A Comparison between Prediction Methods of Incurred but Not Paid (IBNP) Reserve (A Theoretical and Applied Study)

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Abstract

In this study the IBNP reserve has been predicted using the ARIMA model and MLP-ANN model and then the results of both models have been compared, taking into consideration the earned premiums, paid claims and time as independent variables, and concluded that the earned premiums, the paid claims and time have significant effects on the IBNP reserve value and the MLP-ANN model is one of the best statistical models used in predicting the IBNP reserve as it has high accuracy results of RMSE and MAE tests. The model has been applied to actual data obtained from statistical yearbooks to obtain the value of IBNP reserves, earned premiums and paid claims for the period from 1995 to 2020.

Key Words: IBNP reserve, ARIMA model, MLP-ANN model.

1. Introduction

Previous studies differed in the methods used to predict the IBNP reserve, whether by using different mathematical or statistical methods or developing these methods to reach more accurate results in predicting the reserve, But until now the optimal method has not been reached to accurately predict the reserve with values closer to the actual values without overestimation or underestimation, so the study aims to achieve that.

1.1 Previous Studies

There are many studies had the same research objective, so we will present some of them in order to benefit from the results and recommendations in the subject of the research and reach the research gap on which this research is based on. Study [1] aimed to investigate the results of estimating reserves using the chain-ladder method by employing different ways to calculate the development factor from year-to-year over the years following the occurrence of the accident and after applying the chain - ladder method for reserves prediction where the method is investigated in detail by applying a number of suggested approaches to calculate the development factor from year-to-year over the years following the occurrence of the accident, the results show that there is no significant difference between the reserve prediction using different method of calculating the development factors. Study [2] aimed to present the hierarchical reserving model as an intuitive framework for RBNS reserving with a focus on applicability in practice, This framework decomposed the joint likelihood of the development of individual claims since reporting in discrete time. Hierarchical reserving models are tailored to the portfolio at hand by adding layers that represent the events (e.g. settlement, positive or negative payments, changes in the incurred) registered over the lifetime of a claim. This modular approach enables reformulating many existing reserving models as special cases of the hierarchical reserving model, including models based on data aggregated into a run-off triangle. This intuitive model-building workflow allows concentrating on the decisions made during the modeling process, such as model calibration and evaluation, as a best practice, the study minimizes the effect of day-to-day volatility to compare our reserving models, by evaluating the predictive performance over 365 evaluation days. The individual hierarchical models outperform the chain ladder method designed for aggregated data and have the additional benefit that extreme events do not have to be removed prior to reserving. The excellent performance of the hierarchical reserving model is confirmed in a simulation study where its predictive performance was evaluated on portfolios simulated along different scenarios such as a change in the claim mix, an extreme event scenario and a change in the settlement delay of the claims. Study [3] aimed to assess whether it was possible to estimate the adequacy of the estimated claims reserves, since they are liabilities of an uncertain amount, these reserves may be underestimated (which affects insurance companies) or overestimated (burdening shareholders), the application of the model revealed that there are indicators that insurance companies can benefit from in managing profits by estimating the IBNP reserve, which distributes the burden of insufficient claims risks between policyholders and shareholders, and that there are differences in the relative amount of claims recognized by insurance companies, which indicates the Possibility to apply earnings management practice by measuring claims. Study [4] aimed to propose a new method to predict IBNR claim numbers so in order to achieve the study aim a new approach based on a micro-level model for reporting delays involving neural networks is proposed. It is shown by extensive simulation experiments and an application to a large-scale real data set involving motor legal insurance claims that the new approach provides more accurate predictions in the case of non-homogeneous portfolios and shows that the neural network predictors robustly provide more efficient predictions than chain ladder. Study [5] aimed to quantify the prediction error of outstanding claims liability in a run-off triangle of claim amounts rather than developing a new mean structure or utilizing counts data. It is known that over-dispersed Poisson chain-ladder models are widely used in general insurance claims reserving and although such models can accommodate the over-dispersion frequently observed in run-off triangles, they also impose an additional constraint of fixed variance to mean ratio across cells in this paper, this constraint is relaxed and a flexible dispersion structure is developed in a double Poisson chain-ladder model. The proposed model nests the classic over-dispersed Poisson model as a special case. A generalized likelihood ratio test is further proposed to compare different dispersion structures. In contrast to the existing claims reserving methods, our proposed method is more flexible in terms of dispersion modeling. Study [6] aimed to use the double chain ladder method to be able to calculate the IBNR and RBNS separately by using two loss triangles and through the parameters of the Chain ladder method, which are the number and size of claims, and comparing the total reserve IBNP (IBNR +RBNS) when calculating it by the chain ladder method and the double chain ladder method. The study found that the calculation of RBNS and IBNR reserve is 725.7436 and 3,1513 euros, and that there is a large difference in the total value of the reserve (IBNP) when estimated by the double chain ladder method and the chain ladder method, and this may be because there are zero values that affect the prediction. Therefore, the study recommended that the double chain ladder method can be used in the absence of zero values. Study [7] aimed to introduce the Benktander method that combines chain ladder and Bornhuetter-Ferguson by optimal credibility which is obtained through minimum mean squared error and minimum variance. Benktander provides moderate reserve compared to chain ladder and Bornhuetter-Ferguson, and it found that through using the Benktander method which utilizes both information derived from chain ladder and Bornhuetter-Ferguson methods, the predicted claim reserves are not as volatile as the predicted claim reserves with only chain ladder or Bornhuetter-Ferguson methods alone. Study [8] aimed to perform multivariate analysis for intercompany loss triangles through Pooling loss experiences from multiple insurers for prediction purposes and challenging from the modeling perspective. Modelling framework with a data set corresponding to a group of insurers with each of them consisting of multiple lines of business to analyze the intercompany loss triangles a Bayesian hierarchical model is proposed, Numerical analysis was performed for an insurance portfolio of multivariate loss triangles from the NAIC and the study concludes that the Bayesian approach enables one to derive the predictive distributions of outstanding payments at any level of interest, either it portfolio, company, business line, or year and prediction is improved through borrowing strength within and between insurers based on both training and holdout observations. Study [9] aimed to introduce Bayesian copula modelling into the field of multivariate loss reserving and modelling of contemporaneous correlations and the investigation of whether multivariate copula models could improve on their independent counterparts. Supported via the Bayesian computational machinery, the complexity of models that can be entertained with this framework is vast, as the study shows via two examples, where the study presents the Bayesian copula model, computational scheme, model checking and comparison procedures, as well as posterior predictive inference.The study found the models considered may not be “optimal” ones—in specifying our marginal models, the study had left out the examination of other potentially useful factors such as inflation, calendar year effect, and so on. When necessary, one should examine such additional factors in the choice of appropriate marginal to be used in the copula model and use the Bayesian computational scheme to make inference. In general, the study supported the constructive approach, where simpler models are the starting point, and additional complexity is added in stages as necessary. As another result, copula results were not compared to other existing methods such as the (multivariate) chain ladder. The copula model may or may not outperform the (multivariate) chain ladder model, depending, to some extent, on whether the marginal model used in the study is better or worse. This comparison would not provide evidence for the use of copula one way or the other.

