A Review of Decision Support Systems for Manufacturing Systems

Andreas Felsberger[*]
University of Klagenfurt
Operations-, Energy-, and
Environmental Management
Universitätsstrasse 65-67
Klagenfurt, Austria
andreas.felsberger@aau.at

Bernhard Oberegger[†]
University of Klagenfurt
Operations-, Energy-, and
Environmental Management
Universitätsstrasse 65-67
Klagenfurt, Austria
bernhard.oberegger@aau.at

Gerald Reiner[‡]
University of Klagenfurt
Operations-, Energy-, and
Environmental Management
Universitätsstrasse 65-67
Klagenfurt, Austria
gerald.reiner@aau.at

ABSTRACT

In the field of manufacturing systems automated data acquisition and development of technological innovations like manufacturing execution systems (MES), Enterprise Resource Planning (ERP), Advanced Planning Systems (APS) and new trends in Big Data and Business Intelligence (BI) have given rise to new applications and methods of existing decision support technologies. Today manufacturers need an adaptive system that helps to react and adapt to the constantly changing business environment. The internal data processing system of a company can only offer minimum support because it is related to transactions. In this case, decision support systems (DSS) combine human skills with the capabilities of computers to provide efficient management of data, reporting, analytics, modeling and planning issues. DSS provide a distinction between structured, semi structured and unstructured data. In particular, a DSS reduces the quantity of data to a high quality structured amount; due to this, decisions are made to support the manufacturing process. In addition, the goal of these systems is to avoid problems within the production process even before they emerge. This paper gives an overview of the state-of-the-art literature on DSS and describes current techniques of relevant DSS applications within manufacturing environments.

Keywords

Decision Support Systems, Manufacturing, P&OM

---

[*]Andreas Felsberger, Research Assistant at OEE, University of Klagenfurt, Austria

[†]Bernhard Oberegger, Research Assistant at OEE, University of Klagenfurt, Austria

[‡]Gerald Reiner, Head of Department OEE, University of Klagenfurt, Austria

1. INTRODUCTION

Decision support systems (DSS) are about developing and deploying IT-based systems to support decision processes [5, 30]. Since the 1970s researchers,have focused on developing computer technology based solutions that can be used to support complex decision-making and problem solving [31]. The area of the information systems and the technologies have evolved significantly in the last decades. Nowadays, the tendency towards business intelligence (BI) is one of the key drivers for emerging developments in DSS technologies and methods. Overall, a DSS is an interactive computer information system that solves the problem of non-structures and can help decision makers to use data and models [86]. Suri and Whitney showed already in 1984 [78] that especially in flexible manufacturing systems, DSS are installed to improve productivity. Moreover, traditional manufacturing systems are transforming into knowledge-based manufacturing environments based on digitization, computer networks, artificial intelligence and rapid response across supply chains. These aspects are fundamental requirements for today's manufacturing systems to satisfy costumer needs and to produce high quality products within small batch sizes and sustainable consciousness. The way to a fitting DSS is quite marbled. First, the provided data, determined by several data gathering systems like ERP has to be filtered. After conditioning the data, several alternatives can be set to solve a defined problem and make at least a choice of decision design and implement the solution. This literature review focuses on past and current research on decision support systems in manufacturing. The paper is organized as follows: Section 2 gives a general overview and definition about decision support systems, in particular this part describes why DSS are used, how they are used and shows the structural components of the decision-making process. Section 3 describes upcoming trends of automated decision-making processes and new types of intelligent decision support systems (IDSS) in the context of Business Intelligence and Cyber-Physical Production Systems (CPPS). Section 3 concludes the paper and gives an outlook on further research questions.

2. LITERATURE REVIEW ON DECISION SUPPORT SYSTEMS

2.1 Decision Support Systems Definitions and Types

A DSS is defined as a computer system that deals with a problem where at least some stage is semi-structured [72, 43] or unstructured [10, 77]. Simon 1960 described decision problems as existing on a continuum from programmed (routine, well-structured and easily solved) to non-programmed (new, ill-structured and difficult to solve). [73, 16] Keen 1980 defined a DSS as a concept of the role of computers within a decision making process. Defined in terms of the structure of the task, it addresses the requirement of a distinctive design strategy which supports the cognitive processes of individual decision makers and reflects an implementation strategy for making computers useful to managers [43]. Haettenschwiler [26] differentiates between passive, active and cooperative DSS,

- A passive DSS is a system that supports the process of decision making, but that cannot produce decision suggestions or solutions.

- An active DSS can generate such decision suggestions or solutions.

