Review of decision support systems in air transport system

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REVIEW OF DECISION SUPPORT SYSTEMS IN AIR TRANSPORT SYSTEM

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The term Decision Support System (DSS) is widely, though inconsistently used, but in its essence it stands for any kind of “system” which provides valuable information necessary to support decision making (DM) process. These systems are much appreciated in highly complex environments where problems or tasks have varying degrees of structure, majority of them being unstructured or semi-structured. As being safety-critical human-in-the-loop distributed and complex system Air Transport system is for sure such an environment and very fertile soil for the application of various DSS. Through the literature review, the aim of the research described in this paper is to present the usage and application of DSS in air transport system, with the main focus on Airline, Airports and Air Traffic Management field. Further intention is to provide some insights about major historical trends, i.e. how DSS evolved, the problems that have been tackled and the models and techniques used to solve them, as well as to give potential direction for further development of DSS and its application.

KEYWORDS: Decision support system, Air Transport, Airline, Airport, Air Traffic Management

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1. Introduction

Air transport system (ATS) is usually defined as complex system with high level of inter and intra relations between its subsystems: Airlines, Airports and Air Traffic Management – ATM (Janić, 2000). From ever growing and changing ATS, a number of global players emerged (like major airlines, airport operators and air traffic network managers), as well as many regional and local ones (for example, regional airlines and airports, Functional Airspace Blocks) which also play important role in the system. Overall global growth, uneven though, globalisation, changes of regulations and information technology development are some of the most influential factors which have shaped air transport system.

But it is the constant need to satisfy end-users of ATS, i.e. passengers and freight shippers (demand), thus to fulfil own goals, that kept Airlines, Airports and in the end ATM (supply) "riding on a rollercoaster" of changes and improvement, regardless if they were profit seeking (private sector) or trying to maximize output-welfare (public sector)[1]. To produce and maintain high volume of quality and versatile services to end-users, ATS makes use of sophisticated technology, equipment and facilities operated and managed by trained and skilful personnel.

On the other hand, these costly resources have to be utilized in such a manner to balance between level and quality of service to end-users and fulfilling company's goals. Road to this goal is covered by various challenges which should be tackled by means of analytical methods, modelling, planning and management to come up with decisions and actions to overcome them. Decision-making (DM) process is not always straightforward: not only to choose between alternatives, but to come up with them.

No matter the size of an Airline, Airport, Air Navigation Service Provider or Network Manager, they all face similar problems, the scopes being different, in day-to-day operations, short-, mid- and long-term planning, scheduling, and so forth, so having "a system" to support DM process is highly appreciated by managers and planners. These so-called Decision Support Systems (DSS) come in handy to decision makers not only for providing alternatives, but also for data collection and analysis, visualisation, validation, etc.

The aim of this review is to present application of such DSS in ATS, namely, in the fields concerning Airlines, Airports and ATM. Being safety-critical human-in-the-loop distributed and complex system ATS could be recognized as a very fertile soil for the application of various DSS. The origins, definition and categorization of DSS are discussed in Chapter 2. The definition of DSS used in this paper and criteria for an article inclusion in the review is given in Chapter 3. Chapters 4 to 6 present DSS application in Airlines, Airports and ATM, respectively. Conclusions and discussion are left for the last chapter (Chapter 7).

[1] See Gillen, 2011.

2. DSS: Origins, Definition and Classification

Although the field of DSS is already mature (detailed historical timeline is provided by Power, 2007), there is still an ongoing debate on the origins of DSS, DSS classification and in the end, definition of decision support system.

Majority of researchers agree that DSS came along with first computers. Apparently, some of the first decision support systems came from Carnegie Institute of Technology, where researchers were conducting “theoretical studies of organisational decision making” and MIT project on “interactive computer systems” in the late 1950s and early ‘60s (Keen and Morton, 1978). Pioneering papers in this area were published in the mid and late ‘60s (e.g. Scott Morton and Stephens, 1968; Scott Morton and McCosh, 1968; Ferguson and Jones, 1969), but it seems that the first use of the term “decision support system” was in Gorry and Morton’s article from 1971 (Power, 2007). Shim et al. (2002) also stated that the original concept of DSS was first “clearly defined by Gorry and Morton who integrated Anthony’s (Anthony, 1965) categories of management activity and Simons’s (Simon, 1960) description types”.

