ASSESSMENT OF SUPPLY CHAIN EVENT MANAGEMENT DATA BY AN AGENT-BASED SYSTEM WITH FUZZY LOGIC

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ABSTRACT

Software agents which gather event-related information for *Supply Chain Event Management (SCEM)* purposes are confronted with a complex task: analysis of diverse SCEM data. Fuzzy Logic provides mechanisms for heuristic human-like assessments of these data types. A concept for integration of Fuzzy Logic in software agents is presented which is implemented in a prototype. Evaluation of experiments indicates high quality of an agent's Fuzzy Logic analysis results compared to a human actor's heuristic assessments of the same data.

PROBLEM

Supply Chain Event Management promises to identify and correct disruptive events and malfunctions in operational supply chain processes by providing event-related information to decision makers in a timely fashion. An agent-based concept for event management in multi-level supply chains is described in (Bodendorf et al. 2005). It is shown in experiments and in an industrial showcase that monetary benefits of agent-based SCEM are significant (Zimmermann et al. 2005). This concept includes software agents which proactively gather data on orders and related suborders that have been placed with suppliers. Typical data types collected by an agent are planned and estimated dates of delivery for orders and information on disruptive events. One of the major tasks for the software agents is to analyze and interpret gathered data automatically. They decide upon their own assessments whether alerts to actors in a supply chain have to be generated.

Any analysis of event-related data is influenced by developments in fulfillment processes of monitored orders (e.g. production, transportation). These processes are executed by a large variety of actors and resources which influence each other directly or - even more often - indirectly. An example is a disruptive event "traffic jam" which affects transportation processes. It is caused by a multitude of actors - all vehicle drivers within the congestion - and additional factors such as e.g. weather conditions. Consequently, its duration cannot be accurately forecasted with reasonable efforts. Moreover, its effects on orders transported by a certain truck which is stuck in the traffic jam cannot be predicted for certain either, e.g. due to unforeseeable reactions of the truck driver. Hence, each data gathering agent is confronted with various types of data and disruptive events in a multitude of environmental settings. It is not possible to model all influencing factors that would be required to exactly forecast consequences of a disruptive event for an order's future fulfillment. Nevertheless, a human actor is able to gain important insights into an order's status, if data on disruptive events and process performance measurements are available: He generates heuristic interpretations for different aspects of an order's situation. Software agents imitate this heuristic approach.

DATA INTERPRETATION WITH FUZZY LOGIC

Simple calculations (e.g. weighted averages of input data) or simple decision rules (If...Then...Else) are not applicable for a heuristic interpretation which has to act similar to a human actor. Especially the vagueness of implications associated with gathered event management data has to be represented quite like a human actor would assess the situation. For this reason an approach based on Fuzzy Logic is chosen. In contrast to other methodologies, Fuzzy Logic is able to reason with perceptions (Zadeh 1999). Zadeh argues that a perception is a fuzzy evaluation of a concept such as time, distance, weight, likelihood, or truth. An example is "warm" as a perception of temperature. It is opposed to the concept of a measurement which is represented by an exact value (e.g. a temperature of 25.6° Celsius). SCEM data types which are the input to an agent's analysis process are considered to be measurements. An assessment of a situation represented by these measurements has to consider both, the perceptions a human actor would experience regarding these measurements and the reasoning he would apply based on these perceptions. This is achieved by using Fuzzy Logic - a combination of fuzzy perceptions and mathematically grounded logic (Friedrich 1997, pp. 161).

AGENT SOCIETY

Overview

To realize the SCEM concept within a supply chain, each supply chain partner provides one agent society with a discourse and a coordination agent, as well as various surveillance and wrapper agents (see Figure 1) (Bodendorf et al. 2005). A single coordination agent in each enterprise assures that initialization of monitoring efforts as well as management of external status requests and alerts is handled consistently within an enterprise. The coordination agent also provides an overview of all monitored orders of an enterprise and serves as a management cockpit for event management activities.

