다중 에이전트 기반의 고대 국가 형성 시뮬레이션

김순원* · A. 라자** · R. G. 레이놀즈***

The Multi-Agent Simulation of Archaic State Formation

S. Kim · A. Lazar · R. G. Reynolds

Abstract

In this paper we investigate the role that warfare played in the formation of the network of alliances between sites that are associated with the formation of the state in the Valley of Oaxaca, Mexico. A model of state formation proposed by Marcus and Flannery (1996)is used as the basis for an agent-based simulation model. Agents reside in sites and their actions are constrained by knowledge extracted from the Oaxaca Surface Archaeological Survey (Kowalewski 1989). The simulation is run with two different sets of constraint rules for the agents. The first set is based upon the raw data collected in the surface survey. This represents a total of 79 sites and constitutes a minimal level of warfare (raiding) in the Valley. The other site represents the generalization of these constraints to sites with similar locational characteristics. This set corresponds to 987 sites and represents a much more active role for warfare in the Valley. The rules were produced by a data mining technique, Decision Trees, guided by Genetic Algorithms. Simulations were run using the two different rule sets and compared with each other and the archaeological data for the Valley. The results strongly suggest that warfare was a necessary process in the aggregations of resources needed to support the emergence of the state in the Valley.

Key Words: Agent, Data Mining, Decision Tree, Genetic Algorithm

1. Introduction

In this paper we are interested in simulating the emergence of the archaic statein the Valley of Oaxaca, Mexico. A state is among the most sophisticated and powerful structures that has emerged from the social evolution process. In the modern world these are termed "nation states" with a government composed of a hierarchical decision-making structure where the decision-makers are either elected or appointed. States are supported by various economies and are able to interact with each other via warfare, trade, etc. Most states in the ancient world-often called archaic states were ruled by hereditary royal families. These archaic states exhibited much internal diversity with populations numbering from tens of thousands to millions. They had a bureaucracy, organized religion, a military presence, large urban centers, public buildings,

* Solution R&D Center, POSDATA
** Dept. of Computer Science, Youngstown State University, USA
*** Dept. of Computer Science, Wayne State University, USA

public works, and services provided by various professional specialists. The state itself could enter into warfare and trade-based relationships with other states and less complex neighbors.

First, a particular theory of the state formation was selected to be the focus of the implementation. Marcus and Flannery had proposed a process-based model, "Evolution without Stages", of state formation in the Valley based upon the long-term interaction of "actors" (Marcus and Flannery 1996). The goal of the model was to focus on how the interactions of the various actors shaped the emergent social structures over time in a manner that was independent of the archaeological phases in the Valley. The prehistory of the Valley is commonly broken up into phases based upon the characteristics of the pottery produced in each phase. Table 1 gives the basic phases of social evolution in the valley.

Table 1. The Basic Occupational Phases of the Valley

Period	Approximate Date
Tierras Largas	1400 - 1150 BC
San Jose	1150 - 850 BC
Guadalupe	850 - 700 BC
Rosario	700 - 500 BC
Monte Alban Early I	500 - 300 BC
Monte Alban Late I	300 - 150/100 BC
Monte Alban II	150/100 BC - AD 200
Monte Alban IIIA	AD 200 500
Monte Alban IIIB	AD 500 - 700/750
Monte Alban IV	AD 700/750
Monte Alban V	AD 1000 1521

Table 1 gives all of the relevant periods of social evolution in the valley. Tierras Largas marks the beginning of early village settlement there. The state emerged at Monte Alban in period Monte Alban Early I. The valley came under control of the state by Monte Alban II, and Monte Alban IIIAsignaled the decline of the state and itssuccession by a collection of city-states localized in different parts of the valley. The phases as described there represent uneven slices through time. Traditional models of state formation in the Valley have focussed on modeling the changes that are exhibited from one occupational stage to the other. Each occupational stage represents a stable phase of occupation in a given site.

