THE EVOLUTION OF INTELLIGENT SYSTEMS IN THE MINING INDUSTRY

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Abstract

This paper reviews the evolution of computer systems based on the so-called "intelligent" technologies now being applied in different application areas throughout the mining, minerals, and materials industries. These systems have emerged from the field of "Artificial Intelligence" in which expert systems, fuzzy logic, artificial neural networks, genetic algorithms, and agent-based software have dominated. The Mining industry has been particularly receptive to these methods since so many of our operations and processes are understood and controlled in empirical ways that lend themselves well to the use of intelligent technologies. In addition there are few industries with the myriad of heuristics evident in mining; for example:

- Nature does not make uniform orebodies nor ones that can be modeled simply;
- Unit operations tend to be batch or semi-continuous which are more difficult to model and control;
- The traditional approach to problem-solving is empirical and such experiential knowledge can be captured directly into Intelligent Systems.

INTRODUCTION

As the attributes of personal computing hardware (speed, memory, storage capacity, resolution) have doubled every 18 months or so since the 1980s, our society has reached a point where no serious performance limitations exist for "intelligent methods" and the computational complexities are now embedded within or subsumed beneath the Human-Machine Interface. As a result, these approaches can be applied to study and solve extremely complex and intricate problems beyond the ability of the human mind to handle in a time frame appropriate for process control. Process control has traditionally tried to maintain a system at a set-point for as much time as possible in response to upsets or disturbances in load variables. Nowadays, the set-points themselves have become disturbances with updates occurring at increasing frequencies as communication and measurement cycles have sped up to bandwidths previously unimaginable.

Data Management is a major issue today in complex process control. Can we take advantage of so much data using filters or sensor-fusion techniques to increase the performance of systems that may consist of loops at levels higher in the control hierarchy

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than ever before? Techniques are needed to deal with "long" delay times in local loops or ones caused by the transfer of information to remote locations that previously provided supervisory control at time frames measured in minutes to hours, but today operate in seconds to minutes. The future of Intelligent Systems will integrate hardware and software with the field of robotics playing a dominant role. As machines take over more of the "routine" thinking, this provides time now to address tasks that are important, but of lower priority. Complexity Analysis will become the next generation of control systems with software seeking new relationships within the large amounts of data being generated. Automated assembly of hardware parts to create self-replicating systems will become important over the next decade as systems possess the ability to "self-heal" using redundant sensors, actuators, and computer hardware.

A BRIEF HISTORY OF FUZZY LOGIC

It can be argued that Fuzzy Sets have been in use in Mining Engineering and its related disciplines since the very beginning of the industry thousands of years ago. One can find references in De Re Metallica in 1556 (one of the first books ever printed) on the use of linguistic terminology to characterize mining variables [Agricola, 1556], but the formal application of Fuzzy Logic to reveal the mathematics behind this linguistic terminology did not occur until the mid-1980s with the seminal paper by Harris and Meech [1987] that described a fuzzy approach to the control of crushing plants. Since that time, use of Fuzzy Control and Fuzzy Set theory has expanded rapidly into virtually all areas of the industry including geology, mining, metallurgy, and control of environmental pollution.

Mining is one of the oldest professions. Since early woman and man began using stones to crush food and to throw rocks to chase off predators or kill prey for food, people have been mining rocks and minerals for all kinds of use. Stones were crafted into weapons and tools until it was discovered that when placed in fire under the right conditions, components of the rock could be extracted to produce metals. This led our ancestors into the Iron Age and the Bronze Age. As Mankind improved the ability to communicate using speech sounds eventually developing words to share thoughts with friends and foes, new methods evolved to extract rock and ore more easily to create more effective products for agriculture, hunting, and protection. As a science, mathematics came along much later, so it is reasonable to assume that language (Fuzzy Logic) as a method to pass on ideas predates any application of formal mathematics.

The roots of mathematics lie in ancient Egypt and Babylonia, spreading rapidly into ancient Greece where it was translated into Arabic and enriched by computational ideas from the Indian sub-continent. Later, the science passed to the Romans and entered Western Europe where within a relatively short period (200-300 years), methods of computation spread around the world. While not wishing to disparage the importance of mathematics in providing rapid ways to compute solutions with precision and accuracy, many of the in-grained methods of mining, smelting, providing heat and shelter, and producing new products, were well-established prior to widespread use of mathematics.

By far, the most significant development in mathematics was provision of a firm foundation in logics [Fauvel and Gray, 1987] by the ancient Greeks in the centuries just prior to Euclid (~300 B.C.). These foundations gave mathematics more than a certainty– they provided tools to investigate the unknown [Euclid, 295 B.C.]. Despite the pre-existence of "Fuzzy Logic", what was lacking was the ability to make useful and correct decisions in the absence of knowledge or data. The science of Greek logic was bivalent in form–things were either true or false, although "the paradoxes" were identified even in the beginning as problematic for bivalent logic. Despite this deficiency, the world continued to evolve as the workers–farmers, fishers, and miners continued advancing their work habits with linguistics central to their method of communication and to the passing on of ideas (old or new). As mathematics entered the field, formalisms (especially geometry and trigonometry) were applied to characterize relationships among variables, but retention of the old empirical models has prevailed even into modern times.

Perhaps because of the empirical "culture of mining", Fuzzy Set Theory was able to proliferate quickly once a formal scientific basis was given by Zadeh in 1965. Application of this theory established a rationale for relative weights of importance used to characterize underground rock masses, to select underground mining methods, to design excavations from knowledge about the orebody shape and extent together with the physical conditions of the surrounding rock masses for many years. The first successful application of "Fuzzy Sets" occurred in the field of process control with Mamdani's famous paper on the control of a laboratory-scale steam engine in 1975. Shortly thereafter, the Danish cement industry applied the technique developed by Mamdani to control a cement kiln. In 1976, Blue Circle Cement and SIRA in Denmark developed a cement kiln controller that represents the first documented industrial application of Fuzzy Logic Control [Yen, 1999]. Blue Circle was later taken over by the F.L. Smidth Group who then grew this first industrial application into a company called FLS Automation (interestingly enough, FLS can stand for either F.L. Smidth or for Fuzzy Logic Systems). Virtually all cement kilns in the world today use a FL-based control system.

FL has allowed development of successful methods to move processes and operating practices closer to the point of instability and/or failure. This has meant a closer approach to "optimal" solutions. As the environment changes, control (or operating practice) can adapt to maintain desired targets for longer time periods. FL has a self-adapting property to mimic directly how a person "thinks" about the problem-space.

With clinker production, process lag times are measured in tens of hours resulting in poor response of manual control especially when operating personnel are inexperienced or preoccupied with other duties. Often, the term "experience" refers to recognizing conditions that lead to failure. As such, "experience" actually derives from having "failed" and not wanting to be in that condition ever again. With the long lag times that characterize processes such as cement kilns, the ability of an operator to interpret instruments that predict a future "failure" in 10 to 20 hours requires considerable skill that may not be acquired from a single "bad" event. The complexities that lead to problems can be entangled in ways that require more time and effort than are available.

On the other hand, a good Mining Engineer designs a mine to fail–unlike buildings or bridges that must survive for tens or hundreds of years. The stand-up time of a mine opening is supposed to range from a few hours to as long as several months depending on the rock properties and the scheduling of mining activities. To keep the cavity open for longer periods of time is generally uneconomic since support or expensive maintenance work is necessary. This has been the condition of mining since time began, although over the past generation, the importance of worker health and safety has become paramount (with the exception of coal mining in the People's Republic of China where ~4,500 people are reported to die in mines every year). In North America, Europe, and Australia, mining is now a safer activity than that of construction. It has been a hard-fought battle to achieve such statistical improvements and there is still considerable room for additional advances [Hall, 1990], but health and safety are supreme concerns of mining activities in many developed countries replacing production as the first priority of work.

HOW FUZZY LOGIC THEORY ENTERED THE MINING INDUSTRY

The seminal paper in mining described the application of Fuzzy Logic to the control of a secondary crushing plant [Harris and Meech, 1987]. Although crushing is a continuous process, these plants are subject to a large number of discrete upsets ranging from alarms warning of the presence of metal or wood in the ore, to planned shutdowns for daily maintenance. "Mother Nature" was rarely kind when she created orebodies–variations in hardness and feed size can be considerable necessitating close attention to how each individual crusher is performing. A circuit failure can be very expensive and instruments available to monitor these upsets are relatively crude and susceptible to fouling by dust, mud, and other ore contaminants. This is precisely the type of plant in which FL excels, i.e., one that is subject to complex heuristic upsets, one that has non-linear relationships among its key variables, and one in which sensor technologies are lacking.