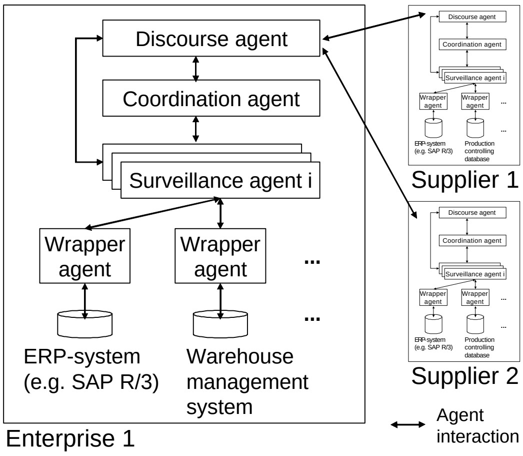

Figure 1. Agent society

For each monitored order of an enterprise a dedicated surveillance agent is triggered by the coordination agent. Thus, the data gathering and analysis functions are encapsulated in dedicated surveillance agents while the coordination agent decides on generation of alerts. Wrapper agents provide a standard interface to internal data sources for surveillance agents. Fuzzy Logic mechanisms are used in both, surveillance and coordination agents.

Surveillance Agents

Different types of SCEM status data are used to calculate deviations from plans, e.g. delays, incomplete quantities or quality measures derived from quality assessments. A human actor who assesses an order's situation considers various such indicators and generates an overall assessment of the order's status. Similarly, a surveillance agent integrates a variety of these inputs to form an aggregate assessment which is termed the *Aggregated Order Status (AOS)*. Calculation of an *AOS* by a specific enterprise is influenced by its strategic goals: For instance, a differentiation strategy based on very high product quality requires to rate quality misses of suppliers higher than delays. A surveillance agent considers these strategic implications for its assessment.

Disruptive events are identified by a surveillance agent during fulfillment of either its monitored order or one of its respective suborders. These events have different effects depending on the time of their identification relative to the remaining fulfillment time of an affected order. The same event (e.g. a machine breakdown) tends to have more serious consequences, if it takes place close to the end of a production process and thus an order's planned fulfillment date: The remaining reaction time is reduced, compared to an earlier identification of the same type of event, and associated follow-up costs rise. Hence, a surveillance agent considers the planned timeline of a process and assesses the severity of an event based on the current fulfillment situation of an affected order. This results in an order specific measurement of a disruptive event's severity, termed the *Endogenous Disruptive Event Severity (EnDS)*.

Coordination Agent

The coordination agent decides whether to generate any alert for a certain order. Data considered in this decision encompasses results of the Fuzzy Logic data analysis conducted by a surveillance agent and further information such as the priority of an order. This mechanism employs a two-step Fuzzy Logic process. It results in an abstract metric value termed *Alert Index (AI)* that is used in subsequent steps by the coordination agent to decide on generation of an alert and to determine recipients and media types.

FUZZY LOGIC ANALYSIS

Aggregated Order Status

SCEM data for a variety of status assessments regarding a specific process (e.g. production) is gathered by a surveillance agent from internal data sources and from suborder recipients. The indicators which are derived from this data are differentiated into absolute and relative indicators: Depending on what types of indicators (e.g. time vs. quality) are to be considered in the *AOS* and on the characteristics of monitored orders (respectively their suborders), either absolute or relative indicators are better suited. For instance, if one suborder has a planned fulfillment duration of two weeks while another suborder of the same order has only two days, a relative indicator "% delay" is not suitable: A 10% delay of the first suborder (~1.5 days late) will affect the superordinate order much more than a 10% delay of the second suborder which is then only about five hours late. However, relative indicators are often used in quality measurements, e.g. a percentage of defect parts in a delivery. These indicators facilitate comparison of different environmental situations (e.g. deliveries of different size).

