Individual claim reserving: A complementary approach to aggregated methods

Eve Elisabeth Titon
Tinhinane Talbi

Milliman

More and more individual claim reserving models have been developed in recent decades. In fact, the availability of increasingly detailed claim data has enabled us to take a fresh look at reserving. However, a key question remains: are these methods, based on individual losses, more efficient than aggregate methods? Our study highlights the benefits of using line-by-line claim data and compares individual reserving methods with conventional aggregate methods. To this end, the different methods are applied to a single database.

Our study is motivated by the context of an increasing need within the reserving practice for more accurate models combined with a digital revolution in the insurance industry and the increased importance of big data. Although traditional aggregate claim models have demonstrated effectiveness in the past, the insurance market is increasingly aware of the limitations of these methods in providing robust and realistic estimates in a wider range of contexts. Furthermore, various considerations have brought attention to numerous potential drawbacks associated with aggregate claim models based on loss triangles, particularly when these triangles reflect the evolution of rare, large, or disparate claims:

- Overestimation or underestimation of the distribution when back-testing realised amounts with forecasts
- Huge estimation error for the latest development periods due to the lack of observed aggregate amounts
- Bias in the case of the presence of atypical claims in the database
- Uncertainty about the ability of these models to properly capture the pattern of claim development, combined with the limited interpretive and predictive power of the accident and development period parameters

To mitigate these limits, individual claim reserving models have been explored. The main goal of individual claim reserving models is to use all the information related to each individual claim to figure out the right reserve for each claim. The primary advantage of these models lies in their adaptable application scope and their capacity to incorporate detailed information.

The use of these models can help insurers improve their estimates of reserves, capture the specific development patterns of clusters of claims within a reserving segment and implement a separate and consistent treatment of incurred but not yet reported (IBNR) claims, which account for granular portfolio characteristics (e.g., mix of risks). In addition, machine learning techniques and artificial intelligence (AI) can be leveraged by these models to incorporate explanatory variables and further enhance their accuracy. By leveraging these models, insurers can make more informed decisions, minimise their exposure to risk and ultimately improve their bottom lines.

Executive summary

In the context of estimating the reported but not settled (RBNS) reserve through a payments-only modelling approach, we have applied various distinct reserving models to a database of severe claims (those surpassing a predefined severity threshold). The objective of the study is to conduct a comparative analysis between the implemented individual claim reserving models and traditional methodologies (e.g., chain-ladder and Mack), all utilising the same claim database. Additionally, the study aims to assess the strengths and weaknesses of these individual claim reserving models.

The two main conclusions of the study are as follows:

1. Individual claim reserving models provide more granular insight into the drivers of development for different subsets of claims aggregated together and can be adjusted to take into consideration specificities. In terms of results, the individual claim reserving methods are in line with those obtained from traditional methods.

2. Individual models are complex compared to aggregate methods and furthermore the parametric model is sensitive to how payments are structured or specified in the model and to the composition of the base in terms of the number of closed cases and RBNS. These models are therefore to be preferred when the chain-ladder method proves ineffective, such as in large claims, but also in subsegments with high-severity variance and inherent heterogeneity.

An ancillary benefit of conclusion 1, above, is that the more detailed understanding enables more informed conversations with claims.

This paper aims to provide an overview of individual reserving methods, including an in-depth review of the relevant literature. The focus then shifts to discussing the various implemented models and how they compare to standard methods. The paper will also explore the flexibility of individual claim reserving models and the potential benefits they offer in terms of accuracy and efficiency. By covering these key topics, this paper aims to provide a valuable resource for those interested in understanding the current state of individual reserving methods and their potential applications in the insurance industry.

Different types of individual claim reserving models

Over the course of many decades, non-life insurance actuaries have used runoff triangles to estimate future payments. Over the past few decades, the actuarial and scientific community has developed different approaches to line-by-line reserving. These approaches consider each claim individually and integrate all its characteristics to predict the ultimate. Several methods have been proposed, each specific to a given type of claim.

PARAMETRIC MODELS

An appropriate probabilistic framework for individual reserving was first introduced by (E. Arjas, 1989) and (W. S. Jewell, 1989) and followed by other studies by (R. Norberg, 1993) and (O. Hesselager, 1994). To our knowledge, (R. Norberg, 1993) and (O. Hesselager, 1994) are among the earliest papers which introduced a proper probabilistic setting for individual claim reserving, recently applied by (K. Antonio and R. Plat, 2014).

