Chapter 2
Intelligent Decision Support Systems

Abstract This chapter presents the latest IDSSs, such as text analytics and mining based DSSs; ambient intelligence and the internet of things-based DSSs; biometrics-based DSSs; recommender, advisory and expert systems; data mining, data analytics, neural networks, remote sensing and their integration with decision support systems and other IDSSs. These other IDSSs include GA-based DSS; fuzzy sets DSS; rough sets-based DSS; intelligent agent-assisted DSS; process mining integration to decision support, adaptive DSS; computer vision based DSS; sensory DSS and robotic DSS. In addition to acquainting these IDSSs, author introduce practical examples where they have been effectively applied.

2.1 Recommender, Advisory and Expert Systems and Their Integration with Decision Support Systems

The two terms—recommender systems and advisory systems—are very often used as synonyms in literature. These along with expert systems and their interconnectedness with decision making are described next. The recommender system (Wang and Wu 2009; Chen et al. 2011; Lee et al. 2007), advisory system (Halim et al. 2014; Lee et al. 2008; Hejlesen et al. 1997) and expert system (Dagnino et al. 2013; Zagonari and Rossi 2013; Chi et al. 2008) are integrated with decision support systems (DSSs). Several such examples are provided at the end of the chapter's section.

Recommender Systems are software tools and techniques providing suggestions for items to be of use to a user. The suggestions provided are aimed at supporting their users in various decision-making processes, such as what items to buy, what music to listen, or what news to read. Recommender systems have proven to be valuable means for online users to cope with the information overload. Development of recommender systems is a multi-disciplinary effort which involves experts from various fields such as Artificial intelligence, Human Computer Interaction, Information Technology, Data Mining, Statistics, Adaptive User Interfaces, Decision Support Systems, Marketing, or Consumer Behavior (Ricci et al. 2011).

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A variety of techniques have been proposed as the basis for recommender systems (Burke 2002, 2007; Ricci et al. 2011):

- Collaborative: The system generates recommendations using only information about rating profiles for different users. Collaborative systems locate peer users with a rating history similar to the current user and generate recommendations using this neighborhood.
- Content-based: The system generates recommendations from two sources—the features associated with products and the ratings that a user has given them.
- Demographic: A demographic recommender provides recommendations based on a demographic profile of the user.
- Knowledge-based: A knowledge-based recommender suggests products based on inferences about a user's needs and preferences.
- Community-based: This type of system recommends items based on the preferences of the users friends. This technique follows the epigram, "Tell me who your friends are, and I will tell you who you are".
- Hybrid recommender systems: These RSs are based on the combination of the above mentioned techniques.

Each of these techniques has known shortcomings, such as the well known cold-start problem for collaborative and content-based systems (what to do with new users with few ratings) and the knowledge engineering bottleneck in knowledge-based approaches. A hybrid recommender system is one that combines multiple techniques together to achieve some synergy between them. For example, a collaborative system and a knowledge-based system might be combined so that the knowledge-based component can compensate for the cold-start problem, providing recommendations to new users whose profiles are too small to give the collaborative technique any traction, and the collaborative component can work its statistical magic by finding peer users who share unexpected niches in the preference space that no knowledge engineer could have predicted (Burke 2007).

In general, there are recommendation techniques that are knowledge poor, i.e., they use very simple and basic data, such as user ratings/evaluations for items. Other techniques are much more knowledge dependent, e.g., using ontological descriptions of the users or the items, or constraints, or social relations and activities of the users. In any case, as a general classification, data used by RSs refers to three kinds of objects: items, users, and transactions, i.e., relations between users and items (Ricci et al. 2011).

Some DSSs may recommend that a particular alternative be picked and explain the rationale underlying that advice (Holsapple 2008). Knowledge-driven DSSs can suggest or recommend actions to managers. These DSSs are person-computer systems with specialized problem-solving expertise (Power 2012a). At the information search stage, intelligent search approaches and intelligent DSSs can sift through the massive amount of information available on the Web to make recommendations that match a customer's taste, personality, budget, previous choice patterns, or choices made by the customer's cohorts (those who share similar profiles, behaviors, and life styles) (Turban et al. 2007).

Since recommendations are usually personalized, different users or user groups receive diverse suggestions. In addition there are also non-personalized recommendations. These are much simpler to generate and are normally featured in magazines or newspapers. Typical examples include the top ten selections of books, CDs etc. While they may be useful and effective in certain situations, these types of non-personalized recommendations are not typically addressed by RS research. In their simplest form, personalized recommendations are offered as ranked lists of items. In performing this ranking, RSs try to predict what the most suitable products or services are, based on the user's preferences and constraints. In order to complete such a computational task, RSs collect from users their preferences, which are either explicitly expressed, e.g., as ratings for products, or are inferred by interpreting user actions. For instance, a RS may consider the navigation to a particular product page as an implicit sign of preference for the items shown on that page (Ricci et al. 2011).

Advisory systems provide the advices and assist for solving problems that are normally solved by human experts. They can be classified as a type of expert systems (ElAlfi and ElAlami 2009). Both advisory systems and expert systems provide expertise to support decision making in a myriad of domains. Expert systems are used to solve problems in well defined, narrowly focused problem domains, whereas advisory systems are designed to support decision making in more unstructured situations which have no single correct answer (Beemer and Gregg 2008).

Both advisory systems and expert systems are problem-solving packages that mimic a human expert in a special area. These systems are constructed by eliciting knowledge from human experts and coding it into a form that can be used by a computer in the evaluation of alternative solutions to problems within that domain of expertise. Advisory systems do not make decisions but rather help guide the decision maker in the decision-making process, while leaving the final decision-making authority up to the human user (Turban and Aronson 2001).

Advisory systems do not make decisions but rather help guide the decision maker in the decision-making process, while leaving the final decision-making authority up to the human user. The human decision maker works in collaboration with the advisory system to identify problems that need to be addressed and to iteratively evaluative the possible solutions to unstructured decisions. Advisory systems help to synthesize knowledge and expertise related to a specific problem situation for the user; however, the ultimate decision-making power and responsibility lies with the user—not the system (Beemer and Gregg 2008).

Advisory systems are designed to support decision making in more unstructured situations, which have no single correct answer. In unstructured situations cooperative advisory systems that provide reasonable answers to a wide range of problems are more valuable and desirable than expert systems that produce correct answers to a very limited number of questions (Gregg and Walczak 2006).

Beemer and Gregg (2008) distinguish between advisory systems which utilize the case-based reasoning methodology and traditional expert systems that use rule-based reasoning. Case-based reasoning is a knowledge-based methodology which allows a problem to be solved based on past experiences (Aamodt and Plaza 1994). Case-based reasoning seeks cases similar to the current one and analyses which decision or classification was taken in order to reuse it in the present solution (Pla et al. 2013). CBR Systems solve problems by using knowledge gained from solving similar problem in the past. Major activities of such systems include retrieval relevant previous cases, adapting and combining them to solve new problems, and recording failures do that they can be avoided in the future. Applications of CRB techniques include story understanding, explanations-based reasoning, adaptive planning, learning and architectural design (Paek et al. 1996). Case-based reasoning is one of the emerging paradigms for designing intelligent systems. It shows significant promise for improving the effectiveness of complex and unstructured decision making. It solves new problems by adopting previously successful solutions to analogous problems (Chang et al. 2006).

In response to the organizational need of intelligent decision support, expert systems were developed by coupling artificial intelligence (AI) and knowledge management techniques. Expert systems are designed to encapsulate the knowledge of experts and to apply it in evaluating and determining solutions to well-structured problems. Unlike expert systems, the suggestions made by advisory systems do not always represent the final answer to the problem. Instead, they represent advice used by the decision maker as a part of the iterative problem solving process (Beemer and Gregg 2008). Beemer and Gregg (2008) highlight the major differences between advisory and expert systems such as the decisions they are each designed for (unstructured versus structured), the AI methodologies that each uses (case-based versus rule-based), the role they each play in the decision-making process (decision support versus decision maker).

Further several examples are provided regarding the integration of the recommender system (Wang and Wu 2009), advisory system (Lee et al. 2008; Hejlesen et al. 1997) and expert system (Dagnino et al. 2013) with decision support systems.

Wang and Wu (2009) developed a recommender system by focusing on the online decision support module with respect to customers' characteristics and supplier's profits. For effective decision support, a mathematical model is developed so that the right product can be recommended to the right person with the best profit for the company.

The design of instrumentation and control (I&C) systems for nuclear power plants (NPPs) is rapidly moving towards fully digital I&C systems and is trending towards the introduction of modern computer techniques into the design of advanced main control rooms (MCRs) of NPPs. In the design of advanced MCRs, human–machine interfaces have improved and various types of decision support systems have been developed. It is important to design highly reliable decision support systems in order to adapt them in actual NPPs. In addition, to evaluate decision support systems in order to validate their efficiency is as important as to design highly reliable decision support systems. In this research, an operation advisory system based on the human cognitive process is evaluated in order to estimate its effect. The Bayesian belief network model is used in the evaluation of the target system, and a model is constructed based on human reliability analysis event trees. In the evaluation results, a target system based on the operator's cognitive process showed better performance compared to independent decision support systems (Lee et al. 2008).

Hejlesen et al. (1997) give a description of the Diabetes Advisory System (DIAS), and the evaluation results obtained so far. DIAS is a decision support system for the management of insulin dependent diabetes. The core of the system is a compartment model of the human carbohydrate metabolism implemented as a causal probabilistic network (CPN or Bayesian network), which gives it the ability to handle the uncertainty, for example, in blood glucose measurements or physiological variations in glucose metabolism. The evaluation results suggest that, at least in our hands, DIAS can generate advice that is safe and of a quality that is at least comparable to what is available from experienced clinicians (Hejlesen et al. 1997).

With the aim of supporting decision makers to manage contamination in freshwater environments, an innovative expert decision support system (EDSS) was developed. The EDSS was applied in a sediment quality assessment along the Bormida River (NW, Italy) which has been heavily contaminated by an upstream industrial site for more than a century. Sampling sites were classified by means of comparing chemical concentrations with effect-based target values (threshold and probable effect concentrations). The level of each contaminant and the combined toxic pressure were used to rank sites into three categories: (i) uncontaminated (8 sites), (ii) mildly contaminated (4) and (iii) heavily contaminated (19). Finally, potential human risk was assessed in selected stations (11 sites) by integrating genotoxicity biomarkers (GTI index falling in the range 0.00–0.53). General conclusions drawn from the EDSS data include: (i) in sites classified as heavily contaminated, only a few exhibited some significant, yet limited, effects on biodiversity; (ii) restrictions in re-using sediments from heavily contaminated sites found little support in ecotoxicological data; (iii) in the majority of the sites classified as mildly contaminated, tested organisms exhibited low response levels and (iv) preliminary results on genotoxicity biomarkers indicate possible negative consequences for humans if exposed to river sediments from target areas (Dagnino et al. 2013).

2.2 Text Analytics and Mining Based DSSs

A brief review of decision support via text analytics and mining definitions and technologies appears in the beginning of this chapter. Specific instances of applying text analytics and mining in IDSS will be provided later.

The types of statements that are emphasized by many scientists and practitioners in their discussions on the interrelationship between text mining and text analytics are akin to the following. "The application of text mining techniques to solve business problems is called text analytics." "Text mining, which is sometimes referred to text analytics—" "Text analytics are also known as text mining." "Text mining is roughly equivalent to text analytics" "Text Analytics is also known as Text Mining" "Text mining, also referred to as text data mining, roughly equivalent to text analytics—" "The application of text mining techniques to solve business problems is called text analytics."

Rao and Dey (2011) hold the opinion that text mining is an interdisciplinary field that brings together concepts from statistics, machine learning, information retrieval, data mining, linguistics and natural language processing. In many ways text mining is similar to data mining, and indeed regarded by some as an extension of the same. The main point of departure from the parent discipline of data mining is in the type of data that needs to be analyzed. Whereas data mining deals with mostly numeric structured data, text, the theme of text mining, is regarded as "unstructured" data. Though the task of text mining based DSS would seem to be more challenging than that of mining of structured data, the existence of vast amounts of information in electronically available text has led to intense research in text mining techniques, and many of the challenges have been overcome (Rao and Dey 2011).

With an exponential growth in the amount of unstructured data, text mining is becoming a part of mainstream decision support technology rather than a luxury. As text-mining tools mature, they become better integrated in existing decision support processes and systems. The acceptance of text mining is growing at an accelerating pace. In combination with sound structured data analysis and reporting techniques, text mining becomes a strong competitive advantage for early adopters of this new decision support technology (Froelich and Ananyan 2008).

Traditional literature analyses are often time and resource intensive. Text analytics overcomes these challenges by applying automated means to extract and discover knowledge in unstructured data sources. Unquestionably, text mining is of significant value to researchers (Delen and Crossland 2008).

Text analytics is a promising method for literature mining. It leverages existing IS tools and databases to search, explore, and make sense of large complex sets of structured and unstructured information (Basole et al. 2013). Basole et al. (2013) study illustrate the applicability of text analytics to a specific topic domain in the organizational and management sciences, but can be easily extended to other topics and fields.

In Feldman and Sanger (2007) opinion, text mining includes several disciplines such as, kaip natural language processing, information retrieval, information extraction, data mining, and computational linguistics. Text mining is based on a combination of technologies from information retrieval, information extraction, natural language processing, and statistics (Froelich and Ananyan 2008).