Any indicator which is used in the Fuzzy Logic analysis process of the surveillance agent is fuzzified in a first step. For each indicator a linguistic variable with different fuzzy variables is defined. An applicable membership function for fuzzy sets in this domain is the trapezoid function. It is suitable for indicators that can be derived from status data types since a human actor typically perceives a deviation within a certain range as high or critical with a value of one (e.g. critical=1). Only the transition to the next fuzzy set (e.g. high to very high) is valued in between one and zero.

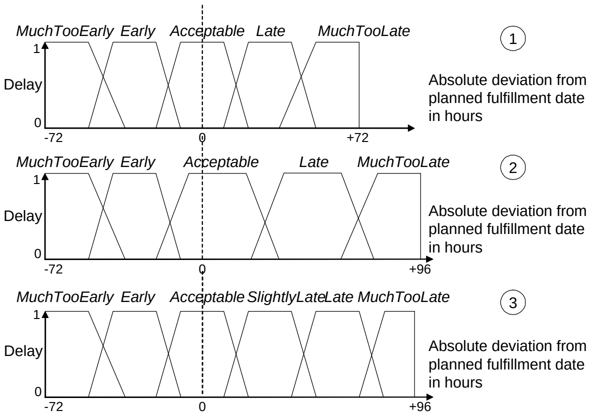

Figure 2. Alternative fuzzy sets

In the example in Figure 2 the linguistic variable *Delay* is defined based on five fuzzy variables within a range of 72 hours before and after the planned fulfillment date of an order (1). Depending on the strategic goals and the specific industry of a supply chain partner, different definitions of delays can be configured. In Figure 2 two other possible definitions are depicted that spread three fuzzy sets to allow for longer delays (2) and that add a sixth fuzzy set to further differentiate delays (3).

To assess fuzzified input values a fuzzy rule set is required which allows creation of an *AOS*. The *AOS* is standardized in the range between zero and one. It is defined as a linguistic variable with fuzzy sets *VeryHigh* for fulfillment that is as planned and *VeryLow*, if large problems are identified. Three intermediate fuzzy sets complete this linguistic variable. For two basic input values - absolute delay of an order (*ProcessTimeAbs*) and absolute deviation from ordered quantity (*ProcessQuantAbs*) a graphical representation of a possible rule sets is given (see Figure 3). The rule set reflects a typical just-in-time strategy of a manufacturer which depends on timely deliveries from its suppliers and has (nearly) no capacities for safety stocks. Both, late or incomplete deliveries result in high follow-up costs for the manufacturer, because his production lines are halted soon, if input material is not delivered continuously. Thus, every kind of late delivery and every type of incomplete delivery is rated very critical and results in a low *AOS*.

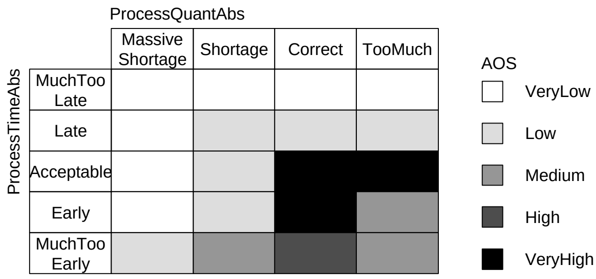

Figure 3. AOS - definition of fuzzy rules

By comparing the fuzzy rule base to the perceptions associated with the input values, a number of evaluations is generated for each perception. These evaluations are aggregated, and a single value for the *AOS* is calculated using a defuzzification method (e.g. the center of gravity). This *AOS* allows to characterize a monitored order's status. For instance, a value of 0.23 with a possible interval of the *AOS* between zero and one indicates a relatively high current criticality of a monitored order.

A surveillance agent gathers the same data types for data on its monitored order as well as its related suborders. Thus, a number of data sets with similar data inputs have to be aggregated and then interpreted by the surveillance agent. A filter is used to select the most important SCEM data inputs and forward these to the fuzzy analysis component of the agent. Depending on how this filter is configured, the agent realizes the individual strategy of its company. A typical strategy is to select worst cases for each type of indicator and forward these to the Fuzzy Logic analysis.

