Chapter 4
Adaptive Business Intelligence: The Integration of Data Mining and Systems Engineering into an Advanced Decision Support as an Integral Part of the Business Strategy

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Abstract IT-based decision support is in the heart of business intelligence. It should be based on a successful integration of data analysis techniques and certain system engineering (like system dynamics) concepts. This contribution introduces in the large realm of IT-based decision support and its meaning for a modern business strategy. Central is the relationship to Business Intelligence with its own characteristics and requirements. The relevant data mining techniques are summarized and characterized by its special role within traditional business intelligence approaches.

As an holistic approach this chapter tends to combine a classical data-centric approach with a modern system-engineering concept ("system of systems"-thinking). As a result, this new approach leads to an advanced concept of Adaptive Business Intelligence. It will be characterized and described by several successful examples.

4.1 Introduction: IT-Based Decision Support

4.1.1 IT-Based Decision Support

The notion *IT-based decision support (IDS)* used in this chapter describes a computer-based information system that assists in decision making regarding business in all its three main levels such as designing, processing and managing.

Another purpose of an *IDS* with information state $\mathcal{I}$ is to offer, once the problem P of the decision maker is formulated and delivered to the *IDS*, an (assessable) set $\mathcal{C}$ of beneficial decisions/alternatives from which the decision maker can choose the one he considers the best in the current situation $\mathcal{I}$. This implies that the *IDS* is capable of solving and listing a compilation of selected solutions of formulated decision problems that are explicitly addressed to the *IDS*.

Further, an *IDS* has a cooperative quality which means that the decision maker can simulate all consequent and related scenarios based on the suggested decisions tendered by the *IDS*.

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The core of an *IDS* in *BI* is the expertise of specialized problem solving techniques for a wide range of business related problems deposited as actual data or equivalent assets, i.e., procedures, algorithms, set of rules, available tools, library of solvers, etc., in short: as information.

The inventory of actual and available information or equivalents like exploitable assets may be strongly fluctuating even over small periods of time, i.e., $\mathcal{I} = \mathcal{I}(t)$. Thus, through the possibly high volatility of the available data and assets itself the potential advantageousness of a decision becomes highly uncertain and, moreover, fluctuating as well. In particular, the inventory of data and equivalent assets are interacting with the decision maker.

Generally speaking, an *IDS* consists of an inventory of information that encompasses raw data as well as equivalent assets, an environment for formulating, editing and processing decision context, and finally an user interface to connect the decision maker along with his personal knowledge and expertise with the *IDS* for interaction. However, the interface also serves as editor, worksheet and display where *IDS* and decision maker meet.

As the suggested decisions of the *IDS* are replies of engineered scenarios played through the *IDS*, the decision itself is engineered. In this chapter we will focus on building an *IDS* in the distinct domain of *BI* including management: a *IT-based Decision Support (System) for Business Intelligence (BIDS).*

Further details concerning the *BI* basics can be found in the introduction chapter of this book.

4.1.2 Business Intelligence

BI signifies the transformation of an organization's capabilities into useful knowledge with the potential to gain competitive advantage in the market. Obviously, *BI* is an enterprise-centered view on the market including participation in it. Whereby, the *IDS* is the core of every *BI*-approach that is devised to provide solutions or beneficial alternatives to a specific problem that the decision maker embedded into an accurate scenario. Stringing together a set of separate potential decisions enables the decision maker to test, modify and improve the business strategy he has in mind.

"While the business world is rapidly changing and the business processes are becoming more and more complex making it more difficult for managers to have comprehensive understanding of business environment. The factors of globalization, deregulation, mergers and acquisitions, competition and technological innovation, have forced companies to re-think their business strategies and many large companies have resorted to Business Intelligence techniques to help them understand and control business processes to gain competitive advantage. *BI* is primarily used to improve the timeliness and quality of information, and enable managers better understand the position of their firm as in comparison to competitors." [17]

On that note, *BI* utilizations and methods enable companies to assess changing trends in market share, alteration in customer attitude, spending behavior, company capabilities, and, even, the condition of the market itself.

