2.4 **COMBINING HUMAN AND COMPUTER GENERATED FORECASTS USING A KNOWLEDGE BASED SYSTEM**

Harvey Stern *

Bureau of Meteorology, Australia

1. PREFACE

'Consider mechanically integrating judgmental and statistical forecasts instead of making judgmental adjustments to statistical forecasts

…Judgmental adjustment (by humans) of (automatically generated statistical forecasts) is actually the least effective way to combine statistical and judgmental forecasts … (because) judgmental adjustment can introduce bias[1] (Mathews and Diamantopoulos, 1986)

…The most effective way to use (human) judgment is as an input to the statistical process

… Cleman (1989) reviewed over 200 empirical studies on combining and found that mechanical combining helps eliminate biases and enables full disclosure of the forecasting process. The resulting record keeping, feedback, and enhanced learning can improve forecast quality' (Sanders and Ritzman, 2001).

2. INTRODUCTION

Sanders and Ritzman (2001) highlight the difficulty associated with utilising (human) judgment as an input to the statistical process 'when the (human) forecaster gets information at the last minute'.

In generating the predictions presented here, the strategy is therefore:

- To take judgmental (human) forecasts (derived with the benefit of knowledge of all available computer generated forecast guidance); and,
- To input these forecasts into a system that incorporates a statistical process to mechanically combine the judgmental (human) forecasts and the computer generated forecast guidance;

Thereby immediately yielding a new set of forecasts.

In this context, the purpose of the present work is:

1. To evaluate the new set of forecasts; and,
2. To document the increase in accuracy achieved by that new set of forecasts over that of the judgmental (human) forecasts.

3. BACKGROUND

Some 30 years ago, Snellman (1977) lamented that whereas the initial impact of guidance material was to increase the accuracy of predictions on account of a healthy human/machine 'mix', operational meteorologists were losing interest and that the gains would eventually be eroded by what he termed the 'meteorological cancer'.

Snellman suggested that producing automated guidance and feeding it to the forecaster who 'modifies it or passes it on', encourages forecasters 'to follow guidance blindly' and concluded by predicting an erosion of recent gains.

Hindsight informs us from forecast verification statistics that the erosion of gains did not take place. In fact, the accuracy of forecasts continued to increase - see, for example, Stern (2005a, 2005c).

Nevertheless, evidence is emerging that the increasing skill displayed by the guidance material is rendering it increasingly difficult for human forecasters to improve upon that guidance (Mass and Baars, 2005; Ryan, 2005).

4. A KNOWLEDGE BASED SYSTEM

Over recent years, the present author has been involved in the development of a knowledge based weather forecasting system (Stern, 2002, 2003, 2004a, 2004b, 2005a, 2005b, 2005c, 2005d). Various

* *Corresponding author address:* Harvey Stern, Bureau of Meteorology, Box 1636, Melbourne, Vic., 3001, Australia; e-mail: h.stern@bom.gov.au

[1] Stern (1996) documents forecaster over-compensation for previous temperature errors.

components of the system may be used to automatically generate worded weather forecasts for the general public, terminal aerodrome forecasts (TAFs) for aviation interests, and marine forecasts for the boating fraternity.

The knowledge based system generates these products by using a range of forecasting aids to interpret NWP model output in terms of such weather parameters as precipitation amount and probability, maximum and minimum temperature, fog and low cloud probability (Stern and Parkyn, 2001), thunderstorm probability (Stern, 2004b), wind direction and speed, and swell (Dawkins, 2002).

For example, Stern's 2005b forecasts in weather graphic format (Figure 1) are generated from an algorithm that has a logical process to yield HTML code by combining predictions of temperature, precipitation, wind, morning and afternoon weather, and special phenomena (thunderstorm, fog), with features of the forecast synoptic type (strength, direction, and cyclonicity of the surface flow).

