Multi-Agent Systems Technology for Composite Decision Making in Complex Systems

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Abstract. Information technologies have evolved into an essential tool for modeling, assessment and support in any domain requiring decision making. The paper presents an approach towards decision making in complex environmental systems. In the article, the authors review the main characteristics of complex systems and offer their general approach for decision support system creation based on the multi-agent systems paradigm. An example of the general approach applied to composite complex systems is described.

1 Introduction

Nowadays, information technologies (IT) have evolved into an essential tool for modeling, assessment and support in any domain requiring decision making. The complexity and uncertainty of the nature of environmental systems, and the heterogeneity of related information, require a complex approach for their study, based on and consisting of data management, pre-processing, modeling, simulation and, lastly, decision making support.

Sustainable development is a broad concept that spans over and across the social, economical, environmental, medical, demographical and political spheres. That is why the concept "sustainable development", as an abstract and highly complex one, includes components (in agreement with the renewed EU Strategy of Sustainable Development), which deal with climate change, sustainable transport, production and consumption, natural resources management, social issues (demography, migration, etc), and public health. The link between sustainable development and public health is obvious and even does not need to be emphasized. The "health" concept represents a complex system, which includes physical, social, mental, spiritual and biological well-being, spanning across all the spheres of their lives.

Now, the use of the multi-agent systems (MAS) paradigm for the modeling of complex systems has many successful applications, as it allows specialists to gather information quickly and process it in various ways. The final intention is to understand the real nature of the processes, their influence and interconnections, and the possible outcomes in order to make preventive actions and to make correct decisions. It also facilitate taking composite decisions, which is the only possible in case of complex systems. Intelligent methods and techniques used by intelligent entities cover the storing and retrieval of necessary records, storing and retrieval of key factors, examination of real-time data gathered from monitors, analysis of tendencies of environmental processes, retrospective time series, making short and long-term forecasting, and many others [2], [3], [4].

In order to understand the current trends and to assess the ability of current agent-based intelligent decision support research, it seems reasonable to survey the current state of the art and to conclude how it may be possible to optimize it.

2 System Approach for Complex Systems Study

The majority of real-life problems related to sustainable development and environment can be classified as complex composite ones, and, as a result, inhabit some particular characteristics, which require interdisciplinary approaches for their study. A system is an integration of interconnected parts and components (through informational, physical, mechanical, energetic exchange, etc.), which result in emerging of new properties, and interact with the environment as a whole entity. If any part is being extracted from the system, it looses its particular characteristics, and converts into an array of components or assemblies. An effective approach to complex system study has to follow the principles of the system analysis, which are:

1. Description of the system. Identification of its main properties and parameters.
2. Study of interconnections amongst parts of the system, which include informational, physical, dynamical, temporal interactions, as well as the functionality of the parts within the system.
3. Study of the system interactions with the environment, in other words, with other systems, nature, etc.
4. System decomposition and partitioning. Decomposition supposes the extraction of series of system parts, and partitioning suggests the extraction of parallel system parts. These methods can be based on cluster analysis (iterative process of integration of system elements into groups) or content analysis (system division into parts, based on physical partitioning or function analysis).
5. Study of each subsystem or system part, utilizing optimal corresponding tools (multidisciplinary approaches, problem-solving methods, expert advice, knowledge discovery tools, etc.)
6. Integration of the results received from the previous stage, and obtaining a pooled fused knowledge about the system. The synthesis of knowledge and

composition of a whole model of the system can include formal methods for design, multi-criteria methods of optimization, decision-based and hierarchical design, artificial intelligence approaches, case-based reasoning, and others such as hybrid methods [9].

3 Decision Support Systems and Their Characteristics

A decision support system (DSS) is an information system that supports decision-making and system management activities. A properly-designed DSS is an interactive software-based system intended to help decision makers in compiling useful information from raw data, documents, personal knowledge, business models, etc., to identify and solve problems and make decisions. Sprague and Carlson [16] identify three fundamental components of a DSS: (a) the database management system (DBMS), (b) the model-based management system (MBMS), and, (c) the dialog generation and management system (DGMS).