BI qualifies the analyst/manager to ascertain which strategic or operational adjustments are the best to answer to changing trends in an overall beneficial way.

In this chapter we understand *BI* as an area of mostly IT-based Decision Support, i.e., an information system that is purposed to support complex decision making, including solving complex, semi-structured, or even ill-structured problems [6, 27, 31]. "The first reference to *BI* was made by [19], which has replaced other terms such as Executive Information Systems and Management Information Systems [26, 35, 36]." [17]

Being resident in the *IDS* discipline, *BI* attracts large interest from both the industry and researchers [3, 10, 14, 15, 26, 29, 30]. *BI* appears as an architecture/system that collects and stores data, analyzes it using designated analytical tools, and delivers information, including, intrinsic relationships: that ultimately enables organizations to improve their process of decision making and finding [10, 18, 24–26, 28, 34, 36].

4.2 Data Mining and Its Role in Business Intelligence

4.2.1 Data Mining

Data Mining in a *BIDS* is the attempt to detect (prevalent and hidden) patterns or functional (inter)dependencies in an existing inventory of information $\mathcal{I}$. Before starting the process of Data Mining the inventory $\mathcal{I}$ has to be preprocessed by suitable filtering $\mathfrak{f}$. The engineering of a suitable filter strongly depends on what the decision maker declares as purpose. Preprocessing of data is a vital part in the data mining process, not least because data collection is loosely implemented and controlled. The collected data may contain, sporadically, values that are out of range, missing, or plain impossible (e.g., pupil of age 40 at local primary school). Interpreting the collected set of data, without examining the current data for further usability, may easily bring about misleading results and possibly wrong conclusions. The final good of data preprocessing is the training set, meaning, a set of data used to discover potentially predictive relationships.

The general tasks of Data Mining are [4]:

- *Clustering* which means creating a set of categories as containers for information of special characteristics,
- *Classification* which deals with compiled information of the past and present and deciding whether an information fits in a given category or not,
- *Prediction* which deals with forecasting/estimating information to occur on the basis of the current inventory,
- *Association*, i.e., detecting information that occur often at the same time or a certain order or with delay, in other words: detecting patterns,

- *Text Analysis* which deals with finding key terms and phrases in a text.

Information may posses the following property such as, to be [13]:

- *qualitative*, meaning without immanent ordering, e.g., Boolean values or a product line etc.,
- *quantitative*, meaning that the information is in $\mathbb{R}^m$ for some $m \in \mathbb{N}$,
- *set valued*, meaning it has more than one attribute,
- *ordinal*, meaning categorical but with obvious ordering, e.g., screen diagonal.

In this day and age businesses, indeed, are more capable of addressing and accessing their target customers. Data mining is a catalyzer for their success, it uses real data collected in real business cases and helps providing models and modifying evolving business strategies. Today, data mining in business intelligence implies a variety of business-oriented applications and has become a indispensable tool for detecting dependencies between business variables or gaining conception of causal relations.

4.2.2 Utilization of Data Mining in Business Intelligence

In fact, businesses are faced with an explosive growth of data that is, mainly, caused by automated data collection tools or database systems. In addition, businesses have access to abundant data that can be obtained from various sources. Of course, overwhelmed with partly disjoint and unrelated data the businesses wish a automated analysis of these massive data sets. That is exactly what data mining achieves. Data mining is detection of patterns from a huge amount of data, it can be used with a both predictive and descriptive purpose. Exemplary for data mining with predictive purpose, we cite classification, regression, time series analysis and prediction. Further, examples for data mining with descriptive purpose are clustering, association rules, summarization/clustering and sequence discovery. Data mining is successfully utilized in market analysis and management (such as target marketing, customer relationship management, market basket analysis, cross selling and market segmentation) as well as risk analysis and management, including forecasting, customer retention, improved underwriting, quality control and competitive analysis.