- A cooperative DSS permits the decision maker to modify, complete, or refine the decision recommendations provided by the system, before sending them back to the system for validation [25]. The system again improves, adds, and refines the suggestions of the decision maker and sends them back for validation. [41]

Sprague and Carlson 1982 defined DSS as a *"class of information system that draws on transaction processing systems and interacts with the other parts of the overall information system to support the decision-making activities of managers and other knowledge workers in organisations".*[77, 63] Power 2002 defines DSS as interactive computer-based systems that help people use computer communications, data, documents, knowledge, and models to solve problems and make decisions [62]. In addition, Power distinguishes between enterprise-wide DSS and desktop DSS. An enterprise-wide DSS is connected to a large data warehouse and is used by many managers in the company. A desktop DSS is a small system that runs on a single PC [60].

2.2 Decision Making Process

The decision-making process was continuously developed over several years amongst others by Simon [73], Harris [29] and Shim [72]. The process is determined as an identification of alternatives as possible solutions for an upcoming ill-structured problem. In this case, the aim is not to identify as many of these alternatives as possible, but rather the one that fits best with the interpreted goals, objectives and values. The decision-making process itself goes through multiple phases. First, it is necessary to identify a problem and to determine who are the decision-makers and stakeholders in the decision process. The original model shows a top to bottom process flow but the current status may always return to a previous step from any point in the process [7]. Figure 1 of this paper shows that we broke down the top to
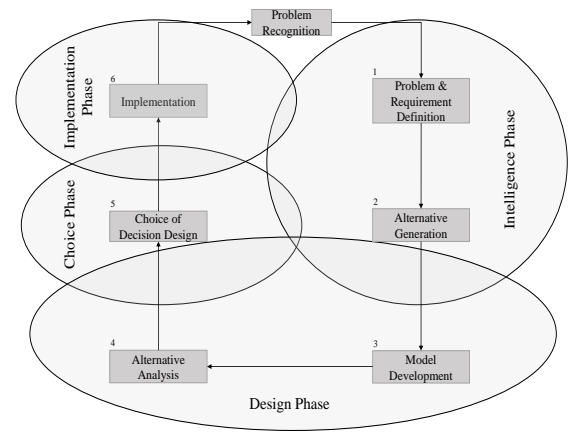

Figure 1: The decision-making process[1]

bottom process into a closed loop variation.

Steps 1 and 2 - Problem Requirement Definition and Alternative Generation: Once the problem has been recognized, the first step in the decision-making process is the problem definition [72]. Step 1 aims to express the issue in a statement that describes the initial and desired conditions. The second part of this step is to determine requirements to obtain a list of absolute exigencies and goals. The requirements define how the solution to the problem acts [7, 57]. Step 2, Alternative Generation, deals with the creation of possible alternative solutions for decision making uncertainties. One key aspect is that the alternatives must meet the determined requirements. This phase of the decision-making process is also called the "Intelligence Phase" which consists of finding, identifying and formulating the problem or situation. It gives an overview about the current status of an identified problem. The result of the intelligence phase should be a decision statement [73].

Steps 3 and 4 - Model Development and Alternative Analysis: After the alternative generation and selection of fitting alternatives the next step is the model development. Models are developed to analyze the various alternatives, simultaneously criteria should be defined to measure the effectiveness of the alternative. The best model to compare alternatives is that which will achieve the selected goals and criteria soonest. Once the model is developed, the next step will be the alternative analysis which concludes the evaluation of alternatives against criteria, selection of a decision making tool e.g. Pros and Cons Analysis, Kepner-Tregoe Decision Analysis (K-T), Analytical Hierarchy Process (AHP), Multi-Attribute Utility Theory Analysis (MAUT) or Multi Criteria Decision Analysis (MCDA) [44, 56, 18, 52, 22]. However, ongoing research aims to find out which method is more appropriate for which type of problem, to differ between advantages and disadvantages of using one method over another and if there is a decision change due to using different methods [83]. Finally, there is also the validation of solutions against the problem statement which aims to ensure that it truly solves the problem identified. As shown in figure 1, this phase is referred to as the so called "Design Phase" [73], where alternatives are developed and objectives

---

[1]Shim et al. (2002) and Simon (1960), modified by authors.

become linked to the decision-model.