Text mining can be broadly defined as a knowledge-intensive process in which a user interacts with a document collection over time by using a suite of analysis tools. In a manner analogous to data mining, text mining seeks to extract useful information from data sources through the identification and exploration of interesting patterns. In the case of text mining, however, the data sources are document collections, and interesting patterns are found not among formalized database records but in the unstructured textual data in the documents in these collections (Feldman and Sanger 2007).

Text-mining systems are comprised of databases, linguistic parsing toolkits, dictionaries of terms and relations such as WordNet or MeSH, and a variety of rule based or probabilistic algorithms. These systems are semi-automatic, involving the application of both machine learning techniques and manual configuration of dictionaries such as lists of words to exclude, names of geographical locations, and syntactic rules. Text processing typically begins with tokenization, where words are extracted and stored in a structured format. In the next stage, tools augment information about the words, such as whether a word is a noun or a verb, or what does the word sound like, or what is the word's root form. With this information, tools focus on looking for entities such as names of people, organizations, dates, and locations. Systems also focus on looking at phrases and sequences of words, or how words are associated with one another based on the statistical analysis of how often words occur within a certain proximity of each other. Together these pieces of information represent key features of text that are used as input to classification systems which assign documents into predefined categories, or clustering systems which group together similar documents. The extracted information is stored so that it can be queried or used in a report or deployed into an operational environment such as a spam filter or a search engine or a stock trading application (Froelich and Ananyan 2008).

Because data mining assumes that data have already been stored in a structured format, much of its preprocessing focus falls on two critical tasks: Scrubbing and normalizing data and creating extensive numbers of table joins. In contrast, for text mining systems, preprocessing operations center on the identification and extraction of representative features for natural language documents. These preprocessing operations are responsible for transforming unstructured data stored in document collections into a more explicitly structured intermediate format, which is a concern that is not relevant for most data mining systems (Feldman and Sanger 2007).

Text mining can help an organization derive potentially valuable business insights from text-based content such as word documents, email and postings on social media streams like Facebook, Twitter and LinkedIn. Mining unstructured data with natural language processing, statistical modeling and machine learning techniques can be challenging, however, because natural language text is often inconsistent. It contains ambiguities caused by inconsistent syntax and semantics, including slang, language specific to vertical industries and age groups, double entendres and sarcasm (Text Mining 2014).

Moreover, because of the centrality of natural language text to its mission, text mining also draws on advances made in other computer science disciplines concerned with the handling of natural language. Perhaps most notably, text mining exploits techniques and methodologies from the areas of information retrieval, information extraction, and corpus-based computational linguistics (Feldman and Sanger 2007).

Text analytics software can help by transposing words and phrases in unstructured data into numerical values which can then be linked with structured data in a database and analyzed with traditional data mining techniques. With an iterative approach, an organization can successfully use text analytics to gain insight into content-specific values such as sentiment, emotion, intensity and relevance. Because text analytics technology is still considered to be an emerging technology, however, results and depth of analysis can vary wildly from vendor to vendor (Text mining 2014).

Froelich and Ananyan (2008) deliberate various decision support via text mining technologies (tokenization, morphological analysis, quality improvement using string similarity, part of speech tagging, collocation analysis, named entity recognition, word association, summarization and concept analysis, classification, clustering, dictionaries). Several decision support via text mining technologies are presented next in-brief (Froelich and Ananyan 2008):

- Word Association. Word association involves the identification and representation of a relationship between any two words or phrases or entities. This type of association in product returns is a keymetric in identifying what influences customer purchase decisions. Analyzing word association can lead to a better understanding of key relationships in text.
- Summarization and Concept Analysis. Document summarization refers to the automated delivery of a concise representation of the contents of a document. Keyword extraction, or concept extraction, is the process of finding the best keywords or phrases which represent a set of documents. Keywords are typically conflated morphologically (inflected forms are merged) and ranked according to some measure of importance such as statistical significance, frequency, or term document frequency, or by the document count. The list of words is filtered by comparing words against a dictionary of words to ignore. A thesaurus may be supplied to provide synonyms that can be used to re-weight terms based on the term frequency and the net frequency of all the term's synonyms. Keyword extraction is one of the final outputs found in most text-mining applications. Along with keywords, summaries can be provided with search results to facilitate better and faster information retrieval. This task is dependent upon accurate weighting of concepts within the text.
- Classification. Document classification is the training of a classification model to assign documents to known categories. The first step is feature extraction, which is equivalent to finding the words or phrases that best represent a document, analogous to tokenization and summarization. Next, depending on the algorithm, specific keywords, frequencies, and other information are used to split the data or group the data according to mathematical or logical rules. The categories can be hierarchical to show a higher level of organization in the topics.
- Clustering. Text clustering places documents into groups based on a measure of similarity. Common algorithms include nearest neighbor and expectation maximization. Divisive clustering algorithms work from the top down, splitting a cluster into smaller clusters. Agglomerative clustering algorithms work from the bottom up, grouping together clusters into hierarchies. This process is similar to building a dendrogram, a tree-like graph of a hierarchy. Unlike

text classification, clustering algorithms are not aware of the desired set of categories. The output of the clustering can be used, like keyword extraction or summarization, to obtain the gist of a set of documents at a glance.

- Semantic Analysis. Semantic analysis is the culmination of basic linguistic and statistical processing techniques to perform a deeper analysis of text. Application domains such as competitive intelligence rely on the ability to identify names of people or places in documents in order to identify correlations and trends.

Various scientific examinations are being performed in the area of decision support via text analytics and mining, and decision support systems are being developed (Chan and Franklin 2011; Abrahams et al. 2012; Gerber 2014; He 2013; Khare and Chougule 2012; Rao and Dey 2011; Rexer et al. 2012; Toivonen et al. 2006; León et al. 2011; Froelich and Ananyan 2008; Cao et al. 2011; Li and Wu 2010; Jiao et al. 2007; Holton 2009). The examinations first mentioned are described in brief henceforth.

Although most quantitative financial data are analyzed using traditional statistical, artificial intelligence or data mining techniques, the abundance of online electronic financial news articles has opened up new possibilities for intelligent systems that can extract and organize relevant knowledge automatically in a usable format. Most information extraction systems require a hand-built dictionary of templates and thus need continual modification to accommodate new patterns that are observed in the text (Chan and Franklin 2011). Chan and Franklin (2011) propose a novel, text-based decision support system (DSS) that (i) extracts event sequences from shallow text patterns and (ii) predicts the likelihood of the occurrence of events using a classifier-based inference engine.

Abrahams et al. (2012) employ text mining on a popular social medium used by vehicle enthusiasts: online discussion forums. Abrahams et al. (2012) find that sentiment analysis, a conventional technique for consumer complaint detection, is insufficient for finding, categorizing, and prioritizing vehicle defects discussed in online forums and describe and evaluate a new process and decision support system for automotive defect identification and prioritization. The Abrahams et al. (2012) findings provide managerial insights into how social media analytics can improve automotive quality management.

Twitter is used extensively in the United States as well as globally, creating many opportunities to augment decision support systems with Twitter-driven predictive analytics. Twitter is an ideal data source for decision support: its users, who number in the millions, publicly discuss events, emotions, and innumerable other topics; its content is authored and distributed in real time at no charge; and individual messages (also known as tweets) are often tagged with precise spatial and temporal coordinates (Gerber 2014). Gerber (2014) presents research investigating the use of spatiotemporally tagged tweets for crime prediction. Gerber (2014) uses Twitter-specific linguistic analysis and statistical topic modeling to automatically identify discussion topics across a major city in the United States. Gerber (2014) then incorporates these topics into a crime prediction model and show that, for 19 of the 25 crime types studied, the addition of Twitter data improves crime prediction performance versus a standard approach based on kernel density estimation. Gerber (2014) identifies a number of performance bottlenecks that could impact the use of Twitter in an actual decision support system (Gerber 2014).

After text collection is ready, different text mining algorithms such as text categorization, text clustering, concept/entity extraction, production of granular taxonomies, sentiment analysis, document summarization, entity relation modelling can be applied to identify key terms, concepts, categories, their frequencies of occurrence and case clusters from the text collection. During this step, CBR developers can use one or more specific text analytics and mining tools such as SPSS Clementine, NVivo 9 and Leximancer to facilitate the text analysis and mining process (He 2013).

Khare and Chougule (2012) present a decision support system 'Domain Aware Text & Association Mining (DATAM)' which has been developed to improve after-sales service and repairs for the automotive domain. A novel approach that compares textual and non-textual data for anomaly detection is proposed. It combines association and ontology based text mining. Association mining has been employed to identify the repairs performed in the field for a given symptom, whereas, text mining is used to infer repairs from the textual instructions mentioned in service documents for the same symptom. These in turn are compared and contrasted to identify the anomalous cases. The developed approach has been applied to automotive field data. Using the top 20 most frequent symptoms, observed in a mid-sized sedan built and sold in North America, it is demonstrated that DATAM can identify all the anomalous symptom—repair code combinations (with a false positive rate of 0.04). This knowledge, in the form of anomalies, can subsequently be used to improve the service/trouble-shooting procedure and identify technician training needs (Khare and Chougule 2012).

Rao and Dey (2011) developed text mining based DSS, which integrate unstructured textual data with predictive analytics to provide an environment for arriving at well-informed citizen-centric decisions in the context of e-governance.

In general, it is probably true that the majority of data analysis activities performed in support of solving some business or other problem involve simple tabulation and cross-tabulation of quantities. This is also true for text mining (or "text analytics"). Computing simple frequency tables or averages of terms can provide very useful information about the nature of the documents, the general sentiments or topics discussed in the documents and the trends or relationships with other variables. Simple text mining operations involve simple indexing and tabulation operations (Rexer et al. 2012).

The problem of the amount of available information has changed from scarcity to abundance. It is also common that a great amount of information appears both in numerical and symbolic form. Better tools for utilizing both quantitative and qualitative information are strongly needed (Toivonen et al. 2006). To help meet that need Toivonen et al. (2006) have developed decision support system for effective value creation management in a company and applied two methods, the self-organizing map (SOM) and text mining and focused them on the logistical decision making of companies.

In this research, an integrated expert system (IES) for the analysis and classification of all the available useful information of the customer is presented. Customer classification identifies the presence of non-technical losses (NTLs) and the problem type. This IES include several modules: text mining module for analysis of inspector commentaries and extraction of additional information on the customer, data mining module to draw up the rules that determine the customer estimate consumption and the Rule Based Expert System module to analyze each customer using the results of the text and data mining modules. IES is used as a Decision support system (DSS), as it contains another module which provides a report with additional information about the customer and a summarized result that the inspectors can use to reach a decision (León et al. 2011).

Froelich and Ananyan (2008) accented that not only companies, governments and individuals are able to make use of decision support via text mining competitive advantage but numerous industries can benefit from text mining including insurance, finance, consumer products, manufacturing, healthcare, life sciences, hospitality, retail, transportation, information technology, government, and education as well. Froelich and Ananyan (2008) also provide several decision support via text mining examples as follows:

- Spam Filtering. Traditional spam filters rely on probability to classify the e-mail as spam based on the presence of keywords. A statistical algorithm such as Naïve Bayes, Support Vector Machines or a decision tree is used to learn how specific keywords cause an e-mail to belong to the spam category.
- Market Research and Survey Analysis. Text mining can assist market researchers through analysis of open-ended survey responses, news articles, press releases, blogs, call center notes, and e-mails. Information about companies, products, major concerns, consumer expectation and other insight can be generated.
- Patent Research. Patents can be classified into a hierarchy of business terminology to assist in finding patents of interest. An analyst could use the set of online patent documents to develop a trend graph of the rise and fall of certain keywords or concepts over the decades to show overall trends in technology. A corporation looking to invest in a specific technology could assess whether prior patents exist. Similarly, a corporation could use its own technology patents as a guide and use text mining to identify similar patents based on frequencies of keywords to determine if infringement has occurred. A business could setup email alerts that monitor all new patent applications for the presence of keywords.
- Competitive Intelligence. Competitive intelligence applications use text mining to extract facts from web pages, industry journals, and newsgroups. Companies can compare themselves against competitors by looking at the density of specific marketing keywords to assess which company is likely to grab prospects from search engines. Companies can monitor competitors to avoid being late in introducing a new product or technology. Other results that can be found through text mining include identifying the direction of innovators, licensing opportunities, patent infringements, and trending and forecasting specific market ideas. Pricing information can be collated to provide a detailed picture of the market and assist in determining the proper cost structure.

- Brand Monitoring. Filters can be configured to monitor occurrences of specific brand keywords. Blogs and press releases can be classified as containing positive or negative comments about a brand. Typographical analysis of the domain name can identify similar domain names to monitor. Information extraction tools can highlight names of brand perpetrators in text and flag these for follow up.
- Job Search. Employers are receiving larger amounts of less specific applications, which have increased the time it takes to review the applications. Job seekers have a larger number of job descriptions to peruse. Both parties can benefit by incorporating text-mining software. Employers can use filters based on keywords to highlight specific applications or discard others. Employers can use the Internet as an additional source of information about an applicant and fill in missing data or look for associations between applications and whether those applicants have published desirable content on the web.

2.3 Data Mining as an Important Component of Intelligent Decision Support Systems

Data mining is applied often enough in fields such as decision support system, analytics, predictive analytics, data analysis, data warehouse, business intelligence, exploratory data analysis and web mining. The beginning of this section will present a short analysis on how data mining can enlarge the opportunities for intelligent decision support systems and their interdependencies as well as the technologies being used. This section will close by providing practical examples for the use of data mining in intelligent decision support systems and by describing what sorts of additional data mining opportunities could be applied in the future while developing IDSS.