We pick up on a few common techniques in data mining that can be used to classify, predict, cluster and/or simply associate present business information, e.g., namely:

• *Decision Trees*: from a business perspective decision trees denote a segmentation of the original inventory $\mathcal{I}$ or parts of it where each segment/class is one leaf of the tree. In fact, segmentation is applicable in classifying, e.g., clients, market trends, behavioral responses to enterprise policies, products, branch offices, their sales districts and service coverage. The classification is essentially a expedient for intended (further) prediction. Information gathered in each leaf of the decision tree is pooled there due to bearing significant resemblance to information being predicted. Whereas, algorithms for generating decision trees may be quite complex, the use of decision trees remains popular, precisely because once presented it can be grasped almost immediately. If not else, decision trees are preferred because of their property to easily build rules, which, moreover, is an implication of the tree structure itself. E.g., let us assume the prediction of a highly probable demand slump on the part of a certain client population concerning a certain class of products. In order to decide, whether these clients are indispensable and thus the enterprise should conduct an expensive marketing intervening, or, a cheaper intervening is acceptable, the decision maker has to test diverse cost models on the current decision tree. Since, otherwise the expenses would exceed the revenues. Further sample applications of decision trees to business issues, besides investigation/exploration and estimation/prediction in general, are concretely the prediction of loan default, the crude oil price, or the exchange rate of currencies [8].

- *Rule-based Methods/Rule Induction*: this method aims at finding rules of interest and value for an enterprise's business, to put it another way, this approach might extract yet undetected dependencies, properties or correlations in parts of an information inventory. E.g., the inventory might provide the information, that if a television is purchased then a DVD player is purchased in 7 out of 10 cases. Rule induction exposes all possible/predictive patterns that can be expressed on the basis of the current information inventory. Consequently, it is inevitable that the presentation of all correlations found by this method exceeds the decision makers capacity to penetrate its response. Rather, the response of rule induction provides an overwhelming collection of isolated alternatives that, furthermore, may even be based on different questions/problems and, in the end, rather appear more to be a collection of mainly disjointed opinions than problem-specific solution suggestions. Basically, rules expose what functional operation holds between information (or sets of it such as classes/segments) captured in the information inventory. The accuracy of a rule is a criterion for its reliability meaning how often the rule turns out to be valid, whereas, coverage is a criterion for how often that rule applies to the current inventory.

- *Nearest Neighbor Classification*: this method exploits the concept of a metric in order to decide whether an information is nearer to a class than to another one. E.g., from a business perspective, a notebook is nearer to a desktop than to a cell phone, because they are alike concerning their resources and capabilities. Often, the decision maker can draw on a variety of conceivable metrics that all may make sense in one way or the other. Given an information i (or a set of it) and given classes $\mathfrak{C}_1, \ldots, \mathfrak{C}_h$ ($h \in \mathbb{N}$) the nearest neighbor method determines whether i should be considered belonging to class $\mathfrak{C}_1, \ldots, \mathfrak{C}_{h-1}$ or $\mathfrak{C}_h$. In the case of predicting stock prices where the enterprise essentially deals with time series, prediction means forecasting the next value of the stock price. Especially, the nearest neighbor approach can be used in early prediction of time series [39]. Further, it should be mentioned that the results obtained by a nearest neighbor approach depend very much on the selected distance measure.

- *Bayesian Classification*: the Bayesian classification method is a knowledge-based graphical representation that shows a set of information and their probabilistic relationships with each other. A less formal representation of that kind would be, e.g., a representation using system dynamics. System dynamics describes a method for depicting the mode of operation of a complex system over time.