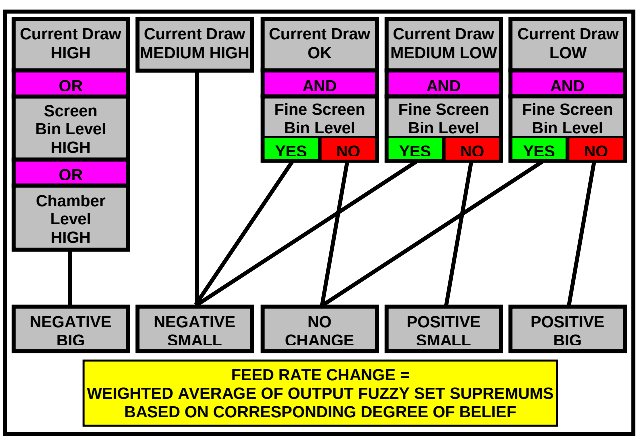


Figure 1 – Secondary Crusher Fuzzy Logic Control System [Harris and Meech, 1987].

The initial work [Harris and Meech, 1987] demonstrated how FL outperforms manual operation and achieves better results than unsupervised PI control. Set-point adjustment of PI control provided gains that matched those from Fuzzy Control, and the potential to fine-tune the system to achieve even higher performance was considered a real possibility. Later work [Meech and Jordan, 1993] established the importance of adaptation with respect to hardness and feed particle size. In addition to achieving a 25% increase in plant throughput, the use of a Fuzzy Confidence Level to delete rules with low Degrees of Belief was shown to influence system stability positively. Figure 1 shows the simplicity of the system to control a secondary crusher (one stage of the entire process). By allowing Fuzzy definitions to change in real-time, significant improvement occurred.

A group at the University of Alabama [Karr, 1991, Karr et al., 1990, Karr and Gentry, 1992a/b, Karr, 1993] began applying soft-computing techniques in the late 1980s–early 1990s. Their initial work used FL to characterize the appearance of flotation tailing material to give plant operators a more consistent analysis. Later, this work was extended to pH control (a particularly difficult non-linear problem), and then to control of a flotation process. They used a genetic algorithm (GA) to alter the shape of Fuzzy Sets used in a given rule base, especially for pH control, and so began the evolution of hybrid systems that employ neural network technologies as well as GA.

MINERAL PROCESSING PLANT CONTROL

Cámara [1999] has reviewed Fuzzy Systems in Mining that provide tools to improve and optimize productivity of processing and metallurgical plants as well as manage maintenance requirements. He pointed to the success of these systems to provide a safer working environment as well as the flexibility to change a process "on the fly". One system operating across adjacent plants providing cross-over control in a coordinated fashion to meet complex corporate objectives. Stability and adaptability of both plants was significantly improved as process supervision attempted to reach a higher goal.

Savolainen [1998] has reported on kiln control using FL. The work compared Fuzzy with multivariable control in terms of: reduced GHG emissions; reduced energy consumption; increased refractory brick life; an easier, more stable kiln operation; and development of tools for remote operation. Fuel consumption was reduced significantly and temperature peaks harmful to refractory life were eliminated. The burnt lime quality defined by residual carbonate improved (lower amount with less variation). See Figure 2.

Raatikainen [1998] demonstrated an advanced control system for cement plants and limestone quarries that helped improve operations by saving raw materials and improving control using a distributed XRF-analyser with a Material Management System based on FL. The system was developed with sub-suppliers, such as General Electric R&D, who played a key role in designing the FL controller.

PCE Engineering in Finland [Kauhanen and Mattila, 1998] developed a Fuzzy System to keep temperature and moisture stable during blending and curing of concrete under changing weather conditions to produce concrete products of uniform quality. The system calculates heating times and estimates temperature and moisture for aggregate materials. The amount of cold and hot water to achieve target temperature and moisture content is then determined. In a related cooperative R&D effort, Peltonen [1999] created a simple MatLab toolkit to configure Fuzzy controllers for various automation tasks where poor performance was obtained with conventional methods–such as control loops with nonlinear processes. Fuzzy systems can be built using either expert knowledge or process data. The toolkit has shown promising results in pilot trials at two Finnish paper mills.

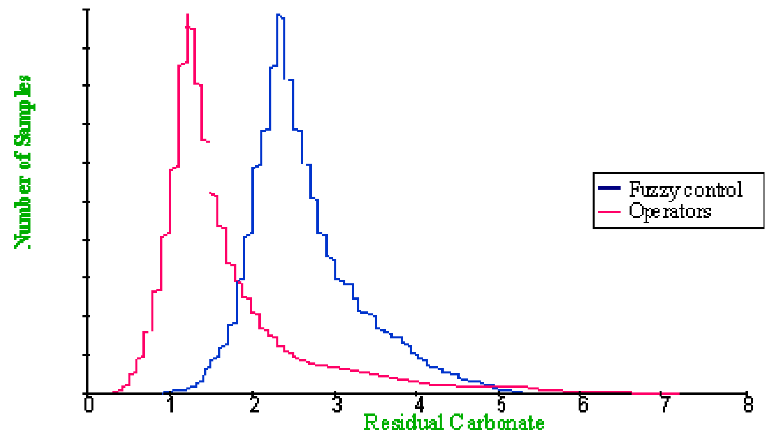


Figure 2 – Significantly decreased carbonate level and variance using Fuzzy Logic in a Finnish lime kiln [Savolainen, 1998].

Applications have been built to control column flotation cells using FL in Japan [Hirajima et al., 1996], Portugal [Carvalho and Durão, 1999], and Canada [Kosick and Harris, 1988]. This latter reference is the seminal paper on applying ES for real-time flotation control. Work in Sweden has applied FL to operate a process to remove phosphorous from magnetite [Su, 1998]. FL has also been applied for hydrocyclone control to prepare ore for flotation [Wong et al, 2004]. Chilean researchers have applied FL to control flotation circuits – both simulation models and real plants [A. Cipriano, 1999]. Baiden and Meech [1987] reported on using simulation to study aspects of the mine-mill interface that cause production bottlenecks–the need for operator training and good inter-department communication with respect to scheduled maintenance was demonstrated using such models.

Several researchers have used FL to assess data trends in on-stream assays. Using a windowing technique, trends were measured over various time horizons to provide input into decision-making with respect to changing reagent addition [Poirier and Meech, 1993], [Kivikunnas, 1999].

While et al. [2004] reported that over 15 intelligent crusher control systems have been installed in the mineral industry since the mid-1990 by Minnovex Technologies. These systems used evolutionary algorithms to design and operate crushing plant circuits.

Chilviet and Meech [1996] have reported on "qualitative modeling" to build intelligent monitoring and control systems for SAG circuits.

At the Carajas Mine in Brazil, FL was used to control a tailing thickener [Santos et al., 1995]. Savings in fresh water pumping and reduced addition of flocculant paid for the system in two months. Other dewatering applications involve the modeling of a rotary dryer by Finnish researchers that follows on from earlier work on lime kiln control [Yliniemi et al., 2003].

With so much reliance on dependable instrumentation, the ability to predict failed sensor readings from other data has been important. FL plays a role in performing these sensor fusion functions [Mahajan, 2001]. Cifuentes et al. in 1995 developed an on-line qualitative model of a semi-autonomous grinding circuit based on FL for use by mill personnel to monitor and evaluate factors responsible for delays and production losses by interpreting combinations of sensor signal trend patterns.

In Australia, BEC Engineering and FLS Automation installed a Fuzzy Logic-based mill control system on the Mt. Rawdon Gold Mine SAG-mill circuit in 2002 to increase circuit efficiency and improve throughput. The process consisted of a SAG mill-screen operation with oversize mill discharge diverted to a pebble-crusher before returning back to the SAG mill. The main throughput limitation was mill power draw and so, the system goal was to maintain SAG Mill power as close to maximum as possible. The level of instrumentation available was sparse although standard PID controllers were available to adjust mill feed rate, water addition and sump level.

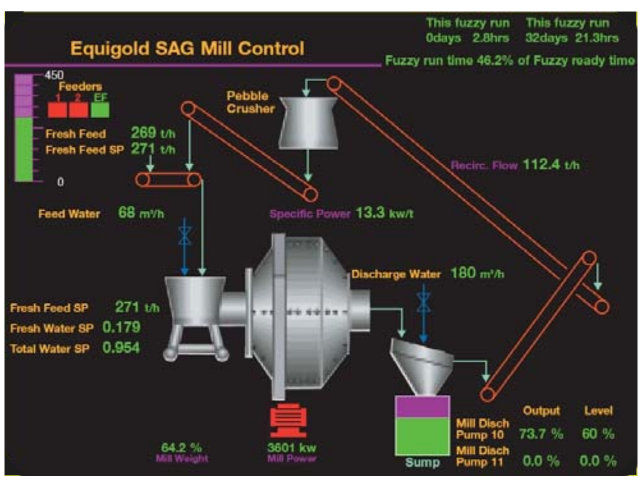


Figure 3 – Equigold's Mt. Rawdon SAG Mill circuit control loops.

