# COMMENTS ON TRENDING METHODS IN AUTOMOBILE INSURANCE RATEMAKING

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## 1. Introduction

In automobile insurance ratemaking, it is necessary to predict what future loss costs per policy will be two to three years beyond the last available data. This paper discusses some methodological questions which arose in connection with ratemaking for the province of New Brunswick. However, the issues are of general importance, and the discussion is relevant to many other situations where costs are to be predicted from historical records.

Automobile insurance rates in New Brunswick require the approval of the Board of Commissioners of Public Utilities of that province. Standard No. 1, issued by the Board in 1978, sets out requirements for methods used to predict future loss costs in rate filings. In particular, Standard No. 1 stipulates that at least ten years' data must be used in trending, and it has been interpreted as requiring that $r^2$, the coefficient of determination, must be at least 0.67 for any trend line used.

Private passenger benchmark rates were published by the Board in November 1981. Individual insurers now have the option of adopting these benchmark rates plus or minus an allowed percentage. In computing benchmark rates, various polynomial models were fitted to the historical data, and a particular model was selected on the basis of statistical tests. The projected loss cost from the model was then subjected to a cyclical adjustment of the sort proposed by McGuinness (1968).

One major difficulty with both Standard No. 1 and the benchmark rate calculations is that they fail to distinguish between model fitting and prediction. An example involving polynomial models is used in Section 2 to show that these two problems are quite different. In Section 3 it is argued that, because of their dramatic tail behaviour and sensitivity to small changes in the historical data, high-degree polynomial models are not a suitable basis for prediction.

The effect of changing the amount of data used for trending is considered in Section 4. It is found that, depending upon the methodology, insistence upon the use of a long data series in trending may cause increased prediction errors. Section 5 contains some observations on the method of cyclical adjustment used in the benchmark rate calculations. A summary and some general recommendations on cost trending are given in Section 6.

## 2. Model fitting versus prediction

Loss costs for New Brunswick private passenger collision insurance (1971-80) are given in Table 1 and are plotted versus year in Figure 1. On the basis of these data, we wish to predict what the loss cost will be for this coverage two or three years in the future.

One approach that might be taken is to seek a model which gives a good fit to the historical data, and then extrapolate to obtain the desired future value. It is clear from Figure 1 that a straight line model does not fit the data well, and that some more general model is needed. Thus we might consider polynomial models of the form

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \ldots + \beta_p x^p$$

where $y$ is the loss cost and $x$ is the year. For any $p \leq 9$, estimates $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_p$ can be found by the method of least squares, and fitted values

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x + \hat{\beta}_2 x^2 + \ldots + \hat{\beta}_p x^p$$

can be computed by substituting $x = 1971, 1972, \ldots$ . Table 1 gives the fitted values for years 1971-83 for polynomials of degrees $p = 1, 2, \ldots, 5$. The fitted polynomials are graphed in Figure 1. The 5th degree curve passes very close to all ten data points, and this portion of the curve has been omitted to simplify the diagram.

Two measures commonly examined in assessing the goodness of fit of a model are the estimated variance about the model

$$s^2 = \frac{1}{9-p} \Sigma (y-\hat{y})^2$$

and the coefficient of determination

$$r^2 = 1 - \frac{\Sigma(y-\hat{y})^2}{\Sigma(y-\bar{y})^2}; \quad \bar{y} = \frac{\Sigma y}{n}$$

where the sums are taken over years 1971-80. The values of $s$ and $r^2$ are given in Table 1 for each of the five polynomial models.

Note the very large differences in predicted values for 1981-3 from the five models. If the model is to be used for prediction, it is extremely important that $p$, the degree of the polynomial, be correctly chosen.

How is $p$ to be determined? One approach is to use standard statistical methods (significance tests and residual plots) to find the simplest model which gives a satisfactory fit to the data. Here the fit of the 5th degree polynomial is satisfactory. The residuals $y-\hat{y}$ from this model show no obvious patterns, and the estimated variance $s^2$ is smaller than for a polynomial of degree 6 or 7. A standard t-test (or F-test) shows that the coefficient of $x^5$ is significantly different from zero, and hence the model cannot be simplified without significantly worsening the fit. Thus, from a model-fitting point of view, a polynomial model of degree 5 looks like a reasonable choice.

