P1.6

THE IMPACT OF WEATHER SENSITIVITY ON THE ECONOMIC VALUE OF ENSEMBLE FORECASTS

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1. INTRODUCTION

Weather variability can have a significant economic impact, especially in weather sensitive industries. The dependence of economic quantities of interest on the weather is generally nonlinear. This nonlinear dependence makes probabilistic forecasts more valuable for rational decision making. Ensemble Prediction Systems (EPS) provide a set of numerical forecasts, which attempt to describe the range of possible outcomes. They can be used as a tool for making probabilistic forecasts. Recent studies have revealed that probabilistic forecasts based on ensemble prediction system provide more information about forecast uncertainty to those making decisions than deterministic forecasts from single model (Wilson et al., 1999; Zhu et al., 2002).

Most studies that use ensemble forecasts to make rational decisions have focused on the cost-loss binary decision making model (Richardson, 2001; Zhu et al., 2002). Smith et al. (2001) described an application of what they called the 'end-to-end approach' in forecasting weather dependent economic variables. The end-to-end ensemble forecast converts each ensemble member directly into a variable relevant to the end user to estimate the future uncertainty in the end user variable. The economic value of ensemble forecasts depends on the quality of the forecasts, and on the sensitivity of the business activity to the weather conditions. Good probabilistic forecasts may lead to better decisions and increased economic returns. However a forecast system, which generally scores well in traditional verifications, may not necessarily lead to better economic returns over time. In some cases, even a small number of inaccurate forecasts may lead to poor economic returns. Therefore, the calibration of ensemble-based probabilistic forecasts is a significant issue.

2. BUSINESS MODEL

Temperature is the most significant weather variable correlated with electricity demand. Following the method of Smith et al. (2001), This study investigated the potential value of ensemble-based probabilistic temperature forecasts to electricity retailers who purchase power from generators and supply it to consumers. We assumed an 'ideal' electricity market, in which the supplier was contracting generation 4 days ahead of delivery. We also assumed that the temperature alone determined the demand for electricity. A deterministic-linear relationship between temperature and demand, modelling the load due to heating in cooler climate, was used to convert ensemble temperature forecasts into electricity demand forecasts:

$$D = 5000 - 100\,T \quad (1)$$

Where D is electricity demand in megawatts and T is temperature in degrees Celsius.

In the electricity market, the supplier has to decide in advance the amount of electricity *(X)* to contract from generators, at a cost price *(CP).* Then the supplier sells electricity to consumers at a sell price *(SP).* However, if, during the contract period, demand *(Y)* exceeds the amount of pre-purchased power, the supplier must pay an imbalance settlement price *(ISP)* on the generation shortfall. Loss of generation capacity, for example due to unexpected plant maintenance, may lead to the imbalance settlement price greatly exceeding the cost price. Let *U (X, Y)* represent the user's utility function, the income of the electricity supplier:

$$U(X,Y) = -CP\times X + SP\times Y \qquad (Y \le X) \quad (2)$$

$$U(X,Y) = -CP\times X - ISP\times(Y - X) + SP\times Y \qquad (Y > X) \quad (3)$$

Given a probabilistic forecast *P(Y)*, then the user's expected utility for a given decision:

$$E[U](X) = \int_Y U(X,Y)P(Y)dY \quad (4)$$

Thus, the supplier can make an optimum pre-purchase choice, which maximizes the user's expected utility:

$$E[U](x) = \max_x (E[U](X)) \quad (5)$$

3. INTERPRETING ENSEMBLE FORECASTS

Two years of ensemble forecasts of midday surface temperature for locations around New Zealand and Australia were extracted from the National Centers for Environmental Prediction (NCEP) ensemble forecast system. A continuous probability function was derived from the individual ensemble members by

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fitting them with a normal distribution. The fitting of the distribution enables an improvement in ensemble probability estimates (Wilson et al.,1999). Bias in the ensemble forecasts was corrected by removing the bias found in the ensemble mean forecast from each individual member. This correction approach is more efficient than a mere subtraction from every ensemble member of the mean error averaged over all ensemble forecasts (Atger, 2003). We found that the ensemble spread among members was too narrow on average compared with that expected from model error in the study region..