The final steps are 5 and 6 - Choice of Decision Design and Implementation: These steps are taken as a basis of the "Choice Phase" [73] of the model. This phase is about the selection of the developed alternatives of the design phase. The final product of the process is a decision or model that is implementable into the decision environment, rolled-out in the so called implementation phase. The solution should satisfy the desired state, meet requirements and best achieve the goals within the values of the decision process. [7, 72]

2.3 The Architecture of DSS

A DSS has several fundamental components. The database management system (DBMS) is a software package, which is responsible for data access and manipulates and manages internal as well as external stored data in databases. Second, the model management system (MBMS) uses various kinds of mathematical and analytical models or simulations to represent and analyze complex data and the user interface component which handles the interaction of the user with the system [79]. Figure 2 gives a conceptual overview of the architecture of a DSS and the components mentioned above.
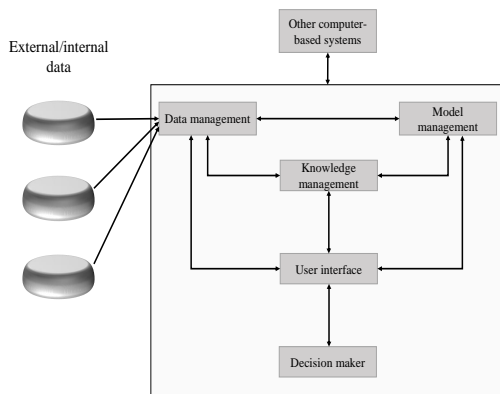

Figure 2: Schematic view of DSS components[2]

Subsequent to this architecture the literature names five relevant applications of DSS. Model-driven DSS, data-driven DSS, communication-driven DSS, document-driven DSS and knowledge-driven DSS. These applications consist of diverse sub technologies and decision support techniques for decision making.

2.4 DSS Application Development

2.4.1 Model-driven DSS

A model-driven DSS uses algebraic decision analytic, financial, optimization, and simulation models for decision support [65]. A model-driven DSS is designed for the manipulation of model parameters by the user and to support decision makers in analyzing a given situation. Usually they are not data intensive. There is no need of large databases for model-driven DSS, but for specific analyses they may need to be extracted. The main component in the model-driven DSS architecture are one or more quantitative models

---

[2]Turban et al. (2005), modified by authors.

that provide the functionality. Analytic tools based on algebraic models allocate an elementary level of functionality. They are used many times in building model-driven DSS applications. Generally algebraic models are developed within spreadsheets. To develop and build more complex models for decision making, decision analysis, optimization and mathematical programming models, and simulation techniques were used.

In general, models in a model-driven DSS represent a simplification of the reality. Decision analysis models refer to statistical tools and methods such as analytical hierarchy process (AHP), decision tree analysis [59], multi-criteria decision analysis [35, 70] , and probabilistic forecasting [28, 48]. The target of a decision analysis is to discover the most favorable alternative under the given situation. Optimization models integrated into a DSS have been developed in many environments. Especially in production & operations management and supply chain management the area of optimization models has become an important field for DSS [11, 50, 76]. Today, various decision support models are available for different levels of the supply chain, including production planning and scheduling [23, 53, 82], demand management [71, 38], and logistics planning [80, 36]. Model-driven DSS using simulation and rapid modeling [68, 69] techniques conduct multiple experiments to show the effects of alternative conditions and courses of action [34]. For decision support in the area of supply chain management several kinds of simulation methods are in common use, e.g. Monte Carlo simulation, discrete simulation, agent-based and multi-agent simulation, system dynamics, and visual simulation [49, 66, 84].

2.4.2 Data-driven DSS

A data-driven DSS enables access to and manipulation of structured data and can handle time-series of internal as well as external company data and real-time data [61]. Data-driven DSS are separated by functionality. While simple file systems accessed by query and retrieval tools facilitate an elementary level of functionality, management reporting systems like Data Warehouses or Executive Information Systems (EIS) which allow the manipulation of data by computerized tools provide more in-depth functionality. Another example of data-driven DSS are Business Intelligence Systems or Online Analytical Processing (OLAP) [63] which provide the highest mode of operation and decision support [21]. Business Intelligence Systems help organizations to make decisions by using technology for reporting and data access and analytical practices. In general, BI systems help to formulate decisions by triggering, manipulating and analyzing data or information stored in historic databases [33]. The main goal of Business Intelligence and Analytic Systems is to increase the quality of the information that is available for decision making induced by the improvement of data processing [15, 58]. In this case, the key requirements of a typical data-driven DSS are access to a large amount of data and, at the same time, high quality of the underlying data. The success of a DSS always depends on the access to accurate, well-structured and organized data [64]. If these requirements are not fulfilled, a data-driven DSS will not work efficiently.

