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AI TOOLS IN DECISION MAKING SUPPORT SYSTEMS: A REVIEW

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AI tools have advanced sufficiently such that they are integrated into decision making support systems for real applications and are impacting decision making in substantive ways. This paper reviews decision making theories and AI tools and the intelligent decision systems that result from the integration of these concepts.[a]

Keywords: Artificial intelligence; decision support systems; intelligent systems.

1. Introduction

Decision making is an inherently human activity that can have significant impacts. It is perhaps not surprising that researchers have attempted to improve the quality of decisions by developing computer technologies to augment and extend human capabilities. Advances in Artificial Intelligence (AI) have made this goal a reality in many applications. These AI-integrated decision making support systems, or intelligent decision support systems (IDSS) for short, are increasingly used to assist decision making in such areas as finance, healthcare, marketing, commerce, command and control, and cybersecurity. In this paper we review current AI tools that are used in IDSS. Such systems are referred to in the literature by various terms, including Active DSS, Knowledge-Based DSS, Expert Systems, Intelligent Decision Systems, and Joint Cognitive Systems.[1]

The term intelligent is used to describe systems that mimic human cognitive capabilities in some way. These systems employ AI tools to reason, learn, remember, plan and analyze. AI tools can be used to extend human capabilities by, for example, surveying and selecting relevant information from extremely large and distributed data sources, applying analytical tools to unstructured data, creating generalized solutions

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[a]The sections on AI tools in this paper closely follows a previous paper on this topic: W. Pedrycz, N. Ichalkaranje, G. Phillips-Wren, and L. Jain. Introduction to computational intelligence for decision making, In Intelligent Decision Making: An AI-Based Approach, Studies in Computational Intelligence, Vol. 97 (Springer-Verlag, New York, 2008), pp. 79–96.

from rule-sets and probabilities, and finding associations in information from multiple sources that may influence a decision. Tools such as Artificial Neural Networks, Fuzzy Logic, Intelligent Agents, Agent Teams, Case-Based Reasoning, Evolutionary Computing, and probabilistic reasoning, when combined with decision support systems, can help a decision maker in evaluating and selecting alternatives.[2] Such systems are particularly helpful in complex problems that involve uncertainty, large amounts of data, and are not deterministic.

This paper offers a review of AI tools used to improve decision making and is organized as follows. We first discuss the decision making process and decision support systems (DSS) in general, with or without AI tools. We illustrate applications of more advanced IDSS with examples from the literature. We then focus on the primary AI tools embedded in IDSS today, i.e. Neural Networks, Fuzzy Logic, Evolutionary Computing, and Intelligent Agents. In the final section we summarize and look to future research in this exciting area.

2. Decision Making Process

The decision making process described by Simon[3] is generally accepted by researchers who develop DSS as consisting of four phases: intelligence, design, choice and implementation. During the intelligence phase the decision maker gathers information and develops an understanding of the problem. He/she identifies criteria, develops the model, and investigates alternatives during the design phase. A selection or decision is made during the choice phase, and the decision maker acts on the decision and learns during the implementation phase. The process proceeds in a generally sequential manner with feedback loops between phases. Researchers in defense-related decision support tend to prefer a related four-step decision making process called the Observe, Orient, Decide, Act (OODA) loop.[4]

Decisions are referred to as structured, unstructured or semi-structured depending on the degree of certainty of the problem representation and solution.[5] A structured decision is deterministic with a known solution, while an unstructured decision depends on the particular decision maker and has little or no agreement on the solution. While structured decisions required no judgment on the part of the decision maker, unstructured decisions are highly dependent on the preferences or experiences of the decision maker. In between these two extremes is a broad range of problems called semi-structured decisions. Semi-structured decisions can be represented with analytical models or based on data, and, as a result, these receive the most attention from technology aiding. Technology can assist human judgment by, for example, locating and selecting relevant input, selecting appropriate data, solving a decision model under a set of conditions, presenting results to the decision maker, or helping the decision maker interpret outcomes from the decision model.