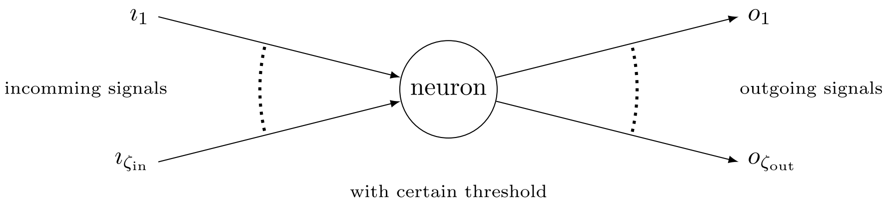

Fig. 4.1 An isolated artificial neuron

This method, especially, highlights how the single elements of the complex system effect each other. In other words, this approach highlights the relationships of the components of a dynamical system, meaning that, e.g., such relations might be circular, interlocking or even time-delayed. More precisely, system dynamics uses, inter alia, so-called internal feedback loops, stocks and flows in order to express the dynamical behavior of the entire (complex) system.

Certainly, the Bayesian classification method is based on conditional probabilities, i.e., the probability of an event given the occurrence of another event. Although, the Bayesian method is computationally nasty, nevertheless, can tender a potential benchmark for algorithms that may apply in classification. Bayesian classification provides, mainly, probabilistic prediction, i.e., it has the potential to predict multiple hypotheses that are weighted by their probabilities.

• *Support Vector Machines (SVM)*: a *SVM* classifies a set of information in such a way in categories/classes that around the boundaries of these categories/classes one obtains a strip as wide as possible that is free of current information, meaning, a strip which contains no data points. By this means, a *SVM* is, essentially, a large margin classifier. *SVM* apply to classification as well as regression, and, indeed, it is a mathematical technique for pattern recognition. E.g., two classes with their corresponding information/ data, at best, can be separated by a hyperplane, i.e., in the 2-dimensional case this reduces to a straight line. Albeit, at worst, there might not exist a separating hyperplane with the result that two classes can be separated properly. In this particular case, other curved surfaces should be taken into account in order to achieve the desired separation. This can be done by using what is called the kernel trick which means implicitly mapping their inputs into high(er)-dimensional feature spaces. In the case of linear classification *SVM* can be considered as special cases of Tikhonov regularization, the most commonly used method of regularization of ill-posed problems, as well. *SVM* apply in web services like spam categorization in email accounts [12].

• *Neural Networks*: inspired by the biological neural network, e.g., in the human brain, a (artificial) neural network denotes a network of (artificial) neurons intending to mathematically emulate, although in a simplified manner, the mechanics of a biological neuron. In the biological case of a neuron one has to keep in mind that the neuron sends out a signal/information only if a default threshold is exceeded by incoming signals(s)/information(s) (Fig. 4.1).

Indeed, several groups of neurons (ordered in so-called layers) in interconnection to each other build up a neural network. In general, the neural networks expresses an

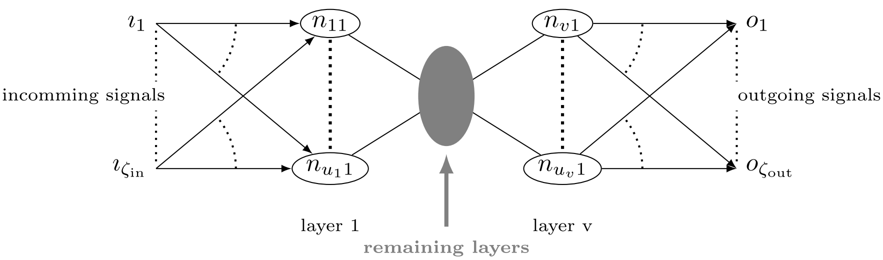

Fig. 4.2 An exemplary neural network

adaptive network that is capable of renewing and adjusting its connectivity, hence, transforming its very structure according to the information flow through the entire network. A neural network is a tool predestined to model functional relations that are inherent in the entirety of input and output, which, explicitly, includes, among others, pattern recognition, prediction as well as association.

Neural networks (Fig. 4.2) apply in a variety of additional business disciplines such as providing *Web Services/Information Retrieval* like intelligent search engines that are based on the clients's preferences, satisfying *Security* needs like making voice recognition systems available for authentication to client access, helping doctors to diagnose/analyse on the basis of afflictions and additional information like X-ray images, hereby, offering *Medical Decision Support*, assisting in *Portfolio Management* and *Optimization* as well as in predicting, e.g., future trends forming or the development of selected stocks or securities, assigning a clients credit rating as application in the field of *Finance & Banking*, right up to, *target recognition* or recognition of critical infrastructure in complex networks and energy grids as actual application in *Military Red Teaming*.