The rule-based expert system uses FL to operate the circuit under normal conditions as well as to recover control following an emergency shut-down or upset. Each sub-control loop (power, tonnage, and sump-level) can be turned on and off (i.e., over-ridden) by an operator. When active, the system cascades set-points to individual PID controllers. The system was well-accepted by all operators and gave a documented throughput increase of 3.5% (~6-month payback). The graph in Figure 4 provides an example of system performance. Initially, changes in mill feed rate done manually caused large excursions in power from the desired set-point. When the control system is turned on at 08:15, many small alterations are made to the mill feed rate which reduced variations in mill power. It is claimed that the FL-based control system is like having the best operator running the mill 24 hours a day [F.L. Smidth Group, 2003] (see Figure 5).

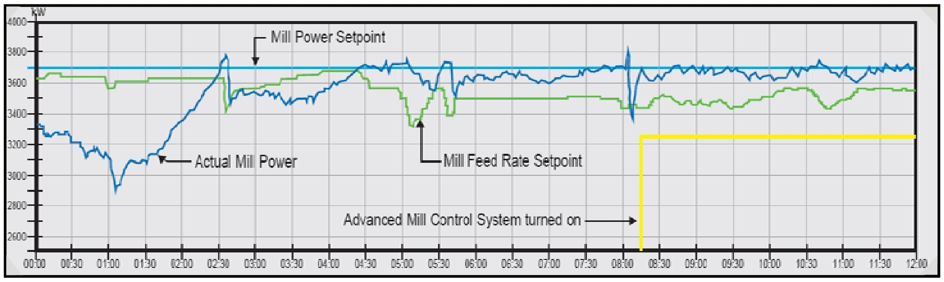


Figure 4 – SAG mill performance at Mt. Rawdon Gold with and without Fuzzy Logic-based advanced control.

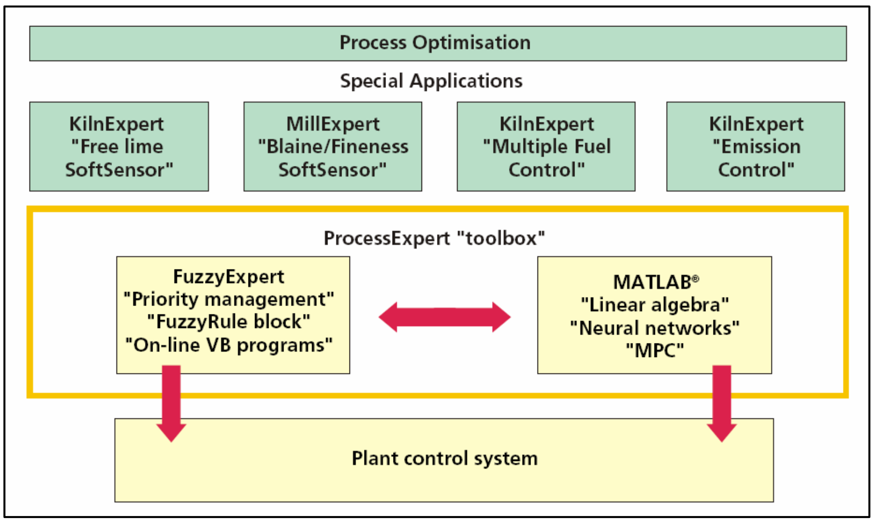


Figure 5 – FLS Automation's ProcessExpert system for cement kiln operation. (note the use of soft sensors to predict "difficult-to-measure" parameters such as Blaine (specific surface area) and free lime determinations.) - from F.L. Smidth Group, 2003

FL is not limited to process control, but is also applied to train new operators [Meech, 1990, Ikonen and Najim, 1997], trouble-shoot control loops [Chang and Chang, 2003], and design gold recovery plants based on mineralogical analysis [Torres et al., 2000]. Monitoring systems are also important applications [National NEMO Network].

GEOLOGICAL AND GEOGRAPHICAL APPLICATIONS

The major applications in geological and geographical systems relate to the generation of maps. These include mapping landslides [Zhu et al., 2004], soil characteristics, [Zhu et al., 2001], uncertainty in GIS [Zhu, 2005], [Carranza and Hale, 2001], [Zeng et al., 1997], [Waters and Evans, 2003]. An excellent comparison of the use of crisp classification versus Fuzzy classification is given by Shalan et al [2003]. They point to the advantage of using Fuzzy boundaries and discuss some pitfalls in using FL without understanding Fuzzy Set definitions.

Considerable literature exists on the characterization of mineralized zones, for example, gold in the Philippines [Carranza and Hale, 2001], copper in Iran [Ranjbar et al., 2002], and copper/gold in Mauritania [Eden et al., 2002a/b]. Evolutionary mapping of satellite images of a national park in Sardinia using Fuzzy techniques is monitoring the extent of development [Manca and Pireddu, 2003]. Fuzzy modeling has also been applied to interpret geophysical data [Bardossy and Duckstein, 1995], while another group created a Fuzzy Expert System to teach mineral identification [Nagel and Meech, 1995].

MINING APPLICATIONS

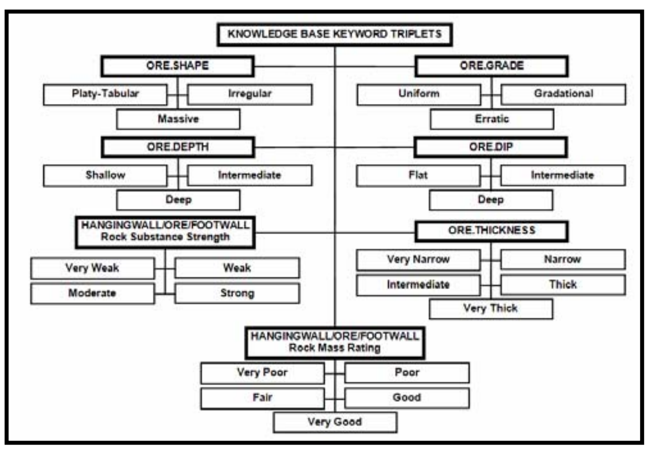


Figure 6 – Knowledge representation in the MMS Expert System [Clayton et al., 2002]

Built on top of the UBC Mining Method Selection algorithm, MMS [Clayton et al., 2002] is a knowledge-based system that incorporates FL in its analysis. The MMS System modifies the UBC approach by considering uncertainty associated with the boundaries between input parameter categories. Through a series of logical operations in the knowledge base, an estimated Degree of Belief in each of the ranked mining methods is calculated. The system was validated against two other selection programs and shown able to provide additional advice to a design engineer by provision of a Degree of Belief. Figure 6 shows the Fuzzy representation that characterizes parameters used to select an appropriate method. The use of words to characterize each variable has been used by expert mining engineers well-prior to the formal application of FL.

The Helsinki University of Technology [Koivo, 1999] in partnership with Sandvik-Tamrock, has built an Artificial Neural Network with an FL-based system to determine the bucket payload of a front-end loader to provide a mine with immediate information on material flow from the mine. This can result in improved control of the whole mine production process and allow monitoring of individual tasks and machines to calculate salary bonuses and pre-plan maintenance. Weighing during movement is not very accurate and requires data pre-processing to account for system nonlinearities. During the project, innovations to solve this weighing problem were discovered leading to a patent application in which a Fuzzy-Neural system is the key.

Rock Mechanics is an important area of modern mining in which a mine is monitored for rock failures on a continuous basis with stope design using empirical methods based on past experience. Stress in rock bolts is measured regularly with data being interpreted using FL [King, 1996]. Other rock mechanics applications using FL methodologies have been reported in India [P. Singh, 1998], [T. Singh et al., 2005].

Telerobotics in underground mining [Tuokko et al., 1994, Sulkanen and Tuokko, 1994] is now being applied in many parts of the world with a trend toward fully-autonomous operation not far-off. A number of applications are using FL to control vehicle operation [Hemami, 1994a], to interpret obstacle detection data [Polotski, 1995], to conduct path planning and tracking [Cohen et al., 1998], [Hemami and Polotski, 1998], and to optimize mucking and bucket loading [Hemami et al., 1994a/b], [Hemami, 1994b/c].