5. THE TRIAL OF FEBRUARY TO MAY 2005

Stern (2005b) conducted a 100-day trial (Feb 14, 2005 to May 24, 2005) of the performance of the knowledge based system, with twice-daily forecasts being generated out to seven days in advance.

During the trial, the overall percentage variance of observed weather explained by the forecasts so generated (the system's forecasts) was 43.24% compared with 42.31% for the official forecasts.

That the knowledge based system achieved some success in its attempt to replicate the cognitive decision making processes in forecasting is confirmed by the closeness of the overall percentage variances explained by the two sets of forecasts.

Specifically for precipitation, the percentage variance explained by the quantitative precipitation forecasts and probability of precipitation forecasts so generated was 26.78% compared with 25.07% explained by the official forecasts.

On a rain/no rain basis, the percentage of correct forecasts so generated was 78.82% compared with 77.64% of the official forecasts.

However, the overall percentage variance of official forecasts explained by the system's forecasts was only 45.91%, indicating that the system’s forecasts were not highly correlated with the official forecasts. This was made up of 63.59% of the variance of officially forecast temperature, and 28.23% of the variance of officially forecast precipitation.

This indicates, that, on a day-to-day basis, there are significant aspects of the processes employed in deriving the official forecasts that are not taken into account by the system's forecasts (in all likelihood what Sanders and Ritzman (2001) refer to as 'domain knowledge'[2]), and vice versa.

Combining forecasts by mathematically aggregating a number of individual forecasts increases the reliability of forecasts (Kelley, 1925; Stroop, 1932) and averages out unsystematic errors (but not systematic biases) in cue utilization.

A common method for combining individual forecasts is to calculate an equal weighted average of individual forecasts' (Stewart, 2001). However, under some conditions unequal weights make sense 'if you have strong evidence to support unequal weighting' (Armstrong, 2001b)[3].

6. COMBINING FORECASTS

Regarding the two sets of forecasts as partially independent and utilising linear regression to optimally combine the estimates of minimum temperature, maximum temperature, precipitation amount, and precipitation probability, Stern (2005b) demonstrated a lift in the overall percentage variance of observed weather explained.

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[2] Sanders and Ritzman (2001) define 'domain knowledge' as 'knowledge practitioners gain through experience as part of their jobs' and make particular reference to that component of domain knowledge named 'contextual knowledge, which is the type of knowledge one develops by working in a particular environment.' 'The quality of domain knowledge is affected by the forecaster's ability to derive the appropriate meaning from the contextual (or environmental) information' (Webby et al., 2001).

[3] Krishnamurti et al. (1999) found that weather forecasts based on a combined forecast using weights based on regression were more accurate than combined forecasts with equal weights.

This result suggested that adopting such a strategy of optimally combining the official and system predictions has the potential to deliver a set of forecasts that are substantially more accurate than those currently issued officially.

Indeed, the overall percentage variance of observed weather explained (an excellent measure of the usefulness of the forecasts) was lifted (by the consensus forecasts) to 50.21% from 43.24% (system) and 42.31% (official), a lift of 7.90% from that achieved by the official forecasts[4].

What these data suggested was that adopting a strategy of combining predictions has the potential to deliver a set of forecasts that explain as much as 7.90% more variance than that explained by forecasts currently issued officially.

In fact, forecast verification data from a new real-time trial presented in the sections that follow, demonstrate that a substantial increase in accuracy is, indeed, achievable, were one to adopt such a strategy.

7. MODIFYING THE SYSTEM

The knowledge based system has been modified so that it now automatically integrates judgmental (human) forecasts and the computer generated guidance, thereby incorporating the forecasters' valuable contextual knowledge into the process[5]. It is undergoing a 'real-time' trial, the results of which are being evaluated.

This process of integrating human and computer generated forecasts is illustrated for *Probability of Precipitation* estimates in Figure 2.