However, each stage may have been formed over a different length of time and reflects the accumulated result of an underlying continuous process. The model developed here views these periods as temporal snapshots that frame an underlying continuous process. Marcus and Flannery characterize this underlying process "in terms of the changing relations between the actors and the environment. In such an analysis it is the social and political institutions, not the stages, that provide the milestones along the way. Transitional periods-those brief phases of rapid evolution during which the system changed, or the actors deliberately changed it-become more crucial to our analysis than the long stable periods which gave rise to the typology of stages" (Marcus and Flannery 1996, p: 236).

The state formation process expressed above in terms of actors and their interactions lends itself readily to agent-based simulation of social evolutionary processes using Cultural Algorithms. The key is that the pressures toward increased aggregation resulted in a sequence of "changes in the meaning of social relations" among the agents or actors. Each change in relations allowed for opportunities to aggregate. The basic processes involved in the model were agricultural production and exchange; craft production; trade; and warfare. In this implementation only agricultural productivity and warfare as used explicitly in the model. Alliances are generated as a result of warfare only. Excess productivity can be exchanged between agents if there is an alliance or relationship between them.

Here, we use rules to constrain how agents interact based upon their environmental location. One rule set only allows those sites for which evidence for raiding exists directly on the surface. We call this the minimal raiding hypothesis. The other 2 sets of rules represent generalizations of the site location characteristics to other sites that have similar situations. This results in a much larger set of sites that can engage in raiding and warfare. The main question of concern here, is the role that warfare and raiding played in the formation of the complex social networks required to sustain a state. If warfare is at a minimal level, does the network of alliances that is formed and the corresponding distribution of sites have the complexity needed to support state formation? If it does not, what complexities are added to the association network with warfare and when do these additional complexities emerge? The results for each approach will be assessed in terms of the archaeological information for the region. The results strongly suggest the presence of warfare as an important process in the production of alliance networks needed to support the emergence of the state in the Valley.

2. Extracting Agent Knowledge from the Oaxaca Database Using Data Maining.

The goal of this project is to produce a large-scale knowledge-based computational model of the origins of the Zapotec State, centered at Monte Alban, in the Valley of Oaxaca, Mexico. State formation took place between 1400 B.C. and 300 B.C.While archaic states have emerged in various parts of the world, the relative isolation of the valley allowed the processes of social evolution to be more visible there. Extensive surveys of the valley were undertaken by the Oaxaca Settlement Pattern Project in the 1970's and 1980's. The location and features of nearly 3,000 sites dating from the archaic period (8000 B.C.) to Late Monte Alban V (just prior to the arrival of the Spaniards) were documented (Kowalewski et. al, 1989). Several hundred variables were recorded for each site. These data are the basis for generating the knowledge used in the model.

The knowledge used to constrain the behavior of agents in the model corresponds to their abilities to conduct warfare, establish trade relations, and support specialized craft production. The presence of each of these factors was supported by the presence at a site of one or more diagnostics variables for the factor. In this section, the general approach will be illustrated using the warfare factor. The diagnostic variables for determining whether a site is a target for raiding and warfare are the presence of defensive walls, the presence of burned daub, and other evidences for burning. Sites that have one or more of those variables resent in a givenperiod were said to be positive examples for the factor. In the case of warfare only 79 sites out of over 3000 sites exhibited these variables on the surface. However, these are just the sites that exhibit this evidence on the surface. We take that as the minimum number of sites that are targets for raiding in the Valley. This is equivalent to assuming a minimal amount of raiding in the Valley.

On the other hand, it is reasonable to assume that if excavation was done at a site, much more information wouldbe available concerning it cultural relations than is still present on the surface. So, we decided to use incremental and non-incremental inductive learning techniques to generalize on properties of positive sites. In other words, the goal is to produce generalized rule sets that would classify all sites associated with one or more of these rules as positive examples of the concept. For warfare, this would reflect a more active pattern of raiding between sites. The approach described here is Decision Tree induction.