Although DSS generally consist of input, processing, and output to mirror the decision making process, the decision maker is viewed as a crucial part of the overall system. More recently, the term decision support has been expanded to embrace broader types of technology support and include systems that encompass business intelligence (BI) and analytics, with or without specific features that interact with the decision maker. Techniques in BI and analytics are able to address problems that encompass widely distributed data and extremely large datasets, problems based on so-called “big data”. AI techniques are often the method of choice for representing and solving such complex problems, and the combination of AI and decision support approaches yields IDSS. These systems have the potential to be deeply embedded into the workspace and align more closely with the decision styles of users and the decision problem itself.

What then, are intelligent decision systems (IDSS)? One definition[5,2] defines an IDSS as a DSS exhibiting some or all of the abilities that are indicative of “intelligent behavior”:

- Learn or understand from experience;
- Make sense out of ambiguous or contradictory messages;
- Respond quickly and successfully to a new situation;
- Use reasoning in solving problems;
- Deal with perplexing situations;
- Understand and infer in ordinary, rational ways;
- Apply knowledge to manipulate the environment;
- Think and reason;
- Recognize the relative importance of different elements in a situation.

Various architectures have been proposed for IDSS. A general architecture separates the decision making tasks into three modules representing input, processing and output with feedback loops.[6,2] The input module includes data directly relevant to the decision problem, knowledge bases to guide selection of decision alternatives or advice in interpreting outcomes, and model bases as a repository for formal decision models and algorithms. In the processing module, inputs are organized, forecasts and recommendations are provided, explanations may be developed, and a “best solution” is computed under the constraints. In the output module analyses may be reported, extended or revised, and even used as input for additional analysis. A different type of framework was presented by Linger and Burnstein[7] with two layers, a pragmatic layer and a conceptual layer. The pragmatic layer was associated with the actual performance of the task, and the conceptual layer was associated with the processes and structure of the task.

AI tools can be embedded within any of these architectures to enable sophisticated computational capabilities. A sample of several recent applications illustrating the breadth of topics and the variety of AI tools utilized in recent reported applications of IDSS is shown in Table 1. As can be seen, the applications are pragmatic and associated with decisions that affect people’s lives such as healthcare and clinical decision making applications. However, the scope of applications ranges from routine activities such as maintaining the power grid to emergency response. AI tools are required to enable these systems to perform intelligently and extend human decision making. Although a number

Table 1. Recent reported applications of Intelligent Decision Support Systems.

Author	AI Tools	Application
Rudin *et al.* (2012)[8]	Machine learning algorithms	Maintaining New York City's electrical grid
Malof *et al.* (2012)[9]	Neural Networks for case selection	Detecting breast masses in screening mammograms
Ocampo *et al.* (2012)[10]	Case-based reasoning	Diagnosis of Acute Bacterial Meningitis (ABM)
Zhou *et al.* (2011)[11]	Expert system	CO_2 capture efficiency and enhancing plant performance
Gladwin *et al.* (2011)[12]	Genetic algorithm	Reducing number of evaluations for hardware in the loop experimentation
Papageorgiou *et al.* (2011)[13]	Fuzzy logic	Prediction of yield in cotton production
Monteserin and Amandi (2011)[14]	Intelligent agents	Planning for negotiation
Thinyane and Millin (2011)[15]	Genetic algorithms; Neural networks	Currency trading
Lee and Wang (2011)[16]	Fuzzy logic	Diabetes monitoring
Cruz-barbosa and Vellido (2011)[17]	Neural networks	Diagnosis of brain tumor types
Lao *et al.* (2011)[18]	Case-based reasoning, Fuzzy logic	Monitoring of different potential risk factors for food handling
Taghezout and Zaraté (2011)[19]	Multi intelligent agent teams	Efficient coordination for product design through evaluation, planning, and real-time monitoring by calculating the cost at the different stages
Han *et al.* (2010)[20]	Intelligent agents	Response to large scale emergencies
Ubeyli (2010)[21]	Recurrent neural networks	Consideration of chaotic electrocardiogram (ECG) signals

of different AI tools are represented in Table 1, we will focus on four of the primary tools: Neural Networks, Fuzzy Logic, Evolutionary Computing, and Intelligent Agents. We briefly describe the AI tool and its contribution to decision making support in the sections that follow.