We simulated the performance of an electricity supplier using different forecasts. In all simulations, the cost price (*CP)* was 1.0 per unit, the sell price (*SP*) was 1.5 per unit, and the imbalance settlement price (*ISP)* ranged from 1 to 40 times the cost price. The different forecasts used to produce electricity demand forecasts were as follows:

(1) Climatology: This study used a 14-day moving average as our climatology. The active forecast strategies were compared against this baseline. Since the climatology was calculated directly from the observations used in this study, the benchmark is higher than a traditional 30-year historical climatology.

(2) Deterministic forecasts: The ensemble high-resolution control member forecasts from 0000 UTC were taken as an example of a single model forecast.

(3) Raw ensemble probabilistic forecasts: All members of the NCEP ensemble forecasts of temperature were converted into a probability distribution function by fitting them with a normal distribution.

(4) Bias-corrected ensemble probabilistic forecasts: The bias corrected ensemble members were converted into a probability distribution function by fitting them with a normal distribution.

(5) Calibrated ensemble probabilistic forecasts: Three methods were tried for correcting ensemble mean and adjusting ensemble spread in order to produce a calibrated probability distribution function.

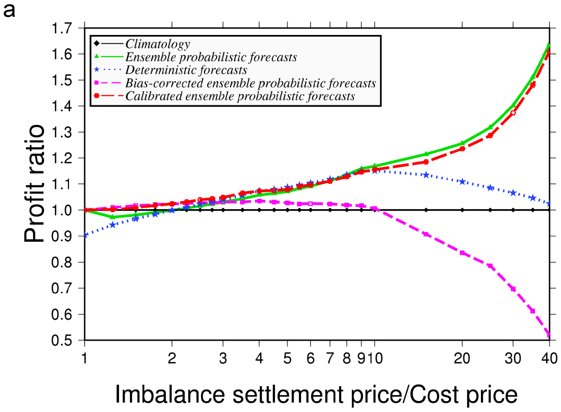
4. RESULTS AND DISCUSSION

To illustrate the profit calculated of the different forecasts, firstly the results for a supplier in Wellington (Figure 1) were considered. Each line shows the ratio of the average profit using the different forecasts relative to the value based on climatology.

4.1 Deterministic forecasts

Treating the ensemble high-resolution control forecasts as deterministic forecasts, shown as a dotted line in Figure 1a, resulted in smaller profits in our idealized model than raw ensemble probabilistic forecasts. This happened particularly at small and large imbalance settlement prices. This is because the single valued forecasting did not allow consideration of alternative scenarios, some of which may greatly affect profit. Dressing the single forecasts with historical errors to produce probabilistic forecasts (not shown) helped somewhat, but results were no better than the raw ensemble probabilistic forecasts or calibrated ensemble probabilistic forecasts.

a



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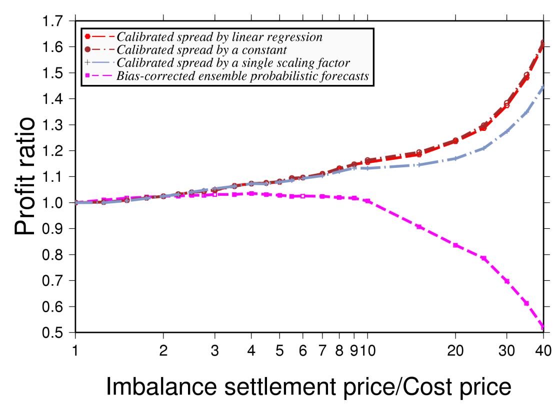

Figure 1: The profits calculated for an electricity supplier with different demand forecasts, relative to climatological demand forecasts for Wellington. This evaluation of electricity demand forecasts was based on NCEP Day 4 different ensemble forecasts for the period July 2002 to February 2004. (a) is the comparison of types of forecasts. (b) is the comparison of calibration techniques.

4.2 Raw ensemble-based probabilistic forecasts

Raw ensemble probabilistic forecasts from NCEP, shown by a solid line in Figure 1a, provided a significant improvement over climatology, particularly at high imbalance settlement prices. This is believed to be partly due to the information about the probability distribution, which allows the supplier to optimize decision making by pre-purchasing an appropriate amount of power. However the cold bias of forecasts at Wellington was a more important factor. In terms of the business model a forecast that is consistently a little too cold equates to ‘playing it safe’. By erring on the cold side the chance of not pre-purchasing enough power, and therefore incurring a large penalty, is reduced. The higher the imbalance settlement prices the more advantage from a cold bias.