The ‘70s could be referred as the beginning of progressive theoretical and practical development in this field. In their three consecutive surveys ([20], [21], [22]), covering period from 1971 to 2001, Eom and others provided detailed information on the DSS articles published: distribution of DSS application in different research fields and in time, underlying techniques used, classification of DSS, etc. A recent review, with DSS origins discussion as well, is Arnott and Pervan (2005).

One of the first definitions of decision support system came from Little (1970), when he defined *decision calculus* as “a model-based set of procedures for processing data and judgments to assist a manager in his decision making”. He also argued that for a successful system there are some prerequisites: a system needs to be simple, robust, easy to control, adaptive and complete on important issues (conflicts with simplicity), which are desirable features of a DSS even nowadays. Also, one early definition of DSS, by Keen and Scott Morton (1978), states that DSS is about pairing the best characteristics of man and machine to improve the quality of decisions: “It is a computer-based support system for management decision makers who deal with semi-structured problems”. Bonczek et al. (1981) defined a DSS as a computer-based system consisting of three interacting components: a language system, a knowledge system and a problem-processing system. According to Turban and Aronson (2001) the central purpose of a DSS is supporting and improving DM process. In practice, decision support system is referred a “tool” when it is packed, and usually, installed on a computer.

One of early DSS classifications is so called Alter’s taxonomy (Alter, 1980). He grouped DSS according to generic decision support operations that can be completed by such systems:

- *File drawer systems* – deal with data on a basic level.
- *Data analysis systems* – add possibility for analysis of data.
- *Analysis information systems* – data from databases is used to “feed” models.
- *Accounting and financial model* – usually used for “what-if” analysis in accounting and finance.
- *Representational models* – scenario analysis using simulation models.
- *Optimization models* – given the constraints and criterion function provide optimal solution.
- *Suggestion models* – provide a number of alternatives and suggest actions.

Frequently cited classification is also Power’s taxonomy (Power, 2002). He differs, on conceptual level, between:

- *Data-driven* DSS (first three categories of Alter’s taxonomy),
- *Model-driven* DSS (second three categories of Alter’s taxonomy),
- *Knowledge-driven* DSS (basically the same as Suggestion DSS),
- *Communication-driven* DSS (collaborative work and DM process) and
- *Document-driven* DSS (handling unstructured data and information).

Obviously, there is no consensus on the origins, definition and classification of DSS. Although widespread use of the term “Decision Support System” may cause some inconsistences and ambiguity, in its essence it stands for any kind of “system” which provides valuable information necessary to support DM process (for example, see Sprague and Carlson, 1982).

3. DSS in Air Transport System

Eom et al. in three consecutive surveys have provided useful insight into early application of DSS ([20], [21], [22]). Based on their selection criteria and available resources (databases) for article searching, they examined 203 articles published from 1971 to April 1988, 271 published from May 1988 till December 1994 and 210 articles from 1995 until 2001. In the first survey 5 of 203 articles were from ATS field, 7 of 271 were from ATS field in the second survey and from 210 articles in the third survey, 9 came from some of ATS fields.

Granted, it seems like that there were very few applications of DSS in ATS field, and the reason for this could lie in the criteria for paper inclusion in their surveys: “a) a description of semi- or unstructured decision, b) a description of the human-machine interface and the nature of the computer-based support for human decision makers’ intuitions and judgements; and c) a description of a data-dialogue model system”. Also, they restricted their search to peer reviewed journals only. Authors themselves were aware that the rigorous criteria setting would cut down the number of articles in their survey and in their words it was: “a trade-off between the quality and the quantity”.

