Using Cultural Algorithms to Learn the Impact of Climate on Local Fishing Behavior in Cerro Azul, Peru

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***Abstract*- *Recently it has been found that the earth's oceans are warming at a pace that is 40% faster than predicted by a United Nations panel a few years ago. As a result, 2018 has become the warmest year on record for the earth's oceans. That is because the oceans have acted as a buffer by absorbing 93% of the heat produced by the greenhouse gases* [1]. *The impact of the oceanic warming has already been felt in terms of the periodic warming of the Pacific Ocean as an effect of the ENSO process. The ENSO process is a cycle of warming and subsequent cooling of the Pacific Ocean that can last over a period of years. This cycle was first documented by Peruvian fishermen in the early 1600's. So it has been part of the environmental challenges that have been presented to economic agents throughout the world since then. It has even been suggested that the cycle has increased in frequency over the years, perhaps in response to the overall issues related to global warming.* [2] [3]**

In this paper Cultural Algorithms are used to develop a multi-objective agent-based model of artisanal (traditional offshore) fishing behavior in coastal Peru, Cerro Azul. The data used to produce this model comes from the observation of fishing behavior over a four year period, 1982-1986. During this period over 6000 individual fishing trips were documented. This observation period overlapped with one of the largest ENSO activities ever recorded. As a result, it was possible to observe the changes in fishing behavior that were the result of this process. While the data is several decades old, the ENSO process was first observed in Peru in 1502. Thus, this data can be considered to reflect the adaptations that have been made to the process in the ensuing centuries.

The model was used to produce Pareto curves that reflected tradeoffs in terms of fish quality and trip effort during each of three phases on the ENSO process. A version of Cultural Algorithms, CAPSO, was then used to compute whether these curves were significantly different from each other. The results suggested that they each represented a different phased response to the local climate change. During the warming phase fisherman had to exert less effort to secure quality fish than in the subsequent cooling off period. In that period there were more types of catches but they were distributed over a wider area. The final, back to normal phase reflected a compromise between the two, where fewer types of catches of slightly lower quality, but with lesser effort than in the previous phases.

Keywords: Cultural Algorithms, Cultural Engine Model, Multi-objective optimization, Pareto Optimality, Climate Change

I. Introduction

Evolutionary computation is a subfield of Artificial Intelligence which is based on Darwinian principles of evolution. Evolutionary computation is often applied to the solution of complex computational problems especially global optimization problems. Several Evolutionary Computation system have been proposed, one of them is the Cultural Algorithms [4] [5].The Cultural Algorithm (CA) is a class of computational models imitating the cultural evolution process in nature. CA has three major components: a population space, a belief space, and a protocol that describes how knowledge is exchanged between the first two components. The population space can support any population based computational model, such as Genetic Algorithms [6] , Evolutionary Programming, etc. Here, evolutionary computational models are used to document the impact of aspects of Global Warming on traditional offshore fishing behaviors. While the impact of global warming is often viewed on a global scale this research aims to document its impact on a local economy based upon fishing in some detail.

Recently it has been found that the earth's oceans are warming at a pace that is 40% faster than predicted by a United Nations panel a few years ago. As a result, 2018 has become the warmest year on record for the earth's oceans. That is because the oceans have acted as a buffer by absorbing 93% of the heat produced by the greenhouse gases **[1]**. The impact of the oceanic warming has already been felt in terms of the periodic warming of the Pacific Ocean as an effect of the ENSO process. The ENSO process is a cycle of warming and subsequent cooling of the Pacific Ocean that can last over a period of years. This cycle was first documented by Peruvian fishermen in the early 1600's. So it has been part of the environmental challenges that have been presented to economic agents throughout the world since then. It has even been suggested that the cycle has increased in frequency over the years, perhaps in response to the overall issues related to global warming. **[2] [3]**

In this paper Cultural Algorithms are used to develop a multi-objective agent-based model of artisanal (traditional offshore) fishing behavior in coastal Peru, Cerro Azul. The data used to produce this model comes from the observation

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The model will be used to produce Pareto curves that reflect tradeoffs in terms of fish quality and trip effort during each of the three phases on the ENSO process. A version of Cultural Algorithms, CAPSO, was then used to compute whether these curves were significantly different from each other. The results suggested that they each represented a different phased response to the local climate change. During the warming phase fisherman had to exert less effort to secure quality fish than in the subsequent cooling off period. In that period there were more types of catches but they were distributed over a wider area. The final, back to normal phase reflected a compromise between the two, where fewer types of catches of slightly lower quality, but with lesser effort than in the previous phases.

The paper is organized as follows. In section II a basic overview of the Fishing Trip data set is described. Section III briefly describes the contents of the database used to produce the multi-objective model. Section IV provides an overview of Cultural Algorithms and the particular version, CAPSO, used here to assess the resultant Pareto functions produced by the model. The Artisanal fishing model is presented in section V. Section VI provides the resultant Pareto fronts. Next, the CAPSO (**C**ultural **A**lgorithm **P**article **S**warm **O**ptimizer) system is used to learn the statistical differences between the curves for the three phases in Section VII. Section VIII presents the conclusions.

II. An Overview of the Cerro Azul Fishing Data Set

A. Introduction

The data we analyze here is from the 1980s while the historic site is more than 500 years prior. Drs. Joyce Marcus and Maria Rostworowski led a team of archaeologists from the University of Michigan from 1982 through 1986 to excavate five seasons of research at ancient nearby site of Cerro Azul. Due to arid weather, architecture, fishing nets, the fish middens from 1100 to 1470 A.D were all well preserved at the site. Dr. Marcus explored early issues of "community self-sufficiency" and "community specialization" during Incan times with respect to the site. The Kingdom of Huarco contained two localities [7]. The coast proper was ruled by the Kingdom of Huarco, and the piedmont was ruled by Kingdom of Lunahuana. Both sites were later defeated by the Inca's in 1470. As in any society, the diet will typically differ based on a person social status. From bone remains found in different housing compounds, Marcus observed that different fish were eaten by different levels of society, such as the diets of the elites' versus that of the commoners'. While modern fishermen use equipment that allows them to catch a wider variety of species, the catches can be destined for local consumption or exported commercially to larger cities, such as Lima. As a result, the movements of certain catches that are targeted for commercial sale are more likely to be tracked than others, and fishermen may want to take more risks or more effort to find them. These factors will be key to the model developed earlier.