Decision support systems (DSS) are a specific class of computerized information system that support business and organizational decision making activities. On the other hand, data mining extends the possibilities for decision support by discovering patterns and relationships hidden in the data and therefore enabling an inductive approach to data analysis (Khademolqorani and Hamadani 2013).

Data mining processes data from different perspectives into useful knowledge, and becomes an important component in designing intelligent decision support systems (IDSS) (Yang et al. 2012).

It has been estimated that the amount of stored information doubles every twenty months. Data mining is a term coined to describe the process of sifting through large databases for interesting patterns and relationships. Given the recent growth of the field, it is not surprising that a wide variety of data mining methods is now available to the researchers and practitioners. No one method is superior to others for all cases (Maimon and Rokach 2010).

Frameworks that bridge the gap between data mining analysis and predictions to actions and decisions in decision support are required to ensure better integration of the two methodologies (Khan et al. 2008). Khan et al. (2008) discuss the use of data mining technologies in the creation of DSS and allied systems for human use. One of the primary implementations of data mining technologies in interpreting business and scientific data is model-driven DSS. DSS can cater to multiple audiences as producers, suppliers, and customers share the same data and information through collaborative planning, forecasting, and replenishment processes (Khan et al. 2008).

Data mining is frequently applied to any form of large-scale data or information processing (collection, extraction, warehousing, analysis, and statistics) as well as any application of decision support system (Data mining 2014).

Data mining is the process of discovering valid, novel, and potentially useful patterns (i.e., knowledge nuggets) in very large data sets by use of a variety of advanced analytical techniques (Fayyad et al. 1996). If the data is textual in nature, then this discovery process is often called text mining (Demirkan and Delen 2013).

There are many methods of Data mining used for different purposes and goals. It is useful to distinguish between two main types of Data mining: verification-oriented (the system verifies the user's hypothesis) and discovery-oriented (the system finds new rules and patterns autonomously). Discovery methods are those that automatically identify patterns in the data. The discovery method branch consists of prediction methods versus description methods. Descriptive methods are oriented to data interpretation, which focuses on understanding (by visualization for example) the way the underlying data relates to its parts (Maimon and Rokach 2010).

The process of data mining converts information to knowledge by using tools from the disciplines of computational statistics, database technologies, machine learning, signal processing, nonlinear dynamics, process modeling, simulation, and allied disciplines. Data mining allows business problems to be analyzed from diverse perspectives, including dimensionality reduction, correlation and co-occurrence, clustering and classification, regression and forecasting, anomaly detection, and change analysis. The predictive insights generated from data mining can be further utilized through real-time analysis and decision sciences, as well as through human-driven analysis based on management by exceptions or objectives, to generate actionable knowledge. The tools that enable the transformation of raw data to actionable predictive insights are collectively referred to as decision support tools (Khan et al. 2008).

Some research in AI, focused on enabling systems to respond to novelty and uncertainty in more flexible ways has been successfully used in IDSS. For example, data mining in AI that searches for hidden patterns in a database has been used in a range of decision support applications. The data mining process involves identifying an appropriate data set to mine or sift through to identify relations and rules for IDSS. Data mining tools include techniques like case-based reasoning, clustering analysis, classification, association rule mining, and data visualization. Data mining increases the "intelligence" of DSS and becomes an important component in designing IDSS (Yang et al. 2012).

The process of knowledge discovery in databases (KDD) is consisting of nine steps (Maimon and Rokach 2010):

1. Developing an understanding of the application domain. The people who are in charge of a KDD project need to understand and define the goals of the end-user and the environment in which the knowledge discovery process will take place.
2. Selecting and creating a data set on which discovery will be performed. Having defined the goals, the data that will be used for the knowledge discovery should be determined. This includes finding out what data is available, obtaining additional necessary data, and then integrating all the data for the knowledge discovery into one data set, including the attributes that will be considered for the process.
3. Preprocessing and cleansing. In this stage, data reliability is enhanced. It includes data clearing, such as handling missing values and removal of noise or outliers.
4. Data transformation. In this stage, the generation of better data for the data mining is prepared and developed. Methods here include dimension reduction (such as feature selection and extraction, and record sampling), and attribute transformation (such as discretization of numerical attributes and functional transformation).
5. Choosing the appropriate Data mining task. We are now ready to decide on which type of Data mining to use, for example, classification, regression, or clustering. This mostly depends on the KDD goals, and also on the previous steps. There are two major goals in Data mining: prediction and description. Prediction is often referred to as supervised Data mining, while descriptive Data mining includes the unsupervised and visualization aspects of Data mining. Most data mining techniques are based on inductive learning, where a model is constructed explicitly or implicitly by generalizing from a sufficient number of training examples.
6. Choosing the Data mining algorithm. Having the strategy, we now decide on the tactics. This stage includes selecting the specific method to be used for searching patterns (including multiple inducers). For example, in considering precision versus understandability, the former is better with neural networks, while the latter is better with decision trees. Thus, this approach attempts to understand the conditions under which a Data mining algorithm is most appropriate. Each algorithm has parameters and tactics of learning (such as ten-fold cross-validation or another division for training and testing).
7. Employing the Data mining algorithm. Finally the implementation of the Data mining algorithm is reached. In this step we might need to employ the algorithm several times until a satisfied result is obtained, for instance by tuning the algorithm's control parameters, such as the minimum number of instances in a single leaf of a decision tree.
8. Evaluation. In this stage we evaluate and interpret the mined patterns (rules, reliability etc.), with respect to the goals defined in the first step.

9. Using the discovered knowledge. We are now ready to incorporate the knowledge into another system for further action. There are many challenges in this step, such as losing the "laboratory conditions" under which we have operated. For instance, the knowledge was discovered from a certain static snapshot (usually sample) of the data, but now the data becomes dynamic. Data structures may change (certain attributes become unavailable), and the data domain may be modified (such as, an attribute may have a value that was not assumed before).

Data mining is applied in various areas of human activity as IDSS is being developed. Brief descriptions of several of them follow.

The use of automated data mining techniques to support pre-established DSS tasks is one implementation of emerging technologies. The ability to merge information from various sources and blend different points of view to create one-number forecasts is a key first step towards enterprise-scale strategic, operational and tactical planning (Khan et al. 2008).

The objective of this research is to provide decision support to assembly line planners when they perform assembly time estimations. There is a lack of consistency in the assembly time analysis performed by planners. The decision support system that was developed in this research is based on mapping controlled language assembly work instructions to Methods-Time Measurement (MTM) tables. Automated analysis of historical work instructions and their related time study analysis were performed by employing knowledge discovery and data mining (KDD) algorithms through the Waikato Environment for Knowledge Analysis (WEKA) interface. As a result of this automated analysis, forty-six mapping rules were created that related work instructions to MTM tables and the data backbone for the decision support system that was created. Analyzing big historical data is crucial while creating decision support systems. KDD provides a sustainable method of analyzing big data (Renu et al. 2013).

Liu (2009) develops a decision support tool for liability authentications of two-vehicle crashes based on generated self-organizing feature maps (SOM) and data mining (DM) models. Factors critical to liability attributions commonly identified theoretically and practically were first selected. Both SOM and DM models were then generated for frontal, side, and rear collisions of two-vehicle crashes. Appropriateness of all generated models was evaluated and confirmed. Finally, a decision support tool was developed using active server pages. Although with small data size, the decision support system was considered capable of giving reasonably good liability attributions and references on given cases (Liu 2009).

El-Sappagh and El-Masri (2014) propose an open and distributed clinical decision support system architecture. This technical architecture takes advantage of Electronic Health Record (EHR), data mining techniques, clinical databases, domain expert knowledge bases, available technologies and standards to provide decision-making support for healthcare professionals. The architecture will work extremely well in distributed EHR environments in which each hospital has its own local EHR, and it satisfies the compatibility, interoperability and scalability objectives of an EHR. The system will also have a set of distributed knowledge bases. Each knowledge base will be specialized in a specific domain (i.e., heart disease), and the model achieves cooperation, integration and interoperability between these knowledge bases. Moreover, the model ensures that all knowledge bases are up-to-date by connecting data mining engines to each local knowledge base. These data mining engines continuously mine EHR databases to extract the most recent knowledge, to standardize it and to add it to the knowledge bases. This framework is expected to improve the quality of healthcare, reducing medical errors and guaranteeing the safety of patients by helping clinicians to make correct, accurate, knowledgeable and timely decisions (El-Sappagh and El-Masri 2014).

Kisilevich et al. (2013) present a GIS-based decision support system that can both, estimate objective hotel room rates using essential hotel and locational characteristics and predict temporal room rate prices. Information about objective hotel room rates allows for an objective comparison and provides the basis for a realistic computation of the contract's profitability. The temporal prediction of room rates can be used for monitoring past hotel room rates and for adjusting the price of the future contract. This research makes three major contributions (Kisilevich et al. 2013). First, Kisilevich et al. (2013) present a GIS-based decision support system, the first of its kind, for hotel brokers. Second, the DSS can be applied to virtually any part of the world, which makes it a very attractive business tool in real-life situations. Third, it integrates a widely used data mining framework that provides access to dozens of ready to run algorithms to be used by a domain expert and it offers the possibility of adding new algorithms once they are developed (Kisilevich et al. 2013).

Decision support systems (DSSs) perform complex computations to provide suggestions regarding decision-making and problem solving. Quite often, the DSS solutions are not fully accepted by users because DSSs work as a black box so that the users cannot fully understand where the results came from and how they were derived. Explanations of the generated DSSs solutions are expected to mitigate this situation. In this research, two machine-learning techniques, called rough set analysis (RSA) and dependency network analysis (DNA), are proposed for mining DSS solutions. The mining results are provided to the users as explanations for those solutions. Two parts of research results are described. First, a framework applying RSA and DNA for generating explanations for DSS solutions is presented. This framework is generic and applicable to many other DSSs. Second, as a proof-of-concept, the applications of RSA and DNA techniques are demonstrated through a case study of mining patterns from input-output pairs of ReleasePlanner™, a specific DSS for product release planning (Du and Ruhe 2014). Du and Ruhe (2014) evaluation indicates that the explanations generated by RSA and DNA improve the overall user acceptance of results provided by this specific DSS.

Data envelopment analysis (DEA) has proven to be a useful tool for assessing efficiency or productivity of organizations, which is of vital practical importance in managerial decision making. DEA provides a significant amount of information from which analysts and managers derive insights and guidelines to promote their existing performances. The main objective of this research is to develop a general decision support system (DSS) framework to analyze the results of basic DEA models. The research formally shows how the results of DEA models should be structured so that these solutions can be examined and interpreted by analysts through information visualization and data mining techniques effectively (Akçay et al. 2012).

Decision-making for the debris-flow management involves multiple decision-makers often with concerning geomorphological and hydraulic conditions. Spatial decision support systems can be developed to improve our understanding of the relations among the natural and socio-economic variables to the occurrence/non-occurrence samples of debris-flow. Accordingly, the goal of this study is to development a debris-flow decision support system to manage and monitor the debris-flows in Nan-Tou County, Taiwan. The present study, more specifically, combines a spatial decision support system with an advanced Data mining technique to investigate the debris-flow problem. In the first stage, the spatial decision support system integrates remote sensing, and aerial photos as three different resources to generate our spatial database. Each of the geomorphological and hydraulic attributes is obtained automatically through our spatial database. Then, a Data mining classifier (hybrid model of decision tree + support vector machine) will be used to analyze and resolve the classification of occurrence of debris-flow (Wan and Lei 2009).

Rupnik and Kukar (2007) introduce decision support system called Data Mining Decision Support System (DMDSS), which is based on data mining. DMDSS enables integration of data mining into decision processes by enabling repeated creation of data mining models. In DMDSS, data mining models are created by data mining experts and exploited by business users. DMDSS supports two roles: data mining expert and business user. Each of the roles has the access to the forms and their functionalities according to the production stage of the process model. DMDSS enables the use of the following data mining methods: classification, clustering and association rules. Depending on the nature of the area of analysis the DMDSS enables the use of one or more data mining methods within the area of analysis. DMDSS is a data mining based decision support system which supports decision processes based on the knowledge acquired from data mining models: rules, patterns and relationships. It is a passive DSS, because it supports decision processes through new knowledge acquired without producing explicit decision suggestions or solutions. The mission of DMDSS is to offer an easy-to-use tool which enables business users to exploit data mining models with only a basic level of understanding of the data mining concepts, which enables them to interpret the models correctly. The process model of DMDSS defines the roles of business user and data mining expert, where phases that demand expertise in data mining are performed by data mining expert and are hidden from business user. Business users only exploit data mining models, which are created by data mining expert (Rupnik and Kukar 2007).

Maimon and Rokach (2010) see several trends for future research and implementation, including (Maimon and Rokach 2010):

- Mining complex objects of arbitrary type—Expanding Data mining inference to include also data from pictures, voice, video, audio, etc. This will require adapting and developing new methods (for example, for comparing pictures using clustering and compression analysis).
- Temporal aspects—many data mining methods assume that discovered patterns are static. However, in practice patterns in the database evolve over time. This poses two important challenges. The first challenge is to detect when concept drift occurs. The second challenge is to keep the patterns up-to-date without inducing the patterns from scratch, etc.

2.4 Integration of Data Analytics and Decision Support Systems

Lately data analytics has been becoming more and more popular. However, data analytics are rarely used as composite parts of IDSS. This section contains a short description of the integration of data analytics and decision support systems.

Predictive analytics is the branch of data mining concerned with forecasting probabilities. The technique uses variables that can be measured to predict the future behavior of a person or other entity. Multiple predictors are combined into a predictive model. In predictive modeling, data is collected to create a statistical model, which is tweaked as additional data becomes available (Matlis 2006).