Haag et al. [5] describe these three components in more detail. The Data Management Component stores information (which can be further subdivided into that derived from an organization's traditional data repositories, from external sources, or from the personal insights and experiences of individual users); the Model Management Component handles representations of events, facts, or situations (using various kinds of models, two examples being optimization models and goal-seeking models); and the User Interface Management Component is, of course, the component that allows a user to interact with the system.

Levin [9] analyzes a number of works and names the following components as essential for a modern DSS: (1) models, which include multi-criteria techniques, problem-solving schemes, data processing and knowledge management; (2) analytical and numerical methods of data pre-processing and identification of problems for the preliminary stages of decision making; (3) human-computer interaction and its organization through graphic interface and others; (4) information support, communication with databases, web-services, etc.

According to Power [11], academics and practitioners have discussed building DSS in terms of four major components: (a) the user interface, (b) the database, (c) the modeling and analytical tools, and (d) the DSS architecture and network. The definition of a DSS, based on Levin and Power, in that a DSS is a system to support and improve decision making, represents, in our opinion, an optimal background for practical DSS creation.

4 A Novel Approach towards DSS Creation

4.1 General Requirements and Assumptions for Decision Support Systems

It is obvious that the DSS structure has to satisfy the requirements, imposed by specialists, and characteristics and restrictions of the application domain. In Fig. 1, there is a general work flow for a decision making process, which is

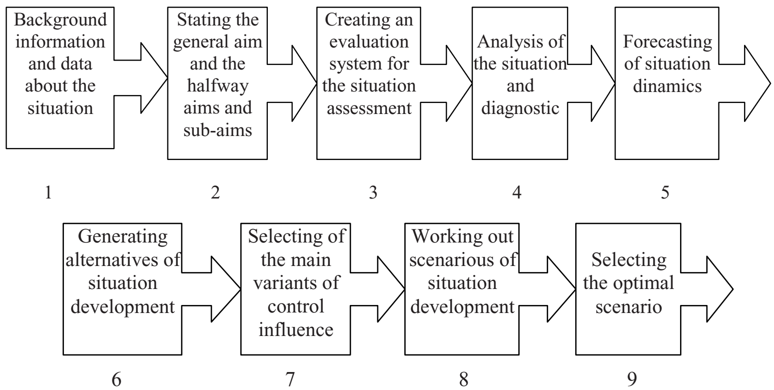

Fig. 1. The standard decision making flow

embodied in a DSS. The traditional "decision making" work flow includes the preparatory period, the development of decisions and, finally, the decision making itself and its realization.

In accordance with Fig. 2, a decision can be seen as an intersection of the spaces of possible decisions and alternatives, and the selection criteria. Complexity increases in the case when all these spaces have a composed organization. In the simplest case, possible alternatives are independent, but they can be grouped into clusters, or form hierarchies; decisions can consist of the best optimal alternative, but can also be formed as a result of a combination (linear, non-linear, parallel, etc.) of alternatives, and their subsets and stratifications; criteria can be both independent or dependent, and, commonly, hierarchically organized (see Fig. 2). Our approach towards DSS for complex system is based on the general DSS structure, discussed in the section 3. The main components of the DSS, which are (a) the user interface, (b) the database, (c) the modeling and analytical tools, and (d) the DSS architecture and network, have been determined for special features and characteristics of possible application domains. The most important difference is that the DSS is realized in form of a multi-agent system, and agents provide system functionality and realize organizational and administrative functions.

A DSS organization in form of a MAS facilitates distributed and concurrent decision making, because the idea of the MAS serves perfectly to deal with the difficulties of a complex system [17]. A MAS, which can be described as a community of intelligent entities - agents -, offers solutions because of the inherent agent properties, which are: reactivity (an agent responds in a timely fashion to changes in the environment); autonomy (an agent exercises control over its own actions); goal-orientation (an agent does not simply act in response to the environment, but intents to achieve its goals); learning (an agent changes its behavior on the basis of its previous experience); reasoning (the ability