When we look at IBNRs, the time between the date of occurrence of the claim and the time of reporting is a crucial element in the study. More recently, (A. Boumezoued and L. Devineau., 2017) revisit the original probabilistic formulations of (R. Norberg, 1993) and (O. Hesselager, 1994) and develop a framework for modelling the occurrence and timing of claims and then provide a coherent presentation of modelling (with simulation and closed formulas) of IBNR.

When the object of study is RBNS, the duration before claim closure and the ultimate are studied separately, as in (M. Ayuso et M. Santolino., 2008) or using a multistate model to model the development of the claim as in (K. Antonio, E. Godecharle et R. V. Oirbeek, 2016) and in (A. Boumezoued and L. Devineau., 2017). They provide a consistent presentation of the modelling (with simulation and closed formulas) of individual claim histories as well as aggregate quantities as a global reserve for RBNS. The model is built on a core component that governs the payment path from reporting to closing.

NONPARAMETRIC MODELS

Machine learning techniques are very flexible for processing structured and unstructured data, so these techniques are increasingly in demand in insurance.

(M. V. Wüthrich, 2018) provides for the first time a contribution to illustrate how regression tree methods can be used in the context of individual reserving. With the increase in the collection of individual claim data, and the improvement of storage methods and computing power, it becomes interesting to consider sophisticated forms of machine learning such as deep neural networks (NNs). These require few restrictions and assumptions on the data, incorporate complex nonlinear trends and have high predictive performance. NNs with various architectures have recently been applied to the reserve of individual claims as in (M. V. Wüthrich, 2018) and (G. Taylor, 2019). Another way to look at past loss histories is to use recurrent neural networks (RNNs), a very popular class of NNs introduced by (J. J. Hopfield, 1982). (S. Hochreiter et J. Schmidhuber, 1997) introduced long short-term memory (LSTM) networks, a class of RNNs, to avoid gradient explosion.

PAYMENT-TO-PAYMENT MODELS

In contrast to the parametric models presented at the beginning of this section, where the approach considered is by development period, (M. Pigeon, 2014) proposes an individual claim reserving model in a parametric and discrete-time framework with a payment-to-payment approach.

The analysis of a line-by-line claim database provides better guidance for claim handlers

Our study is based on a database of the motor third party liability line of business provided by a major French insurer. More specifically, this database is made up of large claims which have exceeded a specific threshold (€500,000 of case reserves). For these claims, it contains developments since notification. Not only are case reserves and payments available, but also certain covariates on the vehicle (e.g., age and use of the vehicle, number of designated drivers, whether or not the car was parked at the time of the claim), on the insured and the victim (gender, socio-professional category, degree of responsibility of the insured towards the victim) and on the claim (location of the claim, status of the claim).

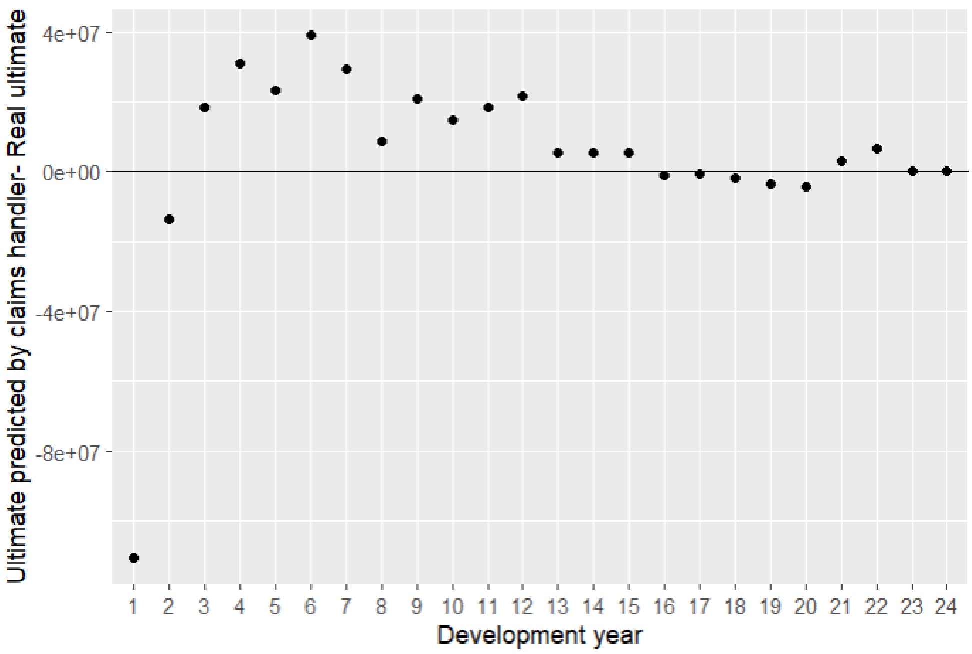
Three separates analyses were carried out on this data:

1. A study of variances between case reserves and ultimate, by year of development and by covariate, enabling a better understanding of managerial reserving.
2. A back-testing exercise to evaluate a "fair" ultimate: A back-testing exercise of case reserves for individual claims closing during the observation period to evaluate a "fair" estimate of ultimate losses for claims that are not yet closed.
3. A clustering analysis of closed claims, to understand which covariates have a significant impact on the ultimate, and also to create subgroupings of claims with homogeneous characteristics (with respect of vehicle, insured, victim and claim), on which we then calibrate certain individual models whose specifications do not allow for the direct inclusion of covariates.

A BETTER UNDERSTANDING OF CLAIM HANDLERS RESERVING

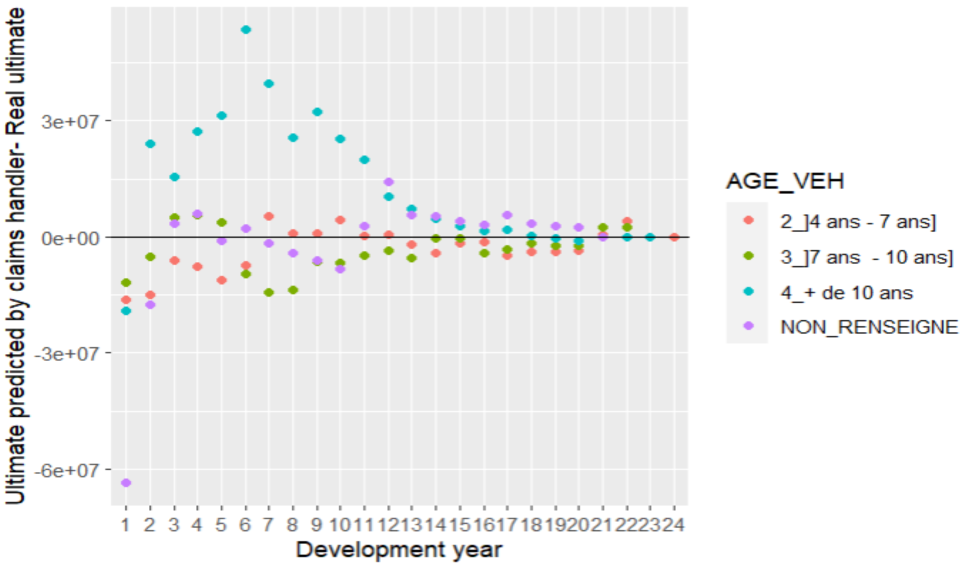
The first involved a detailed study of the errors made by claim handlers in estimating the ultimate cost of closed claims, by year of development. Figure 1 shows these errors.

FIGURE 1: ERRORS MADE BY CLAIM HANDLERS IN ESTIMATING THE ULTIMATE COST OF CLOSED CLAIMS, BY YEAR OF DEVELOPMENT



As we can see from Figure 1, the claim handler overestimates the ultimate load over the majority of development years. In order to refine this study, we carry out an additional descriptive analysis by variable, to determine on which segments the claim handler is most mistaken. Thus, for example, Figure 2, which represents the ultimate's prediction errors as a function of development years and as a function of vehicle age, shows that claim handlers tend to overestimate the expense of claims on vehicles over 10 years old.

FIGURE 2: ERRORS MADE BY CLAIM HANDLERS IN ESTIMATING THE ULTIMATE COST OF CLOSED CLAIMS, BY YEAR OF DEVELOPMENT AND BY VEHICLE AGE



This descriptive analysis does not take into account the cross-effects of the variables. To identify the variables "responsible" for the errors, we need to carry out a generalised linear model (GLM) type of study of the errors.

BACK-TESTING EXERCISE TO EVALUATE A "FAIR" ULTIMATE

For a year N of back-testing, some RBNS claims seen at the end of year N are still not closed in 2020 (the last year of base observation available). On the other hand, some of these RBNS claims are closed between 31 December of N and 2020, and so we have information on their final dates of closure. We then compare the case reserve for year N, for these RBNS claims, with their ultimate. The estimated global provision given by the claim handler overestimates the total ultimate paid by at least 20% (and up to 44%).