The 5th degree polynomial gives an excellent fit to the historical data, the largest difference between observed and fitted values being $0.82 for 1978. Can we expect a similar degree of accuracy if we use this model to predict future costs? Clearly not, for as Table 1 shows, the predicted loss cost is actually negative for 1983!

Although the model gives a good fit to the historical data and seems to be the one indicated by statistical tests, the predictions based on it are unacceptable.

This is an extreme example, and surely no-one would attempt to make predictions from a 5th degree polynomial fitted to ten years' data. Nevertheless, it illustrates an important point: a model which gives a good fit to the historical data may give very bad predictions. One cannot judge how accurate predictions will be by comparing fitted values with previous loss costs.

The implication of this is that statistical methods for curve fitting cannot be relied upon to identify suitable models to use for prediction. Measures such as the estimated variance about the model and the coefficient of determination reflect only the goodness of fit of the model to the historical data, not the likely errors in prediction based on the model. In fact, the models for which $s$ is smallest and $r^2$ is largest may well produce the largest prediction errors.

The most important requirement of any prediction methodology is that it should produce accurate predictions. Prediction methods cannot be evaluated merely by examining the goodness of fit of models to the historical data. What we need to do is to apply the prediction method to actual series of data, and thus to determine how well it would have performed if used in past years.

3. Polynomial Models

Polynomial models were used in the preceding section to describe a series of data for which a straight line model appeared inadequate. Such models can produce a much better fit to the historical data, but as we have seen, this does not guarantee more accurate predictions. In this section we shall argue that polynomial models should not be used for prediction because of their lack of stability.

When $x$ is large, a polynomial is dominated by its highest-order term $\beta_p x^p$, and this term changes very rapidly with $x$ when $p$ is large. As Figure 1 shows, predicted loss costs may increase or decrease dramatically as $x$ increases beyond the last data point. Year-to-year changes in predicted loss costs are much greater than the year-to-year changes in historical loss costs.

Another difficulty with polynomial models is that slight changes in the historical loss costs can produce large changes in predicted future costs. To see this, we consider the way in which historical loss costs enter into the calculation of future loss costs. It can be shown that each fitted or predicted value $\hat{y}$ can be expressed as a linear combination of the historical loss costs,

$$\hat{y} = \Sigma m_i y_i$$

where $\Sigma m_i = 1$. The multiplier $m_i$ is the amount by which $y_i$ would change if the historical loss cost $y_i$ were increased by \$1.00. The $m_i$'s depend upon the degree of the polynomial, the number of years' data used in fitting the model, and the year for which the fitted value $\hat{y}$ is to be calculated.

Table 2 gives the multipliers $m_i$ for predictions two years ahead when the model is fitted to ten years' data. From these we may obtain the fitted values given previously for 1982. For instance, for $p = 2$ we obtain

$$\hat{y} = .52 \times 45.13 + .08 \times 51.71 - .23 \times 60.17 - + \ldots + 1.23 \times 115.19$$
$$= 137.96 \quad \text{(apart from roundoff error).}$$

If the 1971 loss cost \$45.13 is replaced by \$46.13, the predicted cost for 1982 decreases by \$0.25 for the straight line model, increases by \$0.52 for $p = 2$, decreases by \$0.95 for $p = 3$, and so on.

Note how the multipliers increase in magnitude as $p$ increases. For a 5th degree polynomial, an increase of \$1.00 in the loss cost for 1979 - a change that would be barely noticeable in Figure 1 - would produce a decrease of \$12.52 in the predicted value for 1982. Perhaps even more disturbing is the extent to which predictions for 1982 depend on the two earliest loss costs used. Small changes in the positions of the points for 1971 and 1972 in Figure 1 can lead to very substantial changes in the shapes of the curves fitted, and hence in the predicted values for 1982.

Only 10 years' data were used to fit the models in the example considered. The same points could have been illustrated using 20 or 30 years' data, although the effects would have been less pronounced. It is still true that small changes in historical loss costs, even in the earliest values used, can produce substantial changes in the predicted values. The early values have a big influence on the shape of the fitted curve, and hence they have a large effect on the predictions obtained by extrapolation.