1.2 PROBLEM STATEMENT

The problem of the study lies in the fact that the method used in predicting the IBNP reserve often leads to inaccurate estimates, and it wastes the insurance companies to take advantage of the advanced statistical methods that may reach the prediction to the closest possible values to the actual values. Many researchers have tried to reach the optimal method for predicting the reserve, but there is still difficulty and inaccuracy in this estimate, as it sometimes results in overestimation that may deprive the insurance company of obtaining profits despite its entitlement to that, or underestimation which leads to inflating profits.

Therefore, the IBNP reserve is considered as one of the most important liabilities of insurance companies that reflect the real financial position of the company, which helps them to fulfill their obligations towards the insured and improves the position of the competitive insurance company. Therefore, the problem of the study can be summarized as follows:

1- Determine the appropriate method for predicting the IBNP reserve.

2- There are clear differences, by increase or decrease, between the expected and actual reserve figures.

1.3 Objectives of The Study

The study aims to develop a statistical model to reach an accurate prediction of the Incurred But Not Paid (IBNP) reserve by using a Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) while reflecting the impact of the earned premiums and paid claims on the reserve value.

1.4 Significance of The Study:

The importance of the research is due to the importance of accurately predicting the IBNP reserve which is:

-There is a good strategic planning for the investment policy in the insurance companies, as the investment of the insurance companies depends mainly on the technical reserves, the most important of which is the IBNP reserve.

- A good prediction of the reserve represents protection for the rights of policyholders as it guarantees the company's financial ability to fulfill its obligations towards policyholders. As the reserve is formed to cover claims of accidents that have occurred and have been reported, but after preparing the final accounts or accidents that have occurred but not been reported yet.

-To protect the rights of shareholders, the value of the reserve reflects the financial solvency of the insurance companies and confirms that the declared profits are actual profits that can be distributed or reinvested.

-The reserve enables the insurance company to know the full cost of paying claims in order to determine future premium rates.

-It helps companies to ensure that they have sufficient assets to cover their liabilities, as it reflects the solvency margin that enables the company to continue underwriting.

1.5 The Scope and Limitations of The Study:

The study will be applied to the Egyptian insurance market during the time period from 1995 to 2020.

2. Applied study

2.1 Prediction of IBNP reserve using ARIMA model:

In order to determine whether the time, earned premiums and paid claims have an impact on the IBNP reserve, the ARIMA model will be applied by using R software.