Thus, by correcting the case reserves for each RBNS claim seen at the end of 2020 by 20% (to remain conservative and indirectly take into account our expectation that claims which have closed would be the least serious), we would obtain a "fair ultimate" that could be compared to the results of other models.

CLUSTERING ANALYSIS OF CLOSED CLAIMS

Finally, we sought to describe the database intelligently, in order to understand the link between covariates and the ultimate. To do this, we decided to build homogeneous groups of claim files, in terms of claim experience. Thus, we build clusters on closed claim files, using the Classification and Regression Trees (CART) algorithm. This construction is then used to refine the model estimate’s parametric models, which do not necessarily take co-variables into account in their specifications. In this way, these clusters will enable us to calibrate the model for each of the groups constructed, and thus distinguish expected future payments according to clusters.

Modelling framework and calibration

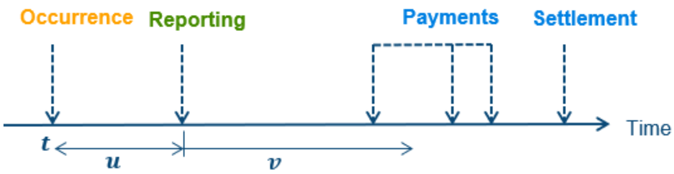
The chain-ladder method is widely recognised as effective for estimating ultimate attritional losses for traditional lines of business. However, it may sometimes be unsuitable for reserving large claims or for lines of business where the application of chain-ladder may be difficult, such as reserving for drought-related claims in the home insurance line of business.

Therefore, the use of individual claim reserving models may be more appropriate in these cases. In order to be able to compare two main families of models when estimating the amount of the RBNS reserve, we test different reserving models using detailed data, both a parametric model, defined by (A. Boumezoued and L. Devineau., 2017), and a nonparametric machine learning model.

A PARAMETRIC MODEL: STOCHASTIC STATE-BASED MODEL

Based on the study framework defined by (A. Boumezoued and L. Devineau., 2017), the analysis of individual claims necessitates methodologies that can capture the intricate development of each claim in detail. To meet this requirement, a modelling framework that is "claim-based" is necessary, which includes a precise, continuous-time description of the claim's life cycle (as depicted in Figure 3). This description should account for the time at which the claim was reported, any delays in its reporting, the various payments made over time, the changes to the case reserve and their respective time stamps, as well as the closure date of the claim. This modelling framework can be made adaptable to accommodate line-of-business specificities, such as recoveries and re-openings.

FIGURE 3: INDIVIDUAL CLAIM PATHS



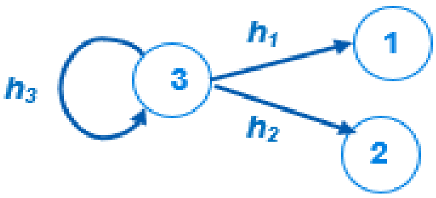
The individual claim paths are modelled with continuous-time stochastic processes. In our study we are interested in the payments and closing block of the claim development.

Payments and settlement events are modelled using three types of events:

1. Settlement without payment at settlement
2. Settlement with payment at settlement
3. Payment without settlement

Each type of event (1, 2 or 3) occurs according to its specific intensity parameter $h_1(v)$, $h_2(v)$ or $h_3(v)$ and can be seen as a recursive competing risk model, as shown in Figure 4.

FIGURE 4: MODELLING PAYMENTS AND SETTLEMENTS



If an event $i \in \{2,3\}$ occurs v time units after reporting, then random payments $Y_i(v)$ are generated.