Stern (1999) published a proposed interpretation of words used in forecasts in terms of *Probability of Precipitation* and *Amount of Precipitation.*

The system includes an algorithm that interprets the (official) worded precis in terms of *Probability of Precipitation* and *Amount of Precipitation*. This algorithm was derived from Stern's (1999) proposed interpretation and a verification of the official precis that was conducted during the trial of February to May 2005.

By way of illustration, an extract of the probability (%) algorithm, and an extract of the amount (mm) algorithm, are respectively given in Tables 1 and 2.

Because the system's weather icons (Figure 1) arise largely from the system's generated *Probability of Precipitation*, and, conversely, the human (official) *Probability of Precipitation*, arises from an an algorithm that interprets the (official) worded precis, any verification of the *Probability of Precipitation* may also be regarded as representing a verification of forecast *sensible weather*.

8. THE TRIAL OF AUGUST TO NOVEMBER 2005

The new 100-day trial, conducted with a fresh set of data (Aug 20, 2005 to November 27, 2005), of the performance of the modified system involves daily forecasts being generated out to seven days in advance.

Preliminary evaluation of the forecasts prepared during the first 70 days of the trial[6] shows that the overall percentage variance of official forecasts explained by the system's forecasts is now lifted to 79.15% (from 45.91% previously)[7].

This is made up of 83.82% of the variance of officially forecast temperature (63.59% previously), and 74.47% of the variance of officially forecast precipitation (28.23% previously).

Furthermore, the overall percentage variance of observed weather explained (a sound measure of the usefulness of the forecasts) is now lifted by the

[4] The accuracy increases because 'Combining is most effective when the forecasts combined are not correlated and bring different kinds of information to the forecasting process' (Sanders and Ritzman, 2001) and that although 'both (human) intuitive and (computer) analytic processes can be unreliable … different kinds of errors will produce that unreliability' (Stewart, 2001).

[5] Sanders and Ritzman (2001) refer to their 1992 study, in which they demonstrated that judgmental forecasts based on contextual knowledge were significantly more accurate than those based on technical knowledge (and) … were even superior to (a) … statistical model.'

[6] For an update on progress with this work, please go to: http://www.weather-climate.com/ams30Jan2006.html

[7] Demonstrating that, in most circumstances, the combining strategy leaves the system's forecasts almost identical to the official forecasts.

system to 43.20% from 36.03% (official) – a rise of 7.17%, which is close to the 7.90% lift suggested previously by Stern's (2005b) consensus forecasts[8].

Figure 3 shows that the overall percentage variance of the observed weather explained is lifted by between 5% and 8% at most lead times.

Specifically for precipitation, the percentage variance explained is lifted by the system to 42.40%[9] from 32.58% (official[10]).

On a rain/no rain basis[11], the percentage of correct forecasts generated by the system is lifted by the system to 78.68% from 72.07% (official).

The root mean square error (rmse) of the √(*Amount of Precipitation* forecast)[12] is reduced by the system to 0.794 mm from 0.943 mm (official[13]).

[8] Demonstrating that, in those few circumstances when the combining strategy substantially changes the official forecasts, the system's forecasts usually represent an improvement on the official forecasts.

[9] Made up of 46.23% for *Probability of Precipitation* and 38.57% for *Amount of Precipitation*.

[10] Made up of 36.13% for *Probability of Precipitation* and 29.03% for *Amount of Precipitation*.

[11] For verification purposes, it is said that there has been rain on a particular day when at least one of the 0300, 0600, 0900, 1200, 1500, 1800, 2100, or 2400 Melbourne CBD present or past weather observations include a report of precipitation, with a recording of at least 0.2 mm during the preceding three hours.

Should at least one of the 0300, 0600, 0900, 1200, 1500, 1800, 2100, or 2400 Melbourne CBD present or past weather observations include a report of precipitation, but with a recording of only a 'trace' during the preceding three hours, the day is not regarded as 'rain day'. However, in this circumstance, for the purposes of verifying the forecast *Amount of Precipitation*, the amount fallen is regarded as being 0.1mm, and for the purposes of verifying the forecast *Probability of Precipitation*, the *Probability of Precipitation* is regarded as 50%.