2.4.3 Communication-driven DSS

Typically, a communication-driven DSS relies on hybrid

network and electronic communication technologies to connect decision-makers and to create an environment of resource and information sharing, collaboration and communication among a group of decision makers [9]. One big subcategory of decision-making, developed over several years of research in this field, is group decision making [19], later extended into so-called Group Decision Support Systems (GDSS) [19, 20]. These systems include problem-structuring techniques, like planning and modeling tools. At this point the link between the single DSS applications is obvious. Another idea of communication-driven DSS are Collaborative Decision Support Systems (CDSS) [40, 42] featured as interactive computer-based systems where a group of decision makers works as a team to find solutions and alternatives for recognized, new and ill-structured problems [46]. Multiple IT technologies with integrated modeling and analysis tools accomplish a user-friendly environment for exploring solutions and making decisions [74].

2.4.4 Document-driven DSS

Over the years document management has become more and more important to companies. Consequently, the amount of documents, correspondence, images, sounds, videos and hypertext documents stored in some kind of system ever increasing. Today there are existing huge document databases and the world wide web technologies increased the development of document-driven DSS [17]. Examples for decision-aiding tools are search engines linked to document-driven DSS like WebCrawler or Alta Vista. Mostly, documents are not standardized in a uniform pattern. In this way information retrieval is used to find documents out of an unstructured form within large data collections. Information retrieval systems like Lexis-Nexis or InfoSys give documents a structure for better decision making support.The use of text based information retrieval systems can help to locate relevant documents and mine the organization data [75].

2.4.5 Knowledge-driven DSS

Knowledge-driven DSS have their origin in Intelligent Decision Support Systems or in a broader sense, in Artificial Intelligence (AI)[54, 55]. Knowledge-driven DSS are computer-based reasoning systems with the distinction that AI technologies, management expert systems, data mining [61] technologies and communication mechanisms are integrated. Intelligent DSS are divided into two evolutionary developments. The first types of these systems were about rule-based expert systems [14] widely used for scheduling in production systems [63]. Expert systems are based on the use of heuristics, which can be understood as strategies that lead to the correct solution for a problem. For these systems it is always necessary to use human expert knowledge collected in a database, to solve problems [2]. The second generation uses neural networks [39], fuzzy logic and genetic algorithms [4], which are similar to linear programming models and conduct random experiments by selecting variables without identified values to find the fitness function. Genetic algorithm systems combine genes to generate optimized value and have been applied to combinatorial and discrete parameter optimization problems [67]. Knowledge-based DSS therefore aims to identify specific knowledge and a variety of data mining tools and technologies.

Nowadays companies try to automate more and more of their processes. One of these automated processes should include data management that is crucial for decision support in a facility. Technological drivers have to be leveraged in order to process data effectively [81]. Decision support systems require filtered, structured data already fed into in a database. Therefore data must be mined and turned into knowledge. The next steps show the process of data mining: [24, 27, 47]

- **Data cleaning and definition of mining goals**
  In the first step inconsistent and erroneous data is filtered out and mining goals are established.

- **Data integration**
  Data arises from different data sources, this step integrates and combines various sources.

- **Data selection**
  Selection of useful data which is relevant for the analysis.

- **Data transformation**
  Data exists in multiple forms, in this phase data is transformed into a suitable basis for the mining process.

- **Data mining**
  The 5th step is the proper key process where mining functions and algorithms are applied to extract data samples for knowledge discovery.

- **Evaluation of results**
  The mined results should fit the mining goals established in the first step of the process. The advantage of the extracted knowledge is now measurable and suitable for further manipulation.

- **Knowledge deployment**
  The final phase is to make decisions based on the mined results.

For the purpose of these applications it is crucial to set up a well designed DSS user interface. The interface or dashboard influences how the user views results of a mining process and hence influences choices [65].

2.5 Trends and further research in the field of decision support

Intelligent decision making is one of the current keywords in this research field and is interrelated to modern business development. The potential of big data and advanced artificial intelligence offers new insights for innovations on DSS and for decision making in the form of more objective and evidence-based smart decisions [1, 87]. The main impact and key aspect of these intelligent systems is an improved method of data analysis. The collection, storage and unregulated use of data has no impact on decision making [6]. Corresponding to the main dimensions named the Big Data "Vs" - "Volume" (data is generated in large amounts), "Variety" (data is generated in different sources and types, structured and unstructured), "Velocity" (data is generated, captured and stored in real-time and continuously), "Veracity" (data is erroneous and inconsistent), "Validity" (ensures that the data is measured in the right way and fits criteria) and "Value" (how data and information is applied or

implemented into the business environment), decisions are made by considering these aspects [8, 37, 51, 85]. A decision making-process is only successful when it achieves all of these characteristics in form of a basis of well-structured and analyzed data. With reference to the mentioned DSS applications in this paper, DSS research and development will benefit from progress in huge data bases, AI and human-machine interactions [63],

- Data-driven DSS will use real-time access to larger and better integrated databases.

