacts comes from regular surveys of bibliographic, patent and product databases performed by autonomic webcrawlers.

A complex real-life system under consideration can now be modelled by (1)-(4), where the states of the discrete component intervene directly in system (1)-(3) causing the changes in its parameters. Thus the non-stationarity of (1)-(3) can be explained by the evolution of (4). Scenarios appear as the results of grouping trends and sequences of events, for different variants of decision variables, random and external drivers.

4 An Example and Concluding Remarks

The intelligent distributed modelling tool presented in this paper aims at discovering an adequate description of complex socio-economic and technological systems. Its current version has been applied to establish a pilot model of the information society evolution in Poland within the research project [18]. The modelling has been performed according to the Procedures 1 and 2 in the following way:

Example 1. The framework for the modelling process has been specified by the research goals of the project [18]. Specifically, the technological and market perspectives for selected AI technologies should be elaborated, focussed on the Polish software market. The field of commercial DSS has been selected for the pilot study, as a main goal of the Task 4 of [18]. The IS model itself constituted the project's Task 3. According to Procedure 1, the model size and the scope of work were determined by the suitability of the model to attain the above research goal, the budget and time frame (18 months) of Tasks 3 and 4, and by the availability of data and computing time. The latter information was used to specify pre-defined model variables. During three brainstorming sessions, a team of experts in Economy and Sociology have gathered a list of 337 variables, out of which 92 variables were selected as the first candidates to model variables. The latter have been associated to the model components and served as an input to the intelligent modelling tool, while all remaining 245 variables have been available on the pick list.

In the next step, the system analysts and computer scientists used the tool to examine the pre-selected variables, to associate the data, and to define the relations between them. It turned out that some of the variables identified previously would be better used as outputs as they were defined as composite indices or rankings (such as e-government readiness index), while some others have shown a high degree of correlation. Although even the initial model could be useful for numerical experiments, the model refinement process using the interactive intelligent tool ended with 11 variables eliminated and new 14 variables defined and accepted by the core expert panel, yielding altogether 95 quantitative variables in 8 model components. This is shown in Tab. 2.

Table 2. Results of IS/IT model building – quantitative variables specified in the 2nd round [18]

No.	Model component	No. of variables	No. of observations	Examples of a characteristic subsystem variable
1.	IT sector	11	6 to 15	Annual volume of software sales
2.	Domestic economy	9	6 to 20	Annual sales via internet (e-commerce)
3.	R&D sector	16	7 to 15	Annual volume of IT transfer
4.	IT infrastructure	11	6 to 15	Total data transfer via main nodes
5.	IT education	15	6 to 17	No. of IT students
6.	Legal system and IS/IT policies	11	6 to 15	No. of computer crimes detected per year
7.	Global trends	12	14 to 20	Total annual IT imports
8.	Demographics	10	15-20	Percentage of citizens living in urban areas

In addition, some of the variables have been identified as controls, for instance the annual value of the direct state aid to innovative IT enterprises, transferred mainly by the Polish Agency for Entrepreneurship Development (PARP), cybersecurity regulations, and IPR protection etc. The length of most of time series that could be applied as observational data and used to determine causalities, as can be observed in Tab.2, was severely restricted by the structural changes in Polish economy and legislation that occurred during the period after 1989 and after the EU accession in 2004. This is why the extrapolation power of the time series was moderate as well as the possibility of using the Granger causality algorithms and other statistical tests. Instead, Bayesian networks, fuzzy-probabilistic inference rules (cf. Sec.3), and moderated direct expert indications (cf. Fig.2) have been used to estimate causal effects. All variables, coefficients, and the associated data have been stored in a knowledge base.

The quantitative output variables (2) have been defined as:

a) the size of the enterprise DSS market in Poland,
b) the income generated by on-line recommenders,
c) the number of users of commercial medical DSS,
d) the share of financial transactions performed by automatic trade engines on Polish stock and commodity exchanges,
e) the sales of DSS developed by Polish companies,

(all above until 2025).

