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Modelling Approaches to Enhance the Quality of Forecasting Processes

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Abstract

The purpose of this paper is to put forward an insight into a mathematical model proposed in concept with the hope that both academicians and practitioners will progress in achieving forecast accuracy. The model explains the use of probability distribution against point forecasts, the cost function and fundamentals of Bayesian methodology in approach.

Previous observations through pilot study, postal survey, case study and a follow-up survey form a basis in formulating the mathematical model explained. In writing this paper, we attempt to give explanations for and cost effects of imperfect forecasts, an oversight which frequently occurs to management.

Keywords: forecasting management, mathematical model, forecasting process, quality, Bayesian Model, cost function.

I. INTRODUCTION

This paper extends the findings of a postal survey and case study on practices and perceptions of forecasting [1], which addresses modelling issues for forecasting scenarios. Its intention is to raise awareness of various modelling approaches that can be used to enhance the quality of forecasting processes, rather than to identify specific models, which tend to be user-specific.

It has been noted that organisations make forecasts and that forecasting accurately is rarely achieved. As many business decisions involve forecasting, successful forecasting practice is crucial to reduce or close the gaps in this process [2]; [3]. This failure is due to the behaviour of forecasters. Three reasons are offered here, namely, the process of interpreting data, forecaster bias and forecaster preferences [4].

Using a Bayesian approach to understand and interpret the above, subjective probabilities for the likelihood of an event are elicited and revised as new information is received. In support of this approach, there is also a need to emphasise to consider the individual's role in the forecasting process [4].

Observing the practice, and learning about the perceptions, of forecasting from the study samples are not complete if the practice and perceptions are not represented by models.

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Ultimately, an organisation or a unit could forecasts for profits, sales, investments, cash flow surplus, student numbers, teaching loads and other resources using such models and, depending on the nature of its activities.

Forecasts are prepared based on estimates, which, in practice, correspond with point predictions. Typically, a single estimate is obtained as a result of group decision-making in predicting future performance. This group decision-making is done through members offering their expert opinions with regard to a particular issue.

Forecasts are said to be imperfect when actual performances do not turn out as predicted. This paper offers some mathematical modelling and consideration of cost implications for this forecasting scenario [5]; [6]; [7].

II. THE ISSUE OF MODELLING

How and why modelling comes into play for forecasting functions in commercial and service industries were highlighted in the literature [1]; [4]; [9]. One particular situation identified is where the reactions of the forecasting team towards a set of available information can affect the initial forecast predictions, which are usually inaccurate.

A case study observation was conducted that uses Fisher's exact test to delineate significant associations in order to identify important variables [7]. We observe the weakness in estimating forecasts using single point predictions, and our study should offer possible and reliable solutions to overcome this weakness. What interests us are issues relating to the outcome of the forecasting teamwork and what forecast estimates are involved. Three parts contribute to our analysis, namely:

1) mathematical modelling involving establishing a suitable probability distribution and loss function in order to apply Bayesian decision theory;
2) cost implications with respect to imperfect forecasts;
3) differential equations involving rates of change among variables, to describe and explain the underlying structural behaviour.

III. BAYESIAN APPROACH FOR ENHANCING POINT PREDICTIONS

From the investigations carried out, we observed that targets or single point predictions determined by an organisation, or particular unit within an organisation, become the platform towards which actual performances are inclined [10]. Even at the setting stage of targets and forecasts, the process of decision-making can be demanding to ensure crucial factors are not excluded. Single point predictions also add to the mood and motivation of people involved with the forecasts, be they preparers or users. These single point predictions do not allow for variations in case the outcomes of the actual performances turn out different from planned due to uncontrollable factors. Once the actual results are noted, the management will look back at their forecasts to identify what and why are the differences. By looking at just one figure, any deviation may incur costs and thereafter affect the people involved.

A previous study indicated that an essential aspect of decision-making involves consulting experts, who usually give differing opinions of information [7]; [8]. A considerable volume of literature is available to provide solutions addressing this problem. It is recommended that expert opinions be treated as data for further analysis in arriving at more reliable point predictions. In this analytical part of the research, three aspects of modelling, namely a probability distribution, cost function and Bayesian decision analysis are described.