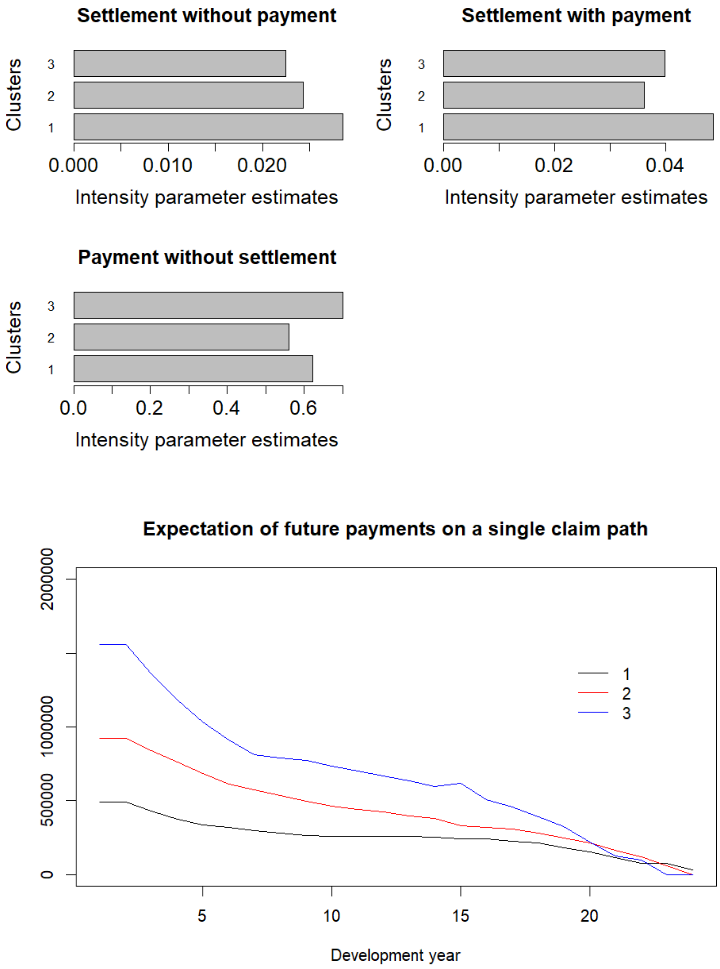
To estimate the parameters for an individual claim model, a calibration procedure is performed based on the likelihood of maximisation. In addition, the estimated parameters can provide a natural explanation of the data, such as average settlement times. In addition, separate specifications for the distribution of payments can provide information on the different elements of the overall claim development trajectory. The parameters thus allow for a more detailed monitoring of key risk indicators, which, unlike the triangle-based approaches, are hidden in the aggregate development factors.

On the other hand, the calibration of the model presents some difficulties regarding the calibration of the payment distribution, and these difficulties arise in the search for a set of rules that fits the payments well.

Finally, once the parameters are estimated and the set of rules for payment is calibrated, the RBNS reserves can be estimated. This can be done using simulation procedures that rely on stochastic trajectories of the future evolution of RBNS claims. The procedure allows the user to predict future events in a very efficient way.

In its specification, the model also allows for closed formulas that provide aggregate estimates of unpaid claims. The main elements of the individual reserving method are illustrated in Figure 5.

FIGURE 5: INDIVIDUAL RESERVING RESULTS



In addition, supervised clustering prior to parametric model calibration enables individual claims to be grouped by homogeneous characteristics and distinguished according to their severity: In this way, we can observe different frequencies associated with payment and closure events, depending on the group. This segmentation also enables us to calculate, using closed formulas, the expectation and variance of future payments by group and by year of development. Furthermore, the implementation of this model shows that it is sensitive to the calibrated set of rules for payment, as well as to the composition of the database in terms of the number of closed claims and RBNS claims.

A NONPARAMETRIC MACHINE LEARNING MODEL

In this section, we present an example of a nonparametric machine learning model, based on random forest learning.

The model is implemented using two different approaches:

1. In a first step the model is trained on closed claims only (Model A).
2. Then in a second step the same model is trained on closed and RBNS claims (Model B) to exploit all the information in the database to the maximum.