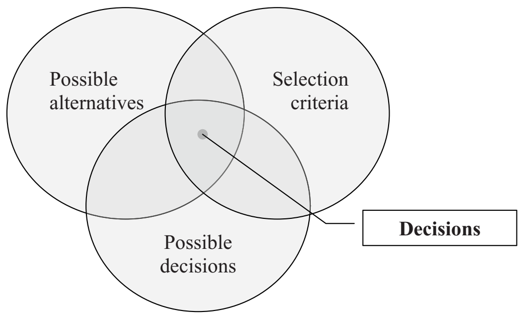

Fig. 2. The composite decision as an intersection of possible alternatives and decisions that satisfy the selection criteria

to analyze and to make decisions); communication (an agent communicates with other agents, including external entities); and, mobility (an agent is able to transport itself from one machine to another) [17], [1], [14].

4.2 Forming Composite Decisions

Composite decision making is hierarchical. It is made by agents of the lower level, then by the agents of superior levels, and is finally corrected, accepted or rejected by a specialist, who interacts with the MAS.

The decision making process needs planning, especially on the previous stages, when the MAS searches for data, retrieves, fuses and pre-processes it. As a rule, these processes can be realized automatically, when they have been planned and described before. And, the agents that execute these procedures are reactive, as the decisions they do are more rigid. Also, a supervising agent is proactive and has liberty in making decisions. The next stage is function approximation and data analysis, and the distribution of "agent rights" is similar: the data mining agents are reactive, they receive tasks from the superior agents and solve them by they means, and, the last ones have to make decisions.

In the scientific research there are several approaches to organize decision making processes (for example, decision tables, decision trees and flows). Some MAS creation tools offer analytical or graphical environments for agent diagrams creation. We have used decision trees, as this is an easily understandable visual method. The general schema of hierarchical decision making is shown on Fig. 3.

These ideas have embodied into planning and creation of an agent-based decision support system that will be discussed in the next section.

4.3 Proposal of the Generalized Agent-Based Decision Support System

We suggest implementing an agent-oriented software system dedicated to environmental situation estimation. The system receives retrospective statistical information in form of direct indicator values - water pollution, solar radiation,

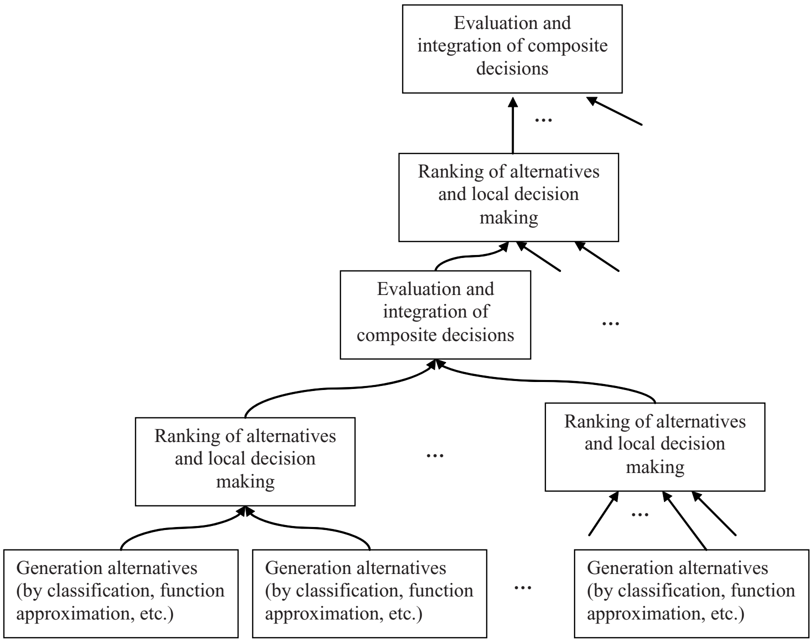

Fig. 3. Hierarchical structure of decision making (adapted from [9])

etc. - and in form of indirect indicator values - types and number of vehicles used, energy used annually and energy conserved, types and quantity of used fuel, etc. [15],[13]. The indirect indicators are utilized in accordance with ISO 14031 "Environmental Performance Evaluation" standard in order to estimate air and soil pollution [7]. The population exposure is registered as number of morbidity cases with respect to International Statistical Classification of Diseases and Related Health Problems, 10th review (ICD-10) [6].