Kwon et al. (2014) define big data analytics as technologies (e.g., database and data mining tools) and techniques (e.g., analytical methods) that a company can employ to analyze large scale, complex data for various applications intended to augment firm performance in various dimensions.

In recent years, numerous machine learning techniques (Multilayer Perceptron, Neural networks, k-nearest neighbours, Radial basis functions, Geospatial predictive modelling, Support vector machines, Naïve Bayes), open source predictive analytic tools (KNIME, Orange, RapidMiner, Weka, R) and commercial predictive analytic tools (BIRT Analytics, IBM SPSS Statistics, IBM SPSS Modeler, KXEN Modeler, Pervasive, SAS, STATISTICA, TIBCO) have been used for predictive analytics.

Analytics refers to quantitative and statistical analysis of data. Analytic capabilities are important in both data-driven and model-driven DSS. Analysis using quantitative and statistical tools is the focus of ad hoc and routine special studies. Various sources identify three categories of analytics: (1) reporting, (2) prescriptive, and (3) predictive. Reporting summarizes data using descriptive statistics. Prescriptive analysis uses data to inform a recommendation for action. Prediction involves causal or correlational analysis. Analytics refers to a broad set of information systems and capabilities that are generally decision support applications (Power 2012a).

Analytics software encompasses three main technologies: (1) database management, (2) mathematical and statistical analysis and models, and (3) data visualization and display. Reporting analytics focuses on generating reports and visualizations from organizational data stores. That task is the main purpose of business intelligence (BI) software. In general, data-driven DSS and business intelligence are considered reporting or data analytic applications. Prescriptive analytics manipulate large data sets to make recommendations. Predictive analytics are based upon quantitative and statistical models and this category of analytics includes model-driven DSS. Analytics includes a broad spectrum of computer-based analyses used to support fact-based decisions (Power 2012a).

Analytics may be part of a data-driven or a model-driven DSS. Predictive analytics is about using models for predicting behavior or results. Predictive analytics can help managers make choices and develop competitive actions. Many banks use analytics and model-driven DSS when making credit and lending decisions. Model-driven DSS may assist in forecasting product demand, aid in employee scheduling, develop pro forma financial statements or assist in choosing plant or warehouse locations. Model-driven DSS are developed for various purposes using a variety of quantitative and statistical techniques. Model-driven decision support provides managers with models and analysis capabilities to use during the process of making a decision. The range and scope of model-driven DSS is very large (Power 2012b).

Two characteristics differentiate a model-driven DSS from the computer support used for a decision analytic: (1) a model in a model-driven DSS is made accessible to a non-technical specialist such as a manager through an easy to use interface, and (2) a specific DSS is intended for some repeated use in the same or a similar decision situation. The general types of quantitative models used in model-driven DSS include algebraic and differential equation models, various decision analysis tools including analytical hierarchy process, decision matrix and decision tree, multi-attribute and multi-criteria models, forecasting models, network and optimization models, Monte Carlo and discrete event simulation models, and quantitative behavioral models for multi-agent simulations (Power and Sharda 2007).

Data analytics are being developed in various areas of human activity. However, they are rarely integrated with decision support systems. Several of such rare examples are briefly described below.

Although the necessity of large-scale data analysis for product design is now being recognized broadly, only a few researchers have attempted to analyze large-scale data in the context of product and design analytics (Ma et al. 2014). Ma et al. (2014) propose Demand Trend Mining (DTM) as one of the analysis tools for large-scale data in order to capture the trend of demand as a function of design attributes.

Electronic Health Record (EHR) system contain large volumes of patient data that could be used for Comparative Effectiveness Research (CER), but the data contained in EHR system are typically accessible only in formats that are not conducive to rapid synthesis and interpretation of therapeutic outcomes. In the time-pressured clinical setting, clinicians faced with large amounts of patient data in formats that are not readily interpretable often feel ‘information overload’. Decision support tools that enable rapid access at the point of care to aggregate data on the most effective therapeutic outcomes derived from CER would greatly aid the clinical decision-making process and individualize patient care (Mane et al. 2012). Mane et al. (2012) highlight the role that visual analytics can play in CER-based clinical decision support. Mane et al. (2012) developed a 'VisualDecisionLinc' (VDL) tool prototype that uses visual analytics to provide summarized CER-derived data views to facilitate rapid interpretation of large amounts of data. Mane et al. (2012) highlight the flexibility that visual analytics offers to gain an overview of therapeutic options and outcomes and if needed, to instantly customize the evidence to the needs of the patient or clinician.

Souza (2014) describes the application of advanced analytics techniques to supply chain management. The applications are categorized in terms of descriptive, predictive, and prescriptive analytics and along the supply chain operations reference (SCOR) model domains plan, source, make, deliver, and return. Descriptive analytics applications center on the use of data from global positioning systems (GPSs), radio frequency identification (RFID) chips, and data-visualization tools to provide managers with real-time information regarding location and quantities of goods in the supply chain. Predictive analytics centers on demand forecasting at strategic, tactical, and operational levels, all of which drive the planning process in supply chains in terms of network design, capacity planning, production planning, and inventory management. Finally, prescriptive analytics focuses on the use of mathematical optimization and simulation techniques to provide decision-support tools built upon descriptive and predictive analytics models (Souza 2014).

MERRA Analytic Services (MERRA/AS) enables MapReduce analytics over NASA's Modern-Era Retrospective Analysis for Research and Applications (MERRA) data collection. The MERRA reanalysis integrates observational data with numerical models to produce a global temporally and spatially consistent synthesis of 26 key climate variables. It represents a type of data product that is of growing importance to scientists doing climate change research and a wide range of decision support applications. MERRA/AS brings together the following generative elements in a full, end-to-end demonstration of CAaaS capabilities: (1) high-performance, data proximal analytics, (2) scalable data management, (3) software appliance virtualization, (4) adaptive analytics, and (5) a domain-harmonized API (Schnase et al. 2014).

2.5 Artificial Neural Networks in Decision Support Systems and Biometrics

The special focus in this section is on the integration of decision support systems, neural networks and biometrics.

Artificial Neural Network (ANN) enables modeling complex nonlinear relations and providing decision support. ANN is inspired by the structure of biological neural networks, and it starts by assigning random weights to included variables and then adjusting these weights in a feed-forward, back-propagation style to minimize the difference between the actual and predicted outputs. The neurons in the hidden layer transfer the weighted input data to the output using nonlinear transfer function (Xu et al. 2013; Bishop 1995). Neural networks (NNs) are defined as massively parallel processors, which tend to preserve the experimental knowledge and enable their further use. They simulate the human brain with the intent to collect the empirical evidence during the learning process, and inter-neural connections (synapses) are used to store the knowledge (Hájek 2011; Haykin 1999).

Delen and Sharda (2008) introduce the concepts of neural networks and present an overview of the applications of neural networks in decision support systems (DSS). Neural networks can be viewed as supporting at least two types of DSS: data driven and model-driven. First, neural networks can be employed as data analysis tools for forecasting and prediction based on historical data in a data-driven DSS. Second, neural networks also can be viewed as a class of quantitative models to be used in a model-driven DSS (Delen and Sharda 2008). DSS employing a neural network are being developed in various areas of human activity (Sidiropoulos et al. 2012; Tsadiras et al. 2013; Arsene et al. 2012; Azadeh et al. 2012; Delen and Sharda 2008; Mendyk et al. 2013; Abpeykar and Ghatee 2014; Srinivasan et al. 2010). Next there is a short description of several DSS that were first mentioned as employing a neural network.

A new strategy is introduced by Sidiropoulos et al. (2012) for designing and developing of an efficient dynamic Decision Support System (DSS) for supporting rare cancers decision making. The proposed DSS operates on a Graphics Processing Unit (GPU) and it is capable of adjusting its design in real time based on user-defined clinical questions in contrast to standard CPU implementations that are limited by processing and memory constrains. The core of the proposed DSS was a Probabilistic Neural Network classifier and was evaluated on 140 rare brain cancer cases, regarding its ability to predict tumors' malignancy, using a panel of 20 morphological and textural features Generalization was estimated using an external tenfold cross-validation.

An Artificial Neural Network (ANN) based decision support system is developed by Tsadiras et al. (2013) to assist production line designers in making decisions concerning the Buffer Allocation Problem in reliable production lines. Arsene et al. (2012) present an efficient and effective decision support system (DSS) for operational monitoring and control of water distribution systems based on a three layer General Fuzzy Min–Max Neural Network (GFMMNN) and graph theory.

Developing decision support system can overcome the issues with personnel attributes and specifications. Personnel specifications have greatest impact on total efficiency. They can enhance total efficiency of critical personnel attributes (Azadeh et al. 2012). Azadeh et al. (2012) present an intelligent integrated decision support system for forecasting and optimization of complex personnel efficiency. DSS assesses the impact of personnel efficiency by data envelopment analysis (DEA), artificial neural network (ANN), rough set theory (RST), and K-Means clustering algorithm.

Quteishat et al. (2009) propose a neural network (NN)-based multi-agent classifier system (MACS) using the trust, negotiation, and communication (TNC) reasoning model. The main contribution of this work is that a novel trust measurement method, based on the recognition and rejection rates, is proposed. Besides, an auctioning procedure, based on the sealed bid, first price method, is adapted for the negotiation phase. Two agent teams are formed; each consists of three NN learning agents. The first is a fuzzy min–max (FMM) NN agent team and the second is a fuzzy ARTMAP (FAM) NN agent team. Modifications to the FMM and FAM models are also proposed so that they can be used for trust measurement in the TNC model. To assess the effectiveness of the proposed model and the bond (based on trust), five benchmark data sets are tested (Quteishat et al. 2009).

Tran et al. (2004) suggests a decision support system for tactical air combat environment where not much prior information is available about the decision regions (Abraham et al. 2004). Tran et al. (2004) proposed a combination of unsupervised learning for clustering the data (to develop decision regions) and a feed forward neural network to classify the decision regions accurately. The clustered data is used as the inputs to the multi-layered feed forward neural network, which is trained using several higher order learning paradigms. The decision support system not only requires being intelligent but also should incorporate human machine interaction and consider human as the integral part of the system. The Decision support systems using hybrid neurocomputing (CWA) is a system design technique to provide corporation between the human and computing system. CWA is suitable to analyze complex systems that has high-level of cognitive input from human operators, which contributes to the strong success during unpredictable situations and assist hard decision-making. The decision support system should have high level of automation and information integration with a role of operation shift to high task level that involves problem solving, hard decision making, conceptual understanding, planning and workload management (Tran et al. 2004).

Applications in theory and in practice involve the integration of various types of neural networks (Feedforward neural network, Radial basis function network, Kohonen self-organizing network, Learning Vector Quantization, Recurrent neural network, Modular neural networks, Physical neural network and other types of networks) and biometrics (DNA Matching, Ear, Eyes [iris and retina], Face, Fingerprint, Finger Geometry, Gait, Odour, Signature, Typing, Vein and Voice [Speaker Verification/Authentication and Speaker Identification]). For example, artificial neural networks (i.e., systems that learn from data) have been used in different biometric applications involving pattern classification and identification (of a human (Dinkar and Sambyal 2012, Melin et al. 2012), of driver (Wu and Ye 2009), of finger-vein patterns (Wu and Liu 2011), of iris recognition (Sibai et al. 2011), of human action (Youssef and Asari 2013), of gait (Zeng and Wang 2012), of the face (Connolly et al. 2013; Kuo et al. 2011; Choi et al. 2012; Banerjee and Datta 2013; Lin and Lin 2013; Müller et al. 2013), of the hand (Michael et al. 2008), of the skin (Zaidan et al. 2014), by keystroke (Uzun and Bicakci 2012) and by gesture, speech, handwritten text recognition and the like). Various biometric systems are being developed in such a manner (face recognition, fingerprint identification, hand geometry biometrics, retina scan, iris scan, signature, voice analysis, palm vein authentication and others). This is accomplished by the application of different types of neural networks. The aforementioned scientific researches are next described in brief.

Dinkar and Sambyal (2012) present new insights and experimental results for the use of ears as a non-invasive biometric for human identification. To determine the uniqueness of the external ear pattern two methods were employed: The Weighted Scoring System and Pattern Recognition by Neural networks. A total of 10 external ear features classified into 37 sub-features for both right and left ears of 400 Indians of Goan origin were studied after acquiring standardized side profile digital photographs. These features were then converted to numeric scores by the 'Weighted Scoring System' which were then compared to ascertain the uniqueness of ear pattern in same and different individuals. The digital analysis of visually similar ear images by Neural networks revealed a recognition rate of 94 % with an Equal Error Rate at threshold value of 0.225 (Dinkar and Sambyal 2012).

Sibai et al. (2011) present a simple methodology for pre-processing iris images and the design and training of a feedforward artificial neural network for iris recognition.

Melin et al. (2012) propose a new approach to genetic optimization of modular neural networks with fuzzy response integration. The architecture of the modular neural network and the structure of the fuzzy system (for response integration) are designed using genetic algorithms. The proposed methodology is applied to the case of human recognition based on three biometric measures, namely iris, ear, and voice (Melin et al. 2012).

Youssef and Asari (2013) consider developing a taxonomic shape driven algorithm to solve the problem of human action recognition and develop a new feature extraction technique using hull convexity defects. To test and validate this approach, Youssef and Asari (2013) use silhouettes of subjects performing ten actions from a commonly used video database by action recognition researchers. Testing and training of the nine test subjects is performed using a leave one out methodology. Classification utilizes both PCA and minimally encoded neural networks (Youssef and Asari 2013).