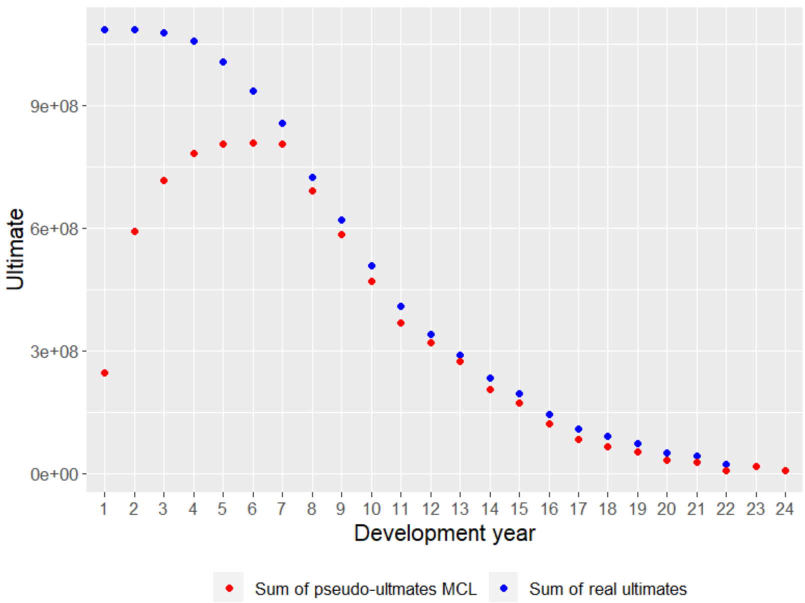
Calibration specifications: The initial database was randomly split into two independent sub-databases, a training database and a test database. In order to keep an identical proportion of claims with cumulative paid to date exceeding 500,000 or more in both databases we used stratified partitioning. The algorithm is trained on 80% of the victim subfiles, then tested on the remaining 20%. Both models (A and B) have almost 90% of variance explained on the training data. On the test database, performance is not as good, and we observe a phenomenon of overlearning despite the optimisation of the model's hyper-parameters. This can be explained by the low volume of observations in the database, as well as by the absence of variables that are particularly predictive of the ultimate outcome (e.g., the type of care provided to the victim, the post-accident victim's disability rate, etc.). With the first approach, Model A, several elements can bias the results:

- A selection bias appears because the claims already closed at the date of provisioning may have a shorter development.
- Claims with a shorter development may tend to have lower total paid amounts.
- In addition, a significant proportion of claims is removed from the analysis (40%), resulting in a loss of information.

In order to overcome the disadvantages of the first approach we can consider a second approach, which consists in including the RBNS in the training database, completing their trajectory thanks to the chain-ladder development coefficients calibrated on the aggregate triangle corresponding to the data. We refer to the completed trajectory values for RBNS based on the Mack chain-ladder as “pseudo-ultimate” values, and the completed trajectory values for closed claims as “real ultimate” values.

By developing RBNS with "pseudo-ultimate" values, we end up with two types of errors: an error carried by the "pseudo-ultimate" value and a prediction error of the model.

FIGURE 6: COMPARISON OF REAL AND PSEUDO MACK CHAIN-LADDER (MCL) ULTIMATES



The calculated "pseudo-ultimates" underestimate the true ultimate in development years 1 to 8, but these differences decrease in the longer development years. These results are not surprising. In fact, the claims of the branch studied have long developments, the payments observed in the first years do not reflect the real ultimate and this is therefore reflected in the calibrated development factors.

In order to judge the performance of the implemented models a back-testing exercise is carried out. The principle of this exercise consists in placing oneself at the end of year N (N going from 2010 to 2018) and then evaluating the RBNS claims which are closed before the end of 2019 and comparing predicted ultimate values with the “real ultimate” values.

FIGURE 7: PREDICTION ERRORS BETWEEN THE REAL ULTIMATE AND THE DIFFERENT MODELS

Year N	Manager	Model A	Model B
2010	25%	-9%	2%
2011	34%	4%	4%
2012	41%	6%	15%
2013	38%	10%	14%
2014	44%	11%	13%
2015	29%	-2%	9%
2016	32%	-3%	29%
2017	28%	17%	31%
2018	21%	14%	37%

The overall reserve estimated by the manager overstates the total ultimate payout by at least 20%. On the other hand, the differences between the actual ultimate values and the predictions of Model A are relatively small, but Model A underestimates the ultimate for the back-test years 2010, 2015 and 2016 and provides overall results that afford little room for caution when compared to other models. Finally, the differences obtained between the actual ultimate values and the predictions of Model B are reduced better than those obtained by the loss manager, although the model still overestimates the ultimate.

Although the machine learning models allowed us to identify the main available variables influencing the amounts of charges and to distinguish the prediction errors on the test base according to the class of ultimate (ultimate lower than €500,000 and ultimate higher than €500,000), the modelling framework provides more opportunity to correct the errors of the model, as we are able to spot where the model is wrong. Nevertheless, machine learning models still present some limits such as:

- The phenomenon of overlearning persists despite the optimisation of the hyper-parameters due to the small volume of the database.
- Predictive covariates are the key: to be efficient, a machine learning model must contain variables that predict the target variable. In the case of our study, we therefore needed variables directly related to the severity of the claims, such as the permanent partial disability rate. However, this type of variable is not widely available in insurance company structured data.
- A very large part of the error of the implemented Model B is carried by the pseudo ultimate and not by the prediction error of the model.