Probability Distribution

At a university in United Kingdom, the current forecasting situation is that point predictions are prepared and then passed on to users [1]. As these are invariably inaccurate, we regard this as a flaw and now propose that forecasts should consist of probability distributions rather than point predictions to allow for this in accuracy. Our emphasis is on the outcome from the interaction of people, not only on the results achieved. We believe that there must be a build up of managerial structures and communication networks to increase and improve stability in the forecasting function. On the basis of extensions to the central limit theorem, the normal distribution is deemed appropriate here. This choice is supported by general theory relating to the laws of error [11].

Adopting the normal distribution, we assume $X|\mu,\sigma \sim N(\mu,\sigma^2)$ where X is the actual profit, which is an unknown random variable at the time of preparing a forecast, $\mu = \hat{x}$ is a point forecast for the value of X and σ is the standard deviation which measures the uncertainty of our point forecast.

The benefits of establishing variations from point predictions and assigning normal distributions to these point predictions are now given. Firstly, as forecast accuracy is unexpected, the variation will improve motivation and drive. As such, management is better prepared in all kinds of possible situations and this does not affect forecasters' capability as a measure of improving the accuracy of forecasts.

Cost Function

The element of costs is introduced and illustrated here as funding and money are important sources of running the business. When actual performance conflicts against forecasts, there is a loss involved and this results in a cost to the organisation [10]. This aspect of loss may take the form of functional relationships which, in their simplest but most common form, are bilinear. The following illustration explains this situation:

Let the forecast be $\hat{x}$ and the actual be x; when the actual conflicts with the forecast, there is a difference and an element of cost is involved. Therefore, for example,

if $\hat{x}$ = RM1000; x = RM500	cost is 5 units
if break-even i.e. $\hat{x}$ = RM1000 and x = RM1000	cost is 0 units
if $\hat{x}$ = RM1000; x = RM1200	cost is 2 units or less

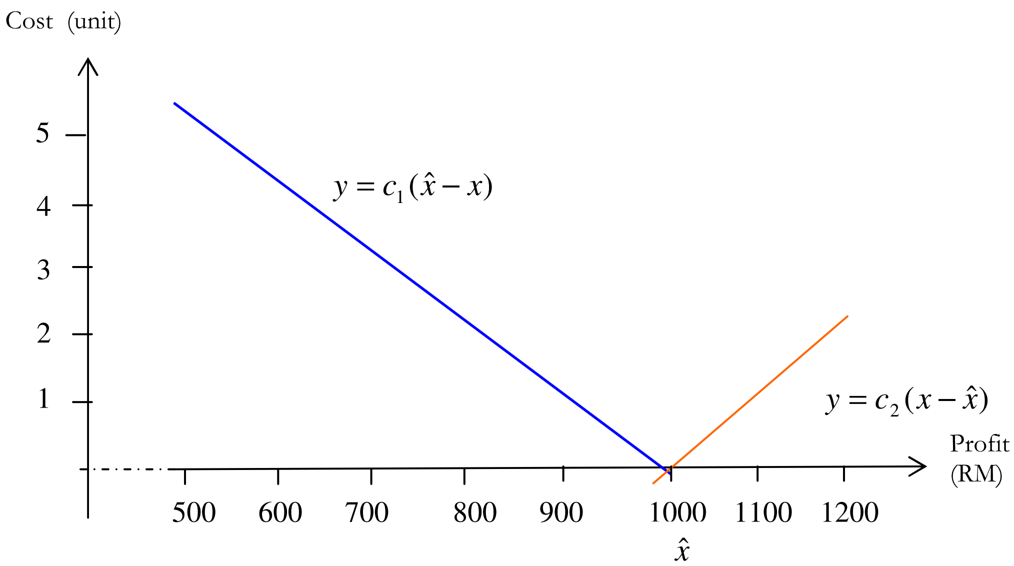
Figure 1 shows a graph depicting the above effects. We measure cost in units to indicate that the costs involved are not just monetary, but include time and effort wasted. Therefore, a measurement for these must be devised collectively by the people involved. This may mean that the cost involved is less when actual is more than forecast rather than when actual is less than forecast. This difference may be due to intangibles and may represent the hidden costs. As long as the difference between actual and forecast results is material, further breakdown of the costs involved must be scrutinised and addressed to find solutions to improve future forecasts. For example, when $\hat{x}$ = RM1000 and x = RM500, this is a situation of over-forecasting. Among the consequences of this condition are:

1) employees will be demotivated as their high expectation of the company to perform is diminished. As a result, this might lead to a high turnover of employees;
2) resources will be over-utilised as unrealised provisions are used;
3) the reliability of forecasts will be in question;.
4) the forecasting exercise will not be cost-effective.

Similarly, when $\hat{x}$ = RM1000 and x = RM1200, this is a situation of under-forecasting. The consequences of this condition are:

1) under-utilisation of resources;
2) potential investments will be withdrawn;
3) doubts about the reliability and cost effectiveness and cost-effectiveness of forecasting will arise.

Figure 1
Graph showing the cost of under- and over-forecast of profits



Bayesian Methodology

The classical, or frequentist, approach to estimation corresponds here to the generation of point predictions enhanced by prediction intervals, though managerial decisions are usually based on the point predictions only. Regarding the observed profit as arising from a normal distribution, however one can establish a subjective predictive distribution by looking at the chances or likelihoods of achieving various targets away from this point prediction. This variation provides an indication of how the actual outcome evolves around its forecast. This explains and allows for the differences between the actual and forecast values.

For example, we might present forecasts in terms of relative likelihoods like this: it is twice as likely to achieve a profit of RM10,000 than a profit of RM15,000. Better still, we could present quantiles or even the full distribution for profit. Bayesian decision theory allows distributions of predictions to model possible departures from point forecasts like this to make sure that the uncertainty of achieving them is considered. This uncertainty is here expressed using a normal distribution of relative likelihoods for the probability density function of profits. As for any density, the area under the normal curve is one. For a simplified analysis, one could consider a two-phased outcome, or binary response, so that if there is two-thirds of a chance that the profit is at least RM10,000, then the chance of not making that amount of profit is one third. This enhances the quality of forecasts but ignores system feedback, which we consider shortly.

The distribution for the variation of profits can be obtained in two ways: subjectively or objectively. For example, we might establish a normal distribution with associated loss function objectively. Using an ARIMA model requires no subjective devising, revising and adjusting. At this point, the expected cost of a poor forecast can be calculated. If profits are more than RM2500, for example, the cost involved is proportional to the difference between the point prediction and the actual profit achieved.

Applying the recommendation given by [9], the mathematical functions involved in this modelling of imperfect forecasts take the following forms for this application, where $\hat{x}$ is a point prediction and x is the actual profit:

1. Normal distribution function for profits

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} ; -\infty < x < \infty \qquad (1)$$

2. Cost function for this application is the bilinear form

$$\text{where } c(x) = \begin{cases} c_1(\mu - x); x < \mu \\ c_2(x-\mu); x > \mu \end{cases} \qquad (2)$$

which is illustrated in Figure 1.

This means that there is a cost involved when the actual profit is more or less than the forecast profit. This cost refers to the cost associated with imperfect forecasting. The costs in this study may include time, effort wasted, opportunity loss, penalty loss, and also not being able to invest in fixed assets, projects and profitable contracts.

Then, decision analysis is based on minimising the expected cost

$$E(c(X)) = \int_{-\infty}^{\infty} c(x) f(x) dx$$

$$= \int_{-\infty}^{\mu} c_1(\mu - x) \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} dx + \int_{\mu}^{\infty} c_2(x-\mu) \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} dx \quad (3)$$

The loss function $c(x)$ can be bilinear, as in our analysis, or of some other unspecified form. The bilinear cost function shows a proportionate increase in cost with the difference between actual and forecast performances. This is true for both sides of the relationship, $x > \mu$ and $\mu > x$. However, it does not assume symmetry unless $c_1 = c_2$ above.