In general, the higher the degree of the polynomial, the greater its instability. As $p$ increases, the model becomes more and more sensitive to small changes in the data, and the tail behaviour becomes more and more extreme. Because of this, high-degree polynomials are not suitable as a basis for prediction.

The multipliers in Table 2 show that even straight lines and quadratic polynomial models have an undesirable property. Intuitively, we feel that the most recent loss costs are the most relevant, and that the influence of historical values on the prediction should steadily decrease as we move back in time. However, with models of this type, the earliest values have a larger influence on predictions than do some of the more recent loss costs.

## 4. Comparison of Trend Periods

The trend period $k$ is the number of years' data used in fitting the model upon which predictions are based. It is sometimes assumed that more data must be better, and that hence $k$ should be chosen as large as possible. For instance, in [2] (pages 3-4) we find the following paragraph:

"Another fact that is slowly finding recognition in insurance is the reason for economic statisticians' insistence that a trend projection be based on a truly long-term series of data. The abrupt change in slope that substitution of the latest year's datum for the oldest year's datum can make in a five-year projection line is extremely great, particularly at the end of a cycle. Even a ten-year projection line is subject to a relatively large shift from one year to the next. By contrast, a trend line based on thirty or forty years' data will change only moderately from the addition of another year's datum, no matter how much it differs from the previous year's figure. As the longer-term data build up, the ratemaker gets a continually better perspective on the shape of the actual trend and also of any cycles and other movements in the data. Ratemaking projections are bound to improve as these facts achieve wider understanding and acceptance among insurance people."

Similarly, it is claimed in [3] (page 206) that

"Ten years' data are mandatory as a minimum for reasonably reliable results, and in many cases will not suffice."

And in [1] we find the requirement that at least ten years' data are to be used in fitting curves and in calculating correlations for trending and any other purposes for rate filings in the province of New Brunswick.

To investigate the effect of varying the trend period k, we consider the loss cost data for New Brunswick private passenger liability insurance from 1947-80 as presented in Exhibit 1 of [2]. The values for 1960-80, rounded to the nearest dollar, are given in the second column of Table 3 and are plotted against time in Figure 2. All 34 values were used without rounding in the calculations to be described.

The third column of Table 3 shows the predictions obtained from a straight line fitted to only four years' data. For instance, a straight line fitted to the data for 1965-8 gives the prediction for 1970, and a new line fitted to the data for 1966-9 gives the prediction for 1971.

The fourth column of Table 3 shows the predictions obtained from a straight line fitted to all prior data. Here the prediction for 1970 comes from a straight line fitted to the data for 1947-68, and that for 1971 comes from a line fitted to the data for 1947-69. Columns 5,6,7, and 8 were obtained in the same way as column 4 except that polynomials of degrees 2,3,4 and 5 were used in place of a straight line. The amount of data used increases from 12 years for the 1960 prediction to 34 years for the 1982 prediction.

The promised advantages of longer trend periods are not apparent from Table 3 or Figure 2. None of the procedures using all available data does consistently better than the four-year trend line. A straight line fitted to all available data reacts so slowly to changing costs that predictions taken from it are consistently low. Predictions from high-degree polynomial models fitted to all the available data are just as volatile as those from a four-year trend line.

A 4th degree polynomial model fitted to all the data was used for benchmark rate calculations, and the following explanatory comment appears in [2] (page PL1):

> "After considerable testing, a fourth degree polynomial curve was judged to be most appropriate. It explains 98.7 per cent of the variation in the data and is significantly better (with over 99.9 per cent assurance) than the other curves that were tested. The other curves were polynomials up to the fifth degree and the exponential."

Table 3 certainly does not support the claim that fourth degree polynomials are better. If all of the data are to be used, then second degree polynomials would appear to give the most accurate predictions. This further illustrates the distinction between curve fitting and prediction, and the dangers of using statistical procedures for curve-fitting to assess prediction methods.

Note that the appropriate choice for the trend period $k$ depends on the methodology employed. If high-degree polynomials are to be used, large values of k are needed to prevent absurd results. However, with straight line models, more accurate predictions are obtained using shorter trend periods. It thus makes little sense to require, as in [1], that at least ten years' data must be used without specifying how they are to be used.