Summarizing, the *AOS* is an individual assessment of a monitored order's situation which incorporates different status aspects of an order and its relevant suborders. The *AOS* is calculated whenever new SCEM information becomes available to a surveillance agent and thus the *AOS* changes over time. The assessment reflects individual valuations and strategies that vary for each supply chain partner.

Endogenous Disruptive Event Severity

Disruptive events which are identified by a surveillance agent have to be analyzed as to their effect on fulfillment processes, in spite of the fact that a complex model of cause-and-effect for each type of event is not feasible (see above). As requested an event is analyzed with respect to the planned timeline of the fulfillment processes it affects. Two input values are needed:

- An external classification of a disruptive event's severity is a measurement of severity which is assumed to be defined for each type of event and which is derived for instance from a ranking list with associated severity values. As an example, a machine failure is rated lower than a power outage. For each event a classification value between zero and one is assumed which is referred to as the *Exogenous Dis-*

ruptive Event Severity (ExDS). This severity is independent of the time of occurrence of an event and is fixed.

- The *Remaining Time (RT)* to a planned fulfillment date is considered under the assumption that an event has a larger negative impact on an order's fulfillment the later it occurs in a fulfillment process and the less time for reaction remains. It is defined as the difference between the planned end date of fulfillment of an order and the date of identification of an event by a surveillance agent.

Using a similar Fuzzy Logic mechanism as for the *AOS*, a so called *Endogenous Disruptive Event Severity EnDS* is determined by a surveillance agent. The *EnDS* reflects a heuristic assessment of the probability to solve the problem that is caused by an event in the remaining planned fulfillment time of an order. A high *EnDS* indicates that propagation of an event to the next supply chain level is highly likely, whereas a low *EnDS* characterizes an event that is solvable within an enterprise. Consequently, *EnDS* is used to determine whether a specific event has to be communicated by a supply chain partner in a message to its customer. Disruptive events with a low *EnDS* are not communicated, in order to avoid an information overflow on following supply chain levels through irrelevant data. Calculation of an *EnDS* for an event is only initiated once for each event identified by a surveillance agent, because its parameters (*ExDS*, *RT*) remain constant as long as no corrections (such as a revision of *ExDS*) occur, in which case a recalculation is initiated.

Alert Index

The coordination agent determines an *Alert Index (AI)* for each order based on the analytical results provided by surveillance agents. Input values for the *AI* are e.g. *AOS* and the maximum *EnDS* of all new disruptive events identified in the last data gathering round by a surveillance agent. Additional data types that a company wants to consider for its alert generation (e.g. a customer's rating) are incorporated in a second step of the coordination agent's Fuzzy Logic analysis.

A two-step stacked Fuzzy Logic process is chosen to limit the complexity of the fuzzy rule sets. An example of a fuzzy rule set for the first step may represent a very precautious strategy regarding the condition of an order. Such a rule set considers severe disruptive events (*Very-High EnDS*) as very important and thus raises the *AI* to the highest level even if the corresponding aggregated order status *AOS* is very high. The strategy is justified under the assumption that a newly discovered severe disruptive event has not yet affected an order's status data, and its negative consequences thus have not yet been measured. However, effects on status data will be reflected in future data gathering rounds while the *AI* is raised instantaneously to a very high level which permits reactions even before any negative consequences of the event are encountered.

The second Fuzzy Logic step is independent of the first step. For instance, a company may value some orders higher than others, depending on their priority. The priority of an order is a value that is determined outside a SCEM system by each supply chain partner. Important sources for definition of an order's priority are e.g. marketing and sales departments that have data and strategies in place to define order priorities. Possible input values are: sales revenues with a customer, profit margin of an order or service level agreements with customers. Ideally, a standardized value for an order's priority is provided that is for instance calculated based on a multi-dimensional scoring model.

After the second Fuzzy Logic step a defuzzification mechanism provides a metrical value between zero and one. This final *AI* is used by the coordination agent to decide on alerts. This decision includes a discrete escalation mechanism not detailed here.