For the purpose of this paper DSS is defined as a system to support and improve DM which contains the three subsystems (at least at conceptual level):

- *data subsystem* - a some kind of database attached or clearly identified data required as input,
- *model subsystem* - a mechanism for processing the data (this could be models, rules, agent-based subsystem or some other techniques) and
- *user interface subsystem* - DSS should be capable of receiving and acting on requests from users (e.g. the user might request the detail that allowed a specific recommendation to be formed in order to see for himself if it is justified) or at least a description of user interface.

Criteria for the paper inclusion in this review are less rigid than in abovementioned surveys, but the restriction to articles from peer reviewed journals stands. The aim of the research was not to have an exhaustive review, but rather to present the application of DSS in ATS field for daily operations and short- and medium-term planning mostly and to focus on the major topics (issues).

4. DSS for Airlines

In his historical overview, Power (2007) claims that "one of the first data-driven DSS was built using an APL-based software package called AAIMS, An Analytical Information Management System. It was developed from 1970-1974 by Richard Klaas and Charles Weiss at American Airlines". So, one can imagine that airline issues initiated application of DSS in ATS[2].

Some of major problems in Airline research field could be classified under "scheduling" category. Basically, any scheduling problem considers optimal allocation of resources in time (slots), given the constraints. First in line in this paper is crew scheduling problem for an airline, which requires covering all flight segments from a given time period with available crew members, taking into account various constraints (like crew bases, licencing, etc.), preferably at minimum costs.

Anbil et al. (1991) described the trip re-evaluation and improvement program (TRIP) which was developed in-house (American Airlines – AA, had 8300 pilots, 16200 flight attendants and more than 510 aircraft at that time) for crew assignment (a typical optimisation model). Crew-pairing relied completely on crew analyst and his skills until 1971, when AA developed TRIP: analyst was required to provide an initial solution and the program would iteratively improve this solution, with respect to all constraints (see also Gershkoff, 1987 and Gershkoff, 1989). Crew-pairing was defined as set-partitioning problem and TRIP used Linear Programming based optimizer to solve it. TRIP was also used for what-if studies and decision-making on if AA should close or open crew base in some city, manpower requirements in each crew base and also to

[2] Taplin, 1973. All 5 papers from the first Eom et al. (1990) survey fall in Airline category.

evaluate economic impact of changes in operational rules. For example, Dijkstra et al. (1991, 1994) also used optimisation based DSS for what-if analysis: to determine required number of aircraft maintenance engineers and their qualification and the impact of KLM contracts with other airlines companies on the size of KLM maintenance organization and workforce. Anbil et al. (1991) provided generous information on the evolution of the system, but very few information on planner-computer interaction and databases used.

To digress, based on experience in developing DSS[3] for strategic manpower planning of airline pilots, Verbeek (1991) emphasised the need for high planner-computer interaction, so that planner could "play" with the output from DSS. The output from a DSS should also provide useful information in appropriate form and preferably a number of alternatives and their respective scores. Schindler and Semmel (1993) reported that Pan Am used a station staffing model based on integer LP ("next step is to expand methodology to be used as an operational tool") to find a solution, and then station planners manually expanded the results to cover requirements for a longer timeframe.

Getting back to crew scheduling problem, one could argue that in an ideal situation with no disruptions of operations, this problem could be classified as *structured*, which basically means that one should have fairly straightforward way to solve it, that is, to come up with *structured decision*. Many DSS pioneers argue that this kind of problems require no support for DM, but merely a model to solve it (see Little, 1970). On the other hand, without a computer help to solve highly complex and computationally demanding model, planners would have difficult time trying to produce (near)optimal solutions (e.g. see AA savings in Anbil et al., 1990). In reality, there are a lot of events that prevent operations from going as planned, which makes crew scheduling *semi-*, or for larger and not common disruptions even *unstructured* problem. To make a decision in this circumstances one cannot rely solely on a model, but the role of experienced staff and their creativity step in to "fill the gaps".