To evaluate equation (3), we make the substitution

$$y = \left(\frac{x-\mu}{\sigma}\right)^2 \Rightarrow dy = \frac{2}{\sigma^2}(x-\mu)\ dx \quad (4)$$

in both integrals, so that

$$E\{c(X)\} = \int_{\infty}^{0} -c_1 \frac{\sigma^2}{2} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{y}{2}}\ dy + \int_{0}^{\infty} c_2 \frac{\sigma^2}{2} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{y}{2}}\ dy$$

$$= \frac{(c_1+c_2)\sigma}{2\sqrt{2\pi}} \int_0^{\infty} e^{-\frac{y}{2}}\ dy$$

$$= \frac{(c_1+c_2)\sigma}{2\sqrt{2\pi}} \left[-2e^{-\frac{y}{2}}\right]_0^{\infty}$$

$$= \frac{(c_1+c_2)\sigma}{\sqrt{2\pi}} \quad (5)$$

$$\text{where } c(x) = \begin{cases} c_1(\mu-x); x<\mu \\ c_2(x-\mu); x>\mu \end{cases} \quad \text{and} \quad X|\ \mu,\sigma \sim N(\mu,\sigma^2) \quad (6)$$

This clearly illustrates how, under the assumption of a normal distribution and bilinear loss function, the expected cost of inaccurate forecasting is directly proportional to the standard deviation of the predictive distribution.

Since forecasting considers the future, which is usually unpredictable, any incidences of unexpected outcomes should be precautioned and any remedial actions should be recommended. These initiatives are taken so that organisations will be ready to face the future. Any strong form of information, available at the last minute, may force the organisation to change forecasts abruptly. It is at this point that top management intervenes to allow forecasts to reflect reality. As events like this may be difficult to measure, the use of modelling will be a helpful support tool for guiding calculations.

IV. EXPLANATIONS FOR AND COST EFFECTS OF IMPERFECT FORECASTS

To explain the cost implications of imperfect forecasts, we now consider these in the context of service industries. There are various indicators that can be used to measure performance, such as patients per day for hospitals, customers per hour of service utilities and passengers per destination for the flight industry, to name a few. In our case, we consider the university scenario in terms of student numbers as a performance measure. If the actual number of students is more than the forecast number of students, there is a need for extra logistics, including space, rooms, lecturers, time-tabling, accommodation, computer facilities and administration. The quality of teaching and success of graduates might be compromised because of mass production. There will be more drop-outs and a higher failure rate which will affect the image of the university.

While universities commit themselves to provide facilities for the extra students, it may be for the short-term only. There will be insufficient budget available to sustain over-capacity as a result of inefficiency on the part of management not being able to forecast and cater for extra students.

However, if the actual number of students is less than the forecast number, these results in under-capacity, as facilities are under-utilised or idle. The university over-pays the lecturers in terms of salary per student and so the marginal cost per student is higher.

The whole idea of this modelling is to arrive at not just effective and efficient solutions to account for and minimise the total loss, but also to be aware of situations and consequences arising from inaccurate forecasting.

V. CONCLUSION

Modelling in our case attempts to describe the mechanism of relationships between variables that operate in practice; an extension we offer to integrate with management accounting. In demarking the selected variables, we use the law of parsimony or Occam's Razor in that the model includes only required and important variables and does not include all reasonable predictor variables automatically. It should also be noted that parsimony is a principle in science where the simplest answer is always preferred.

Several aspects constitute the modelling process. We first saw how single point estimates or predictions can be improved by assigning probability distributions to describe variations that may be possible, hence increasing the reliability and credibility of the forecasts. Then, we saw the measure of loss functions as a result of imperfect forecasts and how it can be quantified, using Bayesian decision theory, according to whether actual results are less than forecast or vice-versa [2]; [4]; [7].

The effects of imperfect forecasts were also explained for both service industries, and manufacturing and trading industries. The cost factor came in as a break-even analysis and differential equations were introduced to render the whole modelling aspect complete. They give a clearer perspective of empirical evidence cultured with mathematics and functional relationships objectively. It can be seen that outcomes of improved teamwork and decision making, for example, are related in this way.

Last but not least, in order to get a total picture of the whole research implication onto practice, future study to reflect impact is recommended.

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