Should at least one of the 0300, 0600, 0900, 1200, 1500, 1800, 2100, or 2400 Melbourne CBD present or past weather observations include a report of distant precipitation, but with a recording of 0.0mm during the preceding three hours, the day is not regarded as 'rain day'. In this circumstance, for the purposes of verifying the forecast *Amount of Precipitation*, the amount fallen is regarded as being 0.0mm, and for the purposes of verifying the forecast *Probability of Precipitation*, the *Probability of Precipitation* is regarded as 25%.

Figure 4 shows that the overall percentage variance of the observed precipitation explained is lifted by between 10% and 15% at most lead times.

Specifically for temperature, the percentage variance explained is lifted by the system to 43.99%[14] from 39.47% (official[15]).

The rmse of the temperature forecasts generated by the system was 2.340 deg C[16] compared with 2.462 deg C[17] for the official forecasts.

Figure 5 shows that the overall percentage variance of the observed temperature explained is lifted by between 2% and 4% at most lead times. Only at Day-1, is the overall percentage variance of the observed temperature explained not lifted.

These results indicate that, on a day-to-day basis, what Sanders and Ritzman (2001) refer to as 'domain knowledge', is now taken into account by the system.

9. OTHER WEATHER ELEMENTS

The system also develops predictions of other weather elements (without directly utilising the combining process), and predictions for other localities. These include:

- Forecasts of 9am and 3pm wind speed and direction at Melbourne Airport. The system's

[12] The rmse of the √(*Amount of Precipitation* forecast) is a preferred verification parameter to (*Amount of Precipitation* forecast) in order to reduce the skewness in the distribution of the latter.

[13] The official *Amount of Precipitation* forecasts are expressed in terms of rainfall ranges and, for verification purposes, the *Amount of Precipitation* forecast is taken to be the mid-point of the range forecast:

Range 0 = No precipitation; Range 1 = 0.2 mm to 2.4 mm (1.3 mm); Range 2 = 2.5mm to 4.9mm (3.7 mm); Range 3 = 5.0mm to 9.9mm (7.5mm); Range 4 = 10.0mm to 19.9mm (14.9mm); Range 5 = 20.0mm to 39.9mm (29.9mm); Range 6 = 40.0mm to 79.9mm (59.9mm); and, Range 7 = 80.0mm or more (119.9mm).

[14] Made up of 48.10% for minimum temperature, and 39.89% for maximum temperature.

[15] Made up of 43.89% for minimum temperature, and 35.05% for maximum temperature.

[16] Made up of 2.455 deg C for minimum temperature, and 2.218 deg C for maximum temperature.

[17] Made up of 2.549 deg C for minimum temperature, and 2.372 deg C for maximum temperature.

forecasts of wind speed explain 46.22% of the variance of the observed wind speed (compared with 50.49% explained by the official forecasts) and predict (within half an octant) the wind direction on 63.77% of occasions (compared with 72.52% of the official forecasts).

- Forecasts of the rare weather elements - thunderstorms[18] and fog[19]. The *Critical Success Index* (Wilks, 1995) of the system's forecasts of these elements is 0.000 for fog (the system failed to forecast fog on the occasions when it occurred), and 0.250 for thunderstorms[20]. The *Critical Success Index* was 0.049 and 0.217 for official forecasts of fog and thunderstorms, respectively.

- Forecasts for a number of other Central District localities. Verification of the maximum temperature component of these forecasts reveals that, expressed as an expected departure from Melbourne's maximum temperature, the mean absolute error of the system's forecasts was 0.885 deg C, compared with 1.053 deg C for the official forecasts.