The variables that could not be retrieved from the model due to the lack of data or too high (probabilistic) uncertainty of model coefficients have been elicited from experts in a Delphi analysis.

The discrete-event part of the model (4) turned out to be useful in describing the results of new legislation, such as e.g. the passing of a bill allowing unrestricted algorithm patenting in Poland and the appearance of new technologies on the market, such as common wearable health monitoring sensors with the appropriate healthcare infrastructure. For the case of legislation the initial states Q_0 have been always identified with the present state-of-the-art, the final states Q_f have been interpreted as the regulations in 2025 that are to be admitted according to international conventions or EU treaties, while Q_f were undefined for technological or research outcomes. The state transition cost function S was estimated in an expert Delphi or during expert panels. The transition function δ could be determined based on bibliographic and patent trends, by reverse analysis of the cost function S, if S occurred as a quantitative variable in (2) and its values determined the plausibility, or directly in an expert Delphi. Finally, let us note that due to the possibility of describing most events as $[0,1]$-valued variables (cf. Sec.3), there was possible a (limited) migration of variables and events between the components (1)-(2) and (4) of the overall model during an interactive and iterative modelling process.

The main goal of the pilot Delphi that involved over 60 participants was to determine the impact of events included in (4) on the state or output variables of (1)-(2). In an on-line questionnaire, the experts assessed the degree of an additional increase or decrease of the structural matrix (1) coefficients, the date and conditions of an occurrence of an event, the type of impact (immediate-distributed). The Delphi also contained speculative technological issues and causal relations between events.

After linking (1)-(2) and (4) the model parameters, state and output variables could be re-calculated. As some of the variables may activate events, there is a feedback between the model components and the calculations can be iterated. For the above presented system three iterations have been performed yielding a sufficient convergence. In addition, the model can function according to the continual computing principles [9] as new quantitative information, bibliographic, and patent data can be perpetually supplied by intelligent autonomous webcrawlers gathering data according to the principles presented in [19]. The experts can also input new and update previously-entered information, thus creating an updated model. A neural-network-based learning scheme, based on the ex-post verification of suppositions and conjectures will be integrated with the Polish IS model as soon as the ex-post information is available.

The first results of the pilot exercise concerning the development of decision support systems (DSS) and recommenders for e-commerce have been presented in [17,18]. The next stage of the study (Task 5) will involve computer vision systems.

The above Example 1 shows that the main goal of the models built with the tool presented in Sec. 3, together with automatic or supervised knowledge acquisition, update and verification, is to respond to queries submitted by users and to support their decisions. Further functionalities, which can be added as separate modules, include supporting the conceptualization of regional development such as in [4] or designing other group interactions useful in a foresight project [1]. The model can also be used to derive technological project rankings, and to identify markets and products with the highest potential. Although the general applicability field of the models presented in [18] 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 collective data processing methods presented here as a background to elicit trends and elaborate scenarios of decision-support and decision-making systems can constitute the input to any future-oriented technological study or decision support.

A good coherence of forecasts and their ex-post verification resulting from the application of a similar, yet less sophisticated model [16] confirms the suitability of the modelling methods presented in this paper. This can be used as an argument supporting our claim that trustworthy trends, scenarios and rankings for the following 12-15 years can be derived using the methods described here, which have been developed based on [16]. These results could have useful applications in planning corporate strategic IT development. In particular, the investigation of selected technology areas within the IT foresight project [18] thus far can provide constructive recommendations to companies interested in the development of e-commerce applications. Moreover, the general IT/IS evolution model presented in Sections 2 and 3 can be useful for the analysis of global IT and socio-economic trends that influence the development of the digital economy in a country or region.

Although the experience thus far with the above modelling tool has been gathered within the IS/IT area, we believe that this approach is a universal one that can be applied in many different markets and technology fields. In particular, based on preliminary experience with e-health, considered in the model described in Sections 2-3, we can expect useful applications to modelling the future development of biotechnologies and medical technologies, their distribution and markets.

Acknowledgement. The results presented in this paper have been obtained during the foresight 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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