A single example is, of course, insufficient to establish the general merits of different prediction methods or trend periods. A further complication which we have ignored here is that the most recent loss costs are only preliminary estimates subject to later correction. An extensive study of prediction methods and trend periods which takes into account the effects of claim development is described in [4]. This study confirms the points made here concerning polynomial models and trend periods.

## 5. Cyclical Adjustment

In the benchmark rate calculations, predicted values from the polynomial model were subjected to a "cyclical adjustment"[†]. Although few details are given in [2], it appears that the method used is that described in [3].

> "...Guide lines are set up one standard error above and below the trend so that roughly two-thirds (68 per cent) of all data points will

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[†] If polynomial curves of arbitrary shape can be used to describe "trend", then what is a "cycle"?

fall between them. A rule such as this can then be adopted for projections:

(1) If the starting point (i.e., the last datum point) falls on the trend line or within one per cent, use only the trend adjustment.

(2) If the starting point falls between the trend line and a guide line, determine toward which of the two lines an arrow placed on the last two data points is aimed. Use a cyclical adjustment equal to half the vertical distance from the starting datum point to that line.

(3) If the starting point falls outside a guide line, use a cyclical adjustment equal to the vertical distance from the starting point to the guide line.

This rule was designed to dampen extreme swings in projections and rates, while still providing a response both to the relative positions of the last datum and the trend line and to the direction of the latest identifiable cyclical movement."

To describe the adjustment procedure algebraically, we let $y_1, y_2, \ldots, y_n$ denote the observed loss costs, and let $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ denote their fitted values from the model. Define

$$d_i = y_i - \hat{y}_i; \qquad c = d_n - d_{n-1}; \quad s = \sqrt{\tfrac{1}{n}\Sigma d_i^2}.$$

The final adjusted value is $\hat{y}+A$ where $\hat{y}$ is the projected loss cost from the model, and the cyclical adjustment $A$ is computed as follows:

(1) If $|d_n| \leq .01\hat{y}_n$, then $A = 0$.

(2) If $.01\hat{y}_n < |d_n| < s$, then

$A = .5d_n$ when $cd_n < 0$

$A = .5(s-d_n)$ when $d_n > 0$ and $c > 0$;

$A = -.5(s+d_n)$ when $d_n < 0$ and $c < 0$.

(3) If $|d_n| \geq s$ then $A = d_n(1-s/|d_n|)$.

For instance, if $0 < d_n < s$ and $c < 0$, the adjustment is half the vertical distance from the last point to the trend line: $A = \frac{1}{2}(y_n-\hat{y}_n) = \frac{1}{2}d_n$. If $0 < d_n < s$ and $c > 0$, the adjustment is half the vertical distance from the last point to the guide line:

$$A = \tfrac{1}{2}\{(\hat{y}_n+s)-y_n\} = \tfrac{1}{2}(s-d_n).$$

The cases with $d_n$ negative are similarly handled.

The introduction of three separate regions within which different rules apply has the effect of creating undesirable discontinuities in the adjustment procedure. In (1) and (3) we have $A \to 0$ as $d_n \to 0$ or $d_n \to \pm s$, but in (2) it is possible to have $A \to 0$, $+.5s$ or $-.5s$ depending upon the signs of $c$ and $d_n$. Also, the adjustment in (2) depends on the sign of $c$ but not its magnitude. A tiny change in $y_{n-1}$ can cause $c$ to change sign, thus altering the adjustment by $\pm .5s$. These general difficulties suggest that the adjustment procedure is rather arbitrary, and that cyclical adjustment may not in fact improve loss cost predictions.

Table 4 gives cyclical adjustments to the predictions obtained in Section 4 by fitting a fourth degree polynomial curve to all available data. The adjustment for 1982 is by far the largest. A fourth degree polynomial fitted to 1947-80 data gives $s = 3.32$ and fitted values $\hat{y}_n = 110.05$ for 1980 and $\hat{y} = 115.57$ for 1982. The 1980 loss cost is $y_n = 101.82$, so $d_n = -8.23$. Now (3) gives $A = d_n + s = -4.91$, and the final adjusted value for 1982 is $\hat{y} + A = 110.67$. The adjustment is downward because the most recent loss cost is well below the fitted curve. However, in [2] an upward adjustment was made, giving $\hat{y} + 4.91 = 120.48$ as the final value. Here and elsewhere in the benchmark rate calculations, the cyclical adjustment was made in the wrong direction!