Results and comparison with aggregated standard methods

We recall from above that the claim manager has overestimated the ultimate values of closed claims by at least 20%. A "fair" ultimate would rather be equal to €2 billion to €2.1 billion, while remaining prudent.

We recall that aggregate methods do not allow us to separate the IBNR reserve from the RBNS one. Thus, the main difficulty with this study lies in estimating the reserves by distinguishing a reserve for RBNS and a reserve for IBNR. In order to build up the RBNS reserve we remove the overall reserve of "severe" late arrivals. To do this, we project the triangle of numbers related to the observation of serious claims: we construct the triangle "Year of claim occurrence" x "Year of exceeding the €500,000 threshold." In this way we project a number of "severe" late claims. Then the number of late arrivals is divided by the total number of files still open in 2019, to constitute a percentage of "serious" late arrivals. The overall reserve is then adjusted by the proportion of "serious" late arrivals in order to constitute the reserve specific to RBNS.

Comparing the results of the parametric model with the results of the trained model on closed claims and completed RBNS (Model B), we find that the parametric model results in ultimate values that are €0.3 billion higher than that estimated by the trained model. The estimate of the global Random Forest Model B is closer to the "fair" ultimate. The results obtained with the chain-ladder and Mack methods are—as expected—almost identical. This estimate is consistent with the estimate of the two individual models and the ultimate "fair."

In terms of uncertainty around the value of the estimated reserve, the implemented models cannot all be compared based on the same measurements, but we have summarised all the measurements available for each model. Moreover, we recall that with Mack's method it is possible to calculate the root-mean-square error (RMSE) and separate it into process error (pure randomness due to the stochastic nature of future trajectories) and estimation error (related to the uncertainty on the value of the estimated parameters), but a study of the IBNR would be necessary to calculate these values specifically for RBNS claims.

The table in Figure 8 summarises the ultimate estimates as well as the 90% confidence intervals constructed on the prediction when possible:

FIGURE 8: COMPARISON OF RESULTS FROM DIFFERENT METHODS FOR RBNS

Model	Ultimate (in Bn €)	RMSE (in Bn €)	Process error (in Bn €)	Estimate error (in Bn €)	Lower bound (in Bn €)	Upper bound (in Bn €)
Parametric Model	2.3	0.37	0.07	0.30	2.2	2.4
Model B	2.0	NA	NA	0.18	1.9	2.1
Chain Ladder	2.1	NA	NA	NA	NA	NA
Mack	2.1	NA	NA	NA	NA	NA

In conclusion, at this stage, we cannot say that one model is better than another: the implementation of these different individual models essentially makes it possible to obtain valuable information on the development of claims according to their characteristics and may make it possible to obtain more refined estimates by subpopulations.

Flexibility of individual claim reserving models

As already mentioned, the fundamental contribution of individual provisioning methods lies in the flexibility of their scope and specification, and in the integration of the detailed information they provide.

The aim, therefore, is to consider the specific features of the portfolio we are working on, in order to exploit the flexibility of the model and assess the extent to which this flexibility can improve results.

The specificity of the database studied here lies in the fact that the claims are severe and have therefore exceeded a certain case reserve threshold during their development. However, the parametric model calibrated above does not take this threshold crossing into account, whereas, intuitively, the payment distributions could be different depending on the position of the cumulative payment to date or the case reserve.

It should be remembered that claims are considered to be serious as soon as the threshold of €500,000 of incurred loss is exceeded. In other words, "a serious claim one day is a serious claim forever." However, a study of the trajectories of closed claims in the database often shows that case reserve corrections bring individual claims below the €500,000 threshold, as shown in Figure 9. Nevertheless, the claim is still considered serious.

FIGURE 9: EXAMPLE OF INCURRED TRAJECTORY (IN RED) AND CUMULATIVE PAYMENT (IN GREEN)