3. Neural Networks as a Framework for Intelligent Decision Support

Artificial Neural Networks (or just neural networks, NN) are a class of nonlinear regression models, discriminant models, and data reduction models that are highly interconnected and working in unison to solve a problem.[22] NN are inspired by the way that the human brain processes information. These useful tools provide a mechanism for analyzing large amounts of data and learning from data to find patterns and detect nonlinear relationships. Based in learning rather than pre-programmed behavior, NN are fundamentally different from a sequential, logic-based, programmed approach. NN have an ability to generalize on the basis of previous cases, much like humans exploit their empirical observations and experiences, and, thus, have the ability to suggest solutions from imprecise and complicated data. Applications that exploit this feature of deriving meaning from previous behavior or patterns are used to offer decision guidance that may be outside the scope of algorithmic-based approaches.

The basic computational element is the neuron which receives inputs and produces an output via a nonlinear transformation of the weighted sum of its inputs. A single neuron has a typical mathematical form of

$$y = f\left(\sum_{i=1}^{n} w_i x_i\right)$$

where $x_1, x_2, \ldots, x_n$ are the inputs of the neuron while $w_1, w_2, \ldots, w_n$ are the associated connections (weights) to model synaptic learning. Weights may be positive or negative, i.e. excitatory or inhibitory.[23]

Architecturally, a NN consists of a collection of neurons arranged in layers that are connected with a net of adjustable numeric connections. Two generic topologies of neural networks are feedforward and recurrent (feedback) networks. In a feedforward NN, signals flow from inputs forward through possibly multi-layers (referred to as hidden layers) to outputs. Feedforward NN have been the most useful to decision problems since they proceed in a manner consistent with the decision making process. Figure 1 shows an illustration of a 3-layer feedforward network with a hidden layer.

Recurrent NN permit feedback loops as shown in Figure 2 and may or may not have hidden layers. They can incorporate full or partial feedback depending on the model.

The strength of NN for decision problems is their ability to approximate any bounded continuous function to any arbitrarily small approximation error. NN "learn"

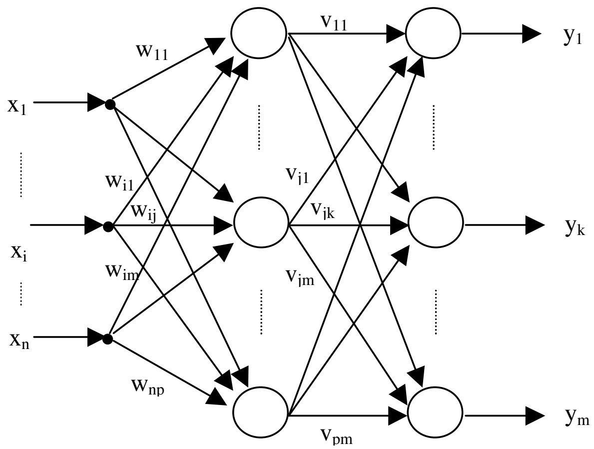

Fig. 1. Illustration of a three-layer feedforward NN with a hidden layer.[24]

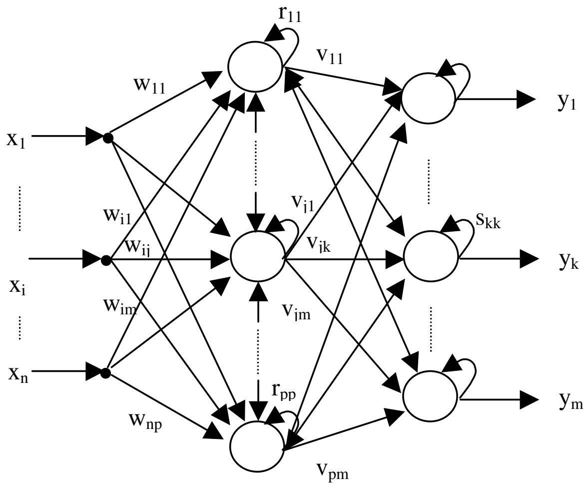

Fig. 2. Illustration of a recurrent neural network.[24]

the function using three main strategies: supervised, unsupervised, and reinforcement learning. In unsupervised learning, the NN is not given any outputs associated with corresponding inputs. The objective is to reveal the underlying structure in the data such as correlations or associations between patterns in data. In supervised learning, the NN is given a training set of data consisting of pairs of inputs and corresponding outputs; the NN attempts to find and adjust weights on the inputs so that outputs produced by the NN are as close as possible to the sample outputs (or targets). The constructed network can then be used to predict the output with a new set of inputs to provide decision guidance. In reinforcement learning the NN receives only summarized or high-level guidance on its correctness such as a numeric assessment of performance over a collection of data rather than at each individual data point. When training a NN for decision problems, one needs to be careful about over-fitting so that the NN learns past behavior (or outputs) so accurately that it is not sufficiently generalized to predict future behavior with a new set of inputs.