Table 4 suggests that, even when correctly applied, the cyclical adjustment is of doubtful value. The last data point is highly influential in fitting polynomial models, so $d_n$ will usually be small. Furthermore, as was pointed out in Section 2, actual prediction errors will likely be much larger than $s$. As a result, the adjustment will almost always be much smaller than the prediction error. Perhaps this is just as well, because in a large percentage of cases, the adjustment makes the prediction worse.

It is possible to devise methods of cyclical adjustment which avoid the most obvious deficiencies of the method just described. However, since it is difficult to define exactly what a cycle is in this context, cyclical adjustments are of necessity rather arbitrary. It is dangerous to apply such adjustments or corrections without a careful study of their purposes and properties. Furthermore, the anticipated benefits of these adjustments should always be tested by trying them out in actual prediction problems.

## 6. Conclusion

The preceding sections have presented some general comments on methods for predicting future loss costs as well as some particular comments relating to Standard No. 1 and the New Brunswick benchmark rate calculations.

With respect to Standard No. 1, it was pointed out that it makes little sense to require that ten years' data be used without specifying how they are to be used. The amount of data which should be used depends on the methodology to be employed. An example was given to show that increasing the amount of data may lead to increased errors of prediction in some cases. The emphasis on the coefficient of determination is misplaced. This coefficient reflects only the fit of the model to the historical data, not its suitability for prediction. More complicated models will generally produce a better fit to the data and a larger coefficient of determination, but such models may give very bad predictions.

The trending methodology in the benchmark rate calculations is arbitrary and excessively complicated. Polynomial models are highly unstable and therefore unsuitable for prediction, and the statistical methods used to decide among alternative models are inadequate for this purpose. Much is made of the fact that a long series of data was used in trending, but in fact the results obtained from a 4-year trend line are at least as accurate. The method of cyclical adjustment, even if correctly applied, does not noticeably improve the predictions.

The most important general point illustrated here is that curve fitting and prediction are very different problems. In order to evaluate a prediction methodology, it is necessary to try it out. If the method would have produced reasonable predictions in recent years for the particular series being considered and other similar series, then we can have some confidence in future applications of the method.

Section 3 suggests some additional features which sensible prediction methods should possess. In general, older data should have less influence on predictions than more recent data, and slight changes in the historical data should not produce large changes in predicted values. These aspects of the method can be investigated, as in Section 3, by examining the way in which the historical values enter into the calculation of future loss costs. From this point of view, autoregressive models and moving averages would seem more attractive than polynomial models. Some models of this sort are described and compared with polynomial models in [4].

Prediction of the future is not an easy job, and no mathematical formula, however pleasant its properties, can be trusted to produce accurate predictions in all situations. In some cases, the ratemaker may possess information about current market conditions which is not reflected in the historical loss costs, and some adjustment of predicted costs will be necessary. Statistical calculations, however sophisticated they may appear, do not remove the necessity for exercising judgement.

One way in which this judgement can be exercised is by trying out several methodologies, and then choosing one that gives approximately the answer desired for that particular year and coverage. This is a dangerous procedure because subjective choices and the reasons for them are concealed. Surely it would be better to use a single methodology, and to permit occasional adjustments for special circumstances. It is important that the methodology be kept simple, and that its properties be carefully investigated. The empirical study described in [4] is a first step in this direction.

## References


1. Standard No. 1: Time Series Adjustment, Including Trending. Board of Commissioners of Public Utilities, Province of New Brunswick, 25 April 1978.

2. The 1981 New Brunswick Automobile Insurance Rating Benchmark. Board of Commissioners of Public Utilities, Province of New Brunswick, 10 November 1981.

3. John S. McGuinness, Elements of Time-Series Analysis in Liability and Property Insurance Ratemaking. Proceedings of the Casualty Actuarial Society 55 (1968), 202-254.