The analysis of the system has resulted in obtaining and describing the system roles and protocols. There, the proposed system is logically and functionally divided into three layers. The first is dedicated to meta-data creation (information fusion), the second is aimed to knowledge discovery (data mining), and the third layer provides real-time generation of alternative scenarios for decision making, as shown in Fig. 4.

We use four agent teams within the system: two are within the first level, and one team on the second and third level each. Each "main" agent plays several roles. During the system work cycle, the agents play with diverse input and output information flows: data transmission protocols, messages, input and output data, etc. These information sources differ by their "life time": they can be permanent and temporary. Some can be used, modified or deleted by agents, and the decisions about others have to be taken by a system user.

The agent-based decision support system (ADSS) design has entirely been modeled following the Prometheus methodology [10], and using the Prometheus

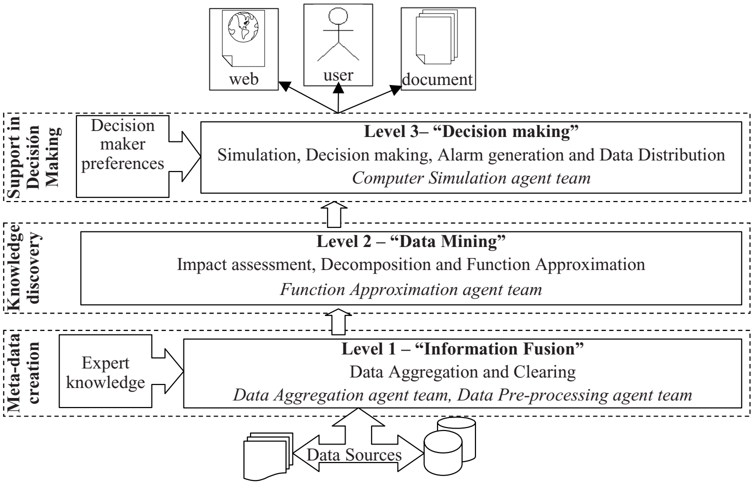

Fig. 4. The general architecture of the decision making system

Design Tool [12]. The tool provides the possibility of checking the consistency of the created system and of generating a skeleton code for JACK Intelligent Agents development tool [8], as well as design reports in HTML.

5 Design of the Environmental Impact Assessment Decision Support System

5.1 The Data Aggregation Agent Team

The Data Aggregation agent (DAA) has a number of subordinate agents under its control; these are the Domain Ontology agent (DOA) and the fusion agents: the Water Data Fusion agent (WFA), the Petroleum Data Fusion agent (PFA), the Mining Data Fusion agent (MFA), the Traffic Pollution Fusion agent (TFA), the Waste Data Fusion agent (WDFA) and the Morbidity Data Fusion agent (MFA).

First, the DAA sends the message *ReadOntology* to the DOA, which reads the OWL-file, which contains information about the ontology of domain, and make it available to the DAA. The DOA terminates its execution, sending the message *OntologyIsBeingRead* to the DAA. Next, the DAA sends the message Start Fusion to the fusion agents, which initiate to execute. When start to execute, each fusion agent searches for the files, which may contain information about the concept of its interest. Each fusion agent works with one or few concepts of the domain ontology, when it change properties (if necessary) of retrieved data and sends it to the DAA, which pools information together. Finally, DAA fills the domain ontology with data, and put data into a standard format. After that, the data files are ready to be preprocessed, and the DAA through the protocol *ReturnDF* says to the DPA, that data is fused and pre-processing can be started.

5.2 The Data Preprocessing Agent Team

The Data Preprocessing agent (DPA) provides data preprocessing and has a number of subordinate agents which specialize in different data clearing techniques: Normalization agent (NA), Correlation agent (CA), Data Smoothing agent (DSA), Gaps and Artifacts Check agent (GAA). They perform all data preprocessing procedures, including outliers and anomalies detection, dealing with missing values, smoothing, normalization, etc.