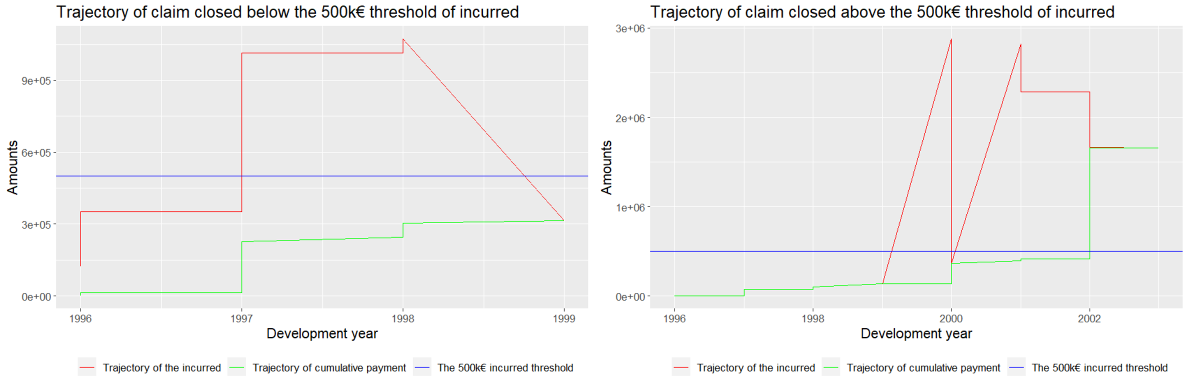


Figure 9 shows that the trajectory of cumulative payments is different depending on whether the claim is closed below or above the threshold. In the first case (claim closed below the threshold), the cumulative payment remains below the €500,000 threshold until it is closed. In the second case (claim closed above the threshold), the cumulative payment exceeds €500,000 and does not fall below it again until it is closed.

Thus, it would be interesting to take the threshold-crossing feature into account in the calibration of the parametric model. Indeed, the intuition underlying this refinement of the parametric model is that the distributions of payments would be different depending on whether we have already passed the threshold or not, with potentially larger payments if we are above the threshold. Moreover, 52% of closed claims in the database have an ultimate value below €500,000, so it is possible that the estimated reserve is lower than with the global model, as we would apply a lower distribution to a large portion of the claims.

In order to consider this threshold-crossing event, we calibrate the payment and closing events according to the position of the last cumulative payment associated with each of the files, then we calibrate two payment laws by separating the payments associated with the files for which the last cumulative payment is greater than €500,000 from those less than €500,000.

The estimated reserve amounts to €1.00 billion, which is significantly lower than the base model of €1.67 billion. Nevertheless, it is in line with the fact that a significant proportion of serious claims are closed at a cost below the severity threshold. Consequently, it questions the principle that assumes that, when a serious claim occurs, it remains serious until the settlement. Besides, individual reserving enables more refined predictions, by distinguishing payments associated with claims that turn out to be nonserious at closing.

Conclusion

In summary, individual claim reserving models, while more intricate in comparison to conventional aggregate approaches, offer a deeper level of insight into estimated provisions. Despite their inherent complexity and potential limitations, these models provide a richer understanding of the underlying data. Furthermore, a thorough examination of reserves established with claim handlers, incorporating covariates, proves highly beneficial for insurers in its own right.

This would enable them to identify the variables that explain the differences between claim-by-claim reserves and reserve revisions, as well as the ultimate reserve estimate, in each year of claim development. It can be particularly useful for setting up provisioning tools that allow better and more objective management of the rules for allocating reserves.

Finally, the modular structure of individual claim reserving models allows for a tailored approach to address the unique characteristics and intricacies of the claims within the specific line of business under examination. This adaptability ensures a more precise and accurate estimation of reserves, as it accommodates the distinctive patterns and behaviours inherent to the studied domain. Individual modelling in non-life reserving is an area in which a great deal of work remains to be done, in particular:

- Further study of IBNR modelling in order to facilitate comparison between the uncertainty indications from individual claim reserving models and those of the classic Mack method.
- Application of the models on a voluminous database including variables directly related to claim severity. Note that the data required to build individual models is also needed to build triangles, so in theory it is available. However, in practice, the information systems may not have kept track of them in a structured way, the quality of the underlying data is not sufficient, or

the joins are not consistently made (e.g., it must be possible to make the link between the contracts and claim databases to obtain the precise characteristics of the policyholder involved, etc.).

- An in-depth study of the variability of the models, and above all the comparison of the different models in terms of overall error, estimation and process.

In conclusion, at this stage, we have no proof that individual models are better, in terms of best estimate, than conventional aggregate methods. Moreover, their implementation may prove more complex. However, in cases where conventional methods struggle to provide stable and reliable results, these innovative models are good alternatives and/or complements, in order to estimate reserves with as little error as possible and identify sub-groupings whose development behaviour is similar, which would reduce heterogeneity.

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CONTACT

Eve-Elisabeth Titon
EveElisabeth.Titon@milliman.com

Tinhinane Talbi
Tinhinane.Talbi@milliman.com