Decision tree induction is a very good method for high-dimensional applications. It is a fast non-linear prediction method and employs dynamic feature selection. The solution complexity is expressed in terms of the number of terminal nodes. The most complex tree covers all cases in the training data. Pruning the tree and measuring the errors in progressively smaller trees find less complex solutions. Any decision tree can be rewritten in a form of decision rule set. An implied decision rule in atree is a complete path to a terminal node. Because these rules are not mutually exclusive, the size of the decision rule set can be much larger then the logic needed for overlapping rules. The decision tree attempts to classify all of the training examples using potentially all of the variables. Genetic Algorithms (Holland 1975)and Cultural Algorithms (CA) (Reynolds 1998) were used to guide the Incremental Decision Tree Induction process performed by Utgoff's ITI system. For Non-incremental Decision Tree Indcuction C4.5 is used. Here the decision tree approaches generalized the collection of sites that can actively initiate raiding activities to 987 and 1382 sites respectively for ITI and C4.5.

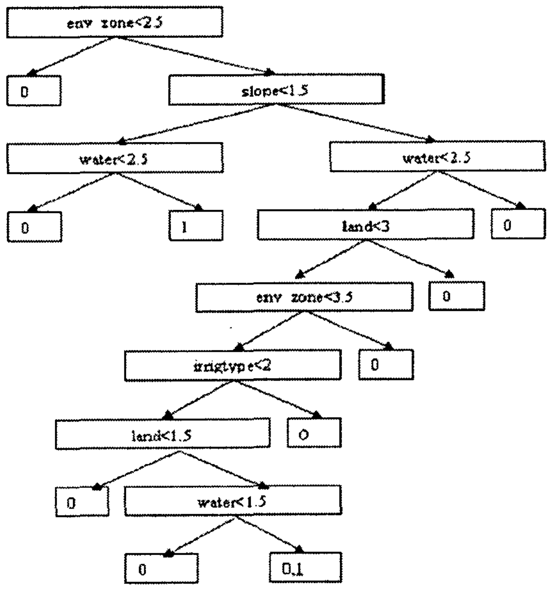

Figure 1. The ITI Decision Tree for the Locations of Sites with Evidence of Raiding

Figure 1 gives an example of a ITI decision tree for warfare in the Etla region for sites dated to the Rosario phase. Each path in the treecan be viewed as a rule whose conclusion is the category that labels its leaf node. If the category is labeled as a "1" then it is a target for raiding, if "0"it is not based upon the archaeological evidence. These are both called homogeneous or pure decisions. Also, there are leaf nodes labeled by both a 1 and 0. This represents the fact that no further distinction can be made between them based upon the available data.

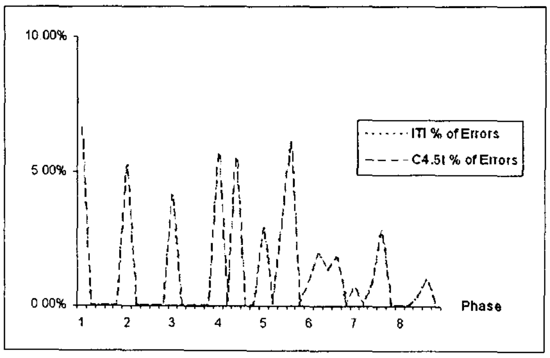

Figure 2. Accuracy of Warfare and Raiding Predictions for Each Phase and Region

Thus, there were two different measures of raiding activity in terms of predicting sites involved with raiding. A minimal degree of raiding was represented by the surface collection with 75 sites. The rules produced by the ITI Decision Tree approach generalized the number of sites that are targets for raiding to 987 based upon similarity in environmental location. The rules produced by the C4.5 generalized more sites than those of ITI. The extent to which the rules based upon the environmental variables predicted original set of examples is given in Figure 2. In Figure 2, the rule prediction accuracy for sites in the training set is given. The x-axis represents a particular phase, and associated region in the valley. It is clear that the generated rules are good predictors of warfare and raiding as measured in terms of the diagnostic variables used here.