In the real electricity market, the very high imbalance settlement price happens rarely. The imbalance settlement price in general is about two times the cost price. In this situation, the absolute penalty is small. Pre-purchasing more power in response to the cold bias would lead to a loss. Therefore, raw ensemble probabilistic forecasts slightly underperformed climatology at low imbalance settlement prices.

4.3 Bias correction of ensemble probabilistic forecasts

The use of bias-corrected ensemble forecasts, shown by a dashed line in Figures 1a and 1b, was problematic. Bias-corrected ensemble forecasts could only provide an improvement where the ratio of imbalance settlement price to cost price was less than two. However, as the imbalance settlement price increased, bias correction became the worst performing of all forecasts. Since the penalty function is not symmetric, a conservative approach is to err on the side of a cooler forecast. However, at Wellington, bias correction acted to produce warmer forecasts and ensemble spread underestimates the uncertainty. Therefore, the penalty overrode the benefits of the bias correction when a colder than expected temperature was observed. The absolute penalty was small at a small imbalance settlement price. However, the more the imbalance settlement price increased, the greater the penalty became. In this situation, even a small number of inaccurate forecasts may lead to heavy losses. This means that electricity demand forecasts are sensitive to the cold temperature forecasts in cold bias locations. It is clear that simply bias correcting the ensemble mean but not adjusting ensemble spread can lead to significant problems.

4.4 Calibration of ensemble-based temperature probabilistic forecasts

We used the following three methods to calibrate ensemble probabilistic forecasts by adjusting for insufficient ensemble spread:

(1) Adjusting ensemble spread by a constant: Using the standard deviation of ensemble forecast error to replace ensemble spread.
(2) Adjusting ensemble spread by a single scaling factor: Multiplying by a seasonal average ratio of ensemble forecast errors to ensemble spread.
(3) Adjusting ensemble spread by regression: Using a linear regression to adjust ensemble spread by taking into account the correlation between ensemble spread and the standard deviation of previous ensemble forecast errors.

Comparing their performance with the electricity demand forecasts, the results for Wellington are shown in Figure 1b. Our findings supported Jewson et al.'s (2003) study, which showed that the regression method did indeed outperform the other two simple methods, although using historical errors to adjust the ensemble spread gave virtually the same results (see Figure 1b). The regression method calibrated both the mean level of uncertainty and the amplitude of the variability of uncertainty. Even though the ensemble spread does contain some information about the uncertainty, we found that the variations of the uncertainty were so small that the amount of information did not make a major difference compared to adjusting spread by a constant historic error. In other words, the commonly assumed relationship between spread and skill was extremely weak.

Probabilistic forecasts for Wellington, based on corrected ensemble mean and adjusted ensemble spread, shown by a long dashed line in Figure 1a, led to a marginal improvement over bias-corrected ensemble probabilistic forecasts at lower imbalance settlement prices, and became increasingly valuable as the imbalance settlement price increased. This method outperformed or came close to raw ensemble probabilistic forecasts at large imbalance settlement prices. This is because the entire distribution of future temperatures is estimated as an optimal combination of information from the ensemble and previous errors.

4.5 Results for New Zealand and Australia

Results for six other cities in New Zealand and Australia are shown in Figure 2. NCEP ensemble probabilistic forecasts performed better than deterministic forecasts from single model at all locations. However, raw ensemble probabilistic forecasts slightly underperformed climatology where the ratio of imbalance settlement price to cost price was less than about three. In this situation, calibrated ensemble probabilistic forecasts provided an improvement, and bias correction was also useful.

As the imbalance settlement price increased, using raw ensemble probabilistic forecasts gave the best, or close to the best results at most locations. Taupo was a notable exception. Significantly, the bias at Taupo was warm, while at all the others it was near zero or negative. Uncorrected warm forecasts at Taupo led to the need to buy extra electricity at the higher imbalance settlement prices more often. Bias correction helped significantly at all imbalance settlement prices, and calibrating ensemble probabilistic forecasts added real value at higher imbalance settlement prices.