- The complexity and realism of model-driven DSS will increase significantly.

- Communication-driven DSS will have more real-time video communication support and the research on collaborative decision support systems reaches a new era and finally knowledge-driven DSS are becoming more and more rich in content.

In the case of the Industry 4.0 paradigm, the massive increase of data allows the optimization and improvement of models to enhance error analysis and the prediction of specific situations to set up counteractive measures. Decisions made to optimize efficiency and effectiveness of manufacturing systems are reaching from the strategic level to tactical and operational production scheduling and control. Automating these decisions by innovative algorithms and intelligent software applications based on the knowledge in the field of production and operations management, the performance of a manufacturing system can be maximized. In order to solve such complex decision making and control problems in practice, usually a structuring of the object into sub-areas is carried out, so that finally a network of agents is realized, which is divided both horizontally and vertically [3]. Such agents may work largely autonomously based on their models and knowledge bases or cooperatively with human decision-makers in the form of recommender systems [12, 13]. To achieve these objectives the improvement of the analysis, diagnosis, prognosis and quality of the decisions of cooperative agents by methods from the fields of model-based reasoning, automated decision-making, machine learning, diagnosis, knowledge-based configuration, planning and scheduling, recommender systems are necessary.

3. CONCLUSION

This paper provides a review of research on DSS. The review of literature has shown that Decision Support Systems offer a variety of application possibilities. Power [63] identified five specialized types of DSS, including data-driven, model-driven, documentation-driven, knowledge-driven and communication-driven DSS,

- Data-driven concepts require the availability of a lot of structured data and can handle time-series of internal as well as external company data and real-time data.

- Model-driven approaches are designed to allow the manipulation of model parameters by the user and to support decision makers in analyzing a given situation. Model-driven DSS are not data intensive.

- Documentation-driven DSS are used to give documents a structure for better decision making support. Information retrieval systems or search engines (decision-aiding tools) linked to databases are types of these systems.

- Knowledge-driven approaches are computer-based reasoning systems with the distinction that AI technologies, management expert systems, data mining technologies and communication mechanisms are integrated.

- Communication-driven approaches rely on hybrid network and electronic communication technologies to connect decision-makers and to create an environment of resource and information sharing, collaboration and communication among a group of decision makers.

Another aspect to come in for criticism is that most results of data processing and decision making are based on mean values as a basis of expectancy values. Expected values are commonly used as justification of decisions and their underlying criteria. If so, it is necessary to distinguish the stochastic properties of the expectation value. Discrepancies between de facto and theoretic decision behavior mostly depend on an erroneous interpretation of expected values [45].

The question that arises is how can new technologies be used to enhance data collection? But more than data collection, how can it be used to enhance data processing and evaluation to improve decision making and behaviour in the future? [32]

4. ACKNOWLEDGEMENT

5. REFERENCES

[1] A. Abbasi, S. Sarker, and R. Chiang. Big data research in information systems: Toward an inclusive research agenda. *Journal of the Association for Information Systems*, 17(2):3, 2016.

[2] A. Abraham. Rule-based expert systems. *Handbook of measuring system design*, 2005.

[3] G. Andreadis, P. Klazoglou, K. Niotaki, and K.-D. Bouzakis. Classification and review of multi-agents systems in the manufacturing section. *Procedia Engineering*, 69:282–290, 2014.

[4] D. Arnott and G. Pervan. A critical analysis of decision support systems research. *Journal of information technology*, 20(2):67–87, 2005.

[5] D. Arnott and G. Pervan. Eight key issues for the decision support systems discipline. *Decision Support Systems*, 44(3):657–672, 2008.

[6] R. F. Babiceanu and R. Seker. Big data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook. *Computers in Industry*, 81:128–137, 2016.

[7] D. Baker, D. Bridges, R. Hunter, G. Johnson, J. Krupa, J. Murphy, and K. Sorenson. Guidebook to decision-making methods. *Retrieved from Department*

of Energy, USA: http://emiweb. inel. gov/Nissmg/Guidebook_2002. pdf, 2002.

[8] J. J. Berman. *Principles of big data: preparing, sharing, and analyzing complex information.* Newnes, 2013.

[9] H. Bhargava and D. Power. Decision support systems and web technologies: a status report. *AMCIS 2001 Proceedings*, page 46, 2001.

[10] R. H. Bonczek, C. W. Holsapple, and A. B. Whinston. *Foundations of decision support systems.* Academic Press, 2014.

[11] V. Borodin, J. Bourtembourg, F. Hnaien, and N. Labadie. Handling uncertainty in agricultural supply chain management: a state of the art. *European Journal of Operational Research*, 254(2):348–359, 2016.