4.3 System of Systems: Challenges and Limitations within Business Intelligence

4.3.1 System of Systems

Whereas systems engineering focuses on designing an appropriate system, *System of System Engineering (SSE)* focuses on choosing the most appropriate system out of all available existing systems in order to satisfy the requirements. Mainly, an *SSE* aims at creating new capabilities through joining systems (may they be separate or sub systems) to a bigger structure, called *System of Systems (SoS)*. In doing so, the *SoS* becomes more than the sum of all its components, for, the *SoS* enables to master tasks none of the *SoS*-components (or even subsets of it) could cope with alone. An *SoS* should be regarded as meta system or, more abstract, as meta model.

Multidimensional data spaces have to be integrated in order to enable complex business analytics processes. Acknowledging modern *BI*-approaches in terms of an

SoS view supports the structured integration of existing (legacy) and additional systems as well as their data spaces within the respective business context.

We mention Maier's crucial characteristics [21] to distinguish a *System of Systems (SoS)* from other big and complex, but, however, monolithic systems:

1. *Operational Independence of Elements:* Separate components disjoint from the system itself can operate independent from each other, for, there is no such join between component and *SoS* that may restrict the functionality of the component or sets of it.
2. *Managerial Independence of Elements:* Separate components or sets of it can be acquired or developed independently.
3. *Evolutionary Development:* An *SoS* is a ever-changing structure whose capabilities, i.e., components are added, removed or modified over time.
4. *Emergent Behavior:* Through interaction of all components of an *SoS* new capabilities form and gain shape that can not be gained by the separate components independently without join to the encompassing *SoS*.
5. *Geographical Distribution of Elements:* The components of an *SoS* are geographically distributed so that the *SoS* covers sufficiently the sphere of its influence.

With reference to Sect. 4.1.1 the transition from inventory $\mathcal{I}$ to the filtered inventory ${}^{\mathfrak{f}}\mathcal{I}$ describes the compilation of a set of components ${}^{\mathfrak{f}}\mathcal{I}$ on the basis of the starting inventory $\mathcal{I}$ that is exactly the *SoS* at time $t = 0$.

Considering the development of integrated *BI* systems [16] present an incremental process model as a possible approach that includes a macro and a micro level view. The macro level determines the conceptional frame that includes decisions that are closely connected to the strategic view of the management [16]. The derived framework will have to be continuously audited and adapted to the dynamically changing business context. The micro level comprises the development and reengineering processes with respect to the single *BI* application systems within the integrated adaptive *BI* system. These processes are closely synchronized to the framework developed at the macro level [16].

When it comes to major unsolved problems in the IT industry, we have to mention the problem of managing semi-structured and unstructured data. Because of the difficulty of assessing unstructured/semi-structured data, companies usually do not incorporate these vast reservoirs of information into the decision making process. This ultimately leads to uninformed decision making.

4.4 Adaptive Business Intelligence as Integral Part of a Business Strategy

A *BIDS* as introduced above is a highly adaptive meta model, so that it is justified to speak of a IT-based decision support (system) in the realm of *Adaptive Business Intelligence (ABI)*, in short: *ABIDS*. An *ABIDS* not just encompasses all the advantages and abilities highlighted yet, it also includes optimization that is a very important feature we left unmentioned so far. Optimization in a business context can mean, e.g., maximizing the market penetration of a specific product line of a company, minimizing costs in terms of production, warehousing and/or transport etc.

An *BIDS* lacking in adaptivity implying flexibility in response to an eventually rapidly changing information inventory/business reality would be rather a burden than a helpful decision support tool. The adaptivity of a *BIDS* is a vital part of the applicability of the *BIDS* in real(-time) business.