The first documented instance was a in coastal Peru in the early 1500's. Data from the ancient site tells\us that local fishing has been a major part of the economy at least 500 years. Thus, we will consider that the data collected from current artisanal fishermen reflects a long term adaptation to the periodic warming and cooling of local waters in order to continue their reliance on fishing as part of their major local economy. The data subsequently collected by Dr. Marcus was designed to reflect on the issues of economic sustainability in the wake of such changes.

B. An Overview of the Database Content as a Complex System

Later, in the last three years of their project, Dr. Marcus began recording the catch of every boat that returned to the Capitanian del Puerto with the cooperation of the local government. In addition, further data on fishing was collected from Peru's Instituto del Mar, [7] Marcus refers to the fishermen as "Artisanal" Fishermen in the sense that they are small scale and independent entities that can provide for both local consumption and export. The dataset consists of 6013 records. Each record has the following properties:

1. Relates to exactly one fishing trip.
2. Contains fish from only one site location. (main source)
3. Contains fish belonging to only one species (main catch).
4. Fishermen always departed from the home site (Cerro Azul).

The fishing activity around Cerro Azul is a complex system that has many different parts that interact with each other. We can view the different levels as Macro, Meso and Micro in terms of their temporal scale. The three basic phases of ENSO constitute the Macro scale. The Meso scale is represented by the monthly statistics. The micro level corresponds to the days of the week for a given week. These form the basic structure of the Cerro Azul database constructed here.

III. Data Mining at the Macro, Meso, and Micro Levels

A. Cerro Azul can be viewed as a complex system

The fishing activity around Cerro Azul is a complex system that has many different parts that interact with each other. We can view the different levels as Macro, Meso and Micro in terms of their temporal scale. The three basic phases of ENSO constitute the Macro scale. The Meso scale is represented by the monthly statistics. The micro level corresponds to the days of the week for a given week. These form the basic structure of the Cerro Azul database constructed here. The ability to investigate the performance of a complex system as difference scales of granularity or detail has been suggested as an important avenue with which to understand ancient societies as complex systems [8].

B. The Basic Scales Used

In this section the three basic scales at which the data was collected are described.

1. Macro – Provides analytics that summarize behavior over the entire period of observation. We consider the data in all three phases: Residual El Nino, La Nina, and Back to Normal.
2. Meso - corresponds to monthly patterns of behavior. We look for patterns that might represent
3. Micro - scale provides statistics about fishing behavior on a daily basis. We look for patterns that might signify differences based on the day of the week.

These results were then used to constrain the multi-objective model and its behavior. The results reflected the importance of both catch quality (PAYOUT) on the one hand and the investment of resources in terms of number of trips and over all distance travelled on the other (SUSTAINABILITY). One of the key themes identified is the LEARNING CURVE where the CATCH COUNTS can increase over time during the week relative to certain targeted species. There are indications that there is a priority in terms of what catch to pursue first. Another interesting pattern can be seen with fall back catches which mimic trends in targeted catches [9]. As the number of desirable catches starts to dwindle in an area, the deficit can be made up by Fall Back categories of catches. These catches include sharks, chancho marino, among others. The goals of catch quality and trip investment will be key to the multi-objective model that we develop. In order to prepare for the computational demands of a multi-objective approach we will employ an extension of the Cultural Algorithm, CAPSO [10]. That will be described in section that follows.

IV. Cultural Algorithms and Multi-Objective Optimization

A. Introduction

Multi-Objective Cultural Algorithms will be used to validate our agent-based model of artisanal fishing. If the goals in our model are conflicting, then we should expect that an optimal decision represents a tradeoff between them. This will result in a hyperbolic model for a Pareto front. Computation of the hyperbolic curves from a set of examples - is an NP-Hard problem. We will use the Cultural Algorithm to do that for us. This hyperbolic model is then can be compared to a best fit linear model to determine which best describes the simulation results. These results can then be statistically compared between the curves generated at each scale.CAPSO is a Cultural Algorithm Particle Swarm Optimizer. It uses collected domain knowledge to implement a parallel recursive search of the problem space using multiple swarms of agents based upon the Particle Swarm methodology [10].

B. Introduction to the Cultural Algorithm

In the late 1970s, a class of evolution programming models was developed by Dr. Robert Reynolds called Cultural Algorithms. Dr. Reynolds drew an analogy between group learning, the Darwinian natural selection, and the process of group knowledge acquisition in the past to influence current decisions by individuals of group in building cultural algorithms. Cultural Algorithms can provide a flexible framework within which to study the emergence of organizational complexity in a multi-agent system. The Cultural Algorithm is a computational model simulating the cultural evolution process in nature [11] [12].

Cultural Algorithm has three major components: the population space; the belief space; and the communication protocol that define how knowledge is exchanged between the first two components. The population space is defined as a networked set of agents that can provide solutions to an optimization problem. These individuals are connected by a social fabric over which information can be passed. The belief space can be defined as the collection of experiential and domain knowledge, which can be influenced by individuals within the population space according to their varying degrees of success. The belief space also has the ability to influence following generations of individuals within the population space.