[12] H.-J. Bullinger. Innovationen live-it als treiber für business excellence. In *GI Jahrestagung (1)*, pages 1–12, 2005.

[13] M. Caridi and S. Cavalieri. Multi-agent systems in production planning and control: an overview. *Production Planning & Control*, 15(2):106–118, 2004.

[14] A. Chakir, M. Chergui, S. Elhasnaou, H. Medromi, and A. Sayouti. A decision approach to select the best framework to treat an it problem by using multi-agent system and expert systems. In *Advances in Ubiquitous Networking*, pages 499–511. Springer, 2016.

[15] S. Chaudhuri, U. Dayal, and V. Narasayya. An overview of business intelligence technology. *Communications of the ACM*, 54(8):88–98, 2011.

[16] J. F. Courtney. Decision making and knowledge management in inquiring organizations: toward a new decision-making paradigm for dss. *Decision support systems*, 31(1):17–38, 2001.

[17] J. Daniel. Power. a brief history of decision support systems. *DSSResourcescom, World Wide Web, http://DSSResources. COM/history/dsshistory. html, version*, 4, 2007.

[18] R. de FSM Russo and R. Camanho. Criteria in ahp: a systematic review of literature. *Procedia Computer Science*, 55:1123–1132, 2015.

[19] G. Desanctis and R. B. Gallupe. A foundation for the study of group decision support systems. *Management science*, 33(5):589–609, 1987.

[20] D. DeTombe. Group decision support systems. In *Handling Societal Complexity*, pages 155–186. Springer, 2015.

[21] V. Dhar and R. Stein. Intelligent decision support methods: the science of knowledge work. 1996.

[22] J. S. Dyer. Multiattribute utility theory (maut). In *Multiple Criteria Decision Analysis*, pages 285–314. Springer, 2016.

[23] G. Figueira, P. Amorim, L. Guimarães, M. Amorim-Lopes, F. Neves-Moreira, and B. Almada-Lobo. A decision support system for the operational production planning and scheduling of an integrated pulp and paper mill. *Computers & Chemical Engineering*, 77:85–104, 2015.

[24] A. Fong, S. Hui, and G. Jha. Data mining for decision support. *IT professional*, 4(2):9–17, 2002.

[25] P. Gourbesville. Integrated river basin management, ict and dss: Challenges and needs. *Physics and Chemistry of the Earth, Parts A/B/C*, 33(5):312–321, 2008.

[26] P. Haettenschwiler. Neues anwenderfreundliches konzept der entscheidungsunterstützung. *Zurich, vdf Hochschulverlag AG*, pages 189–208, 2001.

[27] J. Han, J. Pei, and M. Kamber. *Data mining: concepts and techniques.* Elsevier, 2011.

[28] C. J. Hanlon, J. B. Stefik, A. A. Small, J. Verlinde, and G. S. Young. Statistical decision analysis for flight decision support: The sparticus campaign. *Journal of Geophysical Research: Atmospheres*, 118(10):4679–4688, 2013.

[29] R. Harris. Introduction to decision making. *Home page: http://www. vanguard. edu/rharris/crebook5. htm.[Visited 14 October 2000]*, 1998.

[30] D. N. Hart and S. D. Gregor. *Information systems foundations: Theory, representation and reality.* ANU E Press, 2007.

[31] N. Hassan, Y. M. M. Hassim, Z. A. Afio, S. E. Suan, et al. Online theme landscaping decision support system. *Journal of Engineering and Technology (JET)*, 2:85–92, 2011.

[32] B. T. Hazen, J. B. Skipper, C. A. Boone, and R. R. Hill. Back in business: operations research in support of big data analytics for operations and supply chain management. *Annals of Operations Research*, pages 1–11, 2016.

[33] D. Hedgebeth. Data-driven decision making for the enterprise: an overview of business intelligence applications. *Vine*, 37(4):414–420, 2007.

[34] P. Hilletofth, O.-P. Hilmola, and Y. Wang. Simulation based decision support systems in the supply chain context. *Industrial Management & Data Systems*, 116(2), 2016.

[35] I. Ivlev, J. Vacek, and P. Kneppo. Multi-criteria decision analysis for supporting the selection of medical devices under uncertainty. *European Journal of Operational Research*, 247(1):216–228, 2015.

[36] R. A. Junqueira and R. Morabito. Production and logistics planning considering circulation taxes in a multi-plant seed corn company. *Computers and electronics in agriculture*, 84:100–110, 2012.