NN are used in a number of disciplines and application areas.[25–28] In decision-making, the universal approximation capabilities of NN are key to their usefulness, especially the ability to represent a nonlinear mapping between a set of inputs (or decision variables) and the output (or decision). NN are often called "black boxes" meaning that while the accuracy of the network in producing outputs close to training data is high, the underlying interpretation is difficult in decision problems. Much of the difficulty is that computation is distributed over nodes and possibly hidden layers, and even more complexity may be added with redundant networks. Interpretability would be beneficial to decision makers to assist in understanding the relationships between inputs, or decision variables, and outputs, or decisions being made. Such transparency would also permit domain knowledge such as decision rules to be introduced into the decision problem as part of the NN, possibly making the NN more efficient.

4. Fuzzy Logic as a Framework for Intelligent Decision Support

While NN have the ability to approximate any continuous function and to learn as they encounter new input-output pairs, some decision problems have inputs that are imprecise, ambiguous or incomplete. Fuzzy logic provides a tool for representing this uncertainty by permitting an input to have a value in a range of values between 0 (completely false) to 1 (completely true). It is useful in some decision problems to be able to represent inputs that are not clearly binary. For example, temperature can be characterized as hot, cold, warm or cool. This type of representation corresponds more closely to human reasoning that uses shades of meaning to represent inputs and to reason from them to reach a decision.

Fuzzy logic provides a way to develop and code rule-based behaviors. Since knowledge from an expert can be coded as a set of rules, expertise can be captured and provided to the decision maker. A primary advantage of fuzzy logic is that it can be refined as new information becomes available, providing a level of control throughout the decision making process. Since there is no inherent structure when fuzzy logic is used to express relationships between variables in the decision problem, nonlinear relationships occur naturally.[29]

Fuzzy logic can be combined with NN so that interpretation of the decision variables is more transparent, addressing a major issue when using NN for decision problems. One possibility is to utilize a parametric representation of fuzzy sets considering all of them to have the same type. For example, a triangular membership function requires three values to describe the variable, a minimum, a maximum and a most likely value. In the case of Gaussian-like fuzzy sets, a two-parameter representation space provides a modal value and the distribution or spread. It is possible to envision linkage between NN and fuzzy sets such that fuzzy sets describe decision inputs in an interpretable human form. The decision maker would thus be better able to perceive the relative relationships between inputs and output, enhancing understanding and learning during decision making. Another advantage is that relevant information that the decision maker possesses, such as relevant domain knowledge, is easier to incorporate and use.

A category of NN that is synergistic with fuzzy logic is referred to as a fuzzy logic network.[30] Processing is driven by logic at the individual neuron level. Aggregative neurons carry out *AND-OR* logic aggregation of inputs. Connections between neurons are essential for learning since they allow the modeling of different decision outcomes associated with various inputs. Referential neurons support referential or predicate-based processing such as *less than, greater than, similar, different* where each of these predicates with two arguments is expressed in the language of fuzzy logic.

Fuzzy logic networks help address shortcomings of NN. Since the architecture is transparent, domain knowledge can be integrated into an adaptive network. A trained network can be interpreted to provide logic-based relationships that can be quantified to enhance decision making as illustrated in Figure 3.