The study will be performed by using the time, earned premiums and paid claims as independent variables and the IBNP reserve as a dependent variable for the period from 1995-2020.

Before using the ARIMA model it is important to check whether the time series of each variable is stationary or not by figures and unit root test.

2.1.1 Test stationarity of the variables:

a- Stationary test by graphs:

It is obvious from the following figures of the variables that there is an upward trend in the time series which means that the variables are not stationary.

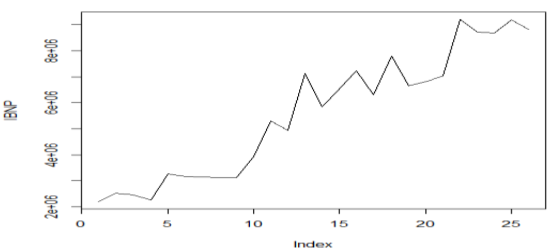

Figure 1

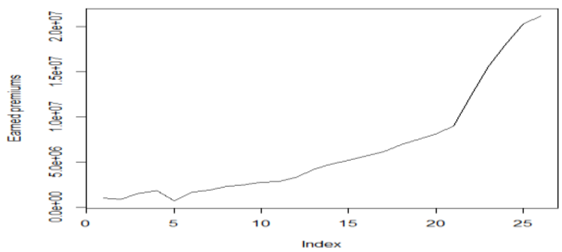

Figure 2

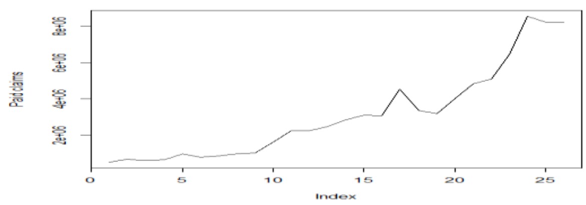

Figure 3

b- Unit Root Test

Augmented Dickey-Fuller (ADF) test is conducted to test the stationary of the data.

The Test Hypothesis:

The null hypothesis (H_0): data is not stationary (has a unit root)

The alternative hypothesis (H_1): data is stationary (has not unit root)

Table 1
UNIT ROOT TEST RESULTS TABLE (ADF)

	Y	**X_1**	**X_2**
Dickey-Fuller test	-2.3859	-0.61356	-0.42666
Lag order	2	2	2
p-value	0.4254	0.9655	0.9781

Prepared by the researcher from the output of statistical analysis of R software .

Table 1 shows the ADF test results and we can note that the p-values of Y, X_1,and X_2 respectively are 0.43, 0.9655 and 0.9781 which are greater than the significance level (5%) so we have no evidence to reject the null hypothesis and that means the data is not stationary. So in order to make the data stationary the model uses a differencing parameter (d) value which is used for data differentiation intended to meet the stationarity.

2.1.2 Model parameters and interpretation:

Table 2
ARIMA model parameters

	coefficient	p-value
AR(1)	-0.4419	0.018
AR(2)	0.0114	0.008
X_1	-0.1029	0.753
X_2	0.2134	0.038

Prepared by the researcher from the output of statistical analysis of R software.

Table 2 showed ARIMA (2,1,0) model and the prediction equation is:

$$\hat{Y} = -0.4419Y_{t-1} + 0.0114Y_{t-2} - 0.1029X_1 + 0.2134X_2$$

2.1.3 Accuracy of The Model:

Table 3 Training Set Error Measures	
Fit Statistics	**Predictions**
Mean error (ME)	178052.8
Root Mean Square Error (RMSE)	764602.1
Mean Absolute Error (MAE)	566305.7
Mean Percentage Error (MPE)	3.503633
Mean Absolute Percentage Error (MAPE)	10.34836
Mean Absolute Square Error (MASE)	0.8483781

Prepared by the researcher from the output of the statistical analysis of R software.

Table 3 shows some statistical tests that are calculated to evaluate the model's reliability and overall accuracy. The results are compiled by fitting the time series models in R software, and tests help in determining the best and most appropriate model when comparing models. Smaller values indicate a better fit

2.1.4 Using ARIMA (2,1,0) Model in Prediction of The IBNP Reserve and comparing predicted values with actual:

	Table 4 Comparing Actual And Predicted Values of ARIMA Model 1	
	Y	$\hat{Y}$
2018	8682276	8713777
2019	9190225	9368183
2020	8826256	9434886

Prepared by the researcher from the output of statistical analysis of R software as

When comparing the actual values of the IBNP reserve and the ARIMA model's expected values for 2018, 2019 and 2020, we can conclude that the model is suitable and appropriate in predicting the reserve as expected values are close enough to actual values, which is also confirmed by statistical tests as MAPE of the model is only 10% which is an acceptable percentage of error.