10. CONCLUDING REMARKS

Stern's (2005b) paper "Defining cognitive decision making processes in forecasting: a knowledge based system to generate weather graphics", presented the results of a 100-day trial which suggested that adopting a strategy of combining human and computer-generated predictions has the potential to deliver a set of forecasts that explain about 7.90% more variance than that explained by forecasts currently issued officially.

Forecast verification data from a new real-time trial, conducted on the knowledge based system (now) modified in order to mechanically combine human and computer-generated predictions and, therefore, to (now) take into account forecasters' valuable domain and contextual knowledge, was analysed.

The analysis confirmed the conclusion presented in the previous paper, showing that an extra 7.17% variance was explained (over that explained by human predictions) therefore demonstrating that a substantial increase in forecast accuracy is, indeed, achievable, were one to adopt such a strategy of combining human and computer-generated predictions.

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[18] For verification purposes, it is said that there has been a thunderstorm in the metropolitan area during a particular day when at least one of the 0300, 0600, 0900, 1200, 1500, 1800, 2100, or 2400 Melbourne CBD and/or Melbourne Airport observations include a report of cumulonimbus with an anvil and/or lightning and/or funnel cloud and/or thunder (with or without precipitation) – refer to Stern (1980).

[19] For verification purposes, it is said that there has been fog in the metropolitan area during a particular day when at least one of the 0300, 0600, 0900, 1200, 1500, 1800, 2100, or 2400 Melbourne CBD and/or Melbourne Airport observations include a report of fog (including shallow fog) and/or distant fog.

[20] There is considerable potential for an increase in accuracy of the rare weather element forecasts. From Figure 6a, it may be seen that the verification data suggests:

(1) Reducing the probability criterion under which there is a categorical reference to fog by the system from 15% to 5% (when also accompanied by *Probability of Precipitation* of 25% or less – to exclude potential drizzle situations); and,

(2) Reducing the probability criterion under which there is a categorical reference to thunderstorms by the system from 25% to 5% (when also accompanied by *Probability of Precipitation* of 50% or more);

would lift the *Critical Success Index* of the system's forecasts of these elements to 0.103 for fog, and 0.310 for thunderstorms.

That the probability criteria were set too high became apparent during the early stages of the trial, and the system was therefore modified to operate with 5% probability criteria from Day-43.

An alternative approach would be to examine the relationship between the probability criterion and the precentage profit to be gained from protecting against the occurrence of one of these rare weather elements (Personal Communication: Ross Keith). This is illustrated in Figure 6b, which suggests (for the case of the cost of protection being one fifth the financial loss suffered if the event occurs without protection) an alternative view that:

- For fog, the probability criterion should be set to 6%; and,
- For thunderstorms, the probability criterion should be set to 12%.

This substantial increase in accuracy arises because:

- In most circumstances, the combining strategy leaves the system's forecasts almost identical to the human (official) forecasts; whilst,
- In those few circumstances when the combining strategy substantially changes the human (official) forecasts, the system's forecasts usually represent an improvement on the human (official) forecasts.

There is an increasing interest in the question of what might be the appropriate future role for the human in the forecast process (Stewart, 2005).

The results presented here suggest that the future role of human forecasts may be as an input to a system that mechanically combines human predictions with computer generated forecasts.

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Acknowledgments. To Stuart Coombs, for drawing attention to the skill displayed by the NOAA Global Forecasting System (used in the trial), to Marco Berghege for his suggestion regarding the programming utilised herein, to Neville Nicholls and Frank Woodcock, for their comments on combining forecasts, to Noel Davidson, for his comments on the NWP output, and to my other Bureau of Meteorology colleagues for their helpful discussions and feedback.

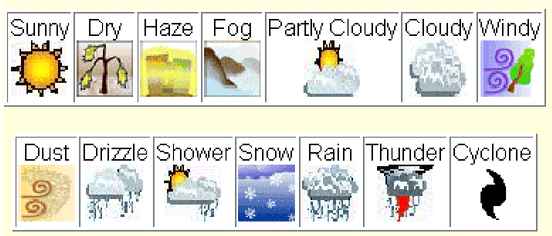

Figure 1. Stern's 2005b weather graphics.