In open pit mining, excavation systems [Bissé et al., 1995], [Babienko, 2001], [Wang and Lever, 1994], [Hemami, 1995a/b] have been developed using FL with emphasis on cooperative or agent-based hardware/software [Niemelä, 1994], [Lacroix et al., 1999]. FL-based expert systems are helping to select open pit mining equipment [Basçetin, 2003] and mobile underground mining equipment [Papavasileiou et al., 2002]. An FL-based production model [Huang and Kumar, 1993] is used at one mine to follow trends and maintain steady operations. In longwall coal mining, an FL system was created to control the load and speed of a coal shearing machine [Heyduk, 2001] allowing the operator to remain in a remote position. Fuzzy control of a ventilation system has been studied with great success. Such systems can direct air where needed and block-off areas not requiring ventilation leading to significant cost savings and enhanced worker health [Poanta and Dojcsar, 2001]. Coal blending and ash monitoring using FL have also been developed in Polish coal mines [Cierpisz and Heyduk, 2001, 2002], Bydon, 2003].

ENVIRONMENTAL APPLICATIONS

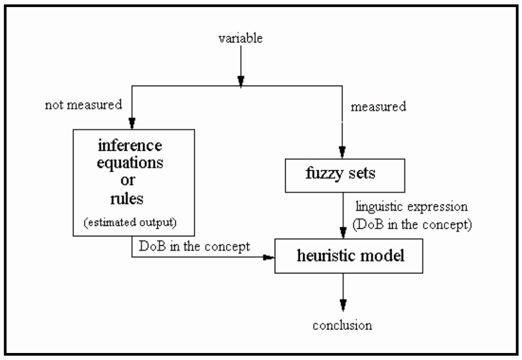
Protection of the environment from mining activity has evolved over the past generation from a small external movement looking for evidence to an essential department of every major company in the world. To receive a permit to mine today, one must plan for closure before starting production. The plan must include all funding arrangements and prove that the land will be restored following the operating cycle which may last for 10-20 years. Monitoring the future environment is essential to ensure problems do not arise after the company has left the region. This may include operating water treatment plants to prevent heavy metals and acid waters from fouling nearby water courses. Fuzzy Logic has an important role to play in creating automated systems. They provide an economic incentive for a company to fulfill these obligations.

Metsä-Serla Oy, Kyro Board Mill and Neles Automation [Puhakka, 1996] developed a fuzzy controller for an active sludge water treatment plant. The results were a reduction in sludge age from 12 to 7 days leading to an increase in sludge removal during the bio-sludge cycle. At the same time, the buffer capacity of the biosludge thickener increased because of improved sludge-drying. With a 35% decrease in phosphoric acid use, suspended solids decreased by 33% and the phosphorus load by 50%.

Virtually all mines attempt to recycle water as much as possible to avoid misuse of a precious resource, particularly in arid or semi-arid climates. Wastewater management and treatment is essential at all mine properties [Bongards, 1999], [Shrestha et al., 1996], [Duckstein et al., 1994]. Prediction of ground water flows through waste dumps or into open pits is being done using Fuzzy Systems [Scott, 1998] to attempt to avoid permanent damage to surface soils [Komac and Sajn, 2001].

Prediction of pollution is an "art-form" fraught with considerable uncertainty as the conditions that generate pollution can take years or decades to show-up since they depend on the microbiology of waste piles and tailings dams. Many systems exist to perform risk assessment [Ghomshei and Meech, 2000], [Veiga and Meech, 1995] with the most successful ones based on Fuzzy Logic [Veiga and Meech, 1995b, 1997]. A fuzzy model has been proposed to show how a new idea can migrate from a small group to become the central theme of a society–this transformation is called Technological Evolution [Meech and Veiga, 1998]. By monitoring the progress of such change, policy-makers can decide on strategies to either promote or head-off the proliferation of a particular activity.

The mining industry is also characterized by small-scale mines. Over 100 million people worldwide are either directly involved or indirectly reliant on such artisanal work [Veiga and Meech, 1995a]. These activities are generally carried out in a disorganized fashion with little respect for the environment leading to severe damage and pollution, particularly in gold mining where mercury is used [Meech and Veiga, 1998]. A fuzzy expert system called HgEx was developed for use by a variety of skilled personnel who are working with these artisanal miners to attempt to improve conditions and reduce their impact on society. Figure 7 shows how the system can deal with either measured data or linguistic concepts to characterize observations at a mine site. Figure 8 shows how fuzzy sets are interpreted from pH measurements causing rules to fire that can determine the degree of danger in a particular environment subject to mercury emissions.



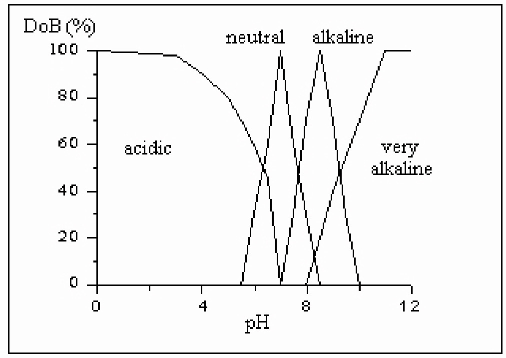


Figure 7 – Process by which HgEx uses FL to conclude on the extent of Hg pollution at a specific small-scale mining site [Meech and Veiga, 1998].

Figure 8 – Fuzzy Sets used to describe pH conditions of soil in assessing the Hg pollution danger at a particular mine site [Veiga and Meech, 1995c].

Figure 9 contains a simplified diagram of the modules used in HgEx to estimate the degree of danger to organisms subject to Hg emissions in the Amazon. Note that the model can be adapted using an "alpha" factor to characterize the economic, socio-political and technical issues in a region that affect how an expert would conclude about danger. In this way, the overall system can be adapted to other situations. For example the presence of one small miner in the Amazon is really a "minor" problem compared to his presence on a major North American river such as the Colorado or Fraser.

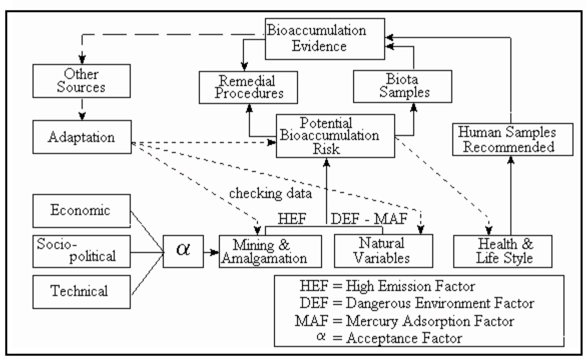


Figure 9 – Modules used in HgEx to predict the potential risk to biota in a particular environment and mining site [Meech and Veiga, 1997].

In North America, there would be a loud reaction to this situation, while in the Amazon the additional contribution is small and priority should be given to larger-scale operations or regions where mercury use is "pandemic".

Figure 10 shows how the value of "alpha" affects conclusions about the danger or concern in a region. The "alpha" factor is determined from a extensive, detailed analysis of the elements that affect mercury pollution in a particular region or country or time. The rules that determine "alpha" are depicted in Figure 11. Note the non-linear nature of this relationship in which the central region of the map forms a broad plateau with changes occurring as the system approaches the edges of the graph.

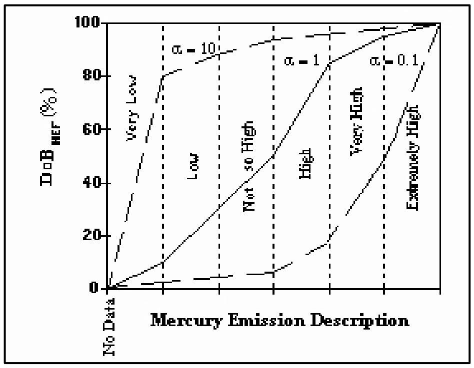


Figure 10 – Linguistic descriptions of the extent of Hg emissions depend on the value of "alpha". [Meech and Veiga, 1997].

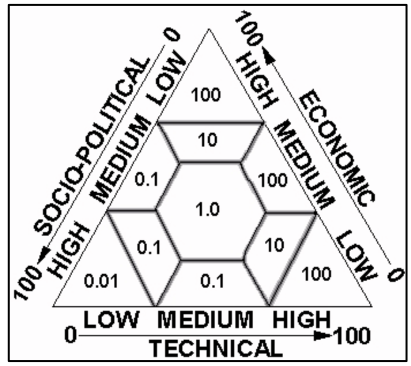


Figure 11 – The rules used to calculate the value of "alpha" in HgEx. [Meech and Veiga, 1997].

Work has been done to extend Eh/pH diagrams to interpret species domination in a particular aquatic system at varying "redox" and pH conditions. Convention Eh/pH diagrams show crisp boundaries between each region. Figure 12 shows a plot of this analysis for mercury speciation. Each graph reflects a single concentration of each reacting ion species (in this case, Hg^{+2}, Cl^{-}, OH^{-}, and S^{-2}).