Such problem is addressed in (Argüello et al., 2003) where airline schedule is disrupted due to unexpected events, thus affecting crew schedules. They developed fully operational DSS for crew scheduling (Continental Airlines) which was fully integrated with the operations centre database and flight scheduling system. The DSS is used by crew coordinator on the day-of-operations "to monitor ongoing crew activities, detect operational disruptions and resolve crew disruptions…whenever a crew-recovery solution is not immediately obvious (up to 3 solutions are proposed)". Due to impractical reasons to solve the problem with set-covering algorithms, authors decided to use heuristic based search (depth-first search) algorithm. One more DSS, on conceptual level though, dealing with similar problem is given in Abdelghany et al. 2004.

[3] For process of designing a DSS see also Zaraté, 1991.

Flight scheduling has also been the subject of research for many decades now. Back in 1967, Hinkle and Kuehn proposed using a DSS (based on heuristics model) for airline scheduling problem. Vasquez-Marquez (1991) gave detailed description of an interactive DSS (network-based heuristics) for rescheduling in American Airlines by slot substitution process. Rakshit et al. (1996) is scholary example of real-time DSS for schedule optimisation[4]; this one being implemented in United Airlines in 1992. They dealt with aircraft shortage problem, i.e. lack of aircraft to complete all scheduled departures on time. Autors adressed issues regarding all the constitute elements of a DSS: a data management system able to obatain operational data in real time, model (a minimum cost network flow model), and graphical human-machine interface with user on mind (who is not technically competent to understand underlying optimisation model, but is still able to “manipulate and use it”). Operations controller had options to monitor current operations and options to delay or swap flights (cancelation of flights was not a part of the model) based on a number of alternatives the DSS provided, but also to exclude some flights from model formulation (e.g. due to high importance, some flights should not be delayed nor swaped). Babic et al. (2010) developed DSS for daily operational fligh scheduling based on heuritics, with delay, cancelation and aircraft subsitiution options for tweaking schedule to optimize cost function (dispecher was given an option to change parameters, through appropriate user interface, of the cost function, e.g. based on his experience). Antes et al. (1998) developed model-based DSS for evaluation of flight schedules for cargo airlines and they generously share their experience during the implementation process with scheduling experts from airline (see also Yau, 1989). Creating flights schedule, improving an existing flight schedule or its manual modification, evaluation of profitability and performing what-if scenarios in the case of fractional aircraft ownership is presented in (Martin, 2003).

Borovits and Neumann (1988) describe airline management information system (MIS) for smaller airlines, which is a combination of airline reservation system and “an interactive DSS which is used for what-if questions regarding scheduling aircraft, crews and general personnel and for assessing and determining schedule and fare changes”. MIS usually provides information to support DM (Davis, 1974) and some researchers argue it should not be classified as a DSS, since it supports structured decisions (Gorry and Scott Morton, 1971). Nevertheless, none neglects usefulness of valuable information well-designed MIS could provide to a decision maker. An evolution of MIS implementation (Continental Airlines) and its use for DM is given in Watson et al. (2006) and Wixom et al. (2008).

In the end, passengers are also using such information systems to find their flights on a daily basis, so in a sense, they are end users of MIS and they make their (travel) decisions based on the information provided.

[4] Similar paper is Mathaisel, 1996.

5. DSS for Airports

One of the common issues regarding airports is how to achieve balance between demand and capacity in short(er) and long(er) term. There are a lot of simulation and modelling tools used in practice for “what-if” analysis and as a support for DM. It is generally accepted that decisions could be classified, according to their *scope* (i.e. time horizon), into three classes: strategic, tactical and operational (see for example Vercellis, 2009). Depending on the industry and particular organization, the time horizon between categories varies and they are usually “overlapping”, but there is also a feedback from one level to another in both directions.

As an example, reaction from an airport supervisor (operational level) that there is, for example, a constant bottleneck in a part of the terminal building and that queues and waiting times are high for the current standards, might have an implication to terminal building managers to rethink some procedures and practices (tactical level) or even on top management to consider expanding (strategic level). And if the decision for renovation, expansion, major repairs, etc. has been made, the construction process itself could have a major influence on airport operations and vice versa, which calls for a great deal of planning and coordination. Shami and Kanafani (1997) introduce “a predictive tool” to report on both: airport operation performance and construction progress. They integrated SIMMOD (airspace and airport simulation tool) and project management program to provide answer to various relevant “what-if” scenarios; the interrelationships between airport operations and construction projects has been achieved through a knowledge base on mutual disturbances.