Recognition of temporal/dynamical patterns is among the most difficult pattern recognition tasks. Human gait recognition is a typical difficulty in the area of dynamical pattern recognition. It classifies and identifies individuals by their time-varying gait signature data (Zeng and Wang 2012). Zeng and Wang (2012) present a new model-based approach for human gait recognition via the aforementioned method, specifically for recognizing people by gait. The approach consists of two phases: a training (learning) phase and a test (recognition) phase. In the training phase, side silhouette lower limb joint angles and angular velocities are selected as gait features. Locally-accurate identification of the gait system dynamics is achieved by using radial basis function neural networks through deterministic learning (Zeng and Wang 2012).

A driver identification system using finger-vein technology and an artificial neural network is presented by Wu and Ye (2009). The principle of the proposed system is based on the function of near infra-red finger-vein patterns for biometric authentication. Finger-vein patterns are required by transmitting near infra-red through a finger and capturing the image with an infra-red CCD camera. The algorithm of the proposed system consists of a combination of feature extraction using Radon transform and classification using the neural network technique. The Radon transform can concentrate the information of an image in a few high-valued coefficients in the transformed domain. The neural networks are used to develop the training and testing modules. The artificial neural network techniques using radial basis function network and probabilistic neural network are proposed to develop a driver identification system (Wu and Ye 2009).

Due to a limited control over changing operational conditions and personal physiology, systems used for video-based face recognition are confronted with complex and changing pattern recognition environments. Although a limited amount of reference data is initially available during enrollment, new samples often become available over time, through re-enrollment, post analysis and labeling of operational data, etc. (Connolly et al. 2013).

Kuo et al. (2011) propose an improved photometric stereo scheme based on improved kernel-independent component analysis method to reconstruct 3D human faces. Next, Kuo et al. (2011) fetch the information of 3D faces for facial face recognition. For reconstruction, Kuo et al. (2011) obtain the correct normal vector's sequence to form the surface, and use a method for enforcing integrability to reconstruct 3D objects. Kuo et al. (2011) test the algorithm on a number of real images captured from the Yale Face Database B, and use three kinds of methods to fetch characteristic values. Those methods are called contour-based, circle-based, and feature-based methods. Then, a three-layer, feed-forward neural network trained by a back-propagation algorithm is used to realize a classifier. All the experimental results were compared to those of the existing human face reconstruction and recognition approaches tested on the same images (Kuo et al. 2011).

Michael et al. (2008) propose to use a low-resolution web camera to capture the user's hand at a distance for recognition. The users do not need to touch any device for their palm print to be acquired. A novel hand tracking and palm print region of interest extraction technique are used to track and capture the user's palm in real-time video stream. The discriminative palm print features are extracted based on a new method that applies local binary pattern texture descriptor on the palm print directional gradient responses. Experiments show promising result using the proposed method. Performance can be further improved when a modified probabilistic neural network is used for feature matching. Verification can be performed in less than one second in the proposed system (Michael et al. 2008).

Due to the rapid growth of social network services such as Facebook and Twitter, incorporation of face recognition in these large-scale web services is attracting much attention in both academia and industry. The major problem in such applications is to deal efficiently with the growing number of samples as well as local appearance variations caused by diverse environments for the millions of users over time (Choi et al. 2012). Choi et al. (2012) focus on developing an incremental face recognition method for Twitter application. Particularly, a data-independent feature extraction method is proposed via binarization of a Gabor filter. Subsequently, the dimension of the Gabor representation is reduced considering various orientations at different grid positions. Finally, an incremental neural network is applied to learn the reduced Gabor features. Choi et al. (2012) apply the proposed method to a novel application which notifies new photograph uploading to related users without having their ID being identified.

Skin colour is considered to be a useful and discriminating spatial feature for many skin detection-related applications, but it is not sufficiently robust to address complex image environments because of light-changing conditions, skin-like colours and reflective glass or water. These factors can create major difficulties in face pixel-based skin detectors when the colour feature is used (Zaidan et al. 2014). Thus, Zaidan et al. (2014) propose a multi-agent learning method that combines the Bayesian method with a grouping histogram technique and the back-propagation neural network with a segment adjacent-nested technique based on the YCbCr and RGB colour spaces, respectively, to improve skin detection performance (Zaidan et al. 2014).

Banerjee and Datta (2013) propose an improved strategy for face recognition using correlation filter under varying lighting conditions and occlusion where spatial domain preprocessing is carried out by two convolution kernels. The first convolution kernel is a contour kernel for emphasizing high frequency components of face image and the other kernel is a smoothing kernel used for minimization of noise those may arise due to preprocessing. The convolution kernels are obtained by training a generalized regression neural network using enhanced face features (Banerjee and Datta 2013).

Human face recognition has been generally researched for the last three decades. Face recognition with thermal image has begun to attract significant attention gradually since illumination of environment would not affect the recognition performance. However, the recognition performance of traditional thermal face recognizer is still insufficient in practical application (Lin and Lin 2013). Lin and Lin (2013) present a novel thermal face recognizer employing not only thermal features but also critical facial geometric features which would not be influenced by hair style to improve the recognition performance. A three-layer back-propagation feed-forward neural network is applied as the classifier. Traditional thermal face recognizers only use the indirect information of the topography of blood vessels like thermogram as features. To overcome this limitation, the proposed thermal face recognizer can use not only the indirect information but also the direct information of the topography of blood vessels which is unique for every human. Moreover, the recognition performance of the proposed thermal features would not decrease even if the hair of frontal bone varies, the eye blinks or the nose breathes. Experimental results show that the proposed features are significantly more effective than traditional thermal features and the recognition performance of thermal face recognizer is improved (Lin and Lin 2013).

Keystroke Dynamics, which is a biometric characteristic that depends on typing style of users, could be a viable alternative or a complementary technique for user authentication if tolerable error rates are achieved. Most of the earlier studies on Keystroke Dynamics were conducted with irreproducible evaluation conditions therefore comparing their experimental results are difficult, if not impossible. One of the few exceptions is the work done by Killourhy and Maxion, which made a dataset publicly available, developed a repeatable evaluation procedure and evaluated the performance of different methods using the same methodology. In their study, the error rate of neural networks was found to be one of the worst-performing (Uzun and Bicakci 2012). Uzun and Bicakci (2012) have a second look at the performance of neural networks using the evaluation procedure and dataset same as in Killourhy and Maxion's work. Uzun and Bicakci (2012) find that performance of artificial neural networks can outperform all other methods by using negative examples.

Autonomous learning is demonstrated by living beings that learn visual invariances during their visual experience. Standard neural network models do not show this sort of learning (Müller et al. 2013). On the example of face recognition in different situations Müller et al. (2013) propose a learning process that separates learning of the invariance proper from learning new instances of individuals. The invariance is learned by a set of examples called model, which contains instances of all situations. New instances are compared with these on the basis of rank lists, which allow generalization across situations. The result is also implemented as a spike-time-based neural network, which is shown to be robust against disturbances. The learning capability is demonstrated by recognition experiments on a set of standard face databases (Müller et al. 2013).

Wu and Liu (2011) present a personal identification system using finger-vein patterns with component analysis and neural network technology. In the proposed system, the finger-vein patterns are captured by a device that can transmit near infrared through the finger and record the patterns for signal analysis. The proposed biometric system for verification consists of a combination of feature extraction using principal component analysis and pattern classification using back-propagation network and adaptive neuro-fuzzy inference system (Wu and Liu 2011).

2.6 Integration of Remote Sensing into a Decision Support Systems

Recently a more active integration into decision support systems (DSSs) is occurring involving active remote sensing (when a signal is first emitted from aircraft or satellites) and passive remote sensing (photography, infrared, charge-coupled devices, radiometers). There are several characteristic example of such an integration (Meyer et al. 2014; Eckman and Stackhouse 2012; Lu et al. 2014; Bonazountas et al. 2007; Qi and Altinakar 2011; Wu et al. 2009; Powell et al. 2008), which are presented next.

Remote sensing plays a critical role in operational volcano monitoring due to the often remote locations of volcanic systems and the large spatial extent of potential eruption pre-cursor signals. Despite the all-weather capabilities of radar remote sensing and its high performance in monitoring of change, the contribution of radar data to operational monitoring activities has been limited in the past (Meyer et al. 2014). Meyer et al. (2014) present new data processing and data integration techniques that mitigate some of these limitations and allow for a meaningful integration of radar data into operational volcano monitoring decision support systems. For a demonstration, Meyer et al. (2014) present an integration of the processing system with an operational volcano monitoring system that was developed for use by the Alaska Volcano Observatory.

Earth observations are playing an increasingly significant role in informing decision making in the energy sector. In renewable energy applications, space-based observations now routinely augment sparse ground-based observations used as input for renewable energy resource assessment applications (Eckman and Stackhouse 2012). Eckman and Stackhouse (2012) describe a coordinated program of demonstration projects conducted by Global Earth Observation System of Systems (GEOSS) member agencies and partners to utilize Earth observations to enhance energy management end-user decision support systems.

Building information is one of the key elements for a range of urban planning and management practices. In this study, an investigation was performed to classify buildings delineated from light detection and ranging (LiDAR) remote sensing data into three types: single-family houses, multiple-family houses, and non-residential buildings. Four kinds of spatial attributes describing the shape, location, and surrounding environment of buildings were calculated and subsequently employed in the classification. The shape attributes, such as width, footprint area, and perimeter, were most useful for identifying building types. Environmental landscape attributes surrounding buildings, such as the number of road and parking lot pixels, also contributed to obtaining building type information. Combining shape and environmental landscape attributes was necessary to obtain accurate and consistent classification results (Lu et al. 2014).

Southern Europe is exposed to anthropogenic and natural forest fires. These result in loss of lives, goods and infrastructure, but also deteriorate the natural environment and degrade ecosystems. The early detection and combating of such catastrophes requires the use of a decision support system (DSS) for emergency management (Bonazountas et al. 2007). Bonazountas et al. (2007) present the results of scientific research aiming to the development of a DSS for managing forest fires. The system integrates GIS technologies under the same data environment and utilises a common user interface to produce an integrated computer system based on semi-automatic satellite image processing (fuel maps), socio-economic risk modelling and probabilistic models that would serve as a useful tool for forest fire prevention, planning and management (Bonazountas et al. 2007).

A new decision support system has been developed for integrated flood management within the framework of ArcGIS based on realistic two dimensional flood simulations. This system has the ability to interact with and use classified Remote sensing (RS) image layers and other GIS feature layers like zoning layer, survey database and census block boundaries for flood damage calculations and loss of life estimations. The analysis of a dam break flood management strategy for Sinclair Dam in Georgia, USA is chosen as a case study to demonstrate the capabilities of the decision support system. The test results compared with HEC-FDA software indicate that this new system provides a very versatile and reliable environment for estimating various flood damage, and may greatly enhance decision making process for future design of the flood proofing facilities (Qi and Altinakar 2011).

Wu et al. (2009) propose an intelligent decision support system based on sensor and computer networks that incorporate various component techniques for sensor deployment, data routing, distributed computing, and information fusion.

Floodplain wetlands rely on catchment flows to maintain the flooding cycles critical to their ecological integrity. The development of water resources has significantly altered the flow patterns in many river systems. Recent research into water requirements for wetland systems shows that duration, frequency, depth, timing and extent of flooding are the most important influences on ecological communities. Modelling these systems is hampered by a lack of data and inappropriate model structures. Remote sensing using AVHRR satellite data were shown to be an effective option for assessing flood dynamics. This study demonstrates that a conceptually based, semi-distributed water balance approach can provide the basis for an effective decision support system for water management (Powell et al. 2008).

2.7 Biometrics-Based Decision Support Systems

Several types of biometrics-based decision support systems (DSSs) are analyzed in this section: Speech Recognition and Understanding DSS, Voice Recognition DSS, Adaptive Biometric DSS and other biometrics-based DSSs.

2.7.1 Voice Recognition Decision Support Systems

The term voice recognition describes the identity of a speaker (for security purpose) and assists the translation of speech more easily (the system helps to implement the speech recognition process by establishing the specific voice of a particular person and by relying on historical experience).

Voice recognition is the ability of a computer to know the voice of a person speaking into it, so that only voices that the computer knows can use the system (Macmillan Dictionary 2009–2014). Ability of an electronic security device is to recognize the voice (which is unique as a fingerprint) of a particular person. In contrast, speech recognition is the ability to recognize spoken words only and not the individual voice characteristics (Business Dictionary 2014). Despite the inherent technological challenges, voice recognition technology's most popular applications will likely provide access to secure data over telephone lines. Voice recognition has already been used to replace number entry on certain Sprint systems. This kind of voice recognition is related to (yet different from) speech recognition. While speech recognition technology interprets what the speaker says, speaker recognition technology verifies the speaker's identity (Phillips et al. 2000).

The terms "voice recognition" and "voice biometrics" are often used as synonyms (Anzar and Sathidevi 2014; Warman 2013; Rashid 2008; Face and voice biometrics set for growth 2013; Banks turn to voice for call centres 2014; Ortega-Garcia et al. 2002). Barclays Bank successfully applies voice biometrics technology in the place of a pin code. Software called "Nuance FreeSpeech" uses voice biometrics technology to compare the customer's voice to their unique voiceprint on file, and silently signals to the Barclays representative when the customer's identity has been verified. Since its introduction, Barclays says more than 84 % of its customers have enrolled in the Nuance voice biometrics solution, with 95 % of those customers successfully verified upon their first use of the system (Warman 2013). Several Voice Recognition Decision Support Systems (Dinh et al. 2006; Browne 1991; Drake 1988) have also been developed. These integrate voice recognition with decision support systems.