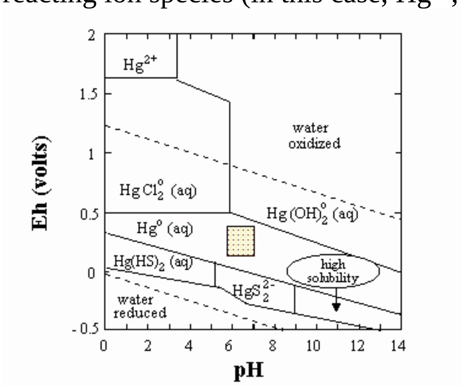


Figure 12 – Eh/pH diagram for the equilibrium of Hg species in an aqueous environment [Meech and Veiga, 1997].

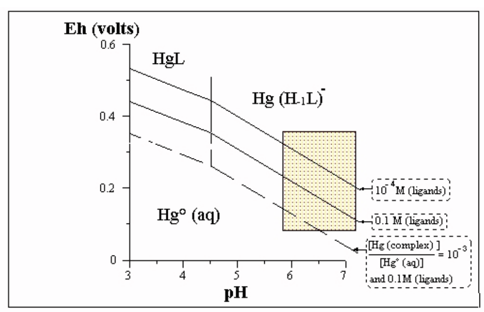


Figure 13 – Effect of ligand concentration on the boundary between Hg^{o} and $Hg(H_{-1}L)^{-}$ in an Eh-pH diagram [Veiga et al., 1995].

Unfortunately in the real-world, there are many other species that can affect the concentration of each of these species. For example, the presence of organics can rapidly change the level of a dangerous species from low to high. Fuzzy Logic can be applied to these thermodynamic calculations to provide a range of conditions under which these changes are understood. Figure 13 shows how the boundary between the "relatively benign" Hg^{o} and the much more dangerous oxidized complex ion $Hg(H_{-1}L)^{-}$ changes as a function of the complex ligand (L) concentration. With chloride present, the change can be even more dramatic as shown in Figure 14 where the situation appears to be stable and then shifts in the presence of organic material found in many parts of the Amazon.

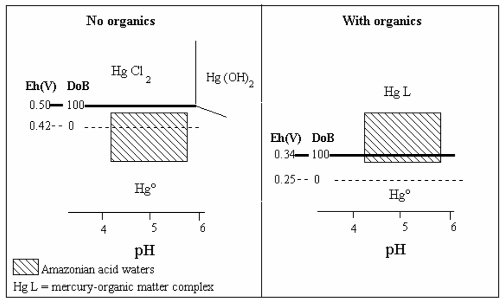


Figure 14 – How the degree of belief in a dangerous situation can change from no danger to certain danger at conditions in many regions of the Amazon [Veiga et al., 1995].

GENETIC ALGORITHMS AND EVOLUTIONARY SYSTEMS

Genetic Algorithms (GAs) are adaptive evolutionary methods used to solve large, complex search and optimization problems [Goldberg, 1989] based on the genetic evolution of biological organisms. Over many generations, natural populations evolve according to the principles of natural selection and "survival of the fittest". By mimicking this process, a GA can evolve solutions to real-world problems. The method works with a population of individuals, each representing a possible solution. Each individual is assigned a "fitness score" according to how well the solution solves the problem. Individuals with high fitness values are given an opportunity to reproduce by "breeding" with other "fit" solutions. This produces new individuals as offspring that share some features from each parent. The least-fit members are less likely to be selected for reproduction, and so, they die off. Selecting the best individuals and mating them to produce a set of offspring produces a new population of solutions. With a well-designed GA, the population converges quickly to the optimal solution.

Genetic Algorithms differ from more traditional optimization procedures in four ways:

1. GAs work with a coding of the set of parameters, not the parameters themselves;
2. GAs search from a population of points, not a single point;
3. GAs use payoff information directly, not derivatives or auxiliary knowledge;
4. GAs use probabilistic rules, not deterministic ones.

The coding of the solution is the most important step in designing a useful GA. Each position on the chromosome string represents one variable in the solution space. The value assigned to each position represents the state of that variable. Binary representations are often used however, human DNA can take on one of 4 possible values. The more levels used, the more complex (and fuzzy) the system becomes. So typically, the value of each element is represented by a 0 or a 1 (on or off).

GAs work from this rich set of database points by simultaneously climbing many peaks in parallel, so the probability of being trapped on a false global peak is lower than that of methods that move from point to point. The mechanics of a GA involves copying strings and swapping partial ones. The simplicity of operation and the attributes of the effect (speed and accuracy) are the main attractions of GA.

The next important step is defining the "fitness function"–a mathematical expression characterizing the importance of variables in the solution space. System constraints on variables can be dealt with within the "fitness function" by creating penalties in the total fitness value. Weighting of the different elements in the fitness function can also be done. A fitness function must be a non-negative measure and so the Maximum or Minimum functions can constrain solutions to a limit of 0 or 1. A selection probability, P_i, is assigned to each individual based on its fitness F_i , so the fittest individuals have an increased chance of selection:

$$P_i = F_i / \sum_{i=1}^{N} F_i \qquad \text{(where N = population size)} \qquad 1.$$

A simple GA that yields good results in many practical problems uses three operators: Reproduction, Crossover, and Mutation.

Reproduction is a process by which individual strings are selected according to their fitness value f . The function f is a measure of profit, utility, or goodness that is to be maximized or a cost that is to be minimized. Selecting a chromosome according to its fitness value means strings with higher (or lower) values have a greater probability of contributing offspring to the next generation.

Crossover proceeds in two steps. First, members of the selected strings in the mating pool are chosen at random. Next, each pair of strings undergoes crossover: an integer position k along the string is selected at random between 1 and the string length (L) less one [1, L-1]. Swapping all characters between position k+1 and L inclusively creates two new strings. For example, if there are two strings:

```
101^011
110^100
```

selected for reproduction with a crossover position of 3, then the offspring created will be

```
101^100
110^011
```

Mutation plays a secondary role in operating a GA. Mutation is necessary since the reproduction and crossover operations occasionally lose useful genetic material. The mutation operation randomly chooses a single individual, randomly selects one position on its chromosome string and transposes it from 0 to 1 or vice-versa. Mutation restores diversity, but does not provide a logical approach to optimization, nor can it prevent a reoccurrence. Its use is important where a local minima (or maxima) traps the algorithm and a new population member is needed to trigger the crossover operator on to a better result. The probability of mutation is typically set to 0.01 to 0.001. Too high a mutation rate can create a high influx of new genetic material upsetting the crossover process. A time-dependent change in probability has demonstrated success with the initial value set high and then declining as a function of the generation [Baker, 1985], [Bramlette, 1991]

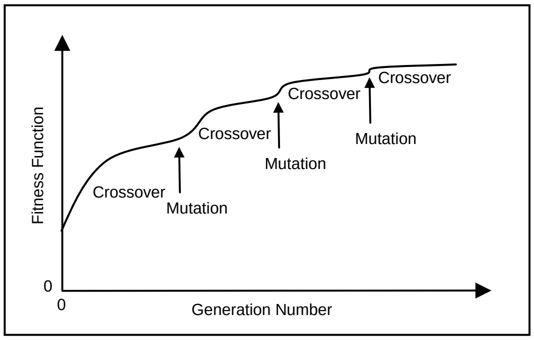


Figure 15 – Idealized effect of mutation operations on convergence of a GA.

ARTIFICIAL NEURAL NETWORKS

The concept of using the actual structure of the human brain to configure a system in which input information is connected to output decisions has existed since the end of the 2nd World War. Concepts of an artificial neuron has progressed through several stages with its roots grounded in neurological work done in the early part of the 20th Century. From studies on the structure of nerve tissue, neurons were shown to be physically separated cells connected to one another. Based on this work, McCulloch and Pitts [1943] claimed that neurons with binary inputs and a step-threshold activation function were analogous to first order systems but their simple model did not use connection weights.

In 1949, Hebb revolutionized the perception of artificial neurons. He proposed that when an axon of cell A is near enough to excite cell B and repeatedly fires, a metabolic change takes place such that A's efficiency, as one of the cells linked to B, is increased. This has become known as Hebb's Rule which implies that when two neurons fire together, their connection strengthens–an operation fundamental for effective learning and memory.

The McCulloch-Pitts model had to be altered to allow the adjustment of the weight of each input. Rosenblatt [1958], using the McCulloch-Pitts neuron and the findings of Hebb, developed the first Perceptron Model of the neuron which is still widely accepted today. A Perceptron learns by weighting its inputs. The model is shown in Figure 16.

Each input is weighted and summed at the node with the total passing through to activation function resulting in an output between 0 and 1. The inputs do not have equal weights and the Perceptron can "learn" these weights through continued stimulation with data. The original activation function was a step-function (or threshold). However, other functions such as Sigmoid, Piecewise-Linear and Gaussian activation have been applied. Figure 17 shows how the Sigmoid function can be changed to provide variations all the way through to a step change by increasing the size of the scaling factor.