An *integrated* adaptive *BI*-approach is needed in order to provide the basis for effective management decisions in the context of a dynamic and rapidly developing market environment. Traditional single business systems are often not able to deal with such a level of complexity. A modern *BI*-approach is needed that is able to efficiently integrate the different information spaces and that adapts to the dynamic decision environment.

4.5 Examples

4.5.1 Clinical Decision Support

"*Clinical decision support (CDS)* systems provide clinicians, staff, patients, and other individuals with knowledge and person-specific information, intelligently filtered and presented at appropriate times, to enhance health and health care." [7]

CDS enables providers and their patients to make the best decision based on the respective circumstances. By comparing a patient's electronic records/information with fixed clinical guidelines, an IT-based *CDS* system can, for instance, remind a provider to ensure that a patient receives, e.g., recommended immunizations, track a diabetic patient's blood sugar level over time or notify a provider that the medication that is about to be prescribed may lead to an undesirable side effect. Obviously, the ultimate goal of *CDS* is to supply the right information, to the right person, in the right format, through the right channel, at the right point in the clinical workflow to improve health and health care decisions and outcomes [38]. Using reminder systems, front office staff can be alerted to make sure that important lab work is done prior to the visit. Documentation of key elements of a patient's exam can be obtained before the provider even sees the patient. *CDS* can support disease management by tracking long-term issues that a given patient may need to have addressed for optimal health outcomes. Also, by using *CDS* with electronic prescribing, the selected drug can be checked against the patient's allergy list, against other drugs for possible interaction, for contraindication based on the patient's problem list [38].

"The ultimate objective of clinical decision support parallels the objective of providers themselves: Provide the best possible care for every patient. Health information technology holds a vast potential to help providers and their patients manage their overall health in the context of daily life. Modern quality improvement theory suggests that sustainable improvement happens when individuals or groups make a series of small, manageable changes over time. This is a logical approach to implementing health information technology and clinical decision support. One practice may choose to use electronic prescribing software as preparation for the ultimate leap to electronic health records. Another practice may use the information available in its practice management system to begin issuing preventive care reminders. However it happens, the important thing is that each practice acknowledges the ongoing need for improvement and takes action as a result." [38]

4.5.2 *Decision Support in Airlines: Business Intelligence in Aviation Management*

Before discussing a case study in the field of aviation management, one should understand the latest problems airlines constantly face. Generally speaking, airlines constantly have to deal with operational disruptions such as delays, cancellations and diversions, resulting in considerable inconvenience to passengers and costs to the airlines. For that specific reason the so-called airline operations control centers need decision-making processes to mitigate the effects of these disruptions. This crucial fact strengthens the necessity of business intelligence in the aviation management sector [9]. One example which can be found happened in the former Continental Airlines company, which did a company fusion with United Airlines in 2010 [37].

Supported by a newly designed data warehouse, Continental Airlines changed their business model. In details, the case study shows that Continental Airlines invested approximately 30 million US Dollar into real-time warehousing technique [2]. These investments were the core part of the business intelligence initiative. With the help of latest hardware, software and personnel training, the company was able to increase their revenues and costs savings by the factor ten. Real-time business intelligence started to become a significant business benefit. Especially the powerful real-time warehouse enabled Continental Airlines after the year 2000 to develop and deploy different application in the area of revenue management, customer relations, flight and ground operations, fraud detection and security, and others. Internal publicity helped a lot to preserve the excitement around the warehouse use and in addition encouraged business users to support warehouse expansion efforts. Finally it can be said that this example shows clearly the benefits of real-time data warehousing and business intelligence. Especially the quick data access seems to be a key for the support of current decision making and business processes, which can directly affect the company's actual situation [2].

4.5.3 IT-Based Complex Decision Support with System Dynamics: Strategic Management

Generally speaking, the types of decisions based on a project can be differentiated in three different types: strategic, tactical and operational. The actual use of system dynamics usually affects the strategic/tactical area of a project. In the context of business intelligence strategic project management can be described as follows: It includes the decision support in the project development phase, the support in making decisions concerning the project schedule with a long-term focus on the realization of these decisions [20].