DPA starts to execute as soon as receives a triggering message from DAA. The main function of the DPA is to coordinate the subordinate agents and decide when they execute and in which order. Starting its execution, DPA sends the *StartDataConsistenceCheck* message, which triggers the GAA, which eliminates artifacts, searches for the double values and fills the gaps. Having finished execution, GAA sends to DPA a message. Then, DPA through the message *StartSmoothing* calls for DSA, which can execute exponential and weighted-average smoothing and terminates sending *SmoothingIsFinished* message to DPA. Then, NA and CA are called for in their turn. The outcomes of the DPA work are: data, ready for further processing and modeling, and additional data sources with correlation and normalization results.

5.3 The Function Approximation Agent Team

The Function Approximation agent (FAA) has a hierarchical team of subordinate agents, which serve to support the roles: “Impact Assessment”, “Decomposition” and “Function Approximation”. FAA has under its control a number of data mining agents: the Regression agent (RA), the ANN agent (AA), and the GMDH agent (GMDHA), which work in a concurrent mode, reading income information and creating models. Then, if any agent from this group finishes modeling, it calls for the Evaluation agent (EA), which evaluate received models, and return the list of the accepted ones, the others are banned and deleted. The FAA pools the outcome of the agents work, creates the list with the accepted models and then, once RA, AA and GMDHA finished their execution, calls for the Committee Machine agent (CMA), which creates the final models in form of committees for each of the dependent variables, and saves them.

5.4 The Computer Simulation Agent Team

The Computer Simulation agent (CSA) interacts with user and performs a set of task within Computer Simulation, Decision Making and Data Distribution roles. It has the agent team, which includes Forecasting agent (FA), Alarm agent (AmA) and View agent (VA).

The CSA execution cycle starts with asking for user preference, to be more precise, for the information of the disease and pollutants of interest, period of the forecast, and the ranges of their values change. Once the information from user is received, CSA sends a message *SimulateAlternative* to FA, which reasons and execute one of the plans, which are *Forecasting*, *ModelSimulation*, and *CriterionApplication*. When the alternative is created, CSA sends the *StartAlarmCheck* message to AmA. The AmA compares the simulation and forecast data from the FA with the permitted and alarm levels for the correspondent indicators. If they exceed the levels, AmA generates alarm alerts.

6 Results and Conclusions

To evaluate the impact of environmental parameters upon human health in the Spanish region of Castilla-La Mancha, in general, and in the city of Albacete in particular, we have collected retrospective data since year 1989, using open information resources, offered by the Spanish Institute of Statistics and by the Institute of Statistics of Castilla-La Mancha, as indicators of human health and the influencing factors of environment, which can cause negative effect upon the noted above indicators of human health.

The MAS has a wide range of methods and tools for modeling, including regression, neural networks, GMDH, and hybrid models. The function approximation agent selected the best models, which were: simple regression - 4381 models; multiple regression - 24 models; neural networks - 1329 models; GMDH - 2435 models. The selected models were included into the committee machines. We have forecasted diseases and pollutants values for the period of four years, with a six month step, and visualized their tendencies, which, in common, and in agreement with the created models, are going to overcome the critical levels. Control under the "significant" factors, which cause impact upon health indicators, could lead to decrease of some types of diseases.

As a result, the MAS provides all the necessary steps for standard decision making procedure by using intelligent agents. The levels of the system architecture, logically and functionally connected, have been presented. Real-time interaction with the user provides a range of possibilities in choosing one course of action from among several alternatives, which are generated by the system through guided data mining and computer simulation. The system is aimed to regular usage for adequate and effective management by responsible municipal and state government authorities.

We used as well traditional data mining techniques, as other hybrid and specific methods, with respect to data nature (incomplete data, short data sets, etc.). Combination of different tools enabled us to gain in quality and precision of the reached models, and, hence, in recommendations, which are based on these models. Received dependencies of interconnections and associations between the factors and dependent variables helps to correct recommendations and avoid errors. To conclude with, it is necessary to about our future plans regarding the work. As the work appeared to be very time consuming during the modeling, we are looking forward to both revise and improve the system and deepen our research. Third, we consider making more experiments varying the overall data structure and trying to apply the system to other but similar application fields.

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