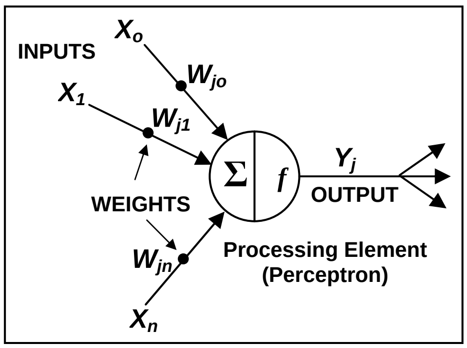


Figure 16 – The Typical Perceptron Model of a neuron (after Rosenblatt, 1958).

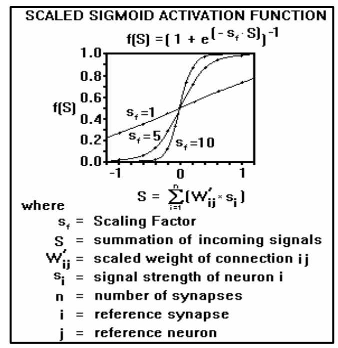


Figure 17 – Effect of scaling factor on the shape of the activation function.

Unfortunately, the Perceptron by itself was limited to solving only certain mathematical relationships. But Rosenblatt was so devoted to his Perceptron that he made the ill-timed declaration that an error correction procedure will always yield a solution in finite time. With this assertion, Rosenblatt essentially challenged head-on the symbol manipulation projects being performed by others, i.e., Expert Systems.

In 1969, Minsky and Papert published a famous (infamous?) monograph entitled *Perceptrons: An Introduction to Computational Geometry* that proved the model could only solve linearly separable functions. They stated that this research was doomed to failure because of these limitations–an equally inopportune remark. As a result, little research was funded in the field. Rosenblatt died in an unfortunate boating accident in 1969 shortly after publication of this monograph–there are rumors he committed suicide. In 1982, Hopfield demonstrated from work on the neuronal structure of the common garden slug that ANNs can solve non-separable problems by placing a hidden layer between the input and output layers [Hopfield, 1982], [Hopfield et al, 1983].

Since those heady days, a huge proliferation in ANN methodologies has occurred. Albus developed the "Cerebellar Model Articulion Controller" in 1975 and this eventually evolved into Agent-based behavioral systems that are becoming vogue today in the field of Robotics. Rumelhart and McCelland's group at Carnegie-Mellon developed the most famous learning algorithm in ANN–Back Propagation–which uses a gradient-descent technique to propagate error through a network to adjust the weights in an attempt to find the global error minimum [Ananthraman and Garg, 1993], [Burgin, 1992], [Jones et al., 1987]. More recently, Sutherland [2001] developed a Holographic Neural Network (H-Net) in which thousands of data points can be "enfolded" onto one neuron (Figure 18). The method involves polar coordinate regression analysis in which each data point is characterized as a complex number with the angle representing its value and the vector being its degree of belief or measurement uncertainty (Figure 19). The claim is made that this technique is three-orders of magnitude faster than conventional connectionist ANNs.

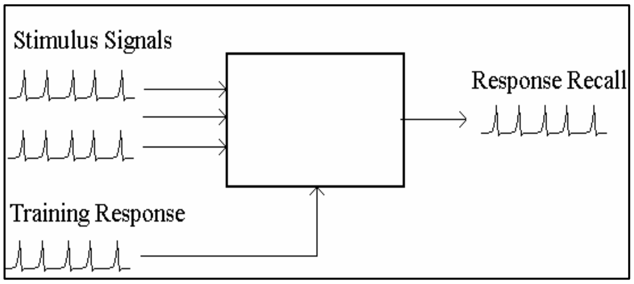


Figure 18 – Cortical Cell block diagram in H-Net.

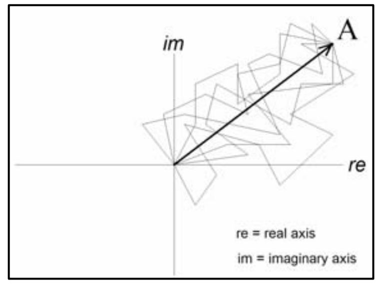


Figure 19 – Multiple Pathways Defining a Complex Scalar in H-Net.

ANN technology is actually an extension of Fuzzy Logic. When a rulebase is designed using Fuzzy Sets, the degrees of belief emanating from each rule are equivalent to the strengths of signals flowing between neurons in an ANN. In the case of known expertise, the weights of recognized important inputs, sub-goals, or final conclusions are set to full-strength, while those of unimportant inputs (according to the expertise) are set to zero. Now if a neural network is designed to test this expertise on real data, the algorithm may discover that some of the "important" links should be diminished while some of the "unimportant" links should be strengthened. In this way, memories that link input facts to outputs become more distributed while the ability to explain the reasoning is reduced.

HYBRID SYSTEMS

Finding ways to combine these techniques has predominated recent research. The initial days of AI considered neural networks and expert systems as unique, separate fields. Neural networks distribute memories and connections throughout the structure of the system using data analysis while expert systems are based directly on expertise of a human being who is willing to express linguistic expressions and relationships of the knowledge. The former systems are black-box models that cannot simply explain their knowledge to the world, while expert systems by their very structure (facts, rules, relationships) have an inherent ability to explain and justify their decision-making.

Expert Systems struggled through the 1970s to develop solutions to significantly-sized problems and once the AI community embraced FL as a technique integral to the process of synthesizing uncertainty, success was realized. FL provides ways in which the number of rules can be contained and the "curse of dimensionality" avoided. The relationship between system size (number of rules) and I/O variable size (number of facts) can be reduced from an exponential function to one based on simple multiples. The tuning of Fuzzy Sets has always been viewed as a limitation by those who don't understand the methodology. One must remember that all systems based on AI produce approximate solutions [Gonzalez and Perez, 1996]. Applying FL requires belief in a "tolerance for imprecision" and so, despite the fuzzy definitions being "in error", methods to adapt these relationships can be implemented to respond to other knowledge. FL, ANN or GA methods can provide this adaptability [Satyadas and Krishna-Kumar, 1996]. These approaches generate a variety of combinations of the basic technologies:

Fuzzy Expert Systems:	ES with adaptable FL
Fuzzy-Neural Systems:	FL with ANN-based adaptation of the Fuzzy Sets
Neuro-Fuzzy Systems:	ANN with FL manipulation of link weights
Fuzzy-GA Systems:	GA with fuzzy values (non-binary) [Herrera Lozano, 1996]
Neuro-GA Systems:	ANN with GA choosing the best network of many solutions
Genetic-Fuzzy Systems:	GA-based adaptation of the Fuzzy Sets [Lee and Takagi, 1996],

INNOVATIVE AGENT-BASED SYSTEMS

Mining companies in the Third Millennium must transform themselves into intelligent, learning organizations able to cope with globalization of information resources. The main problem is not access to information, but the ability to "mine" data and transform it into useful strategic resources. [Szczerbicki and Gomolka, 1999]. As systems increase in complexity, decomposition is the usual way to structure a problem. These atomized structures consist of autonomous subsystems, each deciding on the information it receives and sends [Gunasekaran and Sarhadi, 1997]. In the real-world, autonomous subsystems consist of groups of people and/or machines tied together by service relationships.

An effective architecture [Davis, 1999] has the following features:

- The user can specify high-level tasks decomposable into more detailed execution tasks according to an established hierarchy or distribution network;
- The user can plan and control at different resolutions of time and level of detail;
- The system can decompose complex behaviours into manageable sub-functions;
- The system allows a function to be distributed across several intelligent controllers.

An example of such a structure is the RCS design architecture suggested by NASA/NIST shown in Figure 20. [Albus and Quintero, 1990], [Lumia, 1994], [Moncton, 1997]. The Reference Model Architecture is based on Real-time Control Systems (RCS) developed by NIST and has been widely adopted as a standard by NASA in its tele-robotic missions and has served as inspiration for DoD's JAUS (Joint Architecture for Unmanned Vehicles). In order to achieve the global goal in RCS, the global task is decomposed according to the time scale of different components of the mission. This generates a hierarchical control layer architecture. The bandwidth, as well as the resolution of spatial and temporal patterns is planned so it decreases from bottom to top by about an order of magnitude at each layer. Each layer consists of elements (nodes) of intelligence that independently process their relevant sensory data, make decisions and control their actions. These elements sense their environment and update their World Model. Each has its own unique World Model representation. Agent-based architectures have been included in the Reference Model more recently as building blocks.