PROTOTYPE

A generic prototype with all agent types is realized for conducting experiments in a laboratory environment: Each enterprise in a simulated supply chain hosts one agent society. The main focus of the implementation is on SCEM features provided by coordination and surveillance agents, whereas only basic mechanisms of discourse and wrapper agents are realized. Every agent society is realized on its own instance of the FIPA-conform JADE agent platform. Examples of visualizations for analytical results of a surveillance agent are depicted in Figure 4.

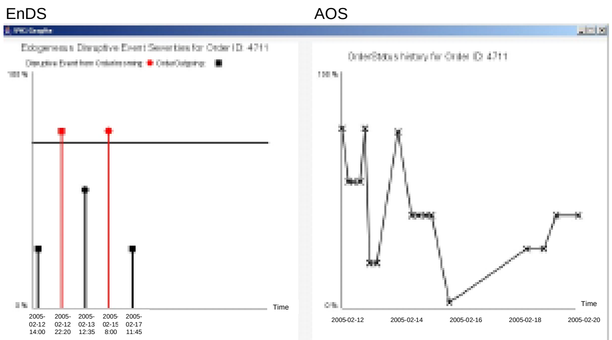

Figure 4. Visualization of EnDS and AOS

This prototype implementation demonstrates the integration of Fuzzy Logic into software agents. It permits intuitive configuration of fuzzy sets and rule bases with a spreadsheet based template. The open-source Fuzzy Logic application programming interface (API) FuzzyJ-API (NRC 2004) for Java is used to realize Fuzzy Logic calculations within the generic prototype. It provides a flexible interface to design and configure Fuzzy Logic applications. Configuration is realized by a MS-Excel file: It specifies all fuzzy variables and fuzzy rules of the application. A Java-Excel-API (Khan 2005) is integrated in the prototype that extracts this configuration data from the MS-Excel file and provides it to the Fuzzy Logic system. This feature offers flexibility for users in maintaining and adapting the analytical behaviors of the SCEM agents.

EVALUATION

Tests

Both, analysis of gathered SCEM data as well as decisions on alerts rely on Fuzzy Logic assessments (see above). In Figure 5 results of tests with the Fuzzy Logic module of the coordination agent are depicted. In these tests several test data sets are analyzed by the coordination agent's Fuzzy Logic behavior. Different strategies are reflected by different Fuzzy Logic rule sets.

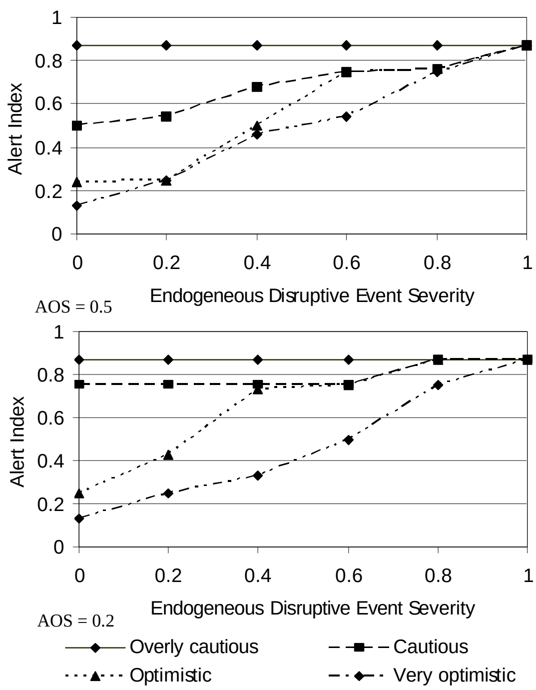

Figure 5. Influence of Fuzzy Logic rule sets

Results of the tests regarding *AOS* and *EnDS* which are both integrated in the *AI* are depicted in Figure 5: *AOS* is fixed and *EnDS* is variable. The same *AI* is calculated with four different Fuzzy Logic rule sets that represent different strategies: Cautious strategies tend to generate alerts even for less severe problems and thus produce higher *AI* than optimistic strategies in the same situation. This behavior is illustrated in Figure 5. For instance, with a medium *AOS* of 0.5 and low *EnDS* an optimistic strategy results in a low *AI*, while a cautious strategy leads to a significantly higher *AI*. This difference increases, if *AOS* is lowered (0.2 in Figure 5, bottom), because cautious strategies value *AOS* higher than *EnDS* and raise *AI* for every disruptive event to a very high level. Optimistic strategies value small disruptive events less, even though the *AOS* is lower.