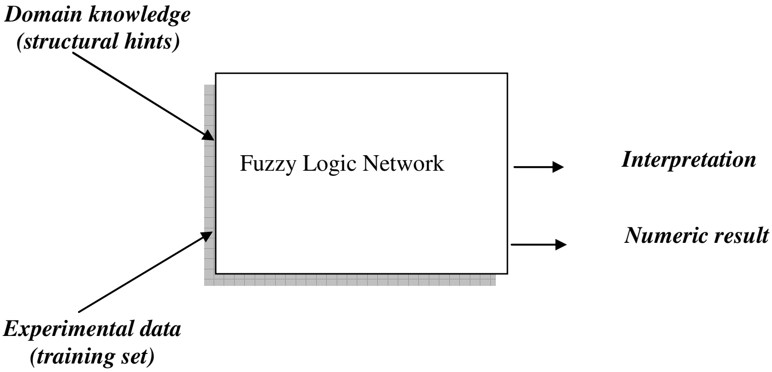

Fig. 3. Learning and interpretation of fuzzy logic networks.[24]

5. Evolutionary Computing as a Framework for Intelligent Decision Support

Biological systems have provided inspiration to AI researchers due to their ability to continually refine themselves in order to adapt to their environment. Improved biological forms emerge and evolve from previous generations, and environmental pressure causes survival of the fittest through natural selection. AI techniques called Evolutionary Computing attempt to mimic these qualities of emergence, survival and refinement in order to adapt to the environment. Genetic Algorithms are perhaps the most utilized of the Evolutionary Computing methods for decision problems. Algorithms mimic a collection of individuals that interact and synchronize activities by communicating, exchanging local findings, and influencing each other over succeeding generations in order to more closely match the environment.

In most Evolutionary Computing approaches for decision problems, a stochastic population-based approach is used. A finite population of individuals, represented as elements of the search space, is randomly initialized at time $t = 0$. Each individual is characterized with a fitness value related to the objective function that expresses the requirements of the environment. The fitness value represents the suitability of the individual for the environment. Individuals with higher fitness values are more likely to survive and be chosen as parents that subsequently form offspring through random recombination and mutation. However, weak individuals may also become parents, albeit with a lower probability of selection. Selection improves overall quality, or fitness, of the population through subsequent generations. The stopping criteria may be based on the number of generations or statistics associated with the fitness function (such as no significant change in the average values of fitness). An illustration of evolutionary adaption (or optimization) is shown in Figure 4. Over time the population becomes more focused in terms of fitness, and the average fitness increases.

Evolutionary computing offers an attractive method to solve decision problems due to its comprehensive exploration of the domain space and potential to locate the global

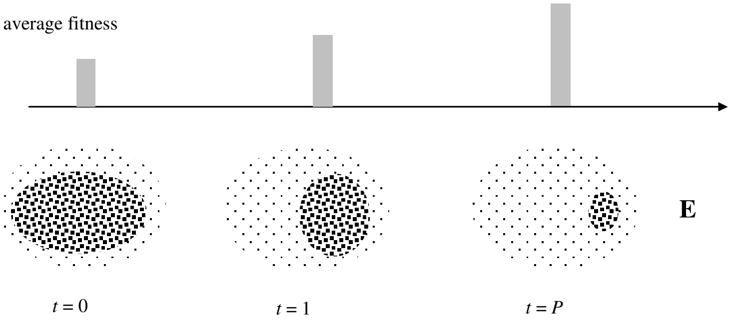

Fig. 4. Illustration of evolutionary optimization in which the population becomes more focused and the average fitness increases.[24]

maximum (providing that crucial parameters of the algorithm can be specified). Decision-making models can benefit from evolutionary computing in several ways:

- Typically several models are available to represent the decision problem. Evolutionary optimization can assist in choosing an optional structure for a decision model.
- Multiple criteria are usually involved in decision problems, and evolutionary computing provides for their simultaneous optimization as part of the solution process.
- Evolutionary computing provides a series of potential solutions on the path to the optimal solution, and these suboptimal solutions can provide insight into the problem that can assist decision making.

6. Agents as a Framework for Intelligent Decision Support

Although various AI techniques such as artificial neural networks, genetic algorithms, case-based reasoning, methods from expert systems, and knowledge representation have been successfully incorporated into intelligent decision systems, intelligent agents (IA) have had the broadest applicability to decision problems.[31] Definitions of an intelligent agent vary, although the one given by Woolridge[32] is often cited: "An agent is a computer system that is situated in some environment and that is capable of autonomous action in this environment in order to meet its design objective". To this definition additional capabilities may be added, including reactivity, proactiveness, social ability, adaptiveness, cooperation, persistence and mobility.[2] Reactivity and adaptiveness mean that an IA can perceive the environment and respond to changes. Proactiveness means that the IA can initiate action to meet its design objective. Social ability and cooperation provides communication capabilities with other agents such as negotiation and cooperation. Persistence provides the ability to maintain state over long periods of time, and mobility allows IA to travel through the system to gain knowledge or perform tasks.