Stamatopoulos et al. (2004) presented in detail “total airport management concept” which could be described as DSS for both short-term (operational) and long(er)-term (tactical and strategic) planning (based on stochastic analytical model for runway capacity estimation and simulation for apron and taxiways). Authors state that unlike stand-alone models (tools), which usually provide information such as runway or apron capacity studies, their DSS concept provides an integrated set of models which treats the individual elements of the airfield, i.e., the runways, taxiways and apron areas together with high level of interaction. Their DSS was first evaluated and validated at Rome's Fiumicino Airport, and after some enhancements, at Amsterdam, Athens, Frankfurt, Madrid, Palma de Mallorca, and Toulouse. Following this research, Zografos and Madas (2006) introduced “a decision support system that will allow decision makers and analysts to evaluate the efficiency of the total airport complex simultaneously by considering the entire spectrum of measures of airport effectiveness and their associated trade-offs”. Aside from their detailed description of the developed DSS, this paper provides references for other existing models and tools. In their most recent paper, Zografos et al. (2013) further develop DSS for airport performance analysis. Similar concept which addresses the problem of strategic airport planning is Wijnen et al. (2008).

Assignment of aircraft to gates, given a set of constraints, to meet certain criteria is so-called Gate assignment problem[5]. The problem is characterized as NP hard and a number of solutions have been proposed in Operations Research (OR), ranging from optimal solution for small scale problems using some of exact methods to heuristics and simulation to near-optimal solutions for large(r) scale problems. To "enhance" existing OR approaches, a number of researchers introduced "soft constraints"[6] in a form of rules defined by experts to get a step closer to real-life gate assignment problem. Gosling (1990) presented expert system (ES) for gate assignment with simple rule-base and inference system (see also Srihari and Muthukrishnan, 1991). ES proposed by Cheng (1997) integrates a knowledge-based system with traditional mathematical programming techniques to optimize multi-objective function. A knowledge-based intelligent agent integrating a quadratic optimization model for gate assignment is presented in Lam et al. (2002).

Expert systems require knowledge to solve particular problems and suggest or recommend actions to managers, and as such were classified as knowledge-driven DSS (Power, 2002). However, many think that one should differentiate DSS from ES, usually emphasising that ES could be used by less experience users or could even replace human and automate decision-making process, whereas DSS facilitates DM and assist even highly experienced users in DM process. One of discussion on this matter leads to discussing "levels of automation in the system", which is left for the last chapter of this paper.

Ansola et al. (2012) also address disturbance issues, but in airport ground handling process. They use wireless communication (based on Radio Frequency Identification – RFID) for real time monitoring and tracking of resources (authors provide fairly detailed technical specification of such system) and combine it with modules based on artificial intelligence to optimally allocate resources. Andreatta et al. (2014) have also used real-time vehicles data and apply heuristics to assign vehicles to apron operations.

Speaking of disturbances of airport operations, it is hard to omit weather related ones, especially in the winter season. Decision support system for aircraft deicing is given in Rasmussen, et al. (2001). The system collects weather data from various sources and provides all users with useful information on winter weather conditions affecting airport operations. This increases situational awareness and "facilitates better and more timely DM regarding the start and stop of winter operations by snow desks, deicing operators, and slot allocation coordinators, and improved real-time decisions regarding deicing operations, runway clearing, aircraft dispatch, and aircraft control during winter storms" [51]. Conceptual DSS which integrates probabilistic weather forecasts with traffic flow management to assist reducing ground delays at San Francisco airport (two pairs of

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[5] Also note that Gate assignment problem is closely linked to minimization of passengers walking distance and allocation of resources in ground handling process.