In addition, experiments with extreme input values are conducted to assess robustness of the system. For instance, a disruptive event with *EnDS=1* (highest possible severity), the lowest possible *AOS=0* and the highest priority of an order *(=1)* is rated with *AI=1*. The results indicate plausible behavior of the Fuzzy Logic components even for these extreme inputs.

Improvement of Configuration

An evaluation of the quality of the heuristic approach is realized with a Fuzzy Logic development tool (XFuzzy 2005). Since no real-world benchmark data is available, realistic assumptions for input and desired output data are provided and tested with the Fuzzy Logic approach.

It is assumed that a human actor can provide consistent heuristic assessments, if confronted with various input data sets. Thus, two input data sets are provided that resemble two similar strategies of two different enterprises for determining an *AI* based on the *AOS* and the *EnDS* (see Figure 6). Specific details of these assessments are of minor importance, only the general structure of the decision graphs is relevant.

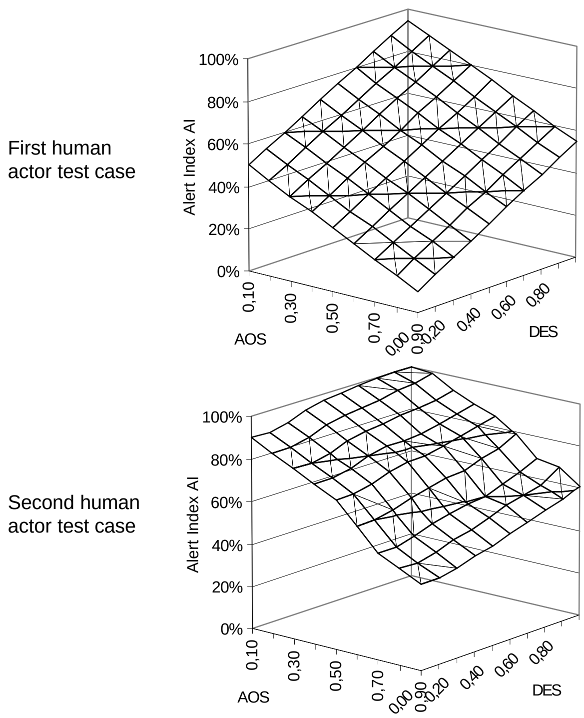

Figure 6. Human assessment samples

Using a simple rule-based system that does not employ Fuzzy Logic would provide a step-like outcome of the *AI*. The result of such a system is also simulated and depicted in Figure 7. The increase of the AI with increasing EnDS and decreasing AOS is realized but not the continuous assessments of the human test cases.

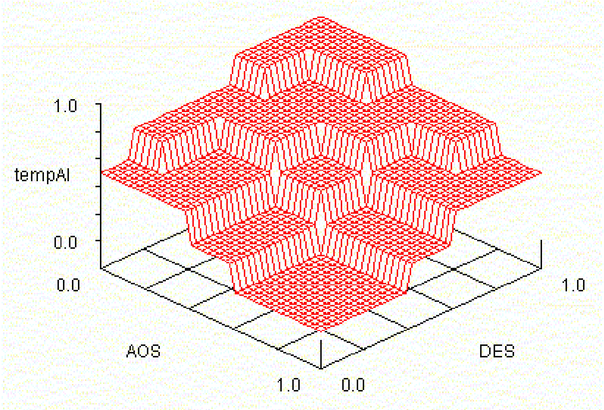

Figure 7. Conventional rule-based system

Figure 7 illustrates binary logic's inability to create continuous assessments with a simple set of rules and functions derived from every day's observations. However, the same rule-base can be used in a Fuzzy-Logic system which provides quite different results (see Figure 8). Depending on what types of fuzzy sets are used, a more or less continuous assessment is realized that resembles the first test case while not so much the less symmetric second test case. In several tests "*Pi*" fuzzy sets established the best results which are depicted in Figure 8.