In the next section, the simulation model is run using the three different knowledge sources. The one effectively represents *minimal raiding* and the other two represent raiding as a much larger component. The question of interest here is the extent to which the degree of warfare impacts the complexity of the network of sites formed in each simulation? If there is a difference, in which phases do the differences emerge and what different properties do they have? And finally, which of the network structures that is produced by the model exhibits the best fit with the archaeological data here?

3. Results

In this section the simulation is run using the warfare knowledge only. The warfare knowledge is used to determine what sites can build up alliances with other sites with agents residing in sites. At this level of granularity a site is modeled as an agent here. If a site is a target for warfare or raiding it is assumed that agents at that site can participate in alliance formation. Each of the three different rulesets used represents a different degree of raiding activity. In those cases each site will have the same productivity potential. However, it is hypothesized that differences in agricultural productivity throughout the Valley provides the potential for the aggregation of population and resources at certain sites. The presence of warfare may allow agents to exploit that potential via the formation of alliance networks. While the actual networks are no longer visible, the simulation will show us how the archaeological distribution of sites, their sizes and locations, reflect the underlying networks that produced them.

The model was implemented in Java and run in the Swarm simulation environment. The details of the model and its Swarm implementation can be found elsewhere (Reynolds and Lazar 2002). In the experiments described here, runs were made using each of the three sets of warfare constraints for agents, the one derived directly from the surface survey and the others inferred using Decision Tree Inductions, ITI and C4.5. The model was run starting from the earliest phase, Tierras Largas for a period of years that lasted until phase 8. At points in time that corresponded to the projected middle of each archaeological phase, data was extracted. The first three phases of the Valley exhibited a similar low level of warfare in each of the two models. So we pick up the simulations in the Rosario phase here. The Rosario phase immediately preceded the emergence of Monte Alban, a site located on a hilltop in a "no man's land" between the Etla arm in the northern part of the Valley and the Valle Grande to its south. The state that was to form was located at the site of Monte Alban.