4. James G. Kalbfleisch and Joe S. Cheng, Comparison of prediction methods for future loss costs in automobile insurance ratemaking. Unpublished manuscript.


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TABLE 1

Polynomial fits to loss costs for New Brunswick private passenger collision insurance

| Year | Loss Cost | Fitted values from polynomial of degree p: p = 1 | p = 2 | p = 3 | p = 4 | p = 5 |
|---|---|---|---|---|---|---|
| 1971 | 45.13 | 42.52 | 51.54 | 43.97 | 43.96 | 45.13 |
| 1972 | 51.71 | 48.87 | 51.88 | 54.40 | 54.41 | 51.70 |
| 1973 | 60.17 | 55.22 | 53.72 | 60.03 | 60.04 | 60.23 |
| 1974 | 64.83 | 61.57 | 57.06 | 62.65 | 62.65 | 64.78 |
| 1975 | 65.24 | 67.93 | 61.91 | 64.07 | 64.06 | 65.23 |
| 1976 | 65.17 | 74.28 | 68.26 | 66.10 | 66.09 | 64.92 |
| 1977 | 67.65 | 80.63 | 76.12 | 70.53 | 70.53 | 68.39 |
| 1978 | 79.80 | 86.98 | 85.48 | 79.17 | 79.17 | 78.98 |
| 1979 | 96.13 | 93.33 | 96.34 | 93.82 | 93.83 | 96.54 |
| 1980 | 115.19 | 99.68 | 108.71 | 116.28 | 116.27 | 115.11 |
| 1981 | ? | 106.04 | 122.58 | 148.37 | 148.30 | 120.56 |
| 1982 | ? | 112.39 | 137.96 | 191.87 | 191.67 | 88.29 |
| 1983 | ? | 118.74 | 154.84 | 248.60 | 248.18 | -19.10 |
| s | | 8.72 | 6.65 | 2.27 | 2.48 | 0.605 |
| $r^2$ | | 0.8455 | 0.9213 | 0.9922 | 0.9922 | 0.9996 |

TABLE 2

Multipliers for predictions 2 years ahead
from polynomial models based on 10 years' data

| Year | Loss Cost $y_i$ | Multipliers for polynomial model of degree p | | | | |
|---|---|---|---|---|---|---|
| | | p = 1 | p = 2 | p = 3 | p = 4 | p = 5 |
| 1971 | 45.13 | -0.25 | 0.52 | -0.95 | 1.59 | -2.51 |
| 1972 | 51.71 | -0.18 | 0.08 | 0.57 | -2.53 | 7.04 |
| 1973 | 60.17 | -0.10 | -0.23 | 0.99 | -1.40 | -2.08 |
| 1974 | 64.83 | -0.02 | -0.40 | 0.68 | 1.10 | -6.42 |
| 1975 | 65.24 | 0.06 | -0.45 | -0.04 | 2.50 | -1.60 |
| 1976 | 65.17 | 0.14 | -0.38 | -0.79 | 1.74 | 5.84 |
| 1977 | 67.65 | 0.22 | -0.17 | -1.25 | -0.83 | 6.69 |
| 1978 | 79.80 | 0.30 | 0.17 | -1.05 | -3.45 | -2.76 |
| 1979 | 96.13 | 0.38 | 0.63 | 0.15 | -2.95 | -12.52 |
| 1980 | 115.19 | 0.45 | 1.23 | 2.69 | 5.23 | 9.33 |
| 1982 | $\Sigma m_i y_i$ | 112.39 | 137.96 | 191.87 | 191.67 | 88.29 |