In particular, the complexity involved in a project in most cases exceeds the human imagination and therefore requires a computer-aided modeling method, such as System Dynamics. One of the strengths of system dynamics is the representation of the interdependencies within a project and the subsequent tracking of changes in the model. It can be said that System Dynamics consists of one of the most developed plans for action, the optimal representation, analysis and detailed explanation of dynamics in complex technical systems as well as in entrepreneurial systems [32].

Especially large, long-term projects are now among the most important, while the least organized activities in the modern society. Large-scale projects are for example the construction of civilian equipment and infrastructure or military projects of all types (e.g.: construction of aircraft, development of weapons systems). Projects of all types typically experience additional costs, delays and quality problems also. Over several years Cooper and Mullen analyzed some major projects in different industries [11]. They reported that commercial projects are more expensive by about 140 % than planned and lasted longer about 190 % as originally scheduled. For military projects, his analysis reported that there were even 310 % additional costs and 460 % delay. Generally speaking, time delays, extra costs and quality problems, especially in connection with advanced technology are significant problems in the long-term planning and the design of a long-term project. Associated with these project-related problems, especially the regional economic situation and their ability to defend are affected dramatically.

In [33] Sterman provided a very good example of the successful use of system dynamics in a large defense project of the US Navy. In this particular case the firm of Ingalls Shipbuilding Pascagoula should build 30 newly developed destroyers for the US Navy in 1969. Mainly due to the fact that the US Navy caused Ingalls various problems, especially with the added cost of the project, they started with the help of system dynamics, to analyze the effects of time delays and the additional costs and to argue correctly about the extra costs to the US Navy. Especially the requirements of the US Navy rebuilding even more modern and effective weapons systems on the destroyers caused extreme costs for Ingalls.

Pugh-Roberts Associates of Cambridge developed a particular model, which included all phases of the project, simulated from the contract creation until the delivery of the ships, even with a forecast of five years. The main result was a system dynamics model with thousands of functions, which needed the latest computer technology of that time to complete. But it began as a much smaller model, which included the most important feedback effects of project delays and cost overruns. Of particular note at this point is the fact that at that time, the modeling team worked closely with all decision makers from various levels of management of the firm Ingalls together and created the first modeling designs [33].

Finding mistakes in the project and especially the extra work for the correction of errors, in both civil and military projects, can cause delays up to nine months. At this point it may be mentioned that changes or adjustments in the project by the customer do not have the same effect as the just mentioned detection and correction of errors in the project.

In general it can be said that the true value lies in the proactive use of system dynamics models. Additional costs and delays can be detected earlier. System Dynamics should be regarded as an additional method for decision support in project management to the existing, traditional project management methods. Especially when handling *complex project dynamics*, based on causal relationships, feedback loops, time delays and non-linearity System Dynamics can regarded as a potential method [32].

4.5.4 Portfolio Management – Example Energy Portfolio in Germany: Risk Management and Performance Optimization

When talking about energy portfolio, the term energy portfolio can have different meanings. On the one hand energy portfolio can stand for a combination of energy sources used for electricity generation and on the other hand energy portfolio can also mean a combination of either private or state energy investment assets. For this chapter only the first explanation of portfolio is relevant. Nevertheless, one of the core advantages of an energy portfolio concept is the following fact. It gives an opportunity to evaluate energy sources and technologies not separately but as a combination or collection of diversified asset. Originally a financial instrument, energy portfolio concept deals with risks and costs of energy supply. In the authors' point of view energy portfolio includes mainly the investment decision problem. This problem has to be further evaluated to manage risk and to maximize the performance of the energy portfolio concept.