2.7.2 Speech Recognition and Understanding Decision Support Systems

Recently, data-driven speech technologies have been widely used to build speech user interfaces. However, developing and managing data-driven spoken dialog systems are laborious and time consuming tasks. Spoken dialog systems have many components and their development and management involves numerous tasks such as preparing the corpus, training, testing and integrating each component for system development and management. In addition, data annotation for natural language understanding and speech recognition is quite burdensome (Jung et al. 2008). Speech understanding is the processing of speech that involves the mapping of the acoustic signal, usually derived from some form of a speech recognition system to some form of abstract meaning of the speech (Dictionary of Computing 2008). It has been quite a considerable time, since speech user interfaces have been designed for decision support (Martin 1989; Jones et al. 1989; Shiffman et al. 1995). These and other studies suggest that such speech-understanding systems can help interested groups to make timely and effective decisions. For example, Conlon et al. (1994) describe a natural language processing based group decision support system. The system consists of database, model base, application programs and natural language interface system. This system is designed to both route questions to appropriate subsystems and translate these questions into the computer language controlling these subsystems (Conlon et al. 1994). Speech biometric and speech recognition are interrelated concepts. Speech biometric is being used to identify a person by that person's speech (by applying speech recognition and understanding technologies) by recognizing the intonation in the voice.

2.7.3 Adaptive Biometrics-Based Decision Support Systems

An adaptive biometric system aims to auto-update the templates or model to the intra-class variation of the operational data (Rattani 2010). Self-update is the most commonly adopted biometric template update technique in which the system adapts itself to the confidently classified samples (Rattani et al. 2013). Scientists from different countries are working in the area of adaptive biometric systems (Huang et al. 2013; Pagano et al. 2014; De Marsico et al. 2012; Guerra-Casanova et al. 2011; Kaklauskas et al. 2013). Several studies by the aforementioned authors are next described in brief.

If fusion rules cannot adapt to the changes of environment and individual users, multimodal systems may perform worse than unimodal systems when one or more modalities encounter data degeneration (Huang et al. 2013). Huang et al. (2013) develop a robust face and ear based multimodal biometric system using Sparse Representation, which integrates the face and ear at feature level, and can effectively adjust the fusion rule based on reliability difference between the modalities.

Recognizing faces corresponding to target individuals remains a challenging problem in video surveillance. Face recognition (FR) systems are exposed to videos captured under various operating conditions, and, since data distributions change over time. Although these models may be adapted when new reference videos become available, incremental learning with faces captured under different conditions may lead to knowledge corruption (Pagano et al. 2014). Pagano et al. (2014) present an adaptive multi-classifier system (AMCS) for video-to-video FR in changing surveillance environments. During enrolment, faces captured in reference videos are employed to design an individual-specific classifier. During operations, a tracker allows to regroup facial captures for individuals in the scene, and accumulate the predictions per track for robust spatiotemporal FR. Given a new reference video, the corresponding facial model is adapted according to the type of concept change. If a gradual pattern of change is detected, the individual-specific classifier(s) are adapted through incremental learning. To preserve knowledge, another classifier is learned and combined with the individual's previously-trained classifier(s) if an abrupt change is detected. For proof-of-concept, the performance of a particular implementation of this AMCS is assessed using videos from the Faces in Action dataset. By adapting facial models according to changes detected in new reference videos, this AMCS allows to sustain a high level of accuracy comparable to the same system that is always updated using a learn-and-combine approach, while reducing time and memory complexity (Pagano et al. 2014).

The lack of communication and of dynamic adaptation to working settings often hinder stable performances of subsystems of present multibiometric architectures. The calibration phase often uses a specific training set, so that (sub) systems are tuned with respect to well determined conditions (De Marsico et al. 2012). De Marsico et al. (2012) investigate the modular construction of systems according to CABALA (Collaborative Architectures based on Biometric Adaptable Layers and Activities) approach. Different levels of flexibility and collaboration are supported. The computation of system reliability (SRR), for each single response of each single subsystem, allows to address temporary decrease of accuracy due to adverse conditions (light, dirty sensors, etc.), by possibly refusing a poorly reliable response or by asking for a new recognition operation (De Marsico et al. 2012).

Guerra-Casanova et al. (2011) focus on the evaluation of a biometric technique based on the performance of an identifying gesture by holding a telephone with an embedded accelerometer in his/her hand. The acceleration signals obtained when users perform gestures are analyzed following a mathematical method based on global sequence alignment. A temporal study of the technique is presented leading to the need to update the template to adapt the manner in which users modify how they perform their identifying gesture over time. Six updating schemes have been assessed within a database of 22 users repeating their identifying gesture in 20 sessions over 4 months, concluding that the more often the template is updated the better and more stable performance the technique presents (Guerra-Casanova et al. 2011).

Kaklauskas et al. (2013) developed a Recommender System to Analyze Student's Academic Performance. One of the main goals in the research was to demonstrate that the interest in learning affects learning productivity, while physiological parameters demonstrate such changes, and this provide another source of data for substantiating the impact of emotional states on learning. The Recommender System can auto-update a student's academic performance model with operational biometrical data. A low bias profile Logistic regression learning algorithm works well at the adaptive stage, when the Recommender System has accumulated enough training data. Other researchers (Poitras and Lajoie 2014; Andersen et al. 2012; Zhang 2004) have also been developing various adaptive systems by applying the logistic regression (logit regression) probabilistic statistical classification model. Then, after having completed the adaptive phase, the Recommender System determines the correlation between a student's learning productivity, interest in learning and the physiological parameters of that student. Then the Recommender System can select learning materials by taking into account a student's learning productivity and the degree to which the learning seems interesting.

2.7.4 Other Biometrics-Based Decision Support Systems

There are also other biometrics-based decision support systems (DSSs) in addition to the three types listed above. These are next described in brief.

Patient empowerment might be one key to reduce the pressure on health care systems challenged by the expected demographic changes. Knowledge based systems can, in combination with automated sensor measurements, improve the patients' ability to review their state of health and make informed decisions (Gietzelt et al. 2012). Gietzelt et al. (2012) introduce ARDEN2BYTECODE for this purpose. It is a newly developed, open source compiler for service-oriented decision support systems based on the OSGi (Open Services Gateway Initiative) platform.

To cope with the increasing number of aging population, a type of care which can help prevent or postpone entry into institutional care is preferable. Activity recognition can be used for home-based care in order to help elderly people to remain at home as long as possible (Chernbumroong et al. 2014). Chernbumroong et al. (2014) propose a practical multi-sensor activity recognition system for home-based care utilizing on-body sensors. Seven types of sensors are investigated on their contributions toward activity classification. Chernbumroong et al. (2014) collected a real data set through the experiments participated by a group of elderly people. Seven classification models are developed to explore contribution of each sensor. Chernbumroong et al. (2014) conduct a comparison study of four feature selection techniques using the developed DSS models and the collected data.

Brahnam et al. (2007) propose that a machine assessment system of neonatal expressions of pain be developed to assist clinicians in diagnosing pain. The facial expressions of 26 neonates (age 18–72 h) were photographed experiencing the acute pain of a heel lance and three nonpain stressors. Four algorithms were evaluated on out-of-sample observations: PCA, LDA, SVMs and NNSOA. NNSOA provided the best classification rate of pain versus nonpain (90.20 %), followed by SVM with linear kernel (82.35 %). Brahnam et al. (2007) believe these results indicate a high potential for developing a decision support system for diagnosing neonatal pain from images of neonatal facial displays.

Petrushin (2002) presents agents for emotion recognition in speech and their application to a real world problem. The agents can recognize five emotional states—unemotional, happiness, anger, sadness, and fear—with good accuracy, and be adapted to a particular environment depending on parameters of speech signal and the number of target emotions. A practical application has been developed using an agent that is able to analyze telephone quality speech signal and to distinguish between two emotional states—“agitation” and “calm”. This agent has been used as a part of a decision support system for prioritizing voice messages and assigning a proper human agent to respond the message at a call center (Petrushin 2002).

According to Gavrilova and Monwar (2013), the best way to develop a biometric security system is to design it as a decision-support system, which can provide information to the system operator empowering him to make an intelligent and correct decision.

2.8 Ambient Intelligence and the Internet of a Things-Based Decision Support Systems

The concepts of ambient intelligence and the Internet of Things and their link to decision support systems are briefly deliberated. Ambient intelligence discusses electronic environments, which are sensitive and responsive to people’s daily activities. According to Aarts et al. (2001), the ambient intelligence paradigm is characterized by systems and technologies that are embedded, context aware, personalized, adaptive and anticipatory. In the opinion held by Höller et al. (2014), the Internet of Things refers to the interconnection of uniquely identifiable embedded computing-like devices within the existing Internet infrastructure. Typically, Internet of Things is expected to offer advanced connectivity of devices, systems, and services that goes beyond machine-to-machine communications and covers a variety of protocols, domains, and applications (Höller et al. 2014). Ambient intelligence is not part of the original concept of the Internet of Things. Ambient intelligence does not necessarily require Internet structures, either. However, there is a shift in research to integrate the concepts of the Internet of Things and ambient intelligence (Uckelmann et al. 2010).

There are identical concepts, such as "pervasive computing", "ambient intelligence" and "the Internet of things". In practice, the differences between these terms is of rather an academic nature: common to all is the goal of assisting people as well as a continuous optimisation and promotion of economic and social processes by numerous microprocessors and sensors integrated into the environment (Friedewald and Raabe 2011).

The topic of smart environments, also called ambient intelligence, has been gaining interest recently. The term ambient intelligence refers to the embedding of sensors and actuators within a room or environment that react automatically to the users within that environment. The sensors are hidden from the user so they become part of the environment and should not require the user to explicitly interact with the devices. These sensors could be in the form of thermometers, microphones, cameras, motion sensors, or any device that can provide information to an automated control system regarding the state of the environment (Torunski et al. 2012). Ambient intelligence is described as a model of interaction in which people are surrounded by intelligent devices, aware of their own presence, context sensitive and able to adapt to the user's needs through embedded technology (Bajo et al. 2010).

The main goal of Ambient intelligence is the development of systems aimed at adapting the surrounding environmental conditions so that they can match the users' needs, whether those are consciously expressed or not, while at the same time satisfying other system-driven goals, such as the minimization of global energy consumption (De Paola et al. 2012).

Gasson and Warwick (2007) claim that a variety of technologies (Bluetooth low energy, RFID, implant, sensors, software agents, affective computing, nanotechnology, biometrics) can be used to enable effective Ambient intelligence environments. Objects in the Internet of Things will not only be devices with sensory capabilities, but also provide actuation capabilities (e.g., bulbs or locks controlled over the Internet) (Ersue et al. 2014). Next are brief write-ups to serve as practical examples of ambient intelligence-based and sensors-based decision support systems that have been developed (Chernbumroong et al. 2014; Droit et al. 2008; Filip 2008; El-Hachem et al. 2012; Dunkel et al. 2011; Rodger 2014; Fricoteaux et al. 2014; Edoura-Gaena et al. 2006; Howells et al. 1999; Paraskevopoulos and Singels 2014; Wu et al. 2009; Kaupp et al. 2010; Qi et al. 2014; Ansola et al. 2012).

Most traditional street lighting systems do not have the function of autonomous control. Inspired by social animals and insects, an autonomous control system for street lighting is presented in this research. All the lamp nodes compose a wireless sensor network (WSN) based lamp group in which there are a lamp leader, a succeeding leader, and some lamp members. All the lamp members communicate with the lamp leader by forming a tree topology. The lamp member collects ambient illumination using a light sensor periodically. When finding the illumination is under the preset threshold, the lamp member will send a turning-on vote to the lamp leader. The lamp leader counts the number of votes received from the members. When the number of the votes is larger than the preset threshold, the lamp leader will send a turning-on command to all the lamp members. Just like the succession behavior in social animals, the succeeding leader in the proposed Group decision making based autonomous control system for street lighting can automatically take the place of the current lamp leader when it is disabled. A failure message can be sent to the remote street lighting maintenance center by a GPRS network. Leader switching and group decision making tests have been carried out for validating these proposed methods. The experimental results show that the proposed Group decision making based autonomous control system for street lighting can automatically response to ambient light changes. The method of group decision making improves the anti-interference capability and the intelligence level of the lighting control system (Zhang et al. 2013).

Chernbumroong et al. (2014) develop a practical, multi-sensor activity recognition system for home-based care. The DSS can be used to generate a monthly activity graph which shows the amount of each activity carried out in different months. This can be used to see the trend and detect changes in activities and support the decision whether to contact the person to come to the hospital and to which department or a home visit or whether further activity data should be requested from the patient. For example, if the graph shows the decline in walking over several months, this could suggest that there is a problem with ambulating. This would help reduce the number of hospital visits, improve hospital resources utilization, and increase earlier detection rate. The DSS can be used to support the decision on the type of carer that is required for different patients. For example, if an activity record shows no decline or changes in activity pattern, a carer may not be needed. If the activity record suggests that the person may have problem with feeding, the carer who can provide assistance with feeding or cooking should be sent. The activity database can be used as part of the other clinical decision support systems to give more information to support the illness diagnostic or disease symptom. For example, if the activity record shows that the patient has very little sleep per day, it could influence the decision of the specific sleeping disorder (Chernbumroong et al. 2014).