Agent teams can balance goal seeking with reaction to the environment and enable complex behaviors. Multi-agent systems (MAS), in which a number of agents interact with each other, provide even more intelligent behaviors. Agent teams may act on behalf of the decision maker or other agents with different goals and objectives. Successful interaction is based on coordination, negotiation, learning and trust, particularly when agents do not share common beliefs, goals or interests. Decision makers can receive recommendations knowing many views have been balanced as prescribed by the system, or even permit the system to make autonomous decisions under certain constraints.

Agent theories form the building blocks for intelligence. As systems have become dispersed over multiple computing platforms, Distributed Artificial Intelligence (DAI) has focused on multi-agent interactions combined with AI paradigms to develop highly complex intelligence. Current research is directly toward incorporating the human into the systems so that agents and humans can interact and learn from one another. The basic notions of agent technology are described as:

Communication: IA need to communicate in order to convey their intentions. Although communication is an integral part of interaction, it does not have to be direct. Indirect communication can occur inferentially by observing action. In a MAS, communication can be implemented using message passing or shared variables.

Coordination: Coordination is the means of organizing agents, their resources and tasks in order to resolve conflicts and improve agent performance.

Teaming agreements: Communication and coordination are required for any IA to interact with another IA and act as a team. Teaming arrangements such as cooperation and collaboration are sub-notions that describe the type of agreement between the IA team.

Human-centric agents: More recent research has addressed the interaction between IA and a human so that the decision maker becomes part of the team.

Learning: Learning as an attribute makes a MAS more human-like and increases the opportunity for successful interaction between humans and agents. Hybrid strategies that combine traditional AI techniques with reasoning models from cognitive science such as that by Simon[3] offer new ways to enhance decision support.

One framework that has received attention for the development of complex reactive systems such as multi-agent teaming or human-agent teaming is the Belief-Desire-Intention framework (BDI).[31,33] The agent's understanding of the external world is its beliefs; the goals it needs to achieve are its desires; and the courses of actions that the agent is committed to follow in order to satisfy its desires are its intentions. The inclusion of an external world view can provide situation awareness, or context, for decision making. Context, or "what constrains something without intervening in it explicitly", is seen as essential to complex decision making applications.[34] Although difficult to quantify in the abstract, context can be characterized as relative to the focus of attention, evolving with the focus of attention, and highly domain-dependent. New frameworks for teaming in MAS and human-agent teams provide support for the notion of context in decision problems.

In order to facilitate interaction between humans and machines for joint decision making, "virtual humans" can be created that not only look like humans but display autonomy, interaction and personification.[35,36] These virtual humans embody such characteristics as emotion and can express them through reactions such as facial expressions, increasing the potential for acceptance of machine reasoning by a human.[33] Such powerful concepts challenge us to accept human limitations and extend our decision making capabilities in problems that can benefit from implementing AI tools.

7. Summary and Future Outlook

The future presents research opportunities and challenges in the application of AI tools to support decision making, particularly in the interfaces between humans and machines. The opportunities for improved decision making are significant, particularly in complex problems in which the environment exceeds our abilities to comprehend and develop relationships between variables. The challenge is to design intelligent decision support systems that are cost-effective, provide tangible benefits, and produce results accepted by humans. Adaptive systems that personalize for different users and perceive user intent in action or language are actively being pursued.

One of the biggest challenges in the application of intelligent decision support systems to real problems is trust in autonomous systems. Future research will need to address questions such as: What decisions are we willing to permit computer systems to make autonomously? What evidence of accuracy do we need in order to allocate a decision to an autonomous system? Will we allow autonomous systems to make decisions and act on that decision, and under what conditions? What security is needed so that computer systems do not exceed our comfort level with their decisions? Do we really trust autonomous systems to act in our best interests? Advances in AI tools applied to decision support offer exciting opportunities to improve decision making and grapple with these questions.

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