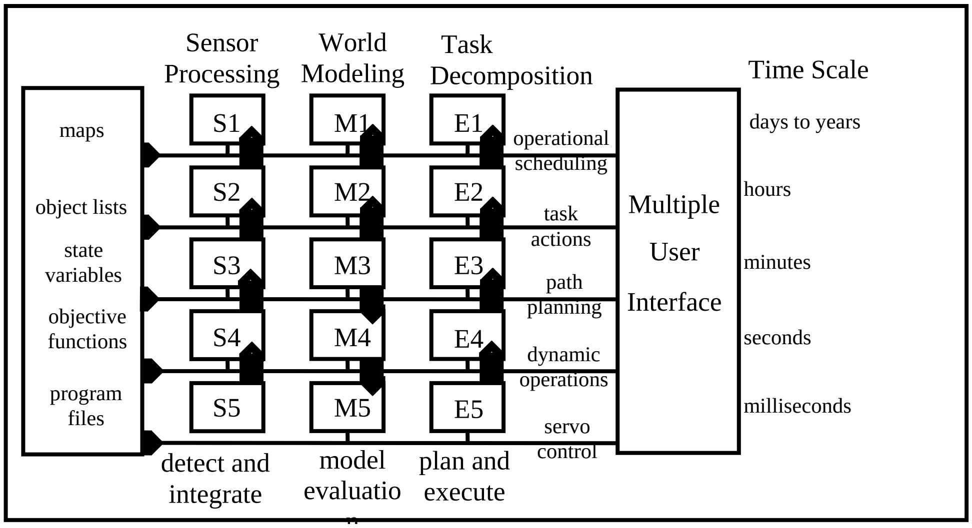


Figure 20 – NASA/NIST Standard Reference Modeling Environment [after Moncton, 1997].

Intelligent control agents run asynchronously and in parallel. To ensure completion of the final goal under time constraints, Agents are organized into a hierarchy in which the top layer is responsible for supervising overall task completion in a timely fashion. This layer is the Main Supervisor Agent and all other activities are controlled by this agent. Most real-world robotic systems and process control applications are dynamic with variables operating at different bandwidths, so this layering of the architecture by time-resolution removes interference from Agent demands for system resources. Bottom layers deal with high bandwidth activities including interfacing with humans who may be sharing the same space. Managing complexity, change, and disturbances are key issues in these systems. A distributed, agent-based structure is an alternative to a hierarchy. The cooperation within an agent-based structure with evolutionary schedulers allows a system to handle complexity, reactivity, disturbances, and optimality issues simultaneously.

An agent is an "encapsulated" software entity with its own identity, state, behavior, thread of control, and ability to interact with other entities including people, other agents and "legacy" systems. An agent, whether real or virtual, can act on itself and on other agents. Its behavior is based on observations, knowledge, and interactions with other agents in the system or process. An agent has several important abilities–to perceive at least a partial representation of its environment, to communicate with other agents, to produce child agents. This knowledge of its own objectives and unique autonomous behavior are often characterized as selfishness. [Monostori and Kádár, 1999].

Holonic Systems (Figure 23) are a relatively new paradigm in manufacturing akin to agent-based systems. They consist of autonomous, intelligent, flexible, distributed, cooperative agents or holons [Valckenaers et al., 1994]. The word holon derives from the field of holography–a holon is a part of a whole. The essential difference between an agent and a holon is that hardware (instruments and actuators) can be included as part of a holon whereas agents refer only to software entities (although not exclusively). Three basic holons exist–**resource**, **product,** and **order holons** [Van Brussel et al., 1998]. These elements use object-oriented concepts to perform their duties. The most promising feature is the transition from hierarchical to heterarchical systems. An object-oriented framework to develop and evaluate distributed agent systems provides a model to represent a plant containing different types of agents. (Figure 24).

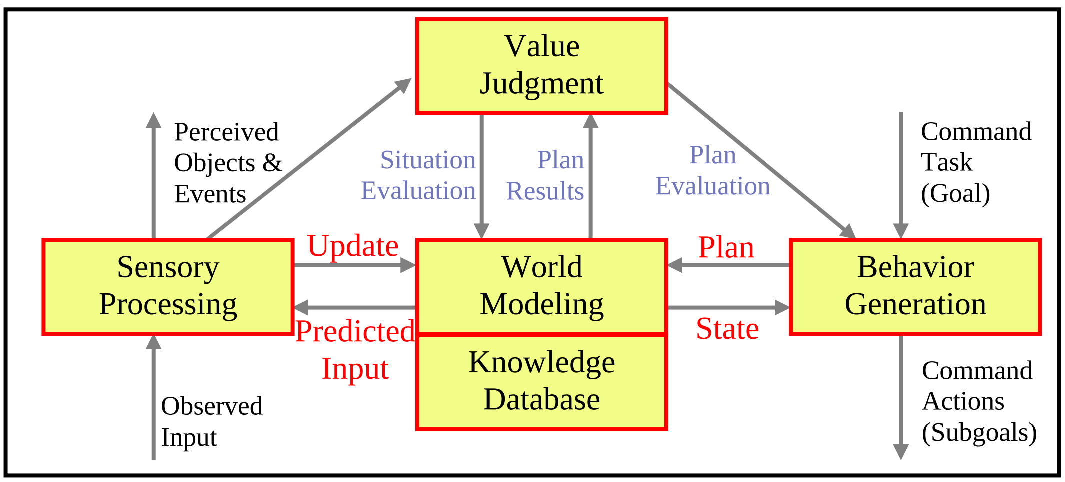


Figure 21 – An Agent-based Real-time Control System node.

An agent contains different, functionally-independent subagents. Each agent incorporates a communication subagent to send and receive messages using a network protocol. A resource agent involves a supervisor subagent to control real-world activities. Agents contain a registration mechanism by which they access system hardware resources. Each agent has a local knowledge and database to store information about machine capacities, time intervals for different work, the groups of interest, etc. Data about the agent is accessed through a communication subagent. (Monostori et al, 1998).

Agent-based software was invented to facilitate interoperability. There has been much interest and development in "middle"-ware to deal with software that is already written–so-called **legacy software** to allow it to remain in productive use. An agent is motivated by intention (goal-oriented) and is modulated by its attention (prioritizing is a function of static information as well as continually-measured dynamic data). A control agent encapsulates a behaviour decomposed into subtasks of a behaviour-based nature that react to environmental changes or action outputs from a decision-procedure analysis. The action can be a message sent to another agent to perform a certain action or receive data. Each agent has at least one active thread. Behavioural agents are feedback controllers designed to achieve specific tasks/goals.

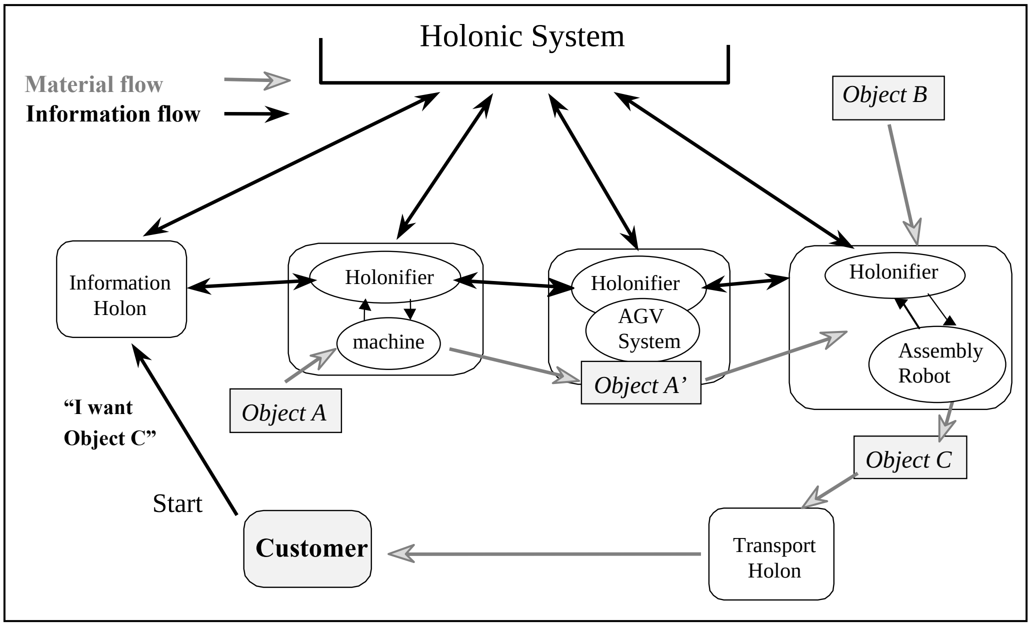


Figure 23 – Heterogeneous Holonic Manufacturing System consisting of real and soft holons. (after Monostori and Kádár, 1999)