Droit et al. (2008) aim to contribute to the design of decision support for the physical access security systems. Droit et al. (2008) address the problem of extracting information helpful for early detection of physiological and psycho-emotional data linked to situational awareness. Face images in visible and infrared bands acquired by the Biometric-Based Decision Support Assistance in Physical Access Control System constitute the input of the module for hyper-spectral face analysis and synthesis. The corresponding 3D models, one for video images and one for infrared, are generated by fitting the generic model onto images. The texture maps representing the hemoglobin and melanin content of the facial skin, as well as the temperature distribution, constitutes the output of the face analysis and modeling module. This information is used for evaluating the physiological and psycho-emotional states of a person (Droit et al. 2008).

The technical and social systems of the present day are ever large, complex and complicated objects. Their models are characterized by numerous state and control variables, time delays, and different time constants. Also they show constraints in their information infrastructure and risk sensitivity aspects. Such systems are called *large-scale complex systems* (LSS). Hierarchical approach which has been for several decades one of the most utilized methodologies for controlling large-scale systems has evolved in recent years toward more collaborative schemes. When human intervention is necessary, *decision support systems* (DSSs) can represent a solution. A DSS is an adaptive and evolving information system meant to implement several of the functions of a human support team that would otherwise be needed to help the decision-maker to overcome his/her limits and constraints he/she may face when approaching decision problems that count in the organization. This research aims at reviewing several aspects concerning the utilization and technology of DSS in the context of LSS control. Particular emphasis is put on real-time DSS and *multi-participant (group) DSS* which support collaborative work. Several advanced solutions such as mixed knowledge systems, that combine numerical methods with AI-based tools, and the prospects of using *Ambient intelligence* concepts in DSS construction are described (Filip 2008).

Amid the extremely active Semantic Web community and the Social Web's exceptionally rising popularity, experts believe that an amplified fusion between the two webs will give rise to the next huge advancement in Web intelligence. Such advances can particularly be translated into ambient and ubiquitous systems and applications (El-Hachem et al. 2012). El-Hachem et al. (2012) delve into the recent advances in knowledge representation, semantic web, natural language processing and online social networking data and concepts, to propose an inclusive platform and framework defining ambient recommender and decision support systems that aim at facilitating cross-sectional analysis of the domain of childhood obesity and generating both generic and customized preventive recommendations.

Decision support systems for traffic management systems have to cope with a high volume of events continuously generated by sensors (Dunkel et al. 2011). Dunkel et al. (2011) propose a reference architecture for event-driven traffic management systems, which enables the analysis and processing of complex event streams in real-time and is therefore well-suited for decision support in sensor-based traffic control systems.

Rodger (2014) address the problem of predicting demand for natural gas for the purpose of realizing energy cost savings. Daily monitoring of a rooftop unit wireless sensor system provided feedback for a decision support system that supplied the demand for the required number of million cubic feet of natural gas used to control heating, ventilation, and air conditioning systems (Rodger 2014).

Modern training through virtual environments is widely used in transport in order to provide a high level of precision and more and more complex situations. These virtual environments provide training scenarios with automatic and repetitive feedback to the trainees. Experienced learners receive too many aids and novice learners receive too few (Fricoteaux et al. 2014). Fricoteaux et al. (2014) have designed and evaluated a fluvial-navigation virtual training system which includes a GULLIVER (decision-making system based on user observation for an adaptive training in informed virtual environments) module to determine the most appropriate level of feedback to display for learner guiding. GULLIVER is based on a decision-making module integrating uncertain data coming from observation of the learner by the system. An evidential network with conditional belief functions is used by the system for making decisions. Several sensors and a predictive model are used to collect data in real time. Metaphors of visualization are displayed to the user in an immersive virtual reality platform as well as audio feedback. GULLIVER was evaluated on 60 novice participants. The experiment was based on a navigation case repetition (Fricoteaux et al. 2014).

A pilot Decision support system to control the aeration of sponge finger batters was developed on the basis of knowledge extraction and formalization, to help the operators to control the aeration of sponge finger batters. This system reproduces the operator's control strategies by integrating the product's sensory properties and by taking into account various operations of the entire process, which influence product quality. The system inputs are 10 sensory measurements and 4 instrumental measurements used by the operators on the production line to characterize the batter and the sponge fingers. Sensory measurements were previously formalized using the "sensory indicators" formalism. The system outputs are the appropriate corrective actions. These actions are selected with a set of 47 "if–then" type rules which represent the formalization of the strategies developed by operators for the feedback control of aeration. The Decision support system to control the aeration of sponge finger batters was implemented with CLIPS, an expert systems shell, and was evaluated by comparing its outputs to the corrective actions proposed by an expert operator. Matching was obtained in 21 cases out of the 27 tested (Edoura-Gaena et al. 2006).

In the defence area, especially that of aerospace systems, extensive use has been made of the expertise of software and system houses in developing validation methodologies (VORTEX), real time (MUSE) and multi-agent (D-MUSE) software and together with Universities, a knowledge acquisition toolkit (PC PACK). In the UK at DERA Farnborough within the Airborne Decision Support Group, Air Sector, these software and tools have been developed and applied to problems in building Decision Support Systems for Maritime Air applications. The demanding aircrew tasks are characterised by the need for assimilation and interpretation of multi-sensor data to devise tactical responses in real time based on prevailing tactical doctrine and aircrew experience. The applications include Decision Support for Anti-Submarine Warfare (ASW), Anti-Surface Warfare (ASuW), Airborne Early Warning (AEW) together with ASW/ASuW and the proposed AEW technology demonstrators (Howells et al. 1999).

Various technologies exist to support scientific irrigation scheduling, each with its own strengths and weaknesses. Weather-based crop models are good at estimating evapotranspiration and future irrigation needs over large areas, while electronic soil water sensors are able to provide good estimates of soil water status at a given point. Synergy may be obtained by combining these technologies to enhance their usefulness for irrigation management. The objective of this study was to incorporate real-time field records of soil water status into a weather based sugarcane simulation system and to evaluate its use for supporting irrigation scheduling in 15 sugarcane fields in South Africa. The integrated system provides enhanced support for irrigation water management for sugarcane production (Paraskevopoulos and Singels 2014).

Wang and Wu (2009) propose an intelligent decision support system for homeland security defense based on sensor and computer networks that incorporates various component techniques for sensor deployment, data routing, distributed computing, and information fusion. The integrated system is deployed in a distributed environment composed of both wireless sensor networks for data collection and wired computer networks for data processing in support of homeland security defense. Wang and Wu (2009) present the system framework and formulate the analytical problems and develop approximate or exact solutions for the subtasks: (i) sensor deployment strategy based on a two-dimensional genetic algorithm to achieve maximum coverage with cost constraints; (ii) data routing scheme to achieve maximum signal strength with minimum path loss, high energy efficiency, and effective fault tolerance; (iii) network mapping method to assign computing modules to network nodes for high-performance distributed data processing; and (iv) binary decision fusion rule that derive threshold bounds to improve system hit rate and false alarm rate. The extensive results demonstrate that these component solutions imbue the integrated system with the desirable and useful quality of intelligence in decision making (Wang and Wu 2009).

Humans and robots need to exchange information if the objective is to achieve a task collaboratively. Two questions are considered in this research: what and when to communicate (Kaupp et al. 2010). To answer these questions, Kaupp et al. 2010) developed a human–robot communication framework which makes use of common probabilistic robotics representations. The data stored in the representation determines what to communicate, and probabilistic inference mechanisms determine when to communicate. One application domain of the framework is collaborative human–robot decision making: robots use decision theory to select actions based on perceptual information gathered from their sensors and human operators. Robots decide when to query operators using Value-Of-Information theory, i.e. humans are only queried if the expected benefit of their observation exceeds the cost of obtaining it. This can be seen as a mechanism for adjustable autonomy whereby adjustments are triggered at run-time based on the uncertainty in the robots' beliefs related to their task. This semi-autonomous decision making system is demonstrated using a navigation task and evaluated by a user study. Participants navigated a robot in simulation using the proposed decision making system and via classical teleoperation (Kaupp et al. 2010).

Temperature monitoring, shelf-life visibility and Least Shelf-life First Out (LSFO) stock strategy are important contents in perishable food cold chain logistics for both cold chain managers and workers in order to reduce quality and economic losses (Qi et al. 2014). Qi et al. (2014) describe a wireless sensor network (WSN) based integrated Cold Chain Shelf Life Decision Support System (C^2SLDS) designed for perishable food product cold chain management. The system is implemented based on the WSN and time temperature indicator (TTI) features. Compared with traditional cold chain management methods used before, the C^2SLDS not only bridges the information gap which exists between different cold chain phase enterprises and provide a seamless information flow along the whole chain but also enables cold chain enterprises to predict perishable food's shelf-life and helps make a smart LSFO strategy to reduce the quality and economic loss. LSFO strategy decision support system in cold chain logistics test and evaluation shows that the infield radio transmission is reliable and the whole system meets most of the users' requirements raised in system analysis (Qi et al. 2014).

Ansola et al. (2012) develop a Distributed decision support system for airport ground handling management in order to allocate resources in an airport, even when disturbances occur by combining artificial intelligent techniques with visibility technologies. Ansola et al. (2012) propose the combined use of Multiagent systems (MAS) along with Wireless Sensor Networks (WSN) to provide the required information on the status of the resources and the environment. The MAS is based on a double layer of decision-taking levels and on a Markov reward function whereas the WSN is based on a Zigbee network of Radio Frequency Identification (RFID) readers with active tags as end nodes, which are carried by the physical resources. The proposed Distributed decision support system for airport ground handling management using WSN and MAS has been tested at Ciudad Real Central Airport in Spain (Ansola et al. 2012).

2.9 Other Intelligent Decision Support Systems

2.9.1 GA-Based Decision Support Systems

Decision support systems can be improved by integrating a genetic algorithm to generate useful solutions for resolving optimization, search and other problems (Leu et al. 2000; Wang et al. 2007a, b; Kuncheva and Jain 1999). For example, a computational optimization technique, genetic algorithms, was employed by Leu et al. (2000) to overcome drawbacks of traditional construction resource leveling algorithms. The proposed algorithm can effectively provide the optimal or near-optimal combination of multiple construction resources, as well as starting and finishing dates of activities subjected to the objective of resource leveling. Furthermore, a prototype of a decision support system for construction resource leveling was also developed. Construction planners can interact with the system to carry out ad hoc analysis through "what-if" queries (Leu et al. 2000). DSS in joint with integrated, genetic algorithms can experience behavioral changes and adapt over time in order to provide improved decision support based on previous experience. In this sort of instance, various GA-based decision support systems are developed as a genetic algorithm is being integrated (Ko and Wang 2010; Juan et al. 2009).

2.9.2 Fuzzy Sets IDSS

Under uncertain and imprecise conditions, fuzzy sets are used with multicriteria decision-making to provide techniques for modelling preferences, evaluating alternatives, aggregating preferences, selecting best alternatives, and ranking or sorting alternatives into categories. MCDM and fuzzy measurement assist in the representation of domain knowledge for modelling decision problems during the Intelligence and Design stages, whereas intelligent features of analogical reasoning, learning, and memory are facilitated by the case-based reasoning component during analysis for making choices and implementing selected strategies (Burstein and Carlsson 2008). Prototypes of fuzzy IDSS have been applied to solving decision-making problems, such as evaluation of services, partnership selection in virtual enterprises, outsourcing of IT services, risk analysis and evaluation of offers in telecommunication markets (Mikhailov and Knowles 2010; Mikhailov et al. 2011).

2.9.3 Rough Sets

Rough sets can be used to enable decision support systems to perform better in uncertain conditions. Pawlak and Skowron (2007) and Pawlak (2002a, b) develop a decision support system for multiple criteria classification problems based on rough sets and dominance relation (4eMka2). 4eMka2 is an implementation of the new approach in multiple criteria decision support, combining advantages of rough sets and dominance relation. The purpose of this system is resolving of multi-criteria sorting problems. System can be used in many different areas e.g., finances, medicine, geology, pharmacology and many other connected with analysis of vast data sets. The main difference between this system and the ones that are already in use is that it bases on rough set theory combined with dominance relation, which is quite new approach in multi-criteria decision support. The main function of the system is extraction of the classification rules from a set of already classified examples. These rules could be used to make partition of new data sets. Rules are presented in very convenient and comprehensible manner as a set of "if… then…" sentences. Another advantage of the system is dealing with inconsistent and incomplete data. This is possible due to use of rough set with dominance relation (Pawlak and Skowron 2007; Pawlak 2002a, b).

2.9.4 Intelligent Agent-Assisted Decision Support Systems

Multi-agent systems have gained much interest of researchers over the last decade. This is evidenced by the widespread application of multi-agent systems to different domains including e-commerce, healthcare, military support, decision support, knowledge management, as well as control systems (Quteishat et al. 2009).

The term agent means different things to different authors; many definitions are not explicitly enunciated. A general list of those software agent attributes frequently mentioned or implied in literature definitions is as follows: An autonomous software agent is a software implementation of a task in a specified domain on behalf or in lieu of an individual or other agent. The implementation will contain homeostatic goal(s), persistence, and reactivity to the degree that the implementation (1) will persist long enough to carry out the goal(s), and (2) will react sufficiently within its domain to allow goal(s) to be met and to know that fact. The potential contributions of software agents to DSS have been described as enormous, and DSS implementations that utilize agent-like programs and agent communities have appeared in numerous journals (Hess et al. 2008). Intelligent agents that are integrated into DSS (Dong and Srinivasan 2013; Gao and Xu 2009; Gao et al. 2009; Favorskaya et al. 2014; Urlings et al. 2006) can perform complex cognitive tasks (knowledge sharing, machine learning, data mining, automated inference, human–machine teaming, image inpainting, etc.) without the intervention of any decision-maker.