There exist few basic approaches that aim to optimize energy portfolio of a certain country. Before speaking about energy portfolio concepts, the one of the main approaches has to be explained in details which is based on H. Markowitz's Modern Portfolio Theory [22]. One of the core issues of Markovitz's modern portfolio theory is the way to calculate cost and risk by diversifying them for achieving an efficient portfolio. Markovitz general idea for defining the optimal portfolio concepts is not only to include the possible profit, he also includes possible risk. Nevertheless the Mean-Variance Portfolio based approach has therefore been criticized for being concentrated on production costs of electricity-generation technologies. Although not production costs but rather expected risks and returns usually serve as a basis for private investment decisions [23]. Especially in the modern energy economy in

Germany this crucial fact can change the amount of energy investment assets and furthermore every portfolio concept. Nevertheless this approach gives an opportunity to evaluate different portfolio concepts of energy sources used for electricity generation in a certain country (see, e.g., [5]). In many cases risk in energy portfolios is mostly associated with the volatility of fossil fuels prices. Therefore the already mentioned diversification is achieved by adding increased share of renewable energy. Generally speaking, Germany will increase the share of renewable energy sources in the energy portfolio dramatically in the next years. Nevertheless Germany has to invest besides renewable energy sources strongly in all kinds of fossil energy sources to stabilize the energy system while phasing out the nuclear power production. Which means that not only Germany's energy portfolio will be more diversified in the year 2025. Although some energy scenarios conclude that photovoltaic will remain uncompetitive until 2030, photovoltaic can be still regarded as a relevant policy option for Germany's energy portfolio in the year 2025. Especially the rapid photovoltaic market growth generates cost reductions in the near future. In addition, photovoltaic can help to limit sudden energy price shocks. Furthermore, photovoltaic and wind energy reduce risk from fossil-fuel dependence (see, e.g., [1]). Similar to Germany, China has also started to adapt their actual energy portfolio concept and is willing to diversify the energy portfolio for a more efficient energy future [40].

4.6 Outlook and Perspectives: IT-Based Decision Support and Critical Infrastructures

Future society depends decisively on the availability of infrastructures such as energy, telecommunication, transportation, banking and finance, health care and governmental and public administration. Even selective disruption of one of these infrastructures may result in disruptions of governmental, industrial or public functions. Vulnerability of infrastructures therefore offers spectacular leverage for natural disasters as well as criminal actions. Threats and risks are part of the technological, economical, and societal development. Increasing complexity of our critical infrastructures exacerbates consequences of natural and/or man-made disasters.

Not only primary effects but also cascading effects as a result of increasing dependencies and interdependencies of our technological and societal systems demand intelligent simulation and optimization techniques in the area of IT-based decision support and computer-based information systems for a comprehensive safety and security management. At the end of this contribution we might mention that business intelligence has to consider also this new *external* dimension.

Therefore, one key element to estimate, analyze and simulate these special aspects within complex supply networks is *a new kind of business intelligence*: Innovative methods like computational intelligence, evolutionary algorithms, system dynamics and data farming should be combined within modern heuristics to master such complex networks via modern soft computing approaches.

This contribution summarizes some of these actual and future decision support approaches in the area of general IT-based decision support to design, process and manage complex systems.

4.7 IRIS Intelligent Reachback Information System – Smart Control Towers

In order to analyze such complex adaptive systems in the future agent-based modeling and simulation might be appropriate. Agent-based modeling and simulation as part of innovative business intelligence methods are an approach for modeling real world systems that are of complex and adaptive nature, such as an adaptive supply chain network. They enable to design each single actor of a supply chain network individually, based on their own decision rules. Moreover, it allows simulating the aggregate behavior of these heterogeneous organizations. At this way, emergent, non-linear behavior can be captured. To adapt as flexible as possible to *unexpected changes*, information along a supply chain network have to be visible. Yet, achieving visibility in a supply chain network still remains a problem. A new approach to overcome this difficulty represents the concept of a supply chain control tower which should be embedded in the global reachback concept as part of a comprehensive business intelligent approach in the future via a special service-orientated approach. This is the center of the research project IRIS (Intelligent Reachback Information System) at COMTESSA where business intelligence is understood as flexible IT-based decision support which is based on intelligent services concerning design, processing and management of an holistic business strategy.

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