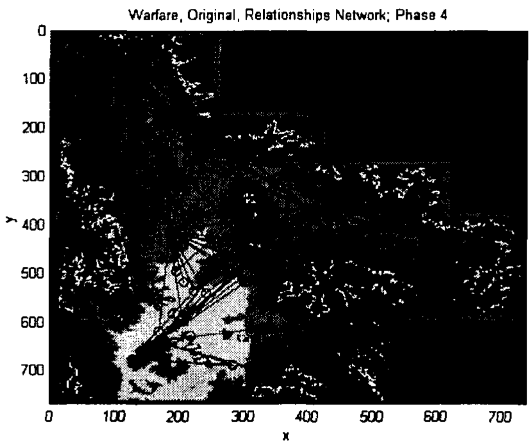

Figure 3. Alliance Network, Rosario (Phase4), Original Warfare

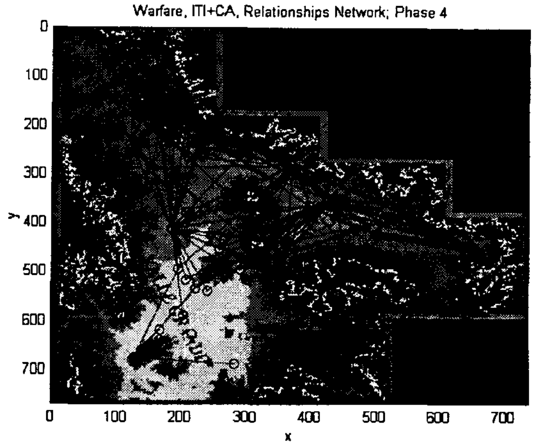

Figure 4. Alliance Network, Rosario (Phase4), ITI+CA Warfare

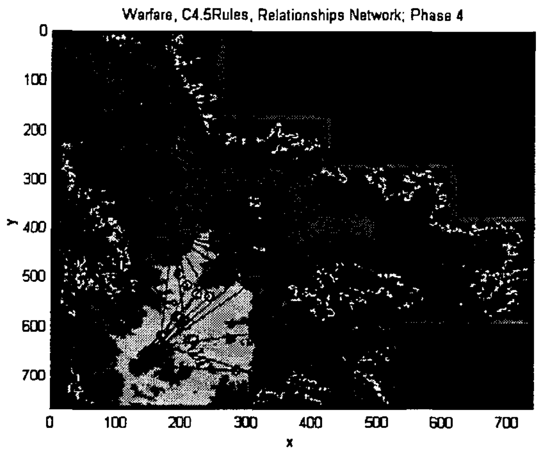

Figure 5. Alliance Network, Rosario (Phase4), C4.5rules Warfare

The Rosario phase was characterized by an increase in raiding activity in all the three data sets. Figures 3, 4 and 5 give the generated network of alliances produced with the original survey data and the two decision tree inferred sets in the Valley. There are several differences to note. In the minimal warfare case there are several centers in the network that exhibit a relatively high in degree in terms of the number of alliances that they participate in. While the Etla arm in the upper left part of the figure exhibits slightly more complexity than the rest they are generally similar in complexity. In figure 4 and 5, there is a marked increase in the complexity of the alliances produced within the Etla arm relative to the rest of valley. The Etla arm is able to acquire a substantially larger population and resources aggregate with the presence of warfare. This is significant since it is hypothesized that the site of Monte Alban was colonized primarily from the Etla arm and represents an extension of this areas network.

In the simulations, the future site of the archaic state, Monte Alban, emerged. It was unoccupied in the previous time step in each. Figure 6, 7 and 8 give the alliances associated with Monte Alban in the three scenarios respectively. What is interesting is that in the minimal warfare model, figure 6, Monte Alban has connections in all directions up to a certain distance away. The distance may reflect limits on the ability to sustain alliances beyond that point. In the other cases, it is interesting to note that few connections are made to the Valle Grande region which lies to its south. This is consistent with archaeological thought that Monte Alban was previously in a no mans land beyond the two regions of relatively high productivity. Thus, in the presence of warfare the two regions do not exhibit the interactions exhibited in the non-warfare case. This tends to confirm the archaeological hypothesis that there was intense friction between the regions.