Holsapple and Whinston (1996) and Hess et al. (2008) hold the opinion that there are various autonomous agents, which can increase the value added by DSS:

- Data-monitoring. Goes to (and stays at) supplier's site. Saves user from having to monitor supplier's prices. Only reports promising prices. This agent enhances the DSS in two fundamental ways: by automating the retrieval of information and by improving the quality of that information (in the sense that the database is updated immediately for changes in vendor prices). This latter benefit implies that additional DSS can now be built possessing real-time, on-line data capabilities.
- Data-gathering. Goes to directory sites; locates potential suppliers of parts, relieving a user from the task and only reports promising suppliers. In an enhanced system, the agent could communicate with other agents and get additional leads on promising directory sites or suppliers. This agent provides a benefit to the DSS user by automating the retrieval of information not typically stored in corporate databases.
- Modeling. The modeling agent provides enhancements to the DSS (1) by providing access to a computational tool, (2) by automatically resolving the model when any relevant data changes, (3) by providing a level of abstraction between the different languages of the DSS and the modeling application and (4) by reporting to the user only those changes in the optimal mix of products within the DSS that are deemed significant.

- Domain-manager agent. Agent provides interoperability by integrating heterogeneous, distributed agents. The agent communicates with all other agents operating on behalf of, or in, the domain the user need not keep track of these other agents.
- Preference-learning. The agent observes and records the user's disposition to follow the modeling agent's recommendations; in an enhanced system, the agent could invoke machine learning to determine the user's preferences. This agent watches the user and provides the benefit of learning his or her style or tendencies (Holsapple and Whinston 1996; Hess et al. 2008).

More and more agent-based decision support systems are developed by integrating autonomous software agents into decision support systems. The next brief description of Intelligent agent-assisted decision support systems serves as examples. Dong and Srinivasan (2013) develop an Agent-enabled service-oriented decision support system. López-Ortega and Rosales (2011) develop an Agent-based decision support system that employs fuzzy clustering to group individual evaluations and the AHP to reach a final decision. Phillips-Wren and Forgionne (2006) present a new decision support system enabled by the analytic hierarchy process and intelligent software agents that can be used by researchers and practitioners in technical fields to aid information retrieval and improve search results from a controlled vocabulary.

Criminal elements in today's technology-driven society are using every means available at their disposal to launder the proceeds from their illegal activities. In response, international anti-money laundering (AML) efforts are being made. The events of September 11, 2001, highlighted the need for more sophisticated AML and anti-terrorist financing programs across the industry and nation. In the wake of this, regulators are focusing on the role that technology can play in compliance with laws and ultimately in law enforcement. Banks will have to employ or enhance AML tools and technology to satisfy rising regulatory expectations. While many AML solutions have been in place for some time within the banks, they are faced with the challenge of adapting to the ever-changing risks and methods related to money laundering (Gao and Xu 2009). In order to provide support for AML decisions, Gao and Xu (2009) have formulated an AML conceptual model. Based on this model, a novel and open multi-agent AML system prototype has been designed and developed. Intelligent agents with their properties of autonomy, reactivity, and proactivity are well suited for dynamic, ill-structured, and complex ML prevention controls. The advanced architecture is able to provide more adaptive, intelligent, and flexible solution for AML (Gao and Xu 2009).

Fyfe and Jain (2005–2006) consider the problem of having an agent respond appropriately to dynamically changing environments. Fyfe and Jain (2005–2006) work within the Beliefs—Desires—Intentions paradigm and show how an agent may use concepts suggested by Artificial Immune Systems to dynamically change its intentions in response to a dynamically changing environment. Fyfe and Jain (2005–2006) illustrate these ideas with teams of agents who must either compete or cooperate in the context of simple artificial games in order to fulfil their specific desires.

2.9.5 Process Mining Integration to Decision Support

Business process mining takes logs to discover process, control, data, organizational, and social structures (Van der Aalst et al. 2007). Business process mining can be seen as business process intelligence, business activity monitoring, business process management, business process analysis, automated business process discovery and workflow mining (Turner et al. 2012).

Process mining stands for a set of techniques to analyze business process models and logs (Accorsi and Stocker 2012). Process mining is a process management technique that allows for the analysis of business processes based on event logs. The basic idea is to extract knowledge from event logs recorded by an information system. Process mining aims at improving this by providing techniques and tools for discovering process, control, data, organizational, and social structures from event logs (Van der Aalst 2011). Process mining provides methods for reconstructing process models from logs (process discovery), checking the conformance of an existing or reconstructed model and logs (conformance checking), and enhancing process models based on the results of analysis (process enhancement) (Accorsi and Stocker 2012).

Process mining techniques allow for the analysis of business processes based on event logs. For example, the audit trails of a workflow management system, the transaction logs of an enterprise resource planning system, and the electronic patient records in a hospital can be used to discover models describing processes, organizations, and products. Moreover, such event logs can also be used to compare event logs with some a priori model to see whether the observed reality conforms to some prescriptive or descriptive model (Van der Aalst 2008).

Although many researchers are developing new and more powerful process mining techniques and software vendors are incorporating these in their software, few of the more advanced process mining techniques have been tested on real-life processes (Van der Aalst et al. 2007). Using a variety of process mining techniques, Van der Aalst et al. (2007) analyzed the processing of invoices sent by the various subcontractors and suppliers from three different perspectives: (1) the process perspective, (2) the organizational perspective and (3) the case perspective.

Unlike many other decision support systems, the focus is on the analysis of the current situation rather than evaluating redesigns or proposing improvements. The outcome of process mining is a better understanding of the process and accurate models that can safely be used for decision support because they reflect reality. To link process mining to decision support, we distinguish between four types of decisions when it comes to operational (i.e., workflow-like) processes (Van der Aalst 2008):

- Design-time decisions, i.e., decision made during the initial modeling of a process. These decisions are recorded in models and specifications which are used to realize information systems. For example, at design time, it may be decided that one activity has to wait for the completion of another because of data dependencies.

- Configuration-time decisions, i.e., decisions related to the customization of a process/system for a specific organizational setting. For example, the designers of the SAP R/3 system developed their system based on a set of reference processes describing the different scenarios in which the ERP system can be used. However, to become operational, the SAP system needs to be configured for a specific organizational setting. In this configuration process, all kinds of decisions are made. For example, most organizations switch off functionality and select the desired mode of operation (such as a particular way of invoicing).
- Control-time decisions, i.e., decisions to manage processes while they are running. Depending on the context, decisions regarding the use of capacity, the selection of paths, prioritization, etc. are taken. These decisions are at the level of the process and not at the level of an individual process instance but change over time depending on the context. For example, based on an unusual demand volume in the weeks before Christmas, it is decided not to accept rush orders, and capacity from other processes is relocated to the bottlenecks.
- Run-time decisions, i.e., decisions made for individual process instances (cases in workflow terminology). These are the decisions typically depicted in process models. For example, based on the value of an order, a particular path through the process is selected. A run-time decision typically depends on the properties of a particular case.

2.9.6 Adaptive Decision Support Systems

Developments of adaptive decision support systems (Chuang and Yadav 1998; Chen et al. 2012; Johnson et al. 2014; Holm et al. 2014) have been ongoing for some time.

Knowledge plays an important role in knowledge-based decision support systems (DSSs). This is especially salient in dynamic environments where knowledge-based adaptive DSS operate. The role played by these DSS necessitates maintaining knowledge current since stale knowledge could lead to poor decision support (Shaw and Piramuthu 2008). Shaw and Piramuthu (2008) present a generic adaptive DSS framework with learning capabilities that continually monitors itself for possible deficit in the knowledge base, expired or stale knowledge already present in the knowledge base, and availability of new knowledge from the environment. The knowledge base is updated through incremental learning. Ideally speaking, an adaptive DSS must be able to support decision-making while being adaptive to changes in both the user preferences and the environment. The dynamics of change can have different sources, including the problem environment; user preference, including changes in performance criteria, as well as whether to be proactive or reactive to decision-making situations later in time (Shaw and Piramuthu 2008).

Dynamics in the problem environment could manifest in several forms including those that are expected and unexpected in the normal course of the system's lifetime. Examples of expected dynamics include the arrival of jobs in a manufacturing shop floor and the arrival of new knowledge in systems used for intelligent tutoring. Examples of unexpected dynamics include the arrival of "hot jobs" in a shop floor and the use of intelligent tutoring systems designed for students without learning disabilities by students with learning disabilities. Dynamics in the system could also be influenced by changes in performance criteria. Examples of changes in performance criteria include a change of emphasis from unit price to quality in a supply chain and from concentrating on thoroughly learning a few concepts to shallow learning of several concepts (Shaw and Piramuthu 2008).

It is hard to envision a real-world application in a dynamic environment where knowledge remains static. Stale knowledge is thus a major problem in any static knowledge-based system. The proposed framework alleviates problems associated with stale knowledge through continuous monitoring of system performance as well as availability of updated and/or new knowledge. The source of knowledge can be both external and internal. Oftentimes, it is desirable to have almost instantaneous access to necessary set of examples for learning purposes to facilitate faster learning and thus minimizing the effects of stale knowledge on system performance. The simulation component aids in quickly generating examples to any desired system parameter specification. Without the simulation component, this would not be possible given the resource constraints under which most real-world systems operate in a dynamic environment. The performance evaluation component plays a vital role in vigilantly monitoring the state of the knowledge base and quickly reacting to any observed deficits in knowledge (Shaw and Piramuthu 2008).

Next, one of the aforementioned systems will be described in brief as an example (Holm et al. 2014). Today's operators on factory shop-floors are often not stationed, dealing with a single or few tasks but have increasing responsibilities demanding enhanced skills and knowledge in a production environment where any disturbance must be settled with adequate actions without delay to keep optimum output. To be able to respond to these demands, the operators need dynamic, distributed and adaptive decision support in real-time, helping them to distinguish decision options and maximizing productivity despite incoming stochastic events. The minimum of time and option for operators to consider appropriate action both during normal production and when facing unexpected or unscheduled events point out the need of adaptive decision support for operators. When initiating this research project the question from the industry partner was the following: In what ways is it possible to support operators in making decisions for optimal productivity? By targeting this problem this research introduces a novel framework for an adaptive decision-support system enabled by event-driven function blocks and based on decision logics. The proposed decision support systems' ability to adapt to the actual conditions on the shop-floor is validated through a case study, and its capability is compared to the voice message system installed on-site (Holm et al. 2014).

2.9.7 Computer Vision Based DSS

Computer vision is a field that includes methods for acquiring, processing, analyzing, and understanding images and, in general, high-dimensional data from the real world in order to produce numerical or symbolic information, e.g., in the forms of decisions (Klette 2014). This technology serves as the basis for developing computer vision based DSS (Gordan et al. 2008; Kumar et al. 2013; Segev 2010). Computer vision includes methods for acquiring, processing, analysing, and understanding images or image sequences from the real world in order to produce information, e.g., in the forms of decisions. It is the combination of Image Processing and Statistical Pattern Recognition. Biometrics deals with the recognition of persons based on physiological characteristics, such as face, fingerprint, vascular pattern or iris, and behavioural traits, such as gait or speech. It combines Computer Vision with knowledge of human physiology and behavior (Spreeuwers 2011; Boom et al. 2011). This is why computer vision and biometrics technologies are being more and more integrated lately.

2.9.8 Sensory Decision Support Systems

Sensory systems (vision, tactile, and signal processing systems), which analyze human vision, hearing, touch, taste, smell and vestibular senses, are being used as a composite part of DSS (Xiaoqiang et al. 2012; Liu et al. 2011). The term "Sensory Processing" refers to our ability to take in information through our senses (touch, movement, smell, taste, sight, hearing, balance), organize and interpret that information and make a meaningful response (SPD Australia 2014). The human eye is one of most remarkable sensory systems (Li and Jain 2009). Sensory systems are being integrated into DSS (Chernbumroong et al. 2014; Xiaoqiang et al. 2012; Liu et al. 2011; Edoura-Gaena et al. 2006; Perrot et al. 2004). One such instance is presented further. Chernbumroong et al. (2014) how the proposed multi-sensor activity recognition can be used to enhance the sensor support system (DSS) for health care. The proposed method is used for classifying the complex sensor data into activities to generate a database of activity records over times. The data management is used for manage databases from several sources. The operations that the data management carries out include organize, search, query, add, update, and delete databases. It also connects to the user interface management to provide interface for the users to perform operations with the databases. Besides the activity database, other databases related to health care information such as medical records, hospital resources, carer records, and independence assessments are connected with the data management so that the DSS can cooperate with several sources to make reliable sensors. The activity database can be used as part of the other clinical sensor support systems to give more information to support the illness diagnostic or disease symptom. For example, if the activity record shows that the patient has very little sleep per day, it could influence the sensor of the specific sleeping disorder (Chernbumroong et al. 2014).

2.9.9 Robotic Decision Support Systems

Robotics is the branch of mechanical engineering, electrical engineering and computer science that deals with the design, construction, operation, and application of robots (Oxford Dictionaries 2014). One of the trends in the development of robotics is human-robot interaction involving communications with people through speech, gestures, and facial expressions by applying biometric technologies. Various DSS are being developed (Weiss and Yung 2009; Mouaddib 2008; Johannsen 2007; Nieten and Fishwick 2007; Pernalete et al. 2007; Heikkilä et al. 2013; Patel and Kamrani 1996). These systems are being integrated with robot technologies. Sensory systems are also combined in robots with a programmable, electromechanical device to perform manual labor.

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