The single most useful method, taken across all stations and recognising the increased likelihood of low valued imbalance settlement price, was ensemble probabilistic forecasts calibrated with a linear regression between ensemble spread and the standard deviation of previous ensemble forecast errors.

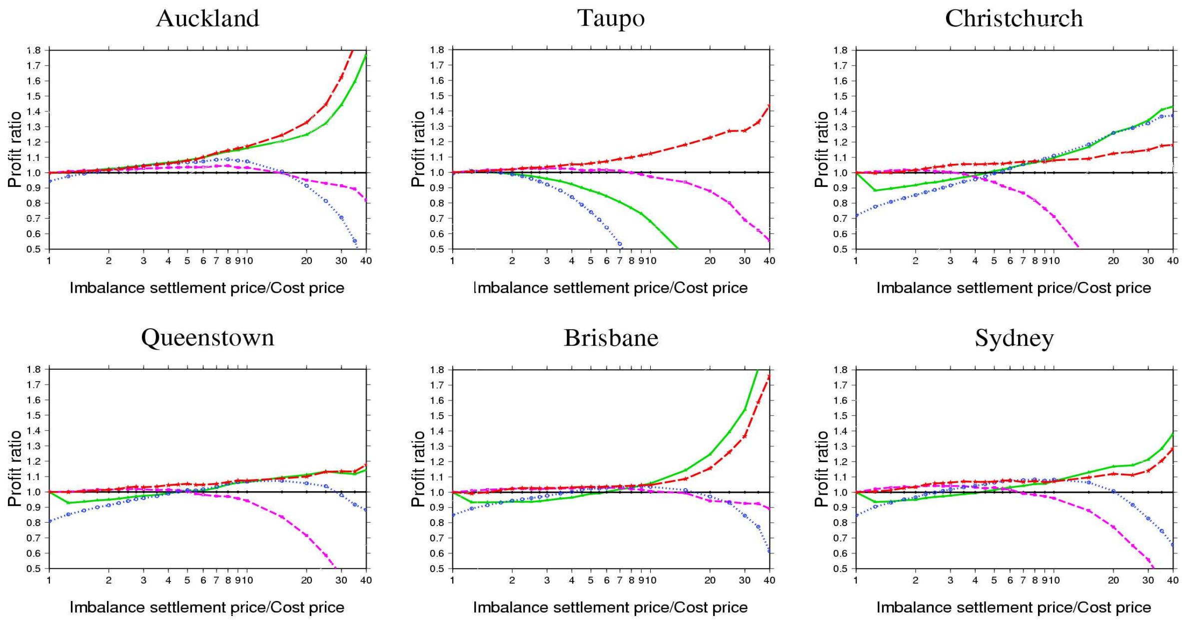

Figure 2: The profits calculated for an electricity supplier based on NCEP Day 4 different electricity demand forecasts, relative to climatological demand forecasts for six locations in New Zealand and Australia. The results were averaged over the period July 2002 to February 2004. The legends are the same as Figure 1a.

5. CONCLUSION

Ensemble-based probabilistic forecasts have been shown to be useful in an idealized electricity market model. Bias correction, while helpful to traditional verification of weather forecasts, does not guarantee a significant improvement in economic returns if the profits are non-linearly related to the weather variables. In the model we considered, the penalty for over-estimating the temperature was greater than for under-estimating. The skill of business demand forecasts is sensitive to the ensemble spread. Calibration of ensemble-based probabilistic forecasts is a significant issue and needs to consider both correction of ensemble mean and adjustment of ensemble spread. Calibrated ensemble probabilistic forecasts were the best of all forecasts by a small margin, and improved business demand forecasts in our simple model. However, the improvement was not as large as expected at high imbalance settlement prices. The quality of the weather dependent economic variable forecasts depends on the quality of the weather forecasts, the business model relating weather to the relevant economic variables, and the user's utility function.

In the study, the business models relating temperature to electricity demand were idealized. In practice the relationship between temperature and electricity demand would be more complicated. It is necessary in further study to develop methods to address the uncertainties in both the ensemble forecast system and the business model to improve the economic variable forecasts. In addition, future studies could consider employing ensemble multi-models to increase the ensemble size in order to produce further improvements, particularly in boosting the spread skill relationship.

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