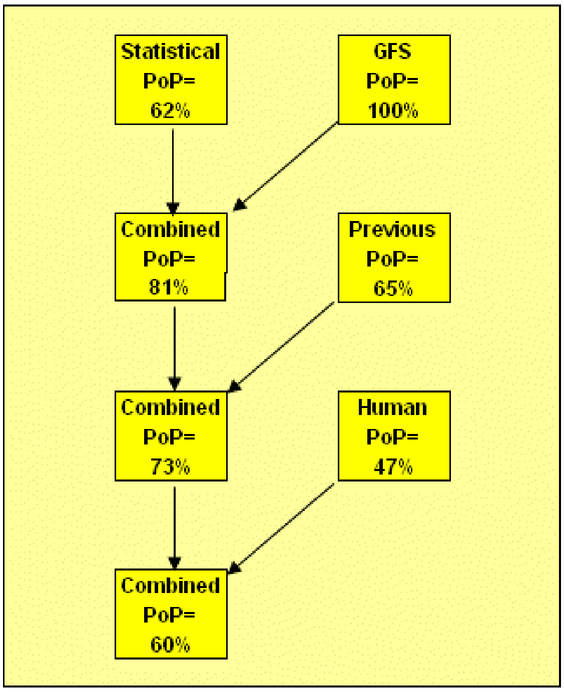

Figure 2. The process of integrating human and computer generated forecasts for *Probability of Precipitation* estimates:

- **Firstly, the estimate from a statistical model (of 62%) is averaged with the implied estimate from the NOAA Global Forecasting System (of 100%) to yield 81%;**
- **Secondly, this 81% outcome is then averaged with the previous estimate (generated 'yesterday') by the knowledge based system (of 65%) to yield 73%; and,**
- **Finally, this 73% is then averaged with the implied estimate from the human (official) forecast (of 47%) to yield 60%.**

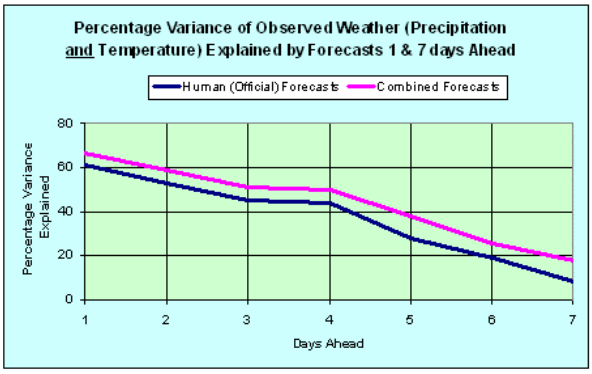

Figure 3. Overall percentage variance of the observed weather explained at different lead times.

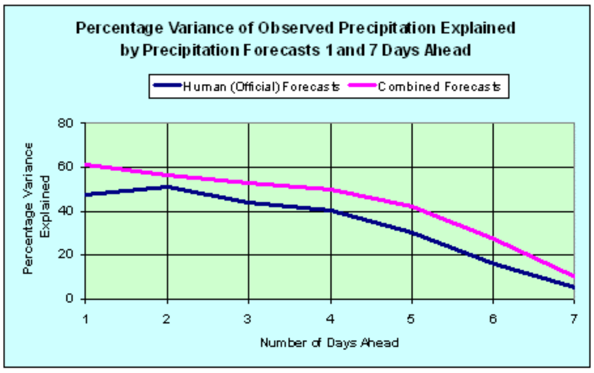

Figure 4. Overall percentage variance of the observed precipitation explained at different lead times.