[6] Rigid and inflexible constraints in model formulation were marked as disadvantage of classical approach.

closely spaced parallel runways) during summer low-cloud-base days is defined in Reynolds et al. (2012).

It is essential to any airport to be operational most of the time and keep traffic flowing in a safe manner. Airport is the place where interaction of the three ATS subsystems is most obvious, especially between Airport and Air Traffic Control (e.g. aircraft departure and arrival sequencing, airport ground operations). Decision support tools for traffic flow management are used by air traffic controllers, but the decisions made have major impact on airports (relate to gate assignment and resource allocation process)[7]. These DSS are addressed further in the text.

6. DSS for Air Traffic Management

Air traffic management and ATM related problems became one of the focal points of applied operations research in ATS in the 1980's and 90's. There are a number of various DSS and their application reported in journals (the focus of this paper) and technical reports, as well as papers presented at some major ATM conferences. In this paper, the focus is majorly on air traffic flow management (ATFM). Few DSS implementations in air traffic control (ATC) are given as well.

Continuing the discussion from previous chapter, DSS for traffic flow management and operations at airport are presented. For airports with high traffic volume managing traffic safely and efficiently is paramount: delaying flights cause disturbances not only to airlines and airports (as discussed), but to passengers as well.

The paper by Venkatakrishnan et al. (1993) addressed problems of unnecessarily large separation for arriving aircraft (imprecise control and planning) and suboptimal landing sequence in terminal area (computational complexity). Authors collected real Landing time interval (LTI) data for pre-processing, analysis and calibrating a model for LTI[8] and proposed and tested three different models for suggesting a sequence of arrival aircraft to air traffic controllers (Boston Airport). They also argued that experienced controllers may overcome some disadvantages of their models and discuss a potential impact of this automation process on controller's workload. Anderson et al. (2003) presented collaborative arrival planner and concluded that benefits from increased communication and collaboration between airlines and air traffic controllers could be significant (see also Vasquez-Marquez, 1991). It is interesting to note that there is an extensive theoretical literature on arrival and departure sequencing in journals, but quite a few actual implementations of DSS reported (to the best of our knowledge). On the other side, there are a number of technical reports on application and use of Arrival, Departure and Surface Management Systems (AMAN, DMAN and SMAN) and conference and workshop papers[9]. For ground operations, Landry et al. (2013) presented

[7] New initiatives for collaborative decision making are discussed in the last chapter.
[8] "To get the collective wisdom of controllers and pilots on what LTIs are acceptable", Venkatakrishnan et al. (1993).
[9] Such as [12], [23], [24], [3].

methodology and conceptual DSS for dynamic taxiway and runway conflict prevention with a toy example (Hartsfield Atlanta International Airport) and García et al. (2005) addressed the problem of optimizing airport ground traffic (see also Burgain et al., 2014).

Weigang et al. (1997) briefly described their initial research on the expert system in ATFM domain[10]. Their system can be used for modifying airline timetables to smooth traffic peak at airports during rush hours, for centralized flow control (establishing balance between demand and capacity) and for analysing ground holding of departing flights.

Nogami et al. (1996) is one of early papers describing planning and decision support system for ATFM. They consider two DSS: one for a single-unit air traffic control sector (small-scale) and one for an airway network (large-scale), and apply machine learning techniques for acquiring knowledge of the best actions (e.g. re-routing to by-pass congested sector) to be taken. Simulation data is used to train neural network and after that to test the trained system in a terminal area and a single-unit enroute sector. Although authors proposed and described in great detail "DSS for real-time in a vast traffic network", they didn't report any results (simulation studies had not been done yet). A very detail description of distributed DSS for tactical air traffic flow management is given in Wiegang et al. (2008). They reported that Brazilian integrated ATC didn't have "a specific system for the tactical management and synchronization of traffic flow, especially where disruptions occur due to abnormal meteorological conditions, aeronautical incidents, or accidents" at that time. DSS was designed as a modular system consisting of (Weigang et al., 2008):