TABLE 3

PREDICTED VALUES TWO YEARS AHEAD
USING POLYNOMIAL MODEL OF DEGREE P
NEW BRUNSWICK PRIVATE PASSENGER LIABILITY INSURANCE

| YEAR | LOSS COST | K=4 P=1 | ALL DATA USED P=1 | ALL DATA USED P=2 | ALL DATA USED P=3 | ALL DATA USED P=4 | ALL DATA USED P=5 |
|---|---|---|---|---|---|---|---|
| 1960 | 27 | 31 | 30 | 28 | 33 | 40 | 8 |
| 1961 | 27 | 30 | 30 | 29 | 33 | 33 | 3 |
| 1962 | 27 | 28 | 30 | 28 | 30 | 25 | 0 |
| 1963 | 31 | 26 | 30 | 27 | 27 | 21 | 7 |
| 1964 | 34 | 26 | 31 | 27 | 27 | 23 | 19 |
| 1965 | 39 | 32 | 31 | 29 | 31 | 32 | 39 |
| 1966 | 45 | 39 | 33 | 32 | 37 | 42 | 52 |
| 1967 | 49 | 46 | 35 | 37 | 45 | 52 | 61 |
| 1968 | 49 | 54 | 38 | 43 | 55 | 65 | 73 |
| 1969 | 50 | 59 | 42 | 49 | 62 | 70 | 69 |
| 1970 | 52 | 57 | 45 | 53 | 65 | 66 | 54 |
| 1971 | 56 | 53 | 47 | 56 | 66 | 61 | 43 |
| 1972 | 65 | 54 | 50 | 60 | 67 | 58 | 41 |
| 1973 | 75 | 60 | 52 | 63 | 69 | 59 | 46 |
| 1974 | 80 | 73 | 56 | 69 | 76 | 69 | 65 |
| 1975 | 92 | 89 | 61 | 77 | 87 | 84 | 89 |
| 1976 | 88 | 98 | 66 | 84 | 95 | 94 | 100 |
| 1977 | 100 | 108 | 72 | 94 | 108 | 109 | 118 |
| 1978 | 107 | 102 | 77 | 100 | 112 | 108 | 107 |
| 1979 | 110 | 109 | 82 | 108 | 120 | 115 | 115 |
| 1980 | 102 | 117 | 88 | 117 | 129 | 123 | 123 |
| 1981 | - | 127 | 94 | 124 | 134 | 126 | 122 |
| 1982 | - | 108 | 98 | 127 | 132 | 116 | 102 |

TABLE 4

CYCLICAL ADJUSTMENT OF PREDICTED VALUES
FROM 4TH DEGREE POLYNOMIAL MODEL

| YEAR | LOSS COST | FITTED VALUE | S | CYCLICAL ADJUSTMENT | FINAL VALUE |
|---|---|---|---|---|---|
| 1960 | 27.09 | 40.11 | 1.22 | -0.26 | 39.85 |
| 1961 | 26.63 | 32.73 | 1.27 | -0.31 | 32.42 |
| 1962 | 27.30 | 24.66 | 1.27 | -0.38 | 24.27 |
| 1963 | 30.57 | 20.98 | 1.23 | 0.00 | 20.98 |
| 1964 | 34.04 | 22.74 | 1.23 | 0.35 | 23.09 |
| 1965 | 38.59 | 32.03 | 1.33 | 0.10 | 32.13 |
| 1966 | 45.43 | 41.80 | 1.36 | 0.27 | 42.07 |
| 1967 | 48.63 | 51.94 | 1.33 | 0.45 | 52.38 |
| 1968 | 48.85 | 64.77 | 1.31 | 0.00 | 64.77 |
| 1969 | 50.05 | 69.73 | 1.41 | -0.05 | 69.68 |
| 1970 | 52.47 | 65.90 | 1.81 | -1.27 | 64.63 |
| 1971 | 55.98 | 60.92 | 2.03 | -0.69 | 60.23 |
| 1972 | 64.96 | 58.26 | 2.06 | -0.28 | 57.98 |
| 1973 | 75.23 | 58.81 | 2.02 | 0.00 | 58.81 |
| 1974 | 79.87 | 68.65 | 2.15 | 0.50 | 69.14 |
| 1975 | 91.90 | 83.90 | 2.41 | 1.31 | 85.21 |
| 1976 | 88.18 | 93.57 | 2.38 | 0.47 | 94.04 |
| 1977 | 99.52 | 108.80 | 2.44 | 0.01 | 108.81 |
| 1978 | 107.25 | 107.80 | 2.71 | -1.77 | 106.03 |
| 1979 | 109.89 | 115.23 | 2.66 | 0.00 | 115.23 |
| 1980 | 101.82 | 123.21 | 2.62 | 0.00 | 123.21 |
| 1981 | ------ | 126.07 | 2.65 | -0.11 | 125.95 |
| 1982 | ------ | 115.57 | 3.32 | -4.91 | 110.67 |