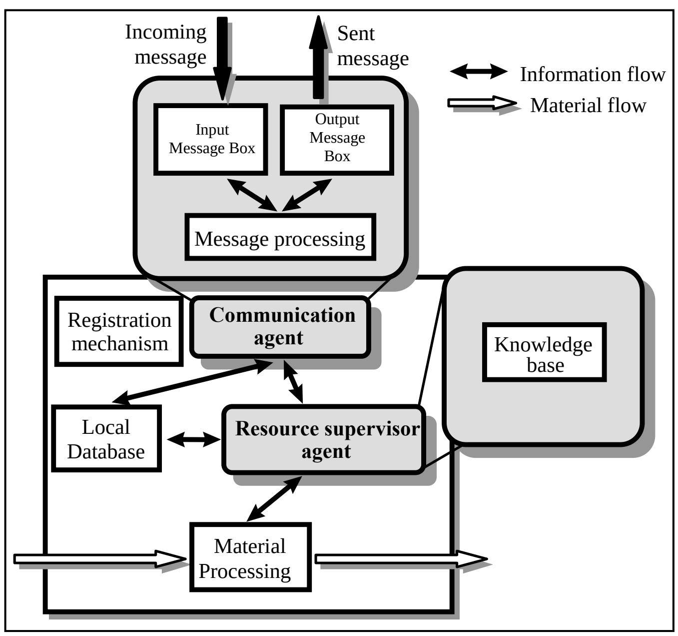


Figure 24 – Structure of a resource agent. (after Monostori and Kadar, 1999)

Behaviours connect sensors to actuators and receive input from and send output to other behaviours. When assembled into distributed representations, behavioural agents can look ahead at a time-scale useful to the rest of the system. Large-scale, cooperative teams, comprising interacting agents, offer capabilities beyond conventional software. An infrastructure with these features uses small pieces of reusable code to solve problems via interactions with other elements, rather than duplicating functions in other modules.

ROBOTIC APPLICATIONS

Intelligent robotic systems are developed within an architecture that enables intelligence to be an integral part of the robot. Behaviour-based systems can express such intelligence based on emergent behaviours of a complex system. When behaviours are implemented by control agents, they express intelligent, flexible, cost-effective, modular, safe, dependable, robust and user-driven qualities. The agents communicate with a human-interaction agent who acts on behalf of the human at the internal software control bandwidth, i.e., the agent's bandwidth is similar to that of other software, so it can close control loops at low frequency with a human and at high frequency with software.

An important aspect of the continuous operation of a robotic system is its ability to respond swiftly and modify its actual physical behaviour as new pieces of data are perceived. Developing a robotic agent-based-system requires event-based monitoring capabilities and management tools. To this end an algorithmic paradigm must be adopted to support such demands based on online and event-driven ideas. An algorithm designed to solve a given problem needs input data and parameter values from the outside environment. The algorithm is not a fixed calculation, but rather, it adapts to changing circumstances and its parameters. These situations are in a state of flux with regular updates at bandwidths sufficient to address task requirements under control of the agent.

The underlying design of safe, robust and dependable robot systems operating in a human environment and co-operating with people is integral to all aspects of robot R&D from architecture development to key component functionality. Safety takes place by having a robot continuously survey its surroundings looking for danger. The robot must possess a self-monitoring ability and be able to shut down or repair itself, even partially, in the event of a self-perceived emergency. They must be equipped with "e-safe" capabilities that enable a distant human to implement immediate rescue action [R. Granot, 2003]. Robot systems cooperate with humans through an intelligent interface agent, so a human can send change-orders on-the-fly providing responses to unexpected events. Activities being monitored by humans in a telerobotic, supervisory mode of operation enable communication between robot and human from a distance.

Advanced integrated modular robotics and the modular design and modelling of new, versatile "plug-and-play" systems are developed in open-source reference architectures with standardized hardware and software building blocks. These enable Agent-based subsystems within a hierarchical-layered architecture as previously discussed. Installing agents within RCS and JAUS is a major robotic advancement. Reusable agent code is available as building blocks for various behaviours by their nature and definition. The capability of tele-robotic and human supervisory systems enables introduction of robots into human environments. It extends the world of information processing by perception of the physical environment using advanced multi-sensors with transfer of the analyzed data as information to either humans or virtual agents for action.

Tele-robotic systems to operate underground and off-road vehicles is now being used by a number of mines around the world (Northpark and Olympic Dam mines in Australia and Inco in Canada). The future of these applications lies with autonomous systems. The successful completion in October 2005 of the DARPA Grand Challenge suggests that the required hardware and software are available today to create successful applications. Safety is the top issue with a system reliability of 99.999% being required (5 minutes downtime in one year). To achieve this level, agent-based software must be self-healing and contain significant redundancy with respect to software components, instrumentation, and final control elements. A diagram of such a system is shown in Figure 25.

FINAL WORDS

With the increasing pressures of globalization and environmental standards, mining companies must examine alternative strategies to deal with these complexities and remain sustainable. The software tools currently being used within the manufacturing sector have potential to provide solutions in integrating systems across our different departments. Although individual departments may find it difficult to communicate effectively due to political situations or personality clashes, the types of computer systems that use these intelligent architectures and components can pass over such constraints.

The field of AI has evolved from Expert Systems and Fuzzy Logic into hybrid systems that include Genetic Algorithms and Artificial Neural Networks. These tools have become embedded today within an overall distributed, reactive architecture known as Agent-based systems. The applications of the future, particularly those which come from the field of robotics will be built using these methodologies.

These methods can collect and store massive amounts of real-time control data for decision-making at various corporate levels from direct-unit control to supervisory and long-range planning. Corporations will develop simulation models inside of which many different behaviours at many different time scales and spatial horizons will interact. Failure to adopt these approaches will result in companies failing to recognize in a timely fashion the inevitable change in high commodity prices. These innovations will be necessary to sustain an enterprise successfully into the future.

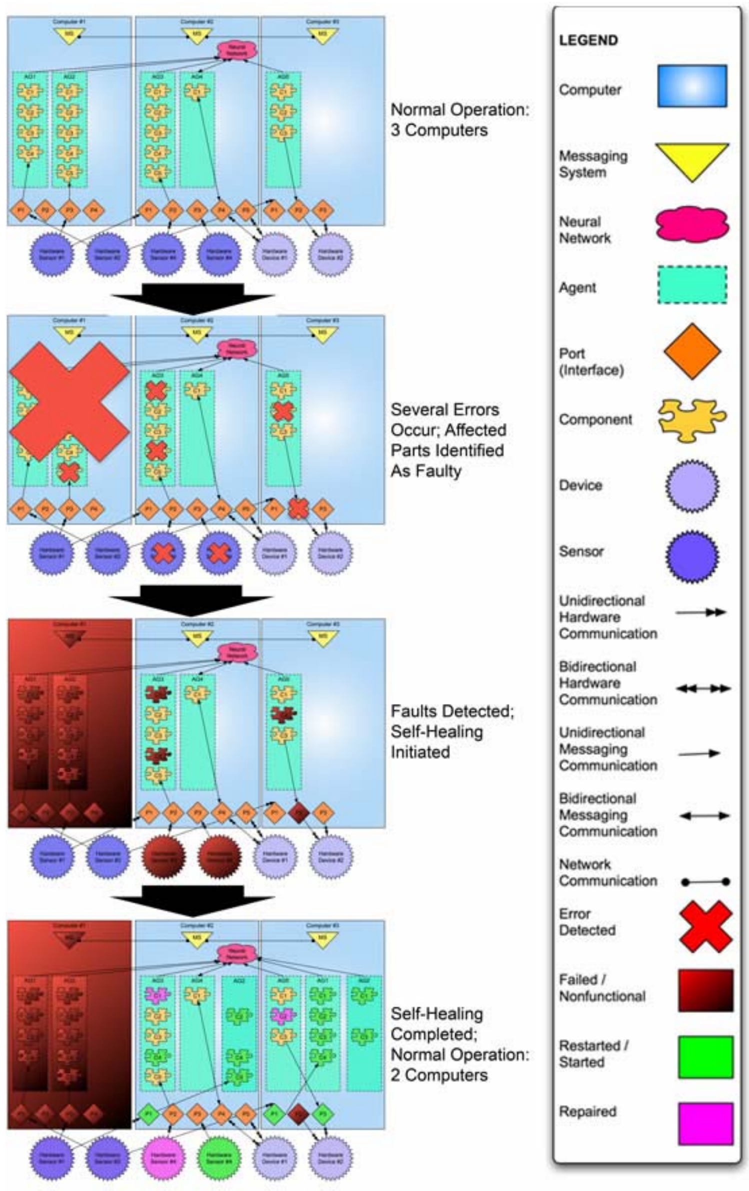


Figure 25 – Example of the Self-Healing Ability of a Mobile Robotic Control System.

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