- module for monitoring flights and expected traffic flows (flight plans and radar data),
- module of flow balancing is activated when projected traffic reaches a certain threshold,
- and module for evaluation and decision support (agent-based with reinforcement learning),

to suggests actions to establish balance between capacity and demand. In more recent paper, Weigang et al. (2010) proposed a multi-agent system for ATFM in grid computing for identifying congestions, negotiations and conflict resolution among airports which are part of the grid. In Europe, Leal de Matos and Powell (2003) proposed DSS for re-routing flights, the focus being on the understanding of the requirements for developing such a DSS. One interesting note from the same authors is that "In assessing the applicability of optimisation approaches to ATFM, a key question is why none of the models proposed in the literature for the allocation of ground-delays has been implemented in a system for use in practice" [41].

[10] Authors also referred to some of the initial implementation of expert systems in ATC.

To better understand the general requirements for developing a DSS for ATFM, hence corresponding *decisions*, consider Figure 1. According to Vercellis (2009), majority of strategic decisions should fall in unstructured category, most of operational decisions could be classified structured with tactical decisions being somewhere in between. Regardless of the timeframe, the further back in time before making a decision, the higher uncertainty managers and planners are facing in general. This has a major implication on the characteristics of information necessary for DM process and development of adequate DSS.

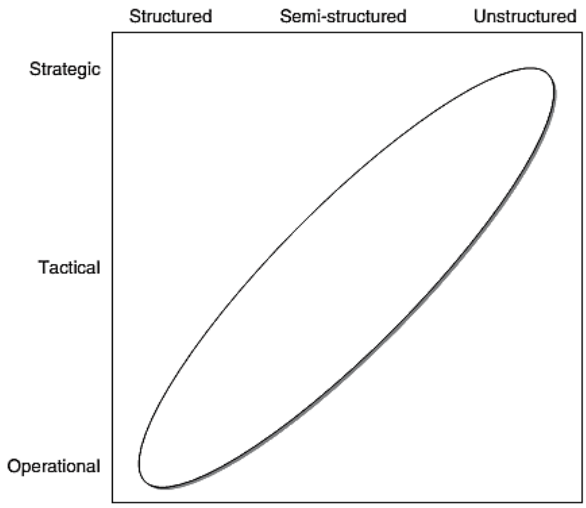

Figure 1. Taxonomy of decisions. (Source: Vercellis, 2009.)

Air traffic flow management (and capacity management) process activities (e.g. planning, forecasting) are divided in three phases:

- strategic – which starts a couple of months before the flight is scheduled until one week before the acctual operation,
- pre-tactical – starts few days to one week before real time operations and
- tactical – on the day of operations [25].

Decisions from one phase are input for another and are updated and modified with update and arrival of new information. Following the above mentioned logic, desirable feature of a DSS for ATFM would be ability to take into account varying degree of characteristics of information (e.g. time horizon, level of detail, precision, scope), regarding both objectives and constraints. Weigang et al. (2008) emphasise one important feature of the DSS they proposed for tactical ATFM: a possibility of integrating that DSS with other already existing tools, thus making a useful "toolbox" to support all three planning phases for air traffic controllers[11].

[11] We draw attention to Iordanova, 2003. She proposed ATM policy changes and discussed the effects and benefits of integrated operational DSS on ATM in general.

7. Conclusions and discussion

This paper provides an insight into application of decision support systems in air transport system, i.e. in its subsystems: Airlines, Airports and Air Traffic Management. For the purpose of this paper, DSS is considered as a system consisting of three basic elements, a database, a model and interface, at least at conceptual level, to support DM process. The focus of the research was on the major topics (issues) in ATS field and DSS application in use, for daily operations and short- and medium-term planning mostly.