FIGURE 1

Polynomial Fits to Loss Costs for New Brunswick Private Passenger Collision Insurance

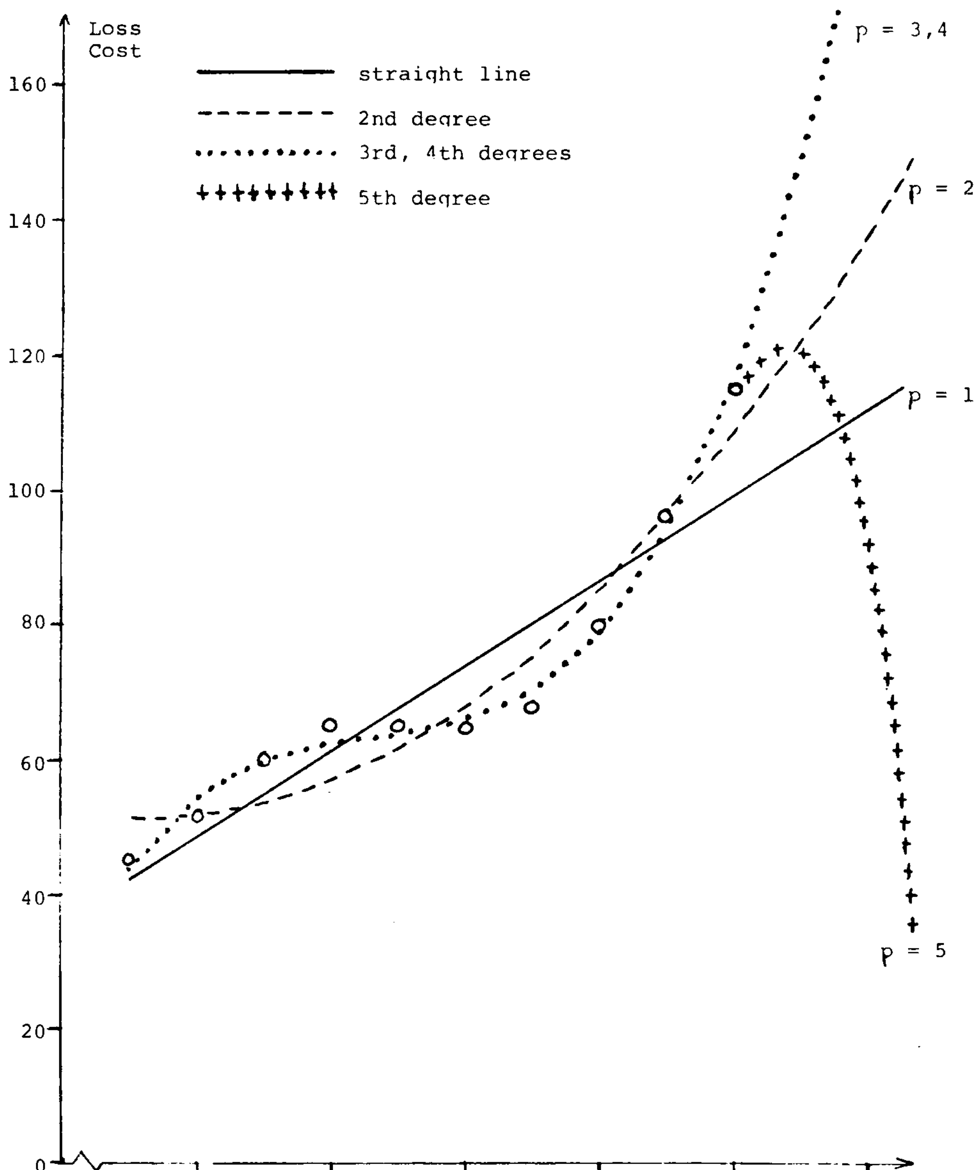

FIGURE 2

Observed and predicted loss costs for N.B. private passenger liability insurance