The following is a general statement of a generic cultural algorithm:

1. The algorithm begins by initializing the Population and Belief Space.
2. Individuals in the Population Space are first evaluated and ranked through a fitness function.
3. An acceptance function, Accept(), is used to determine which individuals within Population Space will be allowed to update the Belief Space.
4. Experiences of those accepted individuals are then recorded in the Belief Space through the function Update ().
5. The resultant updated knowledge sources then compete and cooperate to produce knowledge driven changes to agent problem solving behavior.
6. Steps 2 through 5 are the evolution loop which repeated until the termination condition is satisfied.

```
Begin
        t = 0
        InitPop(t)      // init population
        InitBelief(t)   // init belief space
        Repeat
            EvaluatePop(t)
            Update(Belief(t), Accept(Pop(t)))
            Generate(Pop(t), Influence(Belief(t)))
            t++
            Select Pop(t) from Pop(t – 1)
        Until (termination condition)
    End
```

Fig. 1: Basic Pseudo-code for Cultural Algorithm [5]

The two feedback paths of information, one through the Accept () and Influence () functions, and the other through individual knowledge and the Evaluate function create a system of dual inheritance of both the population and the belief spaces. The Cultural Algorithm repeats this process for each generation until the pre-specified termination condition is met. In this way, the population component and the Belief Space interact with, and support each other, in a similar mode to the evolution of human culture.

A visualization of this process can be found in the following diagram:

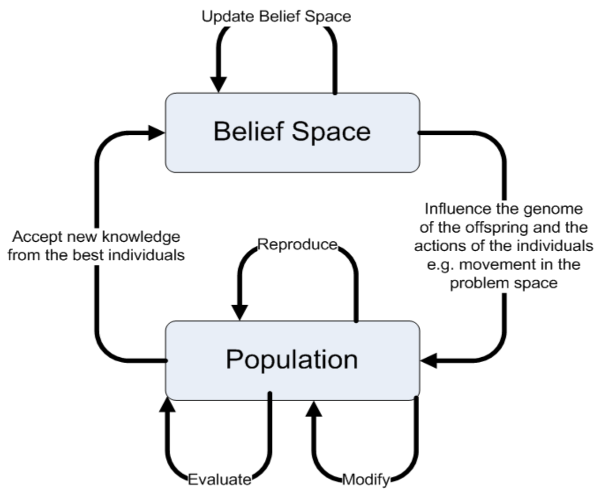

Fig. 2: Schemata of Cultural Algorithms

C. CAPSO, Cultural Algorithm and Particle Swarm Optimizer

The CAPSO system is a hybrid system composed of Particle Swarm and Vector Genetic Algorithm component operating under the control of a Cultural Algorithm framework. The guiding principle in its design is to keep each as vanilla as possible in order to facilitate their interaction and support explicit parallelism in the search process.

The Main function recursively calls SearchInSpace to generate a new swarm thread. A swarm population is associated with that thread via a call to PopSpaceAlg. PopSpaceAlg is in charge of updating the swarm associated with the thread. Each new swarm is given a number of generations to add a new point to the Pareto front, maxGensWoImprov. If it has not by then, it is removed and control is returned to its parent. If it is productive over a maxRepeatsBeforeDivide, it is divided into a number of new subspaces, newSubspace.

In PopSpaceAlg agents are awarded points for the number of agents currently in the Situational Knowledge that it dominates in one or more dimensions. The sum of those points for an agent is its objective function value. The VegaMethod (Vector Genetic Algorithms) is called then called to select the elite points from the swarm.

CASteps is then called and accepts a certain number of points, the elite, into the Belief Space in order to update its content. It then applies the knowledge sources to selectively modify the remaining threads based upon their relative performance as expressed in Relative Roulette Wheel. The process continues recursively until only one thread remains and is unable to generate new points in a certain number of generations. In that case the system can be restarted with a new random swarm but still using the acquired knowledge from the currently completed run that resides in the Belief Space [10].

V. The Artisanal Fishing Model

A. Bi-objective

A traditional single objective problem is the result of a combination of contributing terms. G1 = P1, P2, … PN where N is the number of contributing factors or sub-goals that are correlated with each other. In a multi-objective problem, the goals are conflicting and need to be addressed separately. Neither can be completely achieved without some sacrifice with regards to the other. Based upon the prior statistical analysis two basic goals of the Artisanal fishermen were identified:

Goal #1 reflects the need for profitability with regards to the artisanal fishing activity for a given household. If given the opportunity to choose between a catch that can fetch a higher local market value than another, this goal would be in favor of targeting that catch. To the extent that this can be done over a succession of trips for a family, the presumed social unit here, the fishing agent can even reap a profit over time.

Goal #2 relates broadly to the issue of sustainability. That is, the agent needs to invest sufficient resources into a trip in order to bring back something in order to sustain the family unit and perpetuate the fishing activity. It reflects the general goal of just being able to get out and fish on a given day.

Goal #1: PAYOUT - Maximum Market Value of the catch produced by a trip for a day. For the departing trips on a day, select the one that will yield maximum desirability. HD (High Desirability) [1, 2, or 3]

Goal #2: MAXIMUM REQUIRED EFFORT – the maximum effort needed to produce results for the trips in a day. For the departing trips on a day, select the trip that employs the most resources. MRE (Most Relative Effort) [1, or 3]

The Two Formulas of agent goal achievement:

Payout = Fish Count * Desirability,
where Des. = High Des. = 3, Med. Des = 2, Low Des = 1.

Eq, (1) Payout formula

Effort = ((RTD/MPG) * RE) / Fish-Weight
RTD = Round Trip Distance in KMs from Cerro Azul
MPG = 5 (8 KPG)
Relative Effort = 1 for Cerro Azul and 3 = for North/South
Fish-Weight in Kilograms

Eq (2) Effort Formula

B. The Agent Based Model

This sequence of trips for a given phase will be called a tour. A tour will begin on the first day of the Phase and end on the last day. The parameters used to guide an agent's decision will be:

1. Strategy Goal tuple: The extent to which they wish to follow goal #1 (profitability) vs. goal #2 (sustainability).
2. Phase: (1, 2, 3)
3. The days of the week that they will fish (depart out): (Full Week (FW); No Sundays (NS); MTW; TFRSAT).
4. DT: The downtime between trips. For our experiments here we assume that the agent makes just one trip out a day (does not go out fishing again on the same day they returned).
5. Tour Performance: The sum of the PAYOUT for the trips that it selects through the given phase on the given days, and the corresponding MRE.

C. *The Trip_Graph Model*

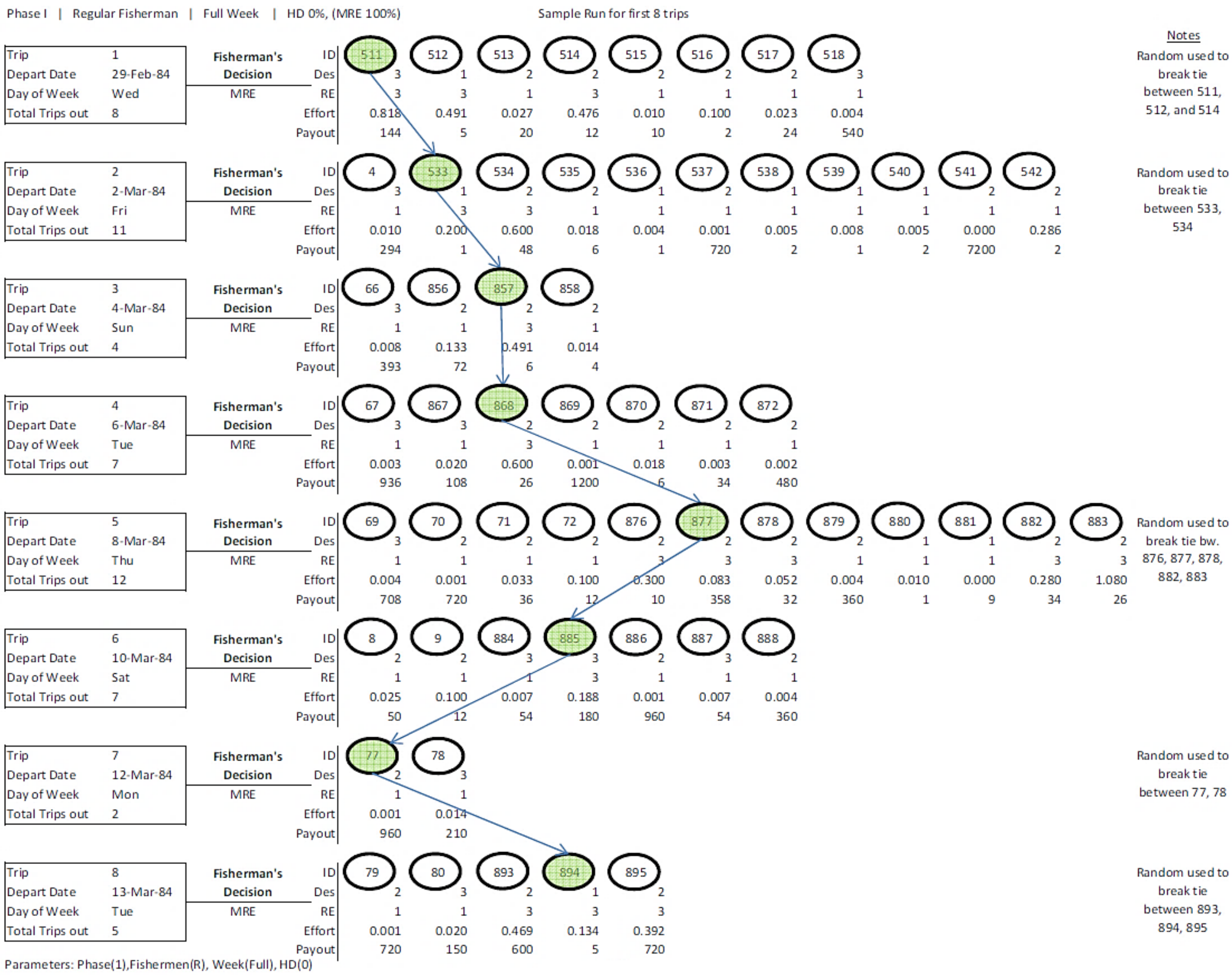

Fig. 3: A Decision Tree of the sample tour for the first 8 days using HD/MRE (0/100)

Trip	Depart Date	Trip Length in Days	Days Skipped so far	Possible Trips so far	Depart Day of Week 1=Mon, 7= Sun	Catch Avail (Branch. Factor)	Fishermen Behavior	HD Percent	Selected Catch ID	Catch	Desir. 3=Highest 2=okay 1=fallback	Catch Count	Payout = Catch Count * Desir.	Site	Round Trip Distance (Kms)	Effort = ((RTD / MPG) * RE) / Catch Weight in KGs
1	29-Feb-84	2	0	1	3	8	MRE	0	**511**	pampano	3	48	144	San Vicente de Canet	18	0.818
2	02-Mar-84	2	1	3	5	11	MRE	0	**533**	chancho marino	1	1	1	Santa Bárbara	10	0.200
3	04-Mar-84	2	2	5	7	4	MRE	0	**857**	tollo	2	3	6	San Vicente de Canet	18	0.491
4	06-Mar-84	2	3	7	2	7	MRE	0	**868**	lenguado	2	13	26	Santa Bárbara	10	0.600
5	08-Mar-84	2	4	9	4	12	MRE	0	**877**	lenguado	2	179	358	San Vicente de Canet	18	0.083
6	10-Mar-84	2	5	11	6	7	MRE	0	**885**	bonito	3	60	180	Los Leones	32	0.188
7	12-Mar-84	1	6	13	1	2	MRE	0	**77**	lorna	2	480	960	Faro	1	0.001
8	13-Mar-84	2	6	14	2	5	MRE	0	**894**	chancho marino	1	5	5	Asia	56	0.134
Performance (Sum of first 8 trips)													1680			2.516

Fig. 4: Details about the Decision Tree of the sample Run.

A tour is a sequence of trips that are produced by the concatenation of individual trips that follow a particular set of goal priorities for an agent.

That is, what would a series of tours look like if individual agents had the same goal priority throughout the phase. The strategy used to generate a path through a Trip_Graph is determined by a tuple, (HD%, MRE%) that represents the likelihood of preferring the one goal or the other.. The likelihood of selecting a trip on a day based upon one or the other goal. Example: (75, 25) means that the likelihood that a profit maximizing trip is selected is 75/100. If there is a more than one trip that has the same HD level, a random number generator then picks the goal for that day which is then used to select the trip

D. Non-Dominance

The Pareto Front is a curve that reflects the best possible tradeoff between conflicting goals that agents can make. This front is produced by the non-dominated sort - in which a point is non-dominated if there is not another point that produces an increase in one goal without a decrease in the other. The non-dominant tours produced from a simulation run are plotted and form a Pareto Curve here.

A curve is produced for tours over specific subsets of the days of a week. The scenarios are: all days of the week; no Sundays; early part of the week (M, T, W); and the later part of the week (Th, Fr, and Sat.). This allows us to see whether the fishing behavior at the beginning of a week is different from them at the weeks end. As an example, we begin with the Full Week Scenario here where every day of the week is an available stop on the fishermen's itinerary for the given phase, Phase 1.

Figure 5 provides all the data points, while figure 6 provides the resultant Pareto Frontier of figure 5. This is for Fishermen whose tours can take place on all 7 days of the week in Phase I, the Residual El Nino. Notice that in this Phase the presence of targeted fish dominates the need to invest in more resources in order to achieve a successful trip. Recall that in the base case for Effort such that a successful trip is one that brings back a catch. All of the trips in our database represent successful trips in that regard [13].

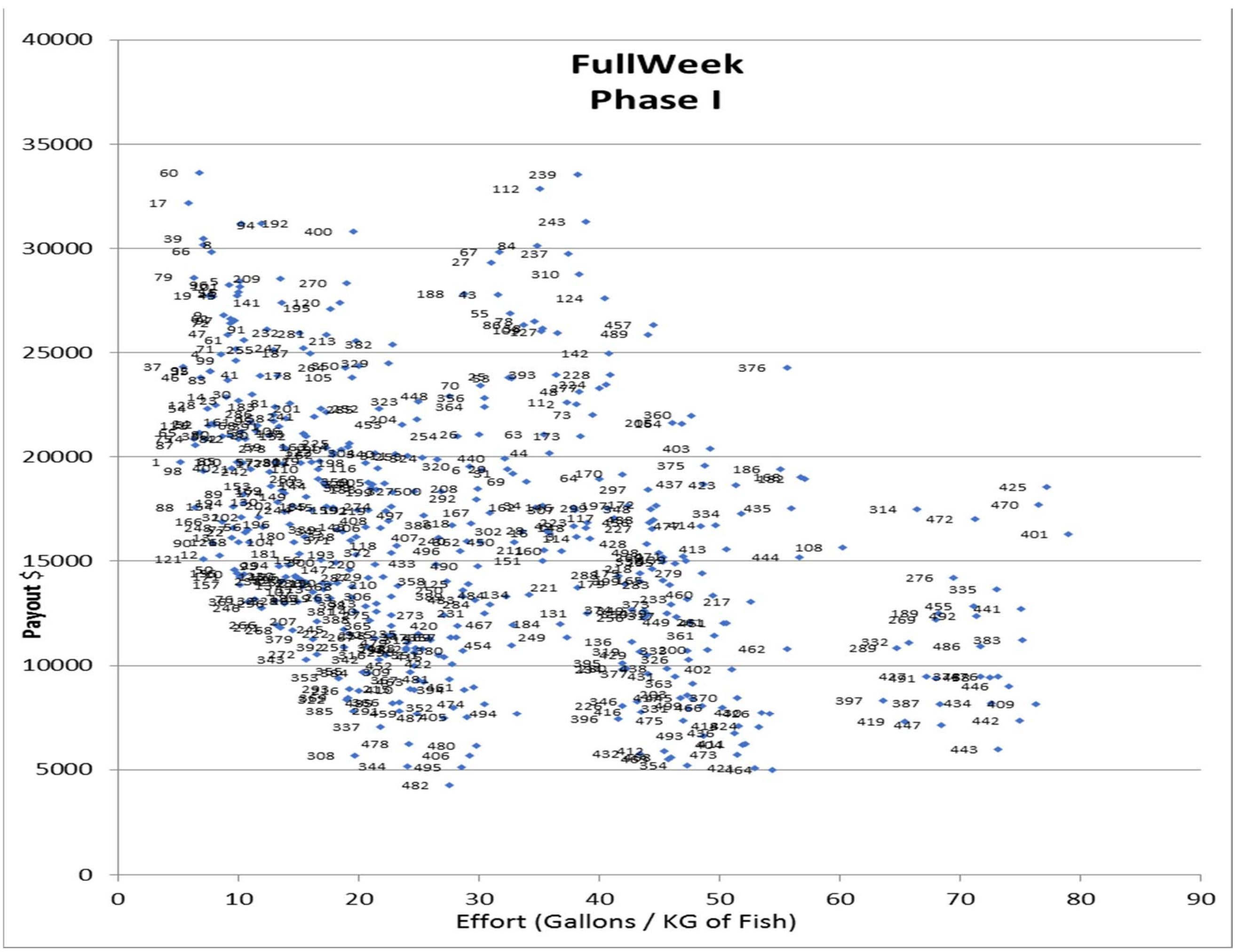

Fig. 5: A plot of 500 tours generated in the search for the Pareto Front in Phase I with all seven days available.

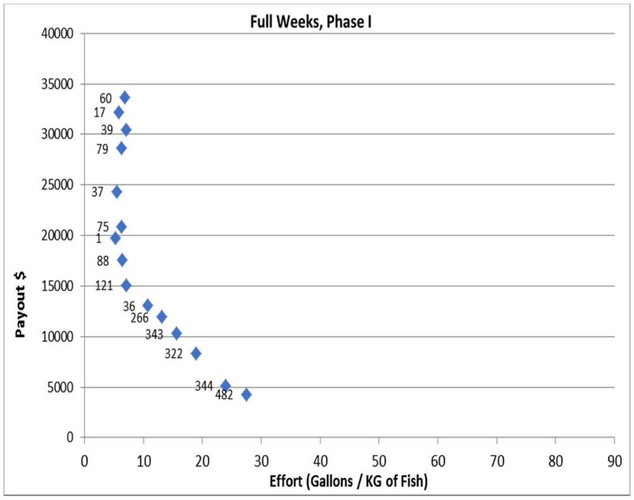

Fig. 6: An example Pareto Front for Payout (Goal #1) and Effort (Goal #2) for trips taken over a Full Week in Phase 1, the Residual El Niño

What the curve in Figure 6 means is that many targeted catches can be found within a short distance from Cerro Azul during the time of March through June. This is the conclusion of the El Nino which is moderated by the fact that it is the tail end of summer and beginning of fall. Warm water fish are enticed to remain in the area even though the warming phase of El Nino has diminished. It suggests that a productive sequence of trips in terms of Payout will be more dependent on timing than on location. Once fishermen are required to put more resources into the tour in this Phase, the Payout drops exponentially. The other phases and their weekly scenarios are presented in the next section.

VI. The Experimental Results

A. Introduction

The agent based model of artisanal fishing was used to generate tours through the trip graph over a given Phase and a corresponding set of days of the week. A Pareto Curve of non-dominated points is produced for each Phase, and each Days of the week scenario. (3 X 4) These curves are now compared graphically in order to identify the decision-making adaptations made by agents to the changing local climate produce by ENSO.

B. Full Week, Pareto Frontier

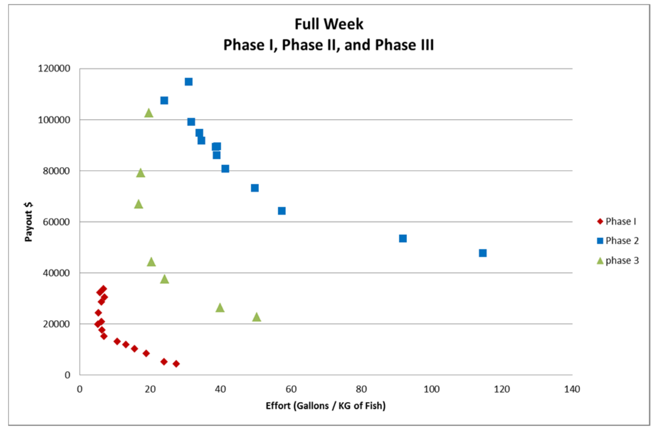

Fig. 9: Full Week, Pareto Frontier with all Three Phases

Figure 9 compares the three phases relative to their tours over all days of the week. Phase I: (March through June 1984) lasts only one-third of a year as opposed to the other two. If the same pattern played out in the missing two thirds of the phase, the maximum total would reach at least that of La Niña. (120,000). Payout declines exponentially with increased effort which suggests that the fishermen did not have to venture far from Cerro Azul in order to achieve the expected payout in el Niño. Sustainable fishing activity could then easily be performed nearby Cerro Azul. In order to achieve similar total payout (120,000) in Phase II, the fisherman need to take more trips and invest more resources in order to produce a successful trip. There is less of an exponential drop with distance from Cerro Azul in Phase III, so this suggests that they have more experience in fishing in the Back to Normal phase and are able to make better predictions about catch behavior and location.

C. No Sundays, Pareto Frontier

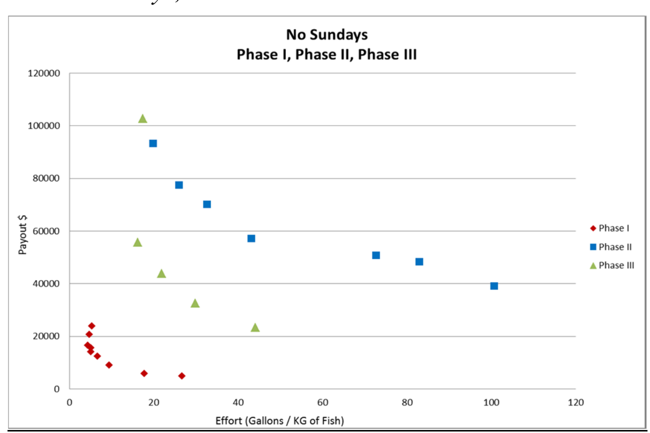

Fig. 10: No Sundays, Pareto Frontier, with all three Phases

Figure 10 represents the produced without the consideration of Sundays. Here, the results are similar to that of the Full Week since few trips went out on Sundays. In addition, often there was not an official at the docks to record trips that went out and came back then. In general, Back to Normal again had less of an exponential drop which suggests that it was an easier curve to plan for as an agent since the environment is now more predictable.. Phase II still needed to expend almost twice as many resources in order to sustain a successful fishing trip. This reflected the transitory nature of Phase II as warm water fish are starting to leave for the north, and cold water fish are beginning to return from the south.

D. Monday, Tuesday, Wednesday, Pareto Frontier

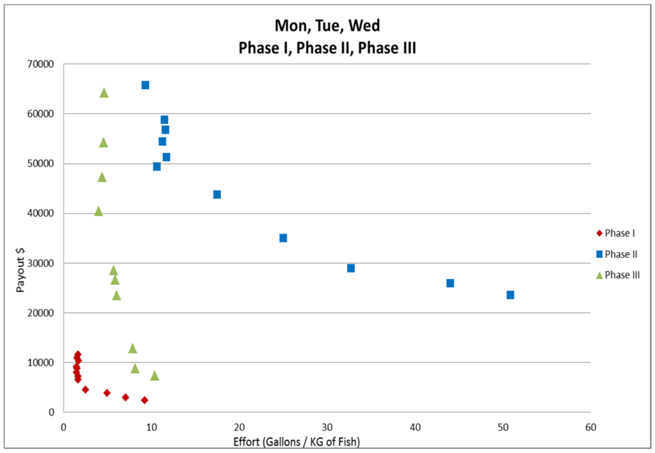

Fig. 11: Mon_Tue_Wed, Pareto Frontier with all three Phases

Figure 11 represents the fishing behavior exhibited by those fishing early in the week. In Phase I fisherman stayed close to Cerro Azul and took in about half of the Full weeks's amount. Since it is the beginning of the week the focus is on nearby areas where knowledge of fish locations can be learned. In Phase II the environmental is less predictable and fishermen may need to travel further at the beginning of the week, than for the other two phases. Likewise, in the Back to Normal Phase III fishing patterns are more predictable as a result of past experience and the slope is very steep since they are able to make good predictions about catch location.

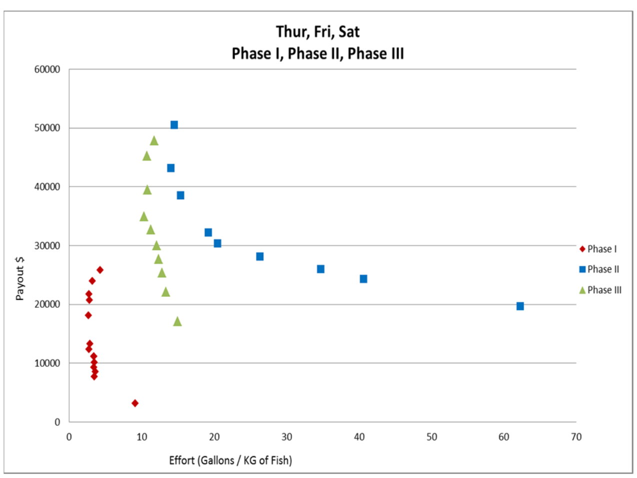

Fig. 12: Thur_Fri_Sat Pareto Frontier with all three Phases

Figure 12 gives the curves for those trips conducted later in the week. What is interesting here is that there is a steep drop in catch quality with increased effort as opposed to the Monday through Wednesday period. This suggests that in all three Phase there was a learning curve such that those trips later in the week benefited from the information collected by trip performed earlier in the week. This suggests that there was a communication network over which previous trip experiences were distributed. That information, made it easier to plan for later in the week.

E. Summary of Experimental Results

A profitability target optimum of 120,000 units emerged. Agents tried to attain that in each phase. However, this was at a cost. The maximum effort needed to produce a successful trip increased from the El Niño to La Niña for example. In order to sustain their fishing endeavor, more resources were invested. Different fishing strategies based upon both phase and days of the week emerged. Clear difference in Monday-Wednesday and Thurs-Sat. tradeoffs were observed. The La Niña Pareto Front had a more gradual decline in profitability with increased effort which suggested that more care had to be taken in the planning process in order to sustain fishing activities in this transitional phase.

VII. Statistical Validation

A. Overall Performance Comparison

The agent-based model produces some interesting emergent behaviors. Those behaviors appear to correspond to patterns extracted from the data via analytics. In terms of the model results, can the patterns be explained by a simple linear regression model that assumes a correlation between the goals? Or do the model results, based on the trip data support the notion of conflicting goals? If there is evidence for conflicting goals, then the results of the simulation should be better expressed as a non-linear curve that reflects the basic tradeoff between them. In this section we use the CAPSO system to generate a hyperbolic curve (an NP-HARD problem) to fit the data produced by the model in each Phase Day and day of the Week scenario and then compare its fit with that of an optimal linear model for that same data. This test is done by comparing the differences of each model prediction for each data point and test to see if the difference is statistically significant using a F-test.

B. Hypothesis

The hypotheses to be tested are as follows. The null hypothesis, H0, is given next.

H0: There is no statistical difference between the models at a given level of significance.

If this hypothesis is rejected, then it suggests that the non-linear tradeoff between the conflicting goals produced a better prediction of the data than a linear model. The level of significance selected here is .01 for testing. How well does the line fit the data is produced using a Residual plot. All computed points were used not just the non-dominated ones to compute the residuals in order to test the relationship over the entire search space. Figures 13 through 15 give the linear models produced for a subset to the (Phase, days of the week pairings. One example is for Non Sundays, one for M T W, and one for Th Fri Sat. It appears that the curve exhibit the greatest differences during the transition phase from to near to far from Cerro Azul.

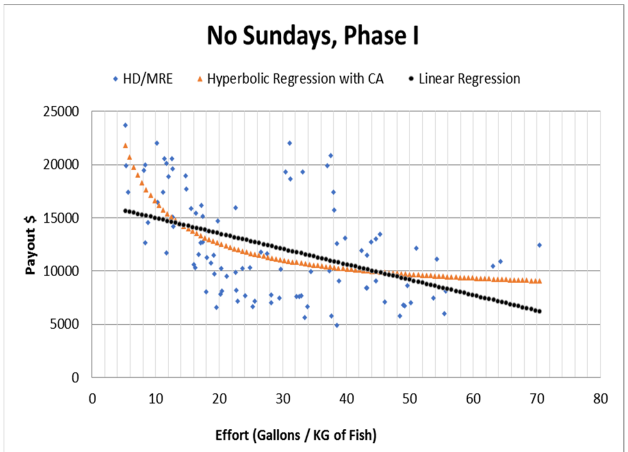

Fig. 13: Curve fitting for Payout, Effort using No Sundays in Phase I

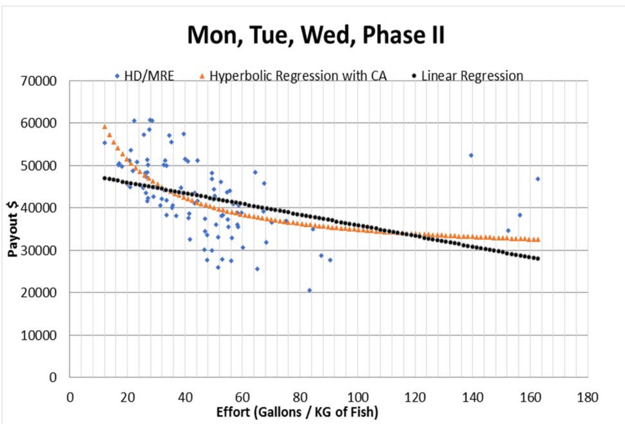

Fig. 14: Curve fitting for Payout, Effort using for 1st half of the week, Phase II

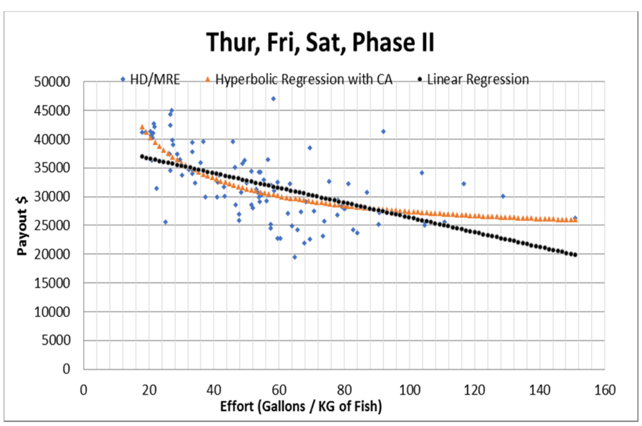

Fig. 15: Curve fitting for Payout, Effort using for 2nd half of the week, Phase II

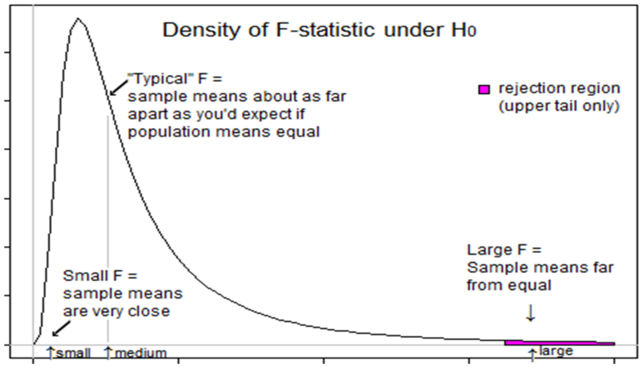

Fig. 16: F Distribution showing Acceptance and Rejection Regions.

Figure 16: shows the F Distribution used to test the difference between the hyperbolic and linear model predictions. The distribution of the F statistic indicates the accept and reject regions when difference in residuals for a pair of functions exceeds a particular value of F. Figure 17 gives the results of the null hypothesis for each of the four scenarios discussed above. The null hypothesis was rejected at the .01 level in all scenarios.

Significant level α	α = 0.05	α = 0.01	α = 0.001
F $(\alpha, _{df1, df2})$	3.07	4.8	7.5

Fig. 17: The Critical value for F-Test at different significant level of α.

Case of Fishermen Trip Durations	PHASE I El Nino	PHASE II La Nina	PHASE III Back to Normal	F $(\alpha, _{df1, df2})$ = 4.8 For α = 0.01
Full week	13.35	25.60	16.08	Ho: are Rejected for all phases
No Sundays	23.90	29.91	18.36	
Mon, Tue and Wed	6.31	24.75	21.31	
Thur, Fri and Sat.	7.27	37.25	14.73	

Fig. 18: Statistical value for (Fstat) for Phase I, II and Phase III.

C. *Summary*

The CAPSO system was used to produce a hyperbolic model for the simulation results. The predictions of that model were compared with those for an optimized linear model using the F-test on the residuals of the predictions. The results show that in ALL Phases and ALL Days of the Week comparisons, the hyperbolic model was a better fit (alpha = .01). This provide support for the multi-objective model produced here.

VIII. Conclusions and Future Work

A. *Conclusions*

Our results suggest that indeed the collective economic response of the fishermen demonstrates an ability to respond to the unpredictabilities of climate change, but at a cost. It is clear that the fishermen have gained the collective knowledge over the years to produce a coordinated response that can be observed at a higher macro level (Pareto Front). Of course, this knowledge can be used to coordinate activities only if it is communicated socially within the society. Although our data does not provide any explicit information about such communication, there is some indirect evidence that the adjustments in strategy are brought about by the increased exchange of experiences among the fishermen.

The Pareto distributions seem to suggest dominant and successor waves of strategies that may be associated with the length of time over which the simulation window is conducted. These waves were suggested to represent how subsequent trips were influenced by knowledge brought back by agents from trips the days right before that trip. For example, Dr. Marcus recalls one brother talking to another brother about his fishing experiences. This knowledge might be shared with close blood relatives or might be conveyed in general to others. Our discussion of analytics in Section 3 suggested that indeed there were at least two waves (learning curves) tpresent in terms of the amount of catches returned in the beginning of the week and the end. Result at the end of the week exhibit greater drop-offs with effort that suggest they have a better knowledge of catch locations and movements.

B. *Future Work*

The model uses only a two-objective model, but the results suggest that there may be evidence for other sub-goals in the acquired data set. Future work would be to expand the hierarchy of goals for agents. Also, there were gaps in some of the Pareto fronts, suggesting environmental constraints may make optimal decision making in those regions problematic (infeasible) [13]. Future work will be to investigate those areas of the curve to identify the reasons why. There is also potential to integrate a virtual reality implementation to show fish movement dynamics using a: Fish Visualizer. In addition, we plan to take advantage of the Social Network capabilities of Cultural Algorithms in order to attempt to model the impact that knowledge acquisition and its subsequent distribution has on strategic decision-making. [2]

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