Regarding DSS application in airlines, attention was mostly on scheduling problems, both crew and flights. Both problems require strategic (seasonal schedule, number of crew members required), tactical (monthly and weekly schedules) and operational planning (daily planning, reaction to disturbances). For crew (staff) scheduling, DSS were used for operational planning mostly, but also for some “what-if” analysis regarding longer term planning. Underlying models for problem (set partitioning) solving were based on linear (with relaxations) programming, integer programming and heuristics. For flight scheduling, DSS were applied to solve disturbances in daily operations, to evaluate planned flight schedules and for manipulation of already existing flight schedules. Techniques used for DSS models are based on heuristics (depth-first search), mixed integer programming and network optimization. All these DSS could be considered as model-driven, except of management information systems reviewed, which could fall in data-driven model.

Even from this modest sample of reviewed DSS application in Airline industry, the impression is that major evolution happened in data and information systems, which evolved from pure repositories into powerful *business intelligence* systems. State-of-the-art information technology enables *data mining* of *big data* and “extraction” of useful information for decision making purpose. Airlines benefit from increased efficiency of in-house operations and also through increased revenues by tailoring their products and services to customers (customer-centric).

Regarding DSS application in airports it was found that aircraft gate assignment and allocation of ground resources for ground handling, as closely coupled problems with high complexity, draw significant attention of DSS practitioners. Due to operational requirements for timely decision-making, reviewed articles propose support systems (expert systems) for both problems, by applying heuristics, expert’s knowledge and artificial intelligence to promptly deliver necessary information. The need for timely information is evident especially in the cases when disturbances occur. For airport planning, a number of simulation and modelling tools are used in practice for “what-if” analysis and as a support for DM. *Total airport management* (TAM) concept for airport planning started with integration of airside elements and is evolving into airside-landside fully integrated platform, even taking into account ground access to the airport. This could be a promising field for application of integrated decision support solutions.

As already explained, airports are most obvious joint for the three ATS subsystems. With ever increasing traffic and delay figures, the need for closer coordination between all three subsystems has grown along. Although a decade old, airport *collaborative* decision making (A-CDM) still represents state-of-the-art initiative in Europe. The concept of sharing data and work experience between all the parties involved opens the door for collaborative DSS to facilitate communication, data sharing and increased situational awareness.

Concerning DSS application in ATM, this review concentrated on ATFM problem, probably one of the most studied problems in ATM field of research. A number of optimization models to establish balance between traffic demand and airspace (airport) capacity have been proposed. However, based on DSS selection criteria, only ES based on neural networks and agent-based DSS made a cut. Evidently, for large-scale real-life problems heuristics, soft-computing and artificial intelligence techniques should be considered as candidates for DSS model. Collaborative decision making is also present in ATM with the aim to improve ATFM through increased information exchange among aviation community stakeholders and should be also considered a potential solid ground for DSS application.

A global tendency in ATM could easily be summed up in one word: *automation*. According to Parasuraman et al. (2000), automation could be simply defined as “partial or complete replacement of function previously carried out by the human operator”. Wickens (1998) identified three factors for automation in ATM: the need to improve safety and efficiency, the availability of the technology and the need to support the controller. This support could be discussed through “levels of automation” of decision and action selection, which basically tells “the share” of computer involvement in decision making. In the lowest level (1) of the Wickens’ scale, computers offer no assistance and human must take all the decisions and actions, whereas in the highest level of automation (10) computer decides everything, ignoring the human. In between are levels of varying degree of human and computer involvement in DM process. DSS reviewed in this paper are somewhere between level 3 where the set of decisions/actions are narrowed to a few for human to choose and up to level 6 where human have a restricted time to cancel or alter the decision before the system itself executes it.

Having in mind many worldwide and regional initiatives (such as Next GEN in USA, SESAR in Europe, CARATS in Japan) emphasizing the need for system-wide information sharing, supporting the business trajectory and other novel concepts, along with ever increasing complexity of ATS itself, it seems that DSS will remain more than necessary for human operators in the future. It is expected that working environment will significantly change (requiring highly interactive interfaces) and probably DSS with real-time big data processing capabilities and possibility of high integration with other DSS will be necessary. Also, it is reasonable to expect that current issues will remain in future (scheduling, assignment, flow management, etc.), but also that some new will emerge, demanding the development of the new models for finding solution.

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