2.2 Prediction of IBNP reserve using MLP-ANN model:

By using the R package, The artificial neural network is formed by using earned premiums and paid claims as independent variables and IBNP reserve as a dependent variable and specifyies the number of inputs and outputs, the neural network divides the data into 70% of the data uses for training, 15% uses for validation, and the remaining 15%for testing, where the sum of the data used equals 100%, then to know the performance of the artificial neural network there is a set of tests that show the performance of the neural network artificial which are

a- Accuracy Measures:

Table 5

Accuracy Measures

ME (mean error)	RMSE	MAE (MAD)	MAPE
19.16973	6094.876	5079.493	0.1148426

b- Using MLP-ANN Model in Prediction of The IBNP Reserve and comparing predicted values with actual:

Table 6

Comparing actual and predicted values

	Y	$\hat{Y}$
2018	8682276	8689778
2019	9190225	9177266
2020	8826256	8832520

Prepared by the researcher from the output of statistical analysis of R software.

When comparing the actual values of the IBNP reserve and the MLP-ANN model expected values for 2018, 2019 and 2020, we can conclude that the model is suitable and appropriate in predicting the reserve as expected values are close enough to actual values, which is also confirmed by statistical tests as MAPE of the model is only 0.11% which is an acceptable percentage of error, RMSE value is 6094.876, and MAE value is 5079.493, which means accuracy of modelling the factors affecting IBNP reserve using MLP artificial neural network that has been conducted is acceptable.

2.3 Comparing the models of predicting the IBNP reserve to determine the best model fit

Table 7

Determining The Best Model Fit

Model	RMSE	MSE	MAPE
ARIMA	764602.1	5.84616E+11	10.34836
MLP-ANN	6094.876	37147513.46	0.1148426

From table 7, we conclude the following:

The comparison between ARIMA and MLP-ANN models, through RMSE, MSE and MAPE accuracy measures ensures that MLP-ANN model is the best model fit as it has the smallest values of RMSE, MSE and MAPE tests.

The comparison ensured the hypothesis which says that there are significant differences between the values of the IBNP reserve using ARIMA and MLP-ANN models.

Results:

The researcher concludes a set of results as follows:

- The earned premiums and paid claims have a significant effect on the IBNP reserve value.
- Multi-layer perceptron artificial neural network (MLP-ANN) model is one of the best models used in predicting the IBNP reserve and has a high accuracy according to RMSE and MAE measures, where:
  - The Root Mean Square Error (RMSE) for the ARIMA model is 764602.1, and for MLP-ANN model is 6094.876, which means MLP-ANN model is better as it has a smaller value.
  - The Mean Absolute Percentage Error (MAPE) for the ARIMA model is 10.34836, and for MLP-ANN model is 0.1148426, which means MLP-ANN model is better as it has a smaller value.

Recommendations

Through the results reached, the researcher recommends the following:

1- Insurance companies should take advantage of statistical methods and technological development in modern methods to predict the IBNP reserve instead of relying on the chain ladder method which is widely used to predict the reserve as in practice it can be easily seen that even one outlier can lead to a huge over-or underestimation of the overall reserve when using it.

2- Regulators and investors could use the optimal reserve prediction technique found in this study to help them to predict the insurers reserve to evaluate the insurers' performance more accurately.

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الملخص باللغة العربية

مقارنة بين أساليب التنبؤ بمخصص التعويضات تحت التسوية (دراسة نظرية و تطبيقية)

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في هذه الدراسة ، تم التنبؤ بمخصص التعويضات تحت التسوية باستخدام نموذج الانحدار الذاتي والمتوسطات المتحركة التكاملية ونموذج الشبكات العصبية الاصطناعية متعددة الطبقات بيرسبترون ثم تمت مقارنة نتائج كلا النموذجين وتم استنتاج الآتي:أن للأقساط المكتسبة والتعويضات المسددة تأثير معنوي علي قيمة مخصص التعويضات تحت التسوية، أن نموذج الشبكات العصبية الاصطناعية متعددة الطبقات بيرسبترون هو أحد أفضل النماذج الإحصائية المستخدمة في التنبؤ بالمخصص وأعطي نتائج عالية الدقة لاختبارات RMSE و MAPE وMAE. تم تطبيق النموذج على البيانات الفعلية التي تم الحصول عليها من الكتاب الإحصائي السنوي للحصول على قيمة مخصص التعويضات تحت التسوية والأقساط المكتسبة والتعويضات المسددة للفترة من ١٩٩٥ إلى ٢٠٢٠.

الكلمات المفتاحية: مخصص التعويضات تحت التسوية ، نموذج الانحدار الذاتي والمتوسطات المتحركة التكاملية، نموذج الشبكات العصبية الاصطناعية متعددة الطبقات بيرسبترون.