[37] S. Kaisler, F. Armour, J. A. Espinosa, and W. Money. Big data: issues and challenges moving forward. In *System Sciences (HICSS), 2013 46th Hawaii International Conference on*, pages 995–1004. IEEE, 2013.

[38] A. Käki, A. Salo, and S. Talluri. Impact of the shape of demand distribution in decision models for operations management. *Computers in Industry*, 64(7):765–775, 2013.

[39] A. K. Kar. A hybrid group decision support system for supplier selection using analytic hierarchy process, fuzzy set theory and neural network. *Journal of Computational Science*, 6:23–33, 2015.

[40] N. Karacapilidis and D. Papadias. Computer supported argumentation and collaborative decision making: the hermes system. *Information systems*, 26(4):259–277, 2001.

[41] M. Karami. Clinical decision support systems and

medical imaging. *Radiology management*, 37(2):25, 2015.

[42] V. Karan, D. S. Kerr, U. S. Murthy, and A. S. Vinze. Information technology support for collaborative decision making in auditing: An experimental investigation. *Decision support systems*, 16(3):181–194, 1996.

[43] P. G. Keen. Decision support systems: a research perspective. *Decision Support Systems: Issues and Challenges (New York: Pergamon Press, 1980)*, pages 23–44, 1980.

[44] C. H. Kepner and B. B. Tregoe. *The new rational manager: An updated edition for a new world.* Kepner-Tregoe Incorporated, 1997.

[45] P. Kischka. Erwartungswerte als entscheidungskriterium: Einige anmerkungen. In *Trendberichte zum Operations Mangement - Eine Festschrift für Werner Jammernegg*, pages 43–54. PL Academic Research, 2013.

[46] K. L. Kraemer and J. L. King. Computer-based systems for cooperative work and group decision making. *ACM Computing Surveys (CSUR)*, 20(2):115–146, 1988.

[47] L. A. Kurgan and P. Musilek. A survey of knowledge discovery and data mining process models. *The Knowledge Engineering Review*, 21(01):1–24, 2006.

[48] B. Li, J. Li, W. Li, and S. A. Shirodkar. Demand forecasting for production planning decision-making based on the new optimised fuzzy short time-series clustering. *Production Planning & Control*, 23(9):663–673, 2012.

[49] C. Li, J. Ren, and H. Wang. A system dynamics simulation model of chemical supply chain transportation risk management systems. *Computers & Chemical Engineering*, 89:71–83, 2016.

[50] S. A. Mansouri, D. Gallear, and M. H. Askariazad. Decision support for build-to-order supply chain management through multiobjective optimization. *International Journal of Production Economics*, 135(1):24–36, 2012.

[51] V. Mayer-Schönberger and K. Cukier. *Big data: A revolution that will transform how we live, work, and think.* Houghton Mifflin Harcourt, 2013.

[52] H. Min. International supplier selection: a multi-attribute utility approach. *International Journal of Physical Distribution & Logistics Management*, 24(5):24–33, 1994.

[53] J. R. Munhoz and R. Morabito. Optimization approaches to support decision making in the production planning of a citrus company: a brazilian case study. *Computers and Electronics in Agriculture*, 107:45–57, 2014.

[54] M. Negnevitsky. *Artificial intelligence: a guide to intelligent systems.* Pearson Education, 2005.

[55] H. R. Nemati, D. M. Steiger, L. S. Iyer, and R. T. Herschel. Knowledge warehouse: an architectural integration of knowledge management, decision support, artificial intelligence and data warehousing. *Decision Support Systems*, 33(2):143–161, 2002.

[56] J. S. Parker and J. D. Moseley. Kepner-tregoe decision analysis as a tool to aid route selection. part 1. *Organic Process Research & Development*,

[57] D. D. Pillai. Developing a decision support system for optimizing automated wafer fabrication. *IEEE Transactions on components, hybrids, and manufacturing technology*, 13(1):94–102, 1990.

[58] A. Popovič, R. Hackney, P. S. Coelho, and J. Jaklič. Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems*, 54(1):729–739, 2012.

[59] Z. Pourabdollahi, B. Karimi, A. Mohammadian, and K. Kawamura. Shipping chain choices in long-distance supply chains: Descriptive analysis and decision tree model. *Transportation Research Record: Journal of the Transportation Research Board*, (2410):58–66, 2014.

[60] D. J. Power. What is a dss. *The On-Line Executive Journal for Data-Intensive Decision Support*, 1(3):223–232, 1997.

[61] D. J. Power. Supporting decision-makers: An expanded framework. In *e-Proceedings Informing Science Conference, Krakow, Poland*, pages 431–436, 2001.

[62] D. J. Power. Decision support systems: Concepts and resources for managers. *NY: Greenwood Publishing Group*, 2002.