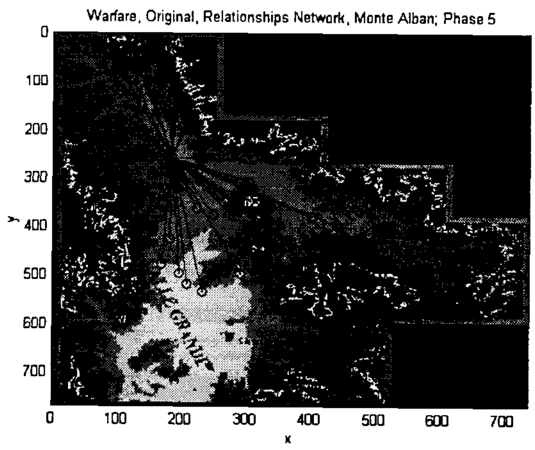

Figure 6. Alliance Network, Monte Alban Early I (Phase5), Original Warfare

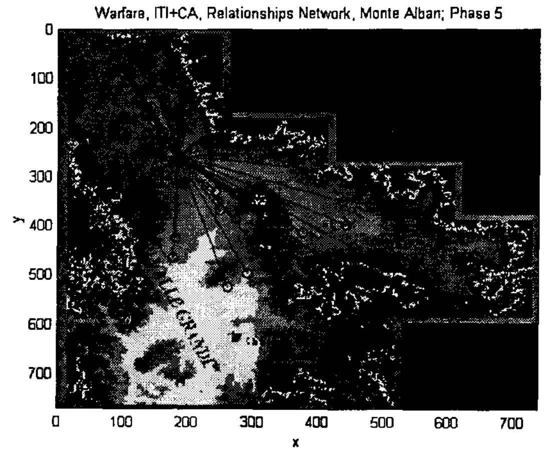

Figure 7. Alliance Network, Monte Alban Early I (Phase5), ITI+CA

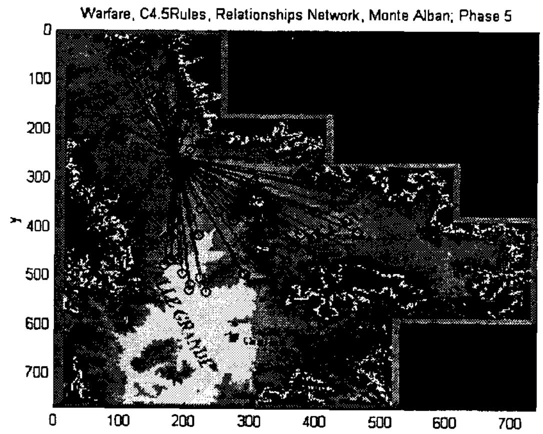

Figure 8. Alliance Network, Monte Alban Early I (Phase5), C4.5rules

What is interesting when comparing Monte Albans' associations in Monte Alban Late I and

Monte Alban II, that there are no real differences in alliances between the three although the entire Valley should come under control of the state by then. What this suggests is that differential productivity and warfare while important in explaining the properties of state emergence in the Valley they are not the only factors involved. In other words, other factors such as craft production and trade may have played a role in providing the additional resources needed by the state to secure these peripheral regions. In fact, it is clear that one of the practices used by the state was to place an embargo on trade with those who were in conflict with it. Monte Alban as a state became a center of craft production and was able to attract additional resources and population through this mechanism. Likewise external trade of its produce and craft would also provide additional resources to aid in its securing of the Valley. In addition, peripheral sites would be more apt to be influenced by issues of trade with those outside of the Valley as well. In future simulation, we will need to add additional constraints on our agents that relate to craft production and trade at each site.

4. Conclusions

In the experiments described here we have attempted to assess the impact of warfare on the process of state formation by looking at impact on the generation of alliance networks that work as conduits for the aggregation of resources to be used in the formation of the states complex social structures. The results of our experiments suggest several things:

1. The model is able to recapitulate many of the patterns associated with the emergent social complexity in the Valley based upon agricultural productivity and warfare concerns alone. Removing or reducing the influence of warfare significantly reduces the rate at which hierarchical structures emerge in the Valley and the influence that Monte Alban has on the Valley.

2. The results of the simulation allow one to monitor the extent of control that Monte Alban can exert over the Valley in terms of the model. The results fit well with the archaeological data. However, there are some areas that do not come under the influence of Monte Alban in the model yet. These areas are often on the periphery of the Valley. We are presently adding in rules for craft production and exchange, as well as external trade for agents. The fit of the model with these components added in will then be assessed.

3. Also, the simulation has suggested the presence of competing networks in the Valley. Thus, the collapse of the state at Monte Alban in Monte III might be profitably examined relative to weaknesses in its network structure that were exploited by its competitors. In other words, Monte Alban was envisioned to be succeeded by a number of smaller city states. The alliance networks generated here might be useful in suggesting the location and relationship between these emergent city states. In addition, it might be able to identify the reasons and regions the larger network collapsed.

In summary, it is clear that warfare has an important role to play in the emergent of social complexity in the Valley of Oaxaca. Without its presence, there is less opportunity for agents to aggregate resources and population in a manner consistent the needs of a complex social system such as the state. Future work will investigate the impact of other factors such as trade and craft specialization.

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