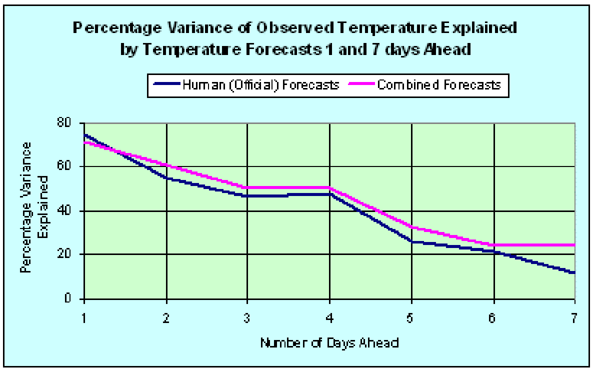

Figure 5. Overall percentage variance of the observed temperature explained at different lead times.

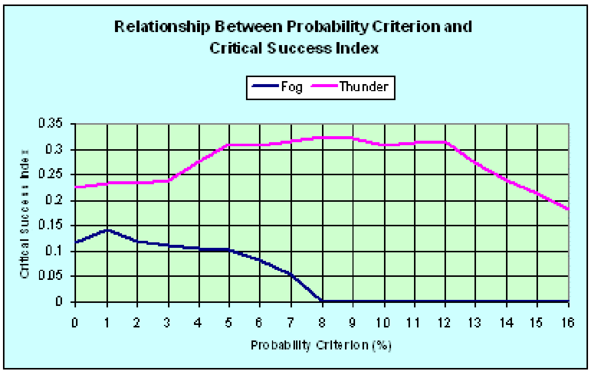

Figure 6a. Probability criterion under which there is a categorical reference to fog and thunder versus *Critical Success Index*.

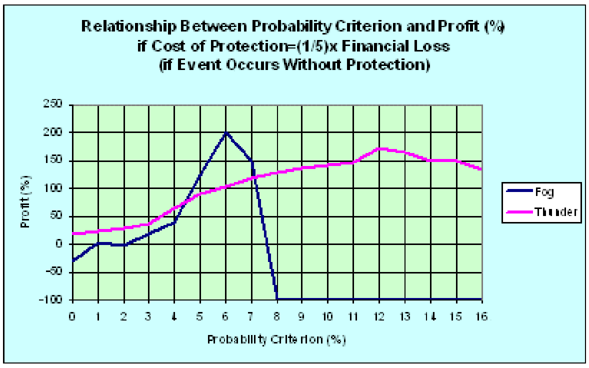

Figure 6b. Probability criterion under which there is a categorical reference to fog and thunder versus *Profit*.

Table 1 An extract of the probability (%) algorithm.

Day: Precis:	1	2	3	4	5	6	7
Sunny	1%	1%	1%	1%	3%	6%	9%
Partly Cloudy	4%	6%	9%	11%	14%	16%	19%
Cloudy	19%	20%	21%	23%	25%	26%	28%
Becoming Fine	34%	33%	34%	35%	36%	36%	37%
Few showers	49%	47%	47%	47%	46%	47%	47%
Drizzle Clearing	63%	61%	59%	58%	57%	57%	56%
Showers Clearing	78%	74%	72%	70%	68%	67%	65%
Showers	93%	88%	85%	82%	79%	77%	75%
Rain	99%	99%	97%	94%	90%	87%	84%
Heavy Rain	99%	99%	97%	94%	90%	87%	84%

Table 2 An extract of the amount (mm) algorithm.

Day: Precis:	1	2	3	4	5	6	7
Sunny	0	0	0	0	0	0	0
Partly Cloudy	0	0	0	0	0	0	0
Cloudy	0	0	0	0	0	0	0
Becoming Fine	0	0	0	0	0	0	0
Few showers	2	1	1	1	1	1	1
Drizzle Clearing	2	1	1	1	1	1	1
Showers Clearing	2	1	1	1	1	1	1
Showers	5	4	3	2	2	1	1
Rain	10	8	6	5	4	2	1
Heavy Rain	20	16	13	10	7	4	1