[63] D. J. Power. Decision support systems: a historical overview. In *Handbook on Decision Support Systems 1*, pages 121–140. Springer, 2008.

[64] D. J. Power. Understanding data-driven decision support systems. *Information Systems Management*, 25(2):149–154, 2008.

[65] D. J. Power and R. Sharda. Model-driven decision support systems: Concepts and research directions. *Decision Support Systems*, 43(3):1044–1061, 2007.

[66] P. O.-P. H. Professor Per Hilletofth, A. Professor Yacan Wang, J. Rouzafzoon, and P. Helo. Developing service supply chains by using agent based simulation. *Industrial Management & Data Systems*, 116(2):255–270, 2016.

[67] B. Rabta and G. Reiner. Batch sizes optimisation by means of queueing network decomposition and genetic algorithm. *International Journal of Production Research*, 50(10):2720–2731, 2012.

[68] G. Reiner. *Rapid Modelling for Increasing Competitiveness.* Springer, 2009.

[69] G. Reiner. *Rapid Modelling and Quick Response.* Springer, 2010.

[70] C. Saha, F. Aqlan, S. S. Lam, and W. Boldrin. A decision support system for real-time order management in a heterogeneous production environment. *Expert Systems with Applications*, 60:16–26, 2016.

[71] R. Seethamraju. Enterprise systems and demand chain management: a cross-sectional field study. *Information Technology and Management*, 15(3):151–161, 2014.

[72] J. P. Shim, M. Warkentin, J. F. Courtney, D. J. Power, R. Sharda, and C. Carlsson. Past, present, and future of decision support technology. *Decision support systems*, 33(2):111–126, 2002.

[73] H. A. Simon. The new science of management decision. 1960.

[74] S. Simonovic and M. Bender. Collaborative

planning-support system: an approach for determining evaluation criteria. *Journal of Hydrology*, 177(3):237–251, 1996.

[75] R. Sindhgatta. Using an information retrieval system to retrieve source code samples. In *Proceedings of the 28th international conference on Software engineering*, pages 905–908. ACM, 2006.

[76] S. A. Smith, N. Agrawal, and A. A. Tsay. Sam: a decision support system for retail supply chain planning for private-label merchandise with multiple vendors. In *Supply Chain Management: Models, Applications, and Research Directions*, pages 163–198. Springer, 2002.

[77] R. H. Sprague Jr and E. D. Carlson. *Building effective decision support systems*. Prentice Hall Professional Technical Reference, 1982.

[78] R. Suri and C. K. Whitney. Decision support requirements in flexible manufacturing. *Journal of Manufacturing Systems*, 3(1):61–69, 1984.

[79] E. Turban, J. Aronson, and T.-P. Liang. *Decision Support Systems and Intelligent Systems 7 âĂIJâĂİ Edition*. Pearson Prentice Hall, 2005.

[80] L. Wang, J. Song, and L. Shi. Dynamic emergency logistics planning: models and heuristic algorithm. *Optimization Letters*, 9(8):1533–1552, 2015.

[81] S. Wang, J. Wan, D. Zhang, D. Li, and C. Zhang. Towards smart factory for industry 4.0: a self-organized multi-agent system with big data based feedback and coordination. *Computer Networks*, 101:158–168, 2016.

[82] M. R. Yadollahpour and B. ArbabShirani. A comprehensive solution for continuous casting production planning and scheduling. *The International Journal of Advanced Manufacturing Technology*, 82(1-4):211–226, 2016.

[83] S. H. Zanakis, A. Solomon, N. Wishart, and S. Dublish. Multi-attribute decision making: A simulation comparison of select methods. *European journal of operational research*, 107(3):507–529, 1998.

[84] F. Zhang, D. Johnson, M. Johnson, D. Watkins, R. Froese, and J. Wang. Decision support system integrating gis with simulation and optimisation for a biofuel supply chain. *Renewable Energy*, 85:740–748, 2016.

[85] L. Zhang. A framework to model big data driven complex cyber physical control systems. In *Automation and Computing (ICAC), 2014 20th International Conference on*, pages 283–288. IEEE, 2014.

[86] F. Zhou, B. Yang, L. Li, and Z. Chen. Overview of the new types of intelligent decision support system. In *Innovative Computing Information and Control, 2008. ICICIC'08. 3rd International Conference on*, pages 267–267. IEEE, 2008.

[87] H. Zhou, C. Noble, and J. Cotter. A big data based intelligent decision support system for sustainable regional development. In *2015 IEEE International Conference on Smart City/SocialCom/SustainCom (SmartCity)*, pages 822–826. IEEE, 2015.