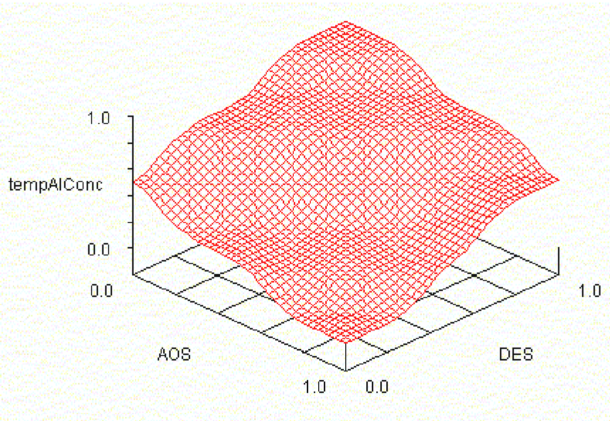

Figure 8. Simple Fuzzy Logic system

To further improve the quality of the Fuzzy Logic assessment and resemble the test cases, the user input is employed as learning material. The fuzzy tool rearranges the fuzzy sets of input und output variables to adapt to the given variable values of the test cases. Several different algorithms are available (i.e. *Steepest Descent*, *Marquardt-Levenberg*, *Downhill Simplex*, *Powell's Algorithm* or *Blind Search*). The aim is to reduce the deviation between test data and Fuzzy Logic assessments to a minimum. The quality is measured by the mean square error (*MSE*). Best results were achieved in experiments with the *Downhill Simplex* (*MSE=0.0015*) and *Powell's* algorithms (*MSE=0.0001*) while a *Blind Search* algorithm, despite its ability to find global maxima, was less successful (*MSE=0.007*). In Figure 9 the result of a successful learning experiment for the second test case is depicted. Compared to the initial human assessment depicted in Figure 6 the similarity of the Fuzzy Logic assessment is very high. Hence, the quality of automated interpretation of SCEM data will resemble a human actor's performance, if configured into a software agent. The optimized configuration is easily extracted from the Fuzzy Logic development tool and configured into the agent-based prototype using the MS-Excel spreadsheet configuration files (see above).

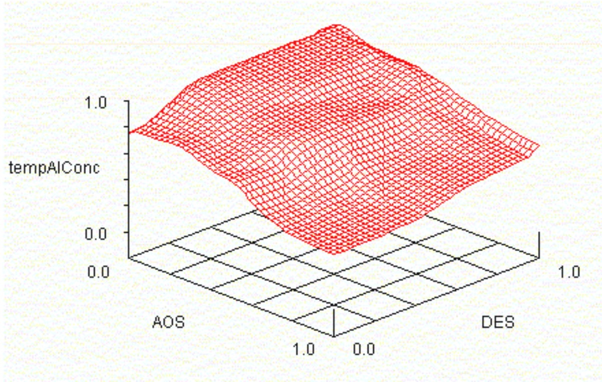

Figure 9. Trained Fuzzy Logic system

CONCLUSIONS

A methodology to heuristically assess data gathered for Supply Chain Event Management purposes is presented and evaluated. Implemented within two types of agents (coordination and surveillance agents) Fuzzy Logic is used to imitate human assessments of complex situations in which an order is situated during its fulfillment. Different strategies a human actor pursues in its interpretations can be adequately reflected by the Fuzzy Logic approach through definition of rule-sets and different fuzzy set types. Besides, automated adjustment of fuzzy sets to learning data is possible. Learning data is derived e.g. from expert interviews.

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