AD-A238 305

NTATION PAGE

Form Approved
OMB No. 0704-0188

t Date.

3. Report Type and Dates Covered.
Proceedings

4. Title and Subtitle.
An Expert System Approach for Prediction of Maritime Visibility Obscuration

5. Funding Numbers.
Program Element No 62435N
Project No RM35G80
Task No 3
Accession No DN656766

6. Author(s).
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7. Performing Organization Name(s) and Address(es).
Naval Oceanographic and Atmospheric Research Laboratory*
Atmospheric Directorate
Monterey, CA 93943-5006

8. Performing Organization Report Number.
PR 90:073:401

9. Sponsoring/Monitoring Agency Name(s) and Address(es).
Naval Ocean Systems Center
San Diego, CA 92152-5000

10. Sponsoring/Monitoring Agency Report Number.
PR 90:073:401

11. Supplementary Notes.
Armed Forces Communications and Electronics Association Conference
*Formerly Naval Environmental Prediction Research Facility

12a. Distribution/Availability Statement.
Approved for public release; distribution is unlimited.

12b. Distribution Code.

13. Abstract (Maximum 200 words).
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14 Subject Terms.
(U) Forecasting; (U) Expert System

15. Number of Pages.
7

16. Price Code.

17. Security Classification of Report.	18. Security Classification of This Page.	19. Security Classification of Abstract.	20. Limitation of Abstract.
Unclassified	Unclassified	Unclassified	SAR

· ARMED FORCES COMMUNICATIONS AND ELECTRONICS ASSOCIATION CONFERENCE
18-20 July 90 Dayton, Ohio

An Expert System Approach for Prediction of Maritime Visibility Obscuration

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ABSTRACT

An Expert system for Shipboard Obscuration Prediction (AESOP), an Artificial Intelligence (AI) approach to forecasting maritime visibility obscurations, has been designed, developed, and tested. AESOP is rule-based, using backward chaining. The current version, AESOP 2.1, has 290 rules and has been designed in terms of nowcasts (0-1 hr) and forecasts (1-6 hr). An extensive explanation feature allows the user to understand the reasoning process behind a particular forecast. AESOP has been evaluated against 100 independent test cases, in which clear, hazy, or foggy conditions are predicted. The overall performance of AESOP is 68% correct. This value indicates considerable forecast skill when compared to 36% for random chance. When the distinction between clear and haze is ignored, the expert system correctly forecasts 79% of the "Fog"/"No fog" situations.

1. Introduction

For ships at sea, a visibility restriction poses just as serious an obstruction to movement as it does over land or in the air. In military operations, ship movement often occurs simultaneously with aircraft flights, as is the case with aircraft carriers. For this reason, and because ship operations can be moved from one location to another to take advantage of more favorable weather conditions, the accurate prediction of maritime visibility has been, and continues to be, an important problem for the Navy.

The Navy is developing a shipboard, environmental diagnosis/forecast system called the Tactical Environmental Support System (TESS). Among the several purposes of TESS is the concept of bringing automation and advanced analysis capabilities to the Navy shipboard oceanographer/meteorologist, primarily on aircraft carriers and other large ships.

NOARL contribution no. 90:073:401.
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Expert systems (ES) have been proposed for TESS problems requiring expertise in a well-defined domain, including the forecasting of visibility obscurations (e.g. fog and haze.) The specific goal is to develop a system that provides a maritime obscuration forecast that follows a reasoning process similar to that of expert, human forecasters.

The purpose of this paper is to summarize the rationale and method that has gone into the 2 1/2-year development of the Navy ES for forecasting obscurations at sea. The reader is referred to Peak and Tag [1] for a more complete description of the system design and development. In this paper a new, independent test of the system's performance not yet completed at the time of publication of Peak and Tag [1] will be presented.

2. Expert system approach

The field of Artificial Intelligence (AI) includes a number of techniques for solving problems that involve reasoning about data and reaching conclusions. Expert Systems have emerged as one of the applications of AI technology to real-world problems. ESs are AI computer programs that perform inference processes based on a collection of expertise and a set of known facts about the situation at hand. This procedure may be based on both formal knowledge and heuristics, and the problem-solving procedure may differ for various sets of input data.

The TESS requirement is that the obscuration expert system predict fog and haze for any maritime location between 70°N and 70°S. Visibility obscuration due to precipitation is not a designated function of the system. The ES is intended to be run onboard Navy ships using data available from local measurements, TESS data fields and satellite images.

There are several advantages to the use of an ES for the prediction of such obscuration phenomena. The prediction of obscuration events such as fog and haze is a very difficult problem requiring the interpretation of many types of data. Since fog may form by several processes [2], there is no pre-defined algorithm for its prediction. Thus, the ES approach is useful because an ES can be made to include expertise on how to approach the forecast problem based on the situation at hand. The expertise to forecast maritime fog is a rare commodity. Since Navy forecasters tend to serve relatively short duty tours at sea, they may not have the time to develop an expert level of skill. By encoding available forecast knowledge into an ES, rare expertise can be disseminated to the fleet.

The ES developed in this project has been named AESOP (An Expert-system for Shipboard Obscuration Prediction). The main source of expertise for this study was a series of research reports (e.g. [3,4]) from the Calspan Corporation detailing the results of maritime fog studies during 1972-1983. In addition, one of the participants in these studies, C. W. Rogers, has acted as a consultant expert to provide input in the development of the AESOP rule base.

3. The AESOP system

In this section the design of AESOP will be summarized. A complete description of AESOP is presented in Peak and Tag [1].

A human expert uses a complicated reasoning process to forecast maritime obscurations. Typically one must follow multiple lines of reasoning using many different types of data. AESOP has been designed to evaluate forecast situations in a fashion similar to that of expert human forecasters.

The problem-solving paradigm for AESOP is a consultation session in which the user of the program, a Navy meteorologist, answers questions about various atmospheric parameters such as temperature, dewpoint, sea surface temperature, etc. Once AESOP has acquired enough information about the current condition of the atmosphere, it applies the expertise contained in its knowledge base to draw conclusions about the future condition of the atmosphere with regard to visibility obscuration.

The knowledge and expertise in AESOP are stored as a series of IF-THEN rules. These rules contain the basic knowledge concerning the relationships of facts about the problem domain. These rules are the major component of the ES, and they form the basis for the formal reasoning process that the system uses to solve problems.

AESOP is implemented in the Prolog language on an IBM-compatible personal computer. The current version, AESOP 2.1, has 290 rules. AESOP has been designed to reason in terms of nowcasts and forecasts. The AESOP nowcasts are for the 0-1 h time frame, while the AESOP forecasts apply to the 1-6 h time frame. This approach is used to differentiate between situations where a change in the atmospheric obscuration condition is imminent, and those where the condition change requires more time to occur.

Since one of the goals of AESOP is to disseminate rare expertise, the predictions are accompanied by a synopsis of the physical reasoning used in arriving at the prediction. AESOP also includes an extensive explanation feature. The user is able to step through the reasoning process, during which AESOP reveals the logic by which its conclusions were made and also the reasons that alternative conclusions were not made. Thus, it effectively tells the user why a certain obscuration is expected, why other obscurations are not expected, and what data were used to make these conclusions.

The major components of the AESOP expert system (Fig. 1) include the Knowledge Base (containing both the Working Memory and the Rule Base), the Fact Acquisition System, the Explanatory Interface, the Inference Engine and the User Interface. The User Interface makes communication between the user and AESOP possible. The Fact Acquisition System systematically makes inquiries to the user concerning atmospheric parameters (e.g. temperature, wind speed, etc.) and records this information as facts in the Working Memory. The Inference Engine applies rules of logic to infer new facts from the existing facts. The Rule Base contains the static knowledge previously obtained from the expert sources in the form of rules of logic. The Working Memory contains the facts that describe what is known about a particular problem. When the program starts, the Working Memory is empty. The dynamic knowledge obtained from the user via the Fact Acquisition System is stored in the Working Memory. As intermediate conclusions are made via the Inference

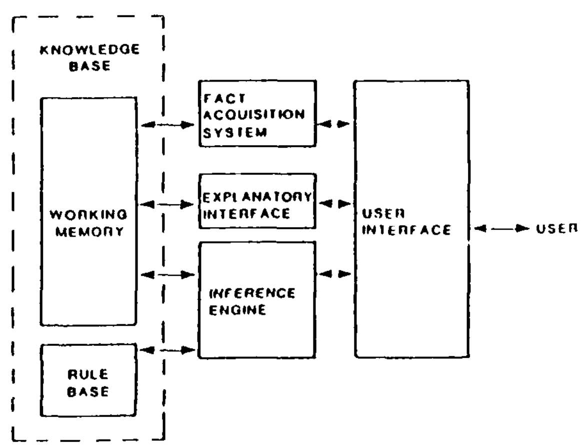

Figure 1. Major components of the AESOP expert system. Arrows indicate data flow.

Engine, the system stores this new knowledge in the Working Memory. Finally, the Explanatory Interface allows the user to step through the many logical paths used by AESOP to arrive at its forecasts.

The Prolog language is designed to use backward chaining [5] to try to verify previously specified goals. In AESOP, these goals are specified based on the current state of the atmosphere with regard to visibility-obscuring phenomena. There are three mutually-exclusive atmospheric states that AESOP diagnoses: Fog is present; Haze is present; and No Obscuration is present. The initial state of the atmosphere is one of these three, and the forecast future state will also be one of these three possibilities (Table 1). The connections between the present and future states are various meteorological processes. These connections have been designated as the following state-change operators: 1) Fog will form, 2) Fog will dissipate, 3) Fog will persist, 4) Haze will form, 5) Haze will dissipate, 6) Haze will persist, and 7) It will stay clear. AESOP is designed to analyze the likelihood of these state changes based on observed meteorological parameters.

For any given initial state, only three of these state-change operators may apply (Table 1). The AESOP Inference Engine uses the current obscuration and a set of lists similar to Table 1 to determine which three state-changes to test. These three state changes are then designated as the goals of the ES. This initial limitation of the number of goals accomplishes a heuristic reduction of the search space.

Table 1. Current and future atmospheric obscuration states. The three possible future states and the corresponding state-change operators are indicated for each initial state.

Current State: No Obscuration

Future States	State-Change Operators
No Obscuration	It will stay clear
Haze	Haze will form
Fog	Fog will form

Current State: Haze

Future States	State-Change Operators
No Obscuration	Haze will dissipate
Haze	Haze will persist
Fog	Fog will form

Current State: Fog

Future States	State-Change Operators
No Obscuration	Fog will dissipate
Haze	Haze will form
Fog	Fog will persist

As AESOP evaluates each potential goal state, a probability of its occurrence is assigned. In general, the goal state with the highest probability is chosen to be the AESOP forecast. However, since fog is the most severe type of visibility obscuration, whenever the probability of its occurrence is greater than 50%, AESOP selects fog as its forecast even if the probability of haze is larger.

"Semantic nets" [5] represent a knowledge domain by a graphic collection of nodes and links where the nodes represent objects or concepts and the links represent relationships between the objects or concepts. Knowledge in AESOP is represented by rules. A set of rules may be represented in an "inference net," which is a special type of semantic network using only the IF-THEN logic relation. Thus, portions of the AESOP rule base may be presented in graphic form.

The inference net depicting the rules that determine the likelihood of forecast (1-6 hr) fog formation is presented in Figure 2. The nodes (boxes) in Figure 2 represent goals and subgoals. Dashed links are defined here as "OR" links because the goal to which they lead succeeds when any one of the OR-links proceeds from a true subgoal. All of the solid AND-links must proceed from true subgoals before the subgoal to which they lead succeeds. This inference net depicts the rule

IF Fog forms by the Taylor process
OR Fog forms by the stratus-lowering process
OR There is advection of existing fog
THEN "Fog will form" is forecast.

Similarly, the rule

IF The marine layer is primed for fog
AND The marine layer is cooled from below to dewpoint
AND The predominant flow is from warmer to colder water
THEN Fog forms by the Taylor process

is also depicted. Thus, the inference net in Figure 2 reveals the fog formation rules and their interdependence.

The major subgoals in Figure 2 are the different formation processes for Taylor and stratus-lowering fog, and for advection of existing fog. AESOP attempts to verify the goal "Fog will form" by chaining backward through the subgoals "Fog forms by the Taylor process," "Fog forms by the stratus-lowering process" and "There is advection of existing fog." Each of these subgoals must itself be verified by determining the truth of the

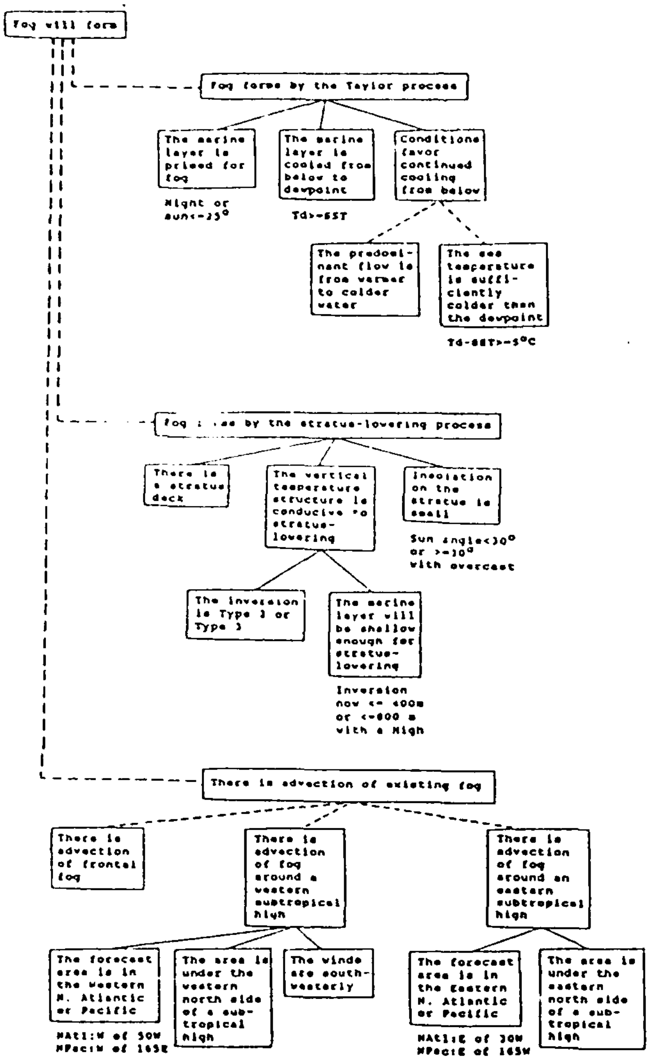

Figure 2. Inference network depicting the AESOP rules for the forecast goal "Fog will form." Dashed lines are OR-links and solid lines are AND-links. Nodes which have no link leading to them are verified based on user-input data in the Working Memory. Backward chaining progresses from top to bottom whereas inferences are made from the bottom to the top.

subgoals upon which it depends. The search for a solution proceeds down the net until there are no further branches. At this point, the last subgoal must be verified by the appropriate data values (not shown) previously input by the user via the Fact Acquisition System.

Similar inference nets (not shown) may be constructed from the AESOP rules for fog dissipation, and those for haze formation and dissipation. A complete set of the AESOP 2.1 inference nets is presented in Peak [6].

The explanatory interface in many ESs is little more than a procedure to list rules that were used to reach a goal. The AESOP explanation feature is expanded to include explanatory text that reveals the motivations behind the different lines of reasoning, the physical causes and effects underlying the obscuration forecasts, the data values used and why the data are important. Another major difference in AESOP's explanation feature is that it reveals not only the lines of reasoning that succeed but also those that fail. The advantage in this approach is that a user may be just as interested in why AESOP did not forecast an obscuration that he may have thought to be likely, as he is interested in why AESOP did forecast an event he thought would not happen.

AESOP does this complete evaluation by testing every possible line of reasoning to the fullest, regardless of the success or failure to meet the logical requirements of each rule. In most ESs, a particular chain of reasoning (e.g. a path from the data to a goal on an inference net) is tested only to the point where one of the subgoals fails. At this point, the system backtracks and tries a different path until eventually a complete path is found. AESOP, however, was designed to record its paths continually in the Working Memory, keeping track of the success or failure of the data to meet the requirements of each subgoal. Thus, the AESOP Inference Engine attempts to satisfy all of the paths between the data and the goals. Even when a subgoal fails, the remainder of the path is still tested. The difference is that the path record in the Working Memory is flagged as not satisfying the subgoal. The explanatory text that is generated by successful subgoals is different from that generated when a subgoal fails. Thus, a complete explanation of all lines of reasoning is available.

One disadvantage of this approach is that it may take a long time to traverse all of the branches of a large rule base. However, the AESOP rule base is not excessively large, plus the search space has been further reduced by the use of meta-rules.

The Explanatory Interface is a routine that steps through these path records in the Working Memory. The path records are stored in tree form with nodes containing a description of the subgoal, the explanatory text, and pointers to the node's parent and successor nodes. The Explanatory Interface displays this information and allows the user to traverse the tree to discover the cause and effect of each subgoal.

The current form of explanation provides the most detailed window on the reasoning process available in ES technology. AESOP also includes an explanation summary to reveal a simple overview of the reasoning behind the forecast choice. This less detailed general explanation accompanies the initial AESOP forecast. The user can still optionally choose to delve into the detailed explanation when the more complete line of reasoning is desired.

4. System performance

A complete AESOP forecast takes only about 2 min of real time to execute. Most of that time is spent responding to the queries of the Fact Acquisition System. An example of an AESOP forecast display is presented in Figure 3. In this case, fog is forecast to occur with a probability of 90%. From the summary explanation of the reasoning process, the user can determine that the fog is expected to form via the stratus-lowering process. The forecasts for all three potential obscurations are listed next for comparison. Finally, an options list gives the user several choices of what to do next. First, he may want to see the 0-1 h nowcast. The second option is to traverse the complete explanation tree so that the reasoning behind any of the expected or not expected processes is revealed. AESOP also includes a feature by which one or more of the data values previously input by the user can be modified and a new forecast generated. This feature enhances the role of the system as a training tool because the user can compare what happens under slightly different conditions. Finally, the user can run a completely new case or exit from the forecast mode altogether.

In this section, the AESOP forecast skill is evaluated for 100 maritime obscuration situations. The test data are taken from various weather ships stationed in the North Pacific and North Atlantic during 1971-1974. Because fog is an infrequent phenomenon, the selection of cases for the independent sample was not made randomly. Instead, available ship data were scanned to find situations where fog and haze were forming, persisting, or dissipating. The cases were not selected on the basis of their being unusual nor overly simple; the only consideration was whether fog or haze was involved either initially or at +6 h. No cases were included that were clear at both the initial time and at +6 h.

Contingency tables (e.g., Table 2) are used to compare the +6 h forecasts to the actual obscuration state. The columns represent the actual +6 h obscuration states while the rows are the AESOP +6 h forecasts. If the cases were all correct-

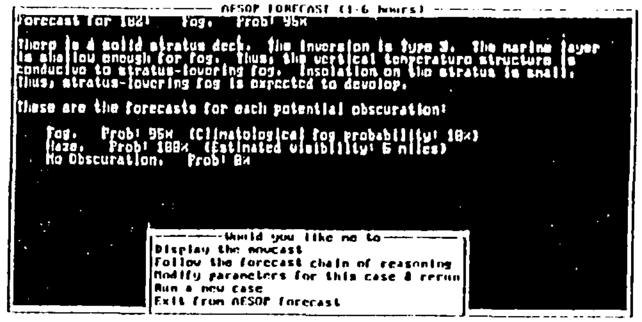

Figure 3. Example AESOP forecast display.

ly forecast, only the diagonal values (bold numbers) would be nonzero. Since the extent of obscuration severity ranges from fog to haze to clear in Table 2, the incorrect forecasts above the diagonal indicate overforecasts, because a more severe visibility obstruction is forecast than actually occurs. Similarly, those cases below the diagonal are underforecasts.

The results of the AESOP 2.1 runs on the 100 independent sample cases are presented in Table 2. The initially fog cases (Table 2a) are correctly forecast 59% of the time. If persistence were used, only 16 forecasts (35%) would be correct so that the AESOP forecasts do seem to indicate skill.

The contingency table for the 31 initially haze cases is presented in Table 2b. AESOP correctly forecasts 68% correct. If persistence were used, only 26% would be correct. Notice that on these cases, there is no overforecast or underforecast bias (Table 2b).

The AESOP performance on the initially clear cases (Table 2c) is excellent, with 87% correct. One should not use persistence as a comparison here because this set was deliberately chosen not to include cases that were clear at +6 h.

When all 100 cases are considered together (Table 2d), AESOP forecasts 68% correct. For the same reason, persistence can not be used as a comparison method here. There is no strong tendency to overforecast (14 cases) or to underforecast (18 cases) the independent sample cases. The random simulations described in the next section indicate that a purely random forecast would result in only 36% correct for these cases.

It is useful to consider the forecast skill in a "Fog"/"No fog" sense so that the more important fog forecast situations are emphasized by excluding the less important haze situations. AESOP correctly forecasts 79% of these cases. The nearly 80% skill of these AESOP 2.1 forecasts is highly encouraging. The random simulations described in the next section

Table 2. Contingency tables for AESOP 2.1 +6 h forecasts (Fcst) (rows) vs. +6 h actual obscuration states (columns) for cases with the initial condition: a. fog (F), b. haze (H), c. clear (C), d. all cases, e. fog/no fog. Bold values on diagonal indicate number of correct forecasts. Tot indicates total of rows or columns, % indicates percent correct.

a. INITIALLY FOG CASES:

Fcst	Actual F	H	C	Tot	%
F	**10**	0	6	16	63
H	3	**10**	3	16	63
C	3	4	**7**	14	50
Tot	16	14	16	**46**	
%	63	71	44		59

b. INITIALLY HAZE CASES:

Fcst	Actual F	H	C	Tot	%
F	**13**	1	2	16	81
H	1	**5**	2	8	63
C	2	2	**3**	7	43
Tot	16	8	7	**31**	
%	81	63	43		68

c. INITIALLY CLEAR CASES:

Fcst	Actual F	H	C	Tot	%
F	**13**	0	0	13	100
H	0	**7**	0	7	100
C	3	0	**0**	3	0
Tot	16	7	0	**23**	
%	81	100	0		87

d. ALL CASES:

Fcst	Actual F	H	C	Tot	%
F	**36**	1	8	45	80
H	4	**22**	5	31	71
C	8	6	**10**	24	42
Tot	48	29	23	**100**	68
%	75	76	43		

e. FOG/NO FOG:

Fcst	Actual F	NF	Tot	%
F	**36**	9	45	80
NF	12	**43**	55	78
Tot	48	52	100	
%	75	83		79

indicate that a purely random forecast would result in approximately 50% correct for these cases.

5. Monte Carlo Significance Tests

In an attempt to measure the significance of these statistics, Monte Carlo simulations have been used (e.g., Peak and Tag, 1989). The method is to use the probability of occurrence of the three obscuration states in Table 2d, and the probability of AESOP forecasts for the three states from the same table. A random number generator based on these probabilities selects a random obscuration state and a random forecast of that state. The process is repeated 100 times to simulate the AESOP forecasts for a test sample the same size as the independent sample. The reason this simulation can measure the significance level is that it is known that the percent correct is achieved purely by chance. If a random percent correct could have occurred by chance, it is less likely that the demonstrated AESOP performance is due to skill.

The random experiment was repeated 50,000 times, which is arbitrarily chosen to be enough trials to generate a distribution of the random forecast skill. Of the 50,000 trials, the 68 correct achieved in the Table 2d results is never accomplished. The highest random skill level is 57 correct. Thus, it is virtually assured, at least in a statistical sense, that the AESOP results are due to forecast skill.

6. Summary and conclusions

An Expert system for Shipboard Obscuration Prediction (AESOP) has been developed over the past 2 1/2 years to provide an Artificial Intelligence approach to short-term forecasting of fog and haze. In this report, the latest version (2.1) is described and an evaluation of the system on an independent data set is made.

In a 100-case independent sample test, AESOP is correct 68% of the time. This value compares favorably with the 36% correct due to random forecasts based on the same sample characteristics.

When the distinction between haze and clear is removed, AESOP correctly forecasts 79% of the "Fog"/"No fog" situations. This level is considerably higher than the approximately 50% correct from random selection. Since persistence of initially clear conditions was deliberately omitted from the sample, a persistence comparison is not possible.

The independent sample results show a slight decrease in performance from the dependent sample results in [1]. This decrease may be an indication that the rule base has been "tailored" to handle cases with the characteristics of the dependent sample because any deficiencies in the rule base concerning those situations have shown up during earlier dependent sample testing. Also, the independent sample includes cases from the N. Pacific. There may be some situations unique to that region that are not handled by the rule base which was developed using only N. Atlantic data.

The AESOP forecast performance is due to forecast skill, as evidenced by the Monte Carlo simulations. The independent sample results demonstrate considerable forecast skill for very difficult forecasting situations. AESOP should prove to be a valuable forecast guidance and training tool for the shipboard meteorologist.

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