Proceedings of the IASTED International Conference
Modeling and Simulation (MS '99)
May 5-8, 1999, Philadelphia, Pennsylvania - USA

TUNING A FUZZY EXPERT SYSTEM FOR SIMULATIONS OF POPULATION BEHAVIOR

CAROLYN HEINEKEN
Advancia Corporation
211 SW A Ave
Lawton, OK 73501
heinekenc@advancia.com

THEODORE METZLER
Advancia Corporation
211 SW A Ave
Lawton, OK 73501
metzlert@advancia.com

RAFAEL ORTIZ
Advancia Corporation
211 SW A Ave
Lawton, OK 73501
ortizr@advancia.com

RAY WONSEWITZ
Advancia Corporation
211 SW A Ave
Lawton, OK 73501
wonsewitzr@advancia.com

ABSTRACT

This paper reports our adjustments ("tuning") of a fuzzy expert system to improve its predictions of the behavior of selected "alien" populations attempting to cross U.S. borders illegally. The work modifies a computer-based modelling and simulation tool we developed to assist the U.S. Border Patrol (USBP) with planning for present and future use of its staff and equipment resources. Currently identified as the USBP Resource Effectiveness Model (REM), the tool is comprised of four major functional components, linked to allow users to simulate interaction of U.S. Border Patrol agents and the alien populations who attempt illegal entry at U.S. borders. An important component of the model, called "Alien Behavior," simulates how aliens along the U.S. borders might react to various incentives and deterrents. Ideally suited for fuzzy logic application, the Alien Behavior component is implemented as a fuzzy expert system. Our testing and tuning of this component has improved its performance, expanded our experience with fuzzy logic methods and prepared the REM for future enhancements.

KEYWORDS

Fuzzy Systems, Expert Systems, Knowledge Systems, Artificial Intelligence

INTRODUCTION

The U.S. Border Patrol (USBP) periodically must estimate future resources of staff and equipment it will need to achieve target levels of effectiveness in its operations. Accounts of the computer-based modelling and simulation tool we developed to assist the USBP with such planning have previously been published [1], [2]. In this paper we report more recent experimental work directed at improving the fuzzy expert system incorporated in this tool.

Currently identified as the USBP Resource Effectiveness Model (REM), the tool is comprised of four major functional components: Graphical User Interface (GUI), Staff Operations, Effectiveness and Alien Behavior. Figure 1 illustrates the components of the USBP REM.

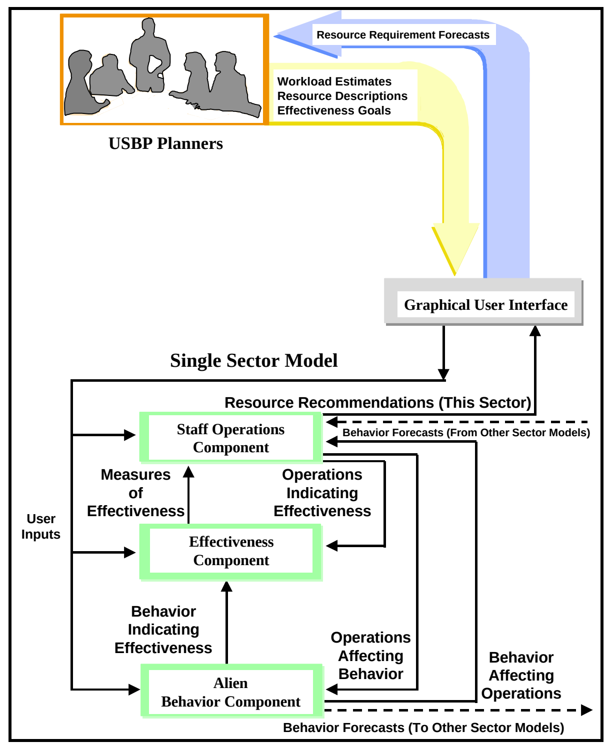

FIGURE 1. MODEL OVERVIEW

The GUI component allows users to enter required start-up data, select operational parameters for each simulation, execute the simulations and obtain displays and reports of the results. The Staff Operations component furnishes a task-based stochastic discrete event simulation of daily operations in multiple USBP stations. It simulates major tasks USBP agents usually perform, such as apprehending illegal border crossers and transporting them to processing sites. The Effectiveness component compares illegal activity (predicted by the

Alien Behavior component) with apprehensions and other factors describing USBP station conditions, yielding daily measures of border control and effectiveness for each station. The Staff Operations component uses these measures in one of the operational modes the user may select, pursuing target effectiveness by adjusting staffing and equipment allocations dynamically. The GUI, Staff Operations and Effectiveness components of our planning tool would not be sufficient for conducting adequate simulations of U.S. Border Patrol activity without the addition of an Alien Behavior component.

The critical function this fourth component supplies is simulation of the ways in which populations of so-called "aliens" along U.S. borders are likely to respond to certain incentives and deterrents. Along our Southwest border, for example, incentives such as Peso devaluation and Mexican/U.S. wage differences can encourage illegal border crossing. On the other hand, deterrents to such behavior presented by the U.S. Border Patrol (nighttime lighting, fences, visibility of Border Patrol Agents, etc.) can lead even those who are strongly motivated to select new locations for illegal border crossing (or to forgo the behavior altogether).

Modelling tradeoffs of this kind, for alien populations, can proceed very naturally in terms of typical fuzzy logic inference rules. For example, one might expect "If nighttime lighting is strong and visibility of Border Patrol Agents is high, then the USBP station deterrent is high." Moreover, we have found that experienced USBP personnel can comfortably estimate the strengths of such graded factors on a numerical scale of zero through ten. Taking into consideration, also, the user requirement for a simulation tool that can explain reasons for its predictions, we have elected to accomplish much of our "alien behavior" modelling with the resources of fuzzy logic.

An immediate technical problem with this approach was the prospect of encountering unacceptably large rule sets as a result of numerous input factors in our application. Modular decomposition, however, is a commonly recognized architectural option [3], [4], [5], [6] we were able to use successfully. By cascading fuzzy logic inference systems (FISs), each constrained to relatively modest size (eighty-one rules, at most), we avoided the problem of rule explosion while accomplishing adequate modelling.

Nonetheless, our testing and "tuning" of the resulting modular network of FISs revealed some qualitative features that called for improvement. For example, one technical penalty with the modular architecture was the tendency of the defuzzified outputs of the FISs to cluster progressively toward mid-range values. We also discovered some FISs in which monotonic increasing of input values did not always produce the monotonic rise in output values we expected. From experiments involving re-scaling of defuzzified outputs and empirical readjustment of membership functions and rules, we were led to methods successfully correcting the undesirable operational features. In the process, we also learned useful information about quantitative properties of interactions between fuzzy logic rules and membership functions.

DISCUSSION

Our first effort at improving the fuzzy expert system consisted of conducting a more detailed analysis of the FISs, as we originally modelled them. An illustration of how we constructed and cascaded our FISs can be seen in Figure 2. Sets of three membership functions were generally defined for each of the fuzzy variables (such as "Artificial Barriers" and "Cameras") shown in Figure 2. Most of our FISs contain, at most, three input variables. Outputs of some FISs (such as "Physical Deterrent") become inputs to subsequent FISs in the modular architecture.

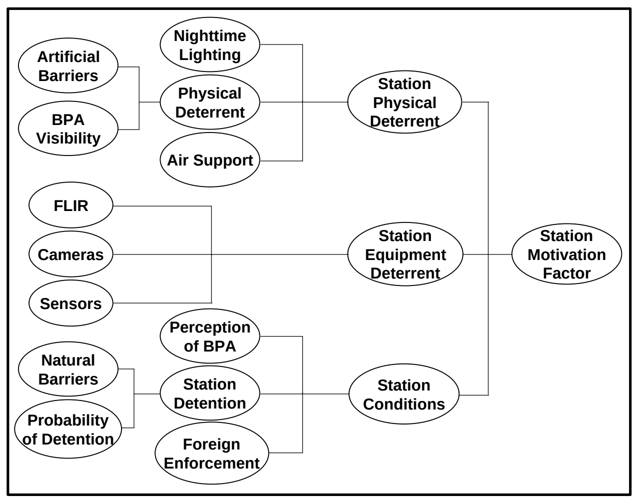

FIGURE 2. MODULAR FIS ARCHITECTURE

Using MATLAB and its associated Fuzzy Logic Toolbox[1], we inspected the "surface view" graphic of each FIS to see how output values varied with monotonic changes to the input variables. A surface view graphic (illustrated in Figures 3, 4 and 5) displays a profile of the FIS output as it varies with changes in the values of the input variables. Where three inputs are involved, all possible values of two input variables are shown on the graphic at a time, while the value of the third variable is held constant.

Our visual inspection of these surface views showed the rule sets tended to produce more mid-range output

[1] MATLAB is a registered trademark of The MathWorks, Inc.

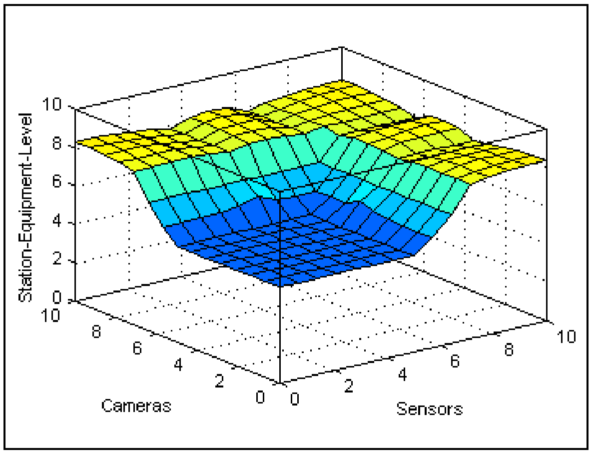

FIGURE 3. SURFACE VIEW - BEFORE IMPROVEMENT

values than expected. Additionally, we observed a far greater likelihood of mid-range output values when there were FISs directing their outputs to other FISs. We also observed areas in the surface view indicating unexpected decreases in the output values accompanying monotonic increases in the input values. These areas of "non-monotonic behavior" were more likely to occur at the lower and higher extremes of the input values. The surface view shown in Figure 3 illustrates this observation, using three input variables (Cameras, Sensors, FLIR) and one output variable (representing the collective "deterrent" impact of the input factors on illegal alien behavior). In this illustration, the value of one of the inputs (FLIR) was fixed at a value of nine while the values of the other inputs (Cameras, Sensors) were varied from zero to ten. The dips in the graphic indicate where the "non-monotonic" behavior is occurring in the FIS. Considering that the output of this particular FIS represents a combined deterrent effect (on illegal border crossers) from elements of the Border Patrol's enforcement equipment (specifically, cameras, sensors and FLIR), the dips we observe are surprising and not consistent with experienced USBP judgment.

As an attempt to correct the observed tendencies toward mid-range output values, we re-scaled the FIS outputs that were used as inputs into other FISs. We did this by computing the possible outputs for each rule set and mapping the range of outputs to a scale of zero through ten. These re-scaled output values were then used as inputs to other FISs. Unfortunately, this method did not significantly reduce the tendency for FISs to produce mostly mid-range output values. Additionally, the method did not provide any improvement to the "non-monotonic behavior" problem. Even after these adjustments, we continued to observe instances of unexpected decreases in output values associated with monotonically increasing input values.

Our next experiment to correct these anomalies involved adjusting the membership functions and rule sets in the FISs. We experimentally adjusted the overlapping areas of the membership functions, expecting to alter the number of rules firing. These adjustments consisted of increasing and decreasing the overlapping areas of the membership functions in each FIS. This method worked reasonably well for FISs with just two input variables. By increasing the amount of overlap among the membership functions of two-variable rule sets, we were able to cause more rules to fire and create a slightly more complex output area. However, this method did not work as well for the rule sets having three input variables. Increasing the overlap in the membership functions of three-variable rule sets produced a smoother output but decreased the range of output values more significantly than with the two-variable rule sets. In the three-variable rule sets, adjustments to the inferences made by each rule tended to have the effect of locking out the impact of one of the input variables. As can be seen in Figure 4, changes to the value of the input variable "Sensors" has very little, if any, impact on the value of the output variable "Station-Equipment-Level."

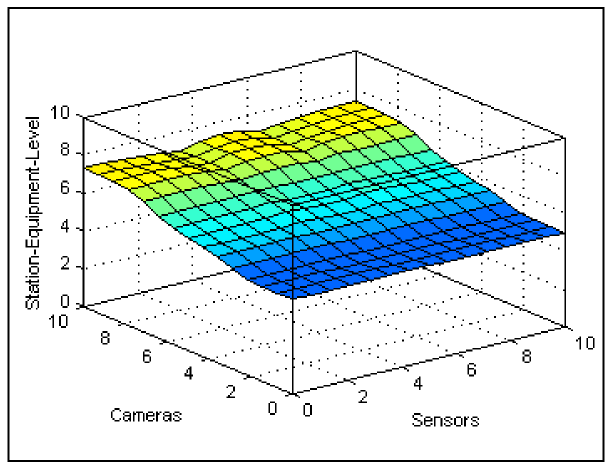

FIGURE 4. SURFACE VIEW - AFTER EMPIRICAL ADJUSTMENTS ADJUSTINGMEMBERSFUNCTIONS AND RULES

Generally, the foregoing methods for correcting the unexpected behaviors of our fuzzy expert system produced unsatisfactory results. Although we realized some improvements in the behavior of two-rule sets in the FISs, the improvements were not significant. For the three-rule set FISs, the results were even less impressive. Additionally, the process of empirically adjusting the membership functions and rules was found to be very tedious and time-consuming with little payoff in results. This led us to another technical approach that produced more satisfactory results.

Our final approach to improving the fuzzy expert system consisted of using the adaptive neuro-fuzzy inference system (ANFIS) in MATLAB to generate the membership functions for the FISs. ANFIS is a toolbox function that constructs a fuzzy inference system based on applying neuro-adaptive learning techniques to a user-provided input/output data set. The concept of the neuro-adaptive learning technique is to "learn" about the data set and compute the membership function parameters that best allow the associated FISs to track the given input/output data set. ANFIS tunes the membership function parameters using a backpropagation algorithm alone, or in combination with a least squares method.

Before deciding to use ANFIS, which requires use of Sugeno-type inferencing, we had to consider whether or not our fuzzy expert system was suited to be a Sugeno-type inference system. We initially developed the system using Mamdani-type inferencing because it is a commonly used fuzzy methodology that allows the judgments of domain experts to be expressed in intuitively "natural" membership functions and rules. However, there are at least two reasons why we believe Sugeno inferencing will also be well suited for our fuzzy expert system. First, the Sugeno inferencing methodology is more computationally efficient--an important advantage with the large number of input variables we are using. A second important advantage of this methodology is the fact that it lends itself to adaptive techniques much more easily than other methods. We are still in the process of learning many of the "real world" relationships between the numerous input variables of our REM simulation tool. As more quantitative information is gathered from the field about these relationships, we will want to incorporate it in the model. By using the Sugeno inferencing methodology, we will be able to incorporate such data and retune the model in a more efficient manner.

To apply ANFIS, we developed a data set representing plausible input values and associated output values for each combination of inputs. We produced this representative input/output data set based on judgments obtained from interviews of experienced USBP personnel. For increasing values of input variables, the data set generally prescribes corresponding increases in the values of output variables. When more precise information describing the relationships between the input and output variables becomes available, we will incorporate it in the model as we did with the representative data set.

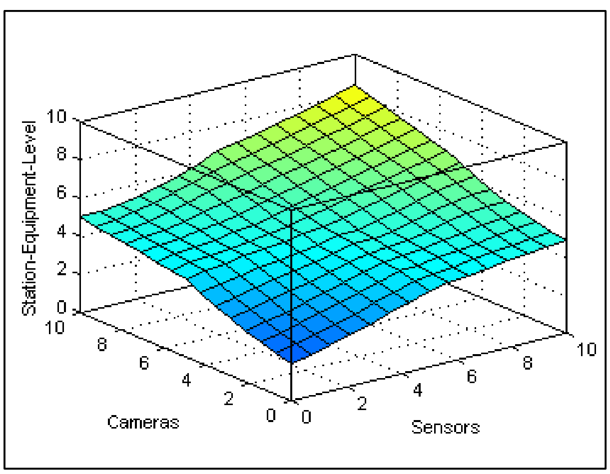

FIGURE 5. SURFACE VIEW - AFTER NEURO-FUZZY LEARNING

The results from using ANFIS were very impressive, as illustrated in the surface view graphic in Figure 5. The surface view exhibits a much smoother curve, with increasing values of output corresponding to monotonic increases among the input variables as expected.

CONCLUSION

Conducting a more detailed analysis of our fuzzy expert system proved to be a valuable experience for us. We acquired a better understanding of how membership functions and rule sets interact. We learned that the process of empirically adjusting membership function parameters can be a very tedious and time-consuming task. We also learned the value of using a tool like ANFIS to produce a fuzzy inference system quickly, based on "learning" a data set representing the relationships between the input and output variables of the model.

We also became more familiar with the Sugeno inferencing system and learned about advantages and disadvantages associated with using this type of inferencing.

One limitation of ANFIS is that it can only be used with Sugeno-type systems that produce a single output and use linear or constant output membership functions. Additionally, there are limits on how much customization one can do to the system, and the user must accept the membership and defuzzification functions provided by ANFIS. In our case, these limitations were not overly restrictive for our fuzzy expert system.

We plan to continue using neuro-fuzzy learning as we proceed with further development of our modelling and simulation tool for the USBP. We anticipate obtaining more precise data describing the interaction of the input and output variables of the model, allowing us to use this technique in developing a genuinely *adaptive* planning tool.

REFERENCES

[1] T. Metzler and R. Ortiz, Modeling Population Behavior with Fuzzy Logic Agents, *Smart Engineering Systems: Neural Networks, Fuzzy Logic, Data Mining, and Evolutionary Programming,* Volume 7, 1997, 273-278.

[2] R. Ortiz and T. Metzler, Planning U.S. Border Patrol Staffing with a Modelling and Simulation Tool, *Modelling and Simulation: Proceedings of the IASTED International Conference on Modelling and Simulation,* 1998, 312-316.

[3] F. Azam and H.F. VanLandingham, An Efficient Dynamic System Identification Technique Using Modular Networks, *Smart Engineering Systems: Neural Networks, Fuzzy Logic, Data Mining, and Evolutionary Programming*, Volume 7, 1997, 225-230.

[4] R. Gore and T. Metzler, Classifying Infrared Spectra of Compounds with Modular Neural Networks, *AI Technologies for Environmental Applications: Workshop Notes, 1994 National Conference on Artificial Intelligence*, 1994, 145-152.

[5] J. Kim and S. Chakrabarti, A Robust Speech Recognition System Using Modular Fuzzy Neural Network, *Smart Engineering Systems: Neural Networks, Fuzzy Logic, Data Mining, and Evolutionary Programming*, Volume 7, 1997, 817-822.

[6] T. Metzler and R. Gore, Application of Hybrid AI to Identification of Chemical Compounds, *TECOM Artificial Intelligence Technology Symposium